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 "real-world" 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 (R) and manual (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 non-constant 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)

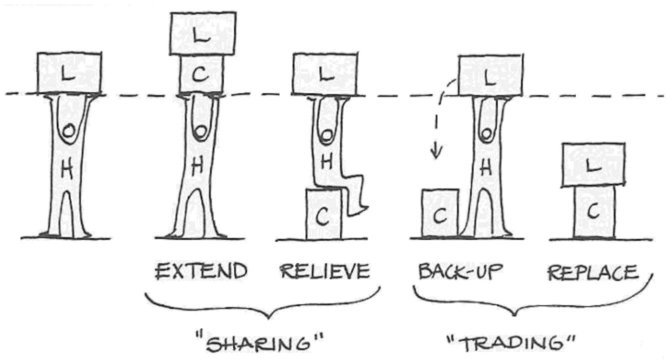

Figure 1: The notions of trading and sharing control between human and computer.
L is the load or task, H is the human, and C is the computer (Sheridan, 1992)

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).

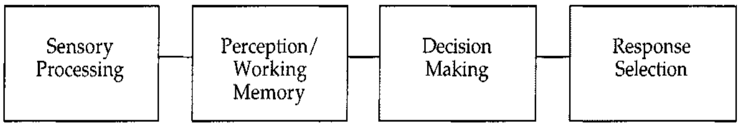

Figure 2: Simple four-stage model of human information processing (Parasuraman et al., 2000)

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 decision-making, that will be introduced later, can be applied, with some modifications, also to the other dimensions.

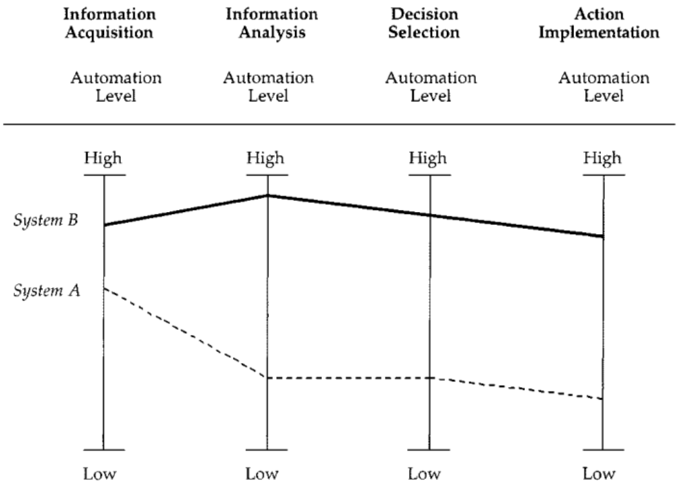

Figure 3: Levels of automation for independent functions of: information acquisition, information analysis, decision selection, and action implementation (Parasuraman et al., 2000)

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 human-robot 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.

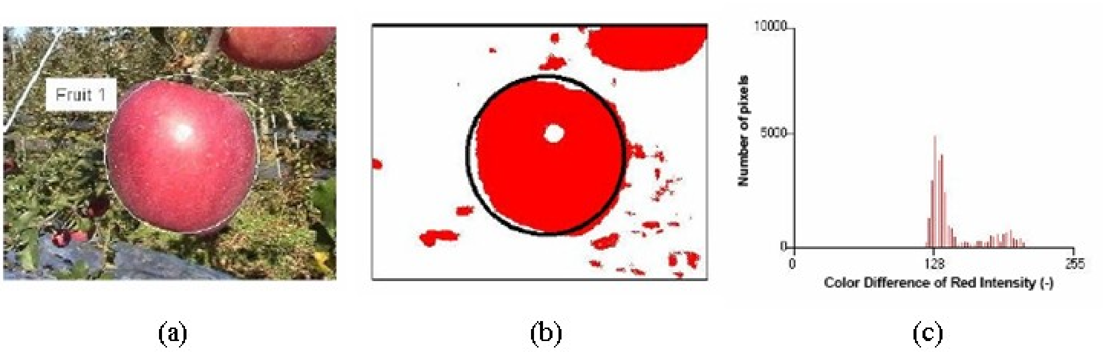

Figure 4: Vision analysis for apple fruit detection (Bulanon et al, 2001)
(a) CCD image, (b) segmentation of color difference of red, (c) color difference of red histogram

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:

$$V_{Is} = V_{Hs} + V_{Ms} + V_{FAs} + V_{CRs} + V_{Ts}$$

Where V_{Hs} is the gain for target detections (hit), V_{FAs} is the penalty for false alarms (FA), V_{Ms} is the system penalty for missing targets (miss), V_{CRs} is the gain for correct rejections (CR), and V_{Ts} 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:

$$V_{Hs} = N \cdot P_S \cdot P_{Hs} \cdot V_H$$

$$V_{Ms} = N \cdot P_S \cdot P_{Ms} \cdot V_M$$

$$V_{FAs} = N \cdot (1 - P_S) \cdot P_{FAs} \cdot V_{FA}$$

$$V_{CRs} = N \cdot (1 - P_S) \cdot P_{CRs} \cdot V_{CR}$$

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_{Xs}, is the system probability for one of the outcomes: hit, miss, false alarm or correct rejection (X can be H, M, FA, CR). 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:

$$P_{Hs} = P_{Hr} \cdot P_{Hrh} + (1 - P_{Hr}) \cdot P_{Hh}$$

$$P_{Ms} = P_{Mr} \cdot P_{Mh} + (1 - P_{Mr}) \cdot P_{Mrh}$$

$$P_{FAs} = P_{FAr} \cdot P_{FArh} + (1 - P_{FAr}) \cdot P_{FAh}$$

$$P_{CRs} = P_{CRr} \cdot P_{CRh} + (1 - P_{CRr}) \cdot P_{CRrh}$$

Where,

(1) P_{Hr} is the robot probability of a hit,

(2) P_{Hrh} is the human probability of confirming a robot hit,

(3) P_{Hh} is the human probability of detecting a target that the robot did not detect,

(4) P_{Mr} is the robot miss probability,

(5) P_{Mrh} is the human probability of un-confirming a robot hit,

(6) P_{Mh} is the human probability of missing a target the robot missed,

(7) P_{FAr} is the robot false alarm probability,

(8) P_{FArh} is the human probability of not correcting a robot false alarm,

(9) P_{FAh} is the human probability of a false alarm on targets the robot correctly rejected,

(10) P_{CRr} is the robot probability of a correct rejection,

(11) P_{CRrh} is the human probability of correcting a robot false alarm, and

(12) P_{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:

$$V_{Ts} = t_S \cdot V_t + [N \cdot P_S \cdot P_{Hs} + N \cdot (1 - P_S) \cdot P_{FAs}] \cdot V_C$$

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.

$$
\begin{aligned}
t_S &= N \cdot P_S \cdot P_{Hr} \cdot P_{Hrh} \cdot t_{Hrh} + N \cdot P_S \cdot (1-P_{Hr}) \cdot P_{Hh} \cdot t_{Hh} + \\
&+ N \cdot P_S \cdot P_{Hr} \cdot (1-P_{Hrh}) \cdot t_{Mrh} + N \cdot P_S \cdot (1-P_{Hr}) \cdot (1-P_{Hh}) \cdot t_{Mh} + \\
&+ N \cdot (1-P_S) \cdot P_{FAr} \cdot P_{FArh} \cdot t_{FArh} + N \cdot (1-P_S) \cdot (1-P_{FAr}) \cdot P_{FAh} \cdot t_{FAh} + \\
&+ N \cdot (1-P_S) \cdot P_{FAr} \cdot (1-P_{FArh}) \cdot t_{CRrh} + N \cdot (1-P_S) \cdot (1-P_{FAr}) \cdot (1-P_{FAh}) \cdot t_{CRh} + N \cdot t_r
\end{aligned}
$$

Where,

(1) t_{Hrh} is the human time required to confirm a robot hit,

(2) t_{Hh} is the human time required to hit a target that the robot did not hit,

(3) t_{Mrh} is the human time lost when a robot hit is missed,

(4) t_{Mh} is the human time invested when missing a target that the robot did not hit,

(5) t_{FArh} is the human time needed not to correct a robot false alarm,

(6) t_{FAh} is the human false alarm time,

(7) t_{CRrh} is the human time to correctly reject a robot false alarm,

(8) t_{CRh} is the human correct rejection time, and (9) t_r is the robot operation time.

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

$$
\begin{aligned}
V_{Is} &= N \cdot P_S \cdot [P_{Hr} \cdot P_{Hrh} \cdot (V_H + V_C + t_{Hrh} \cdot V_t) + (1-P_{Hr}) \cdot P_{Hh} \cdot (V_H + V_C + t_{Hh} \cdot V_t)] + \\
&+ N \cdot P_S \cdot [P_{Hr} \cdot (1-P_{Hrh}) \cdot (V_M + t_{Mrh} \cdot V_t) + (1-P_{Hr}) \cdot (1-P_{Hh}) \cdot (V_M + t_{Mh} \cdot V_t)] + \\
&+ N \cdot (1-P_S) \cdot [P_{FAr} \cdot P_{FArh} \cdot (V_{FA} + V_C + t_{FArh} \cdot V_t) + (1-P_{FAr}) \cdot P_{FAh} \cdot (V_{FA} + V_C + t_{FAh} \cdot V_t)] + \\
&+ N \cdot (1-P_S) \cdot [P_{FAr} \cdot (1-P_{FArh}) \cdot (V_{CR} + t_{CRrh} \cdot V_t) + (1-P_{FAr}) \cdot (1-P_{FAh}) \cdot (V_{CR} + t_{CRh} \cdot V_t)] + N \cdot t_r \cdot V_t
\end{aligned}
$$

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:

$$
\begin{aligned}
V_{Is} &= N \cdot P_S \cdot [P_{Hh} \cdot (V_H + V_C + t_{Hh} \cdot V_t) + (1-P_{Hh}) \cdot (V_M + t_{Mh} \cdot V_t)] + \\
&+ N \cdot (1-P_S) \cdot [P_{FAh} \cdot (V_{FA} + V_C + t_{FAh} \cdot V_t) + (1-P_{FAh}) \cdot (V_{CR} + t_{CRh} \cdot V_t)]
\end{aligned}
$$

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:

$$
\begin{aligned}
V_{Is} &= N \cdot P_S \cdot [P_{Hr} \cdot (V_H + V_C) + (1-P_{Hr}) \cdot V_M] + \\
&+ N \cdot (1-P_S) \cdot [P_{FAr} \cdot (V_{FA} + V_C) + (1-P_{FAr}) \cdot V_{CR}] + N \cdot t_r \cdot V_t
\end{aligned}
$$

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 (CP, TP, TT)	False Alarm (IP, TN, FT)
	Noise	Miss (IN, FN, FF)	Correct Rejection (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 (N) and one of signal-plus-noise (S+N), represent the probability of such a stimulus to be a signal (Bechar, 2006).

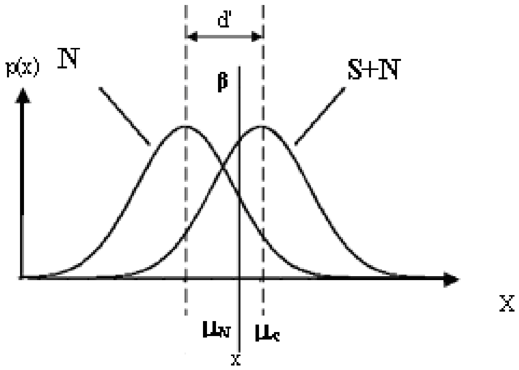

Figure 6: An example of binary decision analyzed with SDT (Bechar, 2006)

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).

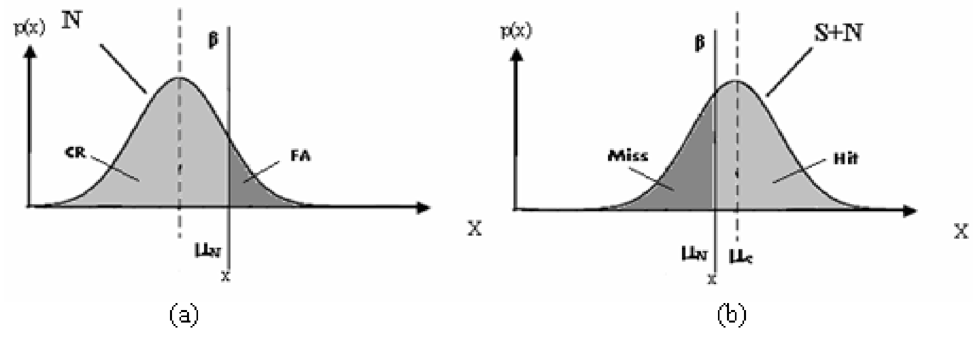

Figure 7: Outcomes probabilities when a signal is absent (a) or is present (b)

The distance between the means of the two distributions (denoted as d' 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 $d'=0$, the two distributions completely overlap and it is impossible to distinguish between them. As d' 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.

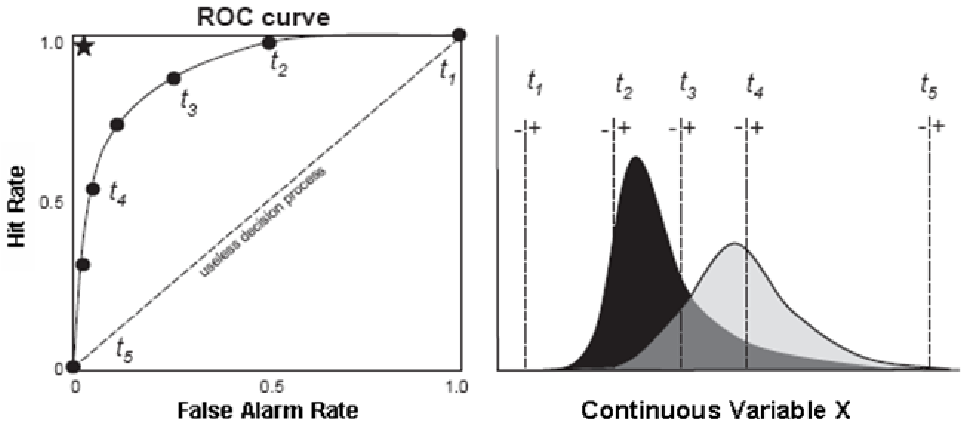

Figure 8: Generation of the ROC curve by evaluating hit and false alarm rates at various decision thresholds on x (Brown & Davis, 2006)

The curve always passes through points (1,1) and (0,0). When the criterion is positioned at 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 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 β 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 $d' \rightarrow \infty$

(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 β. 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 S+N are shown in the left graph (Figure 9). The right distribution of signal-plus-noise can be moved horizontally by dragging d'. Likewise, the criterion value can be modified. The right graph is the ROC curve which is generated automatically corresponding to chosen d' 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.

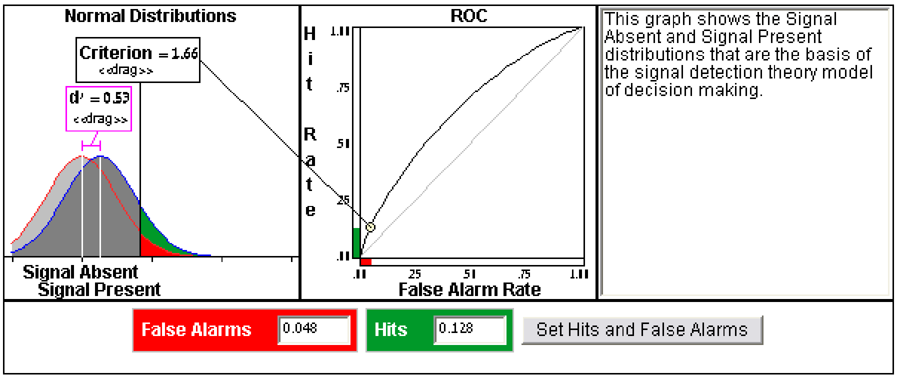

Figure 9: An example of ROC curve applet (http://wise.cgu.edu)

As shown in Figure 9 one distribution is almost totally overlapping the other. Compatibly, d' 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.

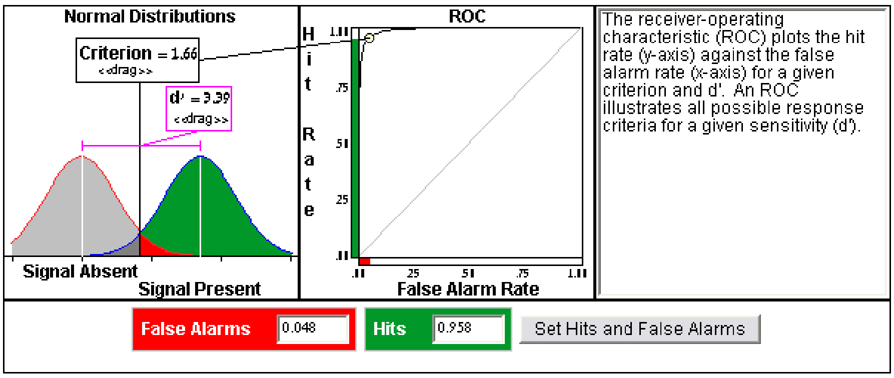

Figure 10: An example of high sensitivity of the observer (http://wise.cgu.edu)

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.

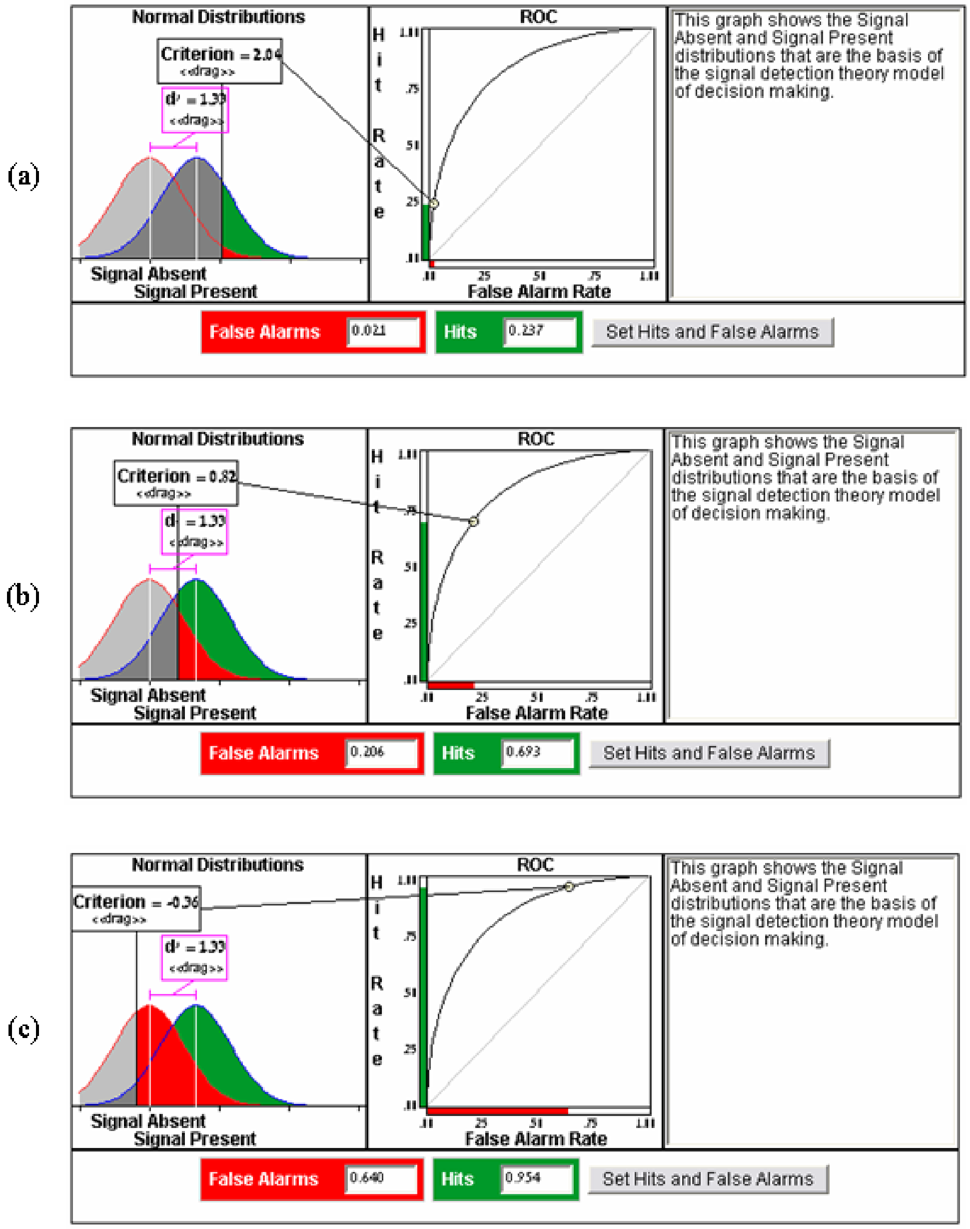

Figure 11: Different criterion values on the same ROC curve (http://wise.cgu.edu): 2.04 (a), 0.82 (b), -0.36 (c).

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.

[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.

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).

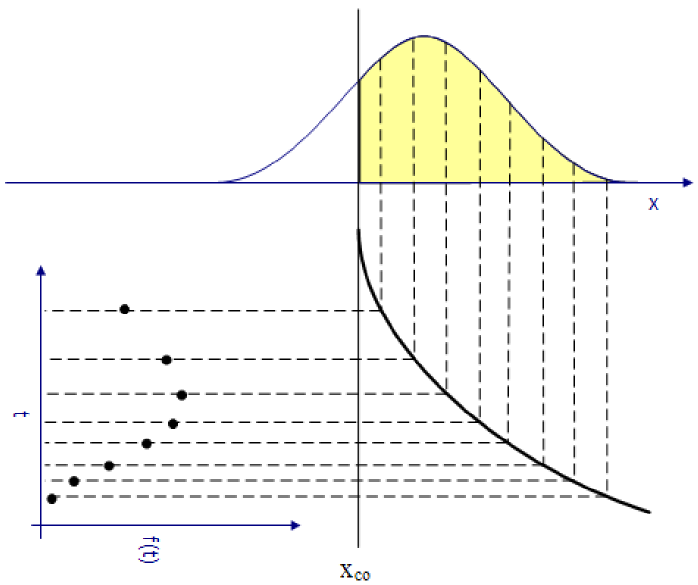

Figure 12: Signal (x) is normally distributed with criterion Xco. Exponential transfer function maps signal strength into latency (t), and the resulting latency distribution f(t) is shown by the dots (Murdock, 1985).

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™, 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 in-depth 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.

$$z_S = \frac{x_{co} - \mu_S}{\sigma_S} \qquad ; \qquad z_N = \frac{x_{co} - \mu_N}{\sigma_N}$$

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, β, between the signal and noise density functions in the cutoff point, x_{co}, and the distance between the means of the signal and noise distributions, d'. 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_{co} 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 x-value of all negative responses is denoted as μ_-, and the mean x-value of all positive responses is denoted as μ_+.

Suppose X is normally distributed with a mean of μ and a variance of σ^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_{co}.

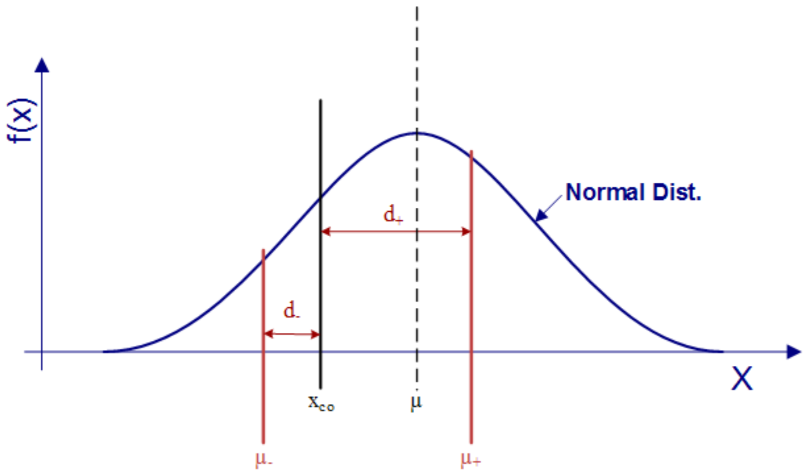

Figure 13: Mean x-values and distances in normal distribution

The mean x-value equations for negative (μ_-) and positive (μ_+) responses are:

$$\mu_-(x_{co}) = \frac{\int_{-\infty}^{x_{co}} x \cdot f(x)dx}{\int_{-\infty}^{x_{co}} f(x)dx} = \ldots = \mu - \sigma \cdot \frac{\varphi(z_{co})}{\Phi(z_{co})}$$

$$\mu_+(x_{co}) = \frac{\int_{x_{co}}^{\infty} x \cdot f(x)dx}{\int_{x_{co}}^{\infty} f(x)dx} = \ldots = \mu + \sigma \cdot \frac{\varphi(z_{co})}{1-\Phi(z_{co})}$$

where

$$f(x) = \frac{1}{\sigma\sqrt{2\pi}} e^{\frac{-(x-\mu)^2}{2\sigma^2}} \quad ; \quad z_{co} = \frac{x_{co}-\mu}{\sigma}$$

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

From the equations, it is obvious that μ_- is lower and μ_+ is higher than the mean of the distribution μ, 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 $|x_{co} - x|$. 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, $\mu_- \le x_{co} \le \mu_+$. 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: $d_-(x_{co}) = x_{co} - \mu_-$, $d_+(x_{co}) = \mu_+ - x_{co}$

The mean distance equations for negative and positive responses are:

$$d_-(x_{co}) = x_{co} - \mu_- = x_{co} - (\mu - \sigma \cdot \frac{\varphi(z_{co})}{\Phi(z_{co})}) = (x_{co} - \mu) + \sigma \cdot \frac{\varphi(z_{co})}{\Phi(z_{co})}$$

$$d_+(x_{co}) = \mu_+ - x_{co} = (\mu + \sigma \cdot \frac{\varphi(z_{co})}{1 - \Phi(z_{co})}) - x_{co} = -(x_{co} - \mu) + \sigma \cdot \frac{\varphi(z_{co})}{1 - \Phi(z_{co})}$$

where

$$z_{co} = \frac{x_{co} - \mu}{\sigma}$$

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

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 σ.

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

$$d_-(x_{co}) / \sigma = \left((x_{co} - \mu) + \sigma \cdot \frac{\varphi(z_{co})}{\Phi(z_{co})} \right) / \sigma = (\frac{x_{co} - \mu}{\sigma}) + \frac{\varphi(z_{co})}{\Phi(z_{co})} = z_{co} + \frac{\varphi(z_{co})}{\Phi(z_{co})}$$

$$d_+(x_{co}) / \sigma = \left(-(x_{co} - \mu) + \sigma \cdot \frac{\varphi(z_{co})}{1 - \Phi(z_{co})} \right) / \sigma = -(\frac{x_{co} - \mu}{\sigma}) + \frac{\varphi(z_{co})}{1 - \Phi(z_{co})} = -z_{co} + \frac{\varphi(z_{co})}{1 - \Phi(z_{co})}$$

where

$$z_{co} = \frac{x_{co} - \mu}{\sigma}$$

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

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

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

$$\varphi(z) = \varphi(-z)$$
$$\Phi(z) = 1-\Phi(-z)$$
$$\Phi(-z) = 1-\Phi(z)$$

where

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

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:

$$d_{-}(x_{co})/\sigma = z_{co} + \frac{\varphi(z_{co})}{\Phi(z_{co})} = z_{co} + \Theta(z_{co})$$
$$d_{+}(x_{co})/\sigma = -z_S + \frac{\varphi(z_{co})}{1-\Phi(z_{co})} = -z_{co} + \Theta(-z_{co})$$

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.

$$\mu_{-}(x_{co}) = \frac{\int_{-\infty}^{x_{co}} x \cdot f(x)dx}{\int_{-\infty}^{x_{co}} f(x)dx} = \frac{\int_{-\infty}^{x_{co}} x \cdot \frac{1}{\sigma\sqrt{2\pi}} e^{\frac{-(x-\mu)^2}{2\sigma^2}} dx}{\int_{-\infty}^{x_{co}} \frac{1}{\sigma\sqrt{2\pi}} e^{\frac{-(x-\mu)^2}{2\sigma^2}} dx} =$$

Changing the domain of integration:

$$z = \frac{x-\mu}{\sigma} \Rightarrow x = \mu + \sigma z$$

$$\frac{dx}{dz} = \frac{d(\mu+\sigma z)}{dz} = \sigma \Rightarrow dx = \sigma dz$$

$$x = -\infty \Rightarrow z = \frac{-\infty - \mu}{\sigma} = -\infty$$

$$x = x_{co} \Rightarrow z = \frac{x_{co} - \mu}{\sigma} = z_{co}$$

$$= \frac{\int_{-\infty}^{z_{co}} (\mu+\sigma z) \cdot \frac{1}{\not\sigma\sqrt{2\pi}} e^{\frac{-z^2}{2}} \not\sigma dz}{\int_{-\infty}^{z_{co}} \frac{1}{\not\sigma\sqrt{2\pi}} e^{\frac{-z^2}{2}} \not\sigma dz} = \frac{\int_{-\infty}^{z_{co}} (\mu+\sigma z) \cdot \frac{1}{\sqrt{2\pi}} e^{\frac{-z^2}{2}} dz}{\int_{-\infty}^{z_{co}} \frac{1}{\sqrt{2\pi}} e^{\frac{-z^2}{2}} dz} =$$

$$= \frac{\int_{-\infty}^{z_{co}} \mu \frac{1}{\sqrt{2\pi}} e^{\frac{-z^2}{2}} dz + \int_{-\infty}^{z_{co}} \sigma z \cdot \frac{1}{\sqrt{2\pi}} e^{\frac{-z^2}{2}} dz}{\int_{-\infty}^{z_{co}} \frac{1}{\sqrt{2\pi}} e^{\frac{-z^2}{2}} dz} = \mu \cdot \frac{\int_{-\infty}^{z_{co}} \frac{1}{\sqrt{2\pi}} e^{\frac{-z^2}{2}} dz}{\int_{-\infty}^{z_{co}} \frac{1}{\sqrt{2\pi}} e^{\frac{-z^2}{2}} dz} + \sigma \cdot \frac{\int_{-\infty}^{z_{co}} z \cdot \frac{1}{\sqrt{2\pi}} e^{\frac{-z^2}{2}} dz}{\int_{-\infty}^{z_{co}} \frac{1}{\sqrt{2\pi}} e^{\frac{-z^2}{2}} dz} =$$

From the standard normal distribution:

$$\int_{-\infty}^{z_{co}} \frac{1}{\sqrt{2\pi}} e^{\frac{-z^2}{2}} dz = \Phi(z_{co})$$

$$= \mu \cdot \frac{\cancel{\Phi(z_{co})}}{\cancel{\Phi(z_{co})}} + \sigma \cdot \frac{\frac{1}{\sqrt{2\pi}} \int_{-\infty}^{z_{co}} z \cdot e^{\frac{-z^2}{2}} dz}{\Phi(z_{co})} =$$

Solving the integral:
$\int u^{n-1} \cdot e^{\frac{-u^n}{n}} du = -e^{\frac{-u^n}{n}}$
Confirmation by derivng the answer:
$\frac{\partial(-e^{\frac{-u^n}{n}})}{\partial u} = -e^{\frac{-u^n}{n}} \cdot \frac{-n \cdot u^{n-1}}{n} = u^{n-1} \cdot e^{\frac{-u^n}{u}}$

$$= \mu + \sigma \cdot \frac{\frac{1}{\sqrt{2\pi}} (-e^{\frac{-z^2}{2}}) \Big|_{-\infty}^{z_{co}}}{\Phi(z_{co})} = \mu + \sigma \cdot \frac{\frac{1}{\sqrt{2\pi}} \left[\left(-e^{\frac{-z_{co}^2}{2}} \right) - \left(-e^{\frac{-(-\infty)^2}{2}} \right) \right]}{\Phi(z_{co})} =$$

$$= \mu + \sigma \cdot \frac{\frac{1}{\sqrt{2\pi}} \left[\left(-e^{\frac{-z_{co}^2}{2}} \right) - (0) \right]}{\Phi(z_{co})} = \mu - \sigma \cdot \frac{\frac{1}{\sqrt{2\pi}} e^{\frac{-z_{co}^2}{2}}}{\Phi(z_{co})} =$$

From the standard normal distribution:
$\frac{1}{\sqrt{2\pi}} e^{\frac{-z^2}{2}} dz = \varphi(z)$

$$= \mu - \sigma \cdot \frac{\varphi(z_{co})}{\Phi(z_{co})}$$

$\mu_{-}(x_{co}) = \mu - \sigma \cdot \frac{\varphi(z_{co})}{\Phi(z_{co})}$
where
$z_{co} = \frac{x_{co} - \mu}{\sigma}$
$\varphi(z) = \frac{1}{\sqrt{2\pi}} \cdot e^{\frac{-z^2}{2}}$; $\Phi(z) = \frac{1}{\sqrt{2\pi}} \int_{-\infty}^{z} e^{\frac{-z^2}{2}} dz$

