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Performance Analysis of Human-Robot Collaboration in Target Recognition Tasks

THESIS SUBMITTED IN PARTIAL FULFILLMENT OF THE REQUIREMENTS FOR THE M.Sc DEGREE

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Abstract

Autonomous robots are systems that can perform tasks, make decisions, and act in real-time without human intervention. They are best-suited for applications that require accuracy in recurrences and high yield under stable conditions. However, application of autonomous robots in dynamic and changeable environment still produces inadequate results. An example can be seen in recognition tasks, where inadequacies in sensor and image processing technology have limited the capabilities of autonomous robotics in complex environments. By integrating the human's perception skills with the autonomous systems' accuracy and consistency, the combined human-robotic system will result in improved performance.

This thesis presents an in-depth evaluation of the performance of various integrated human-robot system in target recognition tasks. The analyses are based on a quantitative model which was developed by Bechar (2006). The model includes four human-robot collaboration levels, which were designed specifically for target recognition tasks and are adjusted to an extensive range of automation; from manual to fully autonomous. The objective function includes four performance measurements which are based on the signal detection theory: hit, false alarm, miss and correct rejection. The objective function quantifies the influence of the robot, human, environment and task parameters through a weighted sum of the performance measurements, and enables it to determine the optimal operational level based on these parameters. In addition, the system's objective function includes an operational cost part aimed at estimating the system's cost associated with time and action.

Bechar (2006) analyzed the objective function, excluding the parts of the reward for correct rejection and the penalty for miss. This thesis expands Bechar's work by conducting a thorough numerical analysis including all parts of the objective function. In addition, comprehensive analysis of the operational costs which was not covered in Bechar's work was conducted.

The numerical analysis of the objective function was conducted in Matlab™ focusing on the influence of different parameters on the optimal operational level of various systems and on the effect of different parameters on the operational cost. In addition, sensitivity analysis of the influencing variables was performed for the optimal cases.

Results reveal two types of systems. The first type consists of systems geared towards minimizing false alarms. The second type consists of systems geared towards detecting a target when one is presented. Symmetry between the objective function weights was found and lead to further investigation which discovered a new property of the objective function. The new property generalizes the model's objective function and facilitates its analysis. In addition, the operational cost analysis reveals that the human decision time has great influence on the system's performance.

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1. Introduction

1.1 Problem description

Application of autonomous robots in unstructured and dynamic environments still produces inadequate results. Having an automated system handle all conceivable scenarios is extremely difficult and the promise of automatic and efficient remote operations has fallen short of expectations (Fletcher et al., 2005; Steinfeld, 2004). Moreover, inadequacies in sensor and image processing technology have limited the capabilities of autonomous robotics in complex environments (Everett and Dubey, 1998). Therefore, the use of an autonomous robotic system is not advisable (Al-Jumaily and Amin, 2000; Penin et al., 1998). Furthermore, when dealing with natural objects (e.g., medical, agriculture objects) the difficulty increases since the objects also have high degrees of variability (in shape, texture, color, size and position) and this leads to more complicated robotic systems and results in a system which is difficult and expensive to develop (Bechar, 2006).

Humans' acute perception capabilities enable them to deal with a flexible, vague, changing, and wide scope of definitions (Chang et al., 1998). Moreover, humans have superior recognition capabilities and can easily adapt to changing environmental and object conditions (Rodriguez and Weisbin, 2003). However, a human operator is not consistent, tends to fatigue, and suffers from distraction (Van Erp et al., 2004).

The human perception, acting and thinking capabilities in dynamic environments are superior to those of robots, however there can be huge potential risks to human safety in getting these benefits. Robots provide complementary skills to work in extremely risky environments, but their ability to perceive, think, and act on their own is far from flawless (Rodriguez and Weisbin, 2003).

By taking advantage of the human perception skills and the autonomous systems' accuracy and consistency the combined human-robotic system can be simplified, resulting in improved performance **(**Parasuraman et al., 2000)**.**

Robots are increasingly being used in assistive technology, rehabilitation, surgery, therapy, service and entertainment domains and methods which will enable easy and effective communication between robots and humans are crucial in all of these areas (Salter et al., 2004).

Target recognition is a common task and usually an essential part of a robotic system. However, target recognition in unstructured environments, such as, agriculture, is characterized by a low detection rate and a high false alarm rate (Bechar, 2006). Based on Sheridan's scale of 'action selection and automation of decision' (table 3), Bechar (2006), defined, tested and evaluated four basic levels for Human-Robot collaboration for target recognition tasks. The system objective function is designed to enable determination of the expected value of task performance, given the parameters of the system, the task, and the environment (Bechar, 2006). The objective function quantifies the influence of the robot, human, environment and task parameters through a weighted sum of performance measures, and enables it to determine the optimal operational level based on these parameters. In addition, the system's objective function includes an operational cost part aimed at estimating the system's cost associated with time and action.

