# Influence of Human Reaction Time 

## in Human-Robot Collaborative

## Target Recognition Systems

Thesis submitted in partial fulfillment of the requirements of the M.Sc degree

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#### Abstract

Autonomous robots show inadequate results in dynamic and unstructured environments. Integrating a human-operator into a robotic system can help improve performance and reduce system complexity. Collaboration between a human-operator and a robot, benefits from both human's perception skills and the robot's accuracy and consistency. Various levels of collaboration can be applied; each level differs by the degree of autonomy of the robot.

This thesis focuses on evaluation of an integrated human-robot system for target recognition tasks. The work is based on previous work developed by Bechar (2006). In his work, four collaboration levels were designed specifically for target recognition and an objective function was developed to quantify the influence of parameters of the robot, human, environment and task, through a weighted sum of performance measures. The model developed by Bechar (2006), enables to determine the optimal level of collaboration based on these parameters.

The human reaction time in target recognition is the time required for the observer to decide whether an object is target or not. Reaction time influences the operational cost of the system. In Bechar's work, the reaction time was constant. This thesis introduces further development of the objective function; considering the fact that reaction time of the human depends on the signal strength of the observed object, which is not constant and equal for all objects. A reaction time model, based on Murdock (1985) is incorporated into Bechar's model and analyzed.

The new model is expected to describe actual systems in a better way by adjusting time parameters to a specific task. The study evaluates the influence of human's reaction time on the performance of an integrated human-robot target recognition system. Particularly, the study focuses on how reaction time affects the level of human-robot collaboration that results in best performance. The thesis presents the mathematical model developed and results of the simulation analysis.

The analysis reveals new collaboration levels that were derived automatically from the defined ones and are preferable when human reaction time cost is high. In these collaboration levels, the human concentrates only on part of the objects and ignores others. Therefore, the system reduces the total human reaction time cost resulting in better performance.

The human ignores objects by setting his cutoff point to an extreme value. The analysis shows how the system type, the human sensitivity, the probability of an object to be a target, and the time cost, all influence the phenomena of extreme cutoff point selection.


When human sensitivity is low, the human badly discriminates between targets and other objects. When the system gives high priority for not causing false alarms, the human prefers an extreme positive cutoff point, resulting in no objects marked as targets, and no false alarms. For systems that give high priority for not missing targets, an extreme negative cutoff point was preferred; resulting in all objects marked as targets and no misses.

The analysis shows that the time costs affect the position of the optimal cutoff point. The phenomenon, introduced above, arises for higher human sensitivities as the time cost is higher. Furthermore, the analysis shows that collaboration with a human is less profitable in cases when the time cost is high.

An extreme cutoff point position decreases the total operation time cost. In the reaction time model, the mean response time reduces as the cutoff point is far from the mean of the distribution; therefore, in the sense of time costs, the extreme cutoff point is always preferred.

The position of the cutoff point influences all other parts of the objective function. An extreme positive cutoff point, for example, causes small probabilities of false alarms and hits; and causes high probabilities of miss and correct rejections. The overall gains and penalties of these outcomes are modified accordingly.

Keywords: Human-robot collaboration, collaboration levels, reaction time, target recognition.

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## 1 Introduction

Despite intensive R\&D efforts in robotics, autonomous robots can still not perform reliably in "realworld" conditions (Bechar et al., 2009). Current robotic systems are best suited for applications that require accuracy and high yield under well defined and known conditions (Bechar, 2006). They cannot cope with unexpected situations encountered in unstructured and changing environments. A major problem in most robotic systems is target recognition. In detection of natural objects, this is especially problematic since the objects have high degrees of variability in shape, texture, color, size and position (Bechar, 2006). This as well as the limitations of sensor technologies and the changing environmental conditions (e.g., lighting, occlusion) prohibits the use of completely autonomous systems in such environments (Dubey \& Everett, 1998). Humans on the other hand, can easily fit themselves into such changing environments. By taking advantage of the human perception skills and the robot's accuracy and consistency, the combined human-robotic system can be simplified, resulting in improved performance (Bruemmer et al., 2005).

This thesis is based on a previous work (Bechar, 2006) which focused on development of an objective function for human robot collaborative systems for target recognition task. Bechar (2006) developed four levels of collaboration for target recognition: two independent levels, autonomous $(\mathrm{R})$ and manual $(\mathrm{H})$, and two levels that define collaboration between the human operator and the robot. The first one (HR) is a collaboration level where the robot indicates potential targets and the human operator, follows and confirms real targets and adds targets the robot missed. In the second collaboration level (HOR), the human supervises the robot. The robot itself marks targets and the human operator checks its' marks. The human operator cancels false targets and mark targets that the robot missed. In addition, a method to determine the best level of collaboration was developed (Bechar, 2006). The best collaboration level is the level that achieved the highest system performance. The system objective function enabled to determine the expected value of task performance, given the parameters of the system, the task, and the environment. The objective function composed of the four penalties or rewards of the recognition process (i.e., hit, correct detection, false alarm and miss) and the system operational costs. The operational costs partially consist of the cost of time, spent during system operation. The cost of the human decision time, which is the time takes the human to decide whether an object is a target or not, is the main part out of the total operational costs.

The objective function of Bechar's model considered the human decision time as a constant. However, it is known that reaction time in target recognition should take into account factors as the strength of the observed object, which is not constant (Murdock \& Dufty, 1972; Pike, 1973; Murdock, 1985). This thesis introduces further development of the model by incorporating nonconstant reaction times. The new model, proposed in this research, provides a better description of actual systems by adjusting time parameters to a specific task and taking into consideration the fact that reaction time of the human depends on the strength of the observed object. Evaluating the best collaboration level according to the new model, considers the influence of human reaction time on system performance.

This thesis evaluates the influence of human reaction time on the performance of a collaborative target recognition system. Particularly, the study focuses on how reaction time affects the recommended level of human-robot collaboration. The research aims to: (1) adjust a reaction time model to the objective function of a collaborative target recognition system, and (2) perform a thorough numerical analysis of the objective function in order to evaluate the influence of the human reaction time.

The dissertation is organized as follows: chapter 2 presents a literature review on autonomous robots, human-robot collaboration, target recognition and reaction time models. The literature review also includes description of Bechar's model and signal detection theory. The methodology chapter (chapter 3) outlines the research. Chapter 4 presents the development of the reaction time model and show how it is incorporated into Bechar's model. Chapters 5 and 6 show the numerical and sensitivity analyses of the new model. The thesis concludes in chapter 7, which includes research limitations and discussion of future research.

## 2 Literature Review

The review includes seven main topics: (1) automation, (2) human-robot collaboration, (3) collaboration types and levels, (4) collaboration in target recognition task, (5) introduction of a collaborative model for target recognition, (6) signal detection theory, and (7) reaction time models.

### 2.1 Automation

"Machines, especially computers, are now capable of carrying out many functions that at one time could only be performed by humans" (Parasuraman et al., 2000).

Parasuraman et al. (2000) defined automation as a device or system that accomplishes (partially or fully) a function that was previously carried out (partially or fully) by a human operator. These functions are often things that humans do not wish to perform, or cannot perform as accurately or reliably as machines.

A teleoperator is a machine that extends a person's sensing and/or manipulating capability to a remote location (Sheridan, 1992). The term Teleoperation refers most commonly to direct and continuous human control of the teleoperator (Sheridan, 1992).

Recently, robots take part of many aspects of our society, from military uses to medicine; from entertainment to home and office laborers; for use on land, sea, air, and space (Bruke et al., 2004). Robot teleoperation, still the primary mode of operation in today's human-robot systems, can be highly successful and irreplaceable, but these systems are also very limited and expensive (Bruke et al., 2004).

### 2.2 Human-robot collaboration

Autonomous robots are systems that can perform tasks without human intervention. They are best suited for applications that require accuracy and high yield under stable conditions, yet they lack the capability to respond to unknown, changing and unpredicted events (Bechar, 2006). Humans, dissimilarly, can easily fit themselves into changing environment (Bechar, 2006). In general, human and robot skills are complementary (Rodriguez \& Weisbin, 2003). By taking advantage of the human perception skills and the robot's accuracy and consistency, the combined human-robotic system can be simplified, resulting in improved performance (Bechar et al., 2009).

The unstructured nature of the tasks as well as the limitations of the current sensor technologies prohibits the use of completely autonomous systems for remote manipulation (Dubey \& Everett, 1998). Hence, teleoperated systems, in which humans are an integral part of the control, are most often used for performing these tasks (Dubey \& Everett, 1998). Usage of remote mobile robots takes advantages of human intelligence and machine proficiency (Bruemmer et al., 2005).

However, many applications still use robots as a passive tool and the cognitive burden of all decisions are placed on the human operator. Sometimes it is assumed that autonomy (i.e., full independence) is the ultimate goal for remote robotic systems (Bruemmer et al., 2005). Bruemmer et al. (2005) suggested that effective teamwork, where the robot is a peer, is an equally profitable aim. In their experiments, they tried to provide evidence for a form of collaborative control where robots are regarded as peers and effectively used as trusted team members (Bruemmer et al., 2005).

Sheridan (1992) states seven motivations to develop supervisory control:
"(1) to achieve the accuracy and reliability of the machine without sacrificing the cognitive and adaptability of the human; (2) to make control faster and unconstrained by the limited pace of the continuous human sensorimotor capability; (3) to make control easier by letting the operator give instructions in terms of objects to be moved and goals to be met, rather than instruments to be used and control signals to be sent; (4) to eliminate the demand for continuous human attention and reduce the operator's workload; (5) to make control possible even where there are time delays in communication between human and teleoperator; (6) to provide a "fail-soft" capability when failure in operator's direct control would be proved catastrophic; and (7) to save lives and reduce cost by eliminating the need for the operator to be present in hazardous environment, and for life support required to send the operator there." (Sheridan, 1992)


Figure 1: The notions of trading and sharing control between human and computer. L is the load or task, H is the human, and C is the computer (Sheridan, 1992)

Sheridan (1992) explained the difference between sharing and trading control. Sharing control means that the human and the computer control different aspects of the system on the same time. When the computer extends human's capabilities or relieves the human by making her job easier, they are sharing control (Figure 1). Trading control, on the other hand, means that either the human or the computer turns over control to the other. When the computer backs up or replaces the human operator, they are trading control (Sheridan, 1992). Both sharing and trading control are relevant in human-robot collaboration.

A main issue in space exploration is to decide what human or robotic system (or a suitable combination of the two) is most appropriate to use in those exploration tasks (Rodriguez and Weisbin, 2003). Rodriguez and Weisbin (2003) introduced a method to evaluate systematically the relative performance of some optional human-robot systems, in order to decide which type of assets to use in a given situation. First, they decompose the space scenario that needs to be analyzed into a set of major functional operations. For each of the functional operations, they define a set of performance metrics to be used in the evaluation. Then they specify the agents (robot, human or a combination) to be evaluated, together with the resources needed for their implementation. The performance of each agent is then evaluated for each of the functional operations, and a score, which estimates the aptitude of each agent for each operation, is determined. A composite score is then computed for each agent and a comparison between systems' performances is done.

### 2.3 Collaboration types and levels

As aforementioned, automation refers to the full or partial replacement of a function previously carried out by a human operator (Parasuraman et al., 2000). This means that automation can differ from the lowest level of manual performance through some levels of collaboration between the human and the robot up to the highest level of full autonomy (Parasuraman et al., 2000).


Figure 2: Simple four-stage model of human information processing (Parasuraman et al., 2000)
Parasuraman et al. (2000), in their article: "Types and Levels of Human Interaction with Automation", revealed a four-stage model of human information processing (see Figure 2). The first stage, Sensory Processing, refers to the acquisition and registration of multiple sources of information. The second stage, Perception/Working Memory, involves conscious perception and manipulation of processed and retrieved information in working memory. This stage also includes cognitive operations, but these operations occur prior to the point of decision. The third stage, Decision Making, is where decisions are made based on such cognitive processing. The fourth and final stage, Response Selection, involves the implementation of a response or action consistent with the chosen decision (Parasuraman et al., 2000).

One can divide system functions into four classes that match each of the four stages in human information processing (Parasuraman et al., 2000): (1) information acquisition, (2) information analysis, (3) decision and action selection, and (4) action implementation. Automation can be implemented in each of these functions. A particular system can involve automation of all four
dimensions at different levels as shown in Figure 3 (Parasuraman et al., 2000). Each of these dimensions can be automated in varying levels of automation. The levels of automation of decisionmaking, that will be introduced later, can be applied, with some modifications, also to the other dimensions.


Figure 3: Levels of automation for independent functions of: information acquisition, information analysis, decision selection, and action implementation (Parasuraman et al., 2000)

Sheridan (1978) described ten levels of automation of decision and action selection. Table 1 shows different levels of automation, with higher levels representing increased autonomy of the system. At the low levels, the operator must get involved in order to accomplish an operation. Under level 6 or higher, the system will automatically execute its own resolution unless the operator intervenes (Parasuraman et al., 2000).

Table 1: Scale of Levels of Automation of Decision and Control Action (Sheridan, 1978)

| HIGH | 10. | The computer decides everything and acts autonomously, ignoring the human. |
| :---: | :---: | :---: |
|  | 9. | Informs the human only if it, the computer, decides to |
|  | 8. | Informs the human only if asked, or |
|  | 7. | Executes automatically, then necessarily informs the human, and |
|  | 6. | Allows the human a restricted time to veto before automatic execution, or |
|  | 5. | Executes that suggestion if the human approves, or |
|  | 4. | Suggests one alternative, and |
|  | 3. | Narrows the selection down to a few, or |
|  | 2. | The computer offers a complete set of decision/action alternatives, or |
| LOW | 1. | The computer offers no assistance: the human must take all decisions and actions |

### 2.4 Examples of collaboration levels

Levels of collaboration are sometimes referred to as modes of operation of the given humanrobot system. Following we describe examples of collaboration levels implementations in different applications. All of the examples include fully autonomy and fully manually levels, which consist of a single collaborator without any cooperation. The collaboration levels differ by nature, scale, structure, and number of levels.

Bechar and Edan (2000) evaluated two collaboration levels for agriculture robot guidance through an off-road path. Two different guidance methods were tested: Directional guidance, where the gross direction of advance is being marked and Waypoint guidance, where the system draws the desired course of advancing along the path. Two collaboration levels were examined for each guidance method: HO, where the human-operator marks the desired direction/course solely; and HO-Rr, here the human-operator marks the desired direction/course with recommendations from the robot (Bechar \& Edan, 2000).

Bruemmer et al. (2005) defined four control modes of a remote mobile robot in an in-door search and exploration task. (1) Tele Mode is a fully manually mode of operation, in which the operator controls all robot movements. (2) Safe Mode is similar to Tele Mode. However, in Safe Mode the robot is equipped with a level of initiative that prevents the operator from colliding with obstacles. (3) Shared Mode, the robot can relieve the operator from the burden of direct control, using reactive navigation to find a path based on perception of the environment. The robot accepts operator intervention and supports dialogue using a finite number of scripted suggestions (e.g., "Path blocked! Continue left or right?"), that appear in a text box within the graphical interface. (4) Autonomous Mode consists of series of high-level tasks such as patrol, search region or follow path. In this mode, the only user intervention occurs on the tasking level; the robot itself manages all decision-making and navigation (Bruemmer et al., 2005).

Bechar (2006) developed four collaboration levels for target recognition: Fully autonomous level (R), in which the robot fulfills the task all by itself; and fully manually level (H), where the human-operator does not use any help of the robot. Two more levels define collaboration between the human operator and the robot. The first one (HR) is a collaboration level where the robot indicates potential targets and the human operator at the following stage needs to mark the targets he thinks are real and to add marks of targets the robot did not indicate. In the second collaboration level (HOR), the human supervises the robot. The robot itself marks targets and the human operator checks its' marks. The human operator unmarks targets that are not real and mark targets that the robot missed (Bechar, 2006).

Hughes and Lewis (2005) designed a remote robotic system for a search and exploration task. In order to control the robot, one or two cameras feed the human operator with live video from the remote environment. Hughes and Lewis used two different levels of control on the cameras. At the first one, Sensor-Driven Orientation, the operator supervises the camera while a guided-orientation system recommends it where to look. Whenever the operator wants to, she can take control over the camera, overriding system's recommendations. The other level, User-Controlled Orientation, the camera is all the time under operator's control.

Czarnecki and Graves (2000) described a scale of five human-robot interaction levels for a telerobotic behavior based system.

Most of these applications determine the best collaboration level for specific system and mission conditions. Experiments were conducted in order to compare performance under different levels of collaboration. Generally, the main conclusion was that systems perform better, in different aspects, when human and robot collaborate. Moreover, the level of autonomy should not be arbitrary and the user should be able to set robot's level of autonomy according to environment or task constraints (Steinfeld, 2004). Team members (humans and robots) must recognize changing situations and adapt the best collaboration level to ensure that the mission is done successfully (Bruke et al., 2004). An expansion of Bechar's research (2006) will follow in the next section.

### 2.5 Collaboration in target recognition tasks

Target recognition is a common and critical element in most robotic systems (Bechar, 2006). For example, the detection of parts in assembly lines, the detection of landmarks in autonomous navigation, or the detection of fruits for robotic harvesters. Target recognition is a common and important topic in many other research areas such as medical and brain research, quality assurance, human factors, agriculture and remote sensing (Bechar, 2006). Automatic target recognition in agriculture environment is characterized by low detection rates and high false alarm rates due to the unstructured nature of both the environment and the objects (Bechar \& Edan, 2003).

Target recognition is a mission in which the system needs to mark objects as targets (Bechar, 2006). Typical systems for target recognition use a sequence of algorithms that operate in different stages in order to achieve recognition (Bhanu et al., 2000). A vision analysis based algorithm is used in order to decide whether an object is a target or not (Bulanon et al, 2001). For example, Bulanon et al. (2001) made use of color difference of red histogram in order to recognize apple fruits in images of CCD camera (Figure 4). Bhanu et al. (2000) went farther and proposed a learning-based target recognition system that is capable of automatically adjusting its procedural parameters in order to achieve adaptive target recognition process.


Figure 4: Vision analysis for apple fruit detection (Bulanon et al, 2001)
(a) CCD image, (b) segmentation of color difference of red, (c) color difference of red histogram

Bechar, in his Ph.D. thesis (2006), examined human-robot collaboration for target recognition. Four collaboration levels were defined and a method to determine the best collaboration level was evaluated. To measure system performance under different collaboration levels an objective function has been developed (Bechar, 2006). The objective function includes five parts: hit (correct detection), false alarm, miss, correct rejection, and operational cost. Each of the first four parts represents penalties or rewards of the recognition process. For instance, when a correct detection occurs, meaning a real target was detected by the system, a reward is summed to the objective function. Likewise, a penalty is taken into account when a target is missed or when the system makes false alarm, marking a non-target as a target (Bechar, 2006).

Bechar (2006) found that the H collaboration level is never the best collaboration level probably due to its high operational cost and low hit rate relative to the other collaboration levels. Thus, collaboration of human and robot in target recognition tasks will always improve the optimal performance. The combination of both human and robot in the HOR collaboration level increases the system sensitivity in most cases and increases the probability of a hit while reducing the probability of false alarms. In addition, findings indicated that when robot sensitivities are higher than human sensitivities the best collaboration level is R (Bechar, 2006).

Oren, in his B.Sc final project (2007), continued Bechar's work and performed sensitivity analyses of the objective function in order to understand how changes in different parameters (human, robot, task, and environment) influence performance of the integrated human-robot system.

Oren et al. (2008) found that an increase in human and/or robot sensitivity causes an increase in the objective function score and in fact, increases system's performance. Superior sensitivity means better capability to discriminate between a signal (target) and a noise (no target) and therefore, more hits and fewer false alarms occur (Oren et al., 2008). In addition, a sensitivity analysis of the thresholds (see interpretation in Signal Detection Theory subchapter, 2.7) exposed that in some cases, a small deviation from the optimal value causes shifts in the best collaboration level.

### 2.6 Collaborative model for target recognition (Bechar, 2006)

This chapter details the objective function of the collaborative model developed by Bechar (2006) for target recognition tasks.

The objective function describes the expected value of system performance, given the properties of the environment and the system. The goal is to maximize the objective function. The value of the objective function can be translated into a monetary value. The objective function composed of the four responses of the target detection process and the system operational costs:

$$
V_{I s}=V_{H s}+V_{M s}+V_{F A s}+V_{C R s}+V_{T s}
$$

Where $V_{H s}$ is the gain for target detections (hit), $V_{F A s}$ is the penalty for false alarms (FA), $V_{M s}$ is the system penalty for missing targets (miss), $V_{C R s}$ is the gain for correct rejections (CR), and $V_{T s}$ is the system operation cost. All gain, penalty and cost values have the same units, which enable us to add them together to a single value, expressed in the objective function.

The gain and penalty functions are:

$$
\begin{aligned}
& V_{H s}=N \cdot P_{S} \cdot P_{H s} \cdot V_{H} \\
& V_{M s}=N \cdot P_{S} \cdot P_{M s} \cdot V_{M} \\
& V_{F A s}=N \cdot\left(1-P_{S}\right) \cdot P_{F A s} \cdot V_{F A} \\
& V_{C R s}=N \cdot\left(1-P_{S}\right) \cdot P_{C R s} \cdot V_{C R}
\end{aligned}
$$

Where, $N$ is the number of objects in the observed image and $P_{S}$ is the probability of an object becoming a target. The third parameter in the equations, $P_{X s}$, is the system probability for one of the outcomes: hit, miss, false alarm or correct rejection ( $X$ can be $H, M, F A, C R$ ). The fourth parameter, $V_{X}$, is the system gain or penalty from the expected outcome.

The system's probability of a certain outcome is influenced from the serial structure of the model and is composed of the robot and the human probabilities:

$$
\begin{aligned}
& P_{H s}=P_{H r} \cdot P_{H r h}+\left(1-P_{H r}\right) \cdot P_{H h} \\
& P_{M s}=P_{M r} \cdot P_{M h}+\left(1-P_{M r}\right) \cdot P_{M r h} \\
& P_{F A s}=P_{F A r} \cdot P_{F A r h}+\left(1-P_{F A r}\right) \cdot P_{F A h} \\
& P_{C R s}=P_{C R r} \cdot P_{C R h}+\left(1-P_{C R r}\right) \cdot P_{C R r h}
\end{aligned}
$$

Where,
(1) $P_{H r}$ is the robot probability of a hit,
(2) $P_{H r h}$ is the human probability of confirming a robot hit,
(3) $P_{H h}$ is the human probability of detecting a target that the robot did not detect,
(4) $P_{M r}$ is the robot miss probability,
(5) $P_{M r h}$ is the human probability of un-confirming a robot hit,
(6) $P_{M h}$ is the human probability of missing a target the robot missed,
(7) $P_{F A r}$ is the robot false alarm probability,
(8) $P_{\text {FArh }}$ is the human probability of not correcting a robot false alarm,
(9) $P_{F A h}$ is the human probability of a false alarm on targets the robot correctly rejected,
(10) $P_{C R r}$ is the robot probability of a correct rejection,
(11) $P_{\text {CRrh }}$ is the human probability of correcting a robot false alarm, and
(12) $P_{\text {CRh }}$ is the human probability of a correct rejection on targets the robot correctly rejected.

The sum of hit and miss probabilities (of the same type) equals one, so does the sum of false alarm and correct rejection probabilities.

The system's operation cost is:

$$
V_{T s}=t_{S} \cdot V_{t}+\left[N \cdot P_{S} \cdot P_{H s}+N \cdot\left(1-P_{S}\right) \cdot P_{F A s}\right] \cdot V_{C}
$$

Where, $t_{S}$ is the time required by the system to perform a task, $V_{t}$ is the cost of one time unit, and $V_{C}$ is the operation cost of one object recognition (hit or false alarm).

The system time consists of the time it takes the human to decide whether to confirm or reject robot detections; and the time it takes the human to decide whether objects not detected by the robot are targets or not. The robot operation time, $t_{r}$, of processing the images and performing hits or false alarms, is also included.

$$
\begin{aligned}
& t_{S}=N \cdot P_{S} \cdot P_{H r} \cdot P_{H r h} \cdot t_{H r h}+N \cdot P_{S} \cdot\left(1-P_{H r}\right) \cdot P_{H h} \cdot t_{H h}+ \\
& +N \cdot P_{S} \cdot P_{H r} \cdot\left(1-P_{H r h}\right) \cdot t_{M r h}+N \cdot P_{S} \cdot\left(1-P_{H r}\right) \cdot\left(1-P_{H h}\right) \cdot t_{M h}+ \\
& +N \cdot\left(1-P_{S}\right) \cdot P_{F A r} \cdot P_{F A t h} \cdot t_{F A r h}+N \cdot\left(1-P_{S}\right) \cdot\left(1-P_{F A r}\right) \cdot P_{F A h} \cdot t_{F A h}+ \\
& +N \cdot\left(1-P_{S}\right) \cdot P_{F A r} \cdot\left(1-P_{F A r h}\right) \cdot t_{C R r h}+N \cdot\left(1-P_{S}\right) \cdot\left(1-P_{F A r}\right) \cdot\left(1-P_{F A h}\right) \cdot t_{C R h}+N \cdot t_{r}
\end{aligned}
$$

Where,
(1) $t_{H r h}$ is the human time required to confirm a robot hit,
(2) $t_{H h}$ is the human time required to hit a target that the robot did not hit,
(3) $t_{M r h}$ is the human time lost when a robot hit is missed,
(4) $t_{M h}$ is the human time invested when missing a target that the robot did not hit,
(5) $t_{F A r h}$ is the human time needed not to correct a robot false alarm,
(6) $t_{F A h}$ is the human false alarm time,
(7) $t_{\text {CRrh }}$ is the human time to correctly reject a robot false alarm,
(8) $t_{C R h}$ is the human correct rejection time, and (9) $t_{r}$ is the robot operation time.

Explicit expression of the system objective function, $V_{I s}$, suitable for all collaboration levels, is:

$$
\begin{aligned}
& V_{I s}=N \cdot P_{S} \cdot\left[P_{H r} \cdot P_{H r h} \cdot\left(V_{H}+V_{C}+t_{H r h} \cdot V_{t}\right)+\left(1-P_{H r}\right) \cdot P_{H h} \cdot\left(V_{H}+V_{C}+t_{H h} \cdot V_{t}\right)\right]+ \\
& +N \cdot P_{S} \cdot\left[P_{H r} \cdot\left(1-P_{H r h}\right) \cdot\left(V_{M}+t_{\text {Mrh }} \cdot V_{t}\right)+\left(1-P_{H r}\right) \cdot\left(1-P_{H h}\right) \cdot\left(V_{M}+t_{M h} \cdot V_{t}\right)\right]+ \\
& +N \cdot\left(1-P_{S}\right) \cdot\left[P_{F A r} \cdot P_{F A t h} \cdot\left(V_{F A}+V_{C}+t_{F A r h} \cdot V_{t}\right)+\left(1-P_{F A r}\right) \cdot P_{F A h} \cdot\left(V_{F A}+V_{C}+t_{F A h} \cdot V_{t}\right)\right]+ \\
& +N \cdot\left(1-P_{S}\right) \cdot\left[P_{F A r} \cdot\left(1-P_{F A t h}\right) \cdot\left(V_{C R}+t_{C R r h} \cdot V_{t}\right)+\left(1-P_{F A r}\right) \cdot\left(1-P_{F A h}\right) \cdot\left(V_{C R}+t_{C R h} \cdot V_{t}\right)\right]+N \cdot t_{r} \cdot V_{t}
\end{aligned}
$$

For the H collaboration level, the system objective function will be a degenerate form of the full objective function, and will not include the robot variables:

$$
\begin{aligned}
V_{I s} & =N \cdot P_{S} \cdot\left[P_{H h} \cdot\left(V_{H}+V_{C}+t_{H h} \cdot V_{t}\right)+\left(1-P_{H h}\right) \cdot\left(V_{M}+t_{M h} \cdot V_{t}\right)\right]+ \\
& +N \cdot\left(1-P_{S}\right) \cdot\left[P_{F A h} \cdot\left(V_{F A}+V_{C}+t_{F A h} \cdot V_{t}\right)+\left(1-P_{F A h}\right) \cdot\left(V_{C R}+t_{C R h} \cdot V_{t}\right)\right]
\end{aligned}
$$

In the R collaboration level, the system objective function will be a degenerate form of the full objective function, and will not include the human variables:

$$
\begin{aligned}
V_{I s} & =N \cdot P_{S} \cdot\left[P_{H r} \cdot\left(V_{H}+V_{C}\right)+\left(1-P_{H r}\right) \cdot V_{M}\right]+ \\
& +N \cdot\left(1-P_{S}\right) \cdot\left[P_{F A r} \cdot\left(V_{F A}+V_{C}\right)+\left(1-P_{F A r}\right) \cdot V_{C R}\right]+N \cdot t_{r} \cdot V_{t}
\end{aligned}
$$

### 2.7 Signal detection theory

This section gives a tutorial for the signal detection theory.
"Reading in a coffee shop, you see someone who looks familiar. Have you met him before? Should you go and talk to him at the risk of embarrassment when you realize he is a stranger? On the other hand, should you pretend to ignore him at the risk of offending your friend? Both paths of action have potential costs and benefits and the correct decision is not clear. Furthermore, the decision you make might be biased by your own previous experience. For example, if in the past you accidentally waved 'hello' to a strange, then you might be less likely to wave to the person who looks familiar" (http://wise.cgu.edu).

This is an example of detection process. A common dimension of these situations is that there is doubt whether a signal is present or not (Sheridan, 1992). Signal detection theory provides a general framework to describe and study decisions that are made in ambiguous situations (Wickens, 2002). This decision theory tries to estimate decision-making processes for binary categorization decisions, i.e., Yes/No or True/False. It is specifically concerned with how these choices are, or should be made under uncertain conditions (Brown \& Davis, 2006).

Four potential types of outcomes are possible in a binary detection process (see Figure 5). An outcome is dependent on the decision-maker decision and on the actual circumstances, i.e., was there a signal or not. Decisions rely on a detector, which must notice a signal (S) when it occurs without being diverted by a noise ( N ). When a detector indicates a signal, only one of the two must be true: signal is present (hit) or is absent (false alarm, FA). When a detector does not indicate a signal, either it missed (miss) the signal, or there is no signal (correct rejection, CR) (Wickens, 2002). These responses are also often called: correct positive (CP), incorrect positive (IP), incorrect negative (IN), and correct negative (CN); or true positive (TP, TT), false positive (FP, FT), false negative (FN, FF), and true negative (TN, TF), respectively (Brown \& Davis, 2006).

|  | Reference |  |  |
| :---: | :---: | :---: | :---: |
|  | Signal | Noise |  |
| Decision | Signal | Hit <br> (CP, TP, TT) | False Alarm <br> (IP, TN, FT) |
|  | Noise | Miss <br> (IN, FN, FF) | Correct Rejection <br> (CN, TN, TF) |

Figure 5: Four potential outcomes of the detection process
In target recognition, the recognition system aims to detect targets. The system gets a set of objects and needs to mark the objects it thinks are targets (Bechar, 2006). The outcomes of the recognition process are specified as follows. Hit - when the system marks a real target; Miss - when
the system misses a target; False Alarm - when the system marks a non-target as a target; and Correct Rejection - when a non-target is not marked (Bechar, 2006).

The decision-maker needs to detect signals while background noise exists all the time. A continuous variable X (e.g., temperature, concentration, density, probability) represents the stimulus of the process (see Figure 6). The specific value of X can be either signal or noise. Two distributions, one of noise-only $(\mathrm{N})$ and one of signal-plus-noise $(\mathrm{S}+\mathrm{N})$, represent the probability of such a stimulus to be a signal (Bechar, 2006).


Figure 6: An example of binary decision analyzed with SDT (Bechar, 2006)
The decision whether a stimulus is a signal or not, leans on a criterion value of X (denoted as x), called also a cutoff point (Cohen \& Ferrell, 1969) or a threshold (Brown \& Davis, 2006). If the detector notices a stimulus higher than the criterion, the decision will be that a signal is in presence, otherwise, there is no signal. When a signal is present, the detector can either detect it or not, resulting in a sum of probabilities of hit and miss equaling one (see Figure 7). The same rule applies to the sum of probabilities of false alarm and correct rejection when a signal is absent (Bechar, 2006).


Figure 7: Outcomes probabilities when a signal is absent (a) or is present (b)
The distance between the means of the two distributions (denoted as $d^{\prime}$ in Figure 6) defines the detector's ability to discriminate between a signal and a noise. The discrimination ability influenced both by the capability of the measured variable to distinguish between signal and noise (Brown \& Davis, 2006), and by the observer's sensitivity (Bechar, 2006). When $d^{\prime}=0$, the two
distributions completely overlap and it is impossible to distinguish between them. As $d^{\prime}$ increases, it becomes easier to distinguish between signal and noise (Bechar, 2006).

The Receiver Operating Characteristic (ROC) curve was introduced in World War II for military radar operations as a means to characterize the operators' ability to identify correctly friendly or hostile aircraft based on a radar signal (Brown \& Davis, 2006; http://wise.cgu.edu). A cross plot of hit and false alarm rates can be generated by moving the cutoff point over the range of X (see different $t_{i}$ in Figure 8). The curve produced is the ROC curve.


Figure 8: Generation of the ROC curve by evaluating hit and false alarm rates at various decision thresholds on $x$ (Brown \& Davis, 2006)

The curve always passes through points $(1,1)$ and $(0,0)$. When the criterion is positioned at $\mathrm{t}_{1}$ (Figure 8), the detector considers all stimulus as signals, therefore, hit and false alarm rates equal one. On the other hand, when positioned in $\mathrm{t}_{5}$, no stimulus would be considered signal and the rates equals zero (Brown \& Davis, 2006). Other properties of the curve will be discussed later.

Common measurements of goodness of the decision process are the classification and likelihood rates (Brown \& Davis, 2006). Classification rate is defined as the proportion of correct decisions (hit and correct rejection) to total decisions. The performance of a decision-maker in a given set of circumstances is fully described by the frequencies of the various possible outcomes (Cohen \& Ferrell, 1969). Therefore, the likelihood ratio (denoted as $\beta$ in Figure 7), which is the proportion of hit rate to false alarm rate at the cutoff point, is another way to measure performance (Bechar, 2006). Good performance achieves high hit rate and low false alarm rate. Hence high likelihood ratio suits system that performs well (Brown \& Davis, 2006). An advantage of likelihood ratios is that they do not depend on the signal rate (Brown \& Davis, 2006).

With the purpose of achieving the highest likelihood rate, one would like to operate at the upper left corner of Figure 8 (indicated by a star in the figure), but cannot because of the overlap of the two distributions (Sheridan, 1992). It is possible that hit rate equals one while false alarm rate equals zero only when the two distributions do not overlap (see example, Figure 10) and $d^{\prime} \rightarrow \infty$
(Sheridan, 1992). In order to get best performances under given distributions of noise and signal, there is a need to find criterion value x adjusted to the optimal likelihood ratio $\beta$. In applying this theory it is of interest to see if human decision makers are optimal and select $x=\beta$, or if they consistently are biased toward lower left (risk-averse behavior) or the upper right (risk-prone behavior) corners (Sheridan, 1992).

The next section illustrates some interesting situations that help understand the theory introduced above. The following figures were produced using a web applet that demonstrates ROC curves (http://wise.cgu.edu). The two distributions of N and $\mathrm{S}+\mathrm{N}$ are shown in the left graph (Figure 9). The right distribution of signal-plus-noise can be moved horizontally by dragging $d^{\prime}$. Likewise, the criterion value can be modified. The right graph is the ROC curve which is generated automatically corresponding to chosen $d^{\prime}$ and criterion. Another way to produce the curve is to determine hit and false alarm rates at the lower part of the applet. Doing so, both graphs will change automatically to fit the input data.


Figure 9: An example of ROC curve applet (http://wise.cgu.edu)
As shown in Figure 9 one distribution is almost totally overlapping the other. Compatibly, $d^{\prime}$ is small. In this situation, the observer's sensitivity is low and only a small hit rate is possible. When the sensitivity is higher (Figure 10), the criterion efficiently discriminates between signal and noise, high hit rate and low false alarm rate are achieved and the ROC curve passes close to the upper left corner of the graph.


Figure 10: An example of high sensitivity of the observer (http://wise.cgu.edu)

Figure 11 illustrates different locations of the criterion value. Actually, the ROC curve is a cross plot of false alarm and hit rates. The dot on the curve is moving respectively with the criterion's movement. Hit and false alarm rates monotonically increase as the criterion moves from right to left and hit rate is always greater than false alarm rate (Brown \& Davis, 2006). The goal is to find the criterion value that gives the highest proportion of hit rate to false alarm rate, the optimal likelihood ratio.
(a)

(b)

(c)


Figure 11: Different criterion values on the same ROC curve (http://wise.cgu.edu): 2.04 (a), 0.82 (b), -0.36 (c).

### 2.8 Reaction time models

Signal detection theory, which was introduced above, provides a general framework to describe decisions and how they should be made under uncertain conditions (Brown \& Davis, 2006). Signal detection theory models provide an account of accuracy only, and are not concerned with the time it takes the observer to make the decision ${ }^{1}$ (Ratcliff \& Smith, 2004).
"Reaction time, that is the time from the onset of a stimulus or signal to the initiation of response, has been recognized as a potentially powerful means of relating mental events to physical measures. ... More recent developments have enhanced the value of reaction time as a measure rather than diminished it (Welford, 1980)".

The relation between response time and accuracy is not constant; it varies according to whether speed or accuracy of performance is emphasized and according to whether one response or another is more probable or weighted more heavily (Ratcliff \& Rouder, 1998). Therefore, previous models have dealt with only one measure, accuracy or response time (Ratcliff \& Rouder, 1998).

Various models were proposed to account for reaction time and accuracy. Ratcliff and Rounder (1998) introduced the diffusion model which is a sequential-sampling model and can explain the relationship between correct and error responses while at the same time fitting all the other response time and response probability aspects of the data. Sequential sampling models are unique in providing a way to understand both the speed and accuracy of performance within a common theoretical framework (Ratcliff \& Smith, 2004).

Ratcliff, Mckoon and Zandt (1999) also claim that the main difficulty in recent modeling is that two dependent variables, reaction time and the probability of responses, must to be modeled in the same integrated framework. They introduced connectionist models that explain how cognitive tasks are learned. Learning is the result of many individual trials with stimuli, each trial with feedback about whether the model's response was correct or not (Ratcliff et al., 1999).

Pike (1973) suggested that latency in response is some inverse function of distance from the criteria, and that latency decreases with the distance. According to Pike (1973), successful description of response latency is necessary for verification of the detection model.

[^0]Murdock (1985) analyzed the strength-latency relationship and introduced a generic reaction time model based on the distance-from-criteria of the observed object. He suggested that an exponential function is the most reasonable to use in order to transfer the object's strength, i.e., distance-from-criteria, into latency (Figure 12). Exponential functions can describe symmetrical descendent of latency on both sides of the yes/no criterion (Murdock, 1985).


Figure 12: Signal (x) is normally distributed with criterion Xco. Exponential transfer function maps signal strength into latency ( t ), and the resulting latency distribution $\mathrm{f}(\mathrm{t})$ is shown by the dots (Murdock, 1985).

## 3 Methodology

### 3.1 Overview

This thesis continues a previous work of Bechar (2006) which focused on developing a human-robot collaboration model for target recognition task. The objective function of the model describes the system score for a given collaboration level and determines the best collaboration level for a given set of parameters. This thesis expands the objective function of the model by incorporating a function for human reaction time instead of a constant value. In this thesis, we check the influence of the reaction time on the objective function score and the best collaboration level.

A reaction time model is developed and integrated into the collaboration model. Numerical and sensitivity analysis of the new model is conducted using simulated data.

### 3.2 Reaction time model development

The objective function of the model developed by Bechar (2006), takes into account the costs related to the time it takes a human-robot system to perform a target detection task. Implementing a detection procedure by the human consist of two stages. First, the human must decide whether an object is target or not. The action on the second stage depends on the human decision and on the collaboration level as follows. In some cases, the human needs to make a motoric action in order to mark or unmark an object (e.g., confirming a robot recommendation in the HR collaboration level, or canceling a wrong robot's mark in the HOR collaboration level). In other cases, the human does not have to perform a motoric action (i.e., when the robot's recommendation is not a real target in the HR collaboration level, or when the robot decided correct in the HOR collaboration level). The time the first stage takes is the reaction time of the human.

Previous work (Bechar, 2006) considered a constant value for the reaction time. This research introduces further development of the model taking into consideration the fact that the reaction time of the human depends on the strength of the observed object (i.e., the distance of the observed object from the cutoff point). In this research, we incorporate a reaction time model, based on Murdock (1985), into Bechar's model.

Furthermore, a mathematical development of a mean distance model is introduced. The model is based on the signal detection theory model, and calculates the mean distance between the cutoff point and objects of the same category (e.g., mean distance of all objects that were 'missed').

### 3.3 Performance measures

This research uses the nine performance measures defined by Bechar (2006). Eight performance measures represent the target identification possible outcomes. Four of them stand for objects the robot marked as targets (i.e., hit, miss, false alarm and correct rejection) and the other four stands for objects the robot did not mark. The ninth performance measure is the time required for the human-robot integrated system to fulfill the task. The system objective function combines all performance measures into a single parameter.

### 3.4 Numerical analysis

A numerical analysis is implemented on a personal computer with Matlab $7^{\mathrm{TM}}$, and detailed in chapter 5 . The objective is to determine the best collaboration levels for different human, robot, and task characteristics, and to examine the influence of the time component.

The analysis is focused on three different system types. The first two types, introduced by Oren (2007), give high emphasis of not causing one of the two possible errors in target recognition: missing targets or making false alarms. The third type gives the same importance for all possible outcomes.

### 3.5 Sensitivity analysis

The numerical analysis is conducted only for the cases in which the human and the robot perform optimally, i.e., optimal cutoff points of the human and the robot. The target detection process of the robot is computerized and it is possible to adjust its cutoff point during the task according to changes in the environment. On the other hand, an optimal cutoff point of the human is less obvious and it is much more difficult to be manipulated. Therefore, the work includes an indepth sensitivity analysis of the human and robot cutoff points. The analysis shows how small changes in the cutoff point position, influence the objective function score and the best collaboration level.

## 4 Model Development

In this research, we incorporate a reaction time model, based on Murdock (1985), into Bechar's collaboration model (2006). According to Murdock (1985), reaction time depends on the strength of the observed object. The strength of an object is relative to the distance of the observed object's value from the criteria. The distance of an object can be measured by the same units of the measured object or by standard deviation units. Normalizing the signal and noise distributions helps us to describe the problem in standard deviation units. It benefits in generalizing the problem rather than using the actual units that fit only to a specific case. The cutoff point gets a different interpretation for each normalized distribution. We denote the cutoff points as $z_{S}$ and $z_{N}$ for the signal and the noise distributions, respectively.

$$
z_{S}=\frac{x_{c o}-\mu_{S}}{\sigma_{S}} \quad ; \quad z_{N}=\frac{x_{c o}-\mu_{N}}{\sigma_{N}}
$$

A short review of the Normal and the Standard Normal distributions, as well as definitions of signal and noise distributions is included in Appendix A.

For a matter of simplicity, all equations of the model will be defined first as functions of the parameters $z_{S}$ and $z_{N}$, and later on, for the numerical analysis, they will be expressed by the likelihood ratio, $\beta$, between the signal and noise density functions in the cutoff point, $x_{c o}$, and the distance between the means of the signal and noise distributions, $d^{\prime}$. See chapter 2.6 for details. All expressions are included in Appendix B.

In this section, we introduce a development of a mean distance of all objects of the same category (miss, hit, correct rejection, and false alarm). Then, we formulate the reaction time model and incorporate it into the human-robot collaboration model.

### 4.1 Mean distance model

### 4.1.1 Mean $x$-values and distances in a normal distribution

In the recognition process, the system marks an object as a target if the object's value is higher than the cutoff point value (denoted as $x_{c o}$ in Figure 13). We use the term 'Positive Response' to describe objects that the system marks. Positive response can be either a hit, if the object is a target; or a false alarm if it is not. The term 'Negative Response' describes objects with a value lower than the cutoff point value, which the system does not mark as targets. A negative response can be either a miss, if the object is a target; or a correct rejection if it is not. The mean xvalue of all negative responses is denoted as $\mu_{-}$, and the mean $x$-value of all positive responses is denoted as $\mu_{+}$.

Suppose $X$ is normally distributed with a mean of $\mu$ and a variance of $\sigma^{2}$. In order to find the mean $x$-value, one must calculate the weighted average of all $x$-values of the same response, where the weight is the frequency of x . The mean x -value depends on the cutoff point value, $x_{c o}$.


Figure 13: Mean $x$-values and distances in normal distribution
The mean x -value equations for negative $\left(\mu_{-}\right)$and positive $\left(\mu_{+}\right)$responses are:

$$
\begin{aligned}
& \mu_{-}\left(x_{c o}\right)=\frac{\int_{-\infty}^{x_{c o}} x \cdot f(x) d x}{\int_{x_{c o}} f(x) d x}=\ldots=\mu-\sigma \cdot \frac{\varphi\left(z_{c o}\right)}{\Phi\left(z_{c o}\right)} \\
& \mu_{+}\left(x_{c o}\right)=\frac{\int_{-\infty}^{\infty} x \cdot f(x) d x}{\int_{x_{c o}}^{\infty} f(x) d x}=\ldots=\mu+\sigma \cdot \frac{\varphi\left(z_{c o}\right)}{1-\Phi\left(z_{c o}\right)}
\end{aligned}
$$

where

$$
\begin{array}{ll}
f(x)=\frac{1}{\sigma \sqrt{2 \pi}} e^{\frac{-(x-\mu)^{2}}{2 \sigma^{2}}} \quad ; \quad z_{c o}=\frac{x_{c o}-\mu}{\sigma} \\
\varphi(z)=\frac{1}{\sqrt{2 \pi}} \cdot e^{\frac{-z^{2}}{2}} \quad ; \quad \Phi(z)=\int_{-\infty}^{z} \frac{1}{\sqrt{2 \pi}} \cdot e^{\frac{-z^{2}}{2}} d z
\end{array}
$$

From the equations, it is obvious that $\mu_{-}$is lower and $\mu_{+}$is higher than the mean of the distribution $\mu$, also supported by Figure 13. Fully detailed development of the equations is included in subchapters 4.1.2 and 4.1.3. Validation of the equations is presented in Appendix C.