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.

$$\mu_+(x_{co}) = \frac{\int_{x_{co}}^{\infty} x \cdot f(x)dx}{\int_{x_{co}}^{\infty} f(x)dx} = \frac{\int_{x_{co}}^{\infty} x \cdot \frac{1}{\sigma\sqrt{2\pi}} e^{\frac{-(x-\mu)^2}{2\sigma^2}} dx}{\int_{x_{co}}^{\infty} \frac{1}{\sigma\sqrt{2\pi}} e^{\frac{-(x-\mu)^2}{2\sigma^2}} dx} =$$

Changing the domain of integration:

$$z = \frac{x-\mu}{\sigma} \Rightarrow x = \mu + \sigma z$$

$$\frac{dx}{dz} = \frac{d(\mu+\sigma z)}{dz} = \sigma \Rightarrow dx = \sigma dz$$

$$x = x_{co} \Rightarrow z = \frac{x_{co}-\mu}{\sigma} = z_{co}$$

$$x = \infty \Rightarrow z = \frac{\infty-\mu}{\sigma} = \infty$$

$$= \frac{\int_{z_{co}}^{\infty} (\mu+\sigma z) \cdot \frac{1}{\not\sigma\sqrt{2\pi}} e^{\frac{-z^2}{2}} \not\sigma dz}{\int_{z_{co}}^{\infty} \frac{1}{\not\sigma\sqrt{2\pi}} e^{\frac{-z^2}{2}} \not\sigma dz} = \frac{\int_{z_{co}}^{\infty} (\mu+\sigma z) \cdot \frac{1}{\sqrt{2\pi}} e^{\frac{-z^2}{2}} dz}{\int_{z_{co}}^{\infty} \frac{1}{\sqrt{2\pi}} e^{\frac{-z^2}{2}} dz} =$$

$$= \frac{\int_{z_{co}}^{\infty} \mu \cdot \frac{1}{\sqrt{2\pi}} e^{\frac{-z^2}{2}} dz + \int_{z_{co}}^{\infty} \sigma z \cdot \frac{1}{\sqrt{2\pi}} e^{\frac{-z^2}{2}} dz}{\int_{z_{co}}^{\infty} \frac{1}{\sqrt{2\pi}} e^{\frac{-z^2}{2}} dz} = \mu \cdot \frac{\int_{z_{co}}^{\infty} \frac{1}{\sqrt{2\pi}} e^{\frac{-z^2}{2}} dz}{\int_{z_{co}}^{\infty} \frac{1}{\sqrt{2\pi}} e^{\frac{-z^2}{2}} dz} + \sigma \cdot \frac{\int_{z_{co}}^{\infty} z \cdot \frac{1}{\sqrt{2\pi}} e^{\frac{-z^2}{2}} dz}{\int_{z_{co}}^{\infty} \frac{1}{\sqrt{2\pi}} e^{\frac{-z^2}{2}} dz} =$$

From the standard normal distribution:

$$\int_{-\infty}^{z_{co}} \frac{1}{\sqrt{2\pi}} e^{\frac{-z^2}{2}} dz = 1 - \Phi(z_{co})$$

$$= \mu \cdot \frac{1-\Phi(z_{co})}{1-\Phi(z_{co})} + \sigma \cdot \frac{\frac{1}{\sqrt{2\pi}} \int_{z_{co}}^{\infty} z \cdot e^{\frac{-z^2}{2}} dz}{1-\Phi(z_{co})} =$$

Solving the integral:
$\int u^{n-1} \cdot e^{\frac{-u^n}{n}} du = -e^{\frac{-u^n}{n}}$
Confirmation by derivng the answer:
$\frac{\partial(-e^{\frac{-u^n}{n}})}{\partial u} = -e^{\frac{-u^n}{n}} \cdot \frac{-n \cdot u^{n-1}}{n} = u^{n-1} \cdot e^{\frac{-u^n}{u}}$

$$= \mu + \sigma \cdot \frac{\frac{1}{\sqrt{2\pi}} (-e^{\frac{-z^2}{2}}) \Big|_{z_{co}}^{\infty}}{1-\Phi(z_{co})} = \mu + \sigma \cdot \frac{\frac{1}{\sqrt{2\pi}} \left[\left(-e^{\frac{-\infty^2}{2}} \right) - \left(-e^{\frac{-z_{co}{}^2}{2}} \right) \right]}{1-\Phi(z_{co})} =$$

$$= \mu + \sigma \cdot \frac{\frac{1}{\sqrt{2\pi}} \left[(0) - \left(-e^{\frac{-z_{co}{}^2}{2}} \right) \right]}{1-\Phi(z_{co})} = \mu + \sigma \cdot \frac{\frac{1}{\sqrt{2\pi}} e^{\frac{-z_{co}{}^2}{2}}}{1-\Phi(z_{co})} =$$

From the standard normal distribution:
$\frac{1}{\sqrt{2\pi}} e^{\frac{-z^2}{2}} dz = \varphi(z)$

$$= \mu + \sigma \cdot \frac{\varphi(z_{co})}{1-\Phi(z_{co})}$$

$\mu_+(x_{co}) = \mu + \sigma \cdot \frac{\varphi(z_{co})}{1-\Phi(z_{co})}$
where
$z_{co} = \frac{x_{co} - \mu}{\sigma}$
$\varphi(z) = \frac{1}{\sqrt{2\pi}} \cdot e^{\frac{-z^2}{2}}$; $\Phi(z) = \frac{1}{\sqrt{2\pi}} \int_{-\infty}^{z} e^{\frac{-z^2}{2}} dz$

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 μ_S, σ_S and μ_N, σ_N. Short reviews of Normal and Standard Normal distributions, as well as definitions of signal and noise distributions are included in Appendix A.

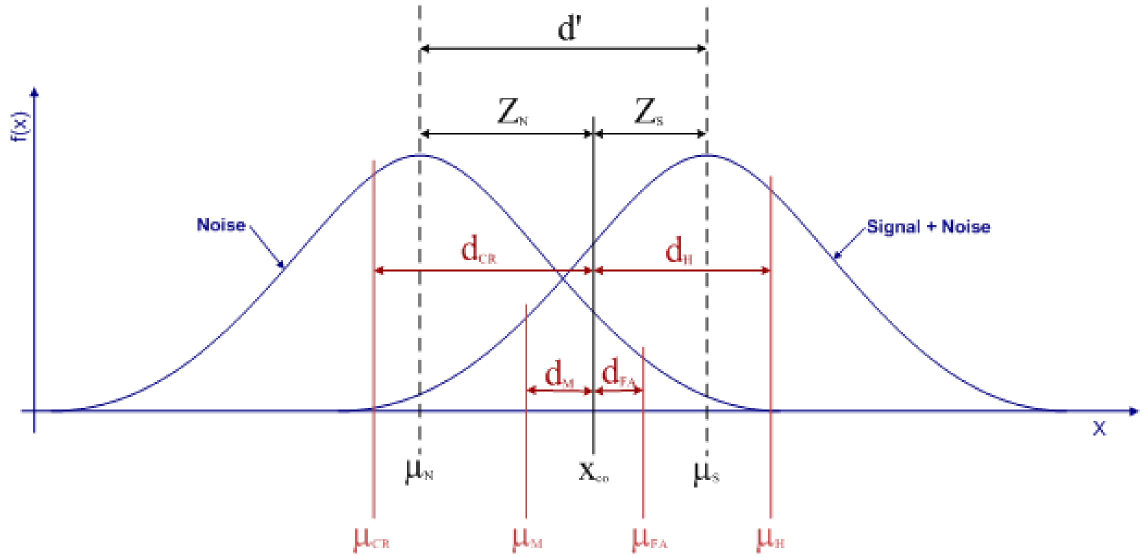

Figure 14: Illustration of mean x-values and mean distances

The mean x-values and the mean distances are denoted as:

μ_M - Mean x-value of undetected signals (miss)

μ_H - Mean x-value of detected signals (hit)

μ_{CR} - Mean x-value of ignored noises (correct rejection)

μ_{FA} - 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_{CR} - Distance from the cutoff point to mean x-value of ignored noises (correct rejection)

d_{FA} - 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):

$$\mu_M(x_{co}) = \mu_S - \sigma_S \cdot \frac{\varphi(z_S)}{\Phi(z_S)}$$

$$\mu_H(x_{co}) = \mu_S + \sigma_S \cdot \frac{\varphi(z_S)}{1-\Phi(z_S)}$$

$$\mu_{CR}(x_{co}) = \mu_N - \sigma_N \cdot \frac{\varphi(z_N)}{\Phi(z_N)}$$

$$\mu_{FA}(x_{co}) = \mu_N + \sigma_N \cdot \frac{\varphi(z_N)}{1-\Phi(z_N)}$$

$$d_M(x_{co}) = (x_{co} - \mu_S) + \sigma_S \cdot \frac{\varphi(z_S)}{\Phi(z_S)}$$

$$d_H(x_{co}) = -(x_{co} - \mu_S) + \sigma_S \cdot \frac{\varphi(z_S)}{1-\Phi(z_S)}$$

$$d_{CR}(x_{co}) = (x_{co} - \mu_N) + \sigma_N \cdot \frac{\varphi(z_N)}{\Phi(z_N)}$$

$$d_{FA}(x_{co}) = -(x_{co} - \mu_N) + \sigma_N \cdot \frac{\varphi(z_N)}{1-\Phi(z_N)}$$

$$d_M(x_{co}) / \sigma_S = z_S + \frac{\varphi(z_S)}{\Phi(z_S)}$$

$$d_H(x_{co}) / \sigma_S = -z_S + \frac{\varphi(z_S)}{1-\Phi(z_S)}$$

$$d_{CR}(x_{co}) / \sigma_N = z_N + \frac{\varphi(z_N)}{\Phi(z_N)}$$

$$d_{FA}(x_{co}) / \sigma_N = -z_N + \frac{\varphi(z_N)}{1-\Phi(z_N)}$$

where

$$z_S = \frac{x_{co} - \mu_S}{\sigma_S} \quad ; \quad z_N = \frac{x_{co} - \mu_N}{\sigma_N}$$

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

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:

$$d(x) = x_{co} - x$$
$$t(x) = A \cdot e^{-B(x_{co} - x)}$$

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

$$d(x) = x - x_{co}$$
$$t(x) = A \cdot e^{-B(x - x_{co})}$$

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

$$t(x) = \begin{cases} A \cdot e^{-B \cdot (x_{co} - x)} & ;\ when\ x \leq x_{co} \\ A \cdot e^{-B(x - x_{co})} & ;\ otherwise \end{cases}$$

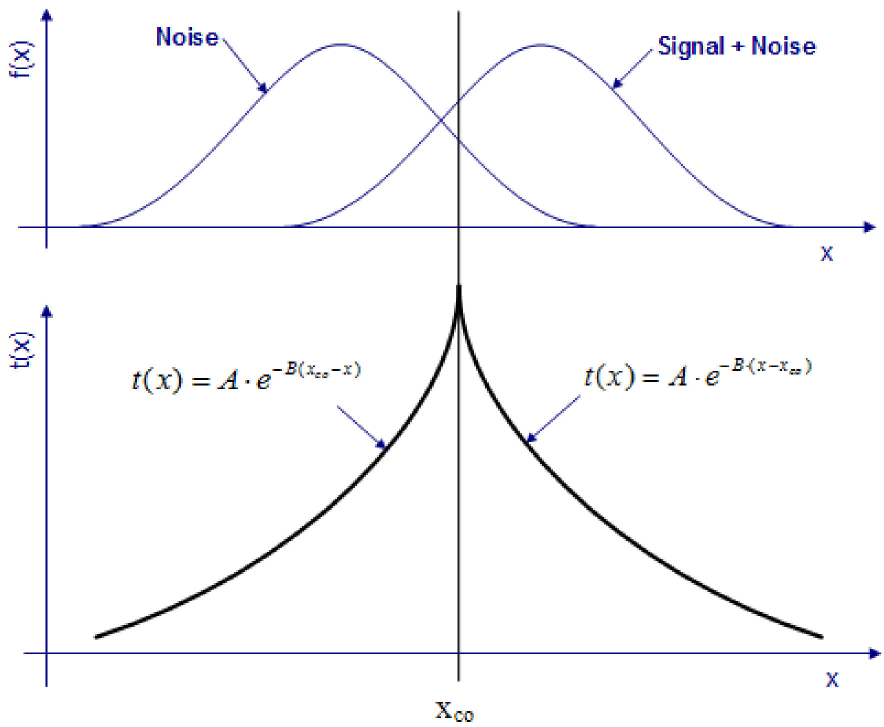

Figure 15: Reaction time function

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 μ and a variance of σ^2 $X \sim \quad (\mu,\sigma^2)$. 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 $T_-(x_{co}), T_+(x_{co})$ for negative and positive responses, respectively.

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

$$T_-(x_{co}) = \frac{\int_{-\infty}^{x_{co}} t(x)\cdot f(x)dx}{\int_{-\infty}^{x_{co}} f(x)dx} = \frac{\int_{-\infty}^{x_{co}} A\cdot e^{-B(x_{co}-x)}\cdot f(x)dx}{\int_{-\infty}^{x_{co}} f(x)dx} = \dots = A\cdot e^{-B\cdot\sigma\cdot z_{co}+\frac{B^2\cdot\sigma^2}{2}}\cdot\frac{\Phi(z_{co}-B\cdot\sigma)}{\Phi(z_{co})}$$

$$T_+(x_{co}) = \frac{\int_{x_{co}}^{\infty} t(x)\cdot f(x)dx}{\int_{x_{co}}^{\infty} f(x)dx} = \frac{\int_{x_{co}}^{\infty} A\cdot e^{-B(x-x_{co})}\cdot f(x)dx}{\int_{x_{co}}^{\infty} f(x)dx} = \dots = A\cdot e^{B\cdot\sigma\cdot z_{co}+\frac{B^2\cdot\sigma^2}{2}}\cdot\frac{1-\Phi(z_{co}+B\cdot\sigma)}{1-\Phi(z_{co})}$$

where

$$f(x) = \frac{1}{\sigma\sqrt{2\pi}} e^{\frac{-(x-\mu)^2}{2\sigma^2}}$$

$$z_{co} = \frac{x_{co}-\mu}{\sigma} \quad ; \quad \Phi(z) = \frac{1}{\sqrt{2\pi}}\int_{-\infty}^{z} e^{\frac{-z^2}{2}} dz$$

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

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

$$T_-(x_{co}) = A\cdot e^{-B\cdot z_{co}+\frac{B^2}{2}}\cdot\frac{\Phi(z_{co}-B)}{\Phi(z_{co})}$$

$$T_+(x_{co}) = A\cdot e^{B\cdot z_{co}+\frac{B^2}{2}}\cdot\frac{1-\Phi(z_{co}+B)}{1-\Phi(z_{co})}$$

The distance functions and the reaction time functions both depend on the value of the cutoff point x_{co}. 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.

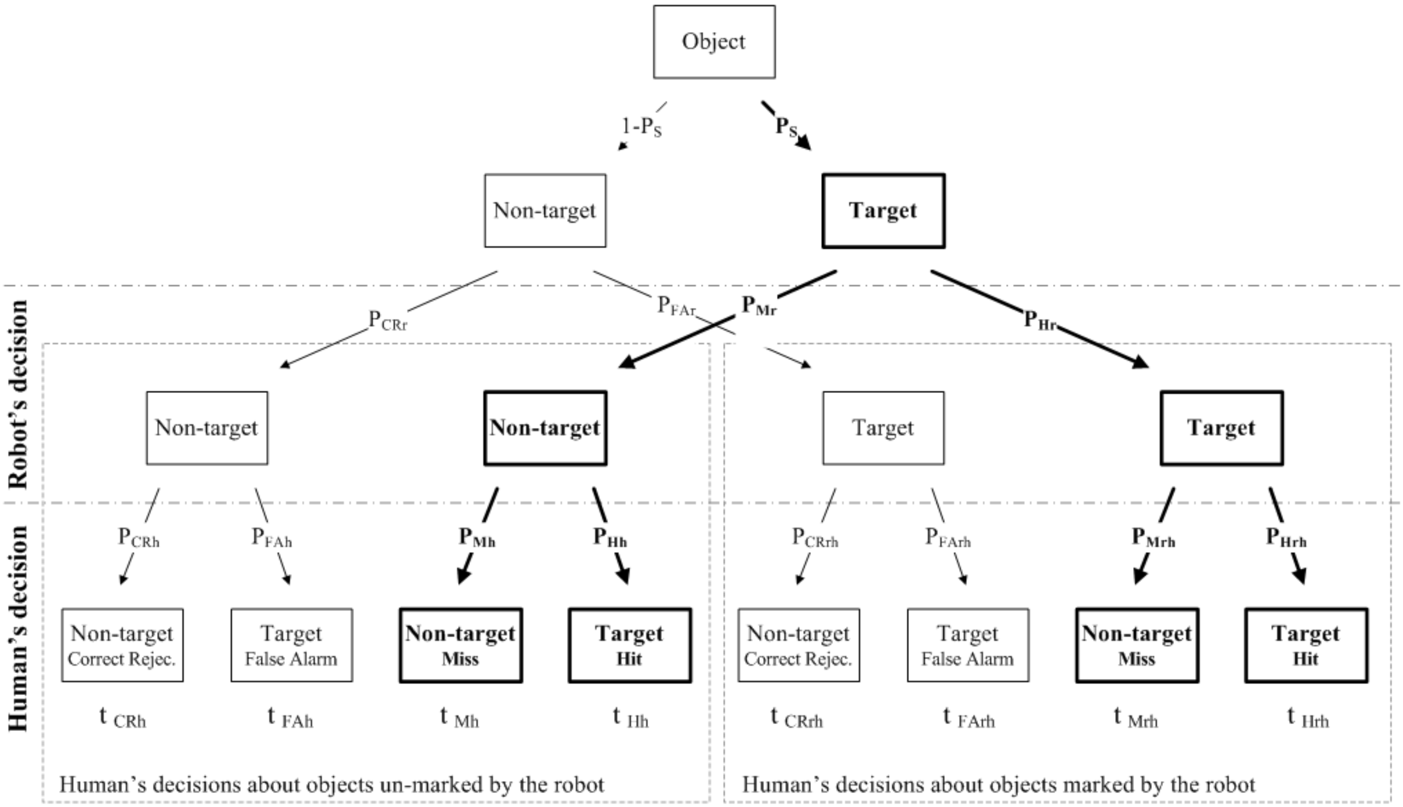

Figure 16: Reaction times flow chart

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_{CR} - Mean reaction time of ignored noises (correct rejection)

T_{FA} - Mean reaction time of mistakenly detected noises (false alarm)

Same denotations with the index rh and h (for instance, T_{CRh}, T_{Hrh} 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 μ_S, σ_S and μ_N, σ_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):

$$T_M = A \cdot e^{-B \cdot \sigma_S \cdot z_S + \frac{B^2 \cdot \sigma_S^2}{2}} \cdot \frac{\Phi(z_S - B \cdot \sigma_S)}{\Phi(z_S)}$$

$$T_H = A \cdot e^{B \cdot \sigma_S \cdot z_S + \frac{B^2 \cdot \sigma_S^2}{2}} \cdot \frac{1 - \Phi(z_S + B \cdot \sigma_S)}{1 - \Phi(z_S)}$$

$$T_{CR} = A \cdot e^{-B \cdot \sigma_N \cdot z_N + \frac{B^2 \cdot \sigma_N^2}{2}} \cdot \frac{\Phi(z_N - B \cdot \sigma_N)}{\Phi(z_N)}$$

$$T_{FA} = A \cdot e^{B \cdot \sigma_N \cdot z_N + \frac{B^2 \cdot \sigma_N^2}{2}} \cdot \frac{1 - \Phi(z_N + B \cdot \sigma_N)}{1 - \Phi(z_N)}$$

where

$$z_S = \frac{x_{co} - \mu_S}{\sigma_S} \quad ; \quad z_N = \frac{x_{co} - \mu_N}{\sigma_N}$$

$$\Phi(z) = \frac{1}{\sqrt{2\pi}} \int_{-\infty}^{z} e^{\frac{-z^2}{2}} dz$$

When $\sigma_S = \sigma_N = 1$, the equations are:

$$T_M = A \cdot e^{-B \cdot z_S + \frac{B^2}{2}} \cdot \frac{\Phi(z_S - B)}{\Phi(z_S)}$$

$$T_H = A \cdot e^{B \cdot z_S + \frac{B^2}{2}} \cdot \frac{1 - \Phi(z_S + B)}{1 - \Phi(z_S)}$$

$$T_{CR} = A \cdot e^{-B \cdot z_N + \frac{B^2}{2}} \cdot \frac{\Phi(z_N - B)}{\Phi(z_N)}$$

$$T_{FA} = A \cdot e^{B \cdot z_N + \frac{B^2}{2}} \cdot \frac{1 - \Phi(z_N + B)}{1 - \Phi(z_N)}$$

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:

$$
\begin{aligned}
V_{Is} &= N \cdot P_S \cdot [P_{Hr} \cdot P_{Hrh} \cdot (V_H + V_C + \underline{t_{Hrh}} \cdot V_t) + (1-P_{Hr}) \cdot P_{Hh} \cdot (V_H + V_C + \underline{t_{Hh}} \cdot V_t)] + \\
&+ N \cdot P_S \cdot [P_{Hr} \cdot (1-P_{Hrh}) \cdot (V_M + \underline{t_{Mrh}} \cdot V_t) + (1-P_{Hr}) \cdot (1-P_{Hh}) \cdot (V_M + \underline{t_{Mh}} \cdot V_t)] + \\
&+ N \cdot (1-P_S) \cdot [P_{FAr} \cdot P_{FArh} \cdot (V_{FA} + V_C + \underline{t_{FArh}} \cdot V_t) + (1-P_{FAr}) \cdot P_{FAh} \cdot (V_{FA} + V_C + \underline{t_{FAh}} \cdot V_t)] + \\
&+ N \cdot (1-P_S) \cdot [P_{FAr} \cdot (1-P_{FArh}) \cdot (V_{CR} + \underline{t_{CRrh}} \cdot V_t) + (1-P_{FAr}) \cdot (1-P_{FAh}) \cdot (V_{CR} + \underline{t_{CRh}} \cdot V_t)] + t_r \cdot V_t
\end{aligned}
$$

Each of the human time variables (denoted as t_{Xrh} or t_{Xh}) 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:

$$
\begin{aligned}
t_{Mh} &= T_{Mh} \\
t_{Hh} &= T_{Hh} + t_M \\
t_{CRh} &= T_{CRh} \\
t_{FAh} &= T_{FAh} + t_M
\end{aligned}
$$

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:

$$
\begin{aligned}
t_{Mh} &= T_{Mh} \\
t_{Hh} &= T_{Hh} + t_M \\
t_{CRh} &= T_{CRh} \\
t_{FAh} &= T_{FAh} + t_M \\
t_{Mrh} &= T_{Mrh} \\
t_{Hrh} &= T_{Hrh} + t_M \\
t_{CRrh} &= T_{CRrh} \\
t_{FArh} &= T_{FArh} + t_M
\end{aligned}
$$

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:

$$t_{Mh} = T_{Mh}$$
$$t_{Hh} = T_{Hh} + t_M$$
$$t_{CRh} = T_{CRh}$$
$$t_{FAh} = T_{FAh} + t_M$$
$$t_{Mrh} = T_{Mrh} + t_M$$
$$t_{Hrh} = T_{Hrh}$$
$$t_{CRrh} = T_{CRrh} + t_M$$
$$t_{FArh} = T_{FArh}$$

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_{FA}, V_{CR}). 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 ($V_H = -V_M = -V_{FA} = V_{CR}$).Table 2 details the values for each type of system.

The time cost (V_T) 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 ($V_T = V_H \cdot V_T 2V_H$). The ratio between the time cost and the gain for a hit, $V_T 2V_H$, was set to the values: -80, -40, -20 (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 (V_C) 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_{FA}	-50	-5	-10
V_{CR}	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 (P_S) 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'), 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 (d'_h) 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, $t(x) = A \cdot e^{-B(x_{co}-x)}$, 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 (d'_r) was varied, same as human sensitivity, between 0.5 and 3. The robot decision time (t_r) 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_{FA}	The penalty from a false alarm			-50	-5	-10
V_{CR}	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'_h	The human's sensitivity	[0.5 : 0.5 : 3]				
d'_r	The robot's sensitivity	[0.5 : 0.5 : 3]				
t_r	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 (X, Y) and a function (one of the components of the overall objective function), and spreads sub-graphs 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 (d'_h) and the robot (d'_r) are varied along X and Y axes. A sub-graph is shown for every value of the target probability (P_S). The other three parameters ($B, A, vT2vH$) are set manually.

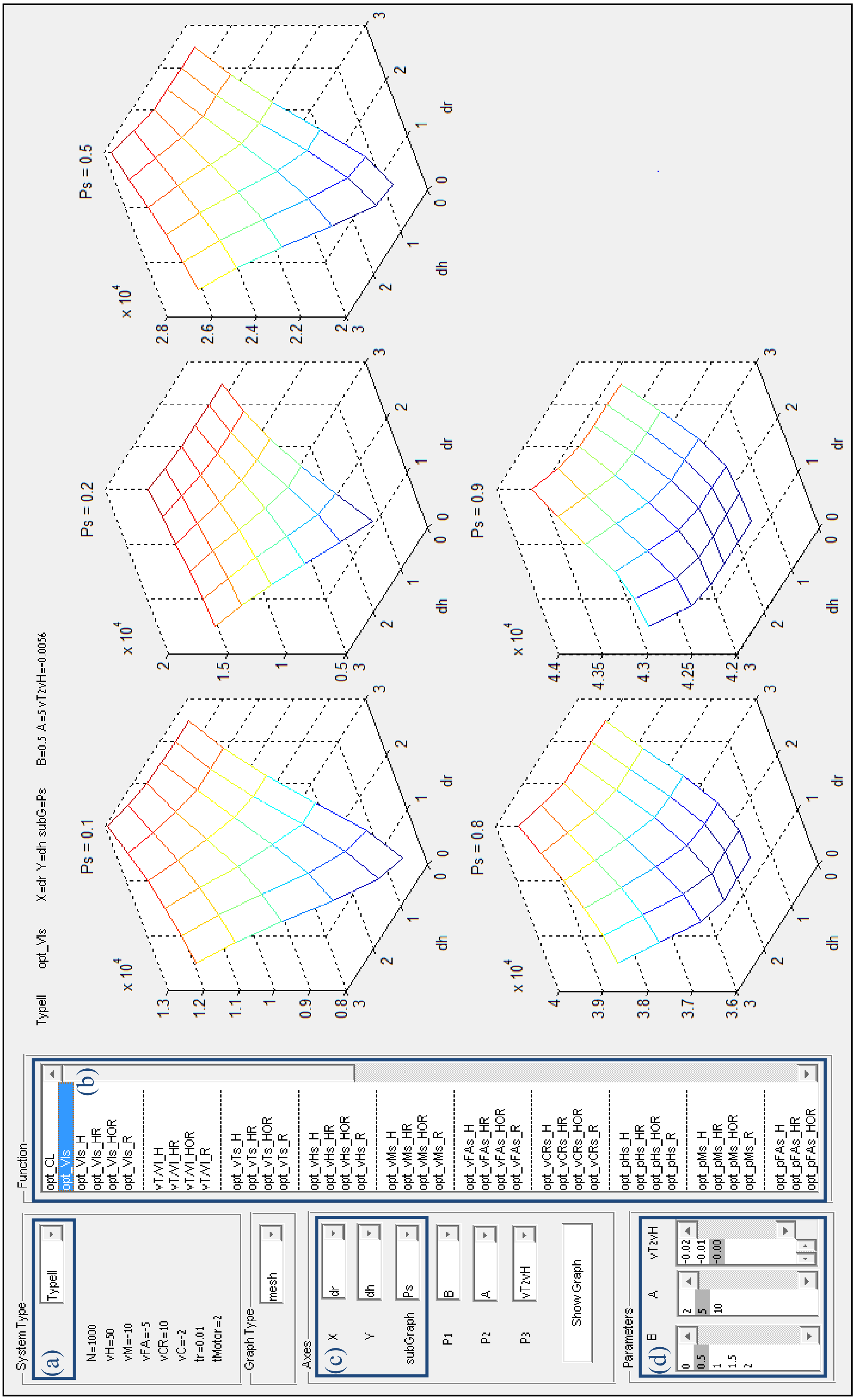

Figure 17: Graph generator application.
The user can choose a system type (a), an objective function (b), two parameters for X and Y axes and a third parameter for the sub graphs (c), and set manually the values of the three other parameters (d).

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.

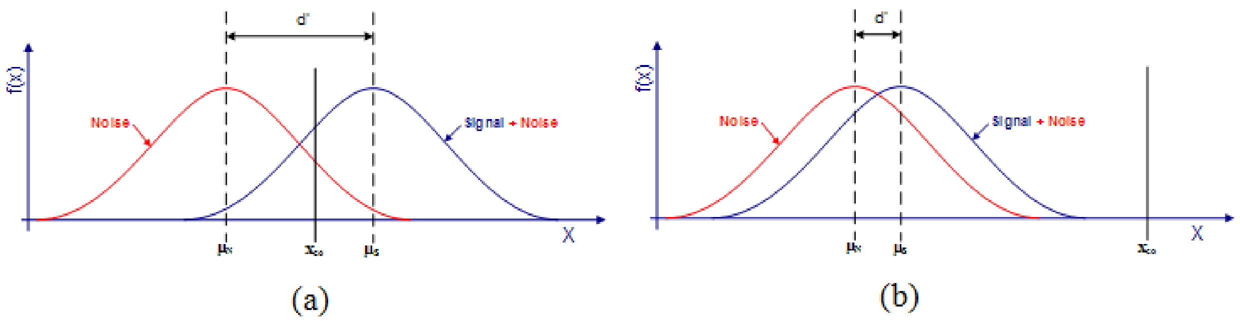

Figure 18: A cutoff point between the distributions' means when the sensetivity is high (a) and extreme cutoff point selection when sensitivity is low (b).

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 (d'_h) and the cost of time unit ($vT2vH$). The analysis was conducted for $Ps = 0.5,\ A = 2,\ B = 0.5,\ dr = 0.5$.

Results for other probabilities for target (Ps) as well as the influence of the time cost ($vT2vH$) and the time parameter A are detailed in Appendix E.

[2] The 'extremes' in this data set are -3 and 6. Explanation is detailed in chapter 6.

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 (d'_h) 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.

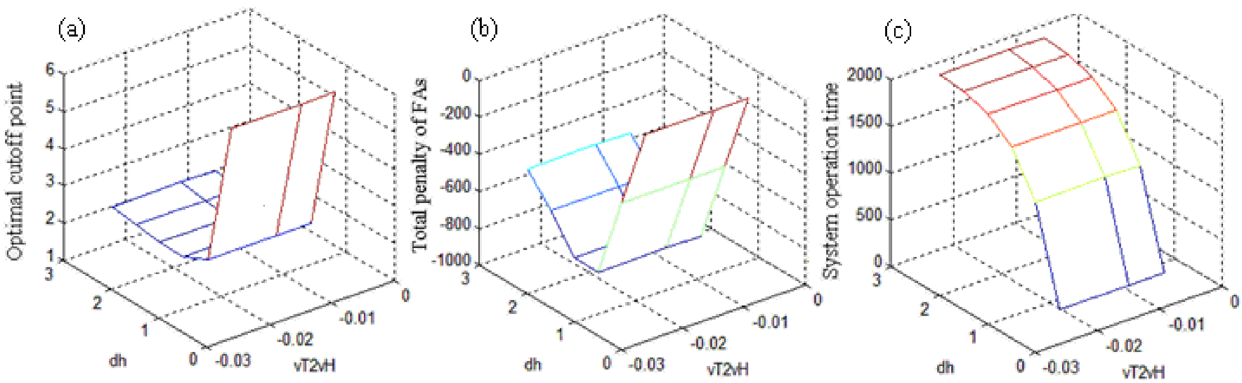

Figure 19: Optimal cutoff point of the human (a), total penalty of false alarms (b), and system operation time (c) in Type I system at the H collaboration level. The human sensitivity and the time cost are ranged along x and y axes.

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 (d'_h) 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.