1.2 Research objectives

The main research objective is to conduct a thorough numerical analysis of the objective function developed by Bechar (2006). Specifically this research aims at:

- Evaluation of the performance of *various* types of human-robot systems for target recognition tasks for different environmental, task, human and robot parameters.
- Extensive analysis of operational costs: investigation of the effect of each of the operational cost's parameters on the system's performance.
- Examination of similarities between different systems based on the behavior of their objective function.

1.3 Research contribution

Autonomous robots are inefficient in complex assignments and unstructured environments. Integrating humans into robotic systems can help simplify the system and improve their performance.

Bechar (2006) analyzed the objective function, excluding the parts of the reward for correct rejection and the penalty for miss. This thesis expands Bechar's work by conducting a thorough numerical analysis including all parts of the objective function. In addition, comprehensive analysis of the operational costs which was not covered in Bechar's work was conducted.

Results of this work confirm previous work and provide a tool in designing new integrated systems and controlling various human-robot systems by mapping the influence of different parameters on the system state.

1.4 Thesis Overview

Chapter 2 presents a literature review and is followed by an in-depth description of the model developed by Bechar, in chapter 3, which serves as the basis for this research. The research methods are presented in chapter 4 followed by an expanded analysis of the best operational level in chapter 5. Chapter 6 details the analysis of the operational costs and its results. Chapter 7 presents the sensitivity analyses. The thesis is summarized with conclusions presented in chapter 8 followed by a discussion and future work presented in chapter 9

2. Literature review

2.1 Human Robot Collaboration

2.1.1 Autonomous robots – advantages and drawbacks

Autonomous robots are systems that can perform tasks, make decisions, and act in real-time without human intervention. They are best-suited for applications that require accuracy in recurrences and high yield under stable conditions (Holland and Nof, 1999). Usually autonomous robots are used in a structured environment, such as the industrial production floor, and are required in applications, which demand reductions in manpower and workload (Holland and Nof, 1999).

According to Rucci et al. (1999), autonomous robotic systems must possess a high degree of flexibility to adapt to the continuously changing conditions of the environment. An important challenge which designers of autonomous robotic systems often face, deals with the nonlinear, real-time response requirements underlying the sensor–motor control formulation (Ng and Trivedi, 1998).

Application of autonomous robots in dynamic and changeable environments still produces inadequate results (Bechar and Edan, 2003). Therefore, the use of an autonomous robotic device is not advisable (Al-Jumaily and Amin, 2000; Penin et al., 1998). An example can be seen in recognition tasks, where inadequacies in sensor and image processing technology have limited the capabilities of autonomous robotics in complex environments (Everett and Dubey, 1998). Moreover, having an automated system handle all conceivable scenarios is extremely difficult and the promise of automatic and efficient remote operations has fallen short of expectations (Fletcher et al., 2005; Steinfeld, 2004).

2.1.2 The Human operator's characteristics

Humans have superior recognition capabilities and can easily adapt to changing environmental and object conditions (Rodriguez and Weisbin, 2003). Their acute perception capabilities enable humans to deal with a flexible, vague, changing, and wide scope of definitions (Chang et al., 1998). However, a human operator is not consistent, tends to fatigue, and suffers from distraction (Van Erp et al., 2004). In addition, human operators are known to make mistakes of overlooking collisions with surrounding objects, which result in expensive repairs and limit the system's effectiveness and utility. People seem to be unable to navigate and manipulate remote equipment without colliding with objects in the environment (Ivanisevic and Lurnehky, 1998).

Another example where the human operator's capabilities are insufficient is guiding the position of a robotic welding gun or spray painting device. These kinds of tasks seem to be particularly difficult for people, even when visual feedback is provided (Ivanisevic and Lurnehky, 1998). Table 1 presents a summary of human and robot advantages and drawbacks.

Table 1: Human operator vs. robot comparison

	Advantages	*Drawbacks*
Human	▪ Superior recognition capabilities ▪ Acute perception ▪ Cognitive capability	▪ Inconsistency ▪ Tends to fatigue ▪ Suffers from distractions
Robot	▪ Accuracy ▪ High yield	▪ Inadequate results in unstructured environment ▪ Complex decision making

2.1.3 Human – Robot collaboration overview

According to Sheridan (1992), human-robot collaboration means that one or more human operators are intermittently or continuously programming and receiving information from a computer that interconnects through artificial effectors and sensors to the controlled process or task environment.