The distance of an object from the cutoff point is the absolute difference $\left|x_{c o}-x\right|$. We use the mean x -values to find the mean distances of negative and positive responses (denoted as $d_{-}, d_{+}$ respectively in Figure 13). By definition and as shown in Figure 13, $\mu_{-} \leq x_{c o} \leq \mu_{+}$. For that reason, we define the distances as a difference between the cutoff point and the appropriate mean x -value where both distances get positive values: $d_{-}\left(x_{c o}\right)=x_{c o}-\mu_{-}, d_{+}\left(x_{c o}\right)=\mu_{+}-x_{c o}$

The mean distance equations for negative and positive responses are:

$$
\begin{aligned}
& d_{-}\left(x_{c o}\right)=x_{c o}-\mu_{-}=x_{c o}-\left(\mu-\sigma \cdot \frac{\varphi\left(z_{c o}\right)}{\Phi\left(z_{c o}\right)}\right)=\left(x_{c o}-\mu\right)+\sigma \cdot \frac{\varphi\left(z_{c o}\right)}{\Phi\left(z_{c o}\right)} \\
& d_{+}\left(x_{c o}\right)=\mu_{+}-x_{c o}=\left(\mu+\sigma \cdot \frac{\varphi\left(z_{c o}\right)}{1-\Phi\left(z_{c o}\right)}\right)-x_{c o}=-\left(x_{c o}-\mu\right)+\sigma \cdot \frac{\varphi\left(z_{c o}\right)}{1-\Phi\left(z_{c o}\right)}
\end{aligned}
$$

where

$$
\begin{aligned}
& z_{c o}=\frac{x_{c o}-\mu}{\sigma} \\
& \varphi(z)=\frac{1}{\sqrt{2 \pi}} \cdot e^{\frac{-z^{2}}{2}} \quad ; \quad \Phi(z)=\int_{-\infty}^{z} \frac{1}{\sqrt{2 \pi}} \cdot e^{\frac{-z^{2}}{2}} d z
\end{aligned}
$$

In order to describe the problem by standard deviation units rather than by actual units, which suit just a specific case, we define normalized distances based on the previous defined distances. We divide each distance by the standard deviation $\sigma$.

The mean normalized distance equations for negative and positive responses are:

$$
\begin{aligned}
& d_{-}\left(x_{c o}\right) / \sigma=\left(\left(x_{c o}-\mu\right)+\sigma \cdot \frac{\varphi\left(z_{c o}\right)}{\Phi\left(z_{c o}\right)}\right) / \sigma=\left(\frac{x_{c o}-\mu}{\sigma}\right)+\frac{\varphi\left(z_{c o}\right)}{\Phi\left(z_{c o}\right)}=z_{c o}+\frac{\varphi\left(z_{c o}\right)}{\Phi\left(z_{c o}\right)} \\
& d_{+}\left(x_{c o}\right) / \sigma=\left(-\left(x_{c o}-\mu\right)+\sigma \cdot \frac{\varphi\left(z_{c o}\right)}{1-\Phi\left(z_{c o}\right)}\right) / \sigma=-\left(\frac{x_{c o}-\mu}{\sigma}\right)+\frac{\varphi\left(z_{c o}\right)}{1-\Phi\left(z_{c o}\right)}=-z_{c o}+\frac{\varphi\left(z_{c o}\right)}{1-\Phi\left(z_{c o}\right)} \\
& \text { where } \\
& z_{c o}=\frac{x_{c o}-\mu}{\sigma} \\
& \varphi(z)=\frac{1}{\sqrt{2 \pi}} \cdot e^{\frac{-z^{2}}{2}} \quad ; \quad \Phi(z)=\int_{-\infty}^{z} \frac{1}{\sqrt{2 \pi}} \cdot e^{\frac{-z^{2}}{2}} d z
\end{aligned}
$$

If we use the equations of the mean distance for standard normal distribution ( $\mu=0, \sigma=1$ ) with the appropriate cutoff point, $Z_{c o}$, we get the same equations of the normalized distance.

To simplify the equations, we use the following symmetric rules of the standard normal distribution:

$$
\begin{aligned}
& \varphi(z)=\varphi(-z) \\
& \Phi(z)=1-\Phi(-z) \\
& \Phi(-z)=1-\Phi(z)
\end{aligned}
$$

where

$$
\varphi(z)=\frac{1}{\sqrt{2 \pi}} \cdot e^{\frac{-z^{2}}{2}} \quad ; \quad \Phi(z)=\int_{-\infty}^{z} \frac{1}{\sqrt{2 \pi}} \cdot e^{\frac{-z^{2}}{2}} d z
$$

We define the function $\Theta(z)$ :

$$
\Theta(z)=\frac{\varphi(z)}{\Phi(z)}
$$

Due to the symmetric rules, the function holds:

$$
\Theta(-z)=\frac{\varphi(-z)}{\Phi(-z)}=\frac{\varphi(z)}{1-\Phi(z)}
$$

We use $\Theta(z)$ to define again the normalized distances as:

$$
\begin{aligned}
& d_{-}\left(x_{c o}\right) / \sigma=z_{c o}+\frac{\varphi\left(z_{c o}\right)}{\Phi\left(z_{c o}\right)}=z_{c o}+\Theta\left(z_{c o}\right) \\
& d_{+}\left(x_{c o}\right) / \sigma=-z_{S}+\frac{\varphi\left(z_{c o}\right)}{1-\Phi\left(z_{c o}\right)}=-z_{c o}+\Theta\left(-z_{c o}\right)
\end{aligned}
$$

### 4.1.2 Mathematical development of Mean $x$-value of negative responses

In order to find the mean $x$-value, one must calculate the weighted average of all $x$-values of the same response, where the weight is the frequency of x .

$$
\mu_{-}\left(x_{c o}\right)=\frac{\int_{-\infty}^{x_{c o}} x \cdot f(x) d x}{\int_{-\infty}^{x_{c o}} f(x) d x}=\frac{\int_{-\infty}^{x_{c o}} x \cdot \frac{1}{\sigma \sqrt{2 \pi}} e^{\frac{-(x-\mu)^{2}}{2 \sigma^{2}}} d x}{\int_{-\infty}^{x_{\infty \infty}} \frac{1}{\sigma \sqrt{2 \pi}} e^{\frac{-(x-\mu)^{2}}{2 \sigma^{2}}} d x}=
$$

Changing the domain of integration:

$$
\begin{aligned}
& z=\frac{x-\mu}{\sigma} \Rightarrow x=\mu+\sigma z \\
& \frac{d x}{d z}=\frac{d(\mu+\sigma z)}{d z}=\sigma \Rightarrow d x=\sigma d z \\
& x=-\infty \Rightarrow z=\frac{-\infty-\mu}{\sigma}=-\infty \\
& x=x_{c o} \Rightarrow z=\frac{x_{c o}-\mu}{\sigma}=z_{c o}
\end{aligned}
$$

$=\frac{\int_{-\infty}^{z_{\infty}}(\mu+\sigma z) \cdot \frac{1}{\varnothing \sqrt{2 \pi}} e^{\frac{-z^{2}}{2}} \phi d z}{\int_{-\infty}^{z_{\infty}} \frac{1}{\sigma \sqrt{2 \pi}} e^{\frac{-z^{2}}{2}} \sigma d z}=\frac{\int_{-\infty}^{z_{\infty}}(\mu+\sigma z) \cdot \frac{1}{\sqrt{2 \pi}} e^{\frac{-z^{2}}{2}} d z}{\int_{-\infty}^{z_{\infty}} \frac{1}{\sqrt{2 \pi}} e^{\frac{-z^{2}}{2}} d z}=$
$=\frac{\int_{-\infty}^{z_{\infty}} \mu \frac{1}{\sqrt{2 \pi}} e^{\frac{-z^{2}}{2}} d z+\int_{-\infty}^{z_{\infty}} \sigma z \cdot \frac{1}{\sqrt{2 \pi}} e^{\frac{-z^{2}}{2}} d z}{\int_{-\infty}^{z_{\infty}} \frac{1}{\sqrt{2 \pi}} e^{\frac{-z^{2}}{2}} d z}=\mu \cdot \frac{\int_{-\infty}^{z_{\infty}} \frac{1}{\sqrt{2 \pi}} e^{\frac{-z^{2}}{2}} d z}{\int_{-\infty}^{z_{\infty}} \frac{1}{\sqrt{2 \pi}} e^{\frac{-z^{2}}{2}} d z}+\sigma \cdot \frac{\int_{-\infty}^{z_{\infty}} z \cdot \frac{1}{\sqrt{2 \pi}} e^{\frac{-z^{2}}{2}} d z}{\int_{-\infty}^{z_{\infty}} \frac{1}{\sqrt{2 \pi}} e^{\frac{-z^{2}}{2}} d z}=$

From the standard normal distribution :
$\int_{-\infty}^{z_{c o}} \frac{1}{\sqrt{2 \pi}} e^{\frac{-z^{2}}{2}} d z=\Phi\left(z_{c o}\right)$
$=\mu \cdot \frac{\Phi\left(z_{c o}\right)}{\Phi\left(z_{c o}\right)}+\sigma \cdot \frac{\frac{1}{\sqrt{2 \pi}} \int_{-\infty}^{z_{\infty}} z \cdot e^{\frac{-z^{2}}{2}} d z}{\Phi\left(z_{c o}\right)}=$

Solving the integral:

$$
\int u^{n-1} \cdot e^{\frac{-u^{n}}{n}} d u=-e^{\frac{-u^{n}}{n}}
$$

Confirmation by derivng the answer:
$\frac{\partial\left(-e^{\frac{-u^{n}}{n}}\right)}{\partial u}=-e^{\frac{-u^{n}}{n}} \cdot \frac{-n \cdot u^{n-1}}{n}=u^{n-1} \cdot e^{\frac{-u^{n}}{u}}$
$=\mu+\sigma \cdot \frac{\left.\frac{1}{\sqrt{2 \pi}}\left(-e^{\frac{-z^{2}}{2}}\right)\right|_{-\infty} ^{z_{\infty}}}{\Phi\left(z_{c o}\right)}=\mu+\sigma \cdot \frac{\frac{1}{\sqrt{2 \pi}}\left[\left(-e^{\frac{-z_{c o}{ }^{2}}{2}}\right)-\left(-e^{\frac{-(-\infty)^{2}}{2}}\right)\right]}{\Phi\left(z_{c o}\right)}=$
$=\mu+\sigma \cdot \frac{\frac{1}{\sqrt{2 \pi}}\left[\left(-e^{\frac{-z_{c}{ }^{2}}{2}}\right)-(0)\right]}{\Phi\left(z_{c o}\right)}=\mu-\sigma \cdot \frac{\frac{1}{\sqrt{2 \pi}} e^{\frac{-z_{c o}{ }^{2}}{2}}}{\Phi\left(z_{c o}\right)}=$

From the standard normal distribution

$$
\frac{1}{\sqrt{2 \pi}} e^{\frac{-z^{2}}{2}} d z=\varphi(z)
$$

$=\mu-\sigma \cdot \frac{\varphi\left(z_{c o}\right)}{\Phi\left(z_{c o}\right)}$

$$
\begin{aligned}
& \mu_{-}\left(x_{c o}\right)=\mu-\sigma \cdot \frac{\varphi\left(z_{c o}\right)}{\Phi\left(z_{c o}\right)} \\
& \text { where } \\
& z_{c o}=\frac{x_{c o}-\mu}{\sigma} \\
& \varphi(z)=\frac{1}{\sqrt{2 \pi}} \cdot e^{\frac{-z^{2}}{2}} \quad ; \quad \Phi(z)=\frac{1}{\sqrt{2 \pi}} \int_{-\infty}^{z} e^{\frac{-z^{2}}{2}} d z
\end{aligned}
$$

### 4.1.3 Mathematical development of Mean $x$-value of positive responses

In order to find the mean $x$-value, one must calculate the weighted average of all $x$-values of the same response, where the weight is the frequency of x .

$$
\mu_{+}\left(x_{c o}\right)=\frac{\int_{x_{c o}}^{\infty} x \cdot f(x) d x}{\int_{x_{c o}}^{\infty} f(x) d x}=\frac{\int_{x_{c o}}^{\infty} x \cdot \frac{1}{\sigma \sqrt{2 \pi}} e^{\frac{-(x-\mu)^{2}}{2 \sigma^{2}}} d x}{\int_{x_{c o}}^{\infty} \frac{1}{\sigma \sqrt{2 \pi}} e^{\frac{-(x-\mu)^{2}}{2 \sigma^{2}}} d x}=
$$

Changing the domain of integration:
$z=\frac{x-\mu}{\sigma} \Rightarrow x=\mu+\sigma z$
$\frac{d x}{d z}=\frac{d(\mu+\sigma z)}{d z}=\sigma \Rightarrow d x=\sigma d z$
$x=x_{c o} \Rightarrow z=\frac{x_{c o}-\mu}{\sigma}=z_{c o}$
$x=\infty \Rightarrow z=\frac{\infty-\mu}{\sigma}=\infty$
$=\frac{\int_{z_{c o}}^{\infty}(\mu+\sigma z) \cdot \frac{1}{\varnothing \sqrt{2 \pi}} e^{\frac{-z^{2}}{2}} \sigma d z}{\int_{z_{c o}}^{\infty} \frac{1}{\sigma \sqrt{2 \pi}} e^{\frac{-z^{2}}{2}} \sigma d z}=\frac{\int_{z_{c o}}^{\infty}(\mu+\sigma z) \cdot \frac{1}{\sqrt{2 \pi}} e^{\frac{-z^{2}}{2}} d z}{\int_{z_{c o}}^{\infty} \frac{1}{\sqrt{2 \pi}} e^{\frac{-z^{2}}{2}} d z}=$
$=\frac{\int_{z_{c o}}^{\infty} \mu \cdot \frac{1}{\sqrt{2 \pi}} e^{\frac{-z^{2}}{2}} d z+\int_{z_{c o}}^{\infty} \sigma z \cdot \frac{1}{\sqrt{2 \pi}} e^{\frac{-z^{2}}{2}} d z}{\int_{z_{c o}}^{\infty} \frac{1}{\sqrt{2 \pi}} e^{\frac{-z^{2}}{2}} d z}=\mu \cdot \frac{\int_{z_{c o}}^{\infty} \frac{1}{\sqrt{2 \pi}} e^{\frac{-z^{2}}{2}} d z}{\int_{z_{c o}}^{\infty} \frac{1}{\sqrt{2 \pi}} e^{\frac{-z^{2}}{2}} d z}+\sigma \cdot \frac{\int_{z_{c o}}^{\infty} z \cdot \frac{1}{\sqrt{2 \pi}} e^{\frac{-z^{2}}{2}} d z}{\int_{z_{c o}}^{\infty} \frac{1}{\sqrt{2 \pi}} e^{\frac{-z^{2}}{2}} d z}=$

$$
\begin{aligned}
& \text { From the standard normal distribution: } \\
& \int_{-\infty}^{z_{c o}} \frac{1}{\sqrt{2 \pi}} e^{\frac{-z^{2}}{2}} d z=1-\Phi\left(z_{c o}\right)
\end{aligned}
$$

$=\mu \cdot \frac{1-\Phi\left(z_{c o}\right)}{\frac{1-\Phi\left(z_{c o}\right)}{1}}+\sigma \cdot \frac{\frac{1}{\sqrt{2 \pi}} \int_{z_{c o}}^{\infty} z \cdot e^{\frac{-z^{2}}{2}} d z}{1-\Phi\left(z_{c o}\right)}=$

> Solving the integral:
> $\int u^{n-1} \cdot e^{\frac{-u^{n}}{n}} d u=-e^{\frac{-u^{n}}{n}}$
> Confirmation by derivng the answer :
> $\frac{\partial\left(-e^{\frac{-u^{n}}{n}}\right)}{\partial u}=-e^{\frac{-u^{n}}{n}} \cdot \frac{-n \cdot u^{n-1}}{n}=u^{n-1} \cdot e^{\frac{-u^{n}}{u}}$
$=\mu+\sigma \cdot \frac{\left.\frac{1}{\sqrt{2 \pi}}\left(-e^{\frac{-z^{2}}{2}}\right)\right|_{z_{00}} ^{\infty}}{1-\Phi\left(z_{c o}\right)}=\mu+\sigma \cdot \frac{\frac{1}{\sqrt{2 \pi}}\left[\left(-e^{\frac{-x^{2}}{2}}\right)-\left(-e^{\frac{-z_{c o}{ }^{2}}{2}}\right)\right]}{1-\Phi\left(z_{c o}\right)}=$
$=\mu+\sigma \cdot \frac{\frac{1}{\sqrt{2 \pi}}\left[(0)-\left(-e^{\frac{-z_{c o}{ }^{2}}{2}}\right)\right]}{1-\Phi\left(z_{c o}\right)}=\mu+\sigma \cdot \frac{\frac{1}{\sqrt{2 \pi}} e^{\frac{-z_{c o}{ }^{2}}{2}}}{1-\Phi\left(z_{c o}\right)}=$
From the standard normal distribution
$\frac{1}{\sqrt{2 \pi}} e^{\frac{-z^{2}}{2}} d z=\varphi(z)$
$=\mu+\sigma \cdot \frac{\varphi\left(z_{c o}\right)}{1-\Phi\left(z_{c o}\right)}$
$\mu_{+}\left(x_{c o}\right)=\mu+\sigma \cdot \frac{\varphi\left(z_{c o}\right)}{1-\Phi\left(z_{c o}\right)}$
where
$z_{c o}=\frac{x_{c o}-\mu}{\sigma}$
$\varphi(z)=\frac{1}{\sqrt{2 \pi}} \cdot e^{\frac{-z^{2}}{2}} \quad ; \quad \Phi(z)=\frac{1}{\sqrt{2 \pi}} \int_{-\infty}^{z} e^{\frac{-z^{2}}{2}} d z$

### 4.1.4 Mean $x$-values and distances for signal and noise distributions

The equations that were developed for the normal distribution are adjusted to the signal and noise distributions. The means and standard deviations of the signal and noise distributions are respectively $\mu_{S}, \sigma_{S}$ and $\mu_{N}, \sigma_{N}$. Short reviews of Normal and Standard Normal distributions, as well as definitions of signal and noise distributions are included in Appendix A.


Figure 14: Illustration of mean x -values and mean distances
The mean x -values and the mean distances are denoted as:
$\mu_{M}$ - Mean x-value of undetected signals (miss)
$\mu_{H}$ - Mean x-value of detected signals (hit)
$\mu_{C R}$ - Mean x-value of ignored noises (correct rejection)
$\mu_{F A}$ - Mean x-value of mistakenly detected noises (false alarm)
$d_{M}$ - Distance from the cutoff point to mean x-value of undetected signals (miss)
$d_{H}$ - Distance from the cutoff point to mean x -value of detected signals (hit)
$d_{C R}$ - Distance from the cutoff point to mean x-value of ignored noises (correct rejection)
$d_{F A}$ - Distance from the cutoff to mean x -value of mistakenly detected noises (false alarm)
Hit and miss are the possible outcomes of observing an object from the signal distribution (i.e., the object is a target). False alarm and correct rejection are the possible outcomes of observing an object from the noise distribution (i.e., the object is not a target). Hits and false alarms are positive responses; misses and correct rejections are negative responses.

In order to define equations for mean x-values, mean distances and normalized mean distances of all four possible outcomes (miss, hit, correct rejection and false alarm), we used the appropriate equations (for positive or negative responses) and parameters (mean and standard deviation of signal or noise distributions):

$$
\begin{aligned}
& \mu_{M}\left(x_{c o}\right)=\mu_{S}-\sigma_{S} \cdot \frac{\varphi\left(z_{S}\right)}{\Phi\left(z_{S}\right)} \\
& \mu_{H}\left(x_{c o}\right)=\mu_{S}+\sigma_{S} \cdot \frac{\varphi\left(z_{S}\right)}{1-\Phi\left(z_{S}\right)} \\
& \mu_{C R}\left(x_{c o}\right)=\mu_{N}-\sigma_{N} \cdot \frac{\varphi\left(z_{N}\right)}{\Phi\left(z_{N}\right)} \\
& \mu_{F A}\left(x_{c o}\right)=\mu_{N}+\sigma_{N} \cdot \frac{\varphi\left(z_{N}\right)}{1-\Phi\left(z_{N}\right)} \\
& d_{M}\left(x_{c o}\right)=\left(x_{c o}-\mu_{S}\right)+\sigma_{S} \cdot \frac{\varphi\left(z_{S}\right)}{\Phi\left(z_{S}\right)} \\
& d_{H}\left(x_{c o}\right)=-\left(x_{c o}-\mu_{S}\right)+\sigma_{S} \cdot \frac{\varphi\left(z_{S}\right)}{1-\Phi\left(z_{S}\right)} \\
& d_{C R}\left(x_{c o}\right)=\left(x_{c o}-\mu_{N}\right)+\sigma_{N} \cdot \frac{\varphi\left(z_{N}\right)}{\Phi\left(z_{N}\right)} \\
& d_{F A}\left(x_{c o}\right)=-\left(x_{c o}-\mu_{N}\right)+\sigma_{N} \cdot \frac{\varphi\left(z_{N}\right)}{1-\Phi\left(z_{N}\right)} \\
& d_{M}\left(x_{c o}\right) / \sigma_{S}=z_{S}+\frac{\varphi\left(z_{S}\right)}{\Phi\left(z_{S}\right)} \\
& d_{H}\left(x_{c o}\right) / \sigma_{S}=-z_{S}+\frac{\varphi\left(z_{S}\right)}{1-\Phi\left(z_{S}\right)} \\
& d_{C R}\left(x_{c o}\right) / \sigma_{N}=z_{N}+\frac{\varphi\left(z_{N}\right)}{\Phi\left(z_{N}\right)} \\
& d_{F A}\left(x_{c o}\right) / \sigma_{N}=-z_{N}+\frac{\varphi\left(z_{N}\right)}{1-\Phi\left(z_{N}\right)}
\end{aligned}
$$

where

$$
\begin{array}{ll}
z_{S}=\frac{x_{c o}-\mu_{S}}{\sigma_{S}} \quad ; \quad z_{N}=\frac{x_{c o}-\mu_{N}}{\sigma_{N}} \\
\varphi(z)=\frac{1}{\sqrt{2 \pi}} \cdot e^{\frac{-z^{2}}{2}} \quad ; \quad \Phi(z)=\int_{-\infty}^{z} \frac{1}{\sqrt{2 \pi}} \cdot e^{\frac{-z^{2}}{2}} d z
\end{array}
$$

### 4.2 Reaction time model

Murdock (1985) suggests an exponential function to transfer the object's strength, i.e., distance-from-criteria, into latency. An exponential function can describe symmetrical descendent of latency on both sides of the yes/no criterion (Murdock, 1985).

For negative responses, the distance and the reaction time functions are:

$$
\begin{aligned}
& d(x)=x_{c o}-x \\
& t(x)=A \cdot e^{-B\left(x_{c o}-x\right)}
\end{aligned}
$$

For positive responses, the distance and the reaction time functions are:

$$
\begin{aligned}
& d(x)=x-x_{c o} \\
& t(x)=A \cdot e^{-B\left(x-x_{c o}\right)}
\end{aligned}
$$

Both functions are presented in Figure 15 and can be conjoined:

$$
t(x)= \begin{cases}A \cdot e^{-B \cdot\left(x_{c o}-x\right)} & ; \text { when } x \leq x_{c o} \\ A \cdot e^{-B\left(x-x_{c o l}\right)} & ; \text { otherwise }\end{cases}
$$



Figure 15: Reaction time function
In order to fit these functions to real data, the parameters $A$ and $B$ must be adjusted. Different parameters values lead to different reaction time functions. One can define different values for negative and positive responses.

Suppose $X$ is normally distributed with a mean of $\mu$ and a variance of $\sigma^{2}$ $X \sim \quad\left(\mu, \sigma^{2}\right)$. In order to find the mean reaction time, one must calculate weighted average of all reaction times (results from x-values) of the same response. The weights are the frequencies of x . The mean reaction time depends on the cutoff point value and denoted as $T_{-}\left(x_{c o}\right), T_{+}\left(x_{c o}\right)$ for negative and positive responses, respectively.

The mean reaction time equations for negative and positive responses are (Murdock, 1985):

$$
\begin{aligned}
& T_{-}\left(x_{c o}\right)=\frac{\int_{-\infty}^{x_{c o}} t(x) \cdot f(x) d x}{\int_{-\infty}^{x_{c o}} f(x) d x}=\frac{\int_{-\infty}^{x_{c o}} A \cdot e^{-B\left(x_{c o}-x\right)} \cdot f(x) d x}{\int_{-\infty}^{x_{c o}} f(x) d x}=\ldots=A \cdot e^{-B \cdot \sigma \cdot z_{c o}+\frac{B^{2} \cdot \sigma^{2}}{2}} \cdot \frac{\Phi\left(z_{c o}-B \cdot \sigma\right)}{\Phi\left(z_{c o}\right)} \\
& T_{+}\left(x_{c o}\right)=\frac{\int_{x_{c o}}^{\infty} t(x) \cdot f(x) d x}{\int_{x_{c o}}^{\infty} f(x) d x}=\frac{\int_{x_{c o}}^{\infty} A \cdot e^{-B\left(x-x_{c o}\right)} \cdot f(x) d x}{\int_{x_{c o}}^{\infty} f(x) d x}=\ldots=A \cdot e^{B \cdot \sigma \cdot z_{c o}+\frac{B^{2} \cdot \sigma^{2}}{2}} \cdot \frac{1-\Phi\left(z_{c o}+B \cdot \sigma\right)}{1-\Phi\left(z_{c o}\right)}
\end{aligned}
$$

where

$$
\begin{aligned}
& f(x)=\frac{1}{\sigma \sqrt{2 \pi}} e^{\frac{-(x-\mu)^{2}}{2 \sigma^{2}}} \\
& z_{c o}=\frac{x_{c o}-\mu}{\sigma} ; \quad \Phi(z)=\frac{1}{\sqrt{2 \pi}} \int_{-\infty}^{z} e^{\frac{-z^{2}}{2}} d z
\end{aligned}
$$

A fully detailed development of the equations is included in Appendix D.

When $\sigma=1$, the equations are:

$$
\begin{aligned}
& T_{-}\left(x_{c o}\right)=A \cdot e^{-B \cdot z_{c o}+\frac{B^{2}}{2}} \cdot \frac{\Phi\left(z_{c o}-B\right)}{\Phi\left(z_{c o}\right)} \\
& T_{+}\left(x_{c o}\right)=A \cdot e^{B \cdot z_{c o}+\frac{B^{2}}{2}} \cdot \frac{1-\Phi\left(z_{c o}+B\right)}{1-\Phi\left(z_{c o}\right)}
\end{aligned}
$$

The distance functions and the reaction time functions both depend on the value of the cutoff point $x_{c o}$. In our collaborative system, the robot observes the objects first followed by the human operator. Accordingly, the human decides about two different types of objects: objects that the robot already marked as targets; and objects the robot did not mark (Figure 16). The human uses two different cutoff points, for the two types of objects. Therefore, two different reaction time functions must be implemented.


Figure 16: Reaction times flow chart

The means of reaction time are denoted as:
$T_{M}$ - Mean reaction time of undetected signals (miss)
$T_{H}$ - Mean reaction time of detected signals (hit)
$T_{C R}$ - Mean reaction time of ignored noises (correct rejection)
$T_{F A}$ - Mean reaction time of mistakenly detected noises (false alarm)

Same denotations with the index $r h$ and $h$ (for instance, $T_{C R h}, T_{H r h}$ etc.), will represent reaction times for objects the robot marked as targets and for those it did not, respectively (see human decisions in Figure 16).

The equations that were developed for the normal distribution are adjusted to the signal and noise distributions. The means and standard deviations of the signal and noise distributions are respectively $\mu_{S}, \sigma_{S}$ and $\mu_{N}, \sigma_{N}$. We used the appropriate equations (for positive or negative responses) and parameters (mean and standard deviation of signal or noise distributions) to define equations for mean reaction time of all four possible outcomes (miss, hit, correct rejection and false alarm):

$$
\begin{aligned}
& T_{M}=A \cdot e^{-B \cdot \sigma_{S} \cdot z_{S}+\frac{B^{2} \cdot \sigma_{S}^{2}}{2}} \cdot \frac{\Phi\left(z_{S}-B \cdot \sigma_{S}\right)}{\Phi\left(z_{S}\right)} \\
& T_{H}=A \cdot e^{B \cdot \sigma_{S} \cdot z_{S}+\frac{B^{2} \cdot \sigma_{S}^{2}}{2}} \cdot \frac{1-\Phi\left(z_{S}+B \cdot \sigma_{S}\right)}{1-\Phi\left(z_{S}\right)} \\
& T_{C R}=A \cdot e^{-B \cdot \sigma_{N} \cdot z_{N}+\frac{B^{2} \cdot \sigma_{N}{ }^{2}}{2}} \cdot \frac{\Phi\left(z_{N}-B \cdot \sigma_{N}\right)}{\Phi\left(z_{N}\right)} \\
& T_{F A}=A \cdot e^{B \cdot \sigma_{N} \cdot z_{N}+\frac{B^{2} \cdot \sigma_{N}{ }^{2}}{2}} \cdot \frac{1-\Phi\left(z_{N}+B \cdot \sigma_{N}\right)}{1-\Phi\left(z_{N}\right)}
\end{aligned}
$$

where

$$
\begin{aligned}
& z_{S}=\frac{x_{c o}-\mu_{S}}{\sigma_{S}} ; \quad z_{N}=\frac{x_{c o}-\mu_{N}}{\sigma_{N}} \\
& \Phi(z)=\frac{1}{\sqrt{2 \pi}} \int_{-\infty}^{z} e^{\frac{-z^{2}}{2}} d z
\end{aligned}
$$

When $\sigma_{S}=\sigma_{N}=1$, the equations are:

$$
\begin{aligned}
& T_{M}=A \cdot e^{-B \cdot z_{S}+\frac{B^{2}}{2}} \cdot \frac{\Phi\left(z_{S}-B\right)}{\Phi\left(z_{S}\right)} \\
& T_{H}=A \cdot e^{B \cdot z_{S}+\frac{B^{2}}{2}} \cdot \frac{1-\Phi\left(z_{S}+B\right)}{1-\Phi\left(z_{S}\right)} \\
& T_{C R}=A \cdot e^{-B \cdot z_{N}+\frac{B^{2}}{2}} \cdot \frac{\Phi\left(z_{N}-B\right)}{\Phi\left(z_{N}\right)} \\
& T_{F A}=A \cdot e^{B \cdot z_{N}+\frac{B^{2}}{2}} \cdot \frac{1-\Phi\left(z_{N}+B\right)}{1-\Phi\left(z_{N}\right)}
\end{aligned}
$$

### 4.3 Collaboration model

The basis of the expanded model developed in this thesis are the four collaboration levels between a human operator and a robot (see subchapter 0 ), and the objective function that describes the expected value of system performance (see subchapter 2.6), as developed by Bechar (2006).

The objective function of the model as described by Bechar (2006) is:

$$
\begin{aligned}
& V_{I s}=N \cdot P_{S} \cdot\left[P_{H r} \cdot P_{H r h} \cdot\left(V_{H}+V_{C}+\underline{t_{H r h}} \cdot V_{t}\right)+\left(1-P_{H r}\right) \cdot P_{H h} \cdot\left(V_{H}+V_{C}+\underline{t_{H h}} \cdot V_{t}\right)\right]+ \\
& +N \cdot P_{S} \cdot\left[P_{H r} \cdot\left(1-P_{H r h}\right) \cdot\left(V_{M}+\underline{t_{M r h}} \cdot V_{t}\right)+\left(1-P_{H r}\right) \cdot\left(1-P_{H h}\right) \cdot\left(V_{M}+\underline{t_{M h}} \cdot V_{t}\right)\right]+ \\
& +N \cdot\left(1-P_{S}\right) \cdot\left[P_{F A r} \cdot P_{F A r h} \cdot\left(V_{F A}+V_{C}+\underline{t_{F A r h}} \cdot V_{t}\right)+\left(1-P_{F A r}\right) \cdot P_{F A h} \cdot\left(V_{F A}+V_{C}+\underline{t_{F A h}} \cdot V_{t}\right)\right]+ \\
& +N \cdot\left(1-P_{S}\right) \cdot\left[P_{F A r} \cdot\left(1-P_{F A r h}\right) \cdot\left(V_{C R}+\underline{t_{C R r h}} \cdot V_{t}\right)+\left(1-P_{F A r}\right) \cdot\left(1-P_{F A h}\right) \cdot\left(V_{C R}+\underline{t_{C R h}} \cdot V_{t}\right)\right]+t_{r} \cdot V_{t}
\end{aligned}
$$

Each of the human time variables (denoted as $t_{X r h}$ or $t_{X h}$ ) represents a superposition of a decision time and a motoric time (denoted as $t_{M}$ ), in accordance with the collaboration level. The decision times, previously considered as constants, are replaced with the mean reaction times functions introduced in the previous page.

When the system operates at the R collaboration level, the robot fulfills the task all by itself and all human time variables equal zero (there is no human intervening).

In the H collaboration level, the human does not use robot's help and the time variables are:

$$
\begin{aligned}
t_{M h} & =T_{M h} \\
t_{H h} & =T_{H h}+t_{M} \\
t_{C R h} & =T_{C R h} \\
t_{F A h} & =T_{F A h}+t_{M}
\end{aligned}
$$

In the HR collaboration level, the robot recommends the human by indicating potential targets. Then, the human confirms targets he thinks are real and marks extra targets the robot did not indicate. The human does a motoric action (marking) if he thinks the robot recommended well. The time variables are:

$$
\begin{aligned}
t_{M h} & =T_{M h} \\
t_{H h} & =T_{H h}+t_{M} \\
t_{C R h} & =T_{\text {CRh }} \\
t_{F A h} & =T_{F A h}+t_{M} \\
t_{M r h} & =T_{M r h} \\
t_{\text {Hrh }} & =T_{H r h}+t_{M} \\
t_{\text {CRrh }} & =T_{\text {CRrh }} \\
t_{\text {FArh }} & =T_{\text {FArh }}+t_{M}
\end{aligned}
$$

In the HOR collaboration level, the human supervises the robot. The robot marks targets and the human checks those marks. The human unmarks targets that are not real and marks extra targets that the robot missed. In this case, the human does a motoric action (unmarking) only if he thinks the robot made a mistake. The time variables are:

$$
\begin{aligned}
& t_{M h}=T_{M h} \\
& t_{H h}=T_{H h}+t_{M} \\
& t_{\text {CRh }}=T_{\text {CRh }} \\
& t_{F A h}=T_{F A h}+t_{M} \\
& t_{M r h}=T_{M r h}+t_{M} \\
& t_{H r h}=T_{H r h} \\
& t_{\text {CRrh }}=T_{\text {CRrh }}+t_{M} \\
& t_{\text {FArh }}=T_{\text {FArh }}
\end{aligned}
$$

The (motoric) time it takes to physically mark or unmark an object depends on the system interface and the environment conditions. Therefore, it should not vary between one object to another and it is considered as constant.

## 5 Numerical Analysis

A numerical analysis of the model was conducted using MatLab 7.1 (Appendix G details the script code). The optimal cutoff points for the human and the robot were determined by numerical computation. At the first stage, the objective function was calculated for a range of possible cutoff points. Then, the cutoff points that yielded the highest objective function score were determined as optimal cutoff points. The analysis of the model was performed for systems that work at the optimal cutoff points. The objective function score was calculated for each possible combination of parameters and variables, for each collaboration level. The best collaboration level is the level that yields the highest objective function score for a given set of parameters' value.

### 5.1 Model parameters

The objective function of the model consists of groups of parameters that describe the task, the environment and the observers. Table 3 introduces the parameters and their values.

### 5.1.1 Task types and parameters

In some systems, as mines detection or medical examinations, not to miss a target is much more important than the cost of making false alarms. In other systems, false alarms have high cost and the system accept to hit fewer targets in order to cause fewer false alarms. The independent parameters of the task were determined to describe different types of tasks and systems. Raising the gain from a hit, for example, induces the observer to make more hits at the expense of more false alarms. The value of costs can be easily changed into any monetary values.

Analysis was focused on three types of systems: Type I system gives high priority for not causing errors of the first type, i.e., detecting a target when a target does not exist (false alarm); Type II system gives high priority for not causing errors of the second type, i.e., missing a target. These two types were introduced by Oren et al. (2008). The different types of systems are characterized by the gains and penalties for each outcome ( $V_{H}, V_{M}, V_{F A}, V_{C R}$ ). For example, a high penalty for false alarms, relatively to the other values, reduces the false alarm ratio. Similarly, relatively high gain for hits reduces the cases of missing a target. System of Type III does not prefer one type of error on another; therefore the values for all four possible outcomes are the same $\left(V_{H}=-V_{M}=-V_{F A}=V_{C R}\right)$.Table 2 details the values for each type of system.

The time cost $\left(V_{T}\right)$ is the cost of one time unit of system operation. It includes the cost of the human operator and the robot. In order to analyze the influence of time cost regardless of the system type, it was set relatively to the gain for a hit ( $V_{T}=V_{H} \cdot V_{T} 2 V_{H}$ ). The ratio between the time cost and the gain for a hit, $V_{T} 2 V_{H}$, was set to the values: $-80,-40,-20\left(\right.$ hour $^{-1}$ ). For example, when $V_{H}$ equals

5 points, $V_{T}$ obtained the values: $-400,-200,-100$ points for an hour. The operational cost $\left(V_{C}\right)$ is the cost of the action conducted when the system detects a target, either if it is a hit or a false alarm. For all analyses, this cost was set to 2 points.

The operational and time costs were arbitrarily predetermined in order to limit its influence on the system decisions. The actual value of the gain-penalty-cost weights was less important in the analysis than the ratio between all weights, which determine the task nature (e.g., whether it is more important to detect melons, to reduce the number of false alarms or to finish the task in minimum time). The parameters' values are consistent with the work of Bechar (2006) and Oren (2007) in order to enable comparison.

Table 2: Gains and penalties for different types of systems

|  | Type I | Type II | Type III |
| :---: | :---: | :---: | :---: |
| $V_{H}$ | 5 | 50 | 10 |
| $V_{M}$ | -10 | -10 | -10 |
| $V_{F A}$ | -50 | -5 | -10 |
| $V_{C R}$ | 10 | 10 | 10 |

### 5.1.2 Environmental parameters

The parameters $N$ and $P_{S}$ determine the environmental condition. The objective function was calculated for 1,000 objects (targets, $N$ ). The target probability $\left(P_{S}\right)$ represents the fraction of targets from all objects. Analysis was conducted for different probability values between 0.1 and 0.9. The mean of the noise distribution was set to zero. The mean of the signal distribution was a positive number, which results from the value of the observer's sensitivity ( $d^{\prime}$ ), as can be seen in Figure 18. The standard deviation of the distributions assumed to be one and other noise and signal distribution should be normalized in order to fit the model.

### 5.1.3 Human parameters

The sensitivity represents the ability of the observer to distinguish between real targets and the other objects. The sensitivity of the human $\left(d^{\prime}{ }_{h}\right)$ was varied between 0.5 and 3 .

The human motoric time (tMotor) of executing an action (i.e., marking an object as a target or unmarking a robot's mark) was set to 2 seconds. The decision time was calculated according to the mean reaction time model (see chapter 4.2). The reaction time model is based on an exponential function, $t(x)=A \cdot e^{-B\left(x_{c o s}-x\right)}$, that includes two parameters. Parameter $A$, which represents the longest detection time, was set to 2,5 or 10 seconds. Parameter $B$ was set to $0,0.5,1,1.5$ or 2 .

These values represent variety of possible exponential functions (see Figure 23). When $B$ receives a zero value, the mean time is $A$.

### 5.1.4 Robot parameters

The sensitivity of the robot $\left(d^{\prime}{ }_{r}\right)$ was varied, same as human sensitivity, between 0.5 and 3 . The robot decision time $\left(t_{r}\right)$ is negligible relatively to the other times and was set to 0.01 seconds on average for one object.

Table 3: Model parameters' values

|  | Description | Range | Constants | Type dependent |  |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  |  |  |  | Type I | Type II | Type III |
| $V_{H}$ | The gain from a hit |  |  | 5 | 50 | 10 |
| $V_{M}$ | The penalty from a miss |  |  | -10 | -10 | -10 |
| $V_{F A}$ | The penalty from a false alarm |  |  | -50 | -5 | -10 |
| $V_{C R}$ | The gain from a correct rejection |  |  | 10 | 10 | 10 |
| $V_{C}$ | The operational cost |  | -2 |  |  |  |
| $V_{T}$ | The time cost | [-80,-40,-20] |  |  |  |  |
| $P_{S}$ | The probability of an object to be target | [0.1,0.2,0.5,0.8,0.9] |  |  |  |  |
| $N$ | Number of objects |  | 1000 |  |  |  |
| tMotor | The motoric time of the human |  | 2 |  |  |  |
| $A$ | Parameter of the response time function | [2,5,10] |  |  |  |  |
| $B$ | Parameter of the response time function | [0,0.5, 1, 1.5,2] |  |  |  |  |
| $d^{\prime}{ }^{\prime}$ | The human's sensitivity | [0.5:0.5:3] |  |  |  |  |
| $d^{\prime}{ }_{r}$ | The robot's sensitivity | [0.5:0.5:3] |  |  |  |  |
| $t \times$ | The robot's decision time |  | 0.01 |  |  |  |

### 5.2 Graph generator

The data included three types of systems. A record was saved for every combination of values of the six parameters that were not constant (see Table 3). To analyze the influence of parameters on different components of the objective function, a graph generator was developed in MatLab (Appendix G). The application that was developed, allows to select the system type, two parameters ( $\mathrm{X}, \mathrm{Y}$ ) and a function (one of the components of the overall objective function), and spreads subgraphs for every value of third parameter. The remained three more parameters are set manually into one of their possible values. This graph generator enabled an easy comprehensive data analysis.

Figure 17 illustrates an example of graph selection. The example describes type II system and the function that is shown is the optimal objective function (opt_VIs). The sensitivities of the human $\left(d^{\prime}{ }_{h}\right)$ and the robot $\left(d^{\prime}{ }_{r}\right)$ are varied along X and Y axes. A sub-graph is shown for every value of the target probability $\left(P_{S}\right)$. The other three parameters $(B, A, v T 2 v H)$ are set manually.


Figure 17: Graph generator application.
The user can choose a system type (a), an objective function (b), two parameters for X and Y axes and a third parameter for the sub graphs (c), and set manually the values of the three other parameters (d).

### 5.3 Cutoff point analysis

When the sensitivity of the human operator is high, the human operator can distinguish between targets. The optimal cutoff point is between the means of the noise and signal distribution (Figure 18, a). When the sensitivity is low, the ability to distinguish reduces and it becomes more effective not to examine the objects and decide the same for all of them. The optimal cutoff point, therefore, goes to the extreme. When the system gives high priority to not causing false alarms (Type I), the cutoff point will be set to infinity, and none of the objects will be marked as targets (Figure 18, b). When there is high priority of not missing a target (Type II), the cutoff point will be set to minus infinity.


Figure 18: A cutoff point between the distributions' means when the sensetivity is high (a) and extreme cutoff point selection when sensitivity is low (b).

This influence finds expression in the analysis, regardless of the response time costs of the observer. The time costs amplify this phenomenon. The mean response time reduces as the cutoff point is far from the mean of the distribution; therefore, in the sense of time costs, extreme ${ }^{2}$ cutoff point is always preferred.

In the analysis, the mean of the noise distribution is set to zero. Therefore, the sensitivity of the observer, that represents the distance between the noise and the signal distributions, is also the mean of the signal distribution.

In the following part, the optimal cutoff point for the human, in the H collaboration level, is presented for each of the three types of systems. The influence of the cutoff point position on other parts of the objective function is demonstrated. The graphs in this part exhibit relevant functions against the human sensitivity $\left(d^{\prime}{ }_{h}\right)$ and the cost of time unit ( $v T 2 v H$ ). The analysis was conducted for $P s=0.5, A=2, B=0.5, d r=0.5$.

Results for other probabilities for target ( $P s$ ) as well as the influence of the time cost $(v T 2 v H)$ and the time parameter $A$ are detailed in Appendix E.

[^1]
### 5.3.1 Human optimal cutoff point influence in Type I systems

Type I systems give high priority for not causing false alarms. When the human has low sensitivity, it is expected to get the highest value possible for the optimal cutoff point. Figure 19(a) shows the optimal cutoff point of the human. When the sensitivity of the human $\left(d^{\prime}{ }_{h}\right)$ is low, the optimal cutoff point value rises to six (the highest value possible).

Furthermore, the analysis shows that the total penalty for false alarms grows (in negative values) as the sensitivity of the observer decreases (Figure 19, b). This phenomenon exists up to the point where the sensitivity is too small. Then, an extreme positive cutoff point is preferred and the human marks less objects as targets. Therefore, the total penalty for false alarms decreases as was expected in Type I systems.

Extreme cutoff point results in redundancy of system operation time. As the cutoff point is drawn away from the means of the distribution (see Figure 18, b), the distance of the objects from the cutoff point increases; and the mean response time, correspondingly, decreases. Figure 19(c) shows the redundancy of the system operation time for low human sensitivity.


Figure 19: Optimal cutoff point of the human (a), total penalty of false alarms (b), and system operation time (c) in Type I system at the H collaboration level. The human sensitivity and the time cost are ranged along x and y axes.

### 5.3.2 Human optimal cutoff point influence in Type II systems

Type II systems give high priority for not missing targets. When the human has low sensitivity, it is expected to get the lowest value possible for the optimal cutoff point. Figure 20(a) shows the optimal cutoff point of the human. When the sensitivity of the human $\left(d^{\prime}{ }_{h}\right)$ is low, the optimal cutoff point value is minus three (the lowest value possible).

The analysis shows that the total penalty for misses grows (in negative values) as the sensitivity of the observer decreases (Figure 20, b). This phenomenon exists up to the point where the observer sensitivity is too small. Then, an extreme negative cutoff point is preferred and the human marks more objects as targets. Therefore, the total penalty for miss decreases as was expected in Type II systems.

As was explained for type I, extreme cutoff point results in redundancy of system operation time. Figure 20(c) shows the redundancy of the system operation time when the sensitivity of the human decreases and an extreme cutoff point is preferred.


Figure 20: Optimal cutoff point of the human (a), total penalty of misses (b), and system operation time (c) in Type II system at the $H$ collaboration level. Human sensitivity and the time cost are ranged along $x$ and $y$ axes.

### 5.3.3 Human optimal cutoff point influence in Type III systems

In type III systems, the gains and penalties are equal for all outcomes, there is no preferable error and the cutoff point remains between the means of the distributions even when the sensitivity of the observer is low. Figure 21(a) shows the optimal cutoff point of the human. The optimal cutoff point gets values that are approximately half of the sensitivity (e.g., when $d^{\prime}{ }_{h}=3$, the cutoff point is 1.6). The sensitivity is the distance between the distributions and it shows that the cutoff point is approximately in the middle of the distributions.

As was explained before, the total penalty for misses and the total penalty for false alarms grow, as the sensitivity of the observer decreases. In systems of type III, as was introduced above, the optimal cutoff point is between the distributions and no extreme cutoff point is preferred. Therefore, the total penalties for misses and false alarms continue to decrease for low sensitivities as shown in Figure 21(b,c).