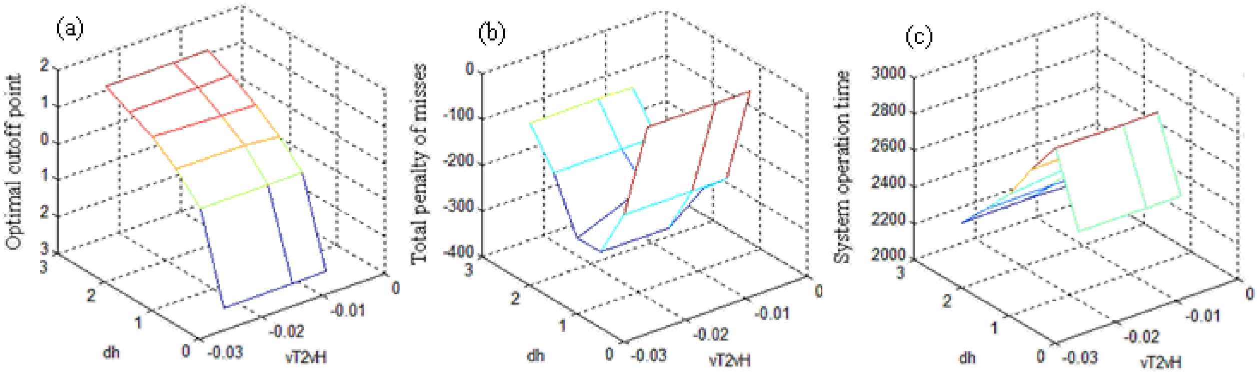

Figure 20: Optimal cutoff point of the human (a), total penalty of misses (b), and system operation time (c) in Type II system at the H collaboration level. Human sensitivity and the time cost are ranged along x and y axes.

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 $d'_h = 3$, 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).

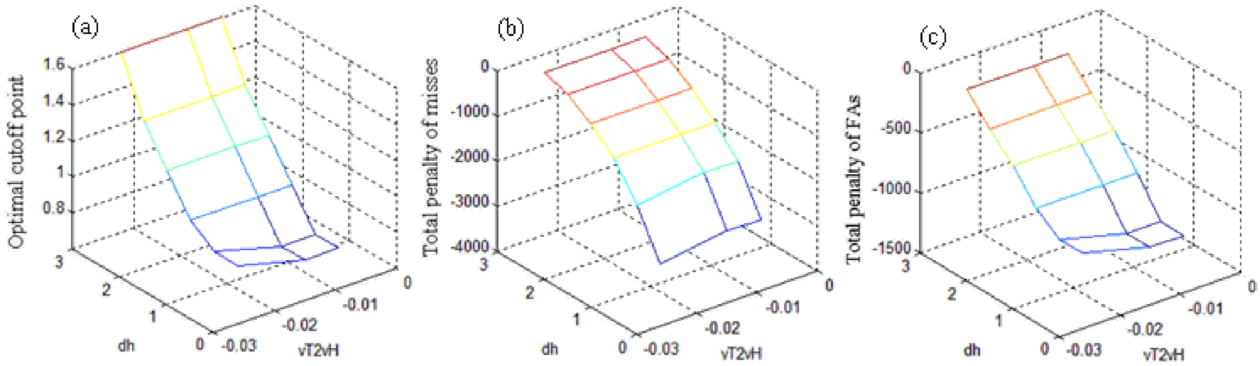

Figure 21: Optimal cutoff point of the human (a), total penalty of misses (b), and total penalty of false alarms (c) in Type III system at the H collaboration level. Human sensitivity and the time cost are ranged along x and y axes.

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 (d'_h) and the robot (d'_r) 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' ($vT2vH = -0.0055$) to graph 'c' ($vT2vH = -0.0222$). 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.

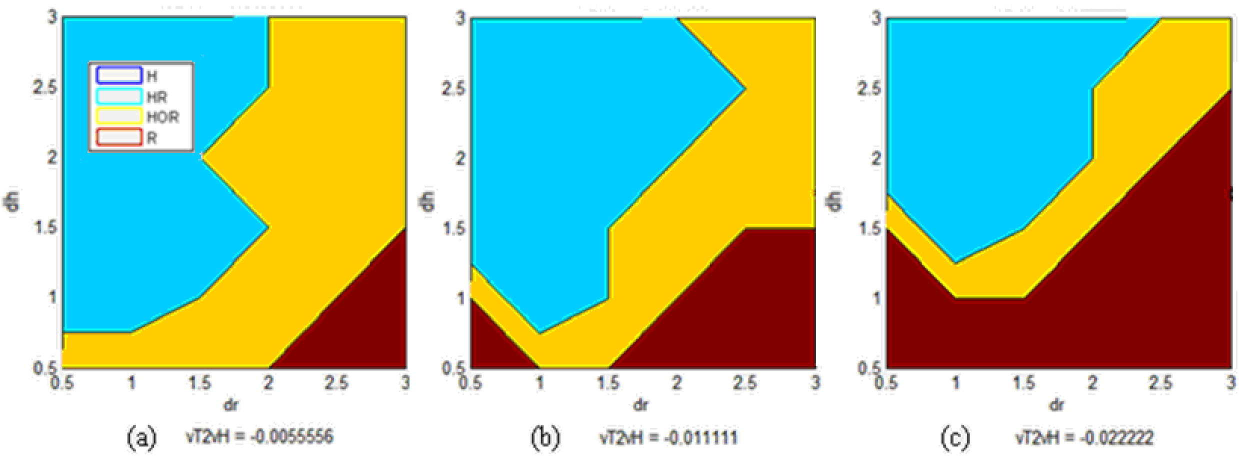

Figure 22: Human dominance reduces as the time cost increases from graph 'a' to graph 'c'.
$A = 10,\ B = 0.5,\ Ps = 0.2$

The reaction time model is based on an exponential function, $t(x) = A \cdot e^{-B(x_{co}-x)}$, 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).

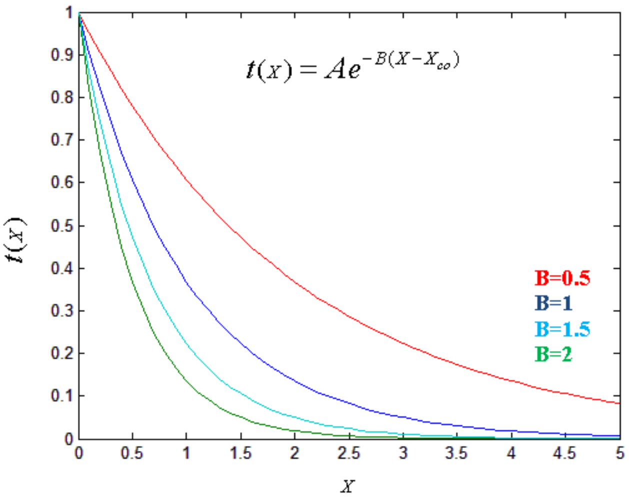

Figure 23: The response time function (y-axis) for different values of B parameter.
$A = 1, \quad X_{co} = 0$

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.

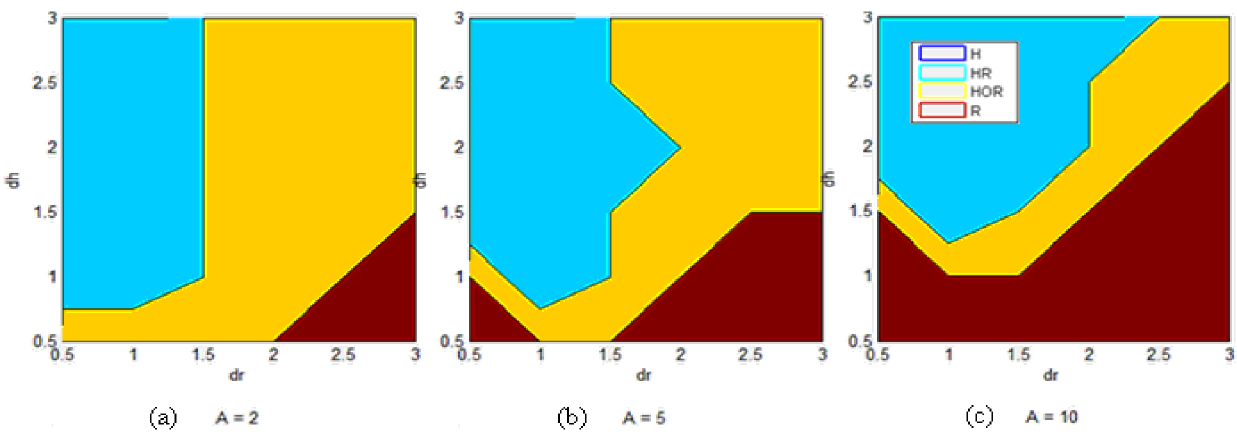

Figure 24: Human dominance reduces as the response time increases from graph 'a' to graph 'c'.
$vT2vH = -0.022, B = 0.5, Ps = 0.2$

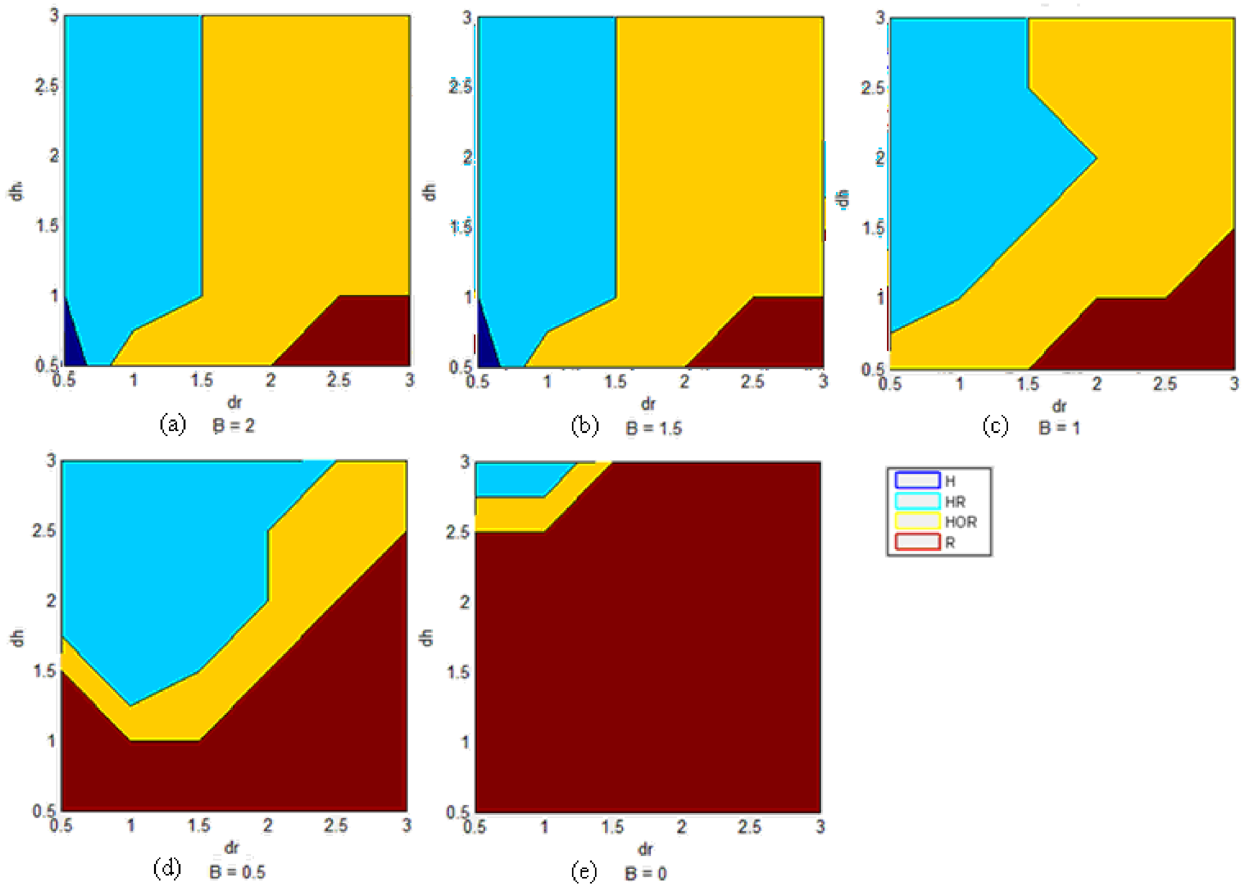

Figure 25: Human dominance reduces as the mean response time increases from graph 'a' to graph 'e'.
$vT2vH = -0.022,\ A = 10,\ Ps = 0.2$

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 (X_{COr}) and two cutoff points of the human for targets the robot already marked and for targets it did not mark (X_{COrh} and X_{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 (d'_r or d'_h), 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 (X_{COh}, X_{COrh} and X_{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 X_{COh}=1.2, X_{COrh}=0.8 and X_{COr}=-1.6. The other parameter's values ($dr, dh, Ps, A, B, vT2vH$) 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, X_{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 X_{COr} may cause best level shifting (i.e., smaller than deviations from X_{COr} when R is not the best collaboration level).

When the best collaboration level is HR or HOR, small deviations from the optimal X_{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 ($d'_r > d'_h$), 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 (d'_h) and the robot (d'_r) were varied between 0 and 3. We denote that the human is remarkably more sensitive than the robot in cases where $1.5 < d'_h - d'_r$. In cases where $0 < d'_h - d'_r < 1.5$ 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, X_{COh}, does not cause a shift in the best collaboration level. However, a small deviation from the optimal X_{COrh} enforces best level shifting to H (Figure 26).

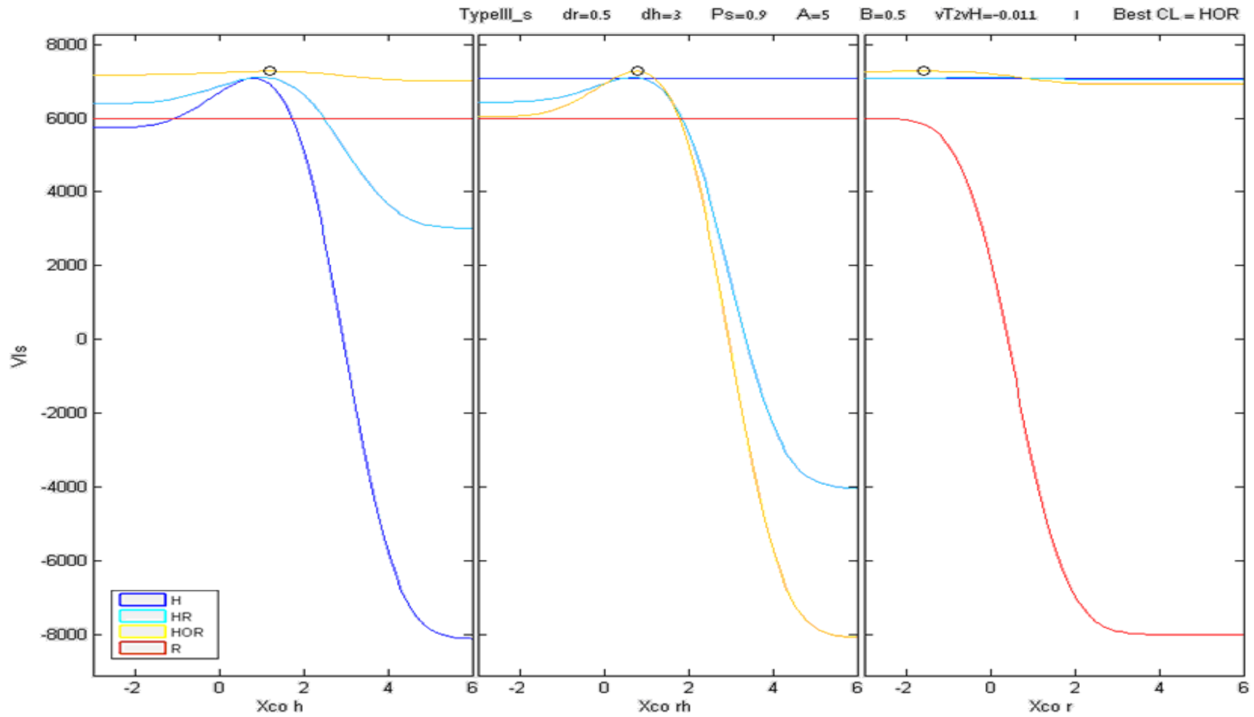

Figure 26: Example of Type III system's score in a case where the human is remarkably more sensitive than the robot.

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 ($0 < d'_h - d'_r < 1.5$), 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 (Ps).

Figure 27 shows one of these cases where the probability for an object to be a target is high ($Ps = 0.9$). A small deviation from the optimal cutoff point of the human, X_{COh}, reduces the system score and may cause a level shifting to R. A change from the optimal value of the second cutoff point, X_{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 ($Ps = 0.1$). In this case, a small deviation from the optimal X_{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 X_{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 ($Ps = 0.5$). A small deviation from optimal X_{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 X_{COrh}, behave the opposite way.

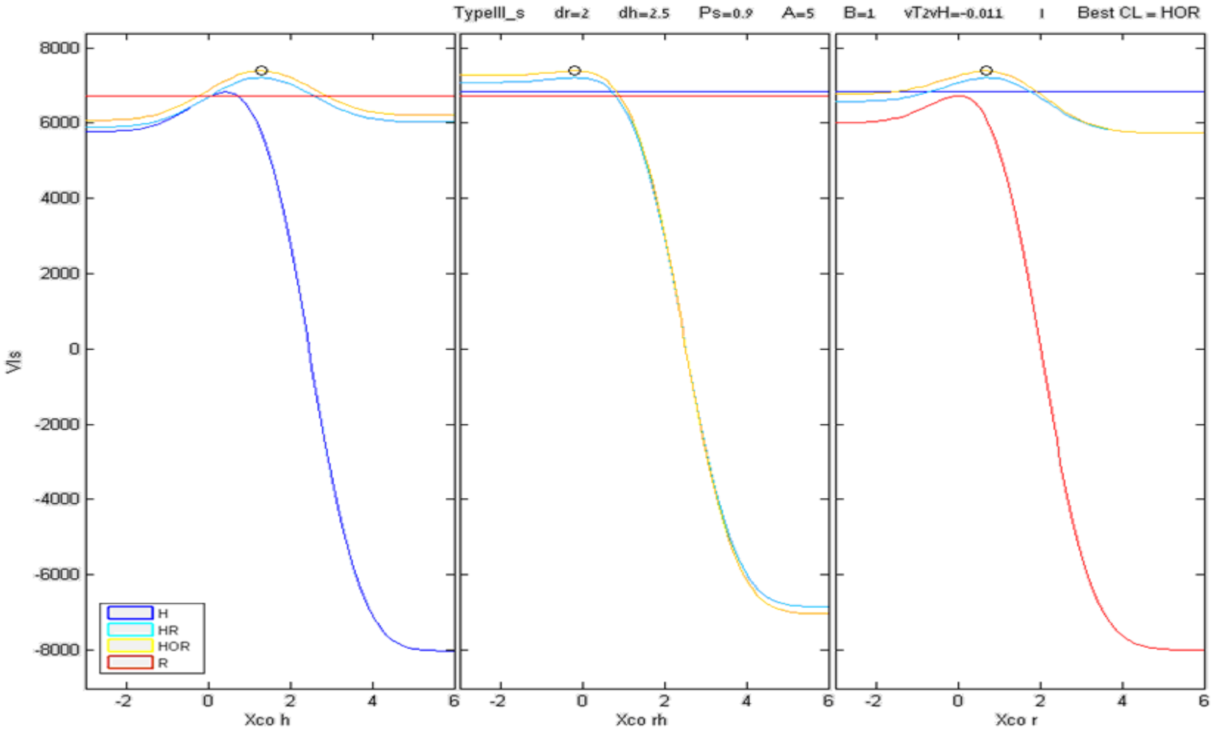

Figure 27: Example of Type III system's score in a case where the human is unremarkably more sensitive than the robot and the probability for a target is high.

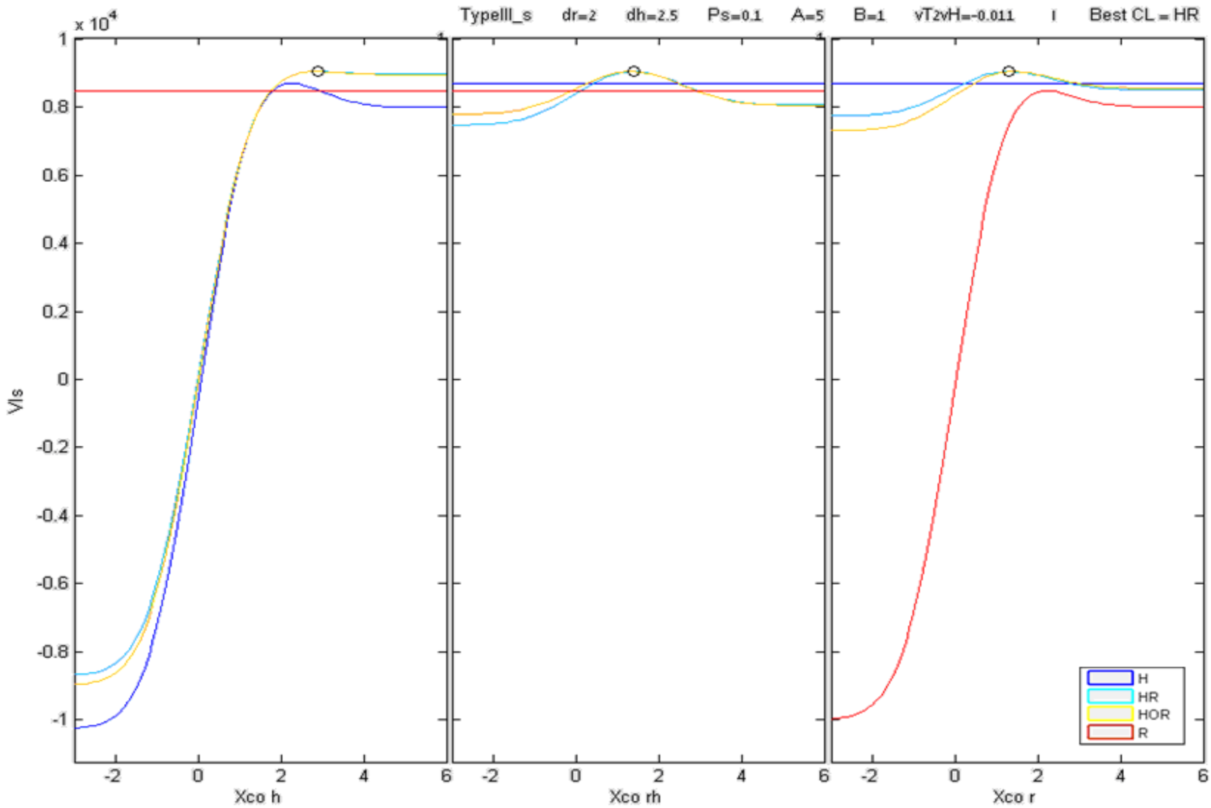

Figure 28: Example of Type III system's score in a case where the human is unremarkably more sensitive than the robot and the probability for a target is low.

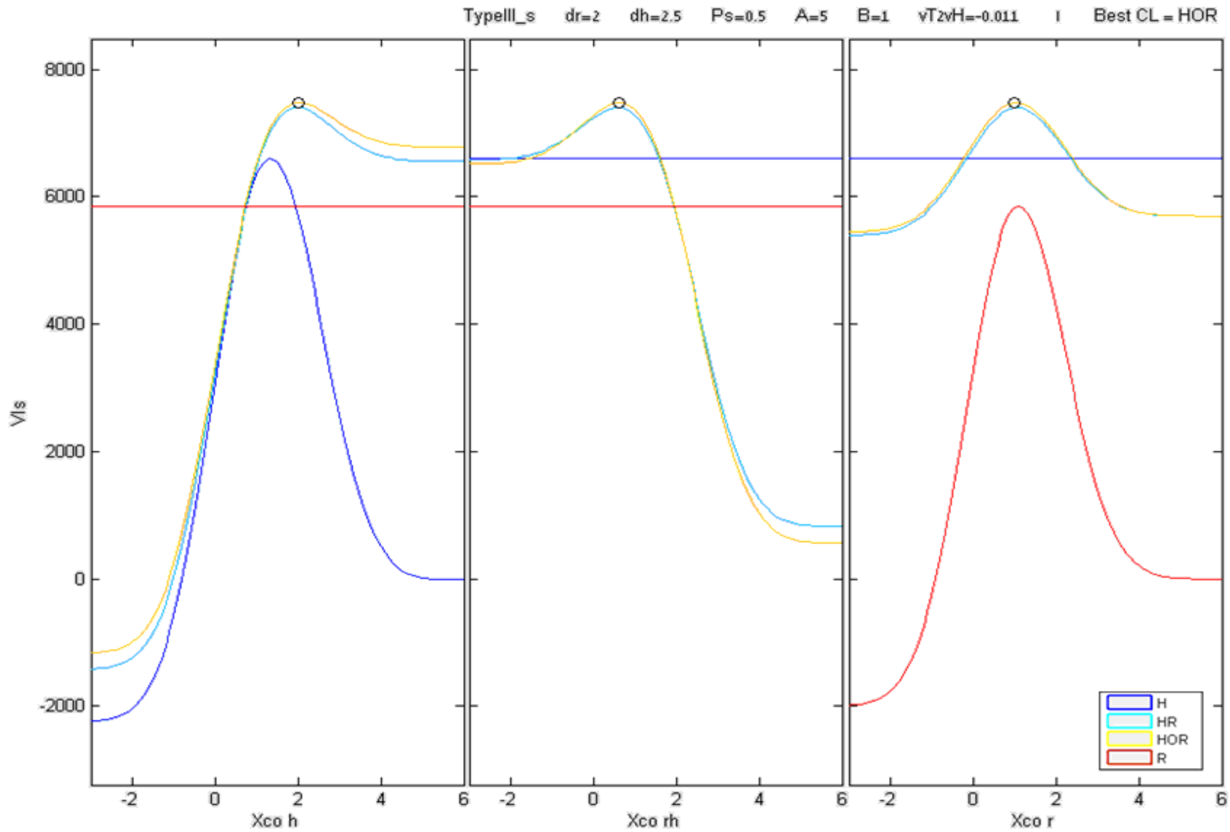

Figure 29: Example of Type III system's score in a case where the human is unremarkably more sensitive than the robot and the probability for a target is medium.

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 ($Ps = 0.9$), 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 ($Ps = 0.1$), 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: $A = 10,\ B = 0.5,\ vT2vH = -0.022$. 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 HR 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 target (Ps).

Figure 30 shows a case where the probability for a target is high ($Ps = 0.9$) 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, X_{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, X_{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.

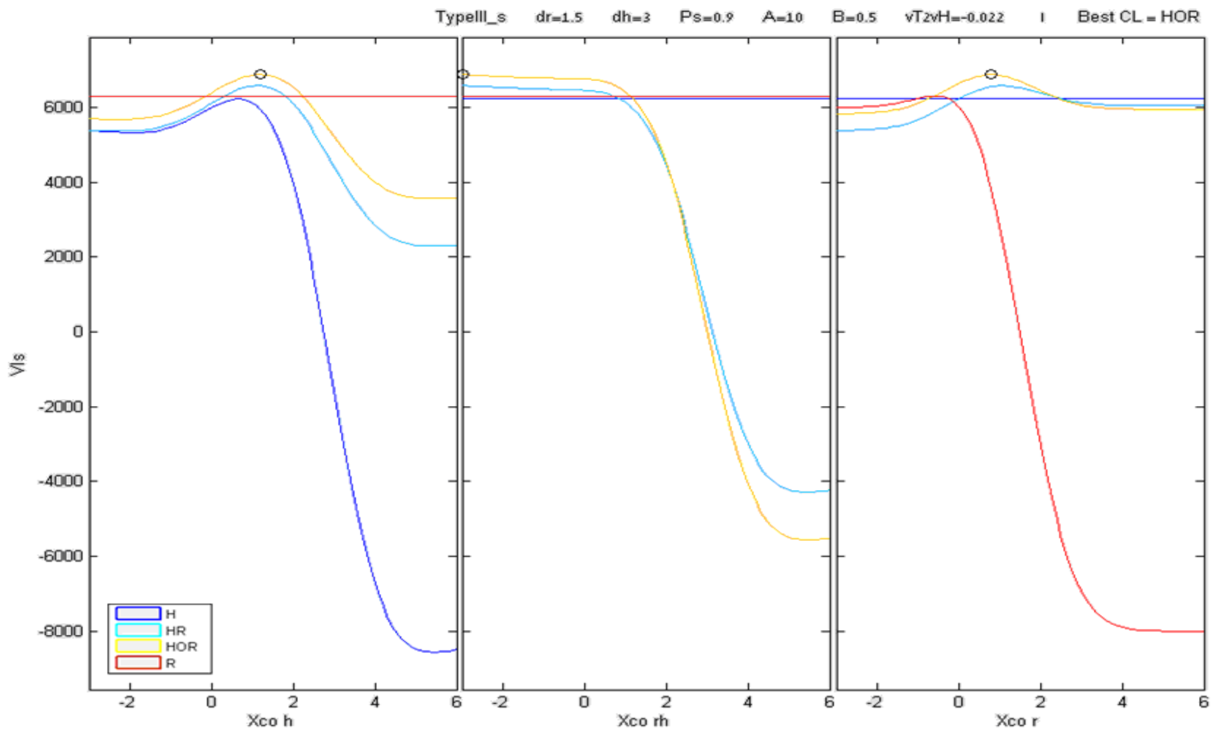

Figure 30: Example of Type III system's score in a case where the human reaction time is expensive and the probability for a target is high.

Figure 31 shows a case where the probability for a target is low ($Ps = 0.1$) 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, X_{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.

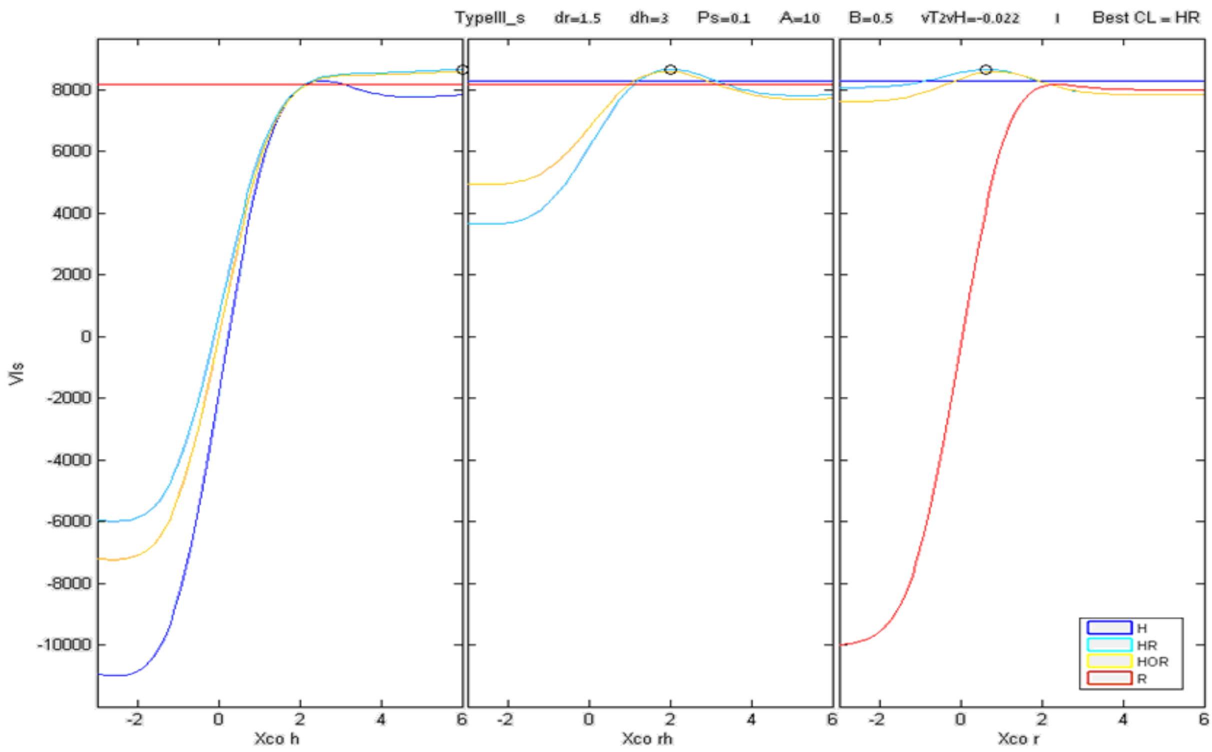

Figure 31: Example of Type III system's score in a case where the human reaction time is expensive and the probability for a target is low.

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 ($Ps = 0.9$) 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 ($Ps = 0.1$), 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.