There are several reasons for developing human-machine control (Sheridan, 1992). First, it combines the advantages of the machine with the advantages of the human operator. Specifically, it achieves the accuracy, reliability and high yield of the machine with the cognitive capability and adaptability of the human. Moreover, by collaboration, the workload of the human operator is reduced and in the event of robot or human failure, either can reduce the damage. Second, it makes control possible even where there are time delays in communication between human and robot. Last, it saves lives and reduces cost by eliminating the need for the human operator to be present in hazardous environments (Sheridan 1992).

According to Rodriguez and Weisbin (2003), human and robot skills are complementary. The human perception, acting and thinking capabilities in dynamic environments are unmatched to those of robots, but there can be huge potential risks to human safety in getting these benefits. Robots provide complementary skills in being able to work in extremely risky environments, but their ability to perceive, think, and act on their own is far from flawless.

Technical developments in computer hardware and software now make it possible to introduce automation into virtually all aspects of human-machine systems. By taking advantage of human perception skills and the accuracy and consistency of autonomous systems, the combined human-robotic system can be simplified, resulting in improved performance (Parasuraman et al., 2000). For example, recent reliance on automation combining human skills has resulted in successful military and space exploration systems (Burke et al., 2004).

A teleoperator is a machine that extends a person's sensing and/or manipulating capability to a location remote from that person (Sheridan, 1992). Virtually, by its definition, every human-robot collaboration system has a teleoperator. Since their first appearance in the 40's, many teleoperated systems have been developed and employed for dealing with unstructured environments and in applications where there is clear and unavoidable danger for the human operator (Sheridan, 1992). In addition, robots are already increasingly being used in assistive technology, rehabilitation, surgery, therapy, service and entertainment domains. Methods which will enable easy and effective communication between robots and humans are crucial in all of these areas (Salter et al., 2004).

According to Parasuraman et al. (2000), machine execution has been extended to functions that humans do not wish to perform, or cannot perform as accurately or reliably as machines. On the other hand, there is a large and rapidly developing class of technical systems that are dependent on human contribution for their operation.

Various teleoperated systems, such as in space, nuclear reactors, and chemical cleanup sites provide excellent examples of human-robot collaboration in which the human operators plan and guide the motion of remotely situated devices through interaction with computer (Ivanisevic and Lurnehky, 1998).

Bechar and Edan (2003), provide an empirical proof of the advantage of such collaborations in a target recognition task. According to their research, collaboration of human and robot increases detection by 4% when compared to a human operator alone and by 14% when compared to a fully autonomous system. In addition, when compared to the human alone, detection times of integrated systems are reduced by 20%.

2.1.4 Human – Robot applications

Different researches focus on different applications of human-robot collaboration. The following section reviews some examples.

Ivanisevic and Lurnehky (1998), worked on improving the performance of human operators in tasks that involve motion planning and control of complex objects in environments with obstacles. They developed a visual computer interface that would allow the operator to visualize and perform the work in the task configuration space rather than in the work space. Essentially, the computer intelligence works alongside with human intelligence in real-time. Their results show that the proposed configuration space control mode performed significantly better than the traditional work space control.

Penin et al. (1998) developed a teleoperated system for electrical live-line maintenance. In their work the human operator commands the manipulators from a cabin on the truck via a pair of master arms, while he or she receives visual feedback through a vision system. With the operator on the ground, a great improvement in human safety has been introduced.

Everett and Dubey (1998) worked on a new methodology to incorporate sensor and model based computer assistance into human controlled teleoperator systems. In this approach human operator input is enhanced but not superseded by the computer.

Salter et al. (2004) focuses on the nature of interactions between children and robots. Their research shows how a simple and robust technique, based on a robot's sensor readings, can be used to automatically detect and distinguish human contact. Their findings may have therapeutic implications for autistic children.

In their research, Fletcher et al. (2005), present an automated detection and recognition system of road signs combined with the monitoring of the driver's response. According to them, cars offer unique challenges in human-machine interaction and vehicles are becoming, in effect, robotic systems that collaborate with the driver. In their work, driver monitoring and real-time sign recognition were combined to correlate eye gaze with the sign direction, which together with the vehicle state developed a system that determines whether the driver should be made aware of the detected sign.

Ayanna and Howard (2006) focused on role allocation in Human-Robot collaboration for space missions. Their objective was to determine an optimal task allocation between the human and robot.

Shoval (2008) introduced a model for coordinated task allocation in distributed multi-agent (human or robot) systems operating in a dynamic environment. A centralized allocation methodology, in which all task allocation decisions are made by a single agent, was developed. His methodology considers a global view of the system, therefore, minimizing the total operational cost.