Figure 21: Optimal cutoff point of the human (a), total penalty of misses (b), and total penalty of false alarms (c) in Type III system at the H collaboration level. Human sensitivity and the time cost are ranged along $x$ and $y$ axes.

### 5.4 Human's dominancy analysis

In the H collaboration level, the human operator operates solely. The human becomes less dominant as the level of autonomy of the robot increases. In the R collaboration level, when the robot is fully autonomous, the human has no influence.

The human operations cause an increase in operation time and costs. The human response time and motoric time are significantly higher than the robot decision time. Therefore, in the sense of time costs, it is reasonable that evolving a human in the recognition process will be less profitable when the time cost is high.

The following graphs present decrease in human dominance, as the response time of the human and the time cost increase. In the graphs, a single collaboration level dominates each zone (each color represents different operating level: H- blue, HR- cyan, HOR- yellow and R- red). The graphs present the collaboration level required to achieve the best system performance. The sensitivities of the human $\left(d^{\prime}{ }_{h}\right)$ and the robot $\left(d^{\prime}{ }_{r}\right)$ are ranged along X and Y axes.

Figure 22(a-c) shows how human dominance reduces as the time cost increases. The time cost increases from graph 'a' ( $v T 2 v H=-0.0055$ ) to graph 'c' $(v T 2 v H=-0.0222)$. Accordingly, the area of the HR (cyan) and HOR (yellow) collaboration levels diminished. In this specific case, the area decreases from $92 \%$ in graph 'a' to $60 \%$ in graph 'c'. In other cases, the area decreases in a different rate.


Figure 22: Human dominance reduces as the time cost increases from graph 'a' to graph 'c'.

$$
A=10, B=0.5, P s=0.2
$$

The reaction time model is based on an exponential function, $t(x)=A \cdot e^{-B\left(x_{c o}-x\right)}$, that includes two parameters: parameter $A$, that determines the height of the function at the cutoff point, and parameter $B$. The reaction time increases, as $A$ increases and $B$ decreases (see Figure 23).


Figure 23: The response time function (y-axis) for different values of B parameter.

$$
A=1, \quad X_{c o}=0
$$

Figure 24(a-c) shows how human dominance reduces as the time parameter $A$ increases. The time parameter increases from graph 'a' $(A=2)$ to graph 'c' $(A=10)$. Accordingly, the area of the HR (cyan) and HOR (yellow) collaboration levels diminished. Figure 25(a-e) shows how human dominance reduces as the time parameter $B$ increases. The time parameter decreases from graph ' a ' ( $B=2$ ) to graph 'e' $(B=0)$. Accordingly, the area of the HR and HOR collaboration levels diminished. In this specific case, the area decreases from $94 \%$ in graph 'a' to $6 \%$ in graph 'e'. In other cases, the area decreases in a different rate. Analysis shows that in some cases the collaboration with a human is not profitable in most of the combinations of human and robot sensitivities. In these cases, the use of a simpler system without an option for collaboration should be considered.


Figure 24: Human dominance reduces as the response time increases from graph 'a' to graph 'c'. $v T 2 v H=-0.022, B=0.5, P s=0.2$


Figure 25: Human dominance reduces as the mean response time increases from graph 'a' to graph 'e'. $v T 2 v H=-0.022, A=10, P s=0.2$

## 6 Sensitivity Analysis

The numerical analysis of the collaboration model was conducted for optimal cutoff points. Sensitivity analysis of human and robot's cutoff points was performed in order to show how small deviation from the optimal values influences the system's objective function score and the optimal collaboration level. Specifically, we focused on the cases where small deviations from the human optimal cutoff point cause a shift in the optimal collaboration level.

The analysis was conducted for all three cutoff points: cutoff point of the robot ( $\mathrm{X}_{\mathrm{COr}}$ ) and two cutoff points of the human for targets the robot already marked and for targets it did not mark ( $\mathrm{X}_{\text {Corh }}$ and $\mathrm{X}_{\mathrm{COh}}$ respectively). In each case analyzed, only one cutoff point was changed.

In the analysis, the signal and noise distributions are normalized. The mean of the noise distribution is zero and the maximum sensitivity $\left(d^{\prime}{ }_{r}\right.$ or $\left.d^{\prime}{ }_{h}\right)$, which is also the position of the signal distribution mean, is three. Therefore, in order to show all possible positions, the cutoff points' value ranged from minus three to six (i.e., three standard deviation units from the means of the distributions).

### 6.1 General description and general conclusions

This section gives general description of the figures, which are shown ahead, and introduces some common phenomena. Figure 26 is used as an example.

Each of the following figures represents a single optimal case for a given set of parameters. One can notice that in Figure 26 there is one graph for each of the three cutoff points ( $\mathrm{X}_{\mathrm{COh}}, \mathrm{X}_{\mathrm{COrh}}$ and $\mathrm{X}_{\mathrm{COr}}$ from left to right). The y -axe represents the system's objective function score. In each graph, four lines illustrate how the objective function value varies according to the change of the cutoff point value. Each line represents one of the four collaboration levels (H-blue, HR-cyan, HOR-yellow and R-red). A black circle marks the optimal cutoff point value on the best collaboration level line (the highest point). In this specific case, the objective function score is 7268 and the optimal cutoff point values are $\mathrm{X}_{\mathrm{COh}}=1.2, \mathrm{X}_{\mathrm{COrh}}=0.8$ and $\mathrm{X}_{\mathrm{COr}}=-1.6$. The other parameter's values $(d r, d h, P s, A, B, v T 2 v H)$ are shown in the header of the figure.

One can see that only the cutoff point of the robot affects the score of the R collaboration level (notice straight red line in the left and middle graphs in Figure 26). Similarly, only the cutoff point of the human, $\mathrm{X}_{\mathrm{COh}}$, affects the score of the H collaboration level (straight blue line in the middle and right graphs). The scores of the HR and HOR collaboration levels are affected from all three cutoff points.

In some cases, small deviation from the optimal cutoff point makes only a slight different in the objective function value (notice almost straight yellow line in left graph in Figure 26). In other
cases, small deviation from the optimum causes a dramatic decrease of the objective function value. If the score of the best collaboration level decreases beneath other collaboration level score, the second level becomes the current best collaboration level (e.g., the yellow line in the middle graph in Figure 26 decreases beneath the blue line). We denote this: a 'shift' in the best collaboration level.

In many of the analyzed cases, the optimal level yields a score that is only slightly better than another collaboration level score. Particularly, the HR and HOR levels yield almost the same score at the optimal cutoff points (see all following figures at this chapter).

### 6.2 Type III systems

### 6.2.1 Cutoff points analysis

### 6.2.1.1 Analysis of the optimal cutoff point of the robot

In all cases, a change in the value of the robot's cutoff point makes more influence on the score of the R collaboration level than on the other levels' score. Therefore, when R is the best collaboration level, a smaller deviation from the optimal $\mathrm{X}_{\mathrm{COr}}$ may cause best level shifting (i.e., smaller than deviations from $\mathrm{X}_{\mathrm{COr}}$ when R is not the best collaboration level).

When the best collaboration level is HR or HOR, small deviations from the optimal $\mathrm{X}_{\text {Cor }}$ usually reduce the objective function score symmetrically in both directions.

### 6.2.1.2 Cases where the robot is more sensitive than the human operator

In most of the cases when the robot is more sensitive than the human $\left(d^{\prime}{ }_{r}>d^{\prime}{ }_{h}\right), \mathrm{R}$ is the best collaboration level. In other cases, HOR is the best collaboration level but it usually has only slightly higher score then R. For all cases, a small deviation from the optimal cutoff point does not cause a shift in the best collaboration level.

### 6.2.1.3 Cases where the human operator is remarkably more sensitive than the robot

In this work, we assumed that collaboration is beneficial because the human performs better than the robot in unstructured environments. Therefore, most of the analysis was focused on cases where the human is more sensitive than the robot. The sensitivities of the human $\left(d^{\prime}{ }_{h}\right)$ and the robot $\left(d^{\prime}{ }_{r}\right)$ were varied between 0 and 3 . We denote that the human is remarkably more sensitive than the robot in cases where $1.5<d^{\prime}{ }_{h}-d^{\prime}{ }_{r}$. In cases where $0<d^{\prime}{ }_{h}-d^{\prime}{ }_{r}<1.5$ we denote that, the human is unremarkably more sensitive than the robot.

In most of the cases, when the human is remarkably more sensitive than the robot, the best collaboration level is HR or HOR. The difference between their score, near the optimal cutoff point, is relatively small. A small deviation from the optimal cutoff point of the human, $\mathrm{X}_{\mathrm{COh}}$, does not
cause a shift in the best collaboration level. However, a small deviation from the optimal $\mathrm{X}_{\text {Corh }}$ enforces best level shifting to H (Figure 26).


Figure 26: Example of Type III system's score in a case where the human is remarkably more sensitive than the robot.

### 6.2.1.4 Cases where the human operator is unremarkably more sensitive than the robot

In most of the cases, when the human is unremarkably more sensitive than the robot ( $0<d^{\prime}{ }_{h}-d^{\prime}{ }_{r}<1.5$ ), the best collaboration level is HR or HOR. The analysis reveals different results for high, medium and low probabilities for an object to be a target ( $P s$ ).

Figure 27 shows one of these cases where the probability for an object to be a target is high $(P s=0.9)$. A small deviation from the optimal cutoff point of the human, $\mathrm{X}_{\mathrm{COh}}$, reduces the system score and may cause a level shifting to R. A change from the optimal value of the second cutoff point, $\mathrm{X}_{\text {Corh }}$, may change the best collaboration level only if the deviation is in the positive direction. A deviation in the negative direction slightly reduces the system score but does not cause a shift in the best collaboration level.

Figure 28 shows a case where the probability for an object to be a target is low $(P s=0.1)$. In this case, a small deviation from the optimal $\mathrm{X}_{\mathrm{COh}}$, may change the best collaboration level only if the deviation is in the negative direction. A deviation in the positive direction slightly reduces the system score but does not cause a shift in the best collaboration level. A change from the optimal value $\mathrm{X}_{\text {Corh }}$, reduces the system score and may cause level shifting.

Figure 29 shows a case where the probability for an object to be a target is medium ( $P s=0.5$ ). A small deviation from optimal $\mathrm{X}_{\mathrm{COh}}$, in the negative direction may change the best collaboration level. On the other hand, a small deviation in the positive direction reduces the system
score but does not cause a shift in the best collaboration level. Deviations from the optimal value $\mathrm{X}_{\text {Corb }}$, behave the opposite way.


Figure 27: Example of Type III system's score in a case where the human is unremarkably more sensitive than the robot and the probability for a target is high.


Figure 28: Example of Type III system's score in a case where the human is unremarkably more sensitive than the robot and the probability for a target is low.


Figure 29: Example of Type III system's score in a case where the human is unremarkably more sensitive than the robot and the probability for a target is medium.

### 6.2.2 Influence of the probability for an object to be a target (Ps)

Generally, for all system types and in all collaboration levels, the system objective function's score reduces more sharp when the deviation from the optimal cutoff point is in one direction than when is in the other direction. The direction depends on the probability for an object to be a target. For a matter of simplicity, we assume in the following discussion that all system's gains and penalties of the four possible outcomes are equal.

In signal detection theory, when the cutoff point moves from the optimal point in the positive direction, the score reduces because more false alarms occur (also, fewer targets are missed, but it affects the score less). When the cutoff point moves from the optimal point in the negative direction, the score reduces because more targets are missed (also, fewer false alarms occur, but it affects the score less). See Figure 6 and Figure 7.

If more objects are targets ( $P s=0.9$ ), then usually the probability for miss is more than the probability for false alarm. Therefore, the score reduces more sharp if the deviation from the optimal cutoff point is in the negative direction (see Figure 30 for example). When less objects are targets ( $P s=0.1$ ), the probability for false alarm is usually more than the probability for miss. In this case, the score reduces sharper if the deviation from the optimal cutoff point is in the positive direction (see Figure 31 for example).

### 6.2.3 Influence of the time parameters

In the following part, we analyze cases where human reaction time is expensive and long. It occurs when the time parameters values are: $A=10, B=0.5, v T 2 v H=-0.022$. The human reaction time in our model depends on the distance of objects value from the cutoff point value. When the cutoff point is far from an object, it takes less time to decide whether it is a target or not.

### 6.2.3.1 New collaboration levels

The analysis reveals new collaboration levels, which are derived from the original levels HOR and $H R$ and preferred when the reaction time of the human is expensive. The analysis reveals different results for high and low probabilities for an object to be a $\operatorname{target}(P s)$.

Figure 30 shows a case where the probability for a target is high ( $P s=0.9$ ) and HOR is the best collaboration level. In practice, the way of collaboration is different from HOR. One can see that the cutoff point of the human for targets that the robot already marked, $\mathrm{X}_{\text {COrh }}$, is set to the lowest value possible in the data set ( -3 ). It means that the human keeps all the marks on targets that the robot detected, without spending time on rechecking them. The human concentrates only on detecting targets that the robot did not mark.

In addition, a small deviation from the optimal cutoff point of the human, $\mathrm{X}_{\mathrm{COh}}$, enforces best level shifting to R. Although the human is much more sensitive, if he does not operate according to the optimal cutoff point, the system operates better without collaboration with the human. This is probably because of the high cost of human time.


Figure 30: Example of Type III system's score in a case where the human reaction time is expensive and the probability for a target is high.

Figure 31 shows a case where the probability for a target is low ( $P s=0.1$ ) and HR is the best collaboration level. In this case, the collaboration is also different. One can see that the cutoff point of the human for targets that the robot did not marked, $\mathrm{X}_{\mathrm{COh}}$, is set to the highest value possible in the data set (6). This implies that the human concentrates only on rechecking the robot's recommendations for targets. The human does not spend time trying to detect other targets that the robot did not recommend.


Figure 31: Example of Type III system's score in a case where the human reaction time is expensive and the probability for a target is low.

In both cases, due to high human time costs, the best way to collaborate is that the human will concentrate only on one type of objects. When many objects are targets ( $P s=0.9$ ) the human observes only objects that the robot did not mark. The human does not need to remark the objects that the robot already marked because this is an inherent property of the HOR collaboration level. When only few of the objects are targets ( $P s=0.1$ ), the human observes only objects that the robot already marked.

Practically the system created new collaboration levels that are derived from the HR and HOR collaboration levels. By ignoring one type of objects by the human, the system reduces the total human reaction time cost and can achieve better performance.

### 6.2.3.2 The system is more sensitive to changes when the time cost is high

As human's reaction time costs increases (and takes longer), the score of the collaboration levels, which include the human, reduces. The score of the R collaboration level is not affected by
the reaction time cost. Therefore, the difference between the scores of the best collaboration level and the R level reduces. Hence, in many cases when the time cost is high, the system becomes more sensitive to changes in human cutoff points' values. The case when the best level shifts to R , becomes more common.

### 6.2.3.3 Constant time parameters

Previous work (Bechar, 2006) assumed that the decision time of the human is equal for all objects. In this work, we introduce a reaction time model that unties this assumption. In the data set, when $B=0$ the time parameters are constant for all objects (as in previous work).

As long as the total cost of human reaction time is not expensive (relatively to other costs of the system), the question whether the time parameters are constant or not, does not make much difference neither in system's objective function value, nor in the best collaboration level. However, when human reaction time becomes relatively expensive, constant time parameters leads to quite different results. The lower part of Figure 32 shows the case of Figure 31 and the upper part shows the same case but with parameter $B$ equals zero. One can see that the scores of the collaboration levels that include the human are lower when $B=0$ and the best collaboration level is R . In this specific case, the score reduced in 1642 points, which are $24 \%$. In other cases, the score reduces in a different rate.


Figure 32: Example of Type III system's score in a case where the human reaction time is expensive and the probability for a target is low. A comparison with constant time parameters $(B=0)$ is presented.

### 6.3 Type I systems

Systems of type I give high priority for not causing errors of the first type, i.e., detecting a target when a target does not exist (false alarm).

In type III system, R is the best collaboration level in most cases where the robot is more sensitive than the human. In type I system, R is the best collaboration level only if the robot is remarkably more sensitive $\left(1<d^{\prime}{ }_{r}-d^{\prime}{ }_{h}\right)$. If the robot is unremarkably more sensitive than the human, then HR or HOR are the best collaboration level.

When the human is more sensitive than the robot and the probability for an object to be a target is high ( $P s=0.9$ ), the system score is more sensitive to deviations from the optimal values (relatively to type III system). A small deviation from the optimal cutoff point, $\mathrm{X}_{\mathrm{COh}}$, reduces the system score and may cause a level shifting to R only if the deviation is in the negative direction. A change from the optimal value of the second cutoff point, $\mathrm{X}_{\text {Corb }}$, may change the best collaboration level if the deviation is in the positive direction. A deviation in the negative direction reduces the system score but does not cause a shift in the best collaboration level. Figure 33 shows a comparison between type I and type III systems in the case that is introduced above.

When the probability for an object to be a target is low ( $P s=0.1$ ), the difference between the collaboration levels scores is very small. A small deviation from the optimal cutoff points' values may cause a best level shifting but the score remains almost the same. This is true even if the human is much more sensitive than the robot (see Figure 34). When the probability for an object to be a target is medium ( $P s=0.5$ ), the results are similar to those of type III system.

Analysis of type III system revealed new collaboration level in cases where human reaction time is expensive. In type I system this phenomena occurs less often. It occurs only when the probability for an object to be a target is low ( $P s=0.1$ ), or when the human is no more sensitive than the robot.


Figure 33: Comparison between Type I and Type III systems' score in a case where the human is more sensitive than the robot and the probability for a target is high.


Figure 34: Example of Type I system's score in a case where the probability for a target is low and the difference between the collaboration levels scores is small.

### 6.4 Type II systems

Systems of type II give high priority for not causing errors of the second type, i.e., missing a target. Systems of type III do not prefer one type of error on another. In type II system, R is the best collaboration level in most cases where the robot is more sensitive than the human is, as in type III.

When the human is more sensitive than the robot and the probability for an object to be a target is high ( $P s=0.9$ ), the difference between the collaboration levels scores is very small. A small deviation from the optimal cutoff points' values may cause a best level shifting but the score remains almost the same. This is true even if the human is much more sensitive than the robot (see Figure 35). When the probability for an object to be a target is low or medium (Ps equals 0.1 or 0.5 ), the results are similar to those of type III system.

Same new collaboration levels come out in type II system in cases where human reaction time is expensive. However, it occurs for relatively lower cost of human reaction time than in type III. The reason for that is probably the fact that the time cost is set relatively to the reward of one hit. The reward for a hit in type II system is five times more than the reward in type III system and therefore the comparison is not reliable.


Figure 35: Example of Type II system's score in a case where the probability for a target is high and the difference between the collaboration levels scores is small.

## 7 Conclusions and Future Research

### 7.1 Conclusions

Bechar (2006) developed a model for evaluating performance of human-robot collaborative target recognition systems. This work introduces further development of the model by incorporating non-constant reaction times. The new model, proposed in this research, might describe actual systems in a better way by adjusting time parameters to a specific task and taking into consideration the fact that reaction time of the human depends on the strength of the observed object. Evaluating the best collaboration level according to the new model, considers the influence of human reaction time on system performance.

The analysis revealed additional collaboration levels, which are derived from the HR and HOR collaboration levels defined in Bechar's work (Bechar, 2006), and are the best collaboration level when human time costs are high. In these collaboration levels, the human concentrates only on one type of objects. When many objects are targets, the human observes only objects that the robot did not mark and does not check objects that the robot marked (based on the HOR collaboration level). When only few of the objects are targets, the human observes only objects that the robot recommended and does not try to detect other targets (based on the HR collaboration level). Since the human ignores one type of objects, the system reduces the total human reaction time cost and can achieve better performance.

The human ignores objects by setting his/her cutoff point to an extreme value. When the cutoff point is the highest positive value possible, none of the objects is higher than the cutoff point so none of them is marked as a target. Similarly, when the cutoff point value is the lowest possible, all the objects are marked as targets. The analysis shows how the system type, the human sensitivity, the probability of an object to be a target, and the time cost all influence the phenomena of extreme cutoff point selection.

When the human sensitivity is low, the human badly discriminates between targets and other objects. If the system gives high priority for not causing false alarms (type I systems), the human prefers an extreme positive cutoff point, resulting in no objects that are marked as targets, and no false alarms. For systems that give high priority for not missing targets (type II systems), an extreme negative cutoff point was preferred, resulting in all objects marked as targets and no misses.

The probability of an object to be a target ( $P s$ ) influences this phenomenon. In type II systems, when there are many targets among the objects (i.e., Ps is high), the system prefers extreme cutoff point for higher sensitivities of the human (relatively to low sensitivities in cases
where $P s$ is not high and an extreme cutoff point is preferred). In a similar manner, when most of the objects are not targets (i.e., Ps is low), in type I systems, an extreme cutoff point is preferred for higher sensitivities of the human. A reasonable explanation for this influence is the potential of misses or false alarms to occur. When there are many targets, the potential of missing a target is higher; and when there are few targets, the potential of false alarms is high.

The analysis shows that mean reaction time and time costs affect the position of the optimal cutoff point. The phenomenon, introduced above, arises for higher human sensitivities as the mean time and/or the time cost are higher. Furthermore, the analysis shows that collaboration with a human is less profitable in cases when the time cost is high. In these cases, the R collaboration level, that does not include a human, is the optimal collaboration level.

An extreme cutoff point position decreases the total operation time cost. The mean response time reduces as the cutoff point is far from the mean of the distribution; therefore, in the sense of time costs, the extreme cutoff point is always preferred.

The position of the cutoff point influences all other parts of the objective function. An extreme positive cutoff point, for example, causes small probabilities of false alarms and hits; and causes high probabilities of miss and correct rejections. The overall gains and penalties of these outcomes are modified accordingly.

### 7.2 Research limitations

It must be noted that although this research includes an in-depth analysis of the new objective function, it was impossible to analyze and investigate all possible variables' combinations due to the multitude of variables that are involved. Hence, the thesis presents the most common trends and the conclusions are limited to the analyzed cases.

Furthermore, the results are strongly linked to the analyzed cases because of the high dependency on the many parameters. Therefore, we presented only trends and did not detail quantitative results, which are specific and highly depend on the chosen parameters.

This work focused only on the optimal collaboration level. In some cases, the optimal level yields a score that is only slightly better than another collaboration level score. In addition, switching the level of operation during the task is related to some operational costs. Hence, it might not always be worthy to operate at the best level. The analysis and conclusions are therefore limited also in this aspect.

### 7.3 Definition of the new collaboration levels

The research discovered a phenomenon, in which the human ignores objects by setting his cutoff point to an extreme value. An in-depth analysis of this phenomenon revealed two new collaboration levels, which are derived from the HR and the HOR collaboration levels defined in Bechar's work (Bechar, 2006), and are the best collaboration level when the human time cost is high. In each of the new collaboration levels, the human observes only one type of objects and ignores another. The new collaboration levels can be defined as follows.

HR2: The human operator observes only objects that the robot recommended to mark as targets. The human acknowledges the robot's correct detections and ignores recommendations that are false alarms. The human operator cannot mark other targets, which the robot did not recommend.

HOR2: Targets are identified and marked automatically by the robot's detection algorithm and the human operator cannot change these marks. The human operator assignment is to detect and mark the targets missed by the robot.

### 7.4 Future research

The following directions are worthy future investigation:

### 7.4.1 Determination of the Reaction time type: constant versus variable

This research analyzes the influence of human reaction time in human robot collaborative systems. Different aspects of the influence were discussed, but one question remained unanswered: When is it essential to regard reaction time as a variable, while designing or analyzing a system, and when can it be considered as constant? One of the three terms should occur in order to determine reaction time as a constant: 1) when the contribution of the reaction time part to the objective function is small relative to the other parts; 2) the difference between the objective function scores when using reaction time as a variable or a constant is small; and 3) when the involvement of the human operation is small. In some cases, considering constant time parameters will most likely produce a good estimation of system performance. However, in other cases, e.g., when the cost of system operation time is high, modeling reaction time is probably essential. Future research should answer this question and differentiate between those cases.

### 7.4.2 New/additional collaboration levels

The analysis revealed two new collaboration levels and future research should investigate these further. These collaboration levels are derived from the HR and HOR collaboration levels by adjusting one of the human cutoff points to extreme positive or negative value. In practice, although the optimal cutoff point should make the human concentrate only on one type of objects, the human might not operate optimally and therefore, might spend time and efforts on the other type of objects. Systems that officially include these two new collaboration levels as part of other levels may perform better. Future research should investigate in what cases these collaboration levels are the best collaboration level.

### 7.4.3 Experiment of human reaction time influence

This work included a preliminary analysis of human reaction time based on data acquired in an experiment conducted by Bechar (2006). Bechar (2006) conducted an experiment simulating melon detection in order to examine the influence of different human-robot collaboration levels in a target recognition task. During the experiment, all human operations were recorded. In this work, we analyzed experimental data, focusing on the human reaction time and regarding them as variables. We showed the relation between image complexity and decision time of the human operator (see Appendix H). However, since this work was very limited in scope it is included only as an Appendix.

An experiment of target recognition, specially designed to examine human reaction time, should check how time pressure on the subjects influences their performance. It can also discover how well the reaction time model of Murdock (1985) and other models, describe reaction time.

### 7.4.4 Examination of different reaction time models

This research used a reaction time model based on Murdock (1985). Other models describe reaction time differently. Future research can examine other models and validate them with experiments. The examination can discover how the influence of human reaction time depends on the reaction time model; and what phenomena do not depend on the models.

### 7.4.5 Analytical development of an optimal cutoff point

The new model, proposed in this research, includes a reaction time function that depends on the cutoff point position. Signal detection theory does not apply to this time function, and therefore, the optimal cutoff point that the theory supply must be adjusted. A further study may provide analytical development of the new optimal cutoff point. One must calculate a derivative of the objective function in order to find the cutoff point results in the maximum value.

### 7.4.6 Use of mean distances to evaluate mean reaction times

This study includes analytical development of the mean distance model, which calculates the mean distance between the cutoff point and objects of the same category (e.g., mean distance of all objects that were 'missed'). Future research can investigate the use of the mean distance model to evaluate mean time.

### 7.4.7 Collaboration level switching

This work focused only on the optimal collaboration level. Future research should apply full system optimization, which should consider the cost of switching between levels (Takach, 2008) and not only the cost of operating at the best collaboration level.

### 7.4.8 Collaboration in other stages of human information processing

Parasuraman et al. (2000) introduce a four-stage model of human information processing (see subchapter 0). The four stages in the model are: (1) information acquisition, (2) information analysis, (3) decision and action selection, and (4) action implementation. In this thesis, we introduce a collaboration model only for the decision and action selection stage. Future work should investigate levels of collaboration for the other stages.

### 7.4.9 Additional analysis

Due to the multitude variables in the model, there are numerous combinations and cases to analyze. This thesis presents the most common trends and additional analyses are required.

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## Appendix A - Normal, Standard Normal, Signal and Noise Distributions

## 1. Normal distribution

Here is a short review of the Normal distribution, also called Gaussian distribution.
If $X$ is normally distributed with mean $\mu_{X}$ and variance $\sigma_{X}{ }^{2}$ we denote:

$$
X \sim \quad\left(\mu_{X}, \sigma_{X}{ }^{2}\right)
$$

The probability density function (PDF) is:

$$
f_{X}(x)=\frac{1}{\sigma_{X} \sqrt{2 \pi}} \cdot e^{-\frac{\left(x-\mu_{X}\right)^{2}}{2 \sigma_{X}^{2}}}
$$

The cumulative density function (CDF) is:

$$
F_{X}(x)=\int_{-\infty}^{x} f_{X}(x) d x=\frac{1}{\sigma_{X} \sqrt{2 \pi}} \int_{-\infty}^{x} e^{-\frac{\left(x-\mu_{X}\right)^{2}}{2 \sigma_{X}^{2}}} d x
$$

## 2. Standard normal distribution

The standard normal distribution is a normal distribution with a mean of zero and a variance of one. If $X$ is normally distributed with mean $\mu_{X}$ and variance $\sigma_{X}{ }^{2}$, we can normalize $X$ by defining new random variable $Z$ :

$$
\begin{aligned}
& z=\frac{x-\mu_{X}}{\sigma_{X}} \Rightarrow \mu_{Z}=0, \sigma_{Z}^{2}=1 \\
& Z \sim \quad(0,1)
\end{aligned}
$$

The PDF of the standard normal distribution is:

$$
f_{Z}(z)=\varphi(z)=\frac{1}{\sigma_{Z} \sqrt{2 \pi}} \cdot e^{-\frac{\left(z-\mu_{Z}\right)^{2}}{2 \sigma_{Z}^{2}}}=\frac{1}{1 \cdot \sqrt{2 \pi}} \cdot e^{-\frac{(z-0)^{2}}{2 \cdot 1^{2}}}=\frac{1}{\sqrt{2 \pi}} \cdot e^{-\frac{z^{2}}{2}}
$$

The CDF of the standard normal distribution is:

$$
\begin{aligned}
& F_{Z}(z)=\Phi(z)=\int_{-\infty}^{z} f_{Z}(z) d z=\frac{1}{\sigma_{Z} \sqrt{2 \pi}} \int_{-\infty}^{z} e^{-\frac{\left(z-\mu_{Z}\right)^{2}}{2 \sigma_{Z}^{2}}} d z=\frac{1}{1 \cdot \sqrt{2 \pi}} \int_{-\infty}^{z} e^{-\frac{(z-0)^{2}}{2 \cdot 1^{2}}} d z=\frac{1}{\sqrt{2 \pi}} \int_{-\infty}^{z} e^{-\frac{z^{2}}{2}} d z \\
& 1-\Phi(z)=1-\int_{-\infty}^{z} f_{Z}(z) d z=\int_{z}^{\infty} f_{Z}(z) d z=\frac{1}{\sqrt{2 \pi}} \int_{z}^{\infty} e^{-\frac{z^{2}}{2}} d z
\end{aligned}
$$

## 3. The relation between normal and standard normal distributions

Here is an interpretation of the link between the normal distribution and the standard normal distribution. If $X$ is normally distributed, then for a specific value $x_{c o}$ we can define $z_{c o}$, a specific value of the random variable $Z$ which is standard normal distributed.

$$
z_{c o}=\frac{x_{c o}-\mu_{X}}{\sigma_{X}}
$$

The PDF of $X$ can be defined, using the PDF of $Z$ :

$$
\begin{aligned}
& f_{X}\left(x_{c o}\right)=\frac{1}{\sigma_{X} \sqrt{2 \pi}} \cdot e^{\frac{-\left(x_{c o}-\mu_{X}\right)^{2}}{2 \sigma_{X}}}=\frac{1}{\sigma_{X}} \cdot \frac{1}{\sqrt{2 \pi}} \cdot e^{\frac{-z_{c o}^{2}}{2}}=\frac{1}{\sigma_{X}} \cdot \varphi\left(z_{c o}\right) \\
& f_{X}\left(x_{c o}\right)=\frac{1}{\sigma_{X}} \cdot \varphi\left(z_{c o}\right)
\end{aligned}
$$

The CDF of $X$ can be defined, using the CDF of $Z$ :

$$
F_{X}\left(x_{c o}\right)=\int_{-\infty}^{x_{c o}} f_{X}(x) d x=\frac{1}{\sigma_{X} \sqrt{2 \pi}} \int_{-\infty}^{x_{c o}} e^{-\frac{1}{2}\left(\frac{x-\mu_{X}}{\sigma_{X}}\right)^{2}} d x=
$$

Changing the domain of integration :

$$
\begin{aligned}
& z=\frac{x-\mu_{X}}{\sigma_{X}} \Rightarrow x=\mu_{X}+\sigma_{X} z \\
& \frac{d x}{d z}=\frac{d\left(\mu_{X}+\sigma_{X} z\right)}{d z}=\sigma_{X} \Rightarrow d x=\sigma_{X} d z \\
& x=-\infty \Rightarrow z=\frac{-\infty-\mu_{X}}{\sigma_{X}}=-\infty \\
& x=x_{c o} \Rightarrow z=\frac{x_{c o}-\mu_{X}}{\sigma_{X}}=z_{c o}
\end{aligned}
$$

$$
=\frac{1}{\not \subset /} \sqrt{2 \pi} \int_{-\infty}^{z_{c o}} e^{\frac{-z^{2}}{2}} \mathscr{C}_{X} d z=\frac{1}{\sqrt{2 \pi}} \int_{-\infty}^{z_{c \infty}} e^{\frac{-z^{2}}{2}} d z=\Phi\left(z_{c o}\right)
$$

$$
F_{X}\left(x_{c o}\right)=\Phi\left(z_{c o}\right)
$$

## 4. Signal distribution

Here are definitions of distribution, PDF and CDF of $X_{S}$ which represents the value of targets the observer need to detect.

$$
\begin{aligned}
& X_{S} \sim\left(\mu_{S}, \sigma_{S}^{2}\right) \\
& f_{S}(x)=\frac{1}{\sigma_{S} \sqrt{2 \pi}} \cdot e^{\frac{-\left(x-\mu_{S}\right)^{2}}{2 \sigma_{S}}} \\
& F_{S}(x)=\int_{-\infty}^{x} f_{S}(x) d x=\frac{1}{\sigma_{S} \sqrt{2 \pi}} \int_{-\infty}^{x} e^{\frac{-\left(x-\mu_{S}\right)^{2}}{2 \sigma_{S}^{2}}} d x \\
& 1-F_{S}(x)=1-\int_{-\infty}^{x} f_{S}(x) d x=\int_{x}^{\infty} f_{S}(x) d x=\frac{1}{\sigma_{S} \sqrt{2 \pi}} \int_{x}^{\infty} e^{\frac{-\left(x-\mu_{S}\right)^{2}}{2 \sigma_{S}^{2}}} d x
\end{aligned}
$$

When a cutoff point $x_{c o}$ is set, we can define the probabilities of miss and hit:

$$
P_{M i s s}\left(x_{c o}\right)=F_{S}\left(x_{c o}\right) ; P_{H i t}\left(x_{c o}\right)=1-F_{S}\left(x_{c o}\right)
$$

## 5. Noise distribution

Here are definitions of distribution, PDF and CDF of $X_{N}$ which represents the value of noises.

$$
\begin{aligned}
& X_{N} \sim\left(\mu_{N}, \sigma_{N}^{2}\right) \\
& f_{N}(x)=\frac{1}{\sigma_{N} \sqrt{2 \pi}} \cdot e^{\frac{-\left(x-\mu_{N}\right)^{2}}{2 \sigma_{N}}} \\
& F(x)=\int_{-\infty}^{x} f_{S}(x) d x=\frac{1}{\sigma_{N} \sqrt{2 \pi}} \int_{-\infty}^{x} e^{\frac{-\left(x-\mu_{N}\right)^{2}}{2 \sigma_{N}}} d x \\
& 1-F_{N}(x)=1-\int_{-\infty}^{x} f_{N}(x) d x=\int_{x}^{\infty} f_{N}(x) d x=\frac{1}{\sigma_{N} \sqrt{2 \pi}} \int_{x}^{\infty} e^{\frac{-\left(x-\mu_{N}\right)^{2}}{2 \sigma_{N}^{2}}} d x
\end{aligned}
$$

When a cutoff point $x_{c o}$ is set, we can define the probabilities of correct rejection and false alarm:

$$
P_{C R}\left(x_{c o}\right)=F_{N}\left(x_{c o}\right) ; P_{F A}\left(x_{c o}\right)=1-F_{N}\left(x_{c o}\right)
$$

## Appendix B - Expression of Z As a Function of Beta and D' (Bechar, 2006)

As developed by Bechar (2006). Normalizing the signal and noise distributions is beneficially in generalizing the problem rather than using the actual units that fit only to a specific case. The cutoff point, $x_{c o}$, gets different interpretation in each normalized distribution. The cutoff points, denote as $z_{S}$ and $z_{N}$ for the signal and the noise distributions, respectively, can be expressed by the likelihood ratio, $\beta$, between the signal and noise density functions in the cutoff point, $x_{c o}$, and the distance between the means of the signal and noise distributions, $d^{\prime}$ (see chapter 2.6 for details). For the expressions, the standard deviations $\sigma_{S}, \sigma_{N}$ were assumed to be equal one (Bechar, 2006).

$$
\begin{aligned}
& Z_{S}=\frac{x_{c o}-\mu_{S}}{\sigma_{S}}=x_{c o}-\mu_{S} \\
& Z_{N}=\frac{x_{c o}-\mu_{N}}{\sigma_{N}}=x_{c o}-\mu_{N} \\
& d^{\prime}=\mu_{S}-\mu_{N}=\left(x_{c o}-Z_{S}\right)-\left(x_{c o}-Z_{N}\right)=x_{c o}-Z_{S}-x_{c o}+Z_{N}=Z_{N}-Z_{S} \\
& \beta=\frac{f_{Z}\left(Z_{S}\right)}{f_{Z}\left(Z_{N}\right)}=\frac{\frac{1}{\sqrt{2 \pi}} \cdot e^{\frac{-Z_{S}}{2}}}{\frac{1}{\sqrt{2 \pi}} \cdot e^{\frac{-Z_{N}}{2}}=e^{-\frac{Z_{S}}{2}+\frac{Z_{N}}{2}}=e^{-\frac{1}{2}\left(Z_{S}^{2}-Z_{N}{ }^{2}\right)}} \\
& \ln (\beta)=-\frac{1}{2}\left(Z_{S}^{2}-Z_{N}^{2}\right) \\
& \text { i) } d^{\prime}=Z_{N}-Z_{S}
\end{aligned}
$$

ii) $\ln (\beta)=-\frac{1}{2}\left(Z_{S}{ }^{2}-Z_{N}{ }^{2}\right)$
i) $\Rightarrow$ iii) $Z_{S}=Z_{N}-d^{\prime}$
$i i+i i i) \Rightarrow \ln (\beta)=-\frac{1}{2}\left(\left(Z_{N}-d^{\prime}\right)^{2}-Z_{N}{ }^{2}\right)=-\frac{1}{2}\left(Z_{N}{ }^{2}-2 Z_{N} d^{\prime}+d^{\prime 2}-Z_{N}{ }^{2}\right)=Z_{N} d^{\prime}-\frac{d^{\prime 2}}{2}$
$Z_{N} d^{\prime}=\ln (\beta)+\frac{d^{\prime 2}}{2}$
$Z_{N}=\frac{\ln (\beta)}{d^{\prime}}+\frac{d^{\prime}}{2}$
i) $\Rightarrow$ iv) $Z_{N}=Z_{S}+d^{\prime}$
$i i+i v) \Rightarrow \ln (\beta)=-\frac{1}{2}\left(Z_{S}{ }^{2}-\left(Z_{S}+d^{\prime}\right)^{2}\right)=-\frac{1}{2}\left(Z_{S}{ }^{2}-Z_{S}{ }^{2}-2 Z_{S} d^{\prime}-d^{\prime 2}\right)=Z_{S} d^{\prime}+\frac{d^{\prime 2}}{2}$
$Z_{S} d^{\prime}=\ln (\beta)-\frac{d^{\prime 2}}{2}$
$Z_{S}=\frac{\ln (\beta)}{d^{\prime}}-\frac{d^{\prime}}{2}$

## Appendix C - Validation of Mean Distance Equations

The development of the mean distances equations is presented in chapter 4.1. This appendix validates them. The equations for mean distance of negative and positive responses are:

$$
\begin{aligned}
& d_{-}=\left(x_{c o}-\mu\right)+\sigma \cdot \frac{\varphi\left(z_{c o}\right)}{\Phi\left(z_{c o}\right)} \\
& d_{+}=-\left(x_{c o}-\mu\right)+\sigma \cdot \frac{\varphi\left(z_{c o}\right)}{1-\Phi\left(z_{c o}\right)}
\end{aligned}
$$

For a standard normal distribution with a mean of zero and a standard deviation of one, the mean distances received from the equations for variable values of the cutoff point, $x_{c o}$ were plotted (solid line in Figure A1).

In addition, 1000 random numbers from the same distribution were used to calculate the mean distance of all positive responses (i.e., objects that are higher from the cutoff point) for each value of the cutoff point. Similarly, the mean distance of all negative responses was calculated (i.e., objects that are lower from the cutoff point). The experiment was repeated 30 times and the mean results between all experiments were plotted (x marks in Figure A1). One can see in Figure A1 that the mean distances gotten from the experiment are exactly the means calculated using the equations. These results validate the equations.


Figure A1: A validation of equation for mean distances

## Appendix D - Development of Mean Reaction Time

The development of mean reaction time is based on Murdock (1985). Different denotations for the parameters of the exponential function $(A, B)$ and for the cutoff point $\left(x_{c o}\right)$ is the only difference from Murdock's model. An exponential function is used in order to transfer the strength of an object into the reaction time of the observer. Strength of an object is its distance from the cutoff point.

For negative responses, the distance and the reaction time functions are:

$$
\begin{aligned}
& d(x)=x_{c o}-x \\
& t(x)=A \cdot e^{-B\left(x_{c o}-x\right)}
\end{aligned}
$$

For positive responses the distance and the reaction time functions are:

$$
\begin{aligned}
& d(x)=x-x_{c o} \\
& t(x)=A \cdot e^{-B\left(x-x_{c o}\right)}
\end{aligned}
$$

Mean reaction times of negative and positive responses depend on the cutoff point and are denoted respectively as $T_{-}\left(x_{c o}\right), T_{+}\left(x_{c o}\right)$.