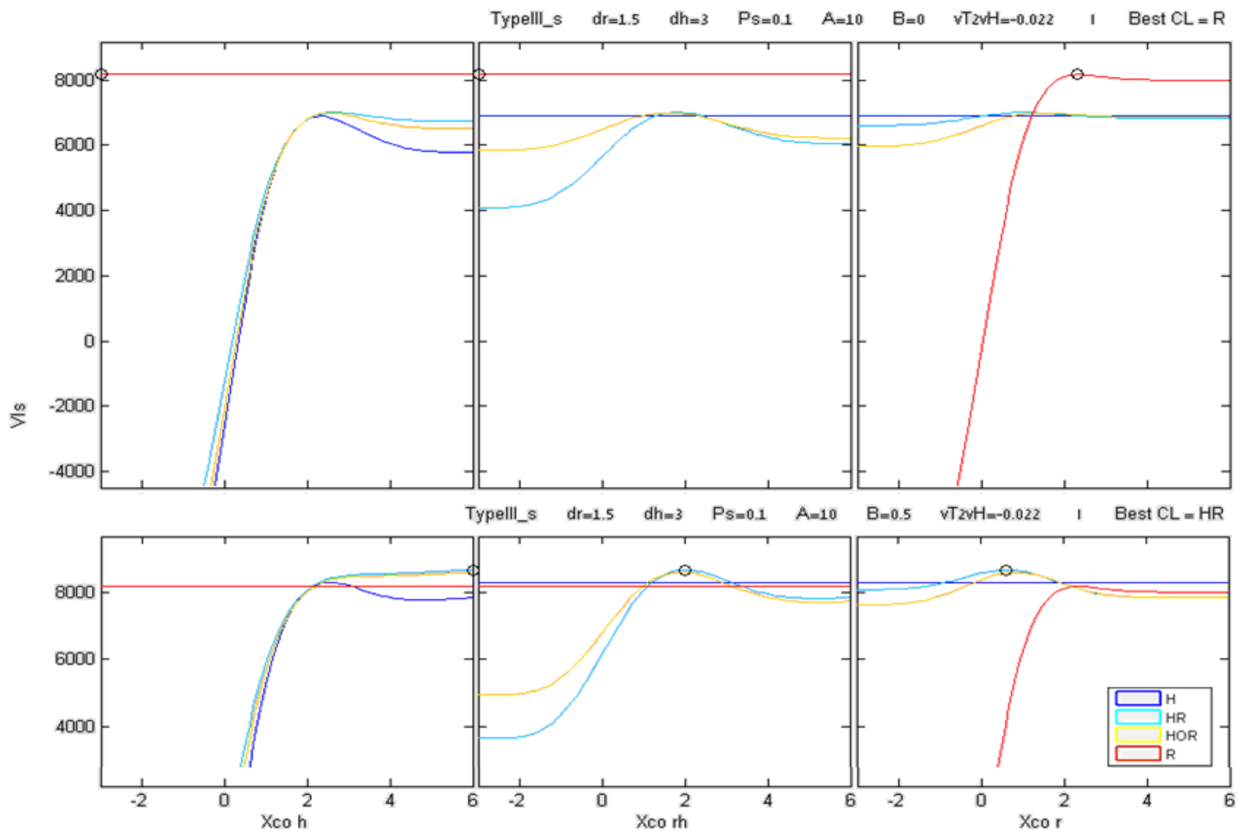

Figure 32: Example of Type III system's score in a case where the human reaction time is expensive and the probability for a target is low. A comparison with constant time parameters ($B = 0$) is presented.

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 ($1 < d'_r - d'_h$). 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 ($Ps = 0.9$), 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, X_{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, X_{COrh}, 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 ($Ps = 0.1$), 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 ($Ps = 0.5$), 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 ($Ps = 0.1$), or when the human is no more sensitive than the robot.

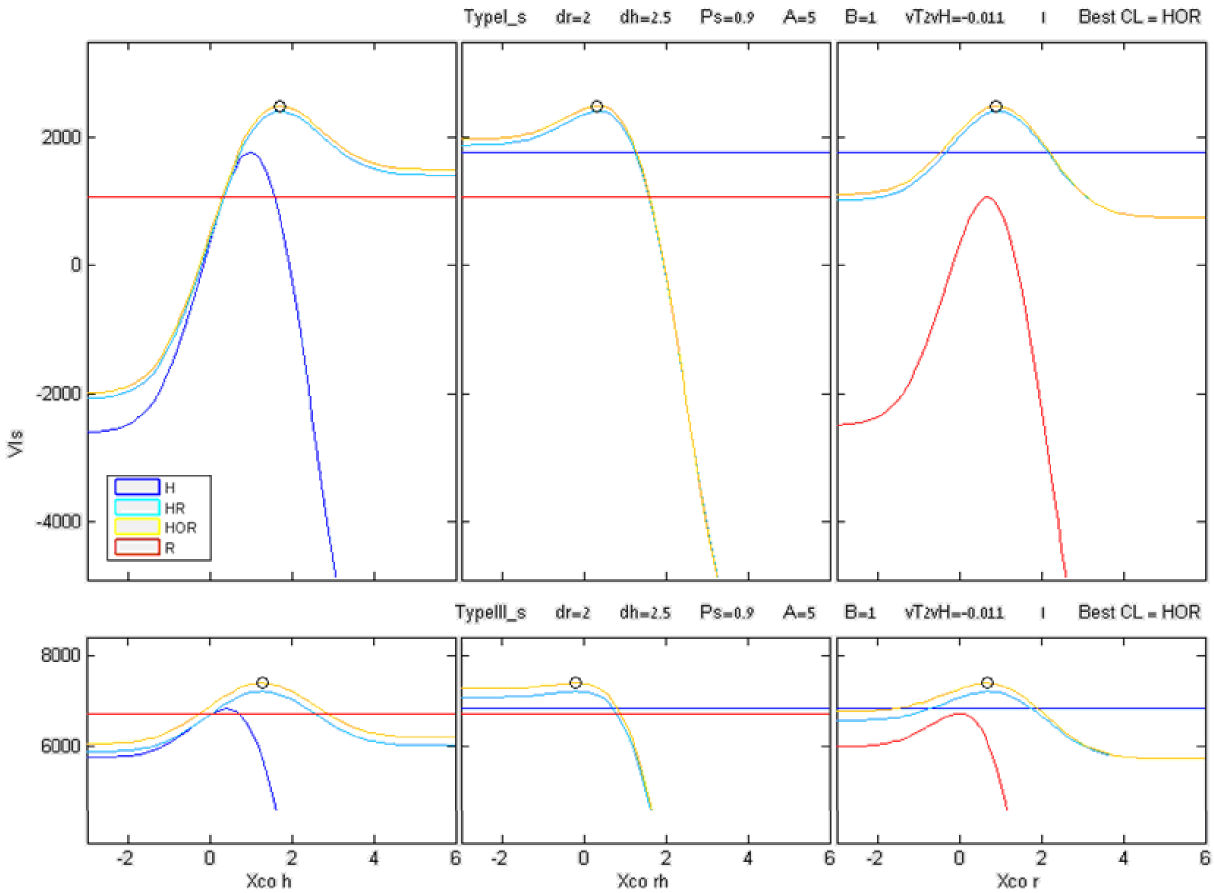

Figure 33: Comparison between Type I and Type III systems' score in a case where the human is more sensitive than the robot and the probability for a target is high.

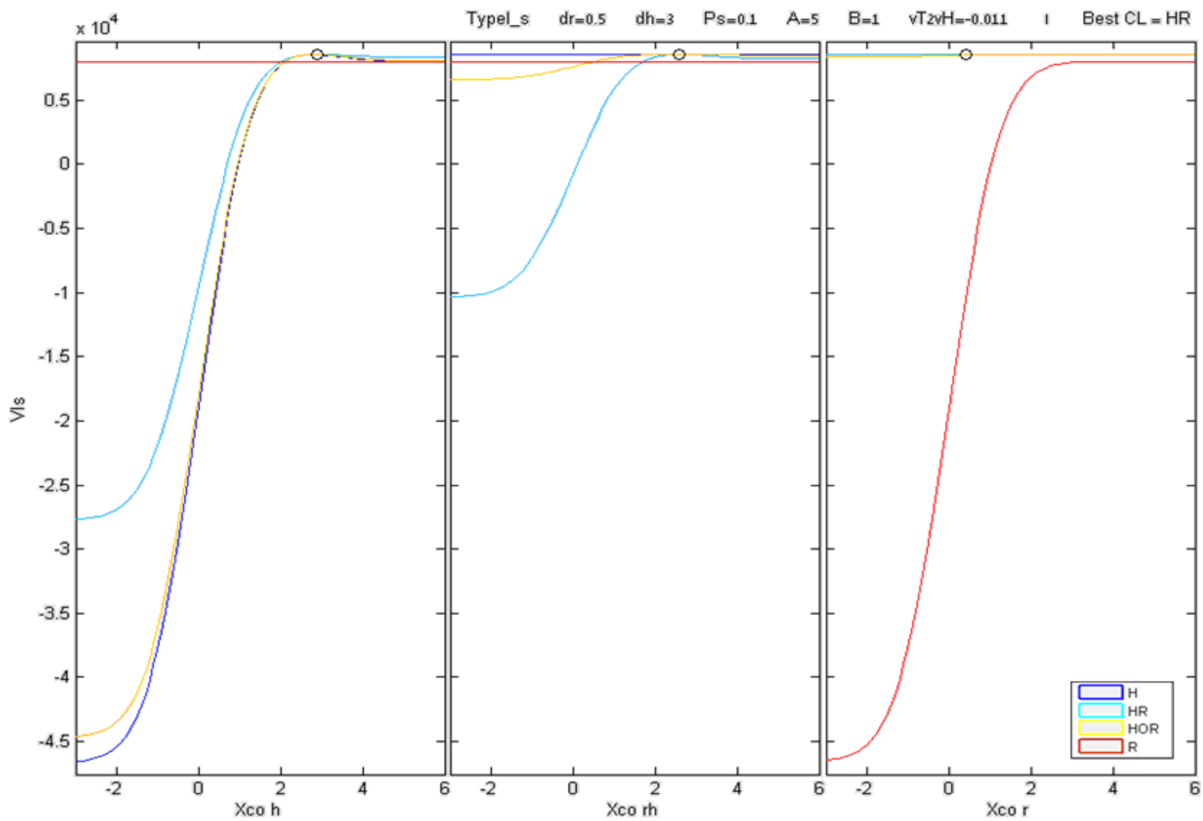

Figure 34: Example of Type I system's score in a case where the probability for a target is low and the difference between the collaboration levels scores is small.

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 ($Ps = 0.9$), 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.

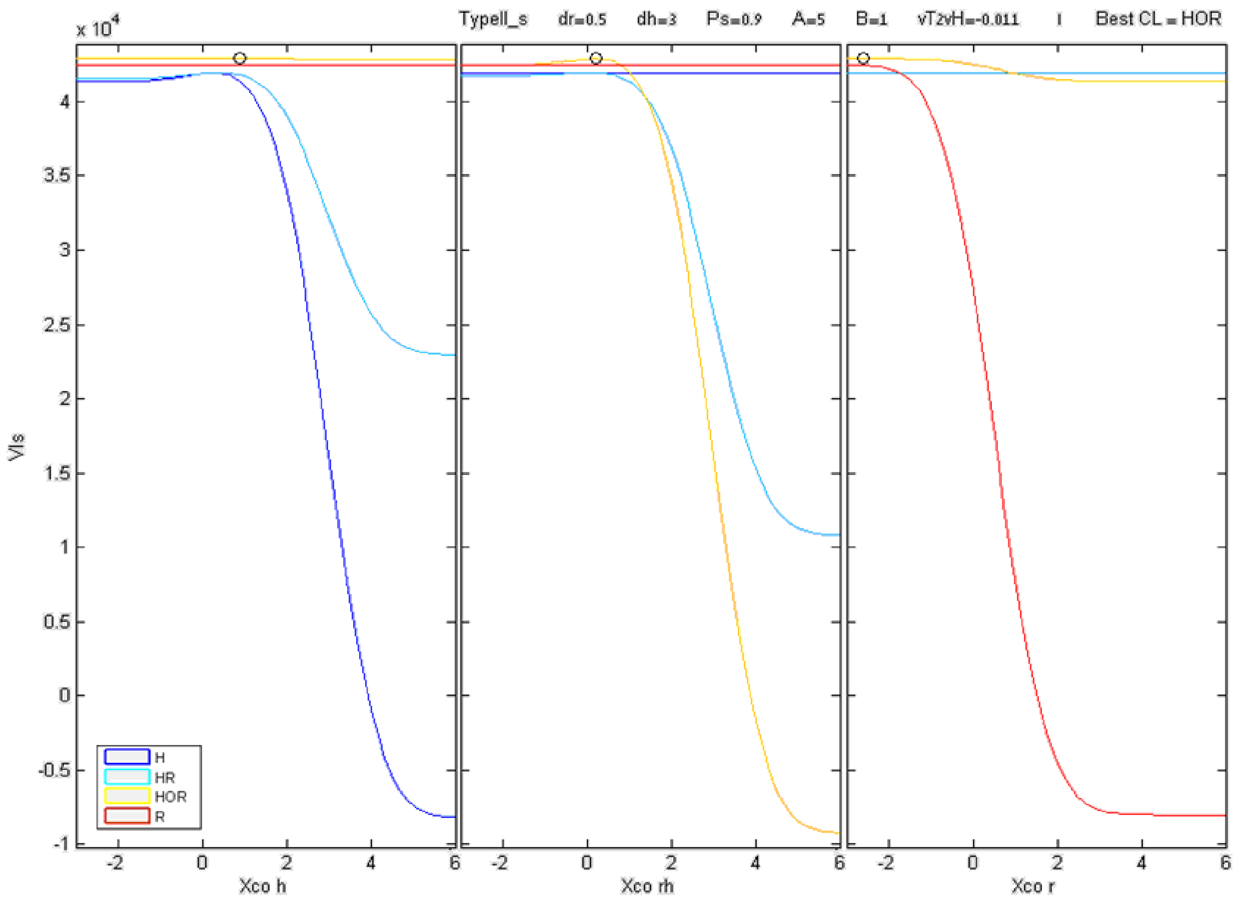

Figure 35: Example of Type II system's score in a case where the probability for a target is high and the difference between the collaboration levels scores is small.

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 (Ps) 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 Ps 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.

8 References

Bechar, A., J. Meyer and Y. Edan (2009). An Objective Function to Evaluate Performance of Human-Robot Collaboration in Target Recognition Tasks. IEEE Transactions on Systems, Man and Cybernetics, Part C (In press).

Bechar A. (2006). Human-Robot Collaboration Methods for Target Recognition in Unstructured Environments. Ph.D. dissertation, Industrial Engineering and Management, Ben-Gurion University of the Negev, Beer-Sheva, Israel.

Bechar A. & Edan Y. (2003). Human-Robot Collaboration for Improved Target Recognition of Agricultural Robots. Industrial Robot 30(5): 432-436.

Bechar A. & Edan Y. (2000). Human-Robot Collaboration for Agricultural Robot Guidance. ASAE Paper No. 00-3135. ASAE, St. Joseph, MI.

Bhanu B., Jones G., Lin Y.Q. & Peng J. (2000). Adaptive Target Recognition. Machine Vision and Applications 11(6): 289-299.

Brown C.D. & Davis H.T. (2006). Receiver Operating Characteristics Curves and Related Decision Measures: A Tutorial. Chemometrics and Intelligent Laboratory Systems 80(1): 24-38.

Bruemmer D.J., Boring R.A., Few D. A., Marble J.A., Nielsen C.W. and Walton M.C. (2005). Shared Understanding for Collaborative Control. IEEE Transactions on Systems, Man and Cybernetics: Part A, vol. 35, no. 4, pp. 494-504.

Bulanon D.M., Hiroma T., Kataoka T., Ota, Y. and Zhang S. (2001). Optimal Thresholding for the Automatic Recognition of Apple Fruits. ASAE Paper No. 01-3133. ASAE, St. Joseph, MI.

Burke J. L., Lumelsky V. J., Murphy R. R., Rogers E. and Scholtz J. (2004). Final Report for the DARPA/NSF Interdisciplinary Study on Human–Robot Interaction. IEEE Transactions on Systems, Man and Cybernetics: Part C, vol. 34, no. 2, pp. 103–112.

Cohen H. & Ferrell W. R. (1969). Human Operator Decision-Making in Manual Control. IEEE Transactions on Man-Machine Systems. Vol. MMS-10, no. 2, pp. 41-53.

Czarnecki C. & Graves A.R. (2000). Design Patterns for Behavior-Based Robotics. IEEE Transactions on Systems, Man and Cybernetics: Part A, vol. 30, no. 1, pp. 36-41.

Dubey R. & Everett S. (1998). Human-Machine Cooperative Telerobotics Using Uncertain Sensor and Model Data. Proceedings of the IEEE International Conference on Robotics and Automation. Leuven, Belgium. pp. 1615-1622.

Hughes S.B. & Lewis M. (2005). Task-Driven Camera Operations for Robotic Exploration. IEEE Transactions on Systems, Man and Cybernetics: Part A, vol. 35, no. 4, pp. 513-522.

http://wise.cgu.edu. Signal Detection Theory Tutorial. Retrieved November 2007, from World Wide Web: http://wise.cgu.edu/sdtmod/index.asp

Murdock B. B. & Dufty P. O. (1972). Strength Theory and Recognition Memory. Journal of Experimental Psychology, vol. 94, No. 3, pp. 284-290.

Murdock B. B. (1985). An analysis of the strength-latency relationship. Memory and Cognition, 13 (6), 511-521.

Obuchowski N.A. (2003). Receiver Operating Characteristic Curves and Their Use in Radiology. Radiology 229 3– 8.

Oren Y. (2007). Performance Analysis of Human-Robot Collaboration in Target Recognition Tasks. B.Sc dissertation, Industrial Engineering and Management, Ben-Gurion University of the Negev, Beer-Sheva, Israel.

Oren Y., Bechar A., Joachim M., Edan Y. (2008). Performance Analysis of Human-Robot Collaboration in Target Recognition Tasks. IEEE International Conference on Distributed Human-Machine Systems. Athens, Greece.

Parasuraman R., Sheridan T.B. and Wickens C.D. (2000). A Model for Types and Levels of Human Interaction with Automation. IEEE Transactions on Systems, Man and Cybernetics: part A, vol. 30, no. 3, pp. 286-197.

Pike R. (1973). Response Latency Models for Signal Detection. Psychological Review, vol. 80, No. 1, pp. 53-68.

Ratcliff R. & Rouder J. F. (1998). Modeling Response Times for Two Choice Decisions. Psychological Science, vol. 9, No. 5, pp. 347-356.

Ratcliff R., Mckoon G., and Zandt T. V. (1999). Connectionist and Diffusion Models of Reaction Time. Psychological Review, vol. 106, No. 2, pp. 261-300.

Ratcliff R. & Smith P. L. (2004). A Comparison of Sequential Sampling Models for Two-Choice Reaction Time. Psychological Review, vol. 111, No. 2, pp. 333-367.

Rodriguez G. & Weisbin C.R. (2003). A New Method to Evaluate Human-Robot System Performance. Autonomous Robots 14: 165–178.

Sheridan T.B. & Verplank W.L. (1978). Human and Computer Control of Undersea Teleoperators. MIT Man-Machine Systems Laboratory. Cambridge, MA, Tech. Rep.

Sheridan T.B. (1992). Telerobotics, Automation and Supervisory Control. Cambridge, MA. MIT.

Steinfeld A. (2004). Interface Lessons for Fully and Semi-Autonomous Mobile Robots. Proceedings of the IEEE International Conference on Robotics and Automation, 3.

Takach I. (2008). Switching between collaboration levels in target recognition tasks. M.Sc. dissertation, Industrial Engineering and Management, Ben-Gurion University of the Negev, Beer-Sheva, Israel.

Welford A. T. (1980). Reaction Times. London, Academic Press.

Wickens T. D. (2002). Elementary Signal Detection Theory. New York, Oxford University. Press.

9 APPENDIXES

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 μ_X and variance $\sigma_X{}^2$ we denote:

$$X \sim \qquad (\mu_X, \sigma_X{}^2)$$

The probability density function (PDF) is:

$$f_X(x) = \frac{1}{\sigma_X \sqrt{2\pi}} \cdot e^{-\frac{(x-\mu_X)^2}{2\sigma_X{}^2}}$$

The cumulative density function (CDF) is:

$$F_X(x) = \int_{-\infty}^{x} f_X(x)dx = \frac{1}{\sigma_X \sqrt{2\pi}} \int_{-\infty}^{x} e^{-\frac{(x-\mu_X)^2}{2\sigma_X{}^2}} dx$$

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 μ_X and variance $\sigma_X{}^2$, we can normalize X by defining new random variable Z:

$$z = \frac{x-\mu_X}{\sigma_X} \Rightarrow \mu_Z = 0,\ \sigma_Z{}^2 = 1$$

$$Z \sim \qquad (0,1)$$

The PDF of the standard normal distribution is:

$$f_Z(z) = \varphi(z) = \frac{1}{\sigma_Z \sqrt{2\pi}} \cdot e^{-\frac{(z-\mu_Z)^2}{2\sigma_Z{}^2}} = \frac{1}{1 \cdot \sqrt{2\pi}} \cdot e^{-\frac{(z-0)^2}{2 \cdot 1^2}} = \frac{1}{\sqrt{2\pi}} \cdot e^{-\frac{z^2}{2}}$$

The CDF of the standard normal distribution is:

$$F_Z(z) = \Phi(z) = \int_{-\infty}^{z} f_Z(z)dz = \frac{1}{\sigma_Z \sqrt{2\pi}} \int_{-\infty}^{z} e^{-\frac{(z-\mu_Z)^2}{2\sigma_Z{}^2}} dz = \frac{1}{1 \cdot \sqrt{2\pi}} \int_{-\infty}^{z} e^{-\frac{(z-0)^2}{2 \cdot 1^2}} dz = \frac{1}{\sqrt{2\pi}} \int_{-\infty}^{z} e^{-\frac{z^2}{2}} dz$$

$$1 - \Phi(z) = 1 - \int_{-\infty}^{z} f_Z(z)dz = \int_{z}^{\infty} f_Z(z)dz = \frac{1}{\sqrt{2\pi}} \int_{z}^{\infty} e^{-\frac{z^2}{2}} dz$$

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_{co} we can define z_{co}, a specific value of the random variable Z which is standard normal distributed.

$$z_{co} = \frac{x_{co} - \mu_X}{\sigma_X}$$

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

$$f_X(x_{co}) = \frac{1}{\sigma_X\sqrt{2\pi}} \cdot e^{\frac{-(x_{co}-\mu_X)^2}{2\sigma_X{}^2}} = \frac{1}{\sigma_X} \cdot \frac{1}{\sqrt{2\pi}} \cdot e^{\frac{-z_{co}{}^2}{2}} = \frac{1}{\sigma_X} \cdot \varphi(z_{co})$$

$$f_X(x_{co}) = \frac{1}{\sigma_X} \cdot \varphi(z_{co})$$

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

$$F_X(x_{co}) = \int_{-\infty}^{x_{co}} f_X(x)dx = \frac{1}{\sigma_X\sqrt{2\pi}} \int_{-\infty}^{x_{co}} e^{-\frac{1}{2}(\frac{x-\mu_X}{\sigma_X})^2} dx =$$

Changing the domain of integration:

$$z = \frac{x-\mu_X}{\sigma_X} \Rightarrow x = \mu_X + \sigma_X z$$

$$\frac{dx}{dz} = \frac{d(\mu_X + \sigma_X z)}{dz} = \sigma_X \Rightarrow dx = \sigma_X dz$$

$$x = -\infty \Rightarrow z = \frac{-\infty - \mu_X}{\sigma_X} = -\infty$$

$$x = x_{co} \Rightarrow z = \frac{x_{co} - \mu_X}{\sigma_X} = z_{co}$$

$$= \frac{1}{\cancel{\sigma_X}\sqrt{2\pi}} \int_{-\infty}^{z_{co}} e^{\frac{-z^2}{2}} \cancel{\sigma_X} dz = \frac{1}{\sqrt{2\pi}} \int_{-\infty}^{z_{co}} e^{\frac{-z^2}{2}} dz = \Phi(z_{co})$$

$$F_X(x_{co}) = \Phi(z_{co})$$

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.

$$X_S \sim \quad (\mu_S, \sigma_S{}^2)$$

$$f_S(x) = \frac{1}{\sigma_S\sqrt{2\pi}} \cdot e^{\frac{-(x-\mu_S)^2}{2\sigma_S{}^2}}$$

$$F_S(x) = \int_{-\infty}^{x} f_S(x)dx = \frac{1}{\sigma_S\sqrt{2\pi}} \int_{-\infty}^{x} e^{\frac{-(x-\mu_S)^2}{2\sigma_S{}^2}} dx$$

$$1 - F_S(x) = 1 - \int_{-\infty}^{x} f_S(x)dx = \int_{x}^{\infty} f_S(x)dx = \frac{1}{\sigma_S\sqrt{2\pi}} \int_{x}^{\infty} e^{\frac{-(x-\mu_S)^2}{2\sigma_S{}^2}} dx$$

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

$$P_{Miss}(x_{co}) = F_S(x_{co}) \;\; ; \;\; P_{Hit}(x_{co}) = 1 - F_S(x_{co})$$

5. Noise distribution

Here are definitions of distribution, PDF and CDF of X_N which represents the value of noises.

$$X_N \sim \quad (\mu_N, \sigma_N{}^2)$$

$$f_N(x) = \frac{1}{\sigma_N\sqrt{2\pi}} \cdot e^{\frac{-(x-\mu_N)^2}{2\sigma_N{}^2}}$$

$$F(x) = \int_{-\infty}^{x} f_S(x)dx = \frac{1}{\sigma_N\sqrt{2\pi}} \int_{-\infty}^{x} e^{\frac{-(x-\mu_N)^2}{2\sigma_N{}^2}} dx$$

$$1 - F_N(x) = 1 - \int_{-\infty}^{x} f_N(x)dx = \int_{x}^{\infty} f_N(x)dx = \frac{1}{\sigma_N\sqrt{2\pi}} \int_{x}^{\infty} e^{\frac{-(x-\mu_N)^2}{2\sigma_N{}^2}} dx$$

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

$$P_{CR}(x_{co}) = F_N(x_{co}) \;\; ; \;\; P_{FA}(x_{co}) = 1 - F_N(x_{co})$$

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_{co}, 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, β, between the signal and noise density functions in the cutoff point, x_{co}, and the distance between the means of the signal and noise distributions, d' (see chapter 2.6 for details). For the expressions, the standard deviations σ_S, σ_N were assumed to be equal one (Bechar, 2006).

$$Z_S = \frac{x_{co} - \mu_S}{\sigma_S} = x_{co} - \mu_S$$

$$Z_N = \frac{x_{co} - \mu_N}{\sigma_N} = x_{co} - \mu_N$$

$$d' = \mu_S - \mu_N = (x_{co} - Z_S) - (x_{co} - Z_N) = x_{co} - Z_S - x_{co} + Z_N = Z_N - Z_S$$

$$\beta = \frac{f_Z(Z_S)}{f_Z(Z_N)} = \frac{\frac{1}{\sqrt{2\pi}} \cdot e^{\frac{-Z_S}{2}}}{\frac{1}{\sqrt{2\pi}} \cdot e^{\frac{-Z_N}{2}}} = e^{-\frac{Z_S}{2}+\frac{Z_N}{2}} = e^{-\frac{1}{2}(Z_S{}^2 - Z_N{}^2)}$$

$$\ln(\beta) = -\frac{1}{2}(Z_S{}^2 - Z_N{}^2)$$

$$i)\ d' = Z_N - Z_S$$

$$ii)\ \ln(\beta) = -\frac{1}{2}(Z_S{}^2 - Z_N{}^2)$$

$$i) \Rightarrow iii)\ Z_S = Z_N - d'$$

$$ii + iii) \Rightarrow \ln(\beta) = -\frac{1}{2}((Z_N - d')^2 - Z_N{}^2) = -\frac{1}{2}(Z_N{}^2 - 2Z_N d' + d'^2 - Z_N{}^2) = Z_N d' - \frac{d'^2}{2}$$

$$Z_N d' = \ln(\beta) + \frac{d'^2}{2}$$

$$\boxed{Z_N = \frac{\ln(\beta)}{d'} + \frac{d'}{2}}$$

$$i) \Rightarrow iv)\ Z_N = Z_S + d'$$

$$ii + iv) \Rightarrow \ln(\beta) = -\frac{1}{2}(Z_S{}^2 - (Z_S + d')^2) = -\frac{1}{2}(Z_S{}^2 - Z_S{}^2 - 2Z_S d' - d'^2) = Z_S d' + \frac{d'^2}{2}$$

$$Z_S d' = \ln(\beta) - \frac{d'^2}{2}$$

$$\boxed{Z_S = \frac{\ln(\beta)}{d'} - \frac{d'}{2}}$$

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:

$$d_- = (x_{co} - \mu) + \sigma \cdot \frac{\varphi(z_{co})}{\Phi(z_{co})}$$

$$d_+ = -(x_{co} - \mu) + \sigma \cdot \frac{\varphi(z_{co})}{1 - \Phi(z_{co})}$$

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_{co} 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.