Matthew et al. (2008) investigated the best way to facilitate the formation of mixed teams of humans and robots that could perform complex tasks in the real world. Using a natural language-based multi-modal interface, they enabled simple interaction for humans, while effective coordination for robots was achieved via policy regulated behavior. Their use of an advanced network infrastructure further enabled robust and reliable communications among team members.

Bernhardt et el. (2008) present an integrated European project called "PISA" which aims to develop intelligent assist systems (IAS) to support human workers in the assignments of assembling complex products. They developed methodologies which enable integration and collaboration between human workers and highly flexible devices and equipment (robot) in a qualitatively new and efficient manner. Table 2 presents various tasks of human-robot applications.

Table 2: Examples of Human – Robot systems' applications in various tasks

Task	*Application*
Tracking	Driver aid, Security systems
Manipulation	Motion planning, Electrical live line maintenance, Surgery
Navigation	Flight control system, Legged robot walking
Recognition	Space exploration, Driver aid, Melon harvest, Military and Medical target recognition

2.2 Human – Robot collaboration models

2.2.1 Basic Structure of Human-Robot Collaboration Systems

The basic structure of human-robot collaboration system, consists of an operator, controls, displays, a human-interactive computer (HIC), a barrier of distance and/or time, a task-interaction computer (TIC) and the robot (figure 1).

The HIC has two main tasks (Sheridan, 1992). First, it acts as the link between the human operator and the TIC, i.e., it receives input from the operator, translates it and sends the output to the TIC. In addition, it receives input from the TIC, translates it, and sends it back to the operator. Second, it contains a data base and different algorithms which support the controlling and decision making process.

The TIC is essentially the "brain" of the robot. It receives input from the HIC and translates it into the appropriate commands which the robot, in turn, executes. Additionally, it sends the HIC feedback messages (Sheridan, 1992).

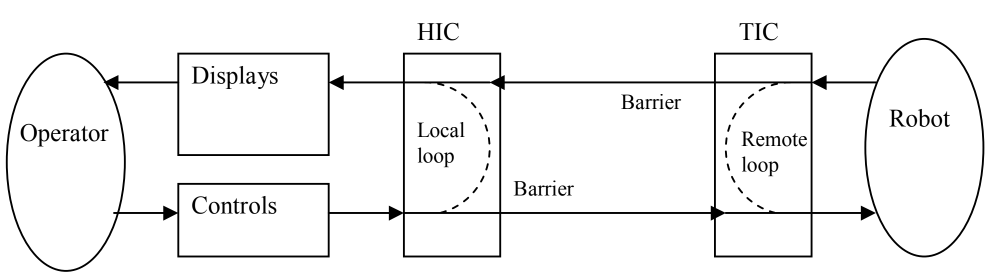

Figure 1: Basic structure of human-robot systems (Sheridan, 1992).

Human-robot collaboration models can be classified into qualitative and quantitative models. Qualitative models are characterized by focusing on helping design the systems, rather than on optimization of the controlling process, which is the main focus of quantitative models. According to Sheridan (1992), even though there is an abundance of human-robot collaboration models, there is no single comprehensive quantitative or qualitative model.

2.2.2 Qualitative Human-Robot Collaboration Models

Focusing on designing the systems is achieved by answering the main question: which parts of the process should be automated? Sheridan (1992) lists some of the more specific questions they target, such as how much detail should the TIC transfer to the HIC and the HIC transfer to the operator? How should responsibilities be allocated among the TIC, the HIC and the human operator?

The following section will review five quantitative models which attempt to answer the above questions. The first three focus on the human operator's characteristics, the fourth one defines human-robot collaboration levels, the last one is an iterative model with evaluation criteria.

Five Operator Functions

Sheridan (1992) proposes a serial model which lists five linked functions of the operator in human-robot collaboration (Fig. 2).

The first function, *planning*, deals with what task to do and how to do it. This is the hardest function to model because it involves setting goals and determining strategy. Second is the *Teaching* function. The operator teaches the computer by translating goals and strategy into detailed instructions to the computer. *Monitoring* is the third function in which the human operator ensures that the robot executes the commands as planned and detects failures. *Intervening*, the fourth function can occur in two situations. In case the computer signals accomplishment of its part-task, the operator intervenes and commands new instructions. If the computer failed to execute the commands given, the operator intervenes, gives new instructions or fully takes over control. The last function is *Learning*. The operator has the capability to learn from former experience of operating the system. This function is at a higher level than teaching because it is inductive, and involves reducing general ideas to specific instructions.