## 1. Mean reaction time of negative responses

In order to find the mean reaction time of negative responses, one must calculate weighted average of all reaction times (results from x-values) of objects with a value lower than the cutoff point. The weights are the frequencies of $x$.

$$
\begin{aligned}
& T_{-}\left(x_{c o}\right)=\frac{\int_{-\infty}^{x_{c o}} t(x) \cdot f(x) d x}{\int_{-\infty}^{x_{c o}} f(x) d x}= \\
& =\frac{\int_{-\infty}^{x_{c o}} A \cdot e^{-B\left(x_{c o}-x\right)} \cdot f(x) d x}{\int_{-\infty}^{x_{c \infty}} f(x) d x}=
\end{aligned}
$$

$$
\begin{aligned}
& \text { From the normal distribution: } \\
& f(x)=\frac{1}{\sigma \sqrt{2 \pi}} e^{\frac{-(x-\mu)^{2}}{2 \sigma^{2}}} \\
& \int_{-\infty}^{x_{c o}} f(x) d x=F\left(x_{c o}\right)
\end{aligned}
$$

$$
=\frac{\int_{-\infty}^{x_{c o}} A \cdot e^{-B\left(x_{c o}-x\right)} \cdot \frac{1}{\sigma \sqrt{2 \pi}} e^{\frac{-(x-\mu)^{2}}{2 \sigma^{2}}} d x}{F\left(x_{c o}\right)}=
$$

$$
=\frac{\int_{-\infty}^{x_{c o}} A \cdot e^{-B \cdot x_{c o}} \cdot e^{B \cdot x} \cdot \frac{1}{\sigma \sqrt{2 \pi}} e^{\frac{-(x-\mu)^{2}}{2 \sigma^{2}}} d x}{F\left(x_{c o}\right)}=
$$

$$
=A \cdot e^{-B \cdot x_{c o c}} \cdot \frac{\int_{-\infty}^{x_{c o}} e^{B \cdot x} \cdot \frac{1}{\sigma \sqrt{2 \pi}} e^{\frac{-(x-\mu)^{2}}{2 \sigma^{2}}} d x}{F\left(x_{c o}\right)}=
$$

$$
=A \cdot e^{-B \cdot x_{c o}} \cdot \frac{\frac{1}{\sigma \sqrt{2 \pi}} \cdot \int_{-\infty}^{x_{c o}} e^{B \cdot x-\frac{(x-\mu)^{2}}{2 \sigma^{2}}} d x}{F\left(x_{c o}\right)}=
$$

$$
\begin{aligned}
& =A \cdot e^{-B \cdot x_{c o}} \cdot \frac{\frac{1}{\sigma \sqrt{2 \pi}} \cdot \int_{-\infty}^{x_{c o}} e^{-\frac{1}{2}\left(-2 B \cdot x+\frac{(x-\mu)^{2}}{\sigma^{2}}\right)} d x}{F\left(x_{c o}\right)}= \\
& =A \cdot e^{-B \cdot x_{c o}} \cdot \frac{\frac{1}{\sigma \sqrt{2 \pi}} \cdot \int_{-\infty}^{x_{c o}} e^{-\frac{1}{2} \cdot \frac{-2 B \cdot x \cdot \sigma^{2}+(x-\mu)^{2}}{\sigma^{2}}} d x}{F\left(x_{c o}\right)}= \\
& =A \cdot e^{-B \cdot x_{c o}} \cdot \frac{\frac{1}{\sigma \sqrt{2 \pi}} \cdot \int_{-\infty}^{x_{c o}} e^{-\frac{-2 B \cdot x \cdot \sigma^{2}+x^{2}-2 x \cdot \mu+\mu^{2}}{2 \sigma^{2}}} d x}{F\left(x_{c o}\right)}= \\
& =A \cdot e^{-B \cdot x_{c o}} \cdot \frac{\frac{1}{\sigma \sqrt{2 \pi}} \cdot \int_{-\infty}^{x_{c o}} e^{\frac{-\mu^{2}}{2 \sigma^{2}}} \cdot e^{-\frac{-2 B \cdot x \cdot \sigma^{2}+x^{2}-2 x \cdot \mu}{2 \sigma^{2}}} d x}{F\left(x_{c o}\right)}= \\
& =A \cdot e^{-B \cdot x_{c o}} \cdot e^{\frac{-\mu^{2}}{2 \sigma^{2}}} \cdot \frac{1}{\sigma \sqrt{2 \pi}} \cdot \int_{-\infty}^{x_{c o}} e^{-\frac{x^{2}-2 x \cdot\left(\mu+B \cdot \sigma^{2}\right)}{2 \sigma^{2}}} d x \\
& F\left(x_{c o}\right)
\end{aligned}=
$$

$$
=A \cdot e^{-B \cdot x_{c o}-\frac{\mu^{2}}{2 \sigma^{2}}} \cdot \frac{\frac{1}{\sigma \sqrt{2 \pi}} \cdot \int_{-\infty}^{x_{c o}} e^{-\frac{x^{2}-2 x \cdot\left(\mu+B \cdot \sigma^{2}\right)+\left(\mu+B \cdot \sigma^{2}\right)^{2}-\left(\mu+B \cdot \sigma^{2}\right)^{2}}{2 \sigma^{2}}} d x}{F\left(x_{c o}\right)}=
$$

$$
=A \cdot e^{-B \cdot x_{c o}-\frac{\mu^{2}}{2 \sigma^{2}}} \cdot \frac{\frac{1}{\sigma \sqrt{2 \pi}} \cdot \int_{-\infty}^{x_{c o}} e^{\frac{-\left(\mu+B \cdot \sigma^{2}\right)^{2}}{-2 \sigma^{2}}} \cdot e^{-\frac{x^{2}-2 x \cdot\left(\mu+B \cdot \sigma^{2}\right)+\left(\mu+B \cdot \sigma^{2}\right)^{2}}{2 \sigma^{2}}} d x}{F\left(x_{c o}\right)}=
$$

$$
=A \cdot e^{-B \cdot x_{c o}-\frac{\mu^{2}}{2 \sigma^{2}}} \cdot e^{\frac{\left(\mu+B \cdot \sigma^{2}\right)^{2}}{2 \sigma^{2}}} \cdot \frac{\frac{1}{\sigma \sqrt{2 \pi}} \cdot \int_{-\infty}^{x_{c o}} e^{-\frac{x^{2}-2 x \cdot\left(\mu+B \cdot \sigma^{2}\right)+\left(\mu+B \cdot \sigma^{2}\right)^{2}}{2 \sigma^{2}}} d x}{F\left(x_{c o}\right)}=
$$

$$
=A \cdot e^{-B \cdot x_{c o}-\frac{\mu^{2}}{2 \sigma^{2}} \frac{\left(\mu+B \cdot \sigma^{2}\right)^{2}}{2 \sigma^{2}}} \cdot \frac{\frac{1}{\sigma \sqrt{2 \pi}} \cdot \int_{-\infty}^{x_{c o}} e^{\frac{-\left(x-\left(\mu+B \cdot \sigma^{2}\right)\right)^{2}}{2 \sigma^{2}}} d x}{F\left(x_{c o}\right)}=
$$

$$
=A \cdot e^{-B \cdot x_{c o}-\frac{\mu^{2}}{2 \sigma^{2}} \frac{\mu^{2}+2 \mu \cdot B \cdot \sigma^{2}+B^{2} \cdot \sigma^{4}}{2 \sigma^{2}}} \cdot \frac{\frac{1}{\sigma \sqrt{2 \pi}} \cdot \int_{-\infty}^{x_{c o}} e^{\frac{-\left(x-\left(\mu+B \cdot \sigma^{2}\right)\right)^{2}}{2 \sigma^{2}}} d x}{F\left(x_{c o}\right)}=
$$

$$
=A \cdot e^{-B \cdot \cdot x_{c o}+\frac{-\mu^{2}+\mu^{2}}{2 \sigma^{2}}+\frac{\not \mu \mu \cdot \cdot \cdot \sigma^{\alpha^{2}}}{\not \theta^{2}}+\frac{B^{2} \cdot \sigma^{2} \cdot \sigma^{2}}{2 \sigma^{2}}} \cdot \frac{\frac{1}{\sigma \sqrt{2 \pi}} \cdot \int_{-\infty}^{x_{c o}} e^{\frac{-\left(x-\left(\mu+B \cdot \sigma^{2}\right)\right)^{2}}{2 \sigma^{2}}} d x}{F\left(x_{c o}\right)}=
$$

$=A \cdot e^{-B \cdot x_{c o}+\mu \cdot B+\frac{B^{2} \cdot \sigma^{2}}{2}} \cdot \frac{\frac{1}{\sigma \sqrt{2 \pi}} \cdot \int_{-\infty}^{x_{c o}} e^{\frac{-\left(x-\left(\mu+B \cdot \sigma^{2}\right)\right)^{2}}{2 \sigma^{2}}} d x}{F\left(x_{c o}\right)}=$
$=A \cdot e^{-B \cdot\left(x_{c o}-\mu\right)+\frac{B^{2} \cdot \sigma^{2}}{2}} \cdot \frac{\frac{1}{\sigma \sqrt{2 \pi}} \cdot \int_{-\infty}^{x_{c o}} e^{-\frac{1}{2}\left(\frac{x-\left(\mu+B \cdot \sigma^{2}\right)}{\sigma}\right)^{2}} d x}{F\left(x_{c o}\right)}=$
Changing the domain of integration:

$$
\begin{aligned}
& u=\frac{x-\left(\mu+B \cdot \sigma^{2}\right)}{\sigma} \Rightarrow x=\mu+B \cdot \sigma^{2}+\sigma u \\
& \frac{d x}{d u}=\frac{d\left(\mu+B \cdot \sigma^{2}+\sigma u\right)}{d u}=\sigma \Rightarrow d x=\sigma d u \\
& x=-\infty \Rightarrow u=\frac{-\infty-\left(\mu+B \cdot \sigma^{2}\right)}{\sigma}=-\infty \\
& x=x_{c o} \Rightarrow u=\frac{x_{c o}-\left(\mu+B \cdot \sigma^{2}\right)}{\sigma}=u_{c o}
\end{aligned}
$$

$=A \cdot e^{-B \cdot\left(x_{c o}-\mu\right)+\frac{B^{2} \cdot \sigma^{2}}{2}} \cdot \frac{\frac{1}{\not \emptyset \sqrt{2 \pi}} \cdot \int_{-\infty}^{u_{c o}} e^{\frac{-u^{2}}{2}} \not \partial d u}{F\left(x_{c o}\right)}=$
From the standard normal distribution:
$\frac{1}{\sqrt{2 \pi}} \cdot \int_{-\infty}^{u_{c o}} e^{\frac{-u^{2}}{2}} d u=\Phi\left(u_{c o}\right)=\Phi\left(\frac{x_{c o}-\left(\mu+B \cdot \sigma^{2}\right)}{\sigma}\right)$
$=A \cdot e^{-B \cdot\left(x_{c o}-\mu\right)+\frac{B^{2} \cdot \sigma^{2}}{2}} \cdot \frac{\Phi\left(\frac{x_{c o}-\left(\mu+B \cdot \sigma^{2}\right)}{\sigma}\right)}{F\left(x_{c o}\right)}=$
$=A \cdot e^{-B \cdot \sigma \cdot \frac{x_{c o o}-\mu}{\sigma}+\frac{B^{2} \cdot \sigma^{2}}{2}} \cdot \frac{\Phi\left(\frac{x_{c o}-\mu}{\sigma}-\frac{B \cdot \sigma^{\not ㇒}}{\not \sigma^{\prime}}\right)}{F\left(x_{c o}\right)}=$
From the standard normal distribution:
$\frac{x_{c o}-\mu}{\sigma}=z_{c o} \quad ; \quad F\left(x_{c o}\right)=\Phi\left(\frac{x_{c o}-\mu}{\sigma}\right)=\Phi\left(z_{c o}\right)$
$=A \cdot e^{-B \cdot \sigma \cdot z_{c o}+\frac{B^{2} \cdot \sigma^{2}}{2}} \cdot \frac{\Phi\left(z_{c o}-B \cdot \sigma\right)}{\Phi\left(z_{c o}\right)}$

$$
T_{-}\left(x_{c o}\right)=A \cdot e^{-B \cdot \sigma \cdot z_{c o}+\frac{B^{2} \cdot \sigma^{2}}{2}} \cdot \frac{\Phi\left(z_{c o}-B \cdot \sigma\right)}{\Phi\left(z_{c o}\right)}
$$

where
$z_{c o}=\frac{x_{c o}-\mu}{\sigma}$
$\Phi(z)=\frac{1}{\sqrt{2 \pi}} \int_{-\infty}^{z} e^{\frac{-z^{2}}{2}} d z$
if $\sigma=1$ then
$T_{-}\left(x_{c o}\right)=A \cdot e^{-B \cdot z_{c o}+\frac{B^{2}}{2}} \cdot \frac{\Phi\left(z_{c o}-B\right)}{\Phi\left(z_{c o}\right)}$

## 2. Mean reaction time of positive responses

In order to find the mean reaction time of positive responses, one must calculate weighted average of all reaction times (results from x-values) of objects with a value higher than the cutoff point. The weights are the frequencies of $x$.

$$
\begin{aligned}
& T_{+}\left(x_{c o}\right)=\frac{\int_{x_{c o}}^{\infty} t(x) \cdot f(x) d x}{\int_{x_{c o}}^{\infty} f(x) d x}= \\
& =\frac{\left.\int_{x_{c o}}^{\infty} A \cdot e^{-B \cdot\left(x-x_{c o}\right.}\right) \cdot f(x) d x}{\int_{x_{c o}}^{\infty} f(x) d x}=
\end{aligned}
$$

$$
\begin{aligned}
& \text { From the normal distribution: } \\
& f(x)=\frac{1}{\sigma \sqrt{2 \pi}} e^{\frac{-(x-\mu)^{2}}{2 \sigma^{2}}} \\
& \int_{x_{c o}}^{\infty} f(x) d x=1-F\left(x_{c o}\right)
\end{aligned}
$$

$$
=\frac{\int_{x_{c o}}^{\infty} A \cdot e^{B \cdot\left(x_{c o}-x\right)} \cdot \frac{1}{\sigma \sqrt{2 \pi}} e^{\frac{-(x-\mu)^{2}}{2 \sigma^{2}}} d x}{1-F\left(x_{c o}\right)}=
$$

$$
=\frac{\int_{x_{c o}}^{\infty} A \cdot e^{B \cdot x_{c o}} \cdot e^{-B \cdot x} \cdot \frac{1}{\sigma \sqrt{2 \pi}} e^{\frac{-(x-\mu)^{2}}{2 \sigma^{2}}} d x}{1-F\left(x_{c o}\right)}=
$$

$$
=A \cdot e^{B \cdot x_{c o}} \cdot \frac{\frac{1}{\sigma \sqrt{2 \pi}} \cdot \int_{x_{c o}}^{\infty} e^{-B \cdot x} \cdot e^{\frac{-(x-\mu)^{2}}{2 \sigma^{2}}} d x}{1-F\left(x_{c o}\right)}=
$$

$$
=A \cdot e^{B \cdot x_{c o}} \cdot \frac{\frac{1}{\sigma \sqrt{2 \pi}} \cdot \int_{x_{c o}}^{\infty} e^{-B \cdot x-\frac{(x-\mu)^{2}}{2 \sigma^{2}}} d x}{1-F\left(x_{c o}\right)}=
$$

$$
\begin{aligned}
& =A \cdot e^{B \cdot x_{c o}} \cdot \frac{\frac{1}{\sigma \sqrt{2 \pi}} \cdot \int_{x_{c o}}^{\infty} e^{-\frac{1}{2}\left(2 B \cdot x+\frac{(x-\mu)^{2}}{\sigma^{2}}\right)} d x}{1-F\left(x_{c o}\right)}= \\
& =A \cdot e^{B \cdot x_{c o}} \cdot \frac{\frac{1}{\sigma \sqrt{2 \pi}} \cdot \int_{x_{c o}}^{\infty} e^{-\frac{1}{2} \cdot \frac{2 B \cdot x \cdot \sigma^{2}+(x-\mu)^{2}}{\sigma^{2}}} d x}{1-F\left(x_{c o}\right)}= \\
& =A \cdot e^{B \cdot x_{c o}} \cdot \frac{\frac{1}{\sigma \sqrt{2 \pi}} \cdot \int_{x_{c o}}^{\infty} e^{-\frac{2 B \cdot x \cdot \sigma^{2}+x^{2}-2 x \cdot \mu+\mu^{2}}{2 \sigma^{2}}} d x}{1-F\left(x_{c o}\right)}= \\
& =A \cdot e^{B \cdot x_{c o}} \cdot \frac{\frac{1}{\sigma \sqrt{2 \pi}} \cdot \int_{x_{c o}}^{\infty} e^{\frac{-\mu^{2}}{2 \sigma^{2}}} \cdot e^{-\frac{2 B \cdot x \cdot \sigma^{2}+x^{2}-2 x \cdot \mu}{2 \sigma^{2}}} d x}{1-F\left(x_{c o}\right)}= \\
& =A \cdot e^{B \cdot x_{c o}} \cdot e^{\frac{-\mu^{2}}{2 \sigma^{2}} \cdot \frac{1}{\sigma \sqrt{2 \pi}} \cdot \int_{x_{c o}}^{\infty} e^{-\frac{x^{2}-2 x \cdot\left(\mu-B \cdot \sigma^{2}\right)}{2 \sigma_{s}^{2}}} d x} 1-F\left(x_{c o}\right)
\end{aligned}=
$$

$$
=A \cdot e^{B \cdot x_{c o} \frac{\mu^{2}}{2 \sigma^{2}}} \cdot \frac{\frac{1}{\sigma \sqrt{2 \pi}} \cdot \int_{x_{c o}}^{\infty} e^{-\frac{x^{2}-2 x \cdot\left(\mu-B \cdot \sigma^{2}\right)+\left(\mu-B \cdot \sigma^{2}\right)^{2}-\left(\mu-B \cdot \sigma^{2}\right)^{2}}{2 \sigma^{2}}} d x}{1-F\left(x_{c o}\right)}=
$$

$$
=A \cdot e^{B \cdot x_{c o} \frac{\mu^{2}}{2 \sigma^{2}}} \cdot \frac{\frac{1}{\sigma \sqrt{2 \pi}} \cdot \int_{x_{c o}}^{\infty} e^{\frac{-\left(\mu-B \cdot \sigma^{2}\right)^{2}}{-2 \sigma^{2}}} \cdot e^{-\frac{x^{2}-2 x \cdot\left(\mu-B \cdot \sigma^{2}\right)+\left(\mu-B \cdot \sigma^{2}\right)^{2}}{2 \sigma^{2}}} d x}{1-F\left(x_{c o}\right)}=
$$

$$
=A \cdot e^{B \cdot x_{c o}-\frac{\mu^{2}}{2 \sigma^{2}}} \cdot e^{\frac{\left(\mu-B \cdot \sigma^{2}\right)^{2}}{2 \sigma^{2}}} \cdot \frac{\frac{1}{\sigma \sqrt{2 \pi}} \cdot \int_{x_{c o}}^{\infty} e^{-\frac{x^{2}-2 x \cdot\left(\mu-B \cdot \sigma^{2}\right)+\left(\mu-B \cdot \sigma^{2}\right)^{2}}{2 \sigma^{2}}} d x}{1-F\left(x_{c o}\right)}=
$$

$$
=A \cdot e^{B \cdot x_{c o} \frac{\mu^{2}}{2 \sigma^{2}}+\frac{\left(\mu-B \cdot \sigma^{2}\right)^{2}}{2 \sigma^{2}}} \cdot \frac{\frac{1}{\sigma \sqrt{2 \pi}} \cdot \int_{x_{c o}}^{\infty} e^{\frac{-\left(x-\left(\mu-B \cdot \sigma^{2}\right)\right)^{2}}{2 \sigma^{2}}} d x}{1-F\left(x_{c o}\right)}=
$$

$$
=A \cdot e^{B \cdot x_{c o}-\frac{\mu^{2}}{2 \sigma^{2}}+\frac{\mu^{2}-2 \mu \cdot \cdot \cdot \sigma^{2}+B^{2} \cdot \sigma^{4}}{2 \sigma^{2}}} \cdot \frac{\frac{1}{\sigma \sqrt{2 \pi}} \cdot \int_{x_{c o}}^{\infty} e^{\frac{-\left(x-\left(\mu-B \cdot \sigma^{2}\right)\right)^{2}}{2 \sigma^{2}}} d x}{1-F\left(x_{c o}\right)}=
$$

$$
=A \cdot e^{B \cdot x_{c o t}+\frac{-\mu^{2}+\mu^{2}}{2 \sigma^{2}}+\frac{-\not \mu \mu \cdot B \cdot \sigma^{z^{2}}}{\not \sigma^{2}}+\frac{B^{2} \cdot \sigma^{2} \cdot \sigma^{2}}{2 \sigma^{2}}} \cdot \frac{\frac{1}{\sigma \sqrt{2 \pi}} \cdot \int_{x_{c o}}^{\infty} e^{\frac{-\left(x-\left(\mu-B \cdot \sigma^{2}\right)\right)^{2}}{2 \sigma^{2}}} d x}{1-F\left(x_{c o}\right)}=
$$

$=A \cdot e^{B \cdot x_{c o}-\mu \cdot B+\frac{B^{2} \cdot \sigma^{2}}{2}} \cdot \frac{\frac{1}{\sigma \sqrt{2 \pi}} \cdot \int_{x_{c o}}^{\infty} e^{\frac{-\left(x-\left(\mu-B \cdot \sigma^{2}\right)\right)^{2}}{2 \sigma}} d x}{1-F\left(x_{c o}\right)}=$
$=A \cdot e^{B \cdot\left(x_{c o}-\mu\right)+\frac{B^{2} \cdot \sigma^{2}}{2}} \cdot \frac{\frac{1}{\sigma \sqrt{2 \pi}} \cdot \int_{x_{c o}}^{\infty} e^{-\frac{1}{2}\left(\frac{x-\left(\mu-B \cdot \sigma^{2}\right)}{\sigma}\right)^{2}} d x}{1-F\left(x_{c o}\right)}=$
Changing the domain of integration:

$$
\begin{aligned}
& u=\frac{x-\left(\mu-B \cdot \sigma^{2}\right)}{\sigma} \Rightarrow x=\mu-B \cdot \sigma^{2}+\sigma u \\
& \frac{d x}{d u}=\frac{d\left(\mu-B \cdot \sigma^{2}+\sigma u\right)}{d u}=\sigma \Rightarrow d x=\sigma d u \\
& x=x_{c o} \Rightarrow u=\frac{x_{c o}-\left(\mu-B \cdot \sigma^{2}\right)}{\sigma}=u_{c o} \\
& x=\infty \Rightarrow u=\frac{\infty-\left(\mu-B \cdot \sigma^{2}\right)}{\sigma}=\infty
\end{aligned}
$$

$=A \cdot e^{B \cdot\left(x_{c o}-\mu\right)+\frac{B^{2} \cdot \sigma^{2}}{2}} \cdot \frac{\frac{1}{\not \sigma \sqrt{2 \pi}} \cdot \int_{u_{c o}}^{\infty} e^{-\frac{1}{2} u^{2}} \not \not \emptyset d u}{1-F\left(x_{c o}\right)}=$
From the standard normal distribution :
$\frac{1}{\sqrt{2 \pi}} \cdot \int_{u_{c o}}^{\infty} e^{\frac{-u^{2}}{2}} d u=1-\Phi\left(u_{c o}\right)=1-\Phi\left(\frac{x_{c o}-\left(\mu-B \cdot \sigma^{2}\right)}{\sigma}\right)$
$=A \cdot e^{B \cdot\left(x_{c o}-\mu\right)+\frac{B^{2} \cdot \sigma^{2}}{2}} \cdot \frac{1-\Phi\left(\frac{x_{c o}-\left(\mu-B \cdot \sigma^{2}\right)}{\sigma}\right)}{1-F\left(x_{c o}\right)}=$
$=A \cdot e^{B \cdot \sigma \cdot \frac{\left(x_{c o}-\mu\right)}{\sigma}+\frac{B^{2} \cdot \sigma^{2}}{2}} \cdot \frac{1-\Phi\left(\frac{x_{c o}-\mu}{\sigma}+\frac{B \cdot \sigma^{\not}}{\sigma}\right)}{1-F\left(x_{c o}\right)}=$
From the standard normal distribution:

$$
\frac{x_{c o}-\mu}{\sigma}=z_{c o} ; F\left(x_{c o}\right)=\Phi\left(\frac{x_{c o}-\mu}{\sigma}\right)=\Phi\left(z_{c o}\right)
$$

$=A \cdot e^{B \cdot \sigma \cdot z_{c o}+\frac{B^{2} \cdot \sigma^{2}}{2}} \cdot \frac{1-\Phi\left(z_{c o}+B \cdot \sigma\right)}{1-\Phi\left(z_{c o}\right)}$

$$
\begin{aligned}
& T_{+}\left(x_{c o}\right)=A \cdot e^{B \cdot \sigma \cdot z_{c o}+\frac{B^{2} \cdot \sigma^{2}}{2}} \cdot \frac{1-\Phi\left(z_{c o}+B \cdot \sigma\right)}{1-\Phi\left(z_{c o}\right)} \\
& \text { where } \\
& z_{c o}=\frac{x_{c o}-\mu}{\sigma} \\
& \Phi(z)=\frac{1}{\sqrt{2 \pi}} \int_{-\infty}^{z} e^{\frac{-z^{2}}{2}} d z
\end{aligned}
$$

$$
\begin{aligned}
& \text { if } \sigma=1 \text { then } \\
& T_{+}\left(x_{c o}\right)=A \cdot e^{B \cdot z_{c o}+\frac{B^{2}}{2}} \cdot \frac{1-\Phi\left(z_{c o}+B\right)}{1-\Phi\left(z_{c o}\right)}
\end{aligned}
$$

## Appendix E - Numerical Analysis - Additional Results

In the following part, the optimal cutoff point of the human in the H collaboration level is analyzed for each of the three types of systems. The graphs in this part exhibit the cutoff point against the human sensitivity $\left(d^{\prime}{ }_{h}\right)$ and the cost of time unit $(v T 2 v H)$, for each value of the time parameter $(A)$. The analysis was conducted for $B=0.5, d r=0.5$.

Figure A2 - Figure A4 show the graphs for systems of type I - III, respectively. Each figure shows graphs for different probabilities of object to be target ( $P s=0.1,0.2,0.5,0.8,0.9$ )

## 1. Type I analysis

Type I systems give high priority for not causing false alarms. Figure A2 shows the optimal cutoff point (z-axis) of the human for different probabilities of targets (Ps). When Ps is 0.1 (Figure A2-a), an extreme positive cutoff point is preferred for relatively high sensitivities $\left(d^{\prime} h \approx 1.5\right)$. As $P s$ increases to 0.5 (Figure A2-c), i.e., half of the objects are targets, the system prefers an extreme cutoff point only for lower sensitivities ( $d^{\prime} h \approx 0.5$ ). As $P s$ increases further to 0.8, 0.9 (Figure A2-d,e), i.e., most of the objects are targets, the system does not prefer an extreme cutoff point.

## 2. Type II analysis

Type II systems give high priority for not missing targets. Figure A3 shows the optimal cutoff point (z-axis) of the human for different probabilities of targets ( $P s$ ). When $P s$ is high, 0.9 (Figure A3-e), an extreme negative cutoff point is preferred for relatively high sensitivities ( $d^{\prime}{ }_{h} \approx 2.5$ ). As $P s$ decreases to 0.5 (Figure A3-c), the system prefers an extreme cutoff point only for lower sensitivities $\left(d^{\prime}{ }_{h} \approx 1\right)$. As Ps decreases further to 0.2, 0.1 (Figure A3-b,a), i.e., most of the objects are not targets, the system prefers an extreme positive cutoff point for low sensitivities ( $d^{\prime}{ }_{h} \approx 1$ ).

## 3. Type III analysis

Type III systems do not prefer one type of error on the other. Figure A4 shows the optimal cutoff point (z-axis) of the human for different probabilities of targets (Ps). When Ps is 0.5 , (Figure A4-c), the optimal cutoff point value is approximately half of the human sensitivity, which represents the distance between the means of the distributions (i.e., the cutoff point is between the means of the distributions). When Ps decreases to 0.2, 0.1 (Figure A4-a,b), the system prefers an extreme positive cutoff point for low sensitivities ( $d^{\prime}{ }_{h} \approx 0.5-1.5$ ). When Ps increases to $0.8,0.9$ (Figure A4-d,e), the system prefers an extreme negative cutoff point for low sensitivities ( $d^{\prime}{ }_{h} \approx 0.5-1$ ).


Figure A2: The optimal cutoff point of the human (z-axis) in the H collaboration level in a Type I system. (a) $P s=0.1$, (b) $P s=0.2$, (c) $P s=0.5$, (d) $P s=0.8$, (e) $P s=0.9 . B=0.5, d r=0.5$.


Figure A3: The optimal cutoff point of the human (z-axis) in the H collaboration level in a Type II system.
(a) $P s=0.1$, (b) $P s=0.2$, (c) $P s=0.5$, (d) $P s=0.8$, (e) $P s=0.9 . B=0.5, d r=0.5$.


Figure A4: The optimal cutoff point of the human (z-axis) in the H collaboration level in a Type III system.
(a) $P s=0.1$, (b) $P s=0.2$, (c) $P s=0.5$, (d) $P s=0.8$, (e) $P s=0.9 . B=0.5, d r=0.5$.

## 4. Time influence on the optimal cutoff point position

An extreme cutoff point position decreases the total operation time cost. The mean reaction time reduces as the cutoff point is far from the mean of the distribution; therefore, in the sense of time costs, extreme cutoff point is always preferred.

In all the graphs (Figure A2 - Figure A4), the cutoff point varies with the change of the time cost $(v T 2 v H)$ along X-axis. When the time cost is high, an extreme cutoff point is preferred for higher human sensitivities. For example, see the left graph in Figure A4-a. When the time cost is high ( $v T 2 v H=-0.03$ ), an extreme cutoff point ( z value is 6) is preferred for human sensitivities that are less than two $\left(d^{\prime}{ }_{h}<=2\right)$. However, when the time cost is low ( $v T 2 v H=-0.01$ ), an extreme cutoff point (6) is preferred only for human sensitivities that are less than one ( $d^{\prime}{ }_{h}<=1$ ).

Parameter $A$ is coordinated with mean reaction time of the human (i.e., high mean reaction time is expected when $A$ holds high values) and has the same influence. Parameter $A$ equals two on the left graphs and increases to ten on the right graphs. An extreme cutoff point is preferred for higher human sensitivities as parameter $A$ increases. For example, see Figure A4-a. In the left graph $A=2$ and an extreme cutoff point (6) is preferred only for human sensitivities that are less than one ( $d^{\prime}{ }_{h}<=1$ ). As parameter $A$ increases to 5 or 10 (in the other two graphs), an extreme cutoff point (6) is preferred also for higher human sensitivities.

To conclude, the analysis shows that parameter $A$ and time cost affect the position of the optimal cutoff point. The phenomenon, of extreme cutoff point position, arises for higher human sensitivities as parameter $A$ and/or the time cost are higher.

# Appendix F-Paper For The $20{ }^{\text {Th }}$ International Conference on Production Research INFLUENCE OF HUMAN REACTION TIME ON PERFORMANCE OF HUMAN-ROBOT TARGET RECOGNITION SYSTEMS 

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#### Abstract

This study aims to evaluate the influence of human's reaction time on performance of integrated humanrobot target recognition. Particularly, the study presents a model to evaluate the effect of reaction time on the human-robot collaboration level. The model's objective function quantifies the influence of robot, human, environment and task parameters, through a weighted sum of performance measures. Simulation analysis considered reaction time that depended on the signal strength of the observed object. Results reveal an extreme threshold selection, in two cases: when human sensitivity reduces, and when the cost of time increases. An extreme threshold selection decreases the total operational time costs.


## Keywords:

Human-robot collaboration, collaboration levels, reaction time, target recognition.

## 1 INTRODUCTION

Autonomous robots are systems that can perform tasks without human intervention. They are best suited for applications that require accuracy and high yield under stable conditions, yet they lack the capability to respond to unknown, changing and unpredicted events [1]. Humans, dissimilarly, can easily fit themselves into changing unstructured environment and undefined targets [1]. By taking advantage of the human perception skills and the robot's accuracy and consistency, the combined humanrobotic system can be simplified, resulting in improved performance [1].
In human-robot collaborative systems, types of collaboration levels differ by nature, scale, structure, and number of levels. Sheridan [2] describes ten levels of automation of decision and action selection. Bechar and Edan [3] evaluate two collaboration levels for agriculture robot guidance through an off-road path. Bruemmer et al. [4] determine four modes of control of a remote mobile robot in an in-door search and exploration task. Hughes and Lewis [5] use two different levels of control on robot's cameras in order to control it in a remote environment. Czarnecki and Graves [6] describe a scale of five humanrobot interaction levels for a telerobotic behavior based system.
Target recognition is a critical element in most robotic systems [1] including industrial and service applications, quality assurance, medical, agriculture and remote sensing [1]. Automatic target recognition in unstructured outdoor environments is characterized by low detection rates and high false alarm rates [7].
Reaction time is the cognitive time required for the observer to decide whether an object is a target or not Accuracy in target recognition measures the ability of the observer to detect targets correctly. The relation between reaction time and accuracy varies according to whether speed or accuracy of performance is emphasized; and according to whether one response or another is more probable or weighted more heavily [8]. Murdock [9] analyses the strength-latency relationship and introduces a generic reaction time model based on the distance-from-
criteria of the observed object. He suggests that an exponential function is the most reasonable to use in order to transfer the object's strength, i.e., distance-from-criteria, into latency. In this research, a reaction time model, based on Murdock [9], is incorporated into Bechar's [1] collaboration model.

The study aims to evaluate the influence of human's reaction time on the performance of an integrated humanrobot system, designated for target recognition tasks. Particularly, the study focuses on how reaction time affects the level of human- robot collaboration that results in best performance.

## 2 METHODOLOGY

### 2.1 Collaboration levels

Four collaboration levels for target recognition were designed based on [1]: i) H - the Human, unaided, detects and marks the desired target; ii) HR - the Human marks targets, aided by recommendations from an automatic detection algorithm, i.e., the targets are automatically marked by a Robot detection algorithm, the human acknowledges the robot's correct detections, ignores false detections and marks targets missed by the robot; iii) HOR

- the Human Operators' assignment is to cancel false detections and to mark the targets missed by an automatic Robot detection algorithm; and iv) R - the targets are marked automatically by the system (Robot).


### 2.2 Collaboration model

The collaboration model was based on a model defined in [1]. An objective function describes the expected value of system performance, given the properties of the environment and the system. The goal is to maximize the objective function. The objective function ( $V_{I S}$, equation 1) is composed of the four responses of the target detection process and the system operational costs:
$V_{I s}=V_{H s}+V_{M s}+V_{F A s}+V_{C R s}+V_{T s}$
Where $V_{H s}$ is the gain for target detections (hits), $V_{F A s}$ is the penalty for false alarms, $V_{M s}$ is the system penalty for missing targets, $V_{C R s}$ is the gain for correct rejections, and $V_{T s}$ is the system operation cost. All gain, penalty and cost values have the same units, which enable us to add them
together to a single value, expressed in the objective function. The gain and penalty functions are:
$V_{H s}=N \cdot P_{S} \cdot P_{H s} \cdot V_{H}$
$V_{M s}=N \cdot P_{S} \cdot P_{M s} \cdot V_{M}$
$V_{F A s}=N \cdot\left(1-P_{S}\right) \cdot P_{F A s} \cdot V_{F A}$
$V_{C R s}=N \cdot\left(1-P_{S}\right) \cdot P_{C R s} \cdot V_{C R}$
Where, $N$ is the number of objects in the observed image and $P_{S}$ is the probability of an object becoming a target. The third parameter in the equations, $P_{X_{s}}$, is the system probability for one of the outcomes: hit, miss, false alarm or correct rejection ( $x$ can be $H_{, ~ M, ~ F A ~ a n d ~}^{C R}$ ). The fourth parameter, $V_{X}$, is the system gain or penalty from an expected outcome.
The system's probability of a certain outcome is influenced by the serial structure of the model and is composed of the robot and the human probabilities:

$$
\begin{align*}
& P_{H s}=P_{H r} \cdot P_{H r h}+\left(1-P_{H r}\right) \cdot P_{H h}  \tag{6}\\
& P_{M s}=P_{M r} \cdot P_{M h}+\left(1-P_{M r}\right) \cdot P_{M r h}  \tag{7}\\
& P_{F A s}=P_{F A r} \cdot P_{F A r h}+\left(1-P_{F A r}\right) \cdot P_{F A h}  \tag{8}\\
& P_{C R s}=P_{C R r} \cdot P_{C R h}+\left(1-P_{C R r}\right) \cdot P_{C R r h}
\end{align*}
$$

Where:
$P_{H r}$ is the robot probability of a hit, $P_{H r h}$ is the probability of confirming a robot hit and $P_{H h}$ is the human probability of detecting a target that the robot did not detect;
$P_{M r}$ is the robot miss probability, $P_{M r h}$ is the human probability of not confirming a robot hit and $P_{M h}$ is the human probability of missing a target the robot missed. $P_{\text {FAr }}$ is the robot false alarm probability, $P_{\text {FArh }}$ is the human probability of not avoiding a robot false alarm and $P_{F A h}$ is the human probability of a false alarm on targets the robot correctly rejected;
$P_{C R r}$ is the robot probability of a correct rejection, $P_{C R r h}$ is the human probability of correcting a robot false alarm and $P_{C R h}$ is the human probability of a correct rejection on targets the robot correctly rejected.
The sum of hit and miss probabilities (of the same type) and the sum of false alarm and correct rejection probabilities equals one.
The system's operation cost is:
$V_{T s}=t_{S} \cdot V_{t}+\left[N \cdot P_{S} \cdot P_{H s}+N \cdot\left(1-P_{S}\right) \cdot P_{F A s}\right] \cdot V_{C}$
Where, $t_{s}$ is the time required by the system to perform a task, $V_{t}$ is the cost of one time unit, and $V_{C}$ is the operation cost of one object recognition (hit or false alarm).
The system time consists of the time it takes the human to decide whether to confirm or reject robot detections; and the time it takes the human to decide whether objects not detected by the robot are targets or not. The robot operation time of processing the images and performing hits or false alarms, is also included.

$$
\begin{align*}
t_{S} & =N \cdot P_{S} \cdot P_{H r} \cdot P_{H r r} \cdot t_{H r h}+ \\
& +N \cdot P_{S} \cdot\left(1-P_{H r}\right) \cdot P_{H h} \cdot t_{H h}+ \\
& +N \cdot P_{S} \cdot P_{H r} \cdot\left(1-P_{H r r}\right) \cdot t_{M r h}+ \\
& +N \cdot P_{S} \cdot\left(1-P_{H r}\right) \cdot\left(1-P_{H h}\right) \cdot t_{M h}+  \tag{11}\\
& +N \cdot\left(1-P_{S}\right) \cdot P_{F A r} \cdot P_{F A r h} \cdot t_{F A r h}+ \\
& +N \cdot\left(1-P_{S}\right) \cdot\left(1-P_{F A r}\right) \cdot P_{F A h} \cdot t_{F A h}+ \\
& +N \cdot\left(1-P_{S}\right) \cdot P_{F A r} \cdot\left(1-P_{F A r h}\right) \cdot t_{C R r h}+ \\
& +N \cdot\left(1-P_{S}\right) \cdot\left(1-P_{F A r}\right) \cdot\left(1-P_{F A h}\right) \cdot t_{C R h}+N \cdot t_{r}
\end{align*}
$$

Where:
$t_{\text {Hrr }}$ is the human time required to confirm a robot hit and $t_{H h}$ is the human time required to hit a target that the robot did not hit;
$t_{\text {Mrh }}$ is the human time lost when a robot hit is missed and $t_{M h}$ is the human time invested when missing a target that the robot did not hit;
$t_{\text {FArh }}$ is the human time needed not to avoid a robot false alarm and $t_{F A h}$ is the human false alarm time;
$t_{\text {CRrh }}$ is the human time to correctly reject a robot false alarm, $t_{C R h}$ is the human correct rejection time, and $t_{r}$ is the robot operation time.
Explicit operation of the system objective function, $V_{I S}$, which is suitable for all collaboration levels, is:

$$
\begin{align*}
V_{l s}= & N \cdot P_{S} \cdot\left[P_{H r} \cdot P_{H r h} \cdot\left(V_{H}+V_{C}+t_{H r r} \cdot V_{t}\right)+\right. \\
& \left.+\left(1-P_{H r}\right) \cdot P_{H h} \cdot\left(V_{H}+V_{C}+t_{H h} \cdot V_{t}\right)\right]+ \\
& +N \cdot P_{S} \cdot\left[P_{H r} \cdot\left(1-P_{H r h}\right) \cdot\left(V_{M}+t_{M r h} \cdot V_{t}\right)+\right. \\
& \left.+\left(1-P_{H r}\right) \cdot\left(1-P_{H h}\right) \cdot\left(V_{M}+t_{M h} \cdot V_{t}\right)\right]+ \\
& +N \cdot\left(1-P_{S}\right) \cdot\left[P_{F A r} \cdot P_{F A r h} \cdot\left(V_{F A}+V_{C}+t_{F A r h} \cdot V_{t}\right)+\right.  \tag{12}\\
& \left.+\left(1-P_{F A r}\right) \cdot P_{F A h} \cdot\left(V_{F A}+V_{C}+t_{F A h} \cdot V_{t}\right)\right]+ \\
& +N \cdot\left(1-P_{S}\right) \cdot\left[P_{F A r} \cdot\left(1-P_{F A r h}\right) \cdot\left(V_{C R}+t_{C R r h} \cdot V_{t}\right)+\right. \\
& \left.+\left(1-P_{F A r}\right) \cdot\left(1-P_{F A h}\right) \cdot\left(V_{C R}+t_{C R h} \cdot V_{t}\right)\right]+N \cdot t_{r} \cdot V_{t}
\end{align*}
$$

For the H collaboration level, the system objective function will be a degenerate form of the full objective function, and will not include the robot variables:

$$
\begin{align*}
V_{I S}= & N \cdot P_{S} \cdot\left[P_{H h} \cdot\left(V_{H}+V_{C}+t_{H h} \cdot V_{t}\right)+\right. \\
& \left.+\left(1-P_{H h}\right) \cdot\left(V_{M}+t_{M h} \cdot V_{t}\right)\right]+  \tag{13}\\
& +N \cdot\left(1-P_{S}\right) \cdot\left[P_{F A h} \cdot\left(V_{F A}+V_{C}+t_{F A h} \cdot V_{t}\right)+\right. \\
& \left.+\left(1-P_{F A h}\right) \cdot\left(V_{C R}+t_{C R h} \cdot V_{t}\right)\right]
\end{align*}
$$

In the R collaboration level, the system objective function will be a degenerate form of the full objective function, and will not include the human variables:

$$
\begin{align*}
V_{I S} & =N \cdot P_{S} \cdot\left[P_{H r} \cdot\left(V_{H}+V_{C}\right)+\left(1-P_{H r}\right) \cdot V_{M}\right]+ \\
& +N \cdot\left(1-P_{S}\right) \cdot\left[P_{F A r} \cdot\left(V_{F A}+V_{C}\right)+\left(1-P_{F A r}\right) \cdot V_{C R}\right]+  \tag{14}\\
& +N \cdot t_{r} \cdot V_{t}
\end{align*}
$$

### 2.3 Reaction time model

The development of the model that considers the mean reaction time is based on Murdock [9]. Different denotations for the parameters of the exponential function $(A, B)$ and for the cutoff point ( $x_{c o}$ ), is the only difference from Murdock's model. An exponential function is used in order to transfer the strength of an object (its distance from the cutoff point) into the reaction time of the observer.
We use the term 'Positive Response' to describe objects that the system marks. A 'Positive Response' can be either a Hit, if the object is a target; or a False Alarm if it is not. The term 'Negative Response' describes objects with a value lower than the cutoff point value, which the system does not mark as targets. A 'Negative response' can be either a Miss, if the object is a target; or a Correct Rejection if it is not. The reaction time function maps the distance of $x$ from a given cutoff point $x_{c o}$ into time units and it is different for positive and negative responses. An exponential function can describe a symmetrical descendent of latency on both sides of the yes/no criterion (Figure 1). The reaction time function is:
$t(x)= \begin{cases}A e^{-B \cdot\left(x_{c 0}-x\right)} & ; \text { when } x \leq x_{c o} \\ A e^{-B\left(x-x_{c 0}\right)} & ; \text { otherwise }\end{cases}$
In order to fit this function to real data, the parameters $A$ and $B$ must be adjusted. Different parameters values lead
to different reaction time functions. One can define different values for negative and positive responses.


Figure 1 - Reaction time function.
Suppose $X$ is normally distributed with a mean of $\mu$ and a variance of $\sigma^{2}$. In order to find the mean reaction time, one must calculate the weighted average of all reaction times (results from $x$-values) of the same response. The weights are the frequencies of $x$. The mean reaction time depends on the cutoff point value and is denoted as $T_{-}\left(x_{c o}\right), T_{+}\left(x_{c o}\right)$ for negative and positive responses, respectively.
The mean reaction time equations for negative and positive responses are:

$$
\begin{align*}
& T_{-}\left(x_{c o}\right)=\frac{\int_{-\infty}^{x_{c o}} t(x) \cdot f(x) d x}{\int_{-\infty}^{x_{c o}} f(x) d x}=\frac{\int_{-\infty}^{x_{c o}} A e^{-B\left(x_{c o}-x\right)} \cdot f(x) d x}{\int_{-\infty}^{x_{c o}} f(x) d x}=  \tag{16}\\
& =\ldots=A \cdot e^{-B \cdot \sigma \cdot z_{c o}+\frac{B^{2} \cdot \sigma^{2}}{2}} \cdot \frac{\Phi\left(z_{c o}-B \cdot \sigma\right)}{\Phi\left(z_{c o}\right)} \\
& T_{+}\left(x_{c o}\right)=\frac{\int_{x_{c o}}^{\infty} t(x) \cdot f(x) d x}{\int_{x_{c o}}^{\infty} f(x) d x}=\frac{\int_{x_{c o}}^{\infty} A e^{-B\left(x-x_{c o}\right)} \cdot f(x) d x}{\int_{x_{c o}}^{\infty} f(x) d x}=  \tag{17}\\
& =\ldots=A \cdot e^{B \cdot \sigma \cdot z_{c o}+\frac{B^{2} \cdot \sigma^{2}}{2}} \cdot \frac{1-\Phi\left(z_{c o}+B \cdot \sigma\right)}{1-\Phi\left(z_{c o}\right)}
\end{align*}
$$

where
$f(x)=\frac{1}{\sigma \sqrt{2 \pi}} e^{\frac{-(x-\mu)^{2}}{2 \sigma^{2}}}$
$z_{c O}=\frac{x_{C O}-\mu}{\sigma} ; \Phi(z)=\frac{1}{\sqrt{2 \pi}} \int_{-\infty}^{z} e^{\frac{-z^{2}}{2}} d z$
The equations that were developed for the normal distribution are adjusted to the signal and noise distributions. The means and standard deviations of the signal and noise distributions are respectively $\mu_{\mathrm{S}}, \sigma_{\mathrm{S}}$ and $\mu_{N}, \sigma_{N}$. We used the appropriate equations (for positive or negative responses) and parameters (mean and standard deviation of signal or noise distributions) to define equations for mean reaction time of all four possible outcomes (miss, hit, correct rejection and false alarm):

$$
\begin{align*}
& T_{M}=A \cdot e^{-B \cdot \sigma_{S} \cdot z_{S}+\frac{B^{2} \cdot \sigma_{S}^{2}}{2}} \cdot \frac{\Phi\left(z_{S}-B \cdot \sigma_{S}\right)}{\Phi\left(z_{S}\right)}  \tag{18}\\
& T_{H}=A \cdot e^{B \cdot \sigma_{S} \cdot z_{S}+\frac{B^{2} \cdot \sigma_{S}^{2}}{2} \cdot \frac{1-\Phi\left(z_{S}+B \cdot \sigma_{S}\right)}{1-\Phi\left(z_{S}\right)}} \tag{19}
\end{align*}
$$

$T_{C R}=A \cdot e^{-B \cdot \sigma_{N} \cdot z_{N}+\frac{B^{2} \cdot \sigma_{N}^{2}}{2}} \cdot \frac{\Phi\left(z_{N}-B \cdot \sigma_{N}\right)}{\Phi\left(z_{N}\right)}$
$T_{F A}=A \cdot e^{B \cdot \sigma_{N} \cdot z_{N}+\frac{B^{2} \cdot \sigma_{N}{ }^{2}}{2}} \cdot \frac{1-\Phi\left(\mathrm{z}_{N}+B \cdot \sigma_{N}\right)}{1-\Phi\left(\mathrm{z}_{N}\right)}$
where
$z_{S}=\frac{x_{C O}-\mu_{S}}{\sigma_{S}} \quad ; \quad z_{N}=\frac{x_{C O}-\mu_{N}}{\sigma_{N}}$
The reaction time function depends on the value of the cutoff point $x_{c o}$. In our collaborative system, the robot observes the objects first followed by the human. Accordingly, the human decides about two different types of objects: objects that the robot already marked as targets; and objects the robot did not mark (Figure 2). The human uses two different cutoff points, for the two types of objects. Accordingly, two different reaction time functions should be implemented. The denotations with the index rh or $h$ (for instance, $T_{\text {CRh }}, T_{\text {Hrh }}$ etc.), will represent reaction times for objects the robot marked as targets and for those it did not, respectively.
In the objective function, each of the human time variables (denoted as $t_{X h}$ or $t_{X h}$ ) represents a superposition of a decision time and a motoric time (denoted as $t_{M}$ ), in accordance with the collaboration level. The decision times in the previous work [1] were considered constant. In this work, the decision times are replaced with the mean reaction times introduced above.
When the system operates in the R collaboration level the robot fulfills the task all by itself and all human time variables equal zero (there is no human intervening).
In the H collaboration level, the human does not use the robot's help and the time variables are:
$\begin{array}{ll}t_{M h}=T_{M h} & t_{C R h}=T_{C R h} \\ t_{H h}=T_{H h}+t_{M} & t_{F A h}=T_{F A h}+t_{M}\end{array}$
In the HR collaboration level, the robot recommends the human by indicating potential targets. Then the human confirms targets he thinks are real and marks extra targets the robot did not indicate. The human does a motoric action (marking) if he thinks the robot recommended well. The time variables are:

$$
\begin{array}{ll}
t_{M h}=T_{M h} & t_{M r h}=T_{M r h} \\
t_{H h}=T_{H h}+t_{M} & t_{\text {Hrh }}=T_{\text {Hrh }}+t_{M} \\
t_{C R h}=T_{C R h} & t_{C R r h}=T_{C R r h} \\
t_{\text {FAh }}=T_{F A h}+t_{M} & t_{\text {FArh }}=T_{\text {FArh }}+t_{M} \tag{23}
\end{array}
$$

In the HOR collaboration level, the human supervises the robot. The robot marks targets and the human is checking those marks. The human unmarks targets that are not real and marks extra targets that the robot missed. In this case, the human does a motoric action (unmarking) only if he thinks the robot made a mistake. The time variables are:
$t_{M h}=T_{M h}$

$$
\begin{align*}
& t_{\text {Mrh }}=T_{\text {Mrh }}+t_{M} \\
& t_{\text {Hrh }}=T_{\text {Hrh }}  \tag{24}\\
& t_{\text {CRrh }}=T_{\text {CRrh }}+t_{M} \\
& t_{\text {FArh }}=T_{\text {FArh }}
\end{align*}
$$

$t_{H h}=T_{H h}+t_{M}$
$t_{C R h}=T_{C R h}$
$t_{F A h}=T_{F A h}+t_{M}$
The (motoric) time it takes to physically mark or unmark an object depends on the system interface and the environment conditions. It should not vary between detected objects and therefore will remain considered constant.


Figure 2 - Reaction times diagram.

## 3 NUMERICAL ANALYSIS

A numerical analysis of the model was conducted using MatLab 7.1 with optimal human and robot cutoff points. The optimal cutoff points were determined by finding the cutoff points that yielded the maximal objective function value. The objective function score was calculated for each possible combination of parameters and variables, for each collaboration level.