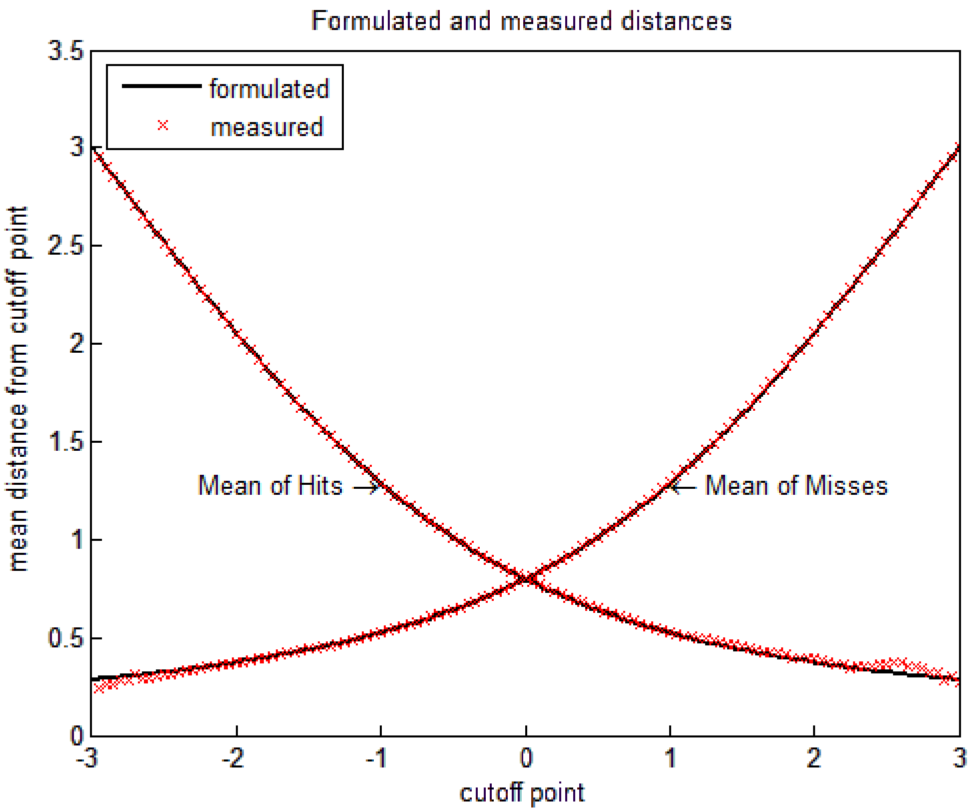

Figure A1: A validation of equation for mean distances

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 (x_{co}) 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:

$$d(x) = x_{co} - x$$
$$t(x) = A \cdot e^{-B(x_{co} - x)}$$

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

$$d(x) = x - x_{co}$$
$$t(x) = A \cdot e^{-B(x - x_{co})}$$

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

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.

$$T_{-}(x_{co}) = \frac{\int_{-\infty}^{x_{co}} t(x) \cdot f(x)dx}{\int_{-\infty}^{x_{co}} f(x)dx} =$$

$$= \frac{\int_{-\infty}^{x_{co}} A \cdot e^{-B(x_{co}-x)} \cdot f(x)dx}{\int_{-\infty}^{x_{co}} f(x)dx} =$$

$\textit{From the normal distribution}:$
$f(x) = \frac{1}{\sigma\sqrt{2\pi}} e^{\frac{-(x-\mu)^2}{2\sigma^2}}$
$\int_{-\infty}^{x_{co}} f(x)dx = F(x_{co})$

$$= \frac{\int_{-\infty}^{x_{co}} A \cdot e^{-B(x_{co}-x)} \cdot \frac{1}{\sigma\sqrt{2\pi}} e^{\frac{-(x-\mu)^2}{2\sigma^2}} dx}{F(x_{co})} =$$

$$= \frac{\int_{-\infty}^{x_{co}} A \cdot e^{-B \cdot x_{co}} \cdot e^{B \cdot x} \cdot \frac{1}{\sigma\sqrt{2\pi}} e^{\frac{-(x-\mu)^2}{2\sigma^2}} dx}{F(x_{co})} =$$

$$= A \cdot e^{-B \cdot x_{co}} \cdot \frac{\int_{-\infty}^{x_{co}} e^{B \cdot x} \cdot \frac{1}{\sigma\sqrt{2\pi}} e^{\frac{-(x-\mu)^2}{2\sigma^2}} dx}{F(x_{co})} =$$

$$= A \cdot e^{-B \cdot x_{co}} \cdot \frac{\frac{1}{\sigma\sqrt{2\pi}} \cdot \int_{-\infty}^{x_{co}} e^{B \cdot x - \frac{(x-\mu)^2}{2\sigma^2}} dx}{F(x_{co})} =$$

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

$$= A \cdot e^{-B \cdot x_{co}} \cdot \frac{\frac{1}{\sigma\sqrt{2\pi}} \cdot \int_{-\infty}^{x_{co}} e^{-\frac{1}{2} \cdot \frac{-2B \cdot x \cdot \sigma^2 + (x-\mu)^2}{\sigma^2}} dx}{F(x_{co})} =$$

$$= A \cdot e^{-B \cdot x_{co}} \cdot \frac{\frac{1}{\sigma\sqrt{2\pi}} \cdot \int_{-\infty}^{x_{co}} e^{-\frac{-2B \cdot x \cdot \sigma^2 + x^2 - 2x \cdot \mu + \mu^2}{2\sigma^2}} dx}{F(x_{co})} =$$

$$= A \cdot e^{-B \cdot x_{co}} \cdot \frac{\frac{1}{\sigma\sqrt{2\pi}} \cdot \int_{-\infty}^{x_{co}} e^{\frac{-\mu^2}{2\sigma^2}} \cdot e^{-\frac{-2B \cdot x \cdot \sigma^2 + x^2 - 2x \cdot \mu}{2\sigma^2}} dx}{F(x_{co})} =$$

$$= A \cdot e^{-B \cdot x_{co}} \cdot e^{\frac{-\mu^2}{2\sigma^2}} \cdot \frac{\frac{1}{\sigma\sqrt{2\pi}} \cdot \int_{-\infty}^{x_{co}} e^{-\frac{x^2 - 2x \cdot (\mu + B \cdot \sigma^2)}{2\sigma^2}} dx}{F(x_{co})} =$$

$$= A \cdot e^{-B \cdot x_{co} - \frac{\mu^2}{2\sigma^2}} \cdot \frac{\frac{1}{\sigma\sqrt{2\pi}} \cdot \int_{-\infty}^{x_{co}} e^{-\frac{x^2 - 2x \cdot (\mu + B \cdot \sigma^2) + (\mu + B \cdot \sigma^2)^2 - (\mu + B \cdot \sigma^2)^2}{2\sigma^2}} dx}{F(x_{co})} =$$

$$= A \cdot e^{-B \cdot x_{co} - \frac{\mu^2}{2\sigma^2}} \cdot \frac{\frac{1}{\sigma\sqrt{2\pi}} \cdot \int_{-\infty}^{x_{co}} e^{\frac{-(\mu + B \cdot \sigma^2)^2}{-2\sigma^2}} \cdot e^{-\frac{x^2 - 2x \cdot (\mu + B \cdot \sigma^2) + (\mu + B \cdot \sigma^2)^2}{2\sigma^2}} dx}{F(x_{co})} =$$

$$= A \cdot e^{-B \cdot x_{co} - \frac{\mu^2}{2\sigma^2}} \cdot e^{\frac{(\mu + B \cdot \sigma^2)^2}{2\sigma^2}} \cdot \frac{\frac{1}{\sigma\sqrt{2\pi}} \cdot \int_{-\infty}^{x_{co}} e^{-\frac{x^2 - 2x \cdot (\mu + B \cdot \sigma^2) + (\mu + B \cdot \sigma^2)^2}{2\sigma^2}} dx}{F(x_{co})} =$$

$$= A \cdot e^{-B \cdot x_{co} - \frac{\mu^2}{2\sigma^2} + \frac{(\mu + B \cdot \sigma^2)^2}{2\sigma^2}} \cdot \frac{\frac{1}{\sigma\sqrt{2\pi}} \cdot \int_{-\infty}^{x_{co}} e^{\frac{-(x - (\mu + B \cdot \sigma^2))^2}{2\sigma^2}} dx}{F(x_{co})} =$$

$$= A \cdot e^{-B \cdot x_{co} - \frac{\mu^2}{2\sigma^2} + \frac{\mu^2 + 2\mu \cdot B \cdot \sigma^2 + B^2 \cdot \sigma^4}{2\sigma^2}} \cdot \frac{\frac{1}{\sigma\sqrt{2\pi}} \cdot \int_{-\infty}^{x_{co}} e^{\frac{-(x - (\mu + B \cdot \sigma^2))^2}{2\sigma^2}} dx}{F(x_{co})} =$$

$$= A \cdot e^{-B \cdot x_{co} + \frac{-\cancel{\mu^2} + \cancel{\mu^2}}{2\sigma^2} + \frac{\cancel{2}\mu \cdot B \cdot \cancel{\sigma^2}}{\cancel{2}\cancel{\sigma^2}} + \frac{B^2 \cdot \sigma^2 \cdot \cancel{\sigma^2}}{2\cancel{\sigma^2}}} \cdot \frac{\frac{1}{\sigma\sqrt{2\pi}} \cdot \int_{-\infty}^{x_{co}} e^{\frac{-(x - (\mu + B \cdot \sigma^2))^2}{2\sigma^2}} dx}{F(x_{co})} =$$

$$= A\cdot e^{-B\cdot x_{co}+\mu\cdot B+\frac{B^2\cdot\sigma^2}{2}}\cdot\frac{\frac{1}{\sigma\sqrt{2\pi}}\cdot\int_{-\infty}^{x_{co}} e^{\frac{-(x-(\mu+B\cdot\sigma^2))^2}{2\sigma^2}}dx}{F(x_{co})} =$$

$$= A\cdot e^{-B\cdot(x_{co}-\mu)+\frac{B^2\cdot\sigma^2}{2}}\cdot\frac{\frac{1}{\sigma\sqrt{2\pi}}\cdot\int_{-\infty}^{x_{co}} e^{-\frac{1}{2}(\frac{x-(\mu+B\cdot\sigma^2)}{\sigma})^2}dx}{F(x_{co})} =$$

Changing the domain of integration:

$$u=\frac{x-(\mu+B\cdot\sigma^2)}{\sigma} \Rightarrow x=\mu+B\cdot\sigma^2+\sigma u$$

$$\frac{dx}{du}=\frac{d(\mu+B\cdot\sigma^2+\sigma u)}{du}=\sigma \Rightarrow dx=\sigma du$$

$$x=-\infty \Rightarrow u=\frac{-\infty-(\mu+B\cdot\sigma^2)}{\sigma}=-\infty$$

$$x=x_{co} \Rightarrow u=\frac{x_{co}-(\mu+B\cdot\sigma^2)}{\sigma}=u_{co}$$

$$= A\cdot e^{-B\cdot(x_{co}-\mu)+\frac{B^2\cdot\sigma^2}{2}}\cdot\frac{\frac{1}{\cancel{\sigma}\sqrt{2\pi}}\cdot\int_{-\infty}^{u_{co}} e^{\frac{-u^2}{2}}\cancel{\sigma}du}{F(x_{co})} =$$

From the standard normal distribution:

$$\frac{1}{\sqrt{2\pi}}\cdot\int_{-\infty}^{u_{co}} e^{\frac{-u^2}{2}}du=\Phi(u_{co})=\Phi(\frac{x_{co}-(\mu+B\cdot\sigma^2)}{\sigma})$$

$$= A\cdot e^{-B\cdot(x_{co}-\mu)+\frac{B^2\cdot\sigma^2}{2}}\cdot\frac{\Phi(\frac{x_{co}-(\mu+B\cdot\sigma^2)}{\sigma})}{F(x_{co})} =$$

$$= A\cdot e^{-B\cdot\sigma\cdot\frac{x_{co}-\mu}{\sigma}+\frac{B^2\cdot\sigma^2}{2}}\cdot\frac{\Phi(\frac{x_{co}-\mu}{\sigma}-\frac{B\cdot\sigma^{\cancel{2}}}{\cancel{\sigma}})}{F(x_{co})} =$$

From the standard normal distribution:

$$\frac{x_{co}-\mu}{\sigma}=z_{co} \quad ; \quad F(x_{co})=\Phi(\frac{x_{co}-\mu}{\sigma})=\Phi(z_{co})$$

$$= A\cdot e^{-B\cdot\sigma\cdot z_{co}+\frac{B^2\cdot\sigma^2}{2}}\cdot\frac{\Phi(z_{co}-B\cdot\sigma)}{\Phi(z_{co})}$$

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

where

$$z_{co} = \frac{x_{co}-\mu}{\sigma}$$

$$\Phi(z)=\frac{1}{\sqrt{2\pi}}\int_{-\infty}^{z} e^{\frac{-z^2}{2}}dz$$

if $\sigma=1$ *then*

$$T_{-}(x_{co}) = A\cdot e^{-B\cdot z_{co}+\frac{B^2}{2}}\cdot\frac{\Phi(z_{co}-B)}{\Phi(z_{co})}$$

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.

$$T_+(x_{co}) = \frac{\int_{x_{co}}^{\infty} t(x)\cdot f(x)dx}{\int_{x_{co}}^{\infty} f(x)dx} =$$

$$= \frac{\int_{x_{co}}^{\infty} A\cdot e^{-B\cdot(x-x_{co})}\cdot f(x)dx}{\int_{x_{co}}^{\infty} f(x)dx} =$$

$$\boxed{\begin{array}{l} \textit{From the normal distribution:} \\ f(x) = \frac{1}{\sigma\sqrt{2\pi}} e^{\frac{-(x-\mu)^2}{2\sigma^2}} \\ \int_{x_{co}}^{\infty} f(x)dx = 1 - F(x_{co}) \end{array}}$$

$$= \frac{\int_{x_{co}}^{\infty} A\cdot e^{B\cdot(x_{co}-x)}\cdot \frac{1}{\sigma\sqrt{2\pi}} e^{\frac{-(x-\mu)^2}{2\sigma^2}} dx}{1-F(x_{co})} =$$

$$= \frac{\int_{x_{co}}^{\infty} A\cdot e^{B\cdot x_{co}}\cdot e^{-B\cdot x}\cdot \frac{1}{\sigma\sqrt{2\pi}} e^{\frac{-(x-\mu)^2}{2\sigma^2}} dx}{1-F(x_{co})} =$$

$$= A\cdot e^{B\cdot x_{co}}\cdot \frac{\frac{1}{\sigma\sqrt{2\pi}}\cdot\int_{x_{co}}^{\infty} e^{-B\cdot x}\cdot e^{\frac{-(x-\mu)^2}{2\sigma^2}} dx}{1-F(x_{co})} =$$

$$= A\cdot e^{B\cdot x_{co}}\cdot \frac{\frac{1}{\sigma\sqrt{2\pi}}\cdot\int_{x_{co}}^{\infty} e^{-B\cdot x-\frac{(x-\mu)^2}{2\sigma^2}} dx}{1-F(x_{co})} =$$

$$= A\cdot e^{B\cdot x_{co}}\cdot\frac{\frac{1}{\sigma\sqrt{2\pi}}\cdot\int\limits_{x_{co}}^{\infty}e^{-\frac{1}{2}(2B\cdot x+\frac{(x-\mu)^2}{\sigma^2})}dx}{1-F(x_{co})}=$$

$$= A\cdot e^{B\cdot x_{co}}\cdot\frac{\frac{1}{\sigma\sqrt{2\pi}}\cdot\int\limits_{x_{co}}^{\infty}e^{-\frac{1}{2}\cdot\frac{2B\cdot x\cdot\sigma^2+(x-\mu)^2}{\sigma^2}}dx}{1-F(x_{co})}=$$

$$= A\cdot e^{B\cdot x_{co}}\cdot\frac{\frac{1}{\sigma\sqrt{2\pi}}\cdot\int\limits_{x_{co}}^{\infty}e^{-\frac{2B\cdot x\cdot\sigma^2+x^2-2x\cdot\mu+\mu^2}{2\sigma^2}}dx}{1-F(x_{co})}=$$

$$= A\cdot e^{B\cdot x_{co}}\cdot\frac{\frac{1}{\sigma\sqrt{2\pi}}\cdot\int\limits_{x_{co}}^{\infty}e^{\frac{-\mu^2}{2\sigma^2}}\cdot e^{-\frac{2B\cdot x\cdot\sigma^2+x^2-2x\cdot\mu}{2\sigma^2}}dx}{1-F(x_{co})}=$$

$$= A\cdot e^{B\cdot x_{co}}\cdot e^{\frac{-\mu^2}{2\sigma^2}}\cdot\frac{\frac{1}{\sigma\sqrt{2\pi}}\cdot\int\limits_{x_{co}}^{\infty}e^{-\frac{x^2-2x\cdot(\mu-B\cdot\sigma^2)}{2\sigma_S^{\,2}}}dx}{1-F(x_{co})}=$$

$$= A\cdot e^{B\cdot x_{co}-\frac{\mu^2}{2\sigma^2}}\cdot\frac{\frac{1}{\sigma\sqrt{2\pi}}\cdot\int\limits_{x_{co}}^{\infty}e^{-\frac{x^2-2x\cdot(\mu-B\cdot\sigma^2)+(\mu-B\cdot\sigma^2)^2-(\mu-B\cdot\sigma^2)^2}{2\sigma^2}}dx}{1-F(x_{co})}=$$

$$= A\cdot e^{B\cdot x_{co}-\frac{\mu^2}{2\sigma^2}}\cdot\frac{\frac{1}{\sigma\sqrt{2\pi}}\cdot\int\limits_{x_{co}}^{\infty}e^{\frac{-(\mu-B\cdot\sigma^2)^2}{-2\sigma^2}}\cdot e^{-\frac{x^2-2x\cdot(\mu-B\cdot\sigma^2)+(\mu-B\cdot\sigma^2)^2}{2\sigma^2}}dx}{1-F(x_{co})}=$$

$$= A\cdot e^{B\cdot x_{co}-\frac{\mu^2}{2\sigma^2}}\cdot e^{\frac{(\mu-B\cdot\sigma^2)^2}{2\sigma^2}}\cdot\frac{\frac{1}{\sigma\sqrt{2\pi}}\cdot\int\limits_{x_{co}}^{\infty}e^{-\frac{x^2-2x\cdot(\mu-B\cdot\sigma^2)+(\mu-B\cdot\sigma^2)^2}{2\sigma^2}}dx}{1-F(x_{co})}=$$

$$= A\cdot e^{B\cdot x_{co}-\frac{\mu^2}{2\sigma^2}+\frac{(\mu-B\cdot\sigma^2)^2}{2\sigma^2}}\cdot\frac{\frac{1}{\sigma\sqrt{2\pi}}\cdot\int\limits_{x_{co}}^{\infty}e^{\frac{-(x-(\mu-B\cdot\sigma^2))^2}{2\sigma^2}}dx}{1-F(x_{co})}=$$

$$= A\cdot e^{B\cdot x_{co}-\frac{\mu^2}{2\sigma^2}+\frac{\mu^2-2\mu\cdot B\cdot\sigma^2+B^2\cdot\sigma^4}{2\sigma^2}}\cdot\frac{\frac{1}{\sigma\sqrt{2\pi}}\cdot\int\limits_{x_{co}}^{\infty}e^{\frac{-(x-(\mu-B\cdot\sigma^2))^2}{2\sigma^2}}dx}{1-F(x_{co})}=$$

$$= A\cdot e^{B\cdot x_{co}+\frac{-\cancel{\mu^2}+\cancel{\mu^2}}{2\sigma^2}+\frac{-\cancel{2}\mu\cdot B\cdot\cancel{\sigma^2}}{\cancel{2}\cancel{\sigma^2}}+\frac{B^2\cdot\sigma^2\cdot\cancel{\sigma^2}}{2\cancel{\sigma^2}}}\cdot\frac{\frac{1}{\sigma\sqrt{2\pi}}\cdot\int\limits_{x_{co}}^{\infty}e^{\frac{-(x-(\mu-B\cdot\sigma^2))^2}{2\sigma^2}}dx}{1-F(x_{co})}=$$

$$= A\cdot e^{B\cdot x_{co}-\mu\cdot B+\frac{B^2\cdot\sigma^2}{2}}\cdot\frac{\frac{1}{\sigma\sqrt{2\pi}}\cdot\int_{x_{co}}^{\infty} e^{\frac{-(x-(\mu-B\cdot\sigma^2))^2}{2\sigma}}dx}{1-F(x_{co})} =$$

$$= A\cdot e^{B\cdot(x_{co}-\mu)+\frac{B^2\cdot\sigma^2}{2}}\cdot\frac{\frac{1}{\sigma\sqrt{2\pi}}\cdot\int_{x_{co}}^{\infty} e^{-\frac{1}{2}(\frac{x-(\mu-B\cdot\sigma^2)}{\sigma})^2}dx}{1-F(x_{co})} =$$

Changing the domain of integration:

$$u=\frac{x-(\mu-B\cdot\sigma^2)}{\sigma} \Rightarrow x=\mu-B\cdot\sigma^2+\sigma u$$

$$\frac{dx}{du}=\frac{d(\mu-B\cdot\sigma^2+\sigma u)}{du}=\sigma \Rightarrow dx=\sigma du$$

$$x=x_{co} \Rightarrow u=\frac{x_{co}-(\mu-B\cdot\sigma^2)}{\sigma}=u_{co}$$

$$x=\infty \Rightarrow u=\frac{\infty-(\mu-B\cdot\sigma^2)}{\sigma}=\infty$$

$$= A\cdot e^{B\cdot(x_{co}-\mu)+\frac{B^2\cdot\sigma^2}{2}}\cdot\frac{\frac{1}{\not\sigma\sqrt{2\pi}}\cdot\int_{u_{co}}^{\infty} e^{-\frac{1}{2}u^2}\not\sigma du}{1-F(x_{co})} =$$

From the standard normal distribution:

$$\frac{1}{\sqrt{2\pi}}\cdot\int_{u_{co}}^{\infty} e^{\frac{-u^2}{2}}du=1-\Phi(u_{co})=1-\Phi(\frac{x_{co}-(\mu-B\cdot\sigma^2)}{\sigma})$$

$$= A\cdot e^{B\cdot(x_{co}-\mu)+\frac{B^2\cdot\sigma^2}{2}}\cdot\frac{1-\Phi(\frac{x_{co}-(\mu-B\cdot\sigma^2)}{\sigma})}{1-F(x_{co})} =$$

$$= A\cdot e^{B\cdot\sigma\cdot\frac{(x_{co}-\mu)}{\sigma}+\frac{B^2\cdot\sigma^2}{2}}\cdot\frac{1-\Phi(\frac{x_{co}-\mu}{\sigma}+\frac{B\cdot\sigma^{\not 2}}{\not\sigma})}{1-F(x_{co})} =$$

From the standard normal distribution:

$$\frac{x_{co}-\mu}{\sigma}=z_{co} \;;\; F(x_{co})=\Phi(\frac{x_{co}-\mu}{\sigma})=\Phi(z_{co})$$

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

$$T_+(x_{co}) = A\cdot e^{B\cdot\sigma\cdot z_{co}+\frac{B^2\cdot\sigma^2}{2}}\cdot\frac{1-\Phi(z_{co}+B\cdot\sigma)}{1-\Phi(z_{co})}$$

where

$$z_{co} = \frac{x_{co}-\mu}{\sigma}$$

$$\Phi(z)=\frac{1}{\sqrt{2\pi}}\int_{-\infty}^{z} e^{\frac{-z^2}{2}}dz$$

if $\sigma=1$ *then*

$$T_+(x_{co}) = A\cdot e^{B\cdot z_{co}+\frac{B^2}{2}}\cdot\frac{1-\Phi(z_{co}+B)}{1-\Phi(z_{co})}$$

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 (d'_h) and the cost of time unit ($vT2vH$), for each value of the time parameter (A). The analysis was conducted for $B = 0.5,\ dr = 0.5$.

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 ($Ps = 0.1, 0.2, 0.5, 0.8, 0.9$)

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 ($d'_h \approx 1.5$). As Ps 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 ($d'_h \approx 0.5$). As Ps 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 (Ps). When Ps is high, 0.9 (Figure A3-e), an extreme negative cutoff point is preferred for relatively high sensitivities ($d'_h \approx 2.5$). As Ps decreases to 0.5 (Figure A3-c), the system prefers an extreme cutoff point only for lower sensitivities ($d'_h \approx 1$). 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 ($d'_h \approx 1$).

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 ($d'_h \approx 0.5-1.5$). When Ps increases to 0.8, 0.9 (Figure A4-d,e), the system prefers an extreme negative cutoff point for low sensitivities ($d'_h \approx 0.5-1$).

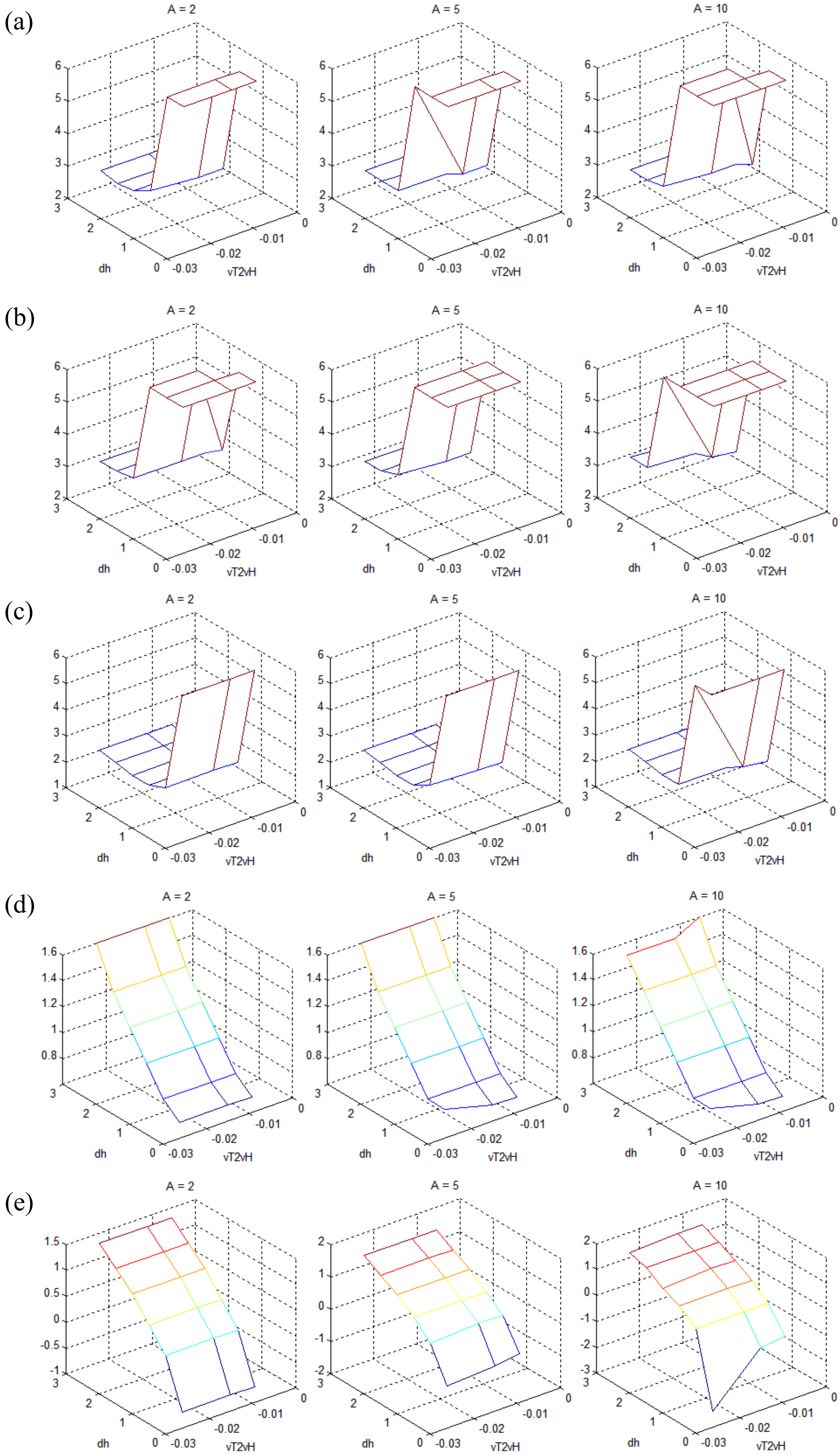

Figure A2: The optimal cutoff point of the human (z-axis) in the H collaboration level in a Type I system.
(a) $Ps = 0.1$, (b) $Ps = 0.2$, (c) $Ps = 0.5$, (d) $Ps = 0.8$, (e) $Ps = 0.9$. $B = 0.5, dr = 0.5$.

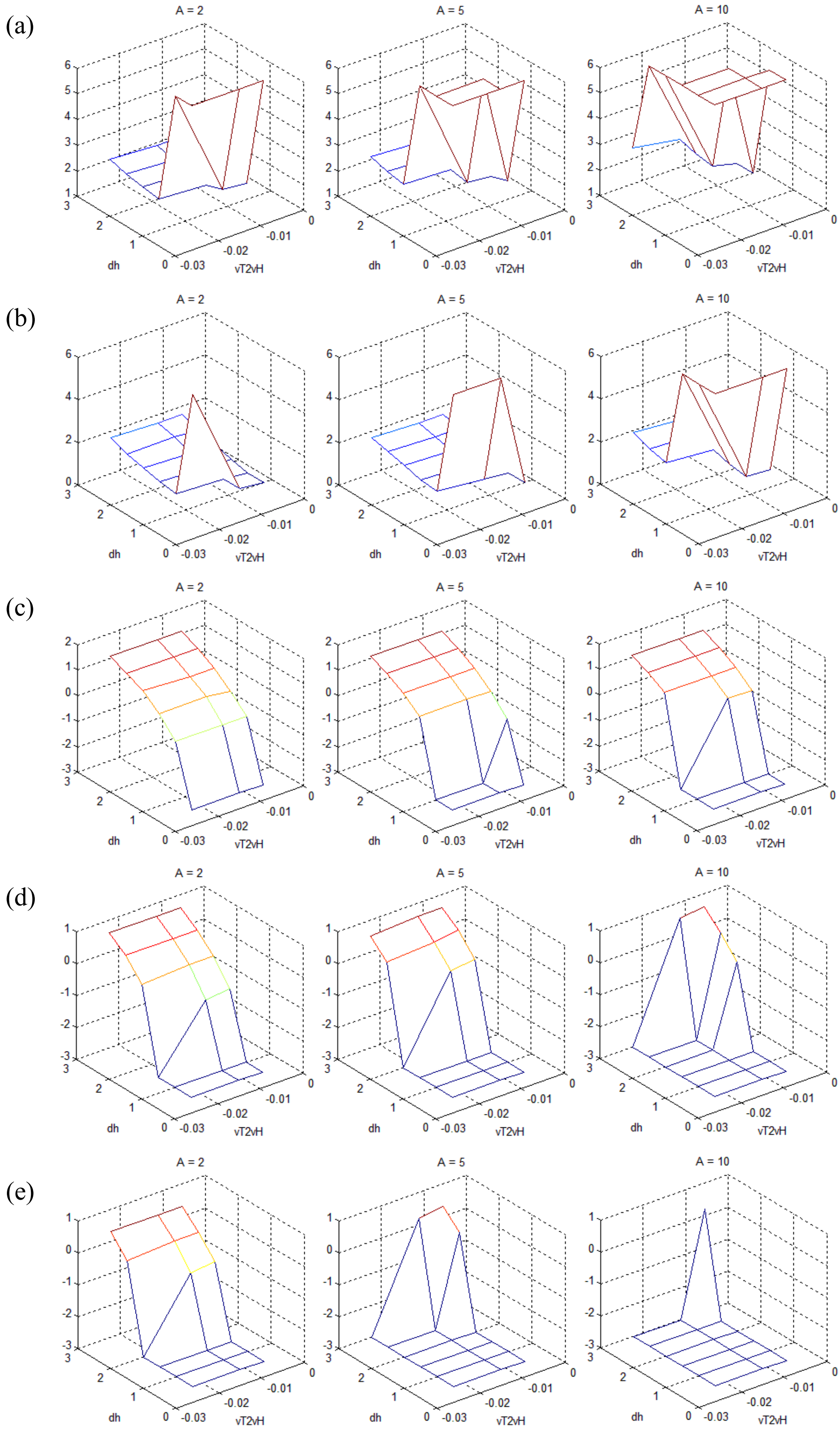

Figure A3: The optimal cutoff point of the human (z-axis) in the H collaboration level in a Type II system.
(a) $Ps = 0.1$, (b) $Ps = 0.2$, (c) $Ps = 0.5$, (d) $Ps = 0.8$, (e) $Ps = 0.9$. $B = 0.5$, $dr = 0.5$.

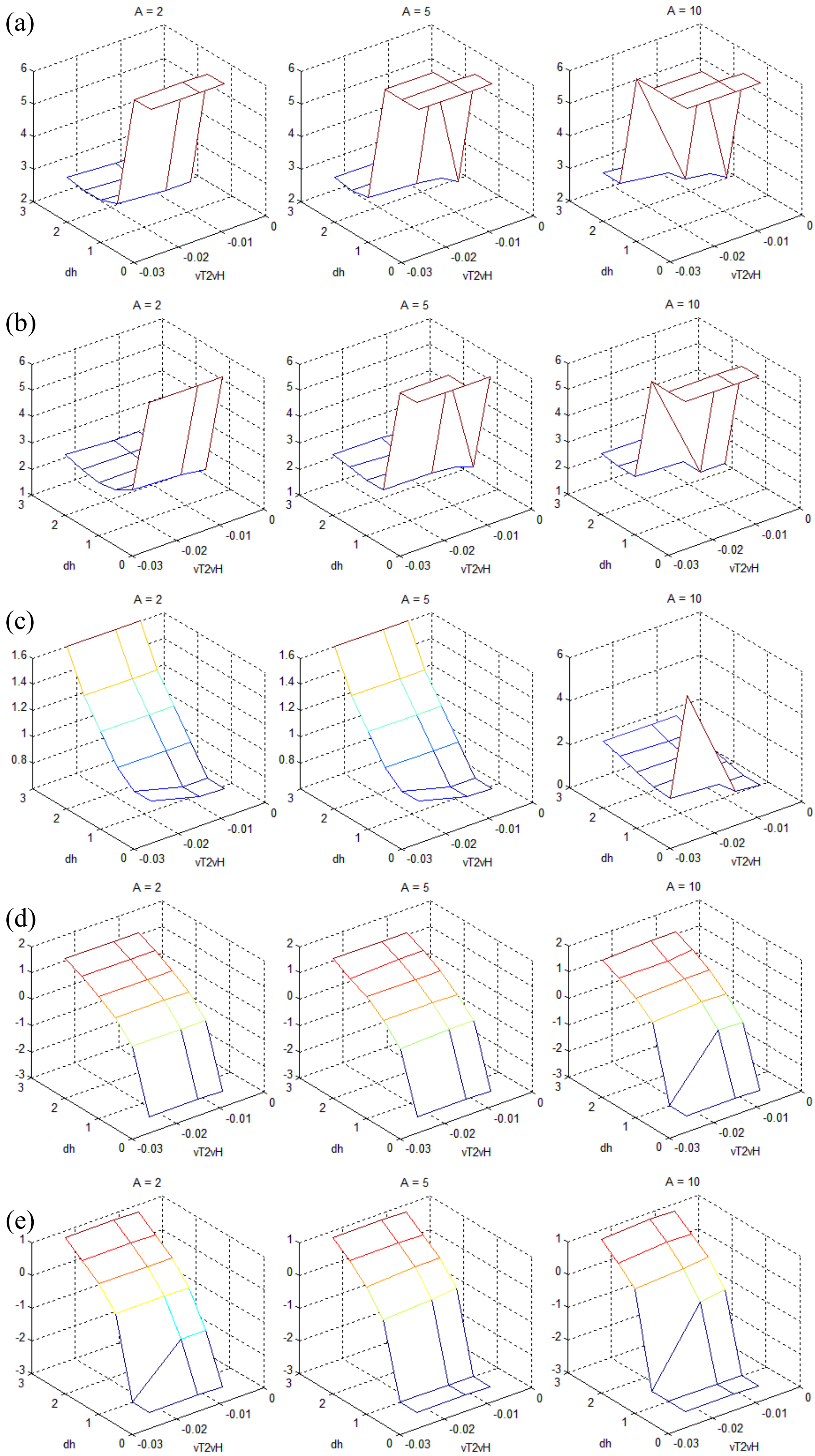

Figure A4: The optimal cutoff point of the human (z-axis) in the H collaboration level in a Type III system. (a) $Ps = 0.1$, (b) $Ps = 0.2$, (c) $Ps = 0.5$, (d) $Ps = 0.8$, (e) $Ps = 0.9$. $B = 0.5, dr = 0.5$.

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 ($vT2vH$) 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 ($vT2vH = -0.03$), an extreme cutoff point (z value is 6) is preferred for human sensitivities that are less than two ($d'_h <= 2$). However, when the time cost is low ($vT2vH = -0.01$), an extreme cutoff point (6) is preferred only for human sensitivities that are less than one ($d'_h <= 1$).

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 ($d'_h <= 1$). 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.