In this model, the functions are operating within three nested control loops. The most inner loop, monitoring, takes place at brief intervals and makes minor system adjustments in the automatic control system that require no significant intervention. The middle loop closes from intervening back to teaching. This loop is like reprogramming, i.e., the human states new goals to process, and occurs at longer intervals. The outer loop closes from learning to planning. Learning and revision in task planning occur at even longer intervals.

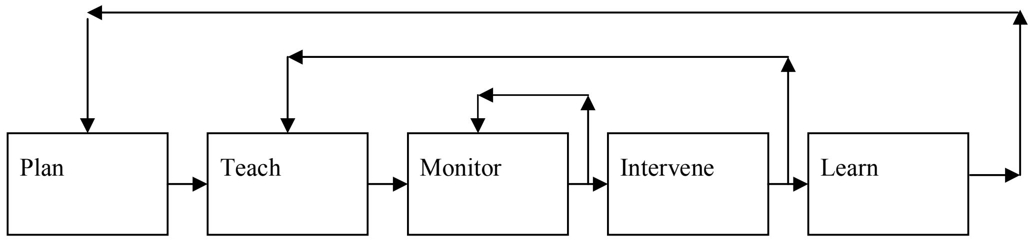

Figure 2: Five operator's functions and their connections (Sheridan, 1992).

Rasmunssen's levels of behavior

Rasmunssen (1976) introduced a paradigm for describing three levels of human behavior. The first level is *Skill based behavior*, and it is analogous to what can be expected from a servo-mechanism. The second level is *Rule based behavior*. It parallels an "artificial intelligent" computer in the sense of recognizing a pattern of stimuli and then triggering an "if-then" algorithm to execute an appropriate response. The third and last level of human behavior is *Knowledge-based behavior*. It includes consideration of alternative action based on various goals, decision and scheduling of implementation. Machines are known not to be good enough at this form of behavior.

Sheridan (1992) parallels between this model and the Five Operator Functions model described above. The *Skill level* is analogous to the inner loop, *monitoring*, because they are both a well-learned and largely perceptual motor skill. The *Rule level* is analogous to the middle loop, *teaching* and *intervening*, in the sense that they both involve instructions. The *Knowledge level* fits the outer loop, *planning* and *learning*, in the sense that both involve goals and problem formulation.

S-C-R paradigm

This model is actually a traditional classification of behavioral activity. The human behavioral activities are divided into three different categories. The first class is S - sensory which usually refers to exteroceptors, e.g., vision, hearing, taste. The second class is C – cognitive which means activity without apparent sensory or motor components, e.g., remembering and making decisions. And the third class is R – response which usually refers to muscle activity (Sheridan, 1992).

Levels of Human-Robot collaboration

Sheridan (1992) divided human-robot collaboration into ten levels from fully autonomous, without human intervention, to fully manual (Table 3).

Table 3: Levels of automation of decision and action selection (Sheridan, 1992)

HIGH 10. the computer decides everything, acts autonomously, ignoring the human

9. informs the human only if it, the computer, decides to

8. informs the human only if asked to, 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. suggest one alternative

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; human must make all decisions and actions

Iterative model with evaluation criteria

Parasuraman et al. (2000) outlined a model for types and levels of automation which attempt to provide a framework and an objective for making such choices. This model proposes that automation can be applied to four generic classes of functions: 1) Information acquisition. 2) Information analysis. 3) Decision and action selection. 4) Action implementation. Each class is independent and has its individual degree of automation which is determined by applying Sheridan's automation scale (Table 3). The model has two evaluation criteria. The primary criterion concerns the reduction in human capabilities due to the degree of automation. The second criterion concerns the automation reliability. Being an iterative model, the degree of automation can be changed after each evaluation.

Taxonomy of Human-Robot interaction

Scholtz (2002) describes five roles that a human may take when interacting with a robot: *supervisor, operator*, *mechanic, peer* and *bystander.* A *supervisor* monitors and controls the robot's overall behavior, and is the only one authorized to change the greater goals. An *operator* is called upon to modify plans or actions when the robot's behavior does not match the greater goals. A *mechanic* needs to physically change the robot's hardware or software. A *peer* can command the robot within the greater goals. It is assumed that even with solid interfaces, peers will not have the necessary time to plan and change the goals. If they do have time then the role switches to supervisor. A *bystander* is given a subset of interactions with the robot. The bystander should be advised of the robot's capabilities with which he can interact.

2.2.4 Quantitative Human-Robot Collaboration Models

Human and controlled process as invariant

Since the 1950s there has been much effort devoted to using conventional linear control theory to model simple manual controls