### 3.1 Model parameters

Task types and parameters
Analysis focused on three system types characterized by the gains and penalties for each outcome ( $V_{H}, V_{M}, V_{F A}, V_{C R}$, [10]). Table 1 details the values for each type of system.
Type I gives high priority for not doing errors of the first type, i.e., detecting a target when a target does not exist (false alarm).
Type II gives high priority for not doing errors of the second type, i.e., missing a target.
Type III systems do not prefer one type of error and therefore yield identical values for all four possible outcomes.
The time cost $\left(V_{T}\right)$ is the cost of one time unit of system operation. It includes the cost of the human operator and the robot since they are operating simultaneously. In order to analyze the influence of time cost regardless of the system type, it was set relatively to the gain for a hit ( $\left.V_{T}=V_{H} \cdot V_{T 2 H}\right)$. The ratio between the time cost and the gain for a hit, $V_{T 2 H}$, was set to the values: -80, -40, $-20\left(\right.$ hour $\left.^{-1}\right)$.
For example, when $V_{H}$ equals 5 points, $V_{T}$ obtained the values: -400, $-200,-100$ points.
The operational cost $\left(V_{C}\right)$ is the cost of the action conducted when the system detects a target, either if it is a hit or a false alarm. This cost was set to 2 points.

## Environmental parameters

The parameters $N$ and $P_{s}$ determine the environmental conditions. The objective function was calculated for 1,000 objects $(N)$. The target probability ( $P_{S}$ ) represents the fraction of targets from all objects and received values between 0.1 and 0.9 .

## Human parameters

The decision time was calculated using the mean reaction time function introduced above. Parameter $A$, of the function, was set to 2,5 or 10 seconds and parameter $B$ was set to $0,0.5,1,1.5$ or 2 . The human motoric time ( $t_{M}$ ) of executing an action was set to 2 seconds.
The sensitivity represents the ability of the observer to distinguish between real targets and the other objects. The human's sensitivity ( $d^{\prime} h$ ) was varied between 0.5 and 3 .

## Robot parameters

The sensitivity of the robot $\left(d_{r}^{\prime}\right)$ was varied between 0.5 and 3 . The robot decision time $\left(t_{r}\right)$ is negligible relatively to the other times and was set to 0.01 seconds.

Table 1. Gains and penalties for different types of systems.

|  | Type I | Type II | Type III |
| :---: | :---: | :---: | :---: |
| $V_{H}$ | 5 | 50 | 10 |
| $V_{M}$ | -10 | -10 | -10 |
| $V_{F A}$ | -50 | -5 | -10 |
| $V_{C R}$ | 10 | 10 | 10 |

### 3.2 Cutoff point analysis

When the sensitivity of the human operator is high, the human operator can better distinguish between targets. The optimal cutoff point is a point between the means of the noise and signal distribution (Figure 3, a). When the sensitivity is low, the ability to distinguish between targets reduces and it becomes more effective not to examine the objects. The optimal cutoff point goes to the extreme and the human actually does not mark any object as a target (Figure 3, b). When the system gives high priority to "not doing false alarms" (Type I), the cutoff point will be set to infinity. When there is high priority of not missing a target (Type II), the cutoff point will be set to minus infinity, and all of the objects will be marked as targets.
(a)



Figure 3 - A cutoff point between the distributions' means when the sensitivity is high (a) and extreme cutoff point selection when sensitivity is low (b).
This influence finds expression in the analysis, regardless of the response time costs of the observer. The time costs amplify this phenomenon. The mean response time reduces as the cutoff point is far from the mean of the distribution; therefore, in the sense of time costs, an extreme cutoff point is always preferred. The 'extremes' in this data set are -3 and 6 .
The position of the cutoff point influences all other parts of the objective function. An extreme positive cutoff point, for example, causes small probabilities of false alarms and hits; and causes high probabilities of miss and correct rejections. The overall gains and penalties of these outcomes are modified accordingly.

Human optimal cutoff point influence in Type I systems
Type I systems give high priority for avoiding false alarms. When the human has low sensitivity, it is expected to get the highest value possible for the optimal cutoff point. Figure 4 (a) shows the optimal cutoff point of the human (z-axis). When the sensitivity of the human is low, the optimal cutoff point value is six (the highest value possible).
As the cutoff point is drawn away from the means of the distribution (see Figure 3, b), the distance of the objects from the cutoff point increases; and the mean response time, correspondingly, decreases. Figure 4 (b) shows decrease in system operation time for low human sensitivity.
Furthermore, the analysis shows that the total penalty for false alarms grows as the sensitivity of the observer decreases (Figure 4, c). This phenomenon exists up to the point where the sensitivity is too small. Then, an extreme cutoff point is preferred and the human marks less objects as targets. Therefore, the total penalty for false alarms decreases as was expected in Type I systems.

## Human optimal cutoff point influence in Type II systems

Type II systems give high priority for not missing targets. Analysis shows that when human has low sensitivity, the optimal cutoff point value -3 (the lowest value possible).
As was explained for Type I, extreme cutoff point results in redundancy of system operation time. The total penalty for misses behaves the same as the total penalty for false alarms in Type I.

## Human optimal cutoff point influence in Type III systems

In Type III systems, the gains and penalties are equal for all outcomes, there is no preferable error and the cutoff point remains between the means of the distributions even when the sensitivity of the observer is low.
The total penalty for misses and the total penalty for false alarms continue to decrease also for low sensitivities.

### 3.3 Human's dominancy analysis

The human operations cause an increase in operation time and costs. The human response time and motoric time are significantly higher than the robot decision time. Therefore, in the sense of time costs, it is reasonable that involving a human in the recognition process will be less profitable when the time cost is high.
In Figure 5, a single collaboration level dominates each zone and the sensitivities of the human and the robot are ranged along $x$ and $y$ axes. The graphs present the collaboration level required to achieve the best system performance.


Figure 4-Optimal cutoff point of the human (a), system operation time (b) and System total penalty for false alarms (c) in the H collaboration level, Type I system. Human sensitivity and the time cost are ranged along $x$ and $y$ axes.


Figure 5 - Human dominance reduces as the time cost increases.
Each color represents different operating level: HR- dark grey, HOR- light grey and R-black

One can see that human dominance reduces as the time cost increases. The time cost increases from the right graph ( $V_{T} 2 V_{H}=-0.0055$ ) to the left graph ( $V_{T} 2 V_{H}=-0.0222$ ). Accordingly, the area of the HR and HOR collaboration levels diminished. Human dominance also reduces as parameter $A$ increases and/or parameter $B$ decreases (Equation 15).

### 3.4 Object probability analysis

The probability of an object to be a target $\left(P_{S}\right)$ influences the phenomenon of the extreme cutoff point selection. In Type II systems when there are many targets among the objects (i.e., $P_{S}$ is high), the system prefers extreme cutoff point for higher sensitivities of the human (relatively to low sensitivities in cases where $P_{S}$ is not high and an extreme cutoff point is preferred). In a similar manner, when most of the objects are not targets (i.e., $P_{s}$ is low), in Type I systems, an extreme cutoff point is preferred for higher human sensitivities.

## 4 CONCLUSIONS

The numerical analysis reveals a phenomenon of extreme optimal cutoff point position for the human, when the sensitivity of the human is low. An extreme cutoff point position decreases the total operation time cost. Therefore, an extreme cutoff point is always preferred when time costs are a priority.
Both mean reaction time and time cost affect the position of the optimal cutoff point. This arises for higher human sensitivities as the mean time and/or the time cost are higher. Furthermore, the analysis shows that collaboration with a human is less profitable when the mean reaction time and/or the time cost are high.
The probability of an object to be a target $\left(P_{S}\right)$ influences the extreme cutoff point selection. A reasonable explanation for this influence is the potential of misses or false alarms to occur. When there are many targets, the potential of miss is higher; and when there are few targets, the potential of false alarm is high. Therefore, when the system tries to avoid false alarms, it "gives up" on trying to detect targets when most of the objects are not targets.

## 5 ACKNOWLEDGMENTS

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## Appendix G-The Numeric Simulation Software

## 1. The experiment program code

```
% This program sets the parameter's values and runs an experiment
clear all;
clc;
% Create directories fot the experiment data
exName='TypeI';% Experiment name
DataPath=['D:\Data\', exName, '\'];
if isdir(DataPath)
    message=['Directory ', DataPath, ' already exist. Either delete it or change experiment
name.'];
    warning(message)
    break
end
mkdir(DataPath);
mkdir(DataPath, 'Parameters');
mkdir(DataPath, 'Optimal');
mkdir(DataPath, 'Graphs');
% Parameters values
N=1000; % # of objects
vH=5; % The gain from Hit
vM=-10; % The panelty for Miss
vFA=-10*vH; % The panelty for False Alarm
vCR=-1*VM; % The gain from Correct Rejection
vT2vH_vector=[-80,-40,-20]./3600; % The cost of one time unit
vC=-2; % Cost of one object recognition operation
tr=0.01; % The robot time. sec/object on average
tMotor=2; % The motoric time of the human
Ps_vector=[0.1,0.2,0.5,0.8,0.9]; % Probability for object to be target
dh_vector=[0.5:0.5:3]; % The sensitivity of the human
dr_vector=[0.5:0.5:3]; % The sensitivity of the robot
XcoRange=[-3:0.1:6]; % All the posible cutoff points
global A; % A and B are parameters of the reaction time function
global B;
A_vector=[2,5,10];
B_vector=[0,0.5,1,1.5,2];
%Save the parameters for the Graphs programs
eval(['save ' DataPath 'Parameters\Parameters.mat'])
% Run the experiment
OptimalBetas
```


## 2. The data base creator code

\% This program create a data set of all possible combination of the parameters.
\% Then, it extracts only the records of the optimal objective function value.
tic
\% All possible cutoff points for the robot (r) and the human (h, rh), Based on their sensitivities
\%-----------
Zn_r(:, : i) =XcoRange (i);
Zn_h(:,i,:)=XcoRange(i);
Zn_rh(i,: : ) =XcoRange (i);
end

```
%===========================================================================
```

\% Loops 1 to 6 spread all combinations of parameters' values
\% Loop 1 : vT/vH aspect ratio
for ivT2vH = 1:length (vT2vH vector)
vT=vH.*vT2vH_vector (ivT2vH);
\% Loop 2 : B parameter of the mean time function
for iB=1:length(B vector)
B=B_vector (iB);
\% Loop 3: A parameter of the mean time function
for iA=1:length(A_vector)
A=A_vector (iA);
\% Loop 4 : Probability for object to be target
for iPs=1:length(Ps_vector)
Ps=Ps_vector(iPs);
\% Loop 5 : The range of $d^{\prime}$ for the human operator sensitivity
for idh=1:length(dh_vector)
dh=dh vector(idh);
\% Loop 6 : The range of $d^{\prime}$ for the robot sensitivity
for idr=1:length(dr_vector)
dr=dr_vector(idr);

```
%====================================================================================================
% START - For each combination of parameters - create data set of all possible cutoff points
Sin
% All possible cutoff points for the robot(r) and the human(h,rh). Based on their sensitivities
%----------------------------------------------------------------------------------------------------
Zs r=Zn r-dr; % Robot's cutoff point for a signal
Zs_h=Zn_h-dh; % Human's cutoff point for a signal
Zs_rh=Zn_rh-dh; % Human's cutoff point for a signal, when collaborate with the robot
% The probabilities for the robot (r) and the human (h, rh). Based on the cutoff points
p------------------------------------------------------------
pFA r=1-normcdf(Zn r); % Robot's probability for a false alarm
pH_\overline{h}=1-normcdf(Zs_\overline{h}); % Human's probability for a hit
pFA
pH r}h=1-normcdf(Zs-rh); % Human's probability for a hit, when collaborate with the robo
pFA_rh=1-normcdf(Zn_rh); % Human's probability for a FA, when collaborate with the robot
% The mean response time of the human for objects the robot did not mark
%--------------------------------------------------------------------------------------------------------
tH_h=meanTime(Zs_h,'p');
tM_h=meanTime(Zs_h,'n');
tF\overline{A}}\textrm{h}=m=anTime(Z\overline{n}h,'p')
tCR_h=meanTime(Zn_h,'n');
```

```
% The mean response time of the human for objects the robot did mark
tH rh=meanTime(Zs rh,'p');
tM_rh=meanTime(Zs_rh,'n');
tFA rh=meanTime(Zn rh,'p');
tCR_rh=meanTime(Zn_rh,'n');
%H collaboration level - human alone
%------------------------------------------------------------------------------------------------------------------
% Probabilities, gains and penalties
pHs_H=pH_h; % Probability for a hit
vHs_H=N.*Ps.*pHs_H.*vH; % Gain from a hit
pMs_H=1-pHs_H; - % Probability for a miss
vMs_H = N.*\overline{Ps.*pMs_H.*vM; % Penalty from a miss}
pFAs_H=pFA_h; % Probability for a false alarm
vFAs_-H=N.*\overline{(1-Ps).*pFAs_H.*vFA; 渞 Penalty from a false alarm}
pCRs_H = 1-pFAs_H; % Probability for a correct rejection
vCRs_H = N.*(1-\overline{Ps}).*pCRs_H.*vCR; % Gain from a correct rejection
% Operational costs
ts_H= N.*Ps.*pH_h.*(tH_h+tMotor)... % The system time
    +N.*(1-PS).*pFA_h.*(tFA_h+tMotor)...
    +N.*Ps.*(1-pH_h).*tM_h...
    +N.* (1-Ps).* (\overline{1}-\textrm{pFA}h)
vTs_H=ts_H.*vT; % Time costs
vCs_H=(N.*Ps.*pH_h... % Action costs (for detected targets)
    +N.*(1-Ps).*pFA_h).*vC;
% The objective function
VIs_H=vHs_H+vMs_H+vFAs_H+vCRs_H+vTs_H+vCs_H;
% HR collaboration level - the robot recommends the human
%---------------------------------------
pHs HR=pH r.*pH rh+(1-pH r).*pH h; % Probability for a hit
vHs_HR=N.`}\mp@subsup{}{}{-}Ps.*p\overline{Hs_HR.*vH;
pMs_HR=1-pHs_HR; - % Probability for a miss
vMs_HR=N.*Ps.*pMs_HR.*vM; % Penalty from a miss
pFA\overline{s}_HR=pFA_r.*pFA
vFAs_HR=N.*\overline{(1-Ps).}\mp@subsup{}{}{*}\mathrm{ pFAs_HR.*/̄FA; - % Penalty from a false alarm}
pCRs_HR=1-pFAs_HR;
Probability for a correct rejection
vCRs_HR=N.*(1-\overline{P}).*pCRs_HR.*vCR; % Gain from a correct rejection
% Operational costs
ts_HR= N.*Ps.*pH_r.*pH_rh.*(tH_rh+tMotor)... % The system time
    +N.*Ps.*(1-pH r).*pH h.*(tH h+tMotor)...
```



```
    +N.*(1-Ps).*(1-pFA r).*pFA h.*(tFA h+tMotor)...
    +N.*Ps.*pH_r.*(1-p\overline{H_rh).*t\overline{M}_rh...}
    +N.*Ps.*(1-pH_r).* (\overline{1}-\textrm{pH_h}).\overline{*}tM_h...
    +N.*(1-Ps).*pFA_r.*(1-pFA_rh).*tCR_rh...
    +N.* (1-Ps) .* (1-\overline{p}FA_r).* (1-pFA_h) .*\overline{t}CR_h...
    +N*tr;
vTs HR=ts HR.*vT; % Time costs
vCs_HR=(N.*Ps.*pH_r.*pH_rh... % Action costs (for detected targets)
    +N.*Ps.*(1-pH_r).*pH_h...
    +N.*(1-Ps).*p\overline{FA_r.*p\overline{FA_rh...}}\mathbf{~}\mathrm{ . }
    +N.* (1-Ps) .* (1-\overline{p}FA_r). *
\% The objective function
VIs_HR=vHs_HR+vMs_HR+vFAs_HR+vCRs_HR+vTs_HR+vCs_HR;
```

```
%HOR collaboration level - the human supervise the robot
% Probabilities, gains and penalties
% Same as for HR collaboration level
pHs HOR=pHs HR;
vHs_HOR=vHs_HR;
pMs_HOR=pMs_HR;
vMs HOR=vMs HR;
pFA\overline{s}_HOR=pFA\overline{s_HR; % Probability for a false alarm}
vFAs HOR=vFAs HR;
pCRs_HOR=pCRs_HR;
pCRs_HOR=pCRs_HR;
% Probability for a hit
% Gain from a hit
Probability for a miss
% Penalty from a miss
% Penalty from a false alarm
% Operational costs
ts_HOR= N.*Ps.*pH_r.*pH_rh.*tH_rh... % The system time
    +N.*Ps.*(1-pH r).*pH h.*(th h+tMotor)...
```



```
    +N.*(1-Ps).*(1-pFA_r).*pFA_h.*(tFA_h+tMotor)...
    +N.*Ps.*pH_r.*(1-p\overline{H_rh).*(TM_rh+tMötor)...}
    +N.*Ps.*(1-1-pH_r).* (\overline{1}-\textrm{pH_h}).*\overline{tM_h...}
    +N.*(1-Ps).*pFA_r.*(1-p\overline{FA_rh).\overline{*}}\mathrm{ (tCR_rh+tMotor)...}
    +N.* (1-Ps) .* (1-\overline{p}FA_r) .* (1-pFA_h) .*t\overline{C}R_h...
    +N*tr;
vTs HOR=ts HOR.*vT; % Time costs
vCs_HOR=(N.*Ps.*pH_r.*pH_rh... % Action costs (for detected targets)
    +N.*Ps.*(1-pH_r).*pH_h...
    +N.*(1-Ps).*p\overline{FA_r.*p\overline{FA_rh...}}\mathbf{~}\mathrm{ . }
    +N.* (1-Ps) .* (1-\overline{\textrm{p}FA_r). *}
% The objective function
VIs_HOR=vHs_HOR+vMs_HOR+vFAs_HOR+vCRs_HOR+vTs_HOR+vCs_HOR;
%R collaboration level - fully autonomous robot
%-------------------------------------
Probabilities, gains and penalties
pHs_R=pH_r;
pMs_R=1-pHs_R;
vMs__R = N.* Ps.*pMs_R.*vM;
pFA\overline{s}_R=pFA_r;
vFAs_R=N.*(1-Ps).*pFAs_R.*vFA;
pCRs_R = 1-pFAs_R; % Probability for a correct rejection
vCRs_R = N.*(1-\overline{P}).*pCRs_R.*vCR; % Gain from a correct rejection
% Operational costs
ts_R=N*tr*ones(sXco,sXco,sXco); % The system time
vTs_R=ts_R.*vT; % Time costs
vCs_R=(N.*Ps.*pH_r+N.*(1-Ps).*pFA_r).*vC; % Action costs (for detected targets)
```

\% The objective function


```
% This part extracts the records of the optimal system objective function
from the data. For each collaboration level, the maximum value of
the objective function is found, and the indices of the cutoff points are
used to extract the value of the other functions.
```

\%H collaboration level - human alone
\% Find index of optimal Betas
opt VIs H(idr,idh,iPs,iB,iA,ivT2vH) =max(VIs H(:))
$[x \bar{y} z]=\bar{f} i n d\left(V I s \_H==o p t \_V I s \_H(i d r, i d h, i P s, i B, i A, i v T 2 v H)\right) ;$
iXrh_H(idr,idh,iPs,iB,iA, ivT2vH)=x(1);
iXh $H(i d r, i d h, i P s, i B, i A, i v T 2 v H)=y z(1)-l e n g t h(V I s H) *(c e i l(y z(1) . / l e n g t h(V I s ~ H))-1)$
$i X r \_H(i d r, i d h, i P s, i B, i A, i v T 2 v H)=\operatorname{ceil}\left(y z(1) . / l e n g \overline{t h}\left(V I s \_H\right)\right) ;$
irh $H=i X r h ~ H(i d r, i d h, i P s, i B, i A, i v T 2 v H) ;$
ih $H=i X h$ H(idr, idh, iPs,iB,iA, ivT2vH);
$i r_{-}^{-} H=i X r_{-}^{-} H(i d r, i d h, i P s, i B, i A, i v T 2 v H)$;
\% Create the optimal data metrix based on optimal Betas opt_pHs_H(idr,idh,iPs,iB,iA,ivT2vH) =pHs_H(irh_H,ih_H,ir_H); opt vHs H(idr,idh,iPs,iB,iA,ivT2vH)=vHs H(irh H,ih H,ir H);
 opt_vMs_H(idr,idh,iPs,iB,iA, ivT2vH) =vMs_H(irh_H,ih_H,ir_H); opt_pFAs_H(idr,idh,iPs,iB,iA,ivT2vH) =pFĀs_H(irh_H, īh_H,ir_H); opt_vFAs_H(idr,idh,iPs,iB,iA,ivT2vH)=vFAs_H(irh_H,ih_H,ir_H); opt pCRs H(idr,idh,iPs,iB,iA,ivT2vH)=pCRs H(irh H,ih H,ir H) ; opt_vCRs_H(idr,idh,iPs,iB,iA,ivT2vH)=vCRs_H(irh_H,ih_H,ir_H); opt_ts_H(idr,idh,iPs,iB,iA,ivT2vH)=ts_H(irh_H,ih_H,ir_H);
 opt_-vCs_H(idr,idh,iPs,iB,iA, ivT2vH) $=v$ cs_ $_{-}^{-} H\left(i r h_{-}^{-} H, i h_{-}^{-} H, i r \_H\right)$; opt tH h H (idr,idh,iPs,iB,iA, ivT2vH)=tH h(irh H,ih H,ir H); opt_tM_h_H(idr,idh,iPs,iB,iA,ivT2vH)=tM_h(irh_H,ih_H,ir_H); opt tFA $\bar{h} H(i d r, i d h, i P s, i B, i A, i v T 2 v H)=t \overline{F A} h(i \bar{r} h \quad H, \bar{i} h H, \bar{i} r ~ H)$ opt_tCR_h_H(idr,idh,iPs,iB,iA,ivT2vH)=tCR_h(irh_H,ih_H,ir_H);
\%HR collaboration level - the robot recommends the human
\% Find index of optimal Betas
opt VIs HR(idr,idh,iPs,iB,iA,ivT2vH)=max((VIs HR(:)));
$[\mathrm{x} \overline{\mathrm{y}} \mathrm{z}]=\overline{\mathrm{f}}$ ind (VIs_HR==opt_VIs_HR(idr,idh,iPs,iB,iA,ivT2vH));
iXrh HR(idr,idh,iPs,iB,iA,ivT2vH)=x(1);
iXh $\overline{H R}(i d r, i d h, i P s, i B, i A, i v T 2 v H)=y z(1)-l e n g t h(V I s ~ H R) *(c e i l(y z(1) . / l e n g t h(V I s ~ H R))-1) ;$
$i X r \_H R(i d r, i d h, i P s, i B, i A, i v T 2 v H)=c e i l\left(y z(1) . / l e n g \overline{t h}\left(V I s \_H R\right)\right)$;
irh HR=iXrh HR(idr,idh,iPs,iB,iA,ivT2vH);
$i h_{-}+\mathrm{HR}=i \mathrm{Xh}_{\mathrm{H}} \mathrm{HR}(i d r, i d h, i P s, i B, i A, i v T 2 v H)$;
$i r_{-}^{-H R=i X r \_H R(i d r, i d h, i P s, i B, i A, i v T 2 v H) ; ~}$
\% Create the optimal data metrix based on optimal Betas
opt pHs_HR(idr,idh,iPs,iB,iA, ivT2vH)=pHs_HR(irh HR,ih HR,ir HR) opt_vHs_HR(idr,idh,iPs,iB,iA,ivT2vH)=vHs_HR(irh_HR,ih_HR,ir_HR); opt_pMs_HR(idr,idh,iPs,iB,iA,ivT2vH)=pMs_HR(irh_HR,ih_HR,ir_HR) opt $v M s$ HR(idr,idh,iPs,iB,iA,ivT2vH)=vMs HR(irh HR,ih HR,ir HR); opt_pFAs_HR(idr,idh,iPs,iB,iA,ivT2vH)=pFĀs_HR(irh_HR,in_HR,ir_HR); opt_vFAs_HR(idr,idh,iPs,iB,iA,ivT2vH)=vFAs_HR(irh_HR,ih_HR,ir_HR); opt pCRs HR(idr,idh,iPs,iB,iA,ivT2vH)=pCRs HR(irh HR,ih HR,ir HR); opt_vCRs_HR(idr,idh,iPs,iB,iA,ivT2vH)=vCRs_HR(irh_HR,ih_HR,ir_HR); opt ts HR (idr,idh,iPs,iB,iA,ivT2vH)=ts HR(irh_HR,ih_HR,ir_HR); opt_vTs_HR(idr,idh,iPs,iB,iA,ivT2vH)=vTs_HR(irh_HR,ih_HR,ir_HR); $o p t \_\mathrm{vCs}_{-}^{-} H R(i d r, i d h, i P s, i B, i A, i v T 2 v H)=v C s \_H R\left(i r h \_H R, i h^{-} H R, i r \_H R\right) ;$ opt ${ }^{-} t H \bar{h} H R(i d r, i d h, i P s, i B, i A, i v T 2 v H)=t H^{-} h(i r h \overline{H R}, i h \overline{H R}$,ir $\overline{H R})$;
 opt ${ }^{-} t F \bar{A} \bar{h} H R(i d r, i d h, i P s, i B, i A, i v T 2 v H)=t \bar{F} A$ h (irh $H R, \bar{i} h$ HR, $\left.\bar{i} r \operatorname{HR}\right)$; opt tCR h HR(idr, idh, iPs,iB,iA, ivT2vH) $=t C R$ (irh HR, ih HR, ir HR); opt_th_一rh_HR(idr,idh,iPs,iB,iA,ivT2vH)=tH_r$h\left(i r h \_H R, i h \_H R, i r \_H R\right) ;$ opt $\mathrm{tM}^{-}$rh $\mathrm{HR}(i d r, i d h, i P s, i B, i A, i v T 2 v H)=t M^{-} r h\left(i r h-H R, i h^{-} H R, i r-H R\right)$; opt_tFA_rh_HR(idr,idh,iPs,iB,iA,ivT2vH)=tFA_rh(irh_HR,ih_HR,ir_HR); opt_tCR_rh_HR(idr,idh,iPs,iB,iA,ivT2vH)=tCR_rh(irh_HR,ih_HR,ir_HR);

```
%HOR collaboration level - the human supervise the robot
% Find index of optimal Betas
    opt_VIs_HOR(idr,idh,iPs,iB,iA,ivT2vH)=max(VIs_HOR(:));
    [x yz]=find(VIs HOR==opt VIs HOR(idr,idh,iPs,iB,iA,ivT2vH));
    iXrh_HOR(idr,idh,iPs,iB,iA,ivT2vH)=x(1);
    iXh \overline{HOR(idr,idh,iPs,iB,iA,ivT2vH)=...}
                yz(1)-length(VIs_HOR)*(ceil(yz(1)./length(VIs_HOR))-1);
    iXr_HOR(idr,idh,iPs,iB,iA,ivT2vH)=ceil(yz(1)./length(VIs_HOR));
    irh HOR=iXrh HOR(idr,idh,iPs,iB,iA,ivT2vH);
    ih_HOR=iXh_HOR(idr,idh,iPs,iB,iA,ivT2vH);
    ir_HOR=iXr_HOR(idr,idh,iPs,iB,iA,ivT2vH);
% Create the optimal data metrix based on optimal Betas
    opt_pHs_HOR(idr,idh,iPs,iB,iA,ivT2vH)=pHs HOR(irh HOR,ih HOR,ir HOR);
    opt vHs HOR(idr,idh,iPs,iB,iA,ivT2vH)=vHs HOR(irh HOR,ih HOR,ir HOR);
    opt_pMs_HOR(idr,idh,iPs,iB,iA,ivT2vH)=pMs_HOR(irh_HOR,ih_HOR,ir_HOR);
    opt_vMs_HOR(idr,idh,iPs,iB,iA,ivT2vH)=vMs_HOR(irh_HOR,ih_HOR,ir_HOR);
    opt_pFAs_HOR(idr,idh,iPs,iB,iA,ivT2vH)=pFAs_HOR(irh_HOR,ih_HOR,ir_HOR);
    opt_vFAs_HOR(idr,idh,iPs,iB,iA,ivT2vH)=vFAs_HOR(irh_HOR,ih_HOR,ir_HOR);
    opt pCRs HOR(idr,idh,iPs,iB,iA,ivT2vH)=pCRs HOR(irh HOR,ih HOR,ir HOR);
    opt_vCRs_HOR(idr,idh,iPs,iB,iA,ivT2vH)=vCRs_HOR(irh_HOR,ih_HOR,ir_HOR);
    opt_ts_HÖ(idr,idh,iPs,iB,iA,ivT2vH)=ts_HOR(irh_HOR,ih_HOR,ir_HOR);
    opt vTs HOR(idr,idh,iPs,iB,iA,ivT2vH)=vTs HOR(irh HOR,ih HOR,ir HOR);
    opt_vCs_HOR(idr,idh,iPs,iB,iA,ivT2vH)=vCs_HOR(irh_HOR,ih_HOR,ir_HOR);
    opt tH h HOR(idr,idh,iPs,iB,iA,ivT2vH)=tH h(irh HOR,ih HOR,ir HOR);
    opt_tM_h_HOR(idr,idh,iPs,iB,iA,ivT2vH)=tM_h(irh_HOR,ih_HOR,ir_HOR);
    opt_tFA_\overline{h_HOR(idr,idh,iPs,iB,iA,ivT2vH)=t\overline{FA_h(ir}\mp@subsup{\}{_}{-}HOR,\overline{ih}_HOR,\overline{ir}_HOR);}
    opt tCR h HOR(idr,idh,iPs,iB,iA,ivT2vH)=tCR h(irh HOR,ih HOR,ir HOR);
    opt_tH_rh_HOR(idr,idh,iPs,iB,iA,ivT2vH)=tH_rh(irh_HOR,ih__HOR,ir_HOR);
    opt_tM_rh_HOR(idr,idh,iPs,iB,iA,ivT2vH)=tM_rh(irh_HOR,ih_HOR,ir_HOR);
    opt tFA_rh_HOR(idr,idh,iPs,iB,iA,ivT2vH)=tFA_rh(irh_HOR,ih_HOR,ir_HOR);
    opt_tCR_rh_HOR(idr,idh,iPs,iB,iA,ivT2vH)=tCR_rh(irh_HOR,ih_HOR,ir_HOR);
%R collaboration level - fully autonomous robot
% Find index of optimal Betas
    opt_VIs_R(idr,idh,iPs,iB,iA,ivT2vH)=max(VIs_R(:));
    [x ȳz]=\overline{find(VIs R==opt VIs R(idr,idh,iPs,iB,iA,ivT2vH));}
    iXrh_R(idr,idh,iPs,iB,iA,ivT2vH)=x(1);
    iXh \overline{R}(idr,idh,iPs,iB,iA,ivT2vH)=yz(1)-length(VIs R)*(ceil(yz(1)./length(VIs R))-1);
    iXr R(idr,idh,iPs,iB,iA,ivT2vH)=ceil(yz(1)./length(VIs R));
    irh_R=iXrh_R(idr,idh,iPs,iB,iA,ivT2vH);
    ih \overline{R}=iXh R(idr,idh,iPs,iB,iA,ivT2vH);
    ir_R=iXr_R(idr,idh,iPs,iB,iA,ivT2vH);
\% Create the optimal data metrix based on optimal Betas opt_pHs_R(idr,idh,iPs,iB,iA,ivT2vH)=pHs_R(irh_R,ih_R,ir_R);
```



``` opt pMs R(idr,idh,iPs,iB,iA, ivT2vH) \(=\mathrm{pMs}\) R(irh R,ih R,ir R); opt_vMs_R(idr,idh,iPs,iB,iA,ivT2vH) \(=\mathrm{vMs}\) _R(irh_R,ih_R,ir_R); opt pFAs R(idr, idh,iPs,iB,iA,ivT2vH) \(=p\) FAs \(R(i \bar{r} h R, \overline{i h} R, \overline{i r} R)\); \(o p t \_v F A s \_R(i d r, i d h, i P s, i B, i A, i v T 2 v H)=v F A s_{-}^{-} R\left(i r h \_R, i h \_R, i r \_R\right)\); opt_pCRs_R(idr, idh, iPs,iB,iA,ivT2vH)=pCRs_R(irh_R,ih_R,ir_R); opt vCRs R(idr,idh,iPs,iB,iA,ivT2vH)=vCRs R(irh R,ih R,ir R); opt_ts_R(idr,idh,iPs,iB,iA,ivT2vH)=ts_R(irh_R,īh_R,ir_R);
opt \({ }^{-} v T \bar{s} R(i d r, i d h, i P s, i B, i A, i v T 2 v H)=v \bar{T} s R(i \bar{r} h R, \bar{i} h R, \overline{i r} R)\); opt_vCs_R(idr,idh,iPs,iB,iA,ivT2vH)=vCs_R(irh_R,ih_R,ir_R);
```

```
%find Max objective function
    all VIs=[opt VIs H(idr,idh,iPs,iB,iA,ivT2vH),opt VIs HR(idr,idh,iPs,iB,iA,ivT2vH),..
        opt_VIs_HOR(idr,idh,iPs,iB,iA,ivT2vH),opt_VIs_R(idr,idh,iPs,iB,iA,ivT2vH)];
    opt_VIs(id\overline{r},id\overline{h},iPs,iB,iA,ivT2vH)=max(all_VIs);
%find best CL based on Max objective function
    CL=find(all VIs==opt VIs(idr,idh,iPs,iB,iA,ivT2vH));
```



```
% Find best Zs, Zn for the optimal CL
    all_pHs=[opt_pHs_H(idr,idh,iPs,iB,iA,ivT2vH),opt_pHs_HR(idr,idh,iPs,iB,iA,ivT2vH),...
                opt_p\overline{Hs_HO}R(idr,idh,iPs,iB,iA,ivT2vH),opt_pHs_R(idr,idh,iPs,iB,iA,ivT2vH)];
    all pFAs=[opt pFAs H(idr,idh,iPs,iB,iA,ivT2vH),opt pFAs HR(idr,idh,iPs,iB,iA,ivT2vH),...
                opt_pFAs_HO\overline{R}(idr,idh,iPs,iB,iA,ivT2vH),opt_\overline{pFAs_\overline{R}(idr,idh,iPs,iB,iA,ivT2vH)];}
    opt_Zss(idr,idh,iPs,iB,iA,ivT2vH)=norminv(all_pHs(CL(1)));
    opt_Zns(idr,idh,iPs,iB,iA,ivT2vH)=norminv(all_pFAs(CL(1)));
% find best dTag of the overall system
    opt_dTags(idr,idh,iPs,iB,iA,ivT2vH)=...
                            opt_Zns(idr,idh,iPs,iB,iA,ivT2vH)-opt_Zss(idr,idh,iPs,iB,iA,ivT2vH);
    opt lnBs(idr,idh,iPs,iB,iA,ivT2vH)=..
    -0.5.*(opt_Zss(idr,idh,iPs,iB,iA,ivT2vH).^2-opt_Zns(idr,idh,iPs,iB,iA,ivT2vH).^2);
%Calculate the optimal Zn (r h rh)
    opt_Zn_r_H(idr,idh,iPs,iB,iA,ivT2vH)=Zn_r(irh_H,ih_H,ir_H);
    opt Zn h H(idr,idh,iPs,iB,iA,ivT2vH)=Zn h(irh H,ih H,ir H);
    opt_Zn_rh_H(idr,idh,iPs,iB,iA,ivT2vH)=Zn_rh(irh_H,ih_H,ir_H);
```



```
    opt_Zn_h_HR(idr,idh,iPs,iB,iA,ivT2vH)=Zn_h(irh_HR,ih_HR,ir_HR);
```



```
    opt_Zn_r_
    opt_Zn_h_HOR(idr,idh,iPs,iB,iA,ivT2vH)=Zn_h(irh_HOR,ih_HOR,ir_HOR);
    opt_Zn_rh_HOR(idr,idh,iPs,iB,iA,ivT2vH)=Zn_r_rh(irh_HOR,ih_HOR,ir_HOR);
    opt Zn-r \overline{R}(idr,idh,iPs,iB,iA,ivT2vH)=Zn r(\overline{irh R,i\overline{h}R,ir \overline{R});}
    opt_Zn_h_R(idr,idh,iPs,iB,iA,ivT2vH)= Zn_h(irh_R,ih_R,ir_R);
    opt_Zn_r\overline{h_R(idr,idh,iPs,iB,iA,ivT2vH)=Z\overline{n}_rh(irh_R,in_R,ir_R);}
%Calculate the optimal Zs (r h rh)
    opt Zs r H(idr,idh,iPs,iB,iA,ivT2vH)=Zs r(irh H,ih H,ir H);
    opt Zs-h-H(idr,idh,iPs,iB,iA,ivT2vH)=Zs h(irh H,ih_H,ir-H);
    opt_Zs_rh_H(idr,idh,iPs,iB,iA,ivT2vH)=Z\overline{s_rh(irh_H,\overline{ih_H,ir_H)}}\mathbf{~}\mathrm{ (in_}
    opt Zs r - पेR(idr,idh,iPs,iB,iA,ivT2vH)=Zs_r(irh \overline{HR,ih_HR,ir HR);}
    opt_Zs_h_HR(idr,idh,iPs,iB,iA,ivT2vH)=Zs_h(irh_HR,ih_HR,ir_HR);
    opt Zs rh HR(idr,idh,iPs,iB,iA,ivT2vH)=Z \s rh(irh HR,\overline{ih HR,ir HR);}
    opt Zs r HOR(idr,idh,iPs,iB,iA,ivT2vH)=Zs r(irh HOR,ih HOR,ir HOR);
    opt_Zs__h_HOR(idr,idh,iPs,iB,iA,ivT2vH)=Zs__h(irh_HOR,ih_HOR,ir_HOR);
```



```
    opt Zs-r \overline{R}(idr,idh,iPs,iB,iA,ivT2vH)=Zs r(\overline{irh R,i\overline{h}R,ir \overline{R});}
    opt_Zs__h_R(idr,idh,iPs,iB,iA,ivT2vH)=Zs_h(irh_R,ih_R,ir_R);
    opt_Zs_r\overline{h_R(idr,idh,iPs,iB,iA,ivT2vH)=Z\overline{s}_rh(irh_R,\overline{ih_R,ir_R);}}\mathbf{~}=\overline{i}
%==========================================================================
% END - For each combination of parameters
```



```
                end % loop 6
            end % loop 5
            end % loop 4
    end
                                % loop 4
                                % loop 3
    end % loop 2
end % loop 1
eval(['save ', DataPath, 'Optimal\', 'OptimalData.mat']) % Save the optimal data
```

toc

## 3. The graph generator code

The graph generator was developed using the GUI assistant of MatLab. The assistant automatically created most of the following code. The bolded parts were added to the generated code.

```
function varargout = GraphGUI(varargin)
gui_Singleton = 1;
gui_State = struct('gui_Name', mfilename, ...
    'gui_Singleton', gui_Singleton, ...
    'gui_OpeningFcn', @GraphGUI_OpeningFcn, ...
    'gui_OutputFcn', @GraphGUI_OutputFcn, ...
    'gui_LayoutFcn', [] , ...
    'gui Callback', []);
if nargin && ischar(varargin{1})
    gui_State.gui_Callback = str2func(varargin{1});
end
if nargout
    [varargout{1:nargout}] = gui_mainfcn(gui_State, varargin{:});
else
    gui_mainfcn(gui_State, varargin{:});
end
global dr dh Ps B A vT2vH;
global exName DataPath GraphType_str;
global x_str y_str z_str subG_st\overline{r}}\mathrm{ P1_str P2_str P3_str iP1 iP2 iP3;
dr=1; dh=2; Ps=3; B=\overline{4}; A=5; v\overline{T}2vH=6;
return;
% --- Executes just before GraphGUI is made visible.
function GraphGUI_OpeningFcn(hObject, eventdata, handles, varargin)
% Choose default \overline{command line output for GraphGUI}
handles.output = hobject;
% Update handles structure
guidata(hObject, handles);
function varargout = GraphGUI_OutputFcn(hObject, eventdata, handles)
varargout{1} = handles.output;
% --- Executes on selection change in funName.
function funName Callback(hObject, eventdata, handles)
global z_str;
val=get(hObject,'Value');
str=get(hObject,'String');
if ~strcmp(str{val}, '------------------------------
    z_str=str{val};
    Graph_CreateFcn(hObject, eventdata, handles);
end
return;
% --- Executes during object creation, after setting all properties.
function funName_CreateFcn(hObject, eventdata, handles)
if ispc && isequàl(get(hobject,'BackgroundColor'), get(0,'defaultUicontrolBackgroundColor'))
    set(hObject,'BackgroundColor','white');
end
% --- Executes on selection change in expName.
function expName_Callback(hobject, eventdata, handles)
global exName DataPath;
val=get(hObject, 'Value') ;
str=get(hObject,'String') ;
exName=str{val};
DataPath=['D:\Data\', exName, '\'];
TypeDetails_CreateFcn(hObject, eventdata, handles);
Graph_CreateFcn(hObject, eventdata, handles);
return;
```

\% --- Executes during object creation, after setting all properties.
function expName_CreateFcn(hObject, eventdata, handles)
if ispc \&\& isequāl (get(hObject,'BackgroundColor'), get(0,'defaultUicontrolBackgroundColor')) set(hObject,'BackgroundColor','white');
end
\% --- Executes during object creation, after setting all properties.
function TypeDetails_CreateFcn(hObject, eventdata, handles)
global DataPath;
var $=\left[{ }^{\prime} \mathrm{N}\right.$ vH vM vFA vCR vC tr tMotor'];
eval(['load ' DataPath 'Parameters\Parameters.mat ' var])
str=\{['N=' num2str(N)]; ['vH=' num2str(vH)];['vM=' num2str(vM)];['vFA=' num2str(vFA)];['vCR=' num2str (vCR)];['vC=' num2str(vC)];['tr=' num2str(tr)];['tMotor=' num2str(tMotor)]\}; set(handles.TypeDetails,'String', str); return;
\% --- Executes on selection change in axisX.
function axisX_Callback(hObject, eventdata, handles)
global x str
val=get(hobject,'Value');
str=get(hObject,'String');
x_str=str\{val\};
return;
\% --- Executes during object creation, after setting all properties.
function axisX_CreateFcn(hObject, eventdata, handles)
if ispc \&\& isequal (get(hObject,'BackgroundColor'), get(0,'defaultUicontrolBackgroundColor')) set(hObject, 'BackgroundColor','white');
end
\% --- Executes on selection change in axis_y.
function axisY Callback(hObject, eventdata, handles)
global y_str;
val=get(hobject, 'Value');
str=get(hObject,'String');
y_str=str\{val\};
return;
\% --- Executes during object creation, after setting all properties.
function axisY CreateFcn(hObject, eventdata, handles)
if ispc \&\& isequal (get(hObject,'BackgroundColor'), get(0,'defaultUicontrolBackgroundColor')) set(hObject,'BackgroundColor','white');
end
\% --- Executes on selection change in axisP1.
function axisP1 Callback(hObject, eventdata, handles)
global P1_str;
val=get(hObject, 'Value')
str=get(hObject,'String');
P1_str=str\{val\};
listP1_CreateFcn (hObject, eventdata, handles);
textP1_CreateFon (hObject, eventdata, handles)
return;
\% --- Executes during object creation, after setting all properties.
function axisP1_CreateFcn(hObject, eventdata, handles)
if ispc \&\& isequal(get(hObject,'BackgroundColor'), get(0,'defaultUicontrolBackgroundColor')) set (hObject, 'BackgroundColor','white');
end
\% --- Executes on selection change in axisP2.
function axisP2_Callback(hObject, eventdata, handles)
global P2_str;
val=get(hObject, 'Value');
str=get (hObject,'String');
P2_str=str\{val\};
listP2 CreateFcn (hObject, eventdata, handles);
textP2_CreateFcn(hObject, eventdata, handles)
return;

```
--- Executes during object creation, after setting all properties.
function axisP2_CreateFcn(hObject, eventdata, handles)
if ispc && isequal(get(hObject,'BackgroundColor'), get(0,'defaultUicontrolBackgroundColor'))
    set(hobject,'BackgroundColor','white');
end
% --- Executes on selection change in axisP3.
function axisP3 callback(hObject, eventdata, handles)
global P3_str;
val=get(hObject,'Value') ;
str=get(hObject,'String');
P3_str=str{val};
listP3_CreateFcn(hObject, eventdata, handles);
textP3_CreateFcn(hObject, eventdata, handles);
return;
```