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 human-robot 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 human-robotic 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 human-robot 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 human-robot 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_{Is}, equation 1) is composed of the four responses of the target detection process and the system operational costs:

$$V_{Is} = V_{Hs} + V_{Ms} + V_{FAs} + V_{CRs} + V_{Ts} \quad (1)$$

Where V_{Hs} is the gain for target detections (hits), V_{FAs} is the penalty for false alarms, V_{Ms} is the system penalty for missing targets, V_{CRs} is the gain for correct rejections, and V_{Ts} 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:

$$V_{Hs} = N \cdot P_S \cdot P_{Hs} \cdot V_H \quad (2)$$

$$V_{Ms} = N \cdot P_S \cdot P_{Ms} \cdot V_M \quad (3)$$

$$V_{FAs} = N \cdot (1 - P_S) \cdot P_{FAs} \cdot V_{FA} \quad (4)$$

$$V_{CRs} = N \cdot (1 - P_S) \cdot P_{CRs} \cdot V_{CR} \quad (5)$$

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_{Xs}, is the system probability for one of the outcomes: hit, miss, false alarm or correct rejection ($_X$ can be $_{H}$, $_{M}$, $_{FA}$ and $_{CR}$). 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:

$$P_{Hs} = P_{Hr} \cdot P_{Hrh} + (1 - P_{Hr}) \cdot P_{Hh} \quad (6)$$

$$P_{Ms} = P_{Mr} \cdot P_{Mh} + (1 - P_{Mr}) \cdot P_{Mrh} \quad (7)$$

$$P_{FAs} = P_{FAr} \cdot P_{FArh} + (1 - P_{FAr}) \cdot P_{FAh} \quad (8)$$

$$P_{CRs} = P_{CRr} \cdot P_{CRh} + (1 - P_{CRr}) \cdot P_{CRrh} \quad (9)$$

Where:

P_{Hr} is the robot probability of a hit, P_{Hrh} is the probability of confirming a robot hit and P_{Hh} is the human probability of detecting a target that the robot did not detect;

P_{Mr} is the robot miss probability, P_{Mrh} is the human probability of not confirming a robot hit and P_{Mh} is the human probability of missing a target the robot missed. P_{FAr} is the robot false alarm probability, P_{FArh} is the human probability of not avoiding a robot false alarm and P_{FAh} is the human probability of a false alarm on targets the robot correctly rejected;

P_{CRr} is the robot probability of a correct rejection, P_{CRrh} is the human probability of correcting a robot false alarm and P_{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) and the sum of false alarm and correct rejection probabilities equals one.

The system's operation cost is:

$$V_{Ts} = t_S \cdot V_t + [N \cdot P_S \cdot P_{Hs} + N \cdot (1 - P_S) \cdot P_{FAs}] \cdot V_C \quad (10)$$

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.

$$\begin{aligned} t_S = {} & N \cdot P_S \cdot P_{Hr} \cdot P_{Hrh} \cdot t_{Hrh} + \\ & + N \cdot P_S \cdot (1 - P_{Hr}) \cdot P_{Hh} \cdot t_{Hh} + \\ & + N \cdot P_S \cdot P_{Hr} \cdot (1 - P_{Hrh}) \cdot t_{Mrh} + \\ & + N \cdot P_S \cdot (1 - P_{Hr}) \cdot (1 - P_{Hh}) \cdot t_{Mh} + \\ & + N \cdot (1 - P_S) \cdot P_{FAr} \cdot P_{FArh} \cdot t_{FArh} + \\ & + N \cdot (1 - P_S) \cdot (1 - P_{FAr}) \cdot P_{FAh} \cdot t_{FAh} + \\ & + N \cdot (1 - P_S) \cdot P_{FAr} \cdot (1 - P_{FArh}) \cdot t_{CRrh} + \\ & + N \cdot (1 - P_S) \cdot (1 - P_{FAr}) \cdot (1 - P_{FAh}) \cdot t_{CRh} + N \cdot t_r \end{aligned} \quad (11)$$

Where:

t_{Hrh} is the human time required to confirm a robot hit and t_{Hh} is the human time required to hit a target that the robot did not hit;

t_{Mrh} is the human time lost when a robot hit is missed and t_{Mh} is the human time invested when missing a target that the robot did not hit;

t_{FArh} is the human time needed not to avoid a robot false alarm and t_{FAh} is the human false alarm time;

t_{CRrh} is the human time to correctly reject a robot false alarm, t_{CRh} is the human correct rejection time, and t_r is the robot operation time.

Explicit operation of the system objective function, V_{Is}, which is suitable for all collaboration levels, is:

$$\begin{aligned} V_{Is} = {} & N \cdot P_S \cdot [P_{Hr} \cdot P_{Hrh} \cdot (V_H + V_C + t_{Hrh} \cdot V_t) + \\ & + (1 - P_{Hr}) \cdot P_{Hh} \cdot (V_H + V_C + t_{Hh} \cdot V_t)] + \\ & + N \cdot P_S \cdot [P_{Hr} \cdot (1 - P_{Hrh}) \cdot (V_M + t_{Mrh} \cdot V_t) + \\ & + (1 - P_{Hr}) \cdot (1 - P_{Hh}) \cdot (V_M + t_{Mh} \cdot V_t)] + \\ & + N \cdot (1 - P_S) \cdot [P_{FAr} \cdot P_{FArh} \cdot (V_{FA} + V_C + t_{FArh} \cdot V_t) + \\ & + (1 - P_{FAr}) \cdot P_{FAh} \cdot (V_{FA} + V_C + t_{FAh} \cdot V_t)] + \\ & + N \cdot (1 - P_S) \cdot [P_{FAr} \cdot (1 - P_{FArh}) \cdot (V_{CR} + t_{CRrh} \cdot V_t) + \\ & + (1 - P_{FAr}) \cdot (1 - P_{FAh}) \cdot (V_{CR} + t_{CRh} \cdot V_t)] + N \cdot t_r \cdot V_t \end{aligned} \quad (12)$$

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:

$$\begin{aligned} V_{Is} = {} & N \cdot P_S \cdot [P_{Hh} \cdot (V_H + V_C + t_{Hh} \cdot V_t) + \\ & + (1 - P_{Hh}) \cdot (V_M + t_{Mh} \cdot V_t)] + \\ & + N \cdot (1 - P_S) \cdot [P_{FAh} \cdot (V_{FA} + V_C + t_{FAh} \cdot V_t) + \\ & + (1 - P_{FAh}) \cdot (V_{CR} + t_{CRh} \cdot V_t)] \end{aligned} \quad (13)$$

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:

$$\begin{aligned} V_{Is} = {} & N \cdot P_S \cdot [P_{Hr} \cdot (V_H + V_C) + (1 - P_{Hr}) \cdot V_M] + \\ & + N \cdot (1 - P_S) \cdot [P_{FAr} \cdot (V_{FA} + V_C) + (1 - P_{FAr}) \cdot V_{CR}] + \\ & + N \cdot t_r \cdot V_t \end{aligned} \quad (14)$$

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_{co}), 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_{co} 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:

$$t(x) = \begin{cases} Ae^{-B \cdot (x_{co} - x)} & ; \text{ when } x \le x_{co} \\ Ae^{-B(x - x_{co})} & ; \text{ otherwise} \end{cases} \quad (15)$$

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.

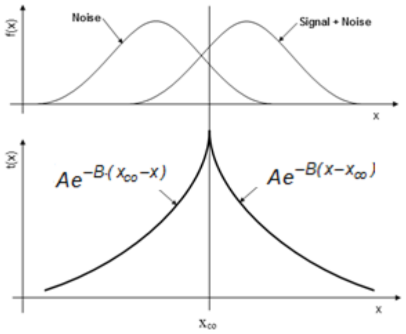

Figure 1 - Reaction time function.

Suppose X is normally distributed with a mean of μ and a variance of σ^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 $T_-(x_{co})$, $T_+(x_{co})$ for negative and positive responses, respectively.

The mean reaction time equations for negative and positive responses are:

$$T_-(x_{co}) = \frac{\int_{-\infty}^{x_{co}} t(x)\cdot f(x)dx}{\int_{-\infty}^{x_{co}} f(x)dx} = \frac{\int_{-\infty}^{x_{co}} Ae^{-B(x_{co}-x)}\cdot f(x)dx}{\int_{-\infty}^{x_{co}} f(x)dx} = \tag{16}$$

$$= \ldots = A\cdot e^{-B\cdot\sigma\cdot z_{co}+\frac{B^2\cdot\sigma^2}{2}}\cdot\frac{\Phi(z_{co}-B\cdot\sigma)}{\Phi(z_{co})}$$

$$T_+(x_{co}) = \frac{\int_{x_{co}}^{\infty} t(x)\cdot f(x)dx}{\int_{x_{co}}^{\infty} f(x)dx} = \frac{\int_{x_{co}}^{\infty} Ae^{-B(x-x_{co})}\cdot f(x)dx}{\int_{x_{co}}^{\infty} f(x)dx} = \tag{17}$$

$$= \ldots = A\cdot e^{B\cdot\sigma\cdot z_{co}+\frac{B^2\cdot\sigma^2}{2}}\cdot\frac{1-\Phi(z_{co}+B\cdot\sigma)}{1-\Phi(z_{co})}$$

where

$$f(x) = \frac{1}{\sigma\sqrt{2\pi}}e^{\frac{-(x-\mu)^2}{2\sigma^2}}$$

$$z_{co} = \frac{x_{co}-\mu}{\sigma} \quad ; \quad \Phi(z) = \frac{1}{\sqrt{2\pi}}\int_{-\infty}^{z} e^{\frac{-z^2}{2}}dz$$

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 μ_S, σ_S and μ_N, σ_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):

$$T_M = A\cdot e^{-B\cdot\sigma_S\cdot z_S+\frac{B^2\cdot\sigma_S^2}{2}}\cdot\frac{\Phi(z_S-B\cdot\sigma_S)}{\Phi(z_S)} \tag{18}$$

$$T_H = A\cdot e^{B\cdot\sigma_S\cdot z_S+\frac{B^2\cdot\sigma_S^2}{2}}\cdot\frac{1-\Phi(z_S+B\cdot\sigma_S)}{1-\Phi(z_S)} \tag{19}$$

$$T_{CR} = A\cdot e^{-B\cdot\sigma_N\cdot z_N+\frac{B^2\cdot\sigma_N^2}{2}}\cdot\frac{\Phi(z_N-B\cdot\sigma_N)}{\Phi(z_N)} \tag{20}$$

$$T_{FA} = A\cdot e^{B\cdot\sigma_N\cdot z_N+\frac{B^2\cdot\sigma_N^2}{2}}\cdot\frac{1-\Phi(z_N+B\cdot\sigma_N)}{1-\Phi(z_N)} \tag{21}$$

where

$$z_S = \frac{x_{co}-\mu_S}{\sigma_S} \quad ; \quad z_N = \frac{x_{co}-\mu_N}{\sigma_N}$$

The reaction time function depends on the value of the cutoff point x_{co}. 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_{CRh}, T_{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_{Xrh} or t_{Xh}) 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:

$$\begin{aligned} t_{Mh} &= T_{Mh} & t_{CRh} &= T_{CRh} \\ t_{Hh} &= T_{Hh}+t_M & t_{FAh} &= T_{FAh}+t_M \end{aligned} \tag{22}$$

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:

$$\begin{aligned} t_{Mh} &= T_{Mh} & t_{Mrh} &= T_{Mrh} \\ t_{Hh} &= T_{Hh}+t_M & t_{Hrh} &= T_{Hrh}+t_M \\ t_{CRh} &= T_{CRh} & t_{CRrh} &= T_{CRrh} \\ t_{FAh} &= T_{FAh}+t_M & t_{FArh} &= T_{FArh}+t_M \end{aligned} \tag{23}$$

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:

$$\begin{aligned} t_{Mh} &= T_{Mh} & t_{Mrh} &= T_{Mrh}+t_M \\ t_{Hh} &= T_{Hh}+t_M & t_{Hrh} &= T_{Hrh} \\ t_{CRh} &= T_{CRh} & t_{CRrh} &= T_{CRrh}+t_M \\ t_{FAh} &= T_{FAh}+t_M & t_{FArh} &= T_{FArh} \end{aligned} \tag{24}$$

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.

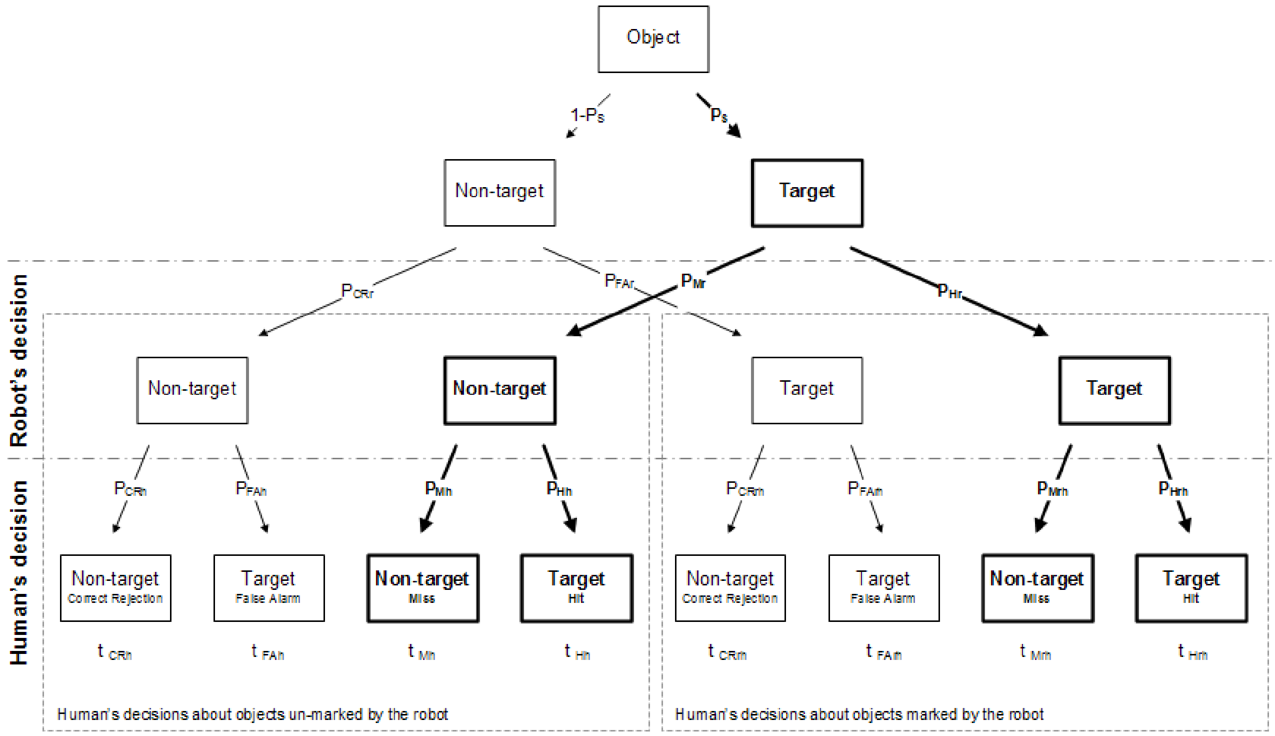

Figure 2 - Reaction times diagram.

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_{FA}, V_{CR}, [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 (V_T) 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 ($V_T=V_H \cdot V_{T2H}$). The ratio between the time cost and the gain for a hit, V_{T2H}, was set to the values: -80, -40, -20 (hour^{-1}).

For example, when V_H equals 5 points, V_T obtained the values: -400, -200, -100 points.

The operational cost (V_C) 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'_h) was varied between 0.5 and 3.

Robot parameters

The sensitivity of the robot (d'_r) was varied between 0.5 and 3. The robot decision time (t_r) 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_{FA}	-50	-5	-10
V_{CR}	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.

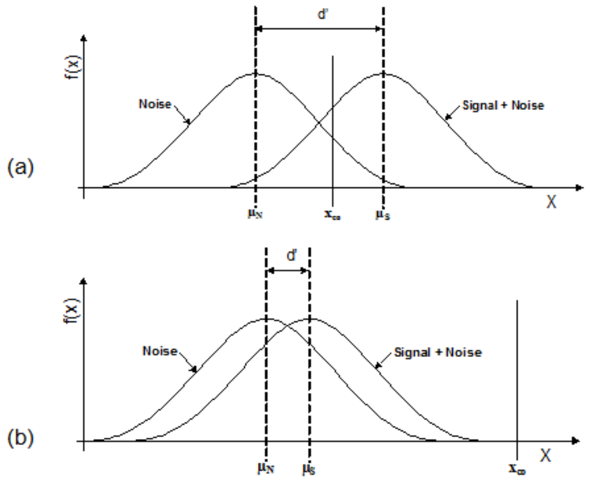

Figure 3 - A cutoff point between the distributions' means when the sensitivity is high (a) and extreme cutoff point selection when sensitivity is low (b).

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.

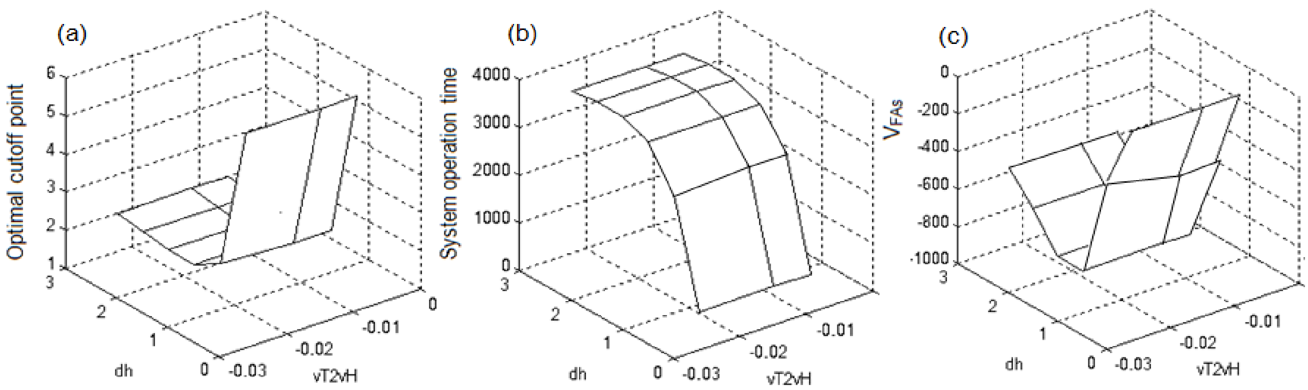

Figure 4 - Optimal cutoff point of the human (a), system operation time (b) and System total penalty for false alarms (c) in the H collaboration level, *Type I* system. Human sensitivity and the time cost are ranged along x and y axes.

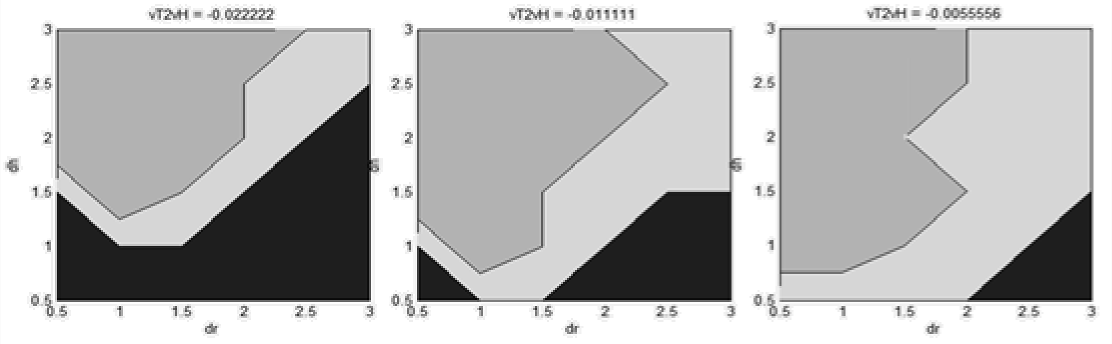

Figure 5 - Human dominance reduces as the time cost increases.
Each color represents different operating level: HR- dark grey, HOR- light grey and R- black

One can see that human dominance reduces as the time cost increases. The time cost increases from the right graph (V_T2V_H=*-0.0055*) to the left graph (V_T2V_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 (P_S) 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 (P_S) 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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6 REFERENCES

[1] Bechar A. , 2006, Human-Robot Collaboration Methods for Target Recognition in Unstructured Environments, Ph.D. dissertation, Industrial Engineering and Management, Ben-Gurion University of the Negev, Beer-Sheva, Israel.

[2] Sheridan T.B., 1992, Telerobotics, Automation and Supervisory Control, Cambridge, MA. MIT Press.

[3] Bechar A. & Edan Y., 2000, Human-Robot Collaboration for Agricultural Robot Guidance, ASAE Paper No. 00-3135.

[4] Bruemmer D.J., Boring R.A., Few D. A., Marble J.A., Nielsen C.W. and Walton M.C., 2005, Shared Understanding for Collaborative Control, IEEE Transactions on Systems, Man and Cybernetics: Part A, vol. 35, no. 4, pp. 494-504.

[5] Hughes S.B. & Lewis M., 2005, Task-Driven Camera Operations for Robotic Exploration, IEEE Transactions on Systems, Man and Cybernetics: Part A, vol. 35, no. 4, pp. 513-522.

[6] Czarnecki C. & Graves A.R., 2000, Design Patterns for Behavior-Based Robotics, IEEE Transactions on Systems, Man and Cybernetics: Part A, vol. 30, no. 1, pp. 36-41.

[7] Bechar A. & Edan Y., 2003, Human-Robot Collaboration for Improved Target Recognition of Agricultural Robots, Industrial Robot 30(5): 432-436.

[8] Ratcliff R. & Rouder J. F., 1998, Modeling Response Times for Two Choice Decisions, Psychological Science, vol. 9, No. 5, pp. 347-356.

[9] Murdock B. B., 1985, An Analysis of The Strength-Latency Relationship, Memory and Cognition, 13 (6), 511-521.

[10] Oren Y., Bechar A., Joachim M., Edan Y., 2008, Performance Analysis of Human-Robot Collaboration in Target Recognition Tasks, IEEE International Conference on Distributed Human-Machine Systems, 1-56.

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
%------------------------------------------------------------------------------------------
for i=1:sXco
            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' for the human operator sensitivity
                        for idh=1:length(dh_vector)
                            dh=dh_vector(idh);

                            % Loop 6 : The range of d' 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
%==========================================================================================

% 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
%------------------------------------------------------------------------------------------
pH_r=1-normcdf(Zs_r);       % Robot's probability for a hit
pFA_r=1-normcdf(Zn_r);      % Robot's probability for a false alarm
pH_h=1-normcdf(Zs_h);       % Human's probability for a hit
pFA_h=1-normcdf(Zn_h);      % Human's probability for a false alarm
pH_rh=1-normcdf(Zs_rh);     % Human's probability for a hit, when collaborate with the robot
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');
tFA_h=meanTime(Zn_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.*Ps.*pMs_H.*vM;                        %  Penalty from a miss
pFAs_H=pFA_h;                                    %  Probability for a false alarm
vFAs_H=N.*(1-Ps).*pFAs_H.*vFA;                   %  Penalty from a false alarm
pCRs_H = 1-pFAs_H;                               %  Probability for a correct rejection
vCRs_H = N.*(1-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).*(1-pFA_h).*tCR_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
%--------------------------------------------------------------------------------------------
% Probabilities, gains and penalties
pHs_HR=pH_r.*pH_rh+(1-pH_r).*pH_h;               %  Probability for a hit
vHs_HR=N.*Ps.*pHs_HR.*vH;                        %  Gain from a hit
pMs_HR=1-pHs_HR;                                 %  Probability for a miss
vMs_HR=N.*Ps.*pMs_HR.*vM;                        %  Penalty from a miss
pFAs_HR=pFA_r.*pFA_rh+(1-pFA_r).*pFA_h;          %  Probability for a false alarm
vFAs_HR=N.*(1-Ps).*pFAs_HR.*vFA;                 %  Penalty from a false alarm
pCRs_HR=1-pFAs_HR;                               %  Probability for a correct rejection
vCRs_HR=N.*(1-Ps).*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).*pFA_r.*pFA_rh.*(tFA_rh+tMotor)...
       +N.*(1-Ps).*(1-pFA_r).*pFA_h.*(tFA_h+tMotor)...
       +N.*Ps.*pH_r.*(1-pH_rh).*tM_rh...
       +N.*Ps.*(1-pH_r).*(1-pH_h).*tM_h...
       +N.*(1-Ps).*pFA_r.*(1-pFA_rh).*tCR_rh...
       +N.*(1-Ps).*(1-pFA_r).*(1-pFA_h).*tCR_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).*pFA_r.*pFA_rh...
       +N.*(1-Ps).*(1-pFA_r).*pFA_h).*vC;

% 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;                                      %  Probability for a hit
vHs_HOR=vHs_HR;                                      %  Gain from a hit
pMs_HOR=pMs_HR;                                      %  Probability for a miss
vMs_HOR=vMs_HR;                                      %  Penalty from a miss
pFAs_HOR=pFAs_HR;                                    %  Probability for a false alarm
vFAs_HOR=vFAs_HR;                                    %  Penalty from a false alarm
pCRs_HOR=pCRs_HR;                                    %  Probability for a correct rejection
vCRs_HOR=vCRs_HR;                                    %  Gain from a correct rejection

% 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).*pFA_r.*pFA_rh.*tFA_rh...
       +N.*(1-Ps).*(1-pFA_r).*pFA_h.*(tFA_h+tMotor)...
       +N.*Ps.*pH_r.*(1-pH_rh).*(tM_rh+tMotor)...
       +N.*Ps.*(1-pH_r).*(1-pH_h).*tM_h...
       +N.*(1-Ps).*pFA_r.*(1-pFA_rh).*(tCR_rh+tMotor)...
       +N.*(1-Ps).*(1-pFA_r).*(1-pFA_h).*tCR_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).*pFA_r.*pFA_rh...
       +N.*(1-Ps).*(1-pFA_r).*pFA_h).*vC;

% 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;                                          %  Probability for a hit
vHs_R=N.*Ps.*pHs_R.*vH;                              %  Gain from a hit
pMs_R=1-pHs_R;                                       %  Probability for a miss
vMs_R = N.*Ps.*pMs_R.*vM;                            %  Penalty from a miss
pFAs_R=pFA_r;                                        %  Probability for a false alarm
vFAs_R=N.*(1-Ps).*pFAs_R.*vFA;                       %  Penalty from a false alarm
pCRs_R = 1-pFAs_R;                                   %  Probability for a correct rejection
vCRs_R = N.*(1-Ps).*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
VIs_R=vHs_R+vMs_R+vFAs_R+vCRs_R+vTs_R+vCs_R;
```

```
%===================================================================
% 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 yz]=find(VIs_H==opt_VIs_H(idr,idh,iPs,iB,iA,ivT2vH));
        iXrh_H(idr,idh,iPs,iB,iA,ivT2vH)=x(1);
        iXh_H(idr,idh,iPs,iB,iA,ivT2vH)=yz(1)-length(VIs_H)*(ceil(yz(1)./length(VIs_H))-1);
        iXr_H(idr,idh,iPs,iB,iA,ivT2vH)=ceil(yz(1)./length(VIs_H));
        irh_H=iXrh_H(idr,idh,iPs,iB,iA,ivT2vH);
        ih_H=iXh_H(idr,idh,iPs,iB,iA,ivT2vH);
        ir_H=iXr_H(idr,idh,iPs,iB,iA,ivT2vH);

% 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_pMs_H(idr,idh,iPs,iB,iA,ivT2vH)=pMs_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)=pFAs_H(irh_H,ih_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_vTs_H(idr,idh,iPs,iB,iA,ivT2vH)=vTs_H(irh_H,ih_H,ir_H);
        opt_vCs_H(idr,idh,iPs,iB,iA,ivT2vH)=vCs_H(irh_H,ih_H,ir_H);
        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_h_H(idr,idh,iPs,iB,iA,ivT2vH)=tFA_h(irh_H,ih_H,ir_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(:)));
        [x yz]=find(VIs_HR==opt_VIs_HR(idr,idh,iPs,iB,iA,ivT2vH));
        iXrh_HR(idr,idh,iPs,iB,iA,ivT2vH)=x(1);
        iXh_HR(idr,idh,iPs,iB,iA,ivT2vH)=yz(1)-length(VIs_HR)*(ceil(yz(1)./length(VIs_HR))-1);
        iXr_HR(idr,idh,iPs,iB,iA,ivT2vH)=ceil(yz(1)./length(VIs_HR));
        irh_HR=iXrh_HR(idr,idh,iPs,iB,iA,ivT2vH);
        ih_HR=iXh_HR(idr,idh,iPs,iB,iA,ivT2vH);
        ir_HR=iXr_HR(idr,idh,iPs,iB,iA,ivT2vH);

% 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_vMs_HR(idr,idh,iPs,iB,iA,ivT2vH)=vMs_HR(irh_HR,ih_HR,ir_HR);
        opt_pFAs_HR(idr,idh,iPs,iB,iA,ivT2vH)=pFAs_HR(irh_HR,ih_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);
        opt_vCs_HR(idr,idh,iPs,iB,iA,ivT2vH)=vCs_HR(irh_HR,ih_HR,ir_HR);
        opt_tH_h_HR(idr,idh,iPs,iB,iA,ivT2vH)=tH_h(irh_HR,ih_HR,ir_HR);
        opt_tM_h_HR(idr,idh,iPs,iB,iA,ivT2vH)=tM_h(irh_HR,ih_HR,ir_HR);
        opt_tFA_h_HR(idr,idh,iPs,iB,iA,ivT2vH)=tFA_h(irh_HR,ih_HR,ir_HR);
        opt_tCR_h_HR(idr,idh,iPs,iB,iA,ivT2vH)=tCR_h(irh_HR,ih_HR,ir_HR);
        opt_tH_rh_HR(idr,idh,iPs,iB,iA,ivT2vH)=tH_rh(irh_HR,ih_HR,ir_HR);
        opt_tM_rh_HR(idr,idh,iPs,iB,iA,ivT2vH)=tM_rh(irh_HR,ih_HR,ir_HR);
        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_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_HOR(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_h_HOR(idr,idh,iPs,iB,iA,ivT2vH)=tFA_h(irh_HOR,ih_HOR,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 yz]=find(VIs_R==opt_VIs_R(idr,idh,iPs,iB,iA,ivT2vH));
        iXrh_R(idr,idh,iPs,iB,iA,ivT2vH)=x(1);
        iXh_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_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_vHs_R(idr,idh,iPs,iB,iA,ivT2vH)=vHs_R(irh_R,ih_R,ir_R);
        opt_pMs_R(idr,idh,iPs,iB,iA,ivT2vH)=pMs_R(irh_R,ih_R,ir_R);
        opt_vMs_R(idr,idh,iPs,iB,iA,ivT2vH)=vMs_R(irh_R,ih_R,ir_R);
        opt_pFAs_R(idr,idh,iPs,iB,iA,ivT2vH)=pFAs_R(irh_R,ih_R,ir_R);
        opt_vFAs_R(idr,idh,iPs,iB,iA,ivT2vH)=vFAs_R(irh_R,ih_R,ir_R);
        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,ih_R,ir_R);
        opt_vTs_R(idr,idh,iPs,iB,iA,ivT2vH)=vTs_R(irh_R,ih_R,ir_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(idr,idh,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));
        opt_CL(idr,idh,iPs,iB,iA,ivT2vH)=CL(1); % 1=H, 2=HR, 3=HOR, 4=R

% 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_pHs_HOR(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_HOR(idr,idh,iPs,iB,iA,ivT2vH),opt_pFAs_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_r_HR(idr,idh,iPs,iB,iA,ivT2vH)=Zn_r(irh_HR,ih_HR,ir_HR);
        opt_Zn_h_HR(idr,idh,iPs,iB,iA,ivT2vH)=Zn_h(irh_HR,ih_HR,ir_HR);
        opt_Zn_rh_HR(idr,idh,iPs,iB,iA,ivT2vH)=Zn_rh(irh_HR,ih_HR,ir_HR);
        opt_Zn_r_HOR(idr,idh,iPs,iB,iA,ivT2vH)=Zn_r(irh_HOR,ih_HOR,ir_HOR);
        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_rh(irh_HOR,ih_HOR,ir_HOR);
        opt_Zn_r_R(idr,idh,iPs,iB,iA,ivT2vH)=Zn_r(irh_R,ih_R,ir_R);
        opt_Zn_h_R(idr,idh,iPs,iB,iA,ivT2vH)=Zn_h(irh_R,ih_R,ir_R);
        opt_Zn_rh_R(idr,idh,iPs,iB,iA,ivT2vH)=Zn_rh(irh_R,ih_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)=Zs_rh(irh_H,ih_H,ir_H);
        opt_Zs_r_HR(idr,idh,iPs,iB,iA,ivT2vH)=Zs_r(irh_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)=Zs_rh(irh_HR,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_rh_HOR(idr,idh,iPs,iB,iA,ivT2vH)=Zs_rh(irh_HOR,ih_HOR,ir_HOR);
        opt_Zs_r_R(idr,idh,iPs,iB,iA,ivT2vH)=Zs_r(irh_R,ih_R,ir_R);
        opt_Zs_h_R(idr,idh,iPs,iB,iA,ivT2vH)=Zs_h(irh_R,ih_R,ir_R);
        opt_Zs_rh_R(idr,idh,iPs,iB,iA,ivT2vH)=Zs_rh(irh_R,ih_R,ir_R);

%=====================================================================
% END - For each combination of parameters
%=====================================================================

                    end     % loop 6
                end         % loop 5
            end             % loop 4
        end                 % 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_str P1_str P2_str P3_str iP1 iP2 iP3;
dr=1; dh=2; Ps=3; B=4; A=5; vT2vH=6;
return;

% --- Executes just before GraphGUI is made visible.
function GraphGUI_OpeningFcn(hObject, eventdata, handles, varargin)
% Choose default 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 && isequal(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;
```

```matlab
% --- Executes during object creation, after setting all properties.
function expName_CreateFcn(hObject, eventdata, handles)
if ispc && isequal(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 =['N 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_CreateFcn(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 dh_vector Ps_vector B_vector A_vector vT2vH_vector'];
eval(['load ' DataPath 'Parameters\Parameters.mat ' var])
global P1_str;
val=get(handles.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(handles.axisP2,'Value');
str=get(handles.axisP2,'String');
P2_str=str{val};
vP2=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(['load ' DataPath 'Optimal\OptimalData.mat opt_vTs_H opt_VIs_H'])
        z=opt_vTs_H./opt_VIs_H;
    case 'vT/VI_HR'
        eval(['load ' DataPath 'Optimal\OptimalData.mat opt_vTs_HR opt_VIs_HR'])
        z=opt_vTs_HR./opt_VIs_HR;
    case 'vT/VI_HOR'
        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 '_vector']);
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(' P1_str '_vector(iP1),2)']) '  ' P2_str '=' eval(['num2str('
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')
        contourf('v6',h,vx,vy,mat(:,:,isubG,iP1,iP2,iP3), [1 2 3 4]);
    elseif strcmp(GraphType_str, 'contour')
        [C,h1] = contour(h,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 non-target 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.