\% --- Executes during object creation, after setting all properties.
function axisP3_CreateFcn(hobject, eventdata, handles
if ispc \&\& isequal (get(hobject,'BackgroundColor'), get(0,'defaultUicontrolBackgroundColor'))
set (hobject, 'BackgroundColor', 'white');
end
\% --- Executes on selection change in axisSubG.
function axisSubG Callback(hObject, eventdata, handles)
global subG_str;
val=get(hObject, 'Value');
str=get (hObject, 'String') ;
subG_str=str\{val\};
return;
\% --- Executes during object creation, after setting all properties.
function axisSubG CreateFcn(hobject, eventdata, handles)
if ispc \&\& isequal (get(hobject, 'BackgroundColor'), get (0, 'defaultUicontrolBackgroundColor'))
set (hObject, 'BackgroundColor', 'white');
end
\% --- Executes on button press in pushbutton1.
function pushbuttonGraph_callback(hobject, eventdata, handles)
listP1_CreateFcn (hObject, eventdata, handles);
textP1 CreateFcn (hObject, eventdata, handles) ;
listP2-CreateFcn (hObject, eventdata, handles);
textP2 CreateFcn (hObject, eventdata, handles)
listP3_CreateFcn (hObject, eventdata, handles);
textP3_CreateFcn (hObject, eventdata, handles);
Graph CreateFcn (hObject, eventdata, handles);
return;
\% --- Executes on selection change in listP1.
function listP1_Callback(hObject, eventdata, handles)
global iP1;
iP1=get(hObject, 'Value') ;
Graph_CreateFcn (hObject, eventdata, handles);
return;
\% --- Executes during object creation, after setting all properties.
function listP1_CreateFcn(hobject, eventdata, handles)
if ispc \&\& isequal (get(hobject,'BackgroundColor'), get(0,'defaultUicontrolBackgroundColor'))
set(hObject, 'BackgroundColor', 'white');
end
global DataPath;
var $=$ ['dr_vector $\left.d h \quad v e c t o r ~ P s \_v e c t o r ~ B \_v e c t o r ~ A ~ v e c t o r ~ v T 2 v H ~ v e c t o r '\right] ; ~$
eval(['load ' DataPath 'Parameters\Parameters.mat ' var])
global P1_str;
val=get (hāndles.axisP1, 'Value') ;
str=get (handles.axisP1,'String');
P1_str=str\{val\};
vP1=eval([P1_str '_vector']);
list=vP1;
set (handles.listP1,'String', list, 'Value', 1);
return;

```
% --- Executes on selection change in listP2.
function listP2_Callback(hObject, eventdata, handles)
global iP2;
iP2=get(hObject,'Value');
Graph_CreateFcn(hObject, eventdata, handles);
return;
% --- Executes during object creation, after setting all properties.
function listP2_CreateFcn(hObject, eventdata, handles)
if ispc && isequal(get(hObject,'BackgroundColor'), get(0,'defaultUicontrolBackgroundColor'))
        set(hObject,'BackgroundColor','white');
end
global DataPath;
var =['dr_vector dh_vector Ps_vector B_vector A_vector vT2vH_vector'];
eval(['load ' DataPath 'Parameters\Parameters.mat ' var])
global P2_str;
val=get(hāndles.axisP2,'Value');
str=get(handles.axisP2,'String');
P2_str=str{val};
vP\overline{2}=eval([P2_str '_vector']);
list=vP2;
set(handles.listP2,'String', list, 'Value', 1);
return;
% --- Executes on selection change in listP3.
function listP3 Callback(hObject, eventdata, handles)
global iP3;
iP3=get(hObject,'Value');
Graph CreateFcn(hObject, eventdata, handles);
return;
% --- Executes during object creation, after setting all properties.
function listP3_CreateFcn(hObject, eventdata, handles)
if ispc && isequal(get(hObject,'BackgroundColor'), get(0,'defaultUicontrolBackgroundColor'))
    set(hobject,'BackgroundColor','white');
end
global DataPath;
var =['dr vector dh vector Ps vector B vector A vector vT2vH vector'];
eval(['load ' DataPath 'Parameters\Parameters.mat ' var])
global P3_str;
val=get(handles.axisP3,'Value');
str=get(handles.axisP3,'String');
P3 str=str{val};
vP3=eval([P3_str '_vector']);
list=vP3;
set(handles.listP3,'String', list, 'Value', 1);
return;
% --- Executes during object creation, after setting all properties.
function textP1_CreateFcn(hobject, eventdata, handles)
global P1 str;
set(handles.textP1, 'String', P1_str);
return;
% --- Executes during object creation, after setting all properties.
function textP2 CreateFcn(hobject, eventdata, handles)
global P2_str;
set(handles.textP2, 'String', P2 str);
return;
% --- Executes during object creation, after setting all properties.
function textP3_CreateFcn(hobject, eventdata, handles)
global P3_str;
set(handles.textP3, 'String', P3_str);
return;
% --- Executes on selection change in GraphType.
function GraphType Callback(hObject, eventdata, handles)
val=get(hObject,'Value');
str=get(hObject,'String');
GraphType_str=str{val};
Graph_CreateFcn(hObject, eventdata, handles);
return;
```

```
--- Executes during object creation, after setting all properties
function Graph_CreateFcn(hObject, eventdata, handles)
global dr dh Ps B A vT2vH;
global exName DataPath GraphType_str;
global x_str y_str z_str subG_str P1_str P2_str P3_str iP1 iP2 iP3;
% Load the matrix for z cordination
eval(['load ' DataPath 'Optimal\OptimalData.mat ' z_str])
% Load parameters values
var =['dr_vector dh_vector Ps_vector B_vector A_vector vT2vH_vector'];
eval(['load ' DataPath 'Parameters\Parameters.mat ' var])
switch z_str
    case''vT/VI H'
        eval(['\overline{load ' DataPath 'Optimal\OptimalData.mat opt_vTs_H opt_VIs_H'])}
        z=opt vTs_H./opt_VIs_H;
    case 'vT/V/VI HR''
        eval(['\overline{load ' DataPath 'Optimal\OptimalData.mat opt_vTs HR opt VIs HR'])}
        z=opt_vTs_HR./opt_VIs_HR;
    case 'vT/\overline{VI_HO}R'
        eval(['load ' DataPath 'Optimal\OptimalData.mat opt vTs HOR opt VIs HOR'])
        z=opt_vTs_HOR./opt_VIs_HOR;
    case 'vT/VI R'
        eval(['load ' DataPath 'Optimal\OptimalData.mat opt_vTs_R opt_VIs_R'])
        z=opt_vTs_R./opt_VIs_R;
    otherwise
        % Load the matrix for z cordination
        eval(['load ' DataPath 'Optimal\OptimalData.mat ' z_str])
        z=eval(z_str);
end
x=eval (x_str);
y=eval (y_str);
subG=eval(subG_str);
P1=eval (P1 str);
P2=eval (P2 str) ;
P3=eval (P3_str);
% Rearrange the data matrix
mat=permute(z,[y,x,subG, P1 ,P2,P3]) ;
vx=eval([x_str '_vector']);
vy=eval([y str ' vector']);
vsubG=eval([subG_str '_vector']);
vP1=eval([P1_str'' vecẼor']);
vP2=eval([P2 str ' vector']);
vP3=eval([P3_str '_vector']);
Gname=[ exName ' 'z_str ' X=' x_str ' Y=' Y_str ' subG=' subG str '
    P1_str '=' eval(['num2str(' P\overline{1_str '_vector(iP1),2)'])' ' ' P2_str}\mp@subsup{\}{}{\prime}=' eval(['num2st\overline{r}('
P2_str '_vector(iP2),2)']) ' ' P3_str '=' eval(['num2str(' P3_str '_vector(iP3),2)'])];
set(handles.GraphsTitle, 'String', Gname);
hold on
for i=1:6
    eval(['h=handles.A' num2str(i) ';'])
    reset(h);
    set(h,'Visible', 'on');
    plot(h,1,1);
    set(h,'Visible', 'off');
end
for isubG=1:length(vsubG)
    eval(['h=handles.A' num2str(isubG) ';'])
    set(h,'Visible', 'on');
    if strcmp(z_str, 'opt_CL')
        contour舟('v6',h,v\overline{x},vy,mat(:,:,isubG,iP1,iP2,iP3), [1 2 3 4]);
    elseif strcmp(GraphType_str, 'contour')
        [C,h1] = contour(h,\overline{vx},vy,mat(:,:,isubG,iP1,iP2,iP3));
        clabel(C,h1,'FontSize',8);
    elseif strcmp(GraphType str, 'mesh')
        mesh(h,vx,vy,mat(:, :,isubG,iP1,iP2,iP3));
    end
    xlabel (h,x str);
    ylabel (h,y_str);
    title(h,[subG_str ' = ' num2str(vsubG(isubG))]);
end
datacursormode on
hold off
return;
```


## 4. The mean time function

```
function [mean]=meanTime(Zco,direction)
% meanTime function calculates mean reaction time for a given cutoff point
% meanTime(Zco,direction)
% Zco - is the cutoff point
% direction can be 'p' or 'n' - result in different calculations for
positive ('p') and negative ('n') decisions
global A; %A and B declared in the main program
global B;
if direction=='p'
    mean=A*exp (B*Zco+B*B/2).*((1-normcdf(Zco+B))./(1-normcdf(Zco)));
elseif direction=='n'
    mean=A*exp (-B*Zco+B*B/2).*(normcdf(Zco-B)./normcdf (Zco));
end;
```


## Appendix H - The Relation Between Image Complexity and Reaction Time

Bechar (2006) designed and performed a melon detection experiment in order to examine different human robot collaboration levels for a specific target detection task in an agriculture environment. In this work, the experimental data is used to analyze the reaction time of the human operator. The analysis focuses on the relation between image complexity and reaction time.

## 1. Melon detection experiment

Full description of the experiment can be found in chapter 6 of Bechar thesis (2006).
Task. The participants of the experiment were asked to detect ready-to-pick melons on a digital image and mark them on the screen (see example in Figure 36). Some of the participants fulfilled the task with a help of a robot according to the level of collaboration.

Subjects. 120 IEM undergraduate students were assigned to 10 groups. The participants were encouraged to achieve high performance through the promise of a monetary award.

Targets database. Melon images were manually selected from a video taken by a camera moving along a melon row in a field, in various illumination conditions. The melons were partially covered by leaves and had different colors and sizes. The images were classified into three levels of complexities (low, intermediate, and high) by a panel of three experts. The image complexity represents the difficulty level of detecting targets in the image. The location of true targets in each image was manually identified and saved in a targets database.

Design. In each session, fifteen participants from all experimental groups were seated in a classroom in front of working stations for target detection that were simulated with a PC and a program written in MatLab. The participants viewed 180 images, a target was defined as any yellow or orange melon, and the task was to mark all the targets in the images. The participants were divided in advance into ten groups, each of which was given one of two objective function weights (represented by a reward system for minimum false alarm rate or for maximum hit rate), one of two different robot detection performance qualities, and one of three collaboration levels as shown in Table 4. In the experiment, the computer simulated the robot operation by picking targets and nontarget objects (marked as false alarms) from the database. The participants received feedback on their performance during the experiment after each image. The feedback included the current objective function score (score), the last image number of hits, false alarms and Misses. The participants had unlimited time to observe the images and the time cost was set to zero.


Figure 36: An example of the graphical user interface of the experiment.

## 2. Data preparation

During the experiment the activities of the human operator, the objects marked, and the time of each action were automatically recorded. The raw data is attached in Appendix I.

Each image in the targets database includes up to three melons. When the human observes some melons at a time, it is impossible to define what the correct reaction time is for each of the melons. Furthermore, the image complexity was determined for the whole image and not per melon. Therefore, only images that contain one melon were used for the analysis (a total of 84 images were used). Among these images, 30 were of the low complexity images, 35 of the intermediate and 19 of the high complexity images. In this case, the image complexity describes the difficulty to detect a single melon in the image.

The analysis was performed for records of subjects that worked in the HR collaboration level and had to remark targets that the robot recommended (if the recommended object is a really a ready to pick melon). Data from 48 subjects was analyzed (groups 7-10 in Bechar's experiment).

Table 4: The experimental groups (Bechar, 2006).

| Group <br> No. | Collaboration level |  |  | Reward system |  | Robot quality |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  | H | HOR | HR | Min FA | Max Hit | High | Low |
| 1 | x |  |  | x |  |  |  |
| 2 | x |  |  |  | x |  |  |
| 3 |  | x |  | x |  | x |  |
| 4 |  | x |  | x |  |  | x |
| 5 |  | x |  |  | x | x |  |
| 6 |  | x |  |  | x |  | x |
| 7 |  |  | x | x |  | x |  |
| 8 |  |  | x | x |  |  | x |
| 9 |  |  | x |  | x | x |  |
| 10 |  |  | x |  | x |  | x |

## 3. Results

Two time measures were used. The first measure (T2mark) is the time it took the subject to mark a target after the image appeared on screen. The second measure (T2next) is the time spent until the subject hits the "Next" button (after the image appeared). The difference between the two time measures is 1.98 seconds on average (with a standard deviation of 1.34). This is the average time, which the subject spends in order to recheck his decision and to look for other targets.

For each analyzed group (groups 7-10), two Single Factor ANOVA tests were used (one for each measure) in order to determine if there is a statistically significant difference between the three image complexity levels. In all groups (except one case), the detection mean time in high complexity images was longer than that of low and medium complexity images. Similarly, the detection mean time in intermediate complexity images was longer than that of low complexity images (see Tables 5-6). Results indicate that for both of the measures, there is a significant ( $\alpha=0.05$ ) difference between the three image complexity levels. P-values in all tests (except for $T 2$ next in group 8) are less than 0.001 (see Tables 7-8). An exceptional case is found in group 8. In this case, T2next of high complexity images (2.56) is lower than that of medium complexity images (2.62). Despite this, there is significant difference between the three image complexity levels $(\mathrm{P}$-value $=0.013)$.

To conclude, the reaction time depends on image complexity and it decreases as image complexity decreases. This result supports the assumption that human reaction depends on the strength of the observed object.

Table 5: Summary of the statistical data of the T2mark measure.

| Group | Complexity | Count | Sum | Average | Variance |
| :---: | :---: | :---: | :---: | :---: | :---: |
| 7 | 1 | 298 | 484.52 | 1.62590604 | 1.156045311 |
|  | 2 | 314 | 631.786 | 2.012057325 | 2.119549172 |
|  | 3 | 169 | 372.206 | 2.202402367 | 1.865087075 |
|  | 1 | 123 | 227.848 | 1.852422764 | 1.046291623 |
|  | 2 | 212 | 556.144 | 2.623320755 | 4.888964987 |
|  | 3 | 57 | 146.153 | 2.564087719 | 1.434097939 |
| 9 | 1 | 299 | 534.032 | 1.786060201 | 2.135163681 |
|  | 2 | 310 | 714.756 | 2.305664516 | 3.605807686 |
|  | 3 | 174 | 412.914 | 2.373068966 | 2.403098446 |
|  | 1 | 140 | 230.172 | 1.644085714 | 0.756511647 |
|  | 2 | 202 | 429.041 | 2.123965347 | 1.564116651 |
|  | 3 | 63 | 171.757 | 2.726301587 | 2.273193956 |

Table 6: Summary of the statistical data of the T2next measure.

| Group | Complexity | Count | Sum | Average | Variance |
| :---: | :---: | :---: | :---: | :---: | :---: |
| 7 | 1 | 298 | 1018.067 | 3.416332215 | 3.730392532 |
|  | 2 | 314 | 1228.389 | 3.912066879 | 4.969930427 |
|  | 3 | 169 | 692.108 | 4.095313609 | 3.861975705 |
|  | 1 | 123 | 483.787 | 3.933227642 | 3.162886587 |
|  | 2 | 212 | 992.536 | 4.681773585 | 8.140790043 |
| 9 | 3 | 57 | 277.333 | 4.865491228 | 5.084170647 |
|  | 1 | 299 | 1135.499 | 3.797655518 | 4.277060817 |
|  | 2 | 310 | 1350.314 | 4.355851613 | 6.847721467 |
| 10 | 3 | 174 | 793.326 | 4.559344828 | 4.85237869 |
|  | 1 | 140 | 501.103 | 3.579307143 | 1.964418833 |
|  | 2 | 202 | 819.215 | 4.055519802 | 3.89106434 |
|  | 3 | 63 | 307.688 | 4.883936508 | 4.116458222 |

Table 7: Results of Single Factor ANOVA tests of the T2mark measure.

| Group | Source of Variation | SS | df | MS | F | P -value | F criteria |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| 7 | Between Groups | 41.75818401 | 2 | 20.87909201 | 12.30508762 | $5.47961 \mathrm{E}-06$ | 3.007297176 |
|  | Within Groups | 1320.098977 | 778 | 1.696785317 |  |  |  |
| 8 | Between Groups | 48.69841737 | 2 | 24.34920869 | 7.641486939 | 0.000555747 | 3.018921644 |
|  | Within Groups | 1239.528675 | 389 | 3.186449035 |  |  |  |
| 9 | Between Groups | 55.16909124 | 2 | 27.58454562 | 9.932532723 | 5.5001E-05 | 3.007267446 |
|  | Within Groups | 2166.209383 | 780 | 2.777191517 |  |  |  |
| 10 | Between Groups | 52.986315 | 2 | 26.4931575 | 19.00199487 | $1.30214 \mathrm{E}-08$ | 3.018168004 |
|  | Within Groups | 560.480591 | 402 | 1.394230326 |  |  |  |

Table 8: Results of Single Factor ANOVA tests of the T2next measure.

| Group | Source of Variation | SS | df | MS | F | P -value | F criteria |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| 7 | Between Groups | 61.45349977 | 2 | 30.72674988 | 7.217105498 | 0.000784101 | 3.007297176 |
|  | Within Groups | 3312.326724 | 778 | 4.257489363 |  |  |  |
| 8 | Between Groups | 53.85755206 | 2 | 26.92877603 | 4.386101883 | 0.013070751 | 3.018921644 |
|  | Within Groups | 2388.292419 | 389 | 6.139569201 |  |  |  |
| 9 | Between Groups | 78.2863356 | 2 | 39.1431678 | 7.21793761 | 0.000783329 | 3.007267446 |
|  | Within Groups | 4229.97157 | 780 | 5.423040474 |  |  |  |
| 10 | Between Groups | 74.46659622 | 2 | 37.23329811 | 11.42248988 | $1.49661 \mathrm{E}-05$ | 3.018168004 |
|  | Within Groups | 1310.37856 | 402 | 3.259648159 |  |  |  |

## Appendix I - Raw Data of The Experiment

The raw data of the experiment is divided by group number and image complexity level (twelve classes in total). The data details the subject number (S \#), the image number (I \#), the time it took the subject to mark the image (T2mark), and the time it took the subject to press the "Next" button (T2next). The list continues from the left column to the right.

| Group 7, image complexity 1 : |  |  |  | 72 | 19 | 0.903 | 2.009 | 74 | 68 | 1.172 | 3.125 |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  |  |  |  | 72 | 26 | 0.903 | 2.212 | 74 | 80 | 1.43 | 2.659 |
|  |  |  |  | 72 | 46 | 1.735 | 2.819 | 74 | 82 | 2.375 | 4.796 |
| S \# 70 | 6 | 12 mark | T2next | 72 | 47 | 0.684 | 1.633 | 74 | 97 | 1.672 | 4.984 |
| 70 70 | 6 7 | 1.875 1.875 | 3.203 | 72 | 48 | 0.919 | 1.775 | 74 | 206 | 1.281 | 3.812 |
| 70 | 15 | 1.872 2.312 | 3.546 | 72 | 54 | 0.898 | 2.106 | 74 | 208 | 1.353 | 3.156 |
| 70 | 19 | 1.797 | 3.109 | 72 | 57 | 1.13 | 2.4 | 74 | 209 | 1.187 | 4.359 |
| 70 | 34 | 3.219 | 4.985 | 72 | 63 | 1.022 | 2.214 | 74 | 211 | 1.166 | 3.032 |
| 70 | 46 | 1.829 | 3.25 | 72 | 64 | 2.146 | 4.634 | 74 | 220 | 2.527 | 3.543 |
| 70 | 47 | 2.078 | 3.25 | 72 | 67 | 1.09 | 2.196 | 74 | 221 | 1.244 | 2.689 |
| 70 | 48 | 1.172 | 2.328 | 72 | 80 | 0.919 | 2.009 | 74 | 230 | 1.094 | 3.312 |
| 70 | 57 | 1.828 | 3.187 | 72 | 97 | 1.14 | 3.687 | 74 | 306 | 1.25 | 4.531 |
| 70 | 63 | 1.907 | 9.141 | 72 | 208 | 0.701 | 2.289 | 74 | 307 | 1.063 | 2.234 |
| 70 | 64 | 1.859 | 3.484 | 72 | 209 | 0.96 | 2.261 | 75 | 6 | 1.36 | 4.078 |
| 70 | 67 | 1.407 | 2.797 | 72 | 220 | 0.824 | 1.788 | 75 | 15 | 1.562 | 2.703 |
| 70 | 68 | 4.969 | 6.234 | 72 | 221 | 0.826 | 2.259 | 75 | 19 | 1.575 | 5.795 |
| 70 | 77 | 1.656 | 3.172 | 72 | 306 | 1.161 | 4.537 | 75 | 26 | 1.105 | 2.057 |
| 70 | 80 | 2.079 | 3.282 | 72 | 307 | 1.648 | 2.799 | 75 | 46 | 1.343 | 4.999 |
| 70 | 82 | 1.359 | 3.062 | 72 73 | 411 6 | 0.82 0.938 | 2.028 | 75 75 | 47 48 | 1.391 1.575 | 2.75 |
| 70 | 97 | 2.703 | 4.187 | 73 | 15 | 1.978 | 2.094 | 75 75 | 48 54 | 1.575 1.578 | 2.615 2.625 |
| 70 | 111 | 1.5 | 2.922 | 73 | 19 | 1.344 | 2.625 | 75 | 57 | 2.437 | 4.483 |
| 70 | 206 | 1.579 | 3 | 73 | 26 | 1.11 | 2.407 | 75 | 63 | 2.171 | 5.249 |
| 70 | 220 | 2.344 | 4.172 | 73 | 46 | 1.094 | 1.922 | 75 | 64 | 1.749 | 5.342 |
| 70 | 221 | 1.359 | 2.5 | 73 | 47 | 1.328 | 2.265 | 75 | 67 | 2.021 | 4.83 |
| 70 | 230 | 1.765 | 3.265 | 73 | 48 | 1.235 | 2.031 | 75 | 68 | 2.297 | 5.359 |
| 70 | 306 | 1.703 2.124 | 3.547 | 73 | 54 | 1.938 | 3 | 75 | 82 | 3.562 | 5.406 |
| 70 | 307 | 2.124 2.734 | 4.031 | 73 | 57 | 1.438 | 2.641 | 75 | 97 | 3.093 | 7.03 |
| 70 | 411 | 2.734 1.203 | 4.297 6.905 | 73 | 63 | 1.297 | 2.406 | 75 | 206 | 3.015 | 5.343 |
| 71 | 6 | 1.203 1.187 | 6.905 3.609 | 73 | 64 | 0.953 | 2.312 | 75 | 208 | 3.076 | 4.577 |
| 71 | 7 15 | 1.187 1.235 | 3.609 2.532 | 73 | 67 | 1.297 | 2.312 | 75 | 209 | 8.218 | 11.045 |
| 71 71 | 15 19 | 1.235 0.843 | 2.532 2.062 | 73 | 68 | 1.297 | 2.203 | 75 | 211 | 1.619 | 2.927 |
| 71 | 26 | 0.992 | 7.634 | 73 | 80 | 1 | 1.625 | 75 | 220 | 1.765 | 3.655 |
| 71 | 46 | 1.078 | 5.764 | 73 | 82 | 1.39 | 2.218 | 75 | 221 | 1.412 | 3.054 |
| 71 | 47 | 1.406 | 2.453 | 73 | 97 | 1.578 | 2.484 | 75 | 306 | 2.577 | 4.28 |
| 71 | 48 | 1.5 | 2.828 | 73 | 206 | 1.203 | 2.078 | 75 | 307 | 1.656 | 3.187 |
| 71 | 54 | 1.734 | 2.953 | 73 | 208 | 0.64 | 1.296 | 76 | 6 | 3.746 | 6.186 |
| 71 | 57 | 2.78 | 4.374 | 73 73 | 209 | 1.156 | 3.609 1.969 | 76 | 7 | 3.249 | 5.802 |
| 71 | 63 | 1.484 | 3.093 | 73 | 220 | 1.484 | 1.969 2.203 | 76 | 15 19 | 1.644 1.925 | 3.122 3.959 |
| 71 | 64 | 1.156 | 3.109 | 73 | 221 | 0.922 | 1.656 | 76 76 | 19 26 | 1.925 1.878 | 3.959 3.383 |
| 71 | 67 | 1.016 | 2.703 | 73 | 230 | 1.031 | 1.828 | 76 | 46 | 3.681 | 5.311 |
| 71 | 68 80 | 2.141 | 3.453 | 73 | 306 | 1.734 | 2.781 | 76 | 47 | 1.493 | 2.987 |
| 71 71 | 80 82 | 0.985 2.312 | 1.938 5.499 | 73 | 307 | 1.485 | 2.36 | 76 | 48 | 1.694 | 3.435 |
| 71 | 97 | 0.921 | 5.499 4.482 | 73 | 411 | 1.485 | 2.797 | 76 | 54 | 3.532 | 5.76 |
| 71 | 206 | 1.047 | 2.718 | 74 | 6 | 1.719 | 3.844 | 76 | 57 | 2.361 | 3.883 |
| 71 | 208 | 1.078 | 2.312 | 74 | 15 | 1.417 | 2.649 | 76 | 63 | 2.794 | 4.539 |
| 71 | 209 | 1.921 | 4.671 | 74 | 19 | 1.109 | 4.252 | 76 | 67 | 1.555 | 3.358 |
| 71 | 211 | 0.609 | 1.766 | 74 | 46 | 1.201 1.687 | 3.463 2.875 | 76 | 68 | 1.832 | 3.432 |
| 71 | 220 | 2.312 | 4.796 | 74 | 46 47 | 1.687 1.064 | 2.875 2.373 | 76 76 | 80 82 | 1.864 1.645 | 3.42 3.774 |
| 71 | 221 | 0.876 | 3.795 | 74 | 48 | 0.964 | 2.379 | 76 | 97 | 3.997 | 9.383 |
| 71 | 230 | 4.594 | 6.187 | 74 | 54 | 1.172 | 3.765 | 76 | 206 | 6.186 | 8.03 |
| 71 | 306 | 1.015 | 2.296 | 74 | 57 | 2.015 | 4.453 | 76 | 208 | 5.823 | 7.472 |
| 71 | 307 | 1.203 | 5.812 | 74 | 63 | 1.156 | 3.812 | 76 | 209 | 5.017 | 6.57 |
| 71 | 411 | 4.859 | 6.296 | 74 | 64 | 1.5 | 4.094 | 76 | 211 | 2.018 | 3.281 |
| 72 | 6 | 1.602 | 4.728 | 74 | 67 | 1.166 | 2.41 | 76 | 220 | 3.499 | 5.007 |
| 72 | 15 | 0.857 | 1.698 |  |  |  |  |  |  |  |  |


| 76 | 221 | 1.335 | 2.825 | 79 | 63 | 1.134 | 3.059 | Group 7, image complexity 2: |  |  |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| 76 | 230 | 2.043 | 3.462 | 79 | 64 | 1.31 | 4.24 |  |  |  |  |
| 76 | 306 | 4.753 | 6.242 | 79 | 67 | 0.733 | 2.544 |  |  |  |  |
| 76 | 307 | 1.252 | 3.092 | 79 | 68 | 0.9 | 3.679 | S \# | I \# | T2mark | T2next |
| 76 | 411 | 2.205 | 3.634 | 79 | 80 | 1.124 | 2.483 | 70 | 16 | 1.734 | 3.25 |
| 77 | 6 | 1.071 | 2.461 | 79 | 82 | 0.901 | 3.462 | 70 | 27 | 1.5 | 3.032 |
| 77 | 15 | 0.889 | 2.452 | 79 | 97 | 1.297 | 4.61 | 70 | 33 | 1.859 | 3.218 |
| 77 | 19 | 1.112 | 2.002 | 79 | 206 | 1.107 | 3.242 | 70 | 35 | 2.593 | 4.062 |
| 77 | 26 | 0.689 | 1.722 | 79 | 208 | 0.749 | 1.858 | 70 | 41 | 1.984 | 4.281 |
| 77 | 34 | 0.737 | 1.64 | 79 | 209 | 1.195 | 4.175 | 70 | 42 | 1.297 | 2.75 |
| 77 | 46 | 7.306 | 9.611 | 79 | 211 | 0.64 | 1.53 | 70 | 62 | 2.188 | 3.782 |
| 77 | 47 | 1.084 | 2.878 | 79 | 220 | 1.013 | 2.307 | 70 | 65 | 3.14 | 4.531 |
| 77 | 48 | 0.792 | 1.626 | 79 | 221 | 0.78 | 1.748 | 70 | 69 | 1.406 | 2.625 |
| 77 | 57 | 2.183 | 4.916 | 79 | 307 | 0.827 | 3.024 | 70 | 72 | 2.188 | 3.688 |
| 77 | 63 | 1.134 | 3.524 | 79 | 411 | 0.962 | 5.215 | 70 | 76 | 1.937 | 3.031 |
| 77 | 64 | 1.517 | 3.601 | 7001 | 6 | 1.209 | 2.434 | 70 | 83 | 1.032 | 2.141 |
| 77 | 68 | 3.619 | 7.483 | 7001 | 7 | 1.608 | 5.587 | 70 | 87 | 1.734 | 3.078 |
| 77 | 77 | 1.363 | 3.16 | 7001 | 15 | 1.377 | 2.097 | 70 | 95 | 1.969 | 3.531 |
| 77 | 82 | 3.863 | 10.261 | 7001 | 19 | 1.734 | 3.283 | 70 | 105 | 1.844 | 3.266 |
| 77 | 97 | 1.748 | 5.896 | 7001 | 26 | 1.679 | 3.136 | 70 | 204 | 2.609 | 4.734 |
| 77 | 111 | 1.626 | 6.764 | 7001 | 46 | 1.437 | 2.592 | 70 | 207 | 1.86 | 3.156 |
| 77 | 206 | 1.241 | 3.969 | 7001 | 47 | 1.102 | 2.066 | 70 | 210 | 2.438 | 3.953 |
| 77 | 209 | 1.777 | 3.355 | 7001 | 48 | 1.055 | 1.762 | 70 | 217 | 5.703 | 6.968 |
| 77 | 211 | 0.695 | 1.599 | 7001 | 54 | 1.762 | 2.814 | 70 | 219 | 1.375 | 2.906 |
| 77 | 220 | 1.548 | 2.851 | 7001 | 57 | 1.999 | 3.199 | 70 | 223 | 2.016 | 3.516 |
| 77 | 221 | 1.084 | 2.516 | 7001 | 63 | 1.347 | 2.725 | 70 | 224 | 1.078 | 2.343 |
| 77 | 306 | 2.176 | 5.777 | 7001 | 64 | 1.857 | 2.76 | 70 | 231 | 3.859 | 5.656 |
| 77 | 307 | 1.536 | 3.833 | 7001 | 67 | 1.124 | 1.943 | 70 | 303 | 1.656 | 3.015 |
| 77 | 411 | 4.473 | 6.046 | 7001 | 68 | 1.467 | 2.518 | 70 | 304 | 1.516 | 2.734 |
| 78 | 6 | 0.875 | 1.859 | 7001 | 80 | 1.52 | 2.575 | 70 | 308 | 2.547 | 3.937 |
| 78 | 7 | 0.984 | 2.203 | 7001 | 82 | 1.881 | 2.784 | 70 | 310 | 1.906 | 3.359 |
| 78 | 15 | 1.125 | 1.922 | 7001 | 97 | 2.229 | 3.411 | 70 | 322 | 6.89 | 8.828 |
| 78 | 19 | 0.969 | 2.172 | 7001 | 206 | 1.111 | 2.37 | 70 | 401 | 3.421 | 4.843 |
| 78 | 26 | 0.844 | 1.719 | 7001 | 208 | 1.595 | 2.725 | 71 | 14 | 1.312 | 3.484 |
| 78 | 46 | 0.734 | 1.828 | 7001 | 209 | 1.348 | 2.503 | 71 | 16 | 1.765 | 5.358 |
| 78 | 47 | 0.984 | 1.828 | 7001 | 211 | 1.203 | 2.119 | 71 | 27 | 1.312 | 2.859 |
| 78 | 48 | 0.828 | 1.781 | 7001 | 220 | 1.117 | 2.372 | 71 | 33 | 0.672 | 2.047 |
| 78 | 54 | 0.781 | 1.687 | 7001 | 221 | 1.638 | 2.498 | 71 | 35 | 2.061 | 9.744 |
| 78 | 57 | 1.578 | 2.797 | 7001 | 306 | 1.422 | 2.74 | 71 | 41 | 12.547 | 14.328 |
| 78 | 63 | 0.89 | 2.078 | 7001 | 307 | 1.378 | 2.327 | 71 | 42 | 2.562 | 4.14 |
| 78 | 64 | 0.735 | 1.672 | 7002 | 6 | 0.754 | 1.715 | 71 | 62 | 1.922 | 3.749 |
| 78 | 67 | 0.765 | 1.765 | 7002 | 7 | 0.842 | 2.675 | 71 | 65 | 2.781 | 4.812 |
| 78 | 68 | 1.078 | 2.156 | 7002 | 15 | 0.947 | 1.935 | 71 | 69 | 0.781 | 4.781 |
| 78 | 80 | 0.937 | 1.703 | 7002 | 19 | 0.813 | 1.788 | 71 | 70 | 1.094 | 2.844 |
| 78 | 82 | 0.734 | 1.734 | 7002 | 26 | 0.765 | 1.713 | 71 | 72 | 2.156 | 10.296 |
| 78 | 97 | 1.859 | 3.094 | 7002 | 34 | 0.576 | 1.374 | 71 | 87 | 0.812 | 2.172 |
| 78 | 206 | 0.938 | 1.953 | 7002 | 46 | 2.455 | 9.022 | 71 | 95 | 4.803 | 6.292 |
| 78 | 208 | 0.578 | 1.828 | 7002 | 47 | 2.868 | 4.08 | 71 | 105 | 1.296 | 6.996 |
| 78 | 209 | 1 | 2.156 | 7002 | 48 | 0.704 | 1.53 | 71 | 204 | 3.64 | 4.968 |
| 78 | 211 | 0.89 | 1.703 | 7002 | 57 | 1.596 | 3.084 | 71 | 207 | 3.489 | 5.284 |
| 78 | 220 | 0.657 | 1.657 | 7002 | 63 | 0.96 | 2.015 | 71 | 217 | 1.906 | 4.828 |
| 78 | 221 | 0.765 | 1.922 | 7002 | 64 | 1.041 | 2.029 | 71 | 219 | 0.938 | 7.547 |
| 78 | 306 | 0.828 | 1.953 | 7002 | 68 | 6.383 | 19.579 | 71 | 223 | 1.031 | 2.859 |
| 78 | 307 | 0.922 | 1.875 | 7002 | 77 | 2.571 | 4.153 | 71 | 231 | 1.639 | 5.887 |
| 78 | 411 | 0.984 | 2.031 | 7002 | 82 | 2.363 | 9.498 | 71 | 303 | 1.219 | 4.125 |
| 79 | 6 | 1.044 | 3.305 | 7002 | 97 | 3.146 | 6.215 | 71 | 304 | 1.016 | 2.735 |
| 79 | 7 | 0.997 | 3.211 | 7002 | 111 | 4.232 | 6.153 | 71 | 319 | 5.294 | 10.369 |
| 79 | 15 | 1.294 | 2.635 | 7002 | 206 | 0.854 | 1.802 | 71 | 322 | 0.921 | 2.187 |
| 79 | 19 | 0.952 | 3.029 | 7002 | 209 | 0.88 | 1.855 | 72 | 14 | 1.121 | 2.32 |
| 79 | 26 | 1.078 | 2.515 | 7002 | 211 | 0.754 | 1.848 | 72 | 16 | 5.173 | 6.288 |
| 79 | 46 | 0.699 | 5.232 | 7002 | 220 | 0.894 | 1.922 | 72 | 27 | 0.929 | 2.014 |
| 79 | 47 | 0.966 | 2.088 | 7002 | 221 | 0.902 | 1.774 | 72 | 33 | 1.059 | 2.227 |
| 79 | 48 | 0.89 | 1.983 | 7002 | 306 | 1.041 | 2.376 | 72 | 35 | 2.657 | 6.422 |
| 79 | 54 | 0.543 | 1.583 | 7002 | 307 | 0.886 | 2.246 | 72 | 41 | 1.106 | 2.274 |
| 79 | 57 | 1.025 | 3.478 | 7002 | 411 | 3.744 | 7.153 | 72 | 42 | 1.259 | 2.364 |


| 72 | 65 | 2.488 | 3.437 | 75 | 33 | 1.724 | 2.853 | 75 | 33 | 1.724 | 2.853 |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| 72 | 69 | 0.917 | 2.285 | 75 | 35 | 5.608 | 9.436 | 75 | 35 | 5.608 | 9.436 |
| 72 | 70 | 1.697 | 2.741 | 75 | 41 | 3.093 | 4.296 | 75 | 41 | 3.093 | 4.296 |
| 72 | 72 | 0.995 | 2.457 | 75 | 42 | 2.156 | 3.39 | 75 | 42 | 2.156 | 3.39 |
| 72 | 87 | 0.919 | 1.62 | 75 | 62 | 2.562 | 7.702 | 75 | 62 | 2.562 | 7.702 |
| 72 | 92 | 0.938 | 2.484 | 75 | 65 | 2.859 | 4.108 | 75 | 65 | 2.859 | 4.108 |
| 72 | 95 | 0.982 | 2.68 | 75 | 69 | 3.265 | 5.873 | 75 | 69 | 3.265 | 5.873 |
| 72 | 105 | 2.157 | 4.094 | 75 | 70 | 1.353 | 2.482 | 75 | 70 | 1.353 | 2.482 |
| 72 | 207 | 0.872 | 2.01 | 75 | 72 | 1.531 | 5.14 | 75 | 72 | 1.531 | 5.14 |
| 72 | 210 | 1.054 | 2.757 | 75 | 87 | 1.753 | 2.898 | 75 | 87 | 1.753 | 2.898 |
| 72 | 212 | 1.791 | 2.913 | 75 | 92 | 3.187 | 5.702 | 75 | 92 | 3.187 | 5.702 |
| 72 | 217 | 1.337 | 2.799 | 75 | 95 | 1.075 | 3.024 | 75 | 95 | 1.075 | 3.024 |
| 72 | 219 | 0.747 | 1.915 | 75 | 105 | 9.357 | 11.935 | 75 | 105 | 9.357 | 11.935 |
| 72 | 231 | 2.406 | 4.047 | 75 | 204 | 3.797 | 6.562 | 75 | 204 | 3.797 | 6.562 |
| 72 | 304 | 1.682 | 3.239 | 75 | 207 | 1.611 | 2.563 | 75 | 207 | 1.611 | 2.563 |
| 72 | 308 | 1.344 | 6.281 | 75 | 210 | 4.187 | 6.515 | 75 | 210 | 4.187 | 6.515 |
| 72 | 322 | 1.791 | 2.834 | 75 | 219 | 1.649 | 2.942 | 75 | 219 | 1.649 | 2.942 |
| 73 | 27 | 1.547 | 2.265 | 75 | 231 | 8.092 | 11.061 | 75 | 231 | 8.092 | 11.061 |
| 73 | 33 | 1.265 | 2.14 | 75 | 303 | 1.921 | 4.452 | 75 | 303 | 1.921 | 4.452 |
| 73 | 35 | 2.422 | 4.094 | 75 | 304 | 1.173 | 2.243 | 75 | 304 | 1.173 | 2.243 |
| 73 | 41 | 1.782 | 2.61 | 75 | 319 | 5.764 | 12.497 | 75 | 319 | 5.764 | 12.497 |
| 73 | 42 | 1.046 | 1.64 | 75 | 322 | 2.511 | 4.903 | 75 | 322 | 2.511 | 4.903 |
| 73 | 62 | 1.5 | 3.141 | 76 | 27 | 2.71 | 4.852 | 76 | 27 | 2.71 | 4.852 |
| 73 | 65 | 1.688 | 2.485 | 76 | 33 | 8.088 | 9.412 | 76 | 33 | 8.088 | 9.412 |
| 73 | 69 | 1.047 | 2.641 | 76 | 35 | 4.12 | 7.685 | 76 | 35 | 4.12 | 7.685 |
| 73 | 70 | 1.328 | 2.437 | 76 | 41 | 1.252 | 2.549 | 76 | 41 | 1.252 | 2.549 |
| 73 | 72 | 1.328 | 2.125 | 76 | 42 | 2.217 | 3.68 | 76 | 42 | 2.217 | 3.68 |
| 73 | 87 | 1.125 | 1.719 | 76 | 62 | 3.618 | 5.761 | 76 | 62 | 3.618 | 5.761 |
| 73 | 92 | 1.891 | 3.188 | 76 | 65 | 2.202 | 3.514 | 76 | 65 | 2.202 | 3.514 |
| 73 | 95 | 1 | 1.656 | 76 | 69 | 2.172 | 3.846 | 76 | 69 | 2.172 | 3.846 |
| 73 | 105 | 2.188 | 4.203 | 76 | 70 | 2.203 | 3.744 | 76 | 70 | 2.203 | 3.744 |
| 73 | 204 | 1.641 | 2.672 | 76 | 72 | 1.433 | 2.956 | 76 | 72 | 1.433 | 2.956 |
| 73 | 207 | 1.016 | 1.766 | 76 | 87 | 2.572 | 4.498 | 76 | 87 | 2.572 | 4.498 |
| 73 | 210 | 1.266 | 2.234 | 76 | 92 | 5.834 | 8.658 | 76 | 92 | 5.834 | 8.658 |
| 73 | 217 | 1.407 | 2.172 | 76 | 95 | 1.366 | 2.887 | 76 | 95 | 1.366 | 2.887 |
| 73 | 219 | 1.093 | 2.046 | 76 | 105 | 5.263 | 7.377 | 76 | 105 | 5.263 | 7.377 |
| 73 | 223 | 1.328 | 2.125 | 76 | 207 | 1.785 | 3.057 | 76 | 207 | 1.785 | 3.057 |
| 73 | 304 | 1.297 | 2.813 | 76 | 217 | 2.284 | 4.057 | 76 | 217 | 2.284 | 4.057 |
| 73 | 308 | 3.125 | 5.016 | 76 | 219 | 4.329 | 6.609 | 76 | 219 | 4.329 | 6.609 |
| 73 | 310 | 1.75 | 2.719 | 76 | 223 | 2.157 | 3.618 | 76 | 223 | 2.157 | 3.618 |
| 73 | 319 | 2.125 | 5.172 | 76 | 304 | 1.648 | 3.373 | 76 | 304 | 1.648 | 3.373 |
| 73 | 322 | 1.25 | 2.141 | 76 | 310 | 3.975 | 5.438 | 76 | 310 | 3.975 | 5.438 |
| 73 | 401 | 2.704 | 4.297 | 77 | 14 | 1.228 | 2.547 | 77 | 14 | 1.228 | 2.547 |
| 74 | 14 | 2.565 | 3.84 | 77 | 16 | 6.954 | 8.797 | 77 | 16 | 6.954 | 8.797 |
| 74 | 16 | 1.312 | 6.046 | 77 | 27 | 1.5 | 3.61 | 77 | 27 | 1.5 | 3.61 |
| 74 | 27 | 1.359 | 4.312 | 77 | 33 | 1.182 | 2.947 | 77 | 33 | 1.182 | 2.947 |
| 74 | 33 | 1.042 | 2.829 | 77 | 35 | 1.315 | 6.981 | 77 | 35 | 1.315 | 6.981 |
| 74 | 35 | 2.203 | 7.312 | 77 | 41 | 1.501 | 2.294 | 77 | 41 | 1.501 | 2.294 |
| 74 | 41 | 1.217 | 2.326 | 77 | 42 | 0.98 | 2.559 | 77 | 42 | 0.98 | 2.559 |
| 74 | 42 | 1.525 | 3.497 | 77 | 62 | 1.348 | 2.911 | 77 | 62 | 1.348 | 2.911 |
| 74 | 62 | 1.86 | 5.516 | 77 | 65 | 2.206 | 3.769 | 77 | 65 | 2.206 | 3.769 |
| 74 | 65 | 1.372 | 3.975 | 77 | 69 | 1.946 | 3.095 | 77 | 69 | 1.946 | 3.095 |
| 74 | 69 | 0.875 | 2.797 | 77 | 70 | 1.094 | 2.622 | 77 | 70 | 1.094 | 2.622 |
| 74 | 70 | 1.756 | 4.714 | 77 | 72 | 1.608 | 3.754 | 77 | 72 | 1.608 | 3.754 |
| 74 | 72 | 1.171 | 4.421 | 77 | 76 | 1.056 | 4.142 | 77 | 76 | 1.056 | 4.142 |
| 74 | 87 | 1.337 | 2.814 | 77 | 105 | 2.391 | 4.796 | 77 | 105 | 2.391 | 4.796 |
| 74 | 92 | 1.781 | 6.172 | 77 | 204 | 2.822 | 4.932 | 77 | 204 | 2.822 | 4.932 |
| 74 | 95 | 0.764 | 2.371 | 77 | 207 | 1.209 | 2.516 | 77 | 207 | 1.209 | 2.516 |
| 74 | 105 | 2.64 | 6.968 | 77 | 210 | 1.257 | 2.559 | 77 | 210 | 1.257 | 2.559 |
| 74 | 204 | 2.594 | 4.641 | 77 | 217 | 1.286 | 3.145 | 77 | 217 | 1.286 | 3.145 |
| 74 | 207 | 1.653 | 3.213 | 77 | 219 | 0.848 | 2.307 | 77 | 219 | 0.848 | 2.307 |
| 74 | 210 | 1.657 | 4.219 | 77 | 223 | 0.976 | 2.695 | 77 | 223 | 0.976 | 2.695 |
| 74 | 217 | 1.937 | 3.375 | 77 | 224 | 1.321 | 2.572 | 77 | 224 | 1.321 | 2.572 |
| 74 | 219 | 1.197 | 3.529 | 77 | 231 | 1.716 | 4.428 | 77 | 231 | 1.716 | 4.428 |
| 74 | 223 | 1.297 | 5.094 | 77 | 303 | 1.784 | 2.886 | 77 | 303 | 1.784 | 2.886 |
| 74 | 231 | 2.937 | 5.437 | 77 | 304 | 1.237 | 2.905 | 77 | 304 | 1.237 | 2.905 |
| 74 | 303 | 2.049 | 4.683 | 77 | 308 | 1.753 | 5.259 | 77 | 308 | 1.753 | 5.259 |
| 74 | 304 | 0.886 | 2.767 | 77 | 310 | 1.223 | 2.335 | 77 | 310 | 1.223 | 2.335 |
| 74 | 308 | 2.719 | 5.281 | 77 | 320 | 1.457 | 5.562 | 77 | 320 | 1.457 | 5.562 |
| 74 | 320 | 1.75 | 4.5 | 77 | 322 | 0.917 | 3.016 | 77 | 322 | 0.917 | 3.016 |
| 74 | 322 | 1.492 | 4.943 | 77 | 401 | 5.756 | 7.034 | 77 | 401 | 5.756 | 7.034 |
| 74 | 401 | 2.313 | 3.938 | 78 | 14 | 0.985 | 2.531 | 78 | 14 | 0.985 | 2.531 |
| 75 | 16 | 5.342 | 7.17 | 78 | 27 | 1.25 | 2.094 | 78 | 27 | 1.25 | 2.094 |
| 75 | 27 | 2.687 | 4.406 | 78 | 33 | 0.75 | 1.656 | 78 | 33 | 0.75 | 1.656 |


| 78 | 35 | 1.625 | 5.968 | 7001 | 322 | 2.529 | 4.188 | 72 | 313 | 1.843 | 4.863 |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| 78 | 42 | 0.891 | 1.797 | 7001 | 401 | 2.78 | 4.083 | 72 | 324 | 2.177 | 3.25 |
| 78 | 62 | 1.843 | 3.703 | 7002 | 14 | 0.903 | 1.729 | 72 | 325 | 1.028 | 1.916 |
| 78 | 69 | 0.875 | 1.828 | 7002 | 16 | 3.286 | 8.184 | 72 | 403 | 1.137 | 3.037 |
| 78 | 70 | 0.843 | 1.671 | 7002 | 27 | 1.134 | 2.535 | 72 | 406 | 1.368 | 2.784 |
| 78 | 72 | 1.328 | 2.25 | 7002 | 33 | 0.887 | 1.947 | 73 | 61 | 1.157 | 1.969 |
| 78 | 92 | 3.328 | 4.625 | 7002 | 35 | 2.278 | 5.611 | 73 | 88 | 1.593 | 2.468 |
| 78 | 95 | 0.891 | 2.75 | 7002 | 41 | 0.887 | 1.656 | 73 | 96 | 2.078 | 3.344 |
| 78 | 105 | 4.843 | 9.203 | 7002 | 42 | 1.268 | 2.269 | 73 | 102 | 4 | 5.234 |
| 78 | 204 | 1.422 | 2.75 | 7002 | 62 | 0.747 | 1.534 | 73 | 201 | 1.593 | 2.39 |
| 78 | 207 | 0.938 | 1.704 | 7002 | 65 | 1.562 | 2.522 | 73 | 227 | 1.297 | 2.187 |
| 78 | 210 | 1.015 | 2.062 | 7002 | 69 | 0.99 | 2.187 | 73 | 309 | 1.891 | 2.75 |
| 78 | 223 | 1.094 | 2.015 | 7002 | 70 | 0.887 | 1.729 | 73 | 312 | 1.562 | 2.906 |
| 78 | 303 | 1.203 | 2.125 | 7002 | 76 | 1.478 | 2.572 | 73 | 324 | 1.61 | 2.532 |
| 78 | 304 | 0.875 | 1.812 | 7002 | 87 | 0.719 | 1.621 | 73 | 325 | 1.704 | 2.375 |
| 78 | 308 | 2.047 | 4.156 | 7002 | 92 | 5.843 | 7.145 | 73 | 327 | 5.234 | 6.421 |
| 78 | 310 | 1.531 | 2.5 | 7002 | 105 | 1.015 | 2.029 | 73 | 402 | 1.922 | 3.062 |
| 78 | 319 | 6.469 | 9.594 | 7002 | 204 | 1.282 | 2.323 | 73 | 403 | 1.515 | 2.359 |
| 78 | 322 | 1.11 | 3.969 | 7002 | 207 | 0.665 | 1.611 | 74 | 61 | 3.066 | 4.314 |
| 78 | 401 | 3.015 | 4.125 | 7002 | 210 | 0.92 | 2.001 | 74 | 88 | 2.124 | 5.859 |
| 79 | 14 | 1.296 | 2.654 | 7002 | 217 | 1.212 | 2.129 | 74 | 96 | 1.703 | 6.046 |
| 79 | 16 | 1.738 | 4.89 | 7002 | 219 | 0.933 | 1.912 | 74 | 102 | 4.015 | 6.578 |
| 79 | 27 | 1.273 | 3.338 | 7002 | 224 | 0.734 | 1.851 | 74 | 104 | 2.296 | 3.775 |
| 79 | 33 | 0.765 | 1.748 | 7002 | 231 | 2.242 | 4.124 | 74 | 109 | 3.405 | 5.299 |
| 79 | 35 | 1.703 | 8.156 | 7002 | 303 | 0.887 | 2.01 | 74 | 201 | 1.648 | 3.342 |
| 79 | 41 | 1.217 | 2.404 | 7002 | 304 | 0.734 | 1.775 | 74 | 227 | 1.578 | 4.765 |
| 79 | 42 | 1.496 | 2.946 | 7002 | 308 | 1.481 | 2.548 | 74 | 309 | 1.781 | 4.64 |
| 79 | 65 | 1.699 | 3.491 | 7002 | 310 | 0.813 | 1.715 | 74 | 312 | 1.197 | 3.218 |
| 79 | 69 | 0.92 | 2.759 | 7002 | 320 | 1.626 | 2.852 | 74 | 313 | 3.5 | 8.188 |
| 79 | 70 | 1.155 | 3.216 | 7002 | 322 | 0.995 | 1.974 | 74 | 324 | 2.634 | 4.205 |
| 79 | 72 | 1.215 | 3.133 | Group 7, image complexity 3: |  |  |  | 74 | 325 | 1.555 | 3.202 |
| 79 | 87 | 1.467 | 2.529 |  |  |  |  | 74 | 327 | 3.672 | 5.562 |
| 79 | 92 | 1.593 | 5.062 |  |  |  |  | 74 | 402 | 1.703 | 7.891 |
| 79 | 95 | 2.296 | 3.296 |  |  |  |  | 74 | 403 | 1.679 | 3.235 |
| 79 | 105 | 2.281 | 19.281 | S \# | I \# | T2mark | T2next | 75 | 61 | 2.124 | 3.296 |
| 79 | 204 | 3.819 | 5.76 | 70 | 61 | 3.328 | 5.109 | 75 | 88 | 6.186 | 7.951 |
| 79 | 207 | 1.53 | 2.624 | 70 | 88 | 3.235 | 4.969 | 75 | 96 | 5.202 | 6.827 |
| 79 | 210 | 0.947 | 4.238 | 70 | 96 | 4.312 | 5.843 | 75 | 102 | 6.342 | 10.404 |
| 79 | 217 | 1.434 | 3.851 | 70 | 102 | 4.766 | 6.391 | 75 | 109 | 2.312 | 4.062 |
| 79 | 219 | 1.03 | 2.17 | 70 | 104 | 2.563 | 3.907 | 75 | 201 | 2.243 | 3.462 |
| 79 | 223 | 1.263 | 2.713 | 70 | 109 | 1.75 | 3.218 | 75 | 227 | 1.718 | 4.749 |
| 79 | 231 | 5.234 | 8.656 | 70 | 309 | 2.562 | 3.781 | 75 | 312 | 1.501 | 3.136 |
| 79 | 303 | 1.045 | 3.788 | 70 | 312 | 1.609 | 3.468 | 75 | 313 | 8.076 | 10.451 |
| 79 | 304 | 0.889 | 2.404 | 70 | 313 | 4.469 | 5.938 | 75 | 324 | 2.375 | 4.187 |
| 79 | 310 | 2.92 | 5.215 | 70 | 324 | 1.687 | 2.812 | 75 | 325 | 2.021 | 4.859 |
| 79 | 322 | 1.14 | 2.514 | 70 | 325 | 1.594 | 2.781 | 75 | 402 | 5.671 | 11.014 |
| 79 | 401 | 1.422 | 4.14 | 70 | 402 | 2.985 | 5.578 | 75 | 403 | 1.594 | 2.844 |
| 7001 | 14 | 1.688 | 2.803 | 70 | 403 | 2.188 | 3.438 | 76 | 227 | 3.675 | 5.562 |
| 7001 | 16 | 2.088 | 3.302 | 70 | 404 | 2.031 | 3.484 | 76 | 312 | 5.06 | 6.442 |
| 7001 | 27 | 1.748 | 2.592 | 70 | 406 | 2.234 | 4.109 | 76 | 324 | 3.092 | 5.415 |
| 7001 | 33 | 2.71 | 3.918 | 71 | 61 | 1.187 | 4.953 | 76 | 325 | 4.098 | 5.469 |
| 7001 | 35 | 3.815 | 6.716 | 71 | 88 | 1.297 | 6.749 | 76 | 403 | 1.885 | 3.303 |
| 7001 | 41 | 1.286 | 2.48 | 71 | 96 | 4.374 | 7.217 | 76 | 406 | 2.986 | 4.253 |
| 7001 | 42 | 1.011 | 2.159 | 71 | 102 | 1.062 | 4.841 | 77 | 61 | 1.778 | 3.724 |
| 7001 | 62 | 1.762 | 2.962 | 71 | 104 | 1.484 | 2.562 | 77 | 88 | 2.51 | 7.694 |
| 7001 | 65 | 1.194 | 2.097 | 71 | 109 | 1.421 | 3.249 | 77 | 96 | 1.517 | 4.03 |
| 7001 | 69 | 1.47 | 2.786 | 71 | 201 | 2.61 | 4.875 | 77 | 102 | 5.287 | 8.472 |
| 7001 | 70 | 1.811 | 2.725 | 71 | 227 | 1.406 | 3.796 | 77 | 104 | 1.363 | 3.37 |
| 7001 | 72 | 1.041 | 2.173 | 71 | 309 | 5.656 | 8.843 | 77 | 109 | 1.44 | 2.743 |
| 7001 | 87 | 2.389 | 3.413 | 71 | 312 | 0.985 | 2.906 | 77 | 201 | 2.187 | 3.64 |
| 7001 | 92 | 2.807 | 4.5 | 71 | 313 | 2.89 | 8.67 | 77 | 227 | 2.298 | 5.348 |
| 7001 | 105 | 3.895 | 5.628 | 71 | 324 | 1.734 | 4.5 | 77 | 309 | 3.551 | 5.021 |
| 7001 | 204 | 1.718 | 3.05 | 71 | 325 | 0.969 | 2.359 | 77 | 312 | 0.974 | 2.112 |
| 7001 | 207 | 2.276 | 3.706 | 71 | 327 | 3.046 | 4.53 | 77 | 313 | 3.417 | 6.236 |
| 7001 | 210 | 2.355 | 3.54 | 71 | 402 | 8.982 | 10.498 | 77 | 324 | 1.001 | 3.114 |
| 7001 | 217 | 2.082 | 2.97 | 71 | 403 | 2.359 | 5.093 | 77 | 325 | 1.633 | 3.25 |
| 7001 | 219 | 1.471 | 2.555 | 71 | 406 | 1.672 | 3.515 | 77 | 327 | 1.648 | 6.952 |
| 7001 | 223 | 1.378 | 2.418 | 72 | 61 | 1.119 | 1.85 | 77 | 402 | 2.198 | 7.873 |
| 7001 | 231 | 4.002 | 5.506 | 72 | 88 | 0.914 | 1.967 | 77 | 404 | 1.251 | 3.42 |
| 7001 | 303 | 1.209 | 2.541 | 72 | 96 | 0.991 | 3.36 | 78 | 61 | 0.828 | 1.781 |
| 7001 | 304 | 1.416 | 2.304 | 72 | 102 | 2.391 | 6.079 | 78 | 88 | 1.344 | 2.485 |
| 7001 | 308 | 1.639 | 2.982 | 72 | 104 | 3.567 | 4.719 | 78 | 104 | 1.219 | 3.016 |
| 7001 | 310 | 3.175 | 5.73 | 72 | 227 | 1.58 | 2.804 | 78 | 109 | 0.953 | 1.797 |
| 7001 | 319 | 2.928 | 4.888 | 72 | 309 | 1.223 | 2.679 | 78 | 201 | 1.375 | 3.39 |
| 7001 | 320 | 1.303 | 2.562 | 72 | 312 | 0.996 | 1.868 | 78 | 227 | 1.344 | 2.625 |


| 78 | 312 | 1.031 | 1.891 | 80 | 306 | 1.985 | 4.766 | 88 | 57 | 2.813 | 4.875 |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| 78 | 324 | 0.875 | 1.657 | 81 | 6 | 1.109 | 3.219 | 88 | 68 | 2.406 | 7.234 |
| 78 | 325 | 0.985 | 1.985 | 81 | 15 | 1.39 | 5.5 | 88 | 77 | 4.562 | 6.937 |
| 78 | 327 | 3.187 | 4.406 | 81 | 19 | 1.281 | 4.172 | 88 | 82 | 2.797 | 5.735 |
| 78 | 402 | 2.25 | 4.25 | 81 | 26 | 0.984 | 2.797 | 88 | 209 | 3.468 | 5.828 |
| 78 | 403 | 0.735 | 1.625 | 81 | 57 | 1.75 | 4.984 | 89 | 6 | 1.562 | 3.546 |
| 78 | 406 | 1.531 | 2.406 | 81 | 68 | 1.563 | 3.219 | 89 | 15 | 2.218 | 4.046 |
| 79 | 61 | 1.013 | 2.697 | 81 | 77 | 1.204 | 3.516 | 89 | 19 | 1.172 | 3 |
| 79 | 88 | 1.351 | 4.75 | 81 | 82 | 1.218 | 2.531 | 89 | 26 | 1.397 | 2.592 |
| 79 | 96 | 1.288 | 5.914 | 81 | 209 | 2.547 | 5.64 | 89 | 57 | 1.406 | 3.813 |
| 79 | 102 | 3.578 | 7.125 | 82 | 6 | 0.921 | 3.718 | 89 | 68 | 1.609 | 4.515 |
| 79 | 104 | 2.108 | 4.153 | 82 | 15 | 3.671 | 9.265 | 89 | 77 | 1.532 | 4.235 |
| 79 | 109 | 0.781 | 2.685 | 82 | 19 | 1.312 | 3.078 | 89 | 82 | 1.531 | 3.39 |
| 79 | 227 | 1.179 | 4.47 | 82 | 26 | 1.172 | 2.656 | 89 | 209 | 2.891 | 6.172 |
| 79 | 312 | 2.498 | 4.512 | 82 | 57 | 1.547 | 2.938 | 8001 | 15 | 1.385 | 3.618 |
| 79 | 313 | 4.609 | 7.906 | 82 | 68 | 1.406 | 2.406 | 8001 | 19 | 1.107 | 3.832 |
| 79 | 324 | 1.419 | 3.274 | 82 | 77 | 1.766 | 3.328 | 8001 | 48 | 0.878 | 1.876 |
| 79 | 325 | 0.796 | 2.123 | 82 | 82 | 1.141 | 2.891 | 8001 | 67 | 1.848 | 2.779 |
| 79 | 402 | 1.717 | 4.107 | 82 | 209 | 1.172 | 2.906 | 8001 | 68 | 1.939 | 3.633 |
| 79 | 403 | 1.218 | 2.389 | 82 | 306 | 1.125 | 3.125 | 8001 | 82 | 1.74 | 3.187 |
| 7001 | 61 | 1.285 | 2.158 | 83 | 6 | 2.391 | 9.344 | 8001 | 97 | 2.017 | 3.31 |
| 7001 | 88 | 2.281 | 3.732 | 83 | 15 | 1.75 | 6.094 | 8001 | 208 | 0.823 | 2.672 |
| 7001 | 96 | 1.926 | 2.903 | 83 | 19 | 1.422 | 5.656 | 8001 | 209 | 2.233 | 4.188 |
| 7001 | 102 | 3.667 | 4.902 | 83 | 26 | 1.391 | 4.516 | 8001 | 211 | 0.985 | 1.889 |
| 7001 | 104 | 2.044 | 3.206 | 83 | 48 | 2.796 | 4.062 | 8002 | 15 | 1.593 | 2.703 |
| 7001 | 109 | 2.128 | 3.414 | 83 | 57 | 3.782 | 5.953 | 8002 | 19 | 1.188 | 2.609 |
| 7001 | 201 | 1.651 | 2.512 | 83 | 68 | 2.078 | 6.406 | 8002 | 26 | 1.078 | 2.421 |
| 7001 | 227 | 2.829 | 4.177 | 83 | 77 | 2.719 | 5.594 | 8002 | 57 | 4.094 | 6.047 |
| 7001 | 309 | 1.925 | 3.391 | 83 | 82 | 3.515 | 6.234 | 8002 | 68 | 1.062 | 2.656 |
| 7001 | 312 | 1.194 | 2.179 | 83 | 306 | 4.047 | 11.594 | 8002 | 77 | 1.094 | 2.75 |
| 7001 | 313 | 3.08 | 4.65 | 84 | 6 | 2.406 | 5.321 | 8002 | 82 | 1.172 | 2.391 |
| 7001 | 324 | 1.24 | 2.51 | 84 | 15 | 1.508 | 4.603 | 8002 | 209 | 1.344 | 3.516 |
| 7001 | 325 | 1.349 | 2.575 | 84 | 19 | 1.928 | 3.686 | Group 8, image complexity 2 : |  |  |  |
| 7001 | 327 | 2.503 | 3.91 | 84 | 26 | 2.16 | 7.552 |  |  |  |  |
| 7001 | 402 | 2 | 3.318 | 84 | 57 | 6.53 | 8.187 |  |  |  |  |
| 7001 | 403 | 1.255 | 2.173 | 84 | 68 | 1.938 | 4.672 |  |  |  |  |
| 7001 | 406 | 1.699 | 2.709 | 84 | 77 | 1.404 | 3.535 | S \# | I \# | T2mark | T2next |
| 7002 | 61 | 1.294 | 2.308 | 84 | 82 | 2.11 | 5.033 | 80 | 27 | 1.641 | 3.828 |
| 7002 | 88 | 1.948 | 3.83 | 84 | 209 | 2.395 | 4.942 | 80 | 33 | 1.328 | 3.031 |
| 7002 | 96 | 1.441 | 2.482 | 85 | 15 | 1.012 | 1.42 | 80 | 41 | 4.344 | 6.375 |
| 7002 | 102 | 2.449 | 7.207 | 85 | 26 | 1.405 | 1.853 | 80 | 69 | 1.016 | 5.828 |
| 7002 | 104 | 0.825 | 1.682 | 85 | 57 | 4.124 | 4.827 | 80 | 83 | 1.344 | 3.547 |
| 7002 | 109 | 0.99 | 1.995 | 85 | 68 | 2.171 | 2.859 | 80 | 95 | 1.547 | 4.484 |
| 7002 | 201 | 1.3 | 2.386 | 85 | 77 | 1.299 | 1.933 | 80 | 105 | 1.407 | 4.875 |
| 7002 | 227 | 1.775 | 3.056 | 85 | 82 | 4.968 | 5.687 | 80 | 217 | 1.687 | 4.249 |
| 7002 | 309 | 2.495 | 3.983 | 85 | 209 | 1.313 | 2.172 | 80 | 231 | 6.406 | 8.874 |
| 7002 | 312 | 1.438 | 2.355 | 85 | 306 | 2.515 | 3.187 | 80 | 303 | 2.437 | 4.593 |
| 7002 | 313 | 1.708 | 2.976 | 86 | 15 | 1.108 | 1.826 | 80 | 304 | 1.015 | 4.796 |
| 7002 | 324 | 1.168 | 2.291 | 86 | 19 | 1.42 | 3.262 | 80 | 308 | 2.39 | 4.609 |
| 7002 | 325 | 1.024 | 1.988 | 86 | 26 | 1.143 | 2.081 | 80 | 310 | 2.374 | 3.874 |
| 7002 | 327 | 1.481 | 2.615 | 86 | 57 | 1.535 | 2.734 | 80 | 319 | 7.031 | 8.656 |
| 7002 | 402 | 2.092 | 3.58 | 86 | 68 | 0.826 | 1.87 | 81 | 27 | 2.719 | 4.656 |
| $\begin{aligned} & 7002 \\ & 7002 \end{aligned}$ | 404 | 0.946 | 1.744 | 86 | 77 | 1.436 | 2.31 | 81 | 33 | 1.359 | 2.89 |
|  | 406 | 0.857 | 1.833 | 86 | 82 | 0.95 | 1.979 | 81 | 41 | 1.688 | $\begin{aligned} & 6.032 \\ & 2.328 \end{aligned}$ |
| Group 8, image complexity 1: |  |  |  | 86 | 209 | 0.857 | 2.088 | 81 | 42 | 1.203 |  |
|  |  |  |  | 86 | 306 | 1.761 | 3.397 | 81 | 62 | 1.437 | 3.968 |
|  |  |  |  | 87 | 15 | 1.239 | 2.522 | 81 | 72 | 1.063 | 3.547 |
|  |  |  |  | 87 | 19 | 1.224 | 2.371 | 81 | 83 | 0.937 | 3.484 |
| S \# | I \# | T2mark T2next |  |  | $87 \quad 48$ | 1.427 | 2.502 | 81 | 87 | 1.515 | 2.594 |
| 80 | 15 | 2.063 | 5.609 | 8787 | 67 | 1.366 | 2.748 | 81 | 92 | 1.531 | 4.531 |
| 80 | 34 | 1.406 | 3.281 |  | 68 | 1.029 | 2.417 | 81 | 95 | 1.281 | 2.765 |
| 80 | 47 | 1.765 | 5.812 | 87 87 | 77 | 1.388 | 2.985 | 81 | 204 | 2.344 | 5.391 |
| 80 | 48 | 1.265 | 2.937 | 87 | 80 | 1.535 | 2.717 | 81 | 207 | 0.907 | 2.016 |
| 80 | 57 | 3.187 | 5.374 | 87 | 82 | 1.268 | 2.462 | 81 | 210 | 1.375 | 2.812 |
| 80 | 63 | 2.609 | 5.093 | 87 | 97 | 1.164 | 2.388 | 81 | 223 | 0.985 | 2.766 |
| 80 | 64 | 1.734 | 3.937 | 87 | 111 | 1.264 | 3.05 | 81 | 224 | 1.875 | 3 |
| 80 | 67 | 1.281 | 3.718 | 87 | 208 | 0.853 | 2.155 | 81 | 310 | 4.969 | 6.859 |
| 80 | 68 | 2.875 | 4.359 | 87 | 209 | 1.104 | 2.506 | 81 | 320 | 1.828 | 3.031 |
| 80 | 80 | 1.422 | 2.734 | 87 | 211 | 0.853 | 1.829 | 81 | 322 | 2.063 | 3.906 |
| 80 | 82 | 1.407 | 3.281 | 87 | 230 | 1.253 | 2.238 | 81 | 401 | 1.266 | 7.109 |
| 80 | 97 | 6.14 | 7.64 | 87 | 306 | 1.314 | 2.567 | 82 | 14 | 1.312 | 3.328 |
| 80 | 206 | 1.203 | 4.531 |  | 411 | 1.704 | 3.985 | 82 | 16 | 7.687 | 9.172 |
| 80 | 208 | 1.187 | 2.437 | 88 | 6 | 2.469 | 4.422 | 82 | 33 | 0.719 | 2.656 |
| 80 | 221 | 1.515 | 3.281 | 88 | 15 | 3.359 | 5.625 | 82 | 42 | 1.516 | 3 |
| 80 | 230 | 1.609 | 4.265 | 88 | 19 | 2.046 | 6.89 | 82 | 62 | 1.125 | 3.234 |


| 82 | 69 | 1.047 | 2.844 | 86 | 16 | 2.384 | 4.348 | 8001 | 224 | 0.85 | 1.754 |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| 82 | 83 | 1.391 | 2.61 | 86 | 27 | 1.449 | 2.384 | 8001 | 231 | 2.032 | 4.511 |
| 82 | 92 | 10.641 | 12.172 | 86 | 33 | 0.984 | 1.905 | 8001 | 308 | 3.495 | 5.804 |
| 82 | 95 | 1.25 | 2 | 86 | 41 | 2.341 | 2.888 | 8002 | 16 | 10.875 | 13.172 |
| 82 | 204 | 1.172 | 3.687 | 86 | 42 | 0.968 | 1.811 | 8002 | 27 | 1.485 | 2.735 |
| 82 | 207 | 1.422 | 2.391 | 86 | 62 | 1.163 | 2.341 | 8002 | 33 | 1.062 | 3.171 |
| 82 | 210 | 1.25 | 2.437 | 86 | 69 | 1.122 | 1.917 | 8002 | 42 | 1.187 | 2.015 |
| 82 | 217 | 2.968 | 4.297 | 86 | 72 | 2.201 | 3.153 | 8002 | 62 | 1.281 | 2.953 |
| 82 | 223 | 2.985 | 7.141 | 86 | 83 | 1.583 | 2.594 | 8002 | 65 | 1.25 | 2.203 |
| 82 | 224 | 2.375 | 3.468 | 86 | 87 | 2.077 | 3.202 | 8002 | 69 | 1.265 | 2.734 |
| 82 | 310 | 1.875 | 3.25 | 86 | 92 | 2.822 | 8.266 | 8002 | 72 | 2.188 | 3.563 |
| 82 | 322 | 1.813 | 3.329 | 86 | 95 | 2.99 | 4.235 | 8002 | 87 | 2.188 | 3.375 |
| 83 | 14 | 2.593 | 10.921 | 86 | 204 | 2.151 | 3.335 | 8002 | 92 | 2.015 | 3.828 |
| 83 | 27 | 3.093 | 8.39 | 86 | 207 | 0.909 | 2.184 | 8002 | 95 | 1.094 | 2.453 |
| 83 | 33 | 3.5 | 5.078 | 86 | 210 | 1.418 | 2.79 | 8002 | 204 | 1.203 | 3.094 |
| 83 | 41 | 6.797 | 9.687 | 86 | 223 | 0.982 | 1.745 | 8002 | 207 | 1.672 | 3.266 |
| 83 | 42 | 5.359 | 7.219 | 86 | 224 | 1.358 | 2.201 | 8002 | 210 | 1.735 | 2.907 |
| 83 | 62 | 2.937 | 9.578 | 86 | 308 | 7.645 | 8.762 | 8002 | 223 | 0.703 | 1.672 |
| 83 | 69 | 1.985 | 4.953 | 86 | 310 | 2.216 | 3.2 | 8002 | 224 | 1.343 | 2.531 |
| 83 | 72 | 7 | 8.454 | 86 | 320 | 3.943 | 4.955 | 8002 | 308 | 1.172 | 4.015 |
| 83 | 83 | 1.375 | 2.734 | 86 | 322 | 1.561 | 2.858 | 8002 | 310 | 1.078 | 2.812 |
| 83 | 87 | 1.922 | 3.937 | 86 | 401 | 3.148 | 11.29 | 8002 | 320 | 1.641 | 2.735 |
| 83 | 92 | 13.485 | 15.11 | 87 | 16 | 8.065 | 9.26 | 8002 | 322 | 2.062 | 3.172 |
| 83 | 95 | 2.156 | 3.375 | 87 | 33 | 0.906 | 2.118 | 8002 | 401 | 3.875 | 5.422 |
| 83 | 204 | 2.406 | 13.343 | 87 | 76 | 1.412 | 2.609 |  |  |  |  |
| 83 | 207 | 1.922 | 4.11 | 87 | 92 | 4.273 | 6.581 | Group 8, image complexity 3: |  |  |  |
| 83 | 217 | 5.265 | 7.906 | 87 | 204 | 1.522 | 2.88 |  |  |  |  |
| 83 | 223 | 2.562 | 5.297 | 87 | 210 | 1.704 | 2.872 |  |  |  |  |
| 83 | 224 | 1.969 | 6.062 | 87 | 224 | 1.117 | 2.359 | S \# | I \# | T2mark | T2next |
| 83 | 310 | 4.312 | 5.921 | 87 | 231 | 3.552 | 4.805 | 80 | 61 | 1.578 | 3.953 |
| 83 | 320 | 5.516 | 8.515 | 87 | 308 | 1.94 | 3.074 | 80 | 88 | 2.359 | 5.921 |
| 83 | 322 | 5.062 | 8.546 | 87 | 401 | 3.572 | 5.276 | 80 | 201 | 2.359 | 4.78 |
| 83 | 401 | 5.062 | 11.922 | 88 | 16 | 12.922 | 14.828 | 80 | 313 | 3.265 | 7.077 |
| 84 | 14 | 2.192 | 4.121 | 88 | 27 | 2.422 | 5.25 | 80 | 402 | 6.328 | 8.249 |
| 84 | 27 | 3.119 | 7.247 | 88 | 33 | 1.875 | 4.5 | 80 | 406 | 1.891 | 3.875 |
| 84 | 33 | 2.24 | 4.044 | 88 | 42 | 1.703 | 4.078 | 81 | 88 | 2.796 | 4.093 |
| 84 | 41 | 2.69 | 3.841 | 88 | 62 | 2.547 | 6.094 | 81 | 96 | 2.546 | 5.327 |
| 84 | 42 | 1.82 | 4.257 | 88 | 69 | 2.563 | 4.391 | 81 | 201 | 3.828 | 5.953 |
| 84 | 62 | 2.078 | 4.874 | 88 | 83 | 1.828 | 3.594 | 81 | 312 | 4.86 | 6.016 |
| 84 | 69 | 1.743 | 4.025 | 88 | 87 | 1.578 | 3.234 | 81 | 324 | 1.234 | 3.5 |
| 84 | 72 | 3.995 | 6.354 | 88 | 92 | 7.406 | 8.906 | 82 | 88 | 2.015 | 3.875 |
| 84 | 83 | 1.431 | 2.904 | 88 | 95 | 2.282 | 4 | 82 | 312 | 1.094 | 2.344 |
| 84 | 87 | 2.504 | 3.903 | 88 | 204 | 6.532 | 8.516 | 82 | 324 | 1.547 | 3.985 |
| 84 | 92 | 14.155 | 15.545 | 88 | 207 | 8.75 | 10.594 | 83 | 88 | 2.968 | 10.109 |
| 84 | 204 | 3.188 | 7.109 | 88 | 217 | 3.485 | 6.172 | 83 | 201 | 3.312 | 7.015 |
| 84 | 207 | 1.545 | 2.718 | 88 | 223 | 5.031 | 6.75 | 83 | 312 | 2.359 | 6.14 |
| 84 | 210 | 2.14 | 12.416 | 88 | 224 | 2.125 | 4.391 | 83 | 324 | 1.437 | 3.875 |
| 84 | 217 | 3.008 | 5.075 | 88 | 308 | 8.39 | 10.515 | 83 | 403 | 1.297 | 5.344 |
| 84 | 223 | 1.867 | 3.671 | 88 | 320 | 2.954 | 4.891 | 84 | 88 | 3.661 | 8.965 |
| 84 | 224 | 2.535 | 3.857 | 88 | 322 | 2.016 | 4.172 | 84 | 96 | 2.657 | 5.031 |
| 84 | 310 | 2.037 | 3.903 | 89 | 14 | 1.688 | 3.781 | 84 | 312 | 2.995 | 7.222 |
| 84 | 320 | 4.52 | 7.081 | 89 | 16 | 4.516 | 7.828 | 84 | 324 | 2.021 | 5.399 |
| 84 | 322 | 1.835 | 3.188 | 89 | 27 | 1.5 | 3.765 | 85 | 88 | 3.234 | 4.14 |
| 84 | 401 | 5.859 | 7.469 | 89 | 33 | 1.594 | 3.063 | 85 | 96 | 3.125 | 4.047 |
| 85 | 14 | 1.193 | 1.767 | 89 | 42 | 1.469 | 3.594 | 85 | 201 | 2.501 | 3.257 |
| 85 | 16 | 3.281 | 3.89 | 89 | 62 | 2.234 | 5.062 | 85 | 312 | 1.821 | 2.423 |
| 85 | 27 | 1.516 | 2.328 | 89 | 69 | 2.281 | 5.281 | 85 | 324 | 0.831 | 1.45 |
| 85 | 33 | 1.194 | 1.994 | 89 | 72 | 2.547 | 3.938 | 85 | 403 | 1.133 | 1.738 |
| 85 | 41 | 1.239 | 1.783 | 89 | 83 | 1.567 | 5.323 | 86 | 88 | 1.246 | 2.228 |
| 85 | 42 | 1.209 | 1.873 | 89 | 87 | 1.719 | 2.828 | 86 | 96 | 2.451 | 4.327 |
| 85 | 62 | 5.687 | 6.625 | 89 | 92 | 3.078 | 4.203 | 86 | 312 | 1.218 | 2.031 |
| 85 | 69 | 1.297 | 2.094 | 89 | 95 | 2.111 | 3.352 | 86 | 324 | 1.046 | 2.107 |
| 85 | 72 | 1.118 | 1.737 | 89 | 204 | 2.547 | 4.453 | 86 | 403 | 1.077 | 2.903 |
| 85 | 83 | 1.497 | 2.068 | 89 | 207 | 1.599 | 2.732 | 87 | 88 | 3.422 | 5.771 |
| 85 | 92 | 2.406 | 3.859 | 89 | 210 | 2.906 | 5.469 | 87 | 327 | 6.004 | 7.612 |
| 85 | 204 | 2.485 | 3.328 | 89 | 223 | 1.469 | 4.578 | 87 | 402 | 2.528 | 5.262 |
| 85 | 207 | 0.942 | 1.606 | 89 | 224 | 1.187 | 2.281 | 87 | 403 | 1.03 | 2.373 |
| 85 | 210 | 1.094 | 1.734 | 89 | 310 | 3.266 | 4.813 | 88 | 88 | 4.891 | 7.156 |
| 85 | 217 | 1.656 | 2.265 | 89 | 401 | 2.718 | 3.984 | 88 | 96 | 4.515 | 6.562 |
| 85 | 223 | 1.078 | 1.75 | 8001 | 33 | 1.039 | 2.065 | 88 | 312 | 2.516 | 4.172 |
| 85 | 224 | 1.677 | 2.266 | 8001 | 72 | 2.894 | 4.11 | 88 | 324 | 2.203 | 3.859 |
| 85 | 310 | 2.024 | 2.628 | 8001 | 76 | 1.164 | 2.452 | 88 | 403 | 2 | 4.156 |
| 85 | 322 | 1.636 | 2.254 | 8001 | 92 | 1.792 | 15.808 | 89 | 88 | 2.203 | 5.469 |
| 85 | 401 | 4.297 | 5.172 | 8001 | 204 | 1.656 | 7.604 | 89 | 96 | 2.735 | 4.282 |
| 86 | 14 | 1.701 | 2.56 | 8001 | 210 | 1.099 | 4.637 | 89 | 312 | 2.078 | 3.187 |


| 89 | 324 | 2.14 | 3.359 | 92 | 63 | 0.86 | 2.297 | 95 | 34 | 1.109 | 3.628 |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| 89 | 403 | 2.969 | 5.781 | 92 | 64 | 0.984 | 2.969 | 95 | 46 | 6.158 | 11.811 |
| 8001 | 61 | 1.474 | 2.622 | 92 | 67 | 0.687 | 2.047 | 95 | 47 | 1.14 | 3.658 |
| 8001 | 102 | 3.252 | 6.594 | 92 | 68 | 0.844 | 2.235 | 95 | 48 | 0.959 | 2.788 |
| 8001 | 309 | 3.077 | 14.298 | 92 | 80 | 0.828 | 2.25 | 95 | 57 | 1.976 | 3.416 |
| 8001 | 403 | 3.356 | 4.557 | 92 | 82 | 0.906 | 2.688 | 95 | 63 | 1.116 | 2.789 |
| 8002 | 88 | 3.14 | 4.781 | 92 | 97 | 1.266 | 2.953 | 95 | 64 | 4.835 | 6.104 |
| 8002 | 96 | 3.812 | 4.765 | 92 | 206 | 1.047 | 2.359 | 95 | 68 | 6.572 | 9.1 |
| 8002 | 201 | 3.125 | 5.579 | 92 | 208 | 0.593 | 1.968 | 95 | 77 | 1.533 | 4.347 |
| 8002 | 312 | 2.468 | 4.234 | 92 | 209 | 1 | 2.406 | 95 | 82 | 16.223 | 18.643 |
| 8002 | 324 | 1.125 | 2.203 | 92 | 211 | 0.593 | 1.75 | 9595 | 97 | 1.287 | 3.202 |
|  |  |  |  | 92 | 220 | 1.078 | 2.594 |  | 111 | 5.469 | 7.016 |
| Group 9, image complexity 1: |  |  |  | 92 | 221 | 0.89 | 2.843 | 95 | 206 | 0.906 | 1.951 |
|  |  |  |  | 92 | 230 | 1.078 | 2.61 | 95 | 209 | 1.177 | 2.401 |
|  |  |  |  | 92 | 306 | 1.032 | 4.735 | 95 | 211 | 0.72 | 2.189 |
| S \# | I \# | T2mark | T2next | 92 | 307 | 1.062 | 3.453 | 95 | 220 | 1.84 | 3.191 |
| 90 | 6 | 1.093 | 2.015 | 92 | 411 | 1.75 | 4.484 | 95 | 221 | 1.649 | 3.538 |
| 90 | 7 | 1.11 | 2.719 | 93 | 6 | 1.704 | 4.875 | 95 | 306 | 2.137 | 4.523 |
| 90 | 15 | 1.093 | 1.937 | 93 | 7 | 2.094 | 6.235 | 95 | 307 | 1.686 | 3.26 |
| 90 | 19 | 0.703 | 1.5 | 93 | 15 | 1.297 | 2.938 | 95 | 411 | 12.899 | 15.948 |
| 90 | 26 | 0.734 | 2.218 | 93 | 19 | 1.609 | 3.406 | 96 | 6 | 1.063 | 2.673 |
| 90 | 46 | 0.968 | 1.89 | 93 | 26 | 1.078 | 3.218 | 96 | 7 | 1.397 | 3.828 |
| 90 | 47 | 1.031 | 2.172 | 93 | 46 | 1.609 | 4 | 96 | 15 | 1.655 | 3.063 |
| 90 | 48 | 0.859 | 1.625 | 93 | 47 | 1.938 | 3.641 | 96 | 19 | 1.299 | 3.31 |
| 90 | 54 | 1.562 | 2.625 | 93 | 48 | 1.219 | 2.969 | 96 | 26 | 1.121 | 5.06 |
| 90 | 57 | 1.484 | 2.594 | 93 | 54 | 1.578 | 3.532 | 96 | 46 | 0.969 | 2.828 |
| 90 | 63 | 0.906 | 2.156 | 93 | 57 | 3.078 | 5.64 | 96 | 47 | 1.207 | 2.553 |
| 90 | 64 | 1.094 | 1.969 | 93 | 63 | 1.828 | 4.578 | 96 | 48 | 1.058 | 3.394 |
| 90 | 67 | 0.735 | 1.594 | 93 | 64 | 9.125 | 11.219 | 96 | 54 | 1.58 | 2.825 |
| 90 | 68 | 0.703 | 2.266 | 93 | 67 | 1.265 | 3.078 | 96 | 57 | 1.578 | 3.812 |
| 90 | 80 | 1.172 | 1.953 | 93 | 68 | 2.047 | 4.609 | 96 | 63 | 1.391 | 2.906 |
| 90 | 82 | 0.984 | 1.843 | 93 | 80 | 1.391 | 3.203 | 96 | 64 | 1.2 | 2.4 |
| 90 | 97 | 1.281 | 7.859 | 93 | 82 | 1.547 | 3.297 | 96 | 67 | 1.121 | 3.3 |
| 90 | 206 | 0.922 | 2.031 | 93 | 97 | 3.016 | 6.906 | 96 | 68 | 1.188 | 2.688 |
| 90 | 208 | 0.547 | 1.578 | 93 | 206 | 1.844 | 7.406 | 96 | 80 | 1.09 | 2.989 |
| 90 | 209 | 1.11 | 3.125 | 93 | 208 | 1.141 | 2.672 | 96 | 82 | 1.469 | 3.672 |
| 90 | 211 | 0.719 | 1.625 | 93 | 209 | 1.875 | 5.328 | 96 | 97 | 2.313 | 8.219 |
| 90 | 220 | 1.171 | 2.406 | 93 | 211 | 1.484 | 3.375 | 96 | 206 | 0.957 | 2.051 |
| 90 | 221 | 1.328 | 2.453 | 93 | 220 | 2.578 | 4.484 | 96 | 208 | 1.083 | 2.599 |
| 90 | 230 | 1.453 | 2.562 | 93 | 221 | 1.891 | 3.641 | 96 | 209 | 1.406 | 3.609 |
| 90 | 306 | 5.234 | 6.359 | 93 | 230 | 2.234 | 5.359 | 96 | 211 | 1.261 | 2.74 |
| 90 | 307 | 0.906 | 1.922 | 93 | 306 | 1.547 | 4.812 | 96 | 220 | 1.578 | 4.099 |
| 90 | 411 | 1.015 | 2.453 | 93 | 307 | 1.844 | 3.235 | 96 | 221 | 1.386 | 3.223 |
| 91 | 6 | 1.817 | 5.622 | 93 | 411 | 4.172 | 6.875 | 96 | 230 | 2.051 | 3.479 |
| 91 | 7 | 1.802 | 5.884 | 94 | 6 | 2.141 | 2.984 | 96 | 306 | 1.922 | 3.359 |
| 91 | 15 | 1.288 | 3.011 | 94 | 15 | 0.789 | 1.887 | 96 | 307 | 1.443 | 4.511 |
| 91 | 19 | 1.66 | 3.6 | 94 | 19 | 1.856 | 2.475 | 96 | 411 | 1.25 | 3.797 |
| 91 | 46 | 1.869 | 4.07 | 94 | 26 | 0.919 | 2.569 | 97 | 6 | 2.205 | 3.441 |
| 91 | 47 | 1.325 | 3.173 | 94 | 46 | 1 | 1.828 | 97 | 7 | 2.756 | 3.84 |
| 91 | 48 | 1.522 | 3.483 | 94 | 47 | 0.819 | 2.227 | 97 | 15 | 1.867 | 3.274 |
| 91 | 54 | 2.85 | 5.111 | 94 | 48 | 0.716 | 1.743 | 97 | 19 | 1.264 | 2.346 |
| 91 | 57 | 4.223 | 5.668 | 94 | 54 | 0.453 | 1.437 | 97 | 26 | 1.924 | 7.11 |
| 91 | 63 | 1.779 | 4.809 | 94 | 57 | 1.094 | 2.719 | 97 | 34 | 2.613 | 3.708 |
| 91 | 64 | 3.634 | 7.026 | 94 | 63 | 2.437 | 3.515 | 97 | 46 | 1.781 | 8.556 |
| 91 | 67 | 2.483 | 3.964 | 94 | 64 | 1.14 | 1.984 | 97 | 47 | 1.602 | 3.849 |
| 91 | 68 | 2.792 | 6.689 | 94 | 67 | 0.881 | 2.521 | 97 | 48 | 1.095 | 2.177 |
| 91 | 80 | 1.302 | 2.633 | 94 | 68 | 0.64 | 1.547 | 97 | 57 | 1.997 | 3.743 |
| 91 | 82 | 1.553 | 5.051 | 94 | 80 | 0.866 | 1.562 | 97 | 63 | 1.494 | 3.048 |
| 91 | 97 | 2.578 | 7.329 | 94 | 82 | 0.531 | 1.453 | 97 | 64 | 1.423 | 2.968 |
| 91 | 206 | 2.065 | 6.92 | 94 | 97 | 1.563 | 5.344 | 97 | 68 | 2.45 | 9.708 |
| 91 | 208 | 1.193 | 3.237 | 94 | 206 | 1.172 | 2.141 | 97 | 82 | 2.517 | 11.569 |
| 91 | 209 | 2.02 | 4.282 | 94 | 208 | 1.206 | 2.042 | 97 | 97 | 1.915 | 4.459 |
| 91 | 211 | 1.495 | 3.388 | 94 | 209 | 1.094 | 2.203 | 97 | 206 | 2.234 | 5.799 |
| 91 | 220 | 1.257 | 2.887 | 94 | 211 | 0.835 | 2.042 | 97 | 209 | 1.908 | 3.062 |
| 91 | 221 | 1.632 | 4.512 | 94 | 220 | 0.929 | 1.779 | 97 | 211 | 1.335 | 2.571 |
| 91 | 230 | 4.128 | 5.622 | 94 | 221 | 1.121 | 2.289 | 97 | 221 | 1.63 | 2.838 |
| 91 | 411 | 2.366 | 9.594 | 94 | 230 | 1.031 | 2.156 | 97 | 306 | 1.928 | 3.014 |
| 92 | 15 | 0.953 | 2.594 | 94 | 306 | 1.125 | 2.078 | 97 | 307 | 3.087 | 5.072 |
| 92 | 19 | 1.109 | 2.812 | 94 | 307 | 1.748 | 2.847 | 97 | 411 | 2.798 | 5.315 |
| 92 | 26 | 0.703 | 2.844 | 94 | 411 | 1.656 | 2.89 | 98 | 6 | 2.156 | 5.281 |
| 92 | 46 | 0.844 | 2.281 | 95 | 6 | 1.439 | 3.988 | 98 | 15 | 1.812 | 3.406 |
| 92 | 47 | 0.921 | 2.093 | 95 | 7 | 2.383 | 5.588 | 98 | 19 | 1.203 | 2.485 |
| 92 | 48 | 0.641 | 1.703 | 95 | 15 | 1.35 | 3.274 | 98 | 26 | 1.703 | 4.016 |
| 92 | 54 | 1 | 2.375 | 95 | 19 | 0.825 | 2.324 | 98 | 34 | 2.235 | 4.11 |
| 92 | 57 | 1.578 | 3.921 | 95 | 26 | 0.876 | 1.89 | 98 | 46 | 2.532 | 5.172 |