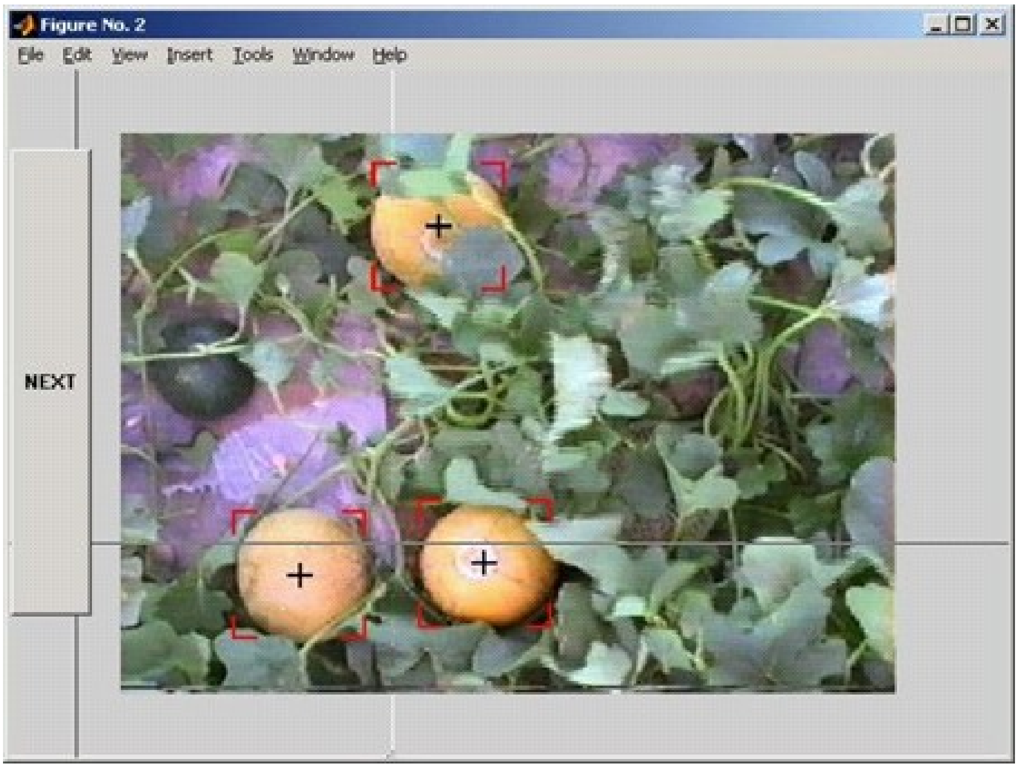

Figure 36: An example of the graphical user interface of the experiment.

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 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 $T2next$ 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 (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
8	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
10	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
8	1	123	483.787	3.933227642	3.162886587
	2	212	992.536	4.681773585	8.140790043
	3	57	277.333	4.865491228	5.084170647
9	1	299	1135.499	3.797655518	4.277060817
	2	310	1350.314	4.355851613	6.847721467
	3	174	793.326	4.559344828	4.85237869
10	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	5.47961E-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	1.30214E-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	1.49661E-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:

S #	I #	T2mark	T2next
70	6	1.875	3
70	7	1.875	3.203
70	15	2.312	3.546
70	19	1.797	3.109
70	34	3.219	4.985
70	46	1.829	3.25
70	47	2.078	3.25
70	48	1.172	2.328
70	57	1.828	3.187
70	63	1.907	9.141
70	64	1.859	3.484
70	67	1.407	2.797
70	68	4.969	6.234
70	77	1.656	3.172
70	80	2.079	3.282
70	82	1.359	3.062
70	97	2.703	4.187
70	111	1.5	2.922
70	206	1.579	3
70	220	2.344	4.172
70	221	1.359	2.5
70	230	1.765	3.265
70	306	1.703	3.547
70	307	2.124	4.031
70	411	2.734	4.297
71	6	1.203	6.905
71	7	1.187	3.609
71	15	1.235	2.532
71	19	0.843	2.062
71	26	0.992	7.634
71	46	1.078	5.764
71	47	1.406	2.453
71	48	1.5	2.828
71	54	1.734	2.953
71	57	2.78	4.374
71	63	1.484	3.093
71	64	1.156	3.109
71	67	1.016	2.703
71	68	2.141	3.453
71	80	0.985	1.938
71	82	2.312	5.499
71	97	0.921	4.482
71	206	1.047	2.718
71	208	1.078	2.312
71	209	1.921	4.671
71	211	0.609	1.766
71	220	2.312	4.796
71	221	0.876	3.795
71	230	4.594	6.187
71	306	1.015	2.296
71	307	1.203	5.812
71	411	4.859	6.296
72	6	1.602	4.728
72	15	0.857	1.698
72	19	0.903	2.009
72	26	0.903	2.212
72	46	1.735	2.819
72	47	0.684	1.633
72	48	0.919	1.775
72	54	0.898	2.106
72	57	1.13	2.4
72	63	1.022	2.214
72	64	2.146	4.634
72	67	1.09	2.196
72	80	0.919	2.009
72	97	1.14	3.687
72	208	0.701	2.289
72	209	0.96	2.261
72	220	0.824	1.788
72	221	0.826	2.259
72	306	1.161	4.537
72	307	1.648	2.799
72	411	0.82	2.028
73	6	0.938	2.094
73	15	1.578	2.406
73	19	1.344	2.625
73	26	1.11	2.407
73	46	1.094	1.922
73	47	1.328	2.265
73	48	1.235	2.031
73	54	1.938	3
73	57	1.438	2.641
73	63	1.297	2.406
73	64	0.953	2.312
73	67	1.297	2.312
73	68	1.297	2.203
73	80	1	1.625
73	82	1.39	2.218
73	97	1.578	2.484
73	206	1.203	2.078
73	208	0.64	1.296
73	209	1.156	3.609
73	211	1.141	1.969
73	220	1.484	2.203
73	221	0.922	1.656
73	230	1.031	1.828
73	306	1.734	2.781
73	307	1.485	2.36
73	411	1.485	2.797
74	6	1.719	3.844
74	15	1.417	2.649
74	19	1.109	4.252
74	26	1.201	3.463
74	46	1.687	2.875
74	47	1.064	2.373
74	48	0.964	2.379
74	54	1.172	3.765
74	57	2.015	4.453
74	63	1.156	3.812
74	64	1.5	4.094
74	67	1.166	2.41
74	68	1.172	3.125
74	80	1.43	2.659
74	82	2.375	4.796
74	97	1.672	4.984
74	206	1.281	3.812
74	208	1.353	3.156
74	209	1.187	4.359
74	211	1.166	3.032
74	220	2.527	3.543
74	221	1.244	2.689
74	230	1.094	3.312
74	306	1.25	4.531
74	307	1.063	2.234
75	6	1.36	4.078
75	15	1.562	2.703
75	19	1.575	5.795
75	26	1.105	2.057
75	46	1.343	4.999
75	47	1.391	2.75
75	48	1.575	2.615
75	54	1.578	2.625
75	57	2.437	4.483
75	63	2.171	5.249
75	64	1.749	5.342
75	67	2.021	4.83
75	68	2.297	5.359
75	82	3.562	5.406
75	97	3.093	7.03
75	206	3.015	5.343
75	208	3.076	4.577
75	209	8.218	11.045
75	211	1.619	2.927
75	220	1.765	3.655
75	221	1.412	3.054
75	306	2.577	4.28
75	307	1.656	3.187
76	6	3.746	6.186
76	7	3.249	5.802
76	15	1.644	3.122
76	19	1.925	3.959
76	26	1.878	3.383
76	46	3.681	5.311
76	47	1.493	2.987
76	48	1.694	3.435
76	54	3.532	5.76
76	57	2.361	3.883
76	63	2.794	4.539
76	67	1.555	3.358
76	68	1.832	3.432
76	80	1.864	3.42
76	82	1.645	3.774
76	97	3.997	9.383
76	206	6.186	8.03
76	208	5.823	7.472
76	209	5.017	6.57
76	211	2.018	3.281
76	220	3.499	5.007

76	221	1.335	2.825
76	230	2.043	3.462
76	306	4.753	6.242
76	307	1.252	3.092
76	411	2.205	3.634
77	6	1.071	2.461
77	15	0.889	2.452
77	19	1.112	2.002
77	26	0.689	1.722
77	34	0.737	1.64
77	46	7.306	9.611
77	47	1.084	2.878
77	48	0.792	1.626
77	57	2.183	4.916
77	63	1.134	3.524
77	64	1.517	3.601
77	68	3.619	7.483
77	77	1.363	3.16
77	82	3.863	10.261
77	97	1.748	5.896
77	111	1.626	6.764
77	206	1.241	3.969
77	209	1.777	3.355
77	211	0.695	1.599
77	220	1.548	2.851
77	221	1.084	2.516
77	306	2.176	5.777
77	307	1.536	3.833
77	411	4.473	6.046
78	6	0.875	1.859
78	7	0.984	2.203
78	15	1.125	1.922
78	19	0.969	2.172
78	26	0.844	1.719
78	46	0.734	1.828
78	47	0.984	1.828
78	48	0.828	1.781
78	54	0.781	1.687
78	57	1.578	2.797
78	63	0.89	2.078
78	64	0.735	1.672
78	67	0.765	1.765
78	68	1.078	2.156
78	80	0.937	1.703
78	82	0.734	1.734
78	97	1.859	3.094
78	206	0.938	1.953
78	208	0.578	1.828
78	209	1	2.156
78	211	0.89	1.703
78	220	0.657	1.657
78	221	0.765	1.922
78	306	0.828	1.953
78	307	0.922	1.875
78	411	0.984	2.031
79	6	1.044	3.305
79	7	0.997	3.211
79	15	1.294	2.635
79	19	0.952	3.029
79	26	1.078	2.515
79	46	0.699	5.232
79	47	0.966	2.088
79	48	0.89	1.983
79	54	0.543	1.583
79	57	1.025	3.478
79	63	1.134	3.059
79	64	1.31	4.24
79	67	0.733	2.544
79	68	0.9	3.679
79	80	1.124	2.483
79	82	0.901	3.462
79	97	1.297	4.61
79	206	1.107	3.242
79	208	0.749	1.858
79	209	1.195	4.175
79	211	0.64	1.53
79	220	1.013	2.307
79	221	0.78	1.748
79	307	0.827	3.024
79	411	0.962	5.215
7001	6	1.209	2.434
7001	7	1.608	5.587
7001	15	1.377	2.097
7001	19	1.734	3.283
7001	26	1.679	3.136
7001	46	1.437	2.592
7001	47	1.102	2.066
7001	48	1.055	1.762
7001	54	1.762	2.814
7001	57	1.999	3.199
7001	63	1.347	2.725
7001	64	1.857	2.76
7001	67	1.124	1.943
7001	68	1.467	2.518
7001	80	1.52	2.575
7001	82	1.881	2.784
7001	97	2.229	3.411
7001	206	1.111	2.37
7001	208	1.595	2.725
7001	209	1.348	2.503
7001	211	1.203	2.119
7001	220	1.117	2.372
7001	221	1.638	2.498
7001	306	1.422	2.74
7001	307	1.378	2.327
7002	6	0.754	1.715
7002	7	0.842	2.675
7002	15	0.947	1.935
7002	19	0.813	1.788
7002	26	0.765	1.713
7002	34	0.576	1.374
7002	46	2.455	9.022
7002	47	2.868	4.08
7002	48	0.704	1.53
7002	57	1.596	3.084
7002	63	0.96	2.015
7002	64	1.041	2.029
7002	68	6.383	19.579
7002	77	2.571	4.153
7002	82	2.363	9.498
7002	97	3.146	6.215
7002	111	4.232	6.153
7002	206	0.854	1.802
7002	209	0.88	1.855
7002	211	0.754	1.848
7002	220	0.894	1.922
7002	221	0.902	1.774
7002	306	1.041	2.376
7002	307	0.886	2.246
7002	411	3.744	7.153

Group 7, image complexity 2:

S #	I #	T2mark	T2next
70	16	1.734	3.25
70	27	1.5	3.032
70	33	1.859	3.218
70	35	2.593	4.062
70	41	1.984	4.281
70	42	1.297	2.75
70	62	2.188	3.782
70	65	3.14	4.531
70	69	1.406	2.625
70	72	2.188	3.688
70	76	1.937	3.031
70	83	1.032	2.141
70	87	1.734	3.078
70	95	1.969	3.531
70	105	1.844	3.266
70	204	2.609	4.734
70	207	1.86	3.156
70	210	2.438	3.953
70	217	5.703	6.968
70	219	1.375	2.906
70	223	2.016	3.516
70	224	1.078	2.343
70	231	3.859	5.656
70	303	1.656	3.015
70	304	1.516	2.734
70	308	2.547	3.937
70	310	1.906	3.359
70	322	6.89	8.828
70	401	3.421	4.843
71	14	1.312	3.484
71	16	1.765	5.358
71	27	1.312	2.859
71	33	0.672	2.047
71	35	2.061	9.744
71	41	12.547	14.328
71	42	2.562	4.14
71	62	1.922	3.749
71	65	2.781	4.812
71	69	0.781	4.781
71	70	1.094	2.844
71	72	2.156	10.296
71	87	0.812	2.172
71	95	4.803	6.292
71	105	1.296	6.996
71	204	3.64	4.968
71	207	3.489	5.284
71	217	1.906	4.828
71	219	0.938	7.547
71	223	1.031	2.859
71	231	1.639	5.887
71	303	1.219	4.125
71	304	1.016	2.735
71	319	5.294	10.369
71	322	0.921	2.187
72	14	1.121	2.32
72	16	5.173	6.288
72	27	0.929	2.014
72	33	1.059	2.227
72	35	2.657	6.422
72	41	1.106	2.274
72	42	1.259	2.364

72	65	2.488	3.437
72	69	0.917	2.285
72	70	1.697	2.741
72	72	0.995	2.457
72	87	0.919	1.62
72	92	0.938	2.484
72	95	0.982	2.68
72	105	2.157	4.094
72	207	0.872	2.01
72	210	1.054	2.757
72	212	1.791	2.913
72	217	1.337	2.799
72	219	0.747	1.915
72	231	2.406	4.047
72	304	1.682	3.239
72	308	1.344	6.281
72	322	1.791	2.834
73	27	1.547	2.265
73	33	1.265	2.14
73	35	2.422	4.094
73	41	1.782	2.61
73	42	1.046	1.64
73	62	1.5	3.141
73	65	1.688	2.485
73	69	1.047	2.641
73	70	1.328	2.437
73	72	1.328	2.125
73	87	1.125	1.719
73	92	1.891	3.188
73	95	1	1.656
73	105	2.188	4.203
73	204	1.641	2.672
73	207	1.016	1.766
73	210	1.266	2.234
73	217	1.407	2.172
73	219	1.093	2.046
73	223	1.328	2.125
73	304	1.297	2.813
73	308	3.125	5.016
73	310	1.75	2.719
73	319	2.125	5.172
73	322	1.25	2.141
73	401	2.704	4.297
74	14	2.565	3.84
74	16	1.312	6.046
74	27	1.359	4.312
74	33	1.042	2.829
74	35	2.203	7.312
74	41	1.217	2.326
74	42	1.525	3.497
74	62	1.86	5.516
74	65	1.372	3.975
74	69	0.875	2.797
74	70	1.756	4.714
74	72	1.171	4.421
74	87	1.337	2.814
74	92	1.781	6.172
74	95	0.764	2.371
74	105	2.64	6.968
74	204	2.594	4.641
74	207	1.653	3.213
74	210	1.657	4.219
74	217	1.937	3.375
74	219	1.197	3.529
74	223	1.297	5.094
74	231	2.937	5.437
74	303	2.049	4.683
74	304	0.886	2.767
74	308	2.719	5.281
74	320	1.75	4.5
74	322	1.492	4.943
74	401	2.313	3.938
75	16	5.342	7.17
75	27	2.687	4.406

75	33	1.724	2.853
75	35	5.608	9.436
75	41	3.093	4.296
75	42	2.156	3.39
75	62	2.562	7.702
75	65	2.859	4.108
75	69	3.265	5.873
75	70	1.353	2.482
75	72	1.531	5.14
75	87	1.753	2.898
75	92	3.187	5.702
75	95	1.075	3.024
75	105	9.357	11.935
75	204	3.797	6.562
75	207	1.611	2.563
75	210	4.187	6.515
75	219	1.649	2.942
75	231	8.092	11.061
75	303	1.921	4.452
75	304	1.173	2.243
75	319	5.764	12.497
75	322	2.511	4.903
76	27	2.71	4.852
76	33	8.088	9.412
76	35	4.12	7.685
76	41	1.252	2.549
76	42	2.217	3.68
76	62	3.618	5.761
76	65	2.202	3.514
76	69	2.172	3.846
76	70	2.203	3.744
76	72	1.433	2.956
76	87	2.572	4.498
76	92	5.834	8.658
76	95	1.366	2.887
76	105	5.263	7.377
76	207	1.785	3.057
76	217	2.284	4.057
76	219	4.329	6.609
76	223	2.157	3.618
76	304	1.648	3.373
76	310	3.975	5.438
77	14	1.228	2.547
77	16	6.954	8.797
77	27	1.5	3.61
77	33	1.182	2.947
77	35	1.315	6.981
77	41	1.501	2.294
77	42	0.98	2.559
77	62	1.348	2.911
77	65	2.206	3.769
77	69	1.946	3.095
77	70	1.094	2.622
77	72	1.608	3.754
77	76	1.056	4.142
77	105	2.391	4.796
77	204	2.822	4.932
77	207	1.209	2.516
77	210	1.257	2.559
77	217	1.286	3.145
77	219	0.848	2.307
77	223	0.976	2.695
77	224	1.321	2.572
77	231	1.716	4.428
77	303	1.784	2.886
77	304	1.237	2.905
77	308	1.753	5.259
77	310	1.223	2.335
77	320	1.457	5.562
77	322	0.917	3.016
77	401	5.756	7.034
78	14	0.985	2.531
78	27	1.25	2.094
78	33	0.75	1.656

75	33	1.724	2.853
75	35	5.608	9.436
75	41	3.093	4.296
75	42	2.156	3.39
75	62	2.562	7.702
75	65	2.859	4.108
75	69	3.265	5.873
75	70	1.353	2.482
75	72	1.531	5.14
75	87	1.753	2.898
75	92	3.187	5.702
75	95	1.075	3.024
75	105	9.357	11.935
75	204	3.797	6.562
75	207	1.611	2.563
75	210	4.187	6.515
75	219	1.649	2.942
75	231	8.092	11.061
75	303	1.921	4.452
75	304	1.173	2.243
75	319	5.764	12.497
75	322	2.511	4.903
76	27	2.71	4.852
76	33	8.088	9.412
76	35	4.12	7.685
76	41	1.252	2.549
76	42	2.217	3.68
76	62	3.618	5.761
76	65	2.202	3.514
76	69	2.172	3.846
76	70	2.203	3.744
76	72	1.433	2.956
76	87	2.572	4.498
76	92	5.834	8.658
76	95	1.366	2.887
76	105	5.263	7.377
76	207	1.785	3.057
76	217	2.284	4.057
76	219	4.329	6.609
76	223	2.157	3.618
76	304	1.648	3.373
76	310	3.975	5.438
77	14	1.228	2.547
77	16	6.954	8.797
77	27	1.5	3.61
77	33	1.182	2.947
77	35	1.315	6.981
77	41	1.501	2.294
77	42	0.98	2.559
77	62	1.348	2.911
77	65	2.206	3.769
77	69	1.946	3.095
77	70	1.094	2.622
77	72	1.608	3.754
77	76	1.056	4.142
77	105	2.391	4.796
77	204	2.822	4.932
77	207	1.209	2.516
77	210	1.257	2.559
77	217	1.286	3.145
77	219	0.848	2.307
77	223	0.976	2.695
77	224	1.321	2.572
77	231	1.716	4.428
77	303	1.784	2.886
77	304	1.237	2.905
77	308	1.753	5.259
77	310	1.223	2.335
77	320	1.457	5.562
77	322	0.917	3.016
77	401	5.756	7.034
78	14	0.985	2.531
78	27	1.25	2.094
78	33	0.75	1.656

78	35	1.625	5.968
78	42	0.891	1.797
78	62	1.843	3.703
78	69	0.875	1.828
78	70	0.843	1.671
78	72	1.328	2.25
78	92	3.328	4.625
78	95	0.891	2.75
78	105	4.843	9.203
78	204	1.422	2.75
78	207	0.938	1.704
78	210	1.015	2.062
78	223	1.094	2.015
78	303	1.203	2.125
78	304	0.875	1.812
78	308	2.047	4.156
78	310	1.531	2.5
78	319	6.469	9.594
78	322	1.11	3.969
78	401	3.015	4.125
79	14	1.296	2.654
79	16	1.738	4.89
79	27	1.273	3.338
79	33	0.765	1.748
79	35	1.703	8.156
79	41	1.217	2.404
79	42	1.496	2.946
79	65	1.699	3.491
79	69	0.92	2.759
79	70	1.155	3.216
79	72	1.215	3.133
79	87	1.467	2.529
79	92	1.593	5.062
79	95	2.296	3.296
79	105	2.281	19.281
79	204	3.819	5.76
79	207	1.53	2.624
79	210	0.947	4.238
79	217	1.434	3.851
79	219	1.03	2.17
79	223	1.263	2.713
79	231	5.234	8.656
79	303	1.045	3.788
79	304	0.889	2.404
79	310	2.92	5.215
79	322	1.14	2.514
79	401	1.422	4.14
7001	14	1.688	2.803
7001	16	2.088	3.302
7001	27	1.748	2.592
7001	33	2.71	3.918
7001	35	3.815	6.716
7001	41	1.286	2.48
7001	42	1.011	2.159
7001	62	1.762	2.962
7001	65	1.194	2.097
7001	69	1.47	2.786
7001	70	1.811	2.725
7001	72	1.041	2.173
7001	87	2.389	3.413
7001	92	2.807	4.5
7001	105	3.895	5.628
7001	204	1.718	3.05
7001	207	2.276	3.706
7001	210	2.355	3.54
7001	217	2.082	2.97
7001	219	1.471	2.555
7001	223	1.378	2.418
7001	231	4.002	5.506
7001	303	1.209	2.541
7001	304	1.416	2.304
7001	308	1.639	2.982
7001	310	3.175	5.73
7001	319	2.928	4.888
7001	320	1.303	2.562
7001	322	2.529	4.188
7001	401	2.78	4.083
7002	14	0.903	1.729
7002	16	3.286	8.184
7002	27	1.134	2.535
7002	33	0.887	1.947
7002	35	2.278	5.611
7002	41	0.887	1.656
7002	42	1.268	2.269
7002	62	0.747	1.534
7002	65	1.562	2.522
7002	69	0.99	2.187
7002	70	0.887	1.729
7002	76	1.478	2.572
7002	87	0.719	1.621
7002	92	5.843	7.145
7002	105	1.015	2.029
7002	204	1.282	2.323
7002	207	0.665	1.611
7002	210	0.92	2.001
7002	217	1.212	2.129
7002	219	0.933	1.912
7002	224	0.734	1.851
7002	231	2.242	4.124
7002	303	0.887	2.01
7002	304	0.734	1.775
7002	308	1.481	2.548
7002	310	0.813	1.715
7002	320	1.626	2.852
7002	322	0.995	1.974

Group 7, image complexity 3:

S #	I #	T2mark	T2next
70	61	3.328	5.109
70	88	3.235	4.969
70	96	4.312	5.843
70	102	4.766	6.391
70	104	2.563	3.907
70	109	1.75	3.218
70	309	2.562	3.781
70	312	1.609	3.468
70	313	4.469	5.938
70	324	1.687	2.812
70	325	1.594	2.781
70	402	2.985	5.578
70	403	2.188	3.438
70	404	2.031	3.484
70	406	2.234	4.109
71	61	1.187	4.953
71	88	1.297	6.749
71	96	4.374	7.217
71	102	1.062	4.841
71	104	1.484	2.562
71	109	1.421	3.249
71	201	2.61	4.875
71	227	1.406	3.796
71	309	5.656	8.843
71	312	0.985	2.906
71	313	2.89	8.67
71	324	1.734	4.5
71	325	0.969	2.359
71	327	3.046	4.53
71	402	8.982	10.498
71	403	2.359	5.093
71	406	1.672	3.515
72	61	1.119	1.85
72	88	0.914	1.967
72	96	0.991	3.36
72	102	2.391	6.079
72	104	3.567	4.719
72	227	1.58	2.804
72	309	1.223	2.679
72	312	0.996	1.868
72	313	1.843	4.863
72	324	2.177	3.25
72	325	1.028	1.916
72	403	1.137	3.037
72	406	1.368	2.784
73	61	1.157	1.969
73	88	1.593	2.468
73	96	2.078	3.344
73	102	4	5.234
73	201	1.593	2.39
73	227	1.297	2.187
73	309	1.891	2.75
73	312	1.562	2.906
73	324	1.61	2.532
73	325	1.704	2.375
73	327	5.234	6.421
73	402	1.922	3.062
73	403	1.515	2.359
74	61	3.066	4.314
74	88	2.124	5.859
74	96	1.703	6.046
74	102	4.015	6.578
74	104	2.296	3.775
74	109	3.405	5.299
74	201	1.648	3.342
74	227	1.578	4.765
74	309	1.781	4.64
74	312	1.197	3.218
74	313	3.5	8.188
74	324	2.634	4.205
74	325	1.555	3.202
74	327	3.672	5.562
74	402	1.703	7.891
74	403	1.679	3.235
75	61	2.124	3.296
75	88	6.186	7.951
75	96	5.202	6.827
75	102	6.342	10.404
75	109	2.312	4.062
75	201	2.243	3.462
75	227	1.718	4.749
75	312	1.501	3.136
75	313	8.076	10.451
75	324	2.375	4.187
75	325	2.021	4.859
75	402	5.671	11.014
75	403	1.594	2.844
76	227	3.675	5.562
76	312	5.06	6.442
76	324	3.092	5.415
76	325	4.098	5.469
76	403	1.885	3.303
76	406	2.986	4.253
77	61	1.778	3.724
77	88	2.51	7.694
77	96	1.517	4.03
77	102	5.287	8.472
77	104	1.363	3.37
77	109	1.44	2.743
77	201	2.187	3.64
77	227	2.298	5.348
77	309	3.551	5.021
77	312	0.974	2.112
77	313	3.417	6.236
77	324	1.001	3.114
77	325	1.633	3.25
77	327	1.648	6.952
77	402	2.198	7.873
77	404	1.251	3.42
78	61	0.828	1.781
78	88	1.344	2.485
78	104	1.219	3.016
78	109	0.953	1.797
78	201	1.375	3.39
78	227	1.344	2.625

78	312	1.031	1.891
78	324	0.875	1.657
78	325	0.985	1.985
78	327	3.187	4.406
78	402	2.25	4.25
78	403	0.735	1.625
78	406	1.531	2.406
79	61	1.013	2.697
79	88	1.351	4.75
79	96	1.288	5.914
79	102	3.578	7.125
79	104	2.108	4.153
79	109	0.781	2.685
79	227	1.179	4.47
79	312	2.498	4.512
79	313	4.609	7.906
79	324	1.419	3.274
79	325	0.796	2.123
79	402	1.717	4.107
79	403	1.218	2.389
7001	61	1.285	2.158
7001	88	2.281	3.732
7001	96	1.926	2.903
7001	102	3.667	4.902
7001	104	2.044	3.206
7001	109	2.128	3.414
7001	201	1.651	2.512
7001	227	2.829	4.177
7001	309	1.925	3.391
7001	312	1.194	2.179
7001	313	3.08	4.65
7001	324	1.24	2.51
7001	325	1.349	2.575
7001	327	2.503	3.91
7001	402	2	3.318
7001	403	1.255	2.173
7001	406	1.699	2.709
7002	61	1.294	2.308
7002	88	1.948	3.83
7002	96	1.441	2.482
7002	102	2.449	7.207
7002	104	0.825	1.682
7002	109	0.99	1.995
7002	201	1.3	2.386
7002	227	1.775	3.056
7002	309	2.495	3.983
7002	312	1.438	2.355
7002	313	1.708	2.976
7002	324	1.168	2.291
7002	325	1.024	1.988
7002	327	1.481	2.615
7002	402	2.092	3.58
7002	404	0.946	1.744
7002	406	0.857	1.833

Group 8, image complexity 1:

S #	I #	T2mark	T2next
80	15	2.063	5.609
80	34	1.406	3.281
80	47	1.765	5.812
80	48	1.265	2.937
80	57	3.187	5.374
80	63	2.609	5.093
80	64	1.734	3.937
80	67	1.281	3.718
80	68	2.875	4.359
80	80	1.422	2.734
80	82	1.407	3.281
80	97	6.14	7.64
80	206	1.203	4.531
80	208	1.187	2.437
80	221	1.515	3.281
80	230	1.609	4.265
80	306	1.985	4.766
81	6	1.109	3.219
81	15	1.39	5.5
81	19	1.281	4.172
81	26	0.984	2.797
81	57	1.75	4.984
81	68	1.563	3.219
81	77	1.204	3.516
81	82	1.218	2.531
81	209	2.547	5.64
82	6	0.921	3.718
82	15	3.671	9.265
82	19	1.312	3.078
82	26	1.172	2.656
82	57	1.547	2.938
82	68	1.406	2.406
82	77	1.766	3.328
82	82	1.141	2.891
82	209	1.172	2.906
82	306	1.125	3.125
83	6	2.391	9.344
83	15	1.75	6.094
83	19	1.422	5.656
83	26	1.391	4.516
83	48	2.796	4.062
83	57	3.782	5.953
83	68	2.078	6.406
83	77	2.719	5.594
83	82	3.515	6.234
83	306	4.047	11.594
84	6	2.406	5.321
84	15	1.508	4.603
84	19	1.928	3.686
84	26	2.16	7.552
84	57	6.53	8.187
84	68	1.938	4.672
84	77	1.404	3.535
84	82	2.11	5.033
84	209	2.395	4.942
85	15	1.012	1.42
85	26	1.405	1.853
85	57	4.124	4.827
85	68	2.171	2.859
85	77	1.299	1.933
85	82	4.968	5.687
85	209	1.313	2.172
85	306	2.515	3.187
86	15	1.108	1.826
86	19	1.42	3.262
86	26	1.143	2.081
86	57	1.535	2.734
86	68	0.826	1.87
86	77	1.436	2.31
86	82	0.95	1.979
86	209	0.857	2.088
86	306	1.761	3.397
87	15	1.239	2.522
87	19	1.224	2.371
87	48	1.427	2.502
87	67	1.366	2.748
87	68	1.029	2.417
87	77	1.388	2.985
87	80	1.535	2.717
87	82	1.268	2.462
87	97	1.164	2.388
87	111	1.264	3.05
87	208	0.853	2.155
87	209	1.104	2.506
87	211	0.853	1.829
87	230	1.253	2.238
87	306	1.314	2.567
87	411	1.704	3.985
88	6	2.469	4.422
88	15	3.359	5.625
88	19	2.046	6.89
88	57	2.813	4.875
88	68	2.406	7.234
88	77	4.562	6.937
88	82	2.797	5.735
88	209	3.468	5.828
89	6	1.562	3.546
89	15	2.218	4.046
89	19	1.172	3
89	26	1.397	2.592
89	57	1.406	3.813
89	68	1.609	4.515
89	77	1.532	4.235
89	82	1.531	3.39
89	209	2.891	6.172
8001	15	1.385	3.618
8001	19	1.107	3.832
8001	48	0.878	1.876
8001	67	1.848	2.779
8001	68	1.939	3.633
8001	82	1.74	3.187
8001	97	2.017	3.31
8001	208	0.823	2.672
8001	209	2.233	4.188
8001	211	0.985	1.889
8002	15	1.593	2.703
8002	19	1.188	2.609
8002	26	1.078	2.421
8002	57	4.094	6.047
8002	68	1.062	2.656
8002	77	1.094	2.75
8002	82	1.172	2.391
8002	209	1.344	3.516