| 98 | 47 | 1.578 | 2.922 | 9002 | 64 | 1.515 | 5.093 | 92 | 35 | 1.531 | 3.344 |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| 98 | 48 | 1.125 | 2.593 | 9002 | 67 | 2.063 | 3.625 | 92 | 41 | 0.937 | 2.484 |
| 98 | 54 | 1.812 | 4.609 | 9002 | 68 | 2.109 | 4.093 | 92 | 42 | 0.907 | 2.297 |
| 98 | 57 | 2.891 | 5.578 | 9002 | 80 | 1.547 | 3.406 | 92 | 62 | 1.031 | 3.422 |
| 98 | 63 | 3.297 | 5.109 | 9002 | 82 | 2.016 | 3.985 | 92 | 65 | 1.11 | 2.5 |
| 98 | 64 | 1.578 | 4.265 | 9002 | 97 | 2.469 | 6.765 | 92 | 69 | 0.891 | 2.141 |
| 98 | 67 | 1.984 | 3.469 | 9002 | 206 | 2.125 | 4.172 | 92 | 70 | 0.89 | 2.593 |
| 98 | 68 | 2.61 | 5.734 | 9002 | 208 | 1.625 | 3.703 | 92 | 72 | 3.453 | 5.235 |
| 98 | 80 | 1.093 | 2.14 | 9002 | 209 | 1.781 | 4.047 | 92 | 87 | 0.922 | 2.438 |
| 98 | 82 | 1.86 | 4.219 | 9002 | 211 | 1.265 | 6.75 | 92 | 92 | 3.031 | 4.39 |
| 98 | 97 | 2.484 | 5.968 | 9002 | 220 | 2.047 | 3.922 | 92 | 95 | 0.734 | 2.343 |
| 98 | 206 | 2.594 | 4.766 | 9002 | 221 | 1.453 | 3.562 | 92 | 105 | 1.281 | 2.843 |
| 98 | 208 | 1.031 | 2.422 | 9002 | 230 | 2.218 | 4.703 | 92 | 204 | 1.266 | 3.672 |
| 98 | 209 | 2.203 | 4.844 | 9002 | 307 | 1.89 | 5.124 | 92 | 207 | 0.719 | 2.203 |
| 98 | 220 | 6.281 | 7.874 | 9002 | 411 | 2.828 | 7.047 | 92 | 210 | 1.016 | 2.61 |
| 98 | 230 | 2.235 | 3.797 | Group 9, image complexity 2: |  |  |  | 92 | 217 | 1.109 | 2.609 |
| 98 | 307 | 2.109 | 3.531 |  |  |  |  | 92 | 219 | 0.688 | 2.359 |
| 99 | 6 | 1.421 | 2.859 |  |  |  |  | 92 | 223 | 0.922 | 2.375 |
| 99 | 7 | 1.734 | 3.843 |  |  |  |  | 92 | 303 | 0.828 | 2.281 |
| 99 | 15 | 1.686 | 2.698 | S \# | I \# | T2mark | T2next | 92 | 304 | 0.781 | 2.39 |
| 99 | 19 | 1.962 | 3.081 | 90 | 14 | 1.312 | 2.312 | 92 | 310 | 1.125 | 3.156 |
| 99 | 26 | 4.64 | 6.177 | 90 | 16 | 2.625 | 4.203 | 92 | 319 | 2.328 | 3.828 |
| 99 | 46 | 1.672 | 2.547 | 90 | 27 | 1.219 | 2.235 | 92 | 322 | 0.922 | 3.063 |
| 99 | 47 | 1.548 | 2.53 | 90 | 33 | 0.765 | 1.562 | 92 | 401 | 3.172 | 4.828 |
| 99 | 48 | 1.738 | 3.026 | 90 | 35 | 5.25 | 7.047 | 93 | 14 | 1.641 | 3.516 |
| 99 | 54 | 1.609 | 2.89 | 90 | 41 | 1 | 1.75 | 93 | 16 | 6.563 | 8.36 |
| 99 | 57 | 2.344 | 4.375 | 90 | 42 | 1.14 | 1.953 | 93 | 27 | 1.765 | 3.828 |
| 99 | 63 | 3.047 | 5.625 | 90 | 62 | 0.735 | 1.703 | 93 | 33 | 1.547 | 3.297 |
| 99 | 64 | 2.187 | 3.859 | 90 | 70 | 1.125 | 2.39 | 93 | 35 | 3.578 | 8 |
| 99 | 67 | 2.079 | 3.181 | 90 | 87 | 2.687 | 3.562 | 93 | 41 | 1.735 | 3.204 |
| 99 | 68 | 2.609 | 4.89 | 90 | 92 | 1.5 | 3.047 | 93 | 42 | 1.766 | 3.078 |
| 99 | 80 | 2.701 | 3.926 | 90 | 95 | 2.391 | 3.625 | 93 | 62 | 3.593 | 5.703 |
| 99 | 82 | 2.906 | 4.75 | 90 | 105 | 3.797 | 7.297 | 93 | 65 | 2.297 | 6 |
| 99 | 97 | 5.359 | 8.593 | 90 | 204 | 1.344 | 2.516 | 93 | 69 | 3.297 | 5.078 |
| 99 | 206 | 1.172 | 2.531 | 90 | 207 | 0.687 | 2.015 | 93 | 70 | 1.422 | 3.172 |
| 99 | 208 | 2.023 | 2.943 | 90 | 210 | 1.031 | 2.687 | 93 | 87 | 3.157 | 5.25 |
| 99 | 209 | 1.703 | 3.156 | 90 | 219 | 0.781 | 1.796 | 93 | 92 | 9 | 10.969 |
| 99 | 211 | 0.947 | 1.63 | 90 | 223 | 0.938 | 2 | 93 | 95 | 1.547 | 4.937 |
| 99 | 220 | 1.426 | 2.576 | 90 | 231 | 2.766 | 7.344 | 93 | 105 | 2.063 | 6.703 |
| 99 | 221 | 1.769 | 2.964 | 90 | 303 | 1.125 | 2.469 | 93 | 204 | 2.875 | 6.172 |
| 99 | 230 | 1.64 | 3 | 90 | 304 | 0.797 | 1.672 | 93 | 207 | 1.64 | 3.297 |
| 99 | 306 | 1.953 | 3.156 | 90 | 319 | 3.063 | 6.672 | 93 | 210 | 2.156 | 4.109 |
| 99 | 307 | 1.226 | 2.437 | 90 | 320 | 1.406 | 2.656 | 93 | 217 | 3.516 | 5.328 |
| 99 | 411 | 2.672 | 4.563 | 90 | 322 | 1.094 | 2.032 | 93 | 219 | 1.594 | 3.875 |
| 9001 | 6 | 0.953 | 2.656 | 90 | 401 | 2.375 | 3.672 | 93 | 223 | 2.281 | 3.828 |
| 9001 | 15 | 1.11 | 2.844 | 91 | 14 | 1.92 | 4.114 | 93 | 231 | 14.203 | 16.625 |
| 9001 | 19 | 1.422 | 2.984 | 91 | 16 | 5.925 | 10.81 | 93 | 303 | 3.015 | 4.343 |
| 9001 | 26 | 1.219 | 2.562 | 91 | 27 | 2.201 | 4.101 | 93 | 304 | 1.359 | 2.687 |
| 9001 | 47 | 1.515 | 3.187 | 91 | 33 | 1.399 | 4.512 | 93 | 319 | 12.11 | 13.641 |
| 9001 | 48 | 1.234 | 2.406 | 91 | 35 | 5.877 | 12.062 | 93 | 322 | 2.219 | 4.875 |
| 9001 | 54 | 0.89 | 2.359 | 91 | 41 | 1.35 | 2.592 | 93 | 401 | 7.765 | 9.593 |
| 9001 | 63 | 1.64 | 3.5 | 91 | 42 | 1.602 | 5.622 | 94 | 14 | 1.609 | 2.414 |
| 9001 | 64 | 1.391 | 2.86 | 91 | 62 | 3.444 | 5.825 | 94 | 27 | 1.063 | 2.109 |
| 9001 | 67 | 1.016 | 2.797 | 91 | 69 | 3.481 | 5.083 | 94 | 33 | 0.68 | 1.485 |
| 9001 | 68 | 1.469 | 4.875 | 91 | 70 | 1.676 | 4.361 | 94 | 35 | 4.718 | 7.093 |
| 9001 | 80 | 1.532 | 3.141 | 91 | 72 | 3.111 | 4.436 | 94 | 41 | 0.851 | 1.779 |
| 9001 | 97 | 1.5 | 6.453 | 91 | 87 | 1.289 | 2.674 | 94 | 42 | 0.82 | 1.763 |
| 9001 | 206 | 1.265 | 2.953 | 91 | 92 | 2.205 | 7.562 | 94 | 62 | 1.203 | 3.407 |
| 9001 | 208 | 0.766 | 2.704 | 91 | 105 | 8.946 | 18.432 | 94 | 65 | 0.735 | 2 |
| 9001 | 211 | 1.062 | 2.625 | 91 | 204 | 2.664 | 5.966 | 94 | 69 | 0.703 | 1.359 |
| 9001 | 220 | 1.703 | 3.156 | 91 | 210 | 1.824 | 2.985 | 94 | 70 | 0.728 | 1.64 |
| 9001 | 221 | 1.187 | 2.453 | 91 | 217 | 1.787 | 4.421 | 94 | 72 | 0.61 | 1.188 |
| 9001 | 230 | 1.375 | 2.812 | 91 | 219 | 1.577 | 3.662 | 94 | 87 | 0.696 | 1.237 |
| 9001 | 307 | 1.281 | 4.547 | 91 | 223 | 2.433 | 5.037 | 94 | 92 | 1.656 | 3.281 |
| 9002 | 6 | 1.812 | 5.671 | 91 | 231 | 4.86 | 8.292 | 94 | 105 | 2.562 | 5.781 |
| 9002 | 7 | 2.391 | 5.188 | 91 | 303 | 1.878 | 3.601 | 94 | 204 | 1.469 | 2.578 |
| 9002 | 15 | 1.609 | 3.5 | 91 | 304 | 2.084 | 3.62 | 94 | 207 | 0.934 | 1.899 |
| 9002 | 19 | 1.391 | 3.25 | 91 | 319 | 4.472 | 14.379 | 94 | 210 | 0.891 | 2.047 |
| 9002 | 26 | 1.204 | 3.703 | 91 | 320 | 1.553 | 4.011 | 94 | 217 | 0.843 | 1.484 |
| 9002 | 46 | 1.265 | 4.312 | 91 | 322 | 1.399 | 4.32 | 94 | 219 | 2.073 | 3.559 |
| 9002 | 47 | 1.313 | 2.937 | 91 | 401 | 7.455 | 9.297 | 94 | 223 | 0.906 | 1.703 |
| 9002 | 48 | 1.5 | 3.219 | 92 | 14 | 0.859 | 2.765 | 94 | 231 | 3.749 | 5.031 |
| 9002 | 54 | 1.766 | 3.156 | 92 | 16 | 1.906 | 4.062 | 94 | 303 | 1.161 | 2.445 |
| 9002 | 57 | 1.547 | 4.203 | 92 | 27 | 1.219 | 3.079 | 94 | 304 | 0.638 | 1.51 |
| 9002 | 63 | 1.859 | 4.281 | 92 | 33 | 0.687 | 2.047 | 94 | 308 | 1.562 | 4.406 |


| 94 | 310 | 1.918 | 2.955 | 97 | 219 | 1.63 | 2.599 | 9001 | 401 | 1.125 | 5.593 |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| 94 | 320 | 0.891 | 1.766 | 97 | 223 | 2.353 | 5.388 | 9002 | 14 | 1.922 | 4.453 |
| 94 | 322 | 1.098 | 2.367 | 97 | 224 | 1.475 | 2.388 | 9002 | 16 | 2.812 | 8.89 |
| 94 | 401 | 1.343 | 3.515 | 97 | 303 | 3.189 | 4.335 | 9002 | 27 | 1.922 | 4.421 |
| 95 | 14 | 0.968 | 2.29 | 97 | 304 | 1.32 | 2.5 | 9002 | 33 | 1.344 | 3.656 |
| 95 | 16 | 2.436 | 3.616 | 97 | 310 | 1.404 | 2.57 | 9002 | 35 | 5.688 | 8.125 |
| 95 | 27 | 3.432 | 4.703 | 97 | 322 | 1.924 | 3.067 | 9002 | 41 | 4.781 | 6.64 |
| 95 | 33 | 1.229 | 2.699 | 98 | 16 | 4.781 | 7.203 | 9002 | 42 | 1.641 | 5.485 |
| 95 | 35 | 4.886 | 6.189 | 98 | 27 | 3.672 | 7.688 | 9002 | 62 | 1.938 | 3.344 |
| 95 | 41 | 1.394 | 2.519 | 98 | 33 | 1.656 | 3.953 | 9002 | 65 | 3 | 4.485 |
| 95 | 42 | 1.184 | 2.215 | 98 | 41 | 1.735 | 3.516 | 9002 | 69 | 2.25 | 4.75 |
| 95 | 62 | 1.163 | 2.746 | 98 | 42 | 2.218 | 4.39 | 9002 | 70 | 1.515 | 6.624 |
| 95 | 69 | 0.975 | 2.034 | 98 | 62 | 3.969 | 6.797 | 9002 | 72 | 1.625 | 4.89 |
| 95 | 70 | 0.795 | 1.719 | 98 | 69 | 1.641 | 4.079 | 9002 | 87 | 1.562 | 3.453 |
| 95 | 76 | 1.739 | 5.742 | 98 | 70 | 1.281 | 3.187 | 9002 | 92 | 3.125 | 5.812 |
| 95 | 87 | 3.073 | 4.077 | 98 | 72 | 1.938 | 3.61 | 9002 | 95 | 1.406 | 3.844 |
| 95 | 92 | 2.574 | 4.075 | 98 | 76 | 1.781 | 3.719 | 9002 | 105 | 4.687 | 8.421 |
| 95 | 105 | 1.843 | 3.872 | 98 | 83 | 1.047 | 2.531 | 9002 | 207 | 1.485 | 3.282 |
| 95 | 204 | 1.487 | 3.082 | 98 | 95 | 1.219 | 2.906 | 9002 | 210 | 1.797 | 4.219 |
| 95 | 207 | 0.974 | 2.278 | 98 | 105 | 4.375 | 7.485 | 9002 | 219 | 1.781 | 5.469 |
| 95 | 210 | 1.599 | 4.221 | 98 | 204 | 4.094 | 6.688 | 9002 | 223 | 1.515 | 6.25 |
| 95 | 219 | 0.885 | 2.114 | 98 | 207 | 1.485 | 2.875 | 9002 | 231 | 4.812 | 8.546 |
| 95 | 223 | 2.021 | 3.108 | 98 | 210 | 1.734 | 4.063 | 9002 | 303 | 15.25 | 17.359 |
| 95 | 224 | 0.96 | 1.994 | 98 | 217 | 2.687 | 3.984 | 9002 | 304 | 1.859 | 3.422 |
| 95 | 231 | 4.492 | 8.427 | 98 | 219 | 1.344 | 3.125 | 9002 | 308 | 8.234 | 12.891 |
| 95 | 303 | 1.421 | 3.595 | 98 | 223 | 1.656 | 4.203 | 9002 | 310 | 1.39 | 3.781 |
| 95 | 304 | 1.17 | 2.489 | 98 | 224 | 1.297 | 3.234 | 9002 | 319 | 8.359 | 12.593 |
| 95 | 308 | 0.96 | 2.014 | 98 | 231 | 2.578 | 6.031 | 9002 | 320 | 2.062 | 4.047 |
| 95 | 320 | 2.327 | 5.769 | 98 | 303 | 3.109 | 6.234 | 9002 | 322 | 2.422 | 5.875 |
| 95 | 322 | 1.154 | 2.308 | 98 | 304 | 1.313 | 2.297 | 9002 | 401 | 4.766 | 7.61 |
| 96 | 14 | 1.454 | 2.862 | 98 | 308 | 4.672 | 6 | Group 9, image complexity 3: |  |  |  |
| 96 | 16 | 6.765 | 11.5 | 98 | 319 | 3.141 | 4.75 |  |  |  |  |
| 96 | 27 | 1.218 | 3.749 | 98 | 322 | 1.485 | 2.797 |  |  |  |  |
| 96 | 33 | 1.16 | 4.811 | 98 | 401 | 4 | 5.078 |  |  |  |  |
| 96 | 35 | 3.078 | 7.562 | 99 | 27 | 1.828 | 3.844 | S \# | I \# | T2mark | T2next |
| 96 | 41 | 2.398 | 4.177 | 99 | 33 | 1.947 | 2.852 | 90 | 88 | 1.656 | 2.781 |
| 96 | 42 | 1.368 | 3.859 | 99 | 35 | 3.547 | 6.469 | 90 | 96 | 1.797 | 2.828 |
| 96 | 62 | 1.5 | 3.156 | 99 | 41 | 1.487 | 2.668 | 90 | 102 | 1.766 | 5.094 |
| 96 | 65 | 1.686 | 3.296 | 99 | 42 | 1.272 | 2.361 | 90 | 104 | 1.75 | 2.703 |
| 96 | 69 | 1.23 | 3.357 | 99 | 65 | 1.375 | 2.578 | 90 | 109 | 1.046 | 2.156 |
| 96 | 70 | 0.959 | 2.645 | 99 | 69 | 2.031 | 3.25 | 90 | 201 | 1.14 | 2.328 |
| 96 | 72 | 1.503 | 3.19 | 99 | 70 | 2.759 | 5.335 | 90 | 227 | 1.14 | 2.328 |
| 96 | 87 | 4.733 | 9.389 | 99 | 72 | 1.063 | 2.25 | 90 | 312 | 0.891 | 1.938 |
| 96 | 92 | 5.391 | 7.141 | 99 | 87 | 2.499 | 3.588 | 90 | 324 | 3.766 | 4.922 |
| 96 | 95 | 1.432 | 3.02 | 99 | 95 | 3.538 | 4.655 | 90 | 325 | 1.015 | 1.984 |
| 96 | 105 | 2.36 | 7.781 | 99 | 105 | 3.64 | 6.25 | 90 | 327 | 1.031 | 3.781 |
| 96 | 204 | 2.374 | 4.968 | 99 | 204 | 2.593 | 3.937 | 90 | 402 | 4.969 | 6.391 |
| 96 | 207 | 1.494 | 3.736 | 99 | 207 | 1.567 | 2.653 | 90 | 403 | 1.172 | 2.469 |
| 96 | 210 | 1.216 | 3.707 | 99 | 210 | 7.422 | 11.031 | 90 | 406 | 1.953 | 3.031 |
| 96 | 217 | 1.929 | 3.251 | 99 | 219 | 2.116 | 3.189 | 91 | 61 | 2.522 | 5.176 |
| 96 | 219 | 1.16 | 3.279 | 99 | 223 | 1.89 | 3.14 | 91 | 88 | 2.744 | 8.548 |
| 96 | 223 | 1.23 | 2.749 | 99 | 304 | 1.676 | 2.839 | 91 | 96 | 3.387 | 6.533 |
| 96 | 231 | 5.296 | 9.937 | 99 | 310 | 2.238 | 4.017 | 91 | 102 | 2.889 | 6.771 |
| 96 | 303 | 2.119 | 5.058 | 99 | 319 | 4.656 | 6.531 | 91 | 104 | 1.94 | 5.183 |
| 96 | 304 | 1.37 | 2.942 | 99 | 320 | 1.812 | 3.218 | 91 | 109 | 3.135 | 4.936 |
| 96 | 319 | 4.266 | 9.984 | 99 | 322 | 1.536 | 2.809 | 91 | 201 | 2.277 | 3.936 |
| 96 | 322 | 5.584 | 8.368 | 99 | 401 | 3.156 | 5.203 | 91 | 227 | 1.673 | 5.261 |
| 96 | 401 | 2.828 | 4.969 | 9001 | 14 | 1.031 | 2.406 | 91 | 309 | 5.653 | 8.669 |
| 97 | 14 | 1.549 | 2.571 | 9001 | 27 | 1.39 | 3.875 | 91 | 312 | 1.686 | 3.524 |
| 97 | 16 | 1.62 | 5.717 | 9001 | 33 | 1.234 | 2.734 | 91 | 313 | 2.919 | 7.156 |
| 97 | 27 | 3.003 | 4.009 | 9001 | 41 | 2.016 | 3.5 | 91 | 324 | 2.557 | 4.482 |
| 97 | 33 | 2.641 | 4.636 | 9001 | 65 | 1.609 | 3.547 | 91 | 325 | 1.427 | 4.43 |
| 97 | 35 | 1.339 | 4.231 | 9001 | 72 | 1.015 | 2.515 | 91 | 327 | 1.956 | 17.176 |
| 97 | 41 | 2.557 | 3.779 | 9001 | 87 | 2.11 | 3.969 | 91 | 402 | 2.013 | 8.503 |
| 97 | 42 | 1.515 | 2.968 | 9001 | 95 | 1.734 | 3.453 | 91 | 403 | 2.67 | 4.299 |
| 97 | 62 | 1.79 | 2.831 | 9001 | 105 | 5.296 | 7.796 | 92 | 61 | 0.828 | 2.313 |
| 97 | 65 | 2.417 | 4.835 | 9001 | 207 | 1.36 | 2.61 | 92 | 88 | 1.281 | 3.14 |
| 97 | 69 | 4.254 | 5.769 | 9001 | 210 | 3.593 | 5.343 | 92 | 96 | 1.344 | 2.797 |
| 97 | 70 | 1.579 | 2.556 | 9001 | 217 | 1.157 | 2.719 | 92 | 102 | 2.281 | 3.703 |
| 97 | 87 | 1.684 | 2.736 | 9001 | 219 | 1.188 | 3.125 | 92 | 104 | 1.11 | 3.453 |
| 97 | 105 | 3.611 | 6.519 | 9001 | 223 | 1.157 | 2.86 | 92 | 109 | 1.563 | 3.344 |
| 97 | 204 | 2.367 | 3.521 | 9001 | 303 | 1.375 | 3.187 | 92 | 201 | 1.094 | 2.609 |
| 97 | 207 | 1.587 | 3.202 | 9001 | 304 | 1.016 | 2.469 | 92 | 227 | 1.172 | 2.812 |
| 97 | 210 | 1.775 | 3.091 | 9001 | 320 | 1.016 | 3.156 | 92 | 309 | 1.313 | 3.141 |
| 97 | 217 | 2.246 | 3.469 | 9001 | 322 | 1.313 | 3.485 | 92 | 312 | 0.953 | 2.547 |


| 92 | 313 | 4.328 | 5.859 | 97 | 313 | 3.259 | 4.957 | 100 | 97 | 1.375 | 2.906 |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| 92 | 324 | 0.844 | 2.344 | 97 | 324 | 2.023 | 3.161 | 100 | 206 | 1.265 | 2.953 |
| 92 | 325 | 1.016 | 4.016 | 97 | 325 | 1.488 | 2.48 | 100 | 208 | 1.609 | 3.859 |
| 92 | 327 | 2.296 | 5.124 | 97 | 327 | 1.776 | 4.794 | 100 | 209 | 1.719 | 5.922 |
| 92 | 402 | 1.328 | 3.047 | 97 | 402 | 4.143 | 5.149 | 100 | 220 | 1.766 | 3.656 |
| 92 | 403 | 0.797 | 2.984 | 97 | 404 | 2.15 | 3.793 | 100 | 221 | 1.281 | 2.515 |
| 92 | 406 | 0.937 | 2.406 | 97 | 406 | 2.137 | 3.562 | 100 | 230 | 1.25 | 2.593 |
| 93 | 61 | 2.281 | 4.015 | 98 | 61 | 2.593 | 5.281 | 100 | 411 | 1.375 | 5.109 |
| 93 | 88 | 2.703 | 4.547 | 98 | 88 | 3.735 | 5.594 | 101 | 6 | 1.611 | 2.477 |
| 93 | 96 | 3.532 | 5.125 | 98 | 96 | 2.25 | 5.422 | 101 | 15 | 1.215 | 2.021 |
| 93 | 102 | 4.985 | 7.203 | 98 | 102 | 7.281 | 11.156 | 101 | 19 | 0.957 | 1.838 |
| 93 | 104 | 2.812 | 4.89 | 98 | 104 | 2 | 3.422 | 101 | 26 | 1.041 | 1.802 |
| 93 | 109 | 2.25 | 4.141 | 98 | 227 | 4.171 | 7.765 | 101 | 57 | 2.48 | 4.177 |
| 93 | 201 | 2.157 | 4.031 | 98 | 309 | 4.219 | 7.375 | 101 | 68 | 1.378 | 3.118 |
| 93 | 227 | 2.015 | 4.359 | 98 | 312 | 1.813 | 3.407 | 101 | 77 | 1.763 | 3.237 |
| 93 | 309 | 3.328 | 5.125 | 98 | 313 | 3.766 | 6.094 | 101 | 82 | 1.16 | 2.349 |
| 93 | 312 | 1.391 | 4.531 | 98 | 325 | 1.969 | 4.016 | 101 | 209 | 1.653 | 3.988 |
| 93 | 324 | 1.734 | 3.781 | 98 | 327 | 4.25 | 6.735 | 101 | 306 | 1.32 | 2.422 |
| 93 | 325 | 2.187 | 3.781 | 98 | 402 | 6.531 | 8.765 | 102 | 15 | 0.875 | 1.86 |
| 93 | 327 | 2.89 | 6.546 | 98 | 403 | 1.594 | 3.25 | 102 | 34 | 2.079 | 3.094 |
| 93 | 402 | 6.891 | 8.75 | 98 | 404 | 1.266 | 2.547 | 102 | 46 | 1.063 | 2.766 |
| 93 | 403 | 2.219 | 4.094 | 99 | 88 | 5.484 | 7.109 | 102 | 47 | 1.219 | 5.625 |
| 93 | 406 | 3.672 | 5.531 | 99 | 109 | 6.746 | 8.202 | 102 | 48 | 1.094 | 2.36 |
| 94 | 61 | 0.773 | 1.485 | 99 | 201 | 1.785 | 3.089 | 102 | 57 | 3.985 | 5.782 |
| 94 | 88 | 0.765 | 1.859 | 99 | 227 | 2.531 | 3.843 | 102 | 63 | 0.843 | 2.156 |
| 94 | 96 | 1.328 | 2.953 | 99 | 312 | 1.987 | 3.104 | 102 | 64 | 1.797 | 3.141 |
| 94 | 102 | 2.469 | 3.641 | 99 | 324 | 1.453 | 2.828 | 102 | 67 | 0.906 | 1.953 |
| 94 | 104 | 1.299 | 2.382 | 99 | 325 | 3.072 | 4.174 | 102 | 68 | 1.422 | 2.5 |
| 94 | 109 | 1.037 | 2.476 | 99 | 402 | 3.921 | 5.327 | 102 | 80 | 0.781 | 2.203 |
| 94 | 227 | 0.922 | 1.813 | 99 | 403 | 1.549 | 3.741 | 102 | 82 | 1.281 | 2.953 |
| 94 | 309 | 0.891 | 1.735 | 9001 | 61 | 1.656 | 3.062 | 102 | 97 | 1.047 | 2.828 |
| 94 | 312 | 0.887 | 1.744 | 9001 | 88 | 2.203 | 5.797 | 102 | 111 | 1.234 | 3.218 |
| 94 | 313 | 1.735 | 3.047 | 9001 | 96 | 1.562 | 6.015 | 102 | 206 | 0.765 | 2.39 |
| 94 | 324 | 0.906 | 1.547 | 9001 | 102 | 9.016 | 10.906 | 102 | 208 | 0.766 | 1.922 |
| 94 | 325 | 0.851 | 1.485 | 9001 | 104 | 1.89 | 3.718 | 102 | 209 | 1.5 | 2.766 |
| 94 | 327 | 2.188 | 3.266 | 9001 | 109 | 3.5 | 4.828 | 102 | 220 | 1.578 | 4.156 |
| 94 | 402 | 1.531 | 2.656 | 9001 | 201 | 1.813 | 4 | 102 | 221 | 1.063 | 6.094 |
| 94 | 403 | 1.238 | 2.939 | 9001 | 227 | 1.328 | 5.359 | 102 | 306 | 1.359 | 3.859 |
| 94 | 406 | 1.609 | 3.435 | 9001 | 309 | 1.125 | 4.203 | 103 | 6 | 1.687 | 5.141 |
| 95 | 88 | 1.272 | 2.758 | 9001 | 312 | 1.359 | 2.953 | 103 | 15 | 1.547 | 4.344 |
| 95 | 96 | 2.014 | 3.424 | 9001 | 324 | 1.469 | 3.313 | 103 | 19 | 2.25 | 7.313 |
| 95 | 104 | 1.999 | 3.167 | 9001 | 325 | 1.437 | 3.281 | 103 | 26 | 1.438 | 2.938 |
| 95 | 109 | 1.951 | 3.846 | 9001 | 403 | 2.047 | 4.172 | 103 | 68 | 2.172 | 5.563 |
| 95 | 201 | 1.921 | 4.32 | 9001 | 406 | 1.187 | 2.656 | 103 | 77 | 1.625 | 3.172 |
| 95 | 227 | 2.633 | 3.966 | 9002 | 61 | 4.156 | 5.969 | 103 | 82 | 2.703 | 3.968 |
| 95 | 309 | 1.623 | 5.576 | 9002 | 88 | 2.203 | 6.656 | 103 | 306 | 1.953 | 5.797 |
| 95 | 324 | 3.283 | 4.363 | 9002 | 96 | 4.985 | 7.172 | 104 | 6 | 1.796 | 2.89 |
| 95 | 325 | 0.922 | 3.305 | 9002 | 102 | 2.859 | 9.172 | 104 | 15 | 1.094 | 2.313 |
| 95 | 327 | 1.828 | 2.835 | 9002 | 104 | 1.375 | 4.141 | 104 | 19 | 4.843 | 5.875 |
| 95 | 404 | 1.245 | 2.624 | 9002 | 109 | 1.234 | 3.468 | 104 | 26 | 1.771 | 2.828 |
| 96 | 61 | 1.454 | 3.171 | 9002 | 227 | 2.172 | 3.828 | 104 | 57 | 1.484 | 2.937 |
| 96 | 88 | 1.437 | 2.875 | 9002 | 309 | 1.531 | 8.312 | 104 | 68 | 2.938 | 3.922 |
| 96 | 96 | 1.937 | 5.265 | 9002 | 312 | 1.938 | 6.469 | 104 | 77 | 1.375 | 2.859 |
| 96 | 102 | 1.766 | 4.75 | 9002 | 313 | 5.562 | 7.468 | 104 | 82 | 1.437 | 2.578 |
| 96 | 104 | 6.992 | 8.538 | 9002 | 324 | 1.703 | 4.218 | 104 | 209 | 2.797 | 4.156 |
| 96 | 109 | 1.671 | 4.161 | 9002 | 325 | 1.766 | 4.797 | 104 | 306 | 1.094 | 2.719 |
| 96 | 227 | 1.5 | 5.219 | 9002 | 327 | 3.172 | 7.297 | 105 | 6 | 1.937 | 8.906 |
| 96 | 309 | 1.359 | 3.171 | 9002 | 402 | 6.109 | 7.703 | 105 | 15 | 1 | 2.641 |
| 96 | 312 | 1.448 | 3.736 | 9002 | 406 | 4.218 | 8.859 | 105 | 19 | 1.047 | 2.422 |
| 96 | 313 | 2.359 | 4.218 |  |  |  |  | 105 | 26 | 0.922 | 6.094 |
| 96 | 324 | 1.169 | 2.628 | Group 10, image complexity 1: |  |  |  | 105 | 57 | 1.157 | 3.235 |
| 96 | 325 | 1.377 | 3.604 |  |  |  |  | 105 | 68 | 0.969 | 4.25 |
| 96 | 327 | 1.5 | 5.437 |  |  |  |  | 105 | 77 | 1.938 | 3.891 |
| 96 | 402 | 2.187 | 5.875 | S \# | I \# | T2mark | T2next | 105 | 82 | 1.031 | 5.156 |
| 96 | 403 | 1.516 | 4.068 | 100 | 15 | 2.047 | 4.125 | 105 | 209 | 1 | 3.266 |
| 96 | 406 | 2.278 | 3.904 | 100 | 34 | 0.954 | 2.532 | 106 | 15 | 1.798 | 5.815 |
| 97 | 61 | 1.362 | 2.586 | 100 | 46 | 1.968 | 3.921 | 106 | 26 | 1.221 | 2.769 |
| 97 | 88 | 8.67 | 10.712 | 100 | 47 | 1.437 | 2.593 | 106 | 34 | 0.953 | 3.626 |
| 97 | 96 | 3.106 | 4.621 | 100 | 48 | 0.922 | 2.156 | 106 | 46 | 2.511 | 4.814 |
| 97 | 102 | 3.307 | 5.771 | 100 | 57 | 3.89 | 5.718 | 106 | 47 | 1.183 | 3.38 |
| 97 | 104 | 6.87 | 8.704 | 100 | 63 | 1.25 | 2.906 | 106 | 48 | 1.845 | 2.917 |
| 97 | 109 | 2.923 | 5.432 | 100 | 64 | 1.469 | 2.656 | 106 | 57 | 2.14 | 3.323 |
| 97 | 227 | 2.188 | 3.703 | 100 | 68 | 1.609 | 4.078 | 106 | 63 | 1.812 | 2.83 |
| 97 | 309 | 2.16 | 4.439 | 100 | 80 | 1.093 | 2.515 | 106 | 64 | 4.621 | 5.862 |
| 97 | 312 | 1.669 | 2.751 | 100 | 82 | 1.734 | 4.891 | 106 | 67 | 1.519 | 3.603 |


| 106 | 68 | 1.197 | 1.991 | 101 | 41 | 1.991 | 2.812 | 105 | 83 | 0.719 | 1.781 |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| 106 | 77 | 1.798 | 3.826 | 101 | 42 | 1.322 | 2.036 | 105 | 87 | 1.25 | 2.75 |
| 106 | 206 | 1.426 | 2.822 | 101 | 62 | 1.944 | 4.496 | 105 | 95 | 1.312 | 3.734 |
| 106 | 208 | 1.282 | 2.674 | 101 | 69 | 0.912 | 1.611 | 105 | 204 | 2.938 | 4.86 |
| 106 | 209 | 1.123 | 2.261 | 101 | 72 | 0.972 | 3.617 | 105 | 207 | 2.125 | 3.453 |
| 106 | 221 | 1.419 | 3.288 | 101 | 83 | 1.103 | 1.724 | 105 | 210 | 1.312 | 5.875 |
| 106 | 411 | 1.901 | 4.102 | 101 | 87 | 1.127 | 2.286 | 105 | 217 | 5.141 | 6.922 |
| 107 | 26 | 1.203 | 3.047 | 101 | 92 | 6.607 | 7.987 | 105 | 223 | 1.453 | 3.156 |
| 107 | 57 | 1.25 | 4.938 | 101 | 95 | 1.228 | 2.004 | 105 | 224 | 1.546 | 5.984 |
| 107 | 68 | 1.5 | 5.312 | 101 | 105 | 5.226 | 6.854 | 105 | 308 | 5.671 | 10.296 |
| 107 | 82 | 2.703 | 4.593 | 101 | 204 | 1.74 | 4.467 | 105 | 310 | 2.266 | 3.891 |
| 107 | 209 | 1.687 | 4.078 | 101 | 207 | 1.43 | 2.098 | 105 | 320 | 6.078 | 7.484 |
| 107 | 306 | 1.812 | 4.781 | 101 | 210 | 1.175 | 2.335 | 105 | 322 | 1.282 | 5.469 |
| 108 | 15 | 1.5 | 3.485 | 101 | 223 | 1.261 | 2.522 | 105 | 401 | 3.859 | 6.219 |
| 108 | 34 | 1.125 | 1.922 | 101 | 224 | 1.189 | 2.224 | 106 | 16 | 2.186 | 4.177 |
| 108 | 47 | 3.031 | 4.859 | 102 | 33 | 1.25 | 2.516 | 106 | 33 | 1.787 | 2.756 |
| 108 | 54 | 1.625 | 2.39 | 102 | 69 | 1.125 | 2.484 | 106 | 41 | 1.706 | 2.827 |
| 108 | 57 | 2.438 | 5 | 102 | 72 | 2.219 | 3.984 | 106 | 42 | 1.768 | 4.063 |
| 108 | 63 | 1.797 | 3.5 | 102 | 83 | 2.578 | 3.875 | 106 | 62 | 1.647 | 2.56 |
| 108 | 64 | 1.672 | 3.672 | 102 | 87 | 1.14 | 2.953 | 106 | 65 | 1.613 | 6.311 |
| 108 | 68 | 1.437 | 4.703 | 102 | 95 | 1.422 | 2.579 | 106 | 69 | 1.429 | 2.75 |
| 108 | 206 | 1.578 | 3.89 | 102 | 105 | 1.625 | 2.812 | 106 | 72 | 2.781 | 4.364 |
| 108 | 208 | 1.172 | 2.031 | 102 | 204 | 1.609 | 3.218 | 106 | 83 | 1.324 | 2.115 |
| 108 | 411 | 2.094 | 4.016 | 102 | 217 | 1.578 | 3.594 | 106 | 87 | 1.76 | 2.524 |
| 109 | 6 | 1.016 | 2.172 | 102 | 223 | 4.063 | 5.688 | 106 | 204 | 3.009 | 3.892 |
| 109 | 15 | 0.781 | 1.813 | 102 | 231 | 3.359 | 5.516 | 106 | 207 | 2.674 | 5.512 |
| 109 | 19 | 1.188 | 2.219 | 102 | 303 | 1.735 | 3.156 | 106 | 219 | 1.474 | 2.754 |
| 109 | 26 | 0.86 | 1.735 | 102 | 304 | 0.984 | 4.874 | 106 | 223 | 1.121 | 1.843 |
| 109 | 57 | 1.047 | 3.203 | 102 | 308 | 4.062 | 5.656 | 106 | 231 | 1.97 | 4.357 |
| 109 | 68 | 1.141 | 2.266 | 102 | 310 | 1.062 | 2.484 | 106 | 303 | 1.429 | 2.243 |
| 109 | 77 | 1.172 | 2.781 | 103 | 14 | 2.313 | 4.875 | 106 | 310 | 2.879 | 3.684 |
| 109 | 82 | 1.125 | 1.922 | 103 | 16 | 4.797 | 8.453 | 106 | 319 | 4.717 | 5.55 |
| 109 | 306 | 1.312 | 2.281 | 103 | 27 | 1.704 | 4.297 | 106 | 320 | 3.994 | 5.392 |
| 110 | 6 | 1.297 | 3.797 | 103 | 33 | 2.937 | 4.125 | 106 | 322 | 1.515 | 4.407 |
| 110 | 15 | 1.047 | 2.672 | 103 | 42 | 2.75 | 6.468 | 107 | 14 | 1.578 | 3.89 |
| 110 | 19 | 1.281 | 3.687 | 103 | 62 | 4.734 | 11.391 | 107 | 16 | 5.093 | 8.578 |
| 110 | 26 | 1.265 | 3.078 | 103 | 69 | 2.203 | 4.719 | 107 | 27 | 1.204 | 4.422 |
| 110 | 57 | 1.703 | 4.125 | 103 | 83 | 1.484 | 3.312 | 107 | 33 | 1.125 | 2.797 |
| 110 | 68 | 1.063 | 4.266 | 103 | 92 | 5.985 | 9.516 | 107 | 41 | 2.5 | 4.171 |
| 110 | 77 | 1.485 | 3.391 | 103 | 95 | 4.062 | 5.687 | 107 | 42 | 1.781 | 2.797 |
| 110 | 82 | 2.5 | 4.906 | 103 | 204 | 5.141 | 14.953 | 107 | 72 | 1.219 | 3.078 |
| 110 | 209 | 1.391 | 3.391 | 103 | 207 | 2.172 | 3.437 | 107 | 83 | 0.984 | 1.859 |
| 110 | 306 | 4.266 | 7.469 | 103 | 210 | 1.657 | 5.75 | 107 | 87 | 0.813 | 1.579 |
| 111 | 15 | 7.186 | 9.812 | 103 | 217 | 2.86 | 4.61 | 107 | 92 | 3.344 | 5.953 |
| 111 | 46 | 3.577 | 5.344 | 103 | 223 | 2.063 | 3.438 | 107 | 95 | 1.109 | 3.171 |
| 111 | 48 | 1.383 | 2.588 | 103 | 224 | 3.968 | 5.375 | 107 | 207 | 1.14 | 2.156 |
| 111 | 68 | 2.042 | 3.609 | 103 | 308 | 5.672 | 9.782 | 107 | 210 | 1.187 | 3.422 |
| 111 | 77 | 1.783 | 3.767 | 103 | 310 | 4.5 | 5.766 | 107 | 223 | 2.25 | 3.36 |
| 111 | 80 | 1.055 | 2.41 | 104 | 14 | 1.219 | 2.781 | 107 | 224 | 1.188 | 2.141 |
| 111 | 82 | 1.797 | 3.133 | 104 | 16 | 2.938 | 4.188 | 107 | 308 | 3.469 | 6 |
| 111 | 97 | 2.15 | 4.131 | 104 | 27 | 2.204 | 3.891 | 107 | 310 | 1.141 | 2.578 |
| 111 | 208 | 1.029 | 2.504 | 104 | 33 | 1.187 | 2.094 | 107 | 320 | 1.828 | 3.687 |
| $\begin{aligned} & 111 \\ & 111 \end{aligned}$ | 209 | 2.411 | 4.0392.639 | 104 | 42 | 1.531 | 2.828 | 107 | 401 | 3.781 | 5.094 |
|  | 211 | 1.193 |  | $\begin{aligned} & 104 \\ & 104 \end{aligned}$ | 62 | 1.703 | 3.156 | 108 | 14 | 3.609 | 5.515 |
| Group 10, image complexity 2 : |  |  |  |  | 69 | 1.297 | 2.484 | 108 | 92 | 1.718 | 6.218 |
|  |  |  |  | $\begin{aligned} & 104 \\ & 104 \\ & 104 \end{aligned}$ | 72 | 1.875 | 2.922 | 108 | 95 | 1.078 | 2.093 |
|  |  |  |  | 83 | 2.952 | 4.568 | 108 | 204 | 3 | 3.875 |
|  |  |  |  | 92 | 2.157 | 4.094 | 108 | 207 | 1.703 | 3.593 |
| S \# | I \# | T2mark | T2next |  | 104 | 95 | 1.849 | 2.781 | 108 | 223 | 1.656 | 3.609 |
| 100 | 27 | 1.563 | 2.969 |  | 104 | 204 | 2.063 | 4.032 | 108 | 224 | 3.297 | 4.047 |
| 100 | 33 | 1.734 | 4.875 | $104$ | 207 | 1.29 | 2.455 | 108 | 401 | 4.25 | 6.016 |
| 100 | 41 | 1.156 | 2.578 | 104 | 210 | 1.438 | 3.86 | 109 | 27 | 1.359 | 2.219 |
| 100 | 69 | 1.156 | 2.656 | 104 | 223 | 1.546 | 2.703 | 109 | 33 | 1.125 | 5.5 |
| 100 | 72 | 1.672 | 3.812 | 104 | 224 | 1.25 | 2.281 | 109 | 41 | 0.969 | 2.625 |
| 100 | 83 | 1.203 | 2.578 | 104 | 310 | 3.641 | 5.016 | 109 | 42 | 1.547 | 2.438 |
| 100 | 87 | 1.375 | 3.156 | $104$ | 322 | 1.249 | 2.718 | 109 | 62 | 1.125 | 3.75 |
| 100 | 105 | 1.187 | 3.047 | 105 | 14 | 1.578 | 9.031 | 109 | 72 | 2.359 | 3.281 |
| 100 | 204 | 1.532 | 4.407 | 105 | 16 | 2.688 | 10.656 | 109 | 83 | 1.906 | 2.734 |
| 100 | 217 | 3.109 | 4.812 |  | 27 | 1.219 | 4.985 | 109 | 87 | 0.907 | 1.86 |
| 100 | 223 | 1.594 | 3.016 | 105 | 33 | 0.906 | 2.5 | 109 | 92 | 1.64 | 2.968 |
| 100 | 310 | 1.313 | 2.766 | $105$ | 41 | 3.125 | 4.296 | 109 | 95 | 1.016 | 2.219 |
| 101 | 14 | 1.992 | 3.151 | 105 | 42 | 1.156 | 2.734 | 109 | 204 | 1.532 | 2.703 |
| 101 | 16 | 4.961 | 7.485 | 105 | 62 | 2 | 6.141 | 109 | 207 | 1.218 | 2.093 |
| 101 | 27 | 1.334 | 2.741 | 105105 | 69 | 1.625 | 4.344 | 109 | 210 | 1.016 | 1.969 |
| 101 | 33 | 1.498 | 2.78 |  | 72 | 1.328 | 2.687 | 109 | 223 | 0.812 | 1.75 |



## תקציר

רובוטים אוטונומיים מוגבלים בבצועיהם כאשר הם פועלים בסביבות דינאמיות ובלתי מובנות. שילוב מפעיל אנושי במערכת רובוטית יכול לתרום לשיפור הביצועים ולהפחתת מורכבות המערכת. מערכות שיתוף פעולה בין אדם לרובוט מפיקות תועלת מיכולות התפיסה של האדם כמו גם מהדיוק והעקביות של הרובוט. ניתן ליישם שיתוף פעולה ברמות שונות הנבדלות בניהן ברמת האוטונומיה של הרובוט.

תיזה זו מתמקדת בהערכת מערכת זיהוי מטרות משולבת אדם-רובוט. ההערכה מתבססת על פיתוח קודם של פונקצית מטרה עבור משימת זיהוי מטרות (בכר, 2006). ארבע רמות שיתוף פעולה הוגזרו במיוחד עבור משימת זיהוי מטרות. פונקצית המטרה של המודל מכמתת את השפעת הפרמטרים השונים של הרובוט, האדם, הסביבה והמשימה באמצעות סכום משוקלל של מדדי ביצוע. המודל מאפשר לקבוע מהי רמת שיתוף הפעולה האופטימאלית בהינתן פרמטרים אלו. זמן התגובה של האדם הוא הזמן הדרוש לאדם כדי להחליט האם אובייקט הוא מטרה או לא. זמן התגובה משפיע על עלויות התפעול של המערכת. עבודה זו מציגה המשך פיתוח של פונקצית המטרה ולוקחת בחשבון שזמן התגובה תלוי בעוצמת האות של האובייקט הנבחן, זמן שאינו קבוע בין אובייקטים. במחקר זה, מודל זמן תגובה המבוסס על מודל של מורדוק (1985) משולב לתוך המודל של בכר (2006). המודל החדש צפוי לתאר מערכות אמיתיות בצורה טובה יותר על ידי התאמת הפרמטרים של פונקצית הזמן למשימה מוגדרת. מטרת המחקר היא להעריך את השפעת זמן התגובה של האדם על ביצועי המערכת. המחקר מתמקד בהשפעת זמן התגובה על רמת שיתוף הפעולה שמניבה את הביצועים המיטביים.

הניתוחים מגלים רמות שיתוף פעולה חדשות אשר מועדפות כאשר עלות זמן התגובה של האדם גבוהה. ברמות שיתוף פעולה אלה, האדם מתמקד בבחינת רק חלק מהאובייקטים ומתעלם מאחרים. כתוצאה מכך, עלות זמן התגובה של האדם יורד והמערכת מציגה ביצועים טובים יותר. האדם מתעלם מאובייקטים על ידי קביעת סף ההחלטה שלו לערך קיצוני. הניתוחים מראים כיצד סוג המערכת, רגישות האדם, ההסתברות של אובייקט להיות מטרה ועלות הזמן, משפיעים על

תופעת בחירת ערך סף קיצוני.

כאשר רגישות האדם נמוכה יכולת ההבחנה שלו בין מטרות לרעש יורדת. הניתוחים מראים, שכאשר המערכת נותנת עדיפות גבוהה למניעת התראות שווא, האדם בוחר ערך סף קיצוני חיובי, אשר גורם לכך שאף אובייקט לא מסומן כמטרה ולא מתרחשות התראות שווא. במערכת אשר נותנת עדיפות גבוהה לא להחטיא מטרות נבחר ערך סף קיצוּ מוני שלילי, אשר גורם לכך שכל האובייקטים מסומנים כמטרות ומכאן שכל המטרות מתגלות. תופעה זו מופיעה עבור רגישויות גבוהות יותר של האדם, ככל שעלות הזמן גדלה. בנוסף, ניתן לראות ששיתוף פעולה עם האדם נהפך פחות כדאי ככל שעלות הזמן גדלה. ערך סף קיצוני גורם לירידה בעלויות הזמן הכוללות. במודל זמן התגובה, זמן התגובה הממוצע יורד ככל שערך הסף מתרחק ממוצע התפלגות האובייקטים. לכן, מבחינת עלויות הזמן, ערך סף קיצוני יועדף תמיד. מיקום ערך הסף משפיע על
 מטרות ולהסתברויות גבוהות להחטאת מטרות ולדחייה נכונה של רעשים. הרווחים והקנסות הכוללים של מקרים אלו

משתנים בהתאם.

מילות מפתח: שיתוף פעולה אדם-רובוט, רמות שיתוף פעולה, זיהוי מטרות, זמן תגובה.

# הששפעת זמן התגובה של האדם על רחת שיתוף הפעולה האופטימאלית במע:רכת זיהוי מטרות רובוטית משולבת אדם 

חיבור זה מהווה חלק מהזרישות לקבלת התואר "מגיסטר" בהנדסה

## דרור ישפה

מנחים: פרופ' יעל אידן, ד"ר אביטל בכר


[^0]:    ${ }^{1}$ Response Time, Response Latency and Decision Time, refer to the common term Reaction Time, which is used to describe the time it takes the observers to decide about an observed object.

[^1]:    ${ }^{2}$ The 'extremes' in this data set are -3 and 6. Explanation is detailed in chapter 6 .