Group 8, image complexity 2:

S #	I #	T2mark	T2next
80	27	1.641	3.828
80	33	1.328	3.031
80	41	4.344	6.375
80	69	1.016	5.828
80	83	1.344	3.547
80	95	1.547	4.484
80	105	1.407	4.875
80	217	1.687	4.249
80	231	6.406	8.874
80	303	2.437	4.593
80	304	1.015	4.796
80	308	2.39	4.609
80	310	2.374	3.874
80	319	7.031	8.656
81	27	2.719	4.656
81	33	1.359	2.89
81	41	1.688	6.032
81	42	1.203	2.328
81	62	1.437	3.968
81	72	1.063	3.547
81	83	0.937	3.484
81	87	1.515	2.594
81	92	1.531	4.531
81	95	1.281	2.765
81	204	2.344	5.391
81	207	0.907	2.016
81	210	1.375	2.812
81	223	0.985	2.766
81	224	1.875	3
81	310	4.969	6.859
81	320	1.828	3.031
81	322	2.063	3.906
81	401	1.266	7.109
82	14	1.312	3.328
82	16	7.687	9.172
82	33	0.719	2.656
82	42	1.516	3
82	62	1.125	3.234

82	69	1.047	2.844
82	83	1.391	2.61
82	92	10.641	12.172
82	95	1.25	2
82	204	1.172	3.687
82	207	1.422	2.391
82	210	1.25	2.437
82	217	2.968	4.297
82	223	2.985	7.141
82	224	2.375	3.468
82	310	1.875	3.25
82	322	1.813	3.329
83	14	2.593	10.921
83	27	3.093	8.39
83	33	3.5	5.078
83	41	6.797	9.687
83	42	5.359	7.219
83	62	2.937	9.578
83	69	1.985	4.953
83	72	7	8.454
83	83	1.375	2.734
83	87	1.922	3.937
83	92	13.485	15.11
83	95	2.156	3.375
83	204	2.406	13.343
83	207	1.922	4.11
83	217	5.265	7.906
83	223	2.562	5.297
83	224	1.969	6.062
83	310	4.312	5.921
83	320	5.516	8.515
83	322	5.062	8.546
83	401	5.062	11.922
84	14	2.192	4.121
84	27	3.119	7.247
84	33	2.24	4.044
84	41	2.69	3.841
84	42	1.82	4.257
84	62	2.078	4.874
84	69	1.743	4.025
84	72	3.995	6.354
84	83	1.431	2.904
84	87	2.504	3.903
84	92	14.155	15.545
84	204	3.188	7.109
84	207	1.545	2.718
84	210	2.14	12.416
84	217	3.008	5.075
84	223	1.867	3.671
84	224	2.535	3.857
84	310	2.037	3.903
84	320	4.52	7.081
84	322	1.835	3.188
84	401	5.859	7.469
85	14	1.193	1.767
85	16	3.281	3.89
85	27	1.516	2.328
85	33	1.194	1.994
85	41	1.239	1.783
85	42	1.209	1.873
85	62	5.687	6.625
85	69	1.297	2.094
85	72	1.118	1.737
85	83	1.497	2.068
85	92	2.406	3.859
85	204	2.485	3.328
85	207	0.942	1.606
85	210	1.094	1.734
85	217	1.656	2.265
85	223	1.078	1.75
85	224	1.677	2.266
85	310	2.024	2.628
85	322	1.636	2.254
85	401	4.297	5.172
86	14	1.701	2.56
86	16	2.384	4.348
86	27	1.449	2.384
86	33	0.984	1.905
86	41	2.341	2.888
86	42	0.968	1.811
86	62	1.163	2.341
86	69	1.122	1.917
86	72	2.201	3.153
86	83	1.583	2.594
86	87	2.077	3.202
86	92	2.822	8.266
86	95	2.99	4.235
86	204	2.151	3.335
86	207	0.909	2.184
86	210	1.418	2.79
86	223	0.982	1.745
86	224	1.358	2.201
86	308	7.645	8.762
86	310	2.216	3.2
86	320	3.943	4.955
86	322	1.561	2.858
86	401	3.148	11.29
87	16	8.065	9.26
87	33	0.906	2.118
87	76	1.412	2.609
87	92	4.273	6.581
87	204	1.522	2.88
87	210	1.704	2.872
87	224	1.117	2.359
87	231	3.552	4.805
87	308	1.94	3.074
87	401	3.572	5.276
88	16	12.922	14.828
88	27	2.422	5.25
88	33	1.875	4.5
88	42	1.703	4.078
88	62	2.547	6.094
88	69	2.563	4.391
88	83	1.828	3.594
88	87	1.578	3.234
88	92	7.406	8.906
88	95	2.282	4
88	204	6.532	8.516
88	207	8.75	10.594
88	217	3.485	6.172
88	223	5.031	6.75
88	224	2.125	4.391
88	308	8.39	10.515
88	320	2.954	4.891
88	322	2.016	4.172
89	14	1.688	3.781
89	16	4.516	7.828
89	27	1.5	3.765
89	33	1.594	3.063
89	42	1.469	3.594
89	62	2.234	5.062
89	69	2.281	5.281
89	72	2.547	3.938
89	83	1.567	5.323
89	87	1.719	2.828
89	92	3.078	4.203
89	95	2.111	3.352
89	204	2.547	4.453
89	207	1.599	2.732
89	210	2.906	5.469
89	223	1.469	4.578
89	224	1.187	2.281
89	310	3.266	4.813
89	401	2.718	3.984
8001	33	1.039	2.065
8001	72	2.894	4.11
8001	76	1.164	2.452
8001	92	1.792	15.808
8001	204	1.656	7.604
8001	210	1.099	4.637
8001	224	0.85	1.754
8001	231	2.032	4.511
8001	308	3.495	5.804
8002	16	10.875	13.172
8002	27	1.485	2.735
8002	33	1.062	3.171
8002	42	1.187	2.015
8002	62	1.281	2.953
8002	65	1.25	2.203
8002	69	1.265	2.734
8002	72	2.188	3.563
8002	87	2.188	3.375
8002	92	2.015	3.828
8002	95	1.094	2.453
8002	204	1.203	3.094
8002	207	1.672	3.266
8002	210	1.735	2.907
8002	223	0.703	1.672
8002	224	1.343	2.531
8002	308	1.172	4.015
8002	310	1.078	2.812
8002	320	1.641	2.735
8002	322	2.062	3.172
8002	401	3.875	5.422

Group 8, image complexity 3:

S #	**I #**	**T2mark**	**T2next**
80	61	1.578	3.953
80	88	2.359	5.921
80	201	2.359	4.78
80	313	3.265	7.077
80	402	6.328	8.249
80	406	1.891	3.875
81	88	2.796	4.093
81	96	2.546	5.327
81	201	3.828	5.953
81	312	4.86	6.016
81	324	1.234	3.5
82	88	2.015	3.875
82	312	1.094	2.344
82	324	1.547	3.985
83	88	2.968	10.109
83	201	3.312	7.015
83	312	2.359	6.14
83	324	1.437	3.875
83	403	1.297	5.344
84	88	3.661	8.965
84	96	2.657	5.031
84	312	2.995	7.222
84	324	2.021	5.399
85	88	3.234	4.14
85	96	3.125	4.047
85	201	2.501	3.257
85	312	1.821	2.423
85	324	0.831	1.45
85	403	1.133	1.738
86	88	1.246	2.228
86	96	2.451	4.327
86	312	1.218	2.031
86	324	1.046	2.107
86	403	1.077	2.903
87	88	3.422	5.771
87	327	6.004	7.612
87	402	2.528	5.262
87	403	1.03	2.373
88	88	4.891	7.156
88	96	4.515	6.562
88	312	2.516	4.172
88	324	2.203	3.859
88	403	2	4.156
89	88	2.203	5.469
89	96	2.735	4.282
89	312	2.078	3.187

89	324	2.14	3.359
89	403	2.969	5.781
8001	61	1.474	2.622
8001	102	3.252	6.594
8001	309	3.077	14.298
8001	403	3.356	4.557
8002	88	3.14	4.781
8002	96	3.812	4.765
8002	201	3.125	5.579
8002	312	2.468	4.234
8002	324	1.125	2.203

Group 9, image complexity 1:

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

98	47	1.578	2.922
98	48	1.125	2.593
98	54	1.812	4.609
98	57	2.891	5.578
98	63	3.297	5.109
98	64	1.578	4.265
98	67	1.984	3.469
98	68	2.61	5.734
98	80	1.093	2.14
98	82	1.86	4.219
98	97	2.484	5.968
98	206	2.594	4.766
98	208	1.031	2.422
98	209	2.203	4.844
98	220	6.281	7.874
98	230	2.235	3.797
98	307	2.109	3.531
99	6	1.421	2.859
99	7	1.734	3.843
99	15	1.686	2.698
99	19	1.962	3.081
99	26	4.64	6.177
99	46	1.672	2.547
99	47	1.548	2.53
99	48	1.738	3.026
99	54	1.609	2.89
99	57	2.344	4.375
99	63	3.047	5.625
99	64	2.187	3.859
99	67	2.079	3.181
99	68	2.609	4.89
99	80	2.701	3.926
99	82	2.906	4.75
99	97	5.359	8.593
99	206	1.172	2.531
99	208	2.023	2.943
99	209	1.703	3.156
99	211	0.947	1.63
99	220	1.426	2.576
99	221	1.769	2.964
99	230	1.64	3
99	306	1.953	3.156
99	307	1.226	2.437
99	411	2.672	4.563
9001	6	0.953	2.656
9001	15	1.11	2.844
9001	19	1.422	2.984
9001	26	1.219	2.562
9001	47	1.515	3.187
9001	48	1.234	2.406
9001	54	0.89	2.359
9001	63	1.64	3.5
9001	64	1.391	2.86
9001	67	1.016	2.797
9001	68	1.469	4.875
9001	80	1.532	3.141
9001	97	1.5	6.453
9001	206	1.265	2.953
9001	208	0.766	2.704
9001	211	1.062	2.625
9001	220	1.703	3.156
9001	221	1.187	2.453
9001	230	1.375	2.812
9001	307	1.281	4.547
9002	6	1.812	5.671
9002	7	2.391	5.188
9002	15	1.609	3.5
9002	19	1.391	3.25
9002	26	1.204	3.703
9002	46	1.265	4.312
9002	47	1.313	2.937
9002	48	1.5	3.219
9002	54	1.766	3.156
9002	57	1.547	4.203
9002	63	1.859	4.281
9002	64	1.515	5.093
9002	67	2.063	3.625
9002	68	2.109	4.093
9002	80	1.547	3.406
9002	82	2.016	3.985
9002	97	2.469	6.765
9002	206	2.125	4.172
9002	208	1.625	3.703
9002	209	1.781	4.047
9002	211	1.265	6.75
9002	220	2.047	3.922
9002	221	1.453	3.562
9002	230	2.218	4.703
9002	307	1.89	5.124
9002	411	2.828	7.047

Group 9, image complexity 2:

S #	I #	T2mark	T2next
90	14	1.312	2.312
90	16	2.625	4.203
90	27	1.219	2.235
90	33	0.765	1.562
90	35	5.25	7.047
90	41	1	1.75
90	42	1.14	1.953
90	62	0.735	1.703
90	70	1.125	2.39
90	87	2.687	3.562
90	92	1.5	3.047
90	95	2.391	3.625
90	105	3.797	7.297
90	204	1.344	2.516
90	207	0.687	2.015
90	210	1.031	2.687
90	219	0.781	1.796
90	223	0.938	2
90	231	2.766	7.344
90	303	1.125	2.469
90	304	0.797	1.672
90	319	3.063	6.672
90	320	1.406	2.656
90	322	1.094	2.032
90	401	2.375	3.672
91	14	1.92	4.114
91	16	5.925	10.81
91	27	2.201	4.101
91	33	1.399	4.512
91	35	5.877	12.062
91	41	1.35	2.592
91	42	1.602	5.622
91	62	3.444	5.825
91	69	3.481	5.083
91	70	1.676	4.361
91	72	3.111	4.436
91	87	1.289	2.674
91	92	2.205	7.562
91	105	8.946	18.432
91	204	2.664	5.966
91	210	1.824	2.985
91	217	1.787	4.421
91	219	1.577	3.662
91	223	2.433	5.037
91	231	4.86	8.292
91	303	1.878	3.601
91	304	2.084	3.62
91	319	4.472	14.379
91	320	1.553	4.011
91	322	1.399	4.32
91	401	7.455	9.297
92	14	0.859	2.765
92	16	1.906	4.062
92	27	1.219	3.079
92	33	0.687	2.047
92	35	1.531	3.344
92	41	0.937	2.484
92	42	0.907	2.297
92	62	1.031	3.422
92	65	1.11	2.5
92	69	0.891	2.141
92	70	0.89	2.593
92	72	3.453	5.235
92	87	0.922	2.438
92	92	3.031	4.39
92	95	0.734	2.343
92	105	1.281	2.843
92	204	1.266	3.672
92	207	0.719	2.203
92	210	1.016	2.61
92	217	1.109	2.609
92	219	0.688	2.359
92	223	0.922	2.375
92	303	0.828	2.281
92	304	0.781	2.39
92	310	1.125	3.156
92	319	2.328	3.828
92	322	0.922	3.063
92	401	3.172	4.828
93	14	1.641	3.516
93	16	6.563	8.36
93	27	1.765	3.828
93	33	1.547	3.297
93	35	3.578	8
93	41	1.735	3.204
93	42	1.766	3.078
93	62	3.593	5.703
93	65	2.297	6
93	69	3.297	5.078
93	70	1.422	3.172
93	87	3.157	5.25
93	92	9	10.969
93	95	1.547	4.937
93	105	2.063	6.703
93	204	2.875	6.172
93	207	1.64	3.297
93	210	2.156	4.109
93	217	3.516	5.328
93	219	1.594	3.875
93	223	2.281	3.828
93	231	14.203	16.625
93	303	3.015	4.343
93	304	1.359	2.687
93	319	12.11	13.641
93	322	2.219	4.875
93	401	7.765	9.593
94	14	1.609	2.414
94	27	1.063	2.109
94	33	0.68	1.485
94	35	4.718	7.093
94	41	0.851	1.779
94	42	0.82	1.763
94	62	1.203	3.407
94	65	0.735	2
94	69	0.703	1.359
94	70	0.728	1.64
94	72	0.61	1.188
94	87	0.696	1.237
94	92	1.656	3.281
94	105	2.562	5.781
94	204	1.469	2.578
94	207	0.934	1.899
94	210	0.891	2.047
94	217	0.843	1.484
94	219	2.073	3.559
94	223	0.906	1.703
94	231	3.749	5.031
94	303	1.161	2.445
94	304	0.638	1.51
94	308	1.562	4.406

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

Group 9, image complexity 3:

S #	I #	T2mark	T2next
90	88	1.656	2.781
90	96	1.797	2.828
90	102	1.766	5.094
90	104	1.75	2.703
90	109	1.046	2.156
90	201	1.14	2.328
90	227	1.14	2.328
90	312	0.891	1.938
90	324	3.766	4.922
90	325	1.015	1.984
90	327	1.031	3.781
90	402	4.969	6.391
90	403	1.172	2.469
90	406	1.953	3.031
91	61	2.522	5.176
91	88	2.744	8.548
91	96	3.387	6.533
91	102	2.889	6.771
91	104	1.94	5.183
91	109	3.135	4.936
91	201	2.277	3.936
91	227	1.673	5.261
91	309	5.653	8.669
91	312	1.686	3.524
91	313	2.919	7.156
91	324	2.557	4.482
91	325	1.427	4.43
91	327	1.956	17.176
91	402	2.013	8.503
91	403	2.67	4.299
92	61	0.828	2.313
92	88	1.281	3.14
92	96	1.344	2.797
92	102	2.281	3.703
92	104	1.11	3.453
92	109	1.563	3.344
92	201	1.094	2.609
92	227	1.172	2.812
92	309	1.313	3.141
92	312	0.953	2.547

92	313	4.328	5.859
92	324	0.844	2.344
92	325	1.016	4.016
92	327	2.296	5.124
92	402	1.328	3.047
92	403	0.797	2.984
92	406	0.937	2.406
93	61	2.281	4.015
93	88	2.703	4.547
93	96	3.532	5.125
93	102	4.985	7.203
93	104	2.812	4.89
93	109	2.25	4.141
93	201	2.157	4.031
93	227	2.015	4.359
93	309	3.328	5.125
93	312	1.391	4.531
93	324	1.734	3.781
93	325	2.187	3.781
93	327	2.89	6.546
93	402	6.891	8.75
93	403	2.219	4.094
93	406	3.672	5.531
94	61	0.773	1.485
94	88	0.765	1.859
94	96	1.328	2.953
94	102	2.469	3.641
94	104	1.299	2.382
94	109	1.037	2.476
94	227	0.922	1.813
94	309	0.891	1.735
94	312	0.887	1.744
94	313	1.735	3.047
94	324	0.906	1.547
94	325	0.851	1.485
94	327	2.188	3.266
94	402	1.531	2.656
94	403	1.238	2.939
94	406	1.609	3.435
95	88	1.272	2.758
95	96	2.014	3.424
95	104	1.999	3.167
95	109	1.951	3.846
95	201	1.921	4.32
95	227	2.633	3.966
95	309	1.623	5.576
95	324	3.283	4.363
95	325	0.922	3.305
95	327	1.828	2.835
95	404	1.245	2.624
96	61	1.454	3.171
96	88	1.437	2.875
96	96	1.937	5.265
96	102	1.766	4.75
96	104	6.992	8.538
96	109	1.671	4.161
96	227	1.5	5.219
96	309	1.359	3.171
96	312	1.448	3.736
96	313	2.359	4.218
96	324	1.169	2.628
96	325	1.377	3.604
96	327	1.5	5.437
96	402	2.187	5.875
96	403	1.516	4.068
96	406	2.278	3.904
97	61	1.362	2.586
97	88	8.67	10.712
97	96	3.106	4.621
97	102	3.307	5.771
97	104	6.87	8.704
97	109	2.923	5.432
97	227	2.188	3.703
97	309	2.16	4.439
97	312	1.669	2.751
97	313	3.259	4.957
97	324	2.023	3.161
97	325	1.488	2.48
97	327	1.776	4.794
97	402	4.143	5.149
97	404	2.15	3.793
97	406	2.137	3.562
98	61	2.593	5.281
98	88	3.735	5.594
98	96	2.25	5.422
98	102	7.281	11.156
98	104	2	3.422
98	227	4.171	7.765
98	309	4.219	7.375
98	312	1.813	3.407
98	313	3.766	6.094
98	325	1.969	4.016
98	327	4.25	6.735
98	402	6.531	8.765
98	403	1.594	3.25
98	404	1.266	2.547
99	88	5.484	7.109
99	109	6.746	8.202
99	201	1.785	3.089
99	227	2.531	3.843
99	312	1.987	3.104
99	324	1.453	2.828
99	325	3.072	4.174
99	402	3.921	5.327
99	403	1.549	3.741
9001	61	1.656	3.062
9001	88	2.203	5.797
9001	96	1.562	6.015
9001	102	9.016	10.906
9001	104	1.89	3.718
9001	109	3.5	4.828
9001	201	1.813	4
9001	227	1.328	5.359
9001	309	1.125	4.203
9001	312	1.359	2.953
9001	324	1.469	3.313
9001	325	1.437	3.281
9001	403	2.047	4.172
9001	406	1.187	2.656
9002	61	4.156	5.969
9002	88	2.203	6.656
9002	96	4.985	7.172
9002	102	2.859	9.172
9002	104	1.375	4.141
9002	109	1.234	3.468
9002	227	2.172	3.828
9002	309	1.531	8.312
9002	312	1.938	6.469
9002	313	5.562	7.468
9002	324	1.703	4.218
9002	325	1.766	4.797
9002	327	3.172	7.297
9002	402	6.109	7.703
9002	406	4.218	8.859

Group 10, image complexity 1:

S #	I #	T2mark	T2next
100	15	2.047	4.125
100	34	0.954	2.532
100	46	1.968	3.921
100	47	1.437	2.593
100	48	0.922	2.156
100	57	3.89	5.718
100	63	1.25	2.906
100	64	1.469	2.656
100	68	1.609	4.078
100	80	1.093	2.515
100	82	1.734	4.891
100	97	1.375	2.906
100	206	1.265	2.953
100	208	1.609	3.859
100	209	1.719	5.922
100	220	1.766	3.656
100	221	1.281	2.515
100	230	1.25	2.593
100	411	1.375	5.109
101	6	1.611	2.477
101	15	1.215	2.021
101	19	0.957	1.838
101	26	1.041	1.802
101	57	2.48	4.177
101	68	1.378	3.118
101	77	1.763	3.237
101	82	1.16	2.349
101	209	1.653	3.988
101	306	1.32	2.422
102	15	0.875	1.86
102	34	2.079	3.094
102	46	1.063	2.766
102	47	1.219	5.625
102	48	1.094	2.36
102	57	3.985	5.782
102	63	0.843	2.156
102	64	1.797	3.141
102	67	0.906	1.953
102	68	1.422	2.5
102	80	0.781	2.203
102	82	1.281	2.953
102	97	1.047	2.828
102	111	1.234	3.218
102	206	0.765	2.39
102	208	0.766	1.922
102	209	1.5	2.766
102	220	1.578	4.156
102	221	1.063	6.094
102	306	1.359	3.859
103	6	1.687	5.141
103	15	1.547	4.344
103	19	2.25	7.313
103	26	1.438	2.938
103	68	2.172	5.563
103	77	1.625	3.172
103	82	2.703	3.968
103	306	1.953	5.797
104	6	1.796	2.89
104	15	1.094	2.313
104	19	4.843	5.875
104	26	1.771	2.828
104	57	1.484	2.937
104	68	2.938	3.922
104	77	1.375	2.859
104	82	1.437	2.578
104	209	2.797	4.156
104	306	1.094	2.719
105	6	1.937	8.906
105	15	1	2.641
105	19	1.047	2.422
105	26	0.922	6.094
105	57	1.157	3.235
105	68	0.969	4.25
105	77	1.938	3.891
105	82	1.031	5.156
105	209	1	3.266
106	15	1.798	5.815
106	26	1.221	2.769
106	34	0.953	3.626
106	46	2.511	4.814
106	47	1.183	3.38
106	48	1.845	2.917
106	57	2.14	3.323
106	63	1.812	2.83
106	64	4.621	5.862
106	67	1.519	3.603

106	68	1.197	1.991
106	77	1.798	3.826
106	206	1.426	2.822
106	208	1.282	2.674
106	209	1.123	2.261
106	221	1.419	3.288
106	411	1.901	4.102
107	26	1.203	3.047
107	57	1.25	4.938
107	68	1.5	5.312
107	82	2.703	4.593
107	209	1.687	4.078
107	306	1.812	4.781
108	15	1.5	3.485
108	34	1.125	1.922
108	47	3.031	4.859
108	54	1.625	2.39
108	57	2.438	5
108	63	1.797	3.5
108	64	1.672	3.672
108	68	1.437	4.703
108	206	1.578	3.89
108	208	1.172	2.031
108	411	2.094	4.016
109	6	1.016	2.172
109	15	0.781	1.813
109	19	1.188	2.219
109	26	0.86	1.735
109	57	1.047	3.203
109	68	1.141	2.266
109	77	1.172	2.781
109	82	1.125	1.922
109	306	1.312	2.281
110	6	1.297	3.797
110	15	1.047	2.672
110	19	1.281	3.687
110	26	1.265	3.078
110	57	1.703	4.125
110	68	1.063	4.266
110	77	1.485	3.391
110	82	2.5	4.906
110	209	1.391	3.391
110	306	4.266	7.469
111	15	7.186	9.812
111	46	3.577	5.344
111	48	1.383	2.588
111	68	2.042	3.609
111	77	1.783	3.767
111	80	1.055	2.41
111	82	1.797	3.133
111	97	2.15	4.131
111	208	1.029	2.504
111	209	2.411	4.039
111	211	1.193	2.639

Group 10, image complexity 2:

S #	I #	T2mark	T2next
100	27	1.563	2.969
100	33	1.734	4.875
100	41	1.156	2.578
100	69	1.156	2.656
100	72	1.672	3.812
100	83	1.203	2.578
100	87	1.375	3.156
100	105	1.187	3.047
100	204	1.532	4.407
100	217	3.109	4.812
100	223	1.594	3.016
100	310	1.313	2.766
101	14	1.992	3.151
101	16	4.961	7.485
101	27	1.334	2.741
101	33	1.498	2.78
101	41	1.991	2.812
101	42	1.322	2.036
101	62	1.944	4.496
101	69	0.912	1.611
101	72	0.972	3.617
101	83	1.103	1.724
101	87	1.127	2.286
101	92	6.607	7.987
101	95	1.228	2.004
101	105	5.226	6.854
101	204	1.74	4.467
101	207	1.43	2.098
101	210	1.175	2.335
101	223	1.261	2.522
101	224	1.189	2.224
102	33	1.25	2.516
102	69	1.125	2.484
102	72	2.219	3.984
102	83	2.578	3.875
102	87	1.14	2.953
102	95	1.422	2.579
102	105	1.625	2.812
102	204	1.609	3.218
102	217	1.578	3.594
102	223	4.063	5.688
102	231	3.359	5.516
102	303	1.735	3.156
102	304	0.984	4.874
102	308	4.062	5.656
102	310	1.062	2.484
103	14	2.313	4.875
103	16	4.797	8.453
103	27	1.704	4.297
103	33	2.937	4.125
103	42	2.75	6.468
103	62	4.734	11.391
103	69	2.203	4.719
103	83	1.484	3.312
103	92	5.985	9.516
103	95	4.062	5.687
103	204	5.141	14.953
103	207	2.172	3.437
103	210	1.657	5.75
103	217	2.86	4.61
103	223	2.063	3.438
103	224	3.968	5.375
103	308	5.672	9.782
103	310	4.5	5.766
104	14	1.219	2.781
104	16	2.938	4.188
104	27	2.204	3.891
104	33	1.187	2.094
104	42	1.531	2.828
104	62	1.703	3.156
104	69	1.297	2.484
104	72	1.875	2.922
104	83	2.952	4.568
104	92	2.157	4.094
104	95	1.849	2.781
104	204	2.063	4.032
104	207	1.29	2.455
104	210	1.438	3.86
104	223	1.546	2.703
104	224	1.25	2.281
104	310	3.641	5.016
104	322	1.249	2.718
105	14	1.578	9.031
105	16	2.688	10.656
105	27	1.219	4.985
105	33	0.906	2.5
105	41	3.125	4.296
105	42	1.156	2.734
105	62	2	6.141
105	69	1.625	4.344
105	72	1.328	2.687
105	83	0.719	1.781
105	87	1.25	2.75
105	95	1.312	3.734
105	204	2.938	4.86
105	207	2.125	3.453
105	210	1.312	5.875
105	217	5.141	6.922
105	223	1.453	3.156
105	224	1.546	5.984
105	308	5.671	10.296
105	310	2.266	3.891
105	320	6.078	7.484
105	322	1.282	5.469
105	401	3.859	6.219
106	16	2.186	4.177
106	33	1.787	2.756
106	41	1.706	2.827
106	42	1.768	4.063
106	62	1.647	2.56
106	65	1.613	6.311
106	69	1.429	2.75
106	72	2.781	4.364
106	83	1.324	2.115
106	87	1.76	2.524
106	204	3.009	3.892
106	207	2.674	5.512
106	219	1.474	2.754
106	223	1.121	1.843
106	231	1.97	4.357
106	303	1.429	2.243
106	310	2.879	3.684
106	319	4.717	5.55
106	320	3.994	5.392
106	322	1.515	4.407
107	14	1.578	3.89
107	16	5.093	8.578
107	27	1.204	4.422
107	33	1.125	2.797
107	41	2.5	4.171
107	42	1.781	2.797
107	72	1.219	3.078
107	83	0.984	1.859
107	87	0.813	1.579
107	92	3.344	5.953
107	95	1.109	3.171
107	207	1.14	2.156
107	210	1.187	3.422
107	223	2.25	3.36
107	224	1.188	2.141
107	308	3.469	6
107	310	1.141	2.578
107	320	1.828	3.687
107	401	3.781	5.094
108	14	3.609	5.515
108	92	1.718	6.218
108	95	1.078	2.093
108	204	3	3.875
108	207	1.703	3.593
108	223	1.656	3.609
108	224	3.297	4.047
108	401	4.25	6.016
109	27	1.359	2.219
109	33	1.125	5.5
109	41	0.969	2.625
109	42	1.547	2.438
109	62	1.125	3.75
109	72	2.359	3.281
109	83	1.906	2.734
109	87	0.907	1.86
109	92	1.64	2.968
109	95	1.016	2.219
109	204	1.532	2.703
109	207	1.218	2.093
109	210	1.016	1.969
109	223	0.812	1.75

109	224	1.016	2
109	308	2.656	5.078
109	310	1.25	2.203
109	320	0.828	1.75
109	322	1.297	3.516
109	401	2.078	4.344
110	14	6.516	8.047
110	16	2.187	5.406
110	27	2.547	4.593
110	33	1.218	3.343
110	41	1.172	3.453
110	42	2.25	4.828
110	62	1.656	4.187
110	69	1.594	3.907
110	72	1.329	3.438
110	83	1.265	2.547
110	87	2.109	3.39
110	95	1.204	2.813
110	204	4.765	8.046
110	207	1.562	3.641
110	210	1.172	4.781
110	217	2.094	3.734
110	223	1.235	3.61
110	224	1.547	2.907
110	310	2.578	3.812
110	322	2.063	4.11
110	401	2.125	4.11
111	33	1.63	4.012
111	76	1.177	2.67
111	92	3.342	4.585
111	210	3.931	5.71
111	224	1.058	2.251
111	231	4.315	5.636
111	308	2.78	3.854
111	320	2.666	4.449
111	401	2.085	5.22

Group 10, image complexity 3:

S #	I #	T2mark	T2next
100	61	2.375	3.75
100	88	1.813	9.828
100	96	2.703	6.219
100	201	3.953	5.531
100	402	5.469	6.938
100	406	2.281	3.469
101	88	2.597	4.178
101	96	3.158	6.425
101	312	1.035	2.611
101	324	1.17	1.793
101	403	1.282	2.394
102	61	1.141	3.422
102	96	2.343	3.968
102	201	2.5	6.265
102	402	3.188	5.188
103	88	5.531	8.375
103	201	6.359	12.234
103	312	6.203	7.562
103	324	1.469	2.906
104	88	2.125	3.969
104	96	2.578	3.937
104	324	2.094	3.157
104	403	1.828	3.766
105	88	2.016	6.61
105	96	5.547	7.141
105	201	2.078	9.516
105	312	2.344	4.625
105	324	1.36	3.204
105	403	1.968	4.171
106	61	2.822	4.885
106	96	2.305	3.982
106	102	2.317	5.674
106	104	2.51	4.12
106	109	1.444	4.102
106	309	2.575	3.458
106	312	4.032	6.173
106	324	2.295	4.589
106	327	7.007	7.812
106	403	1.368	2.996
107	88	7.703	8.75
107	96	3.734	4.844
107	201	4.312	5.234
107	312	1.297	2.188
107	324	1.828	2.89
108	96	3.046	4.562
108	325	1.828	3.469
108	402	3.187	6.405
108	403	1.203	2.797
108	404	1.563	4.109
109	88	3.282	4.391
109	96	1.079	3.328
109	201	2.484	4.265
109	312	2.39	3.64
109	324	3.594	4.328
109	403	1.281	3.016
110	88	1.875	4.578
110	96	2.688	7.454
110	201	3.484	5.406
110	312	1.687	3.562
110	324	1.172	2.891
110	403	1.719	4.156
111	88	3.466	5.261
111	403	2.672	5.221

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 הוגדרו 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 קיצוני 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 שאר החלקים של פונקציית המטרה. ערך סף קיצוני חיובי, לדוגמה, גורם להסתברויות נמוכות להתראות שווא ולאיתור 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.

השפעת זמן התגובה של האדם על רמת שיתוף הפעולה האופטימאלית במערכת זיהוי מטרות רובוטית משולבת אדם

חיבור זה מהווה חלק מהדרישות לקבלת התואר "מגיסטר" בהנדסה

דרור ישפה

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המחלקה להנדסת תעשייה וניהול

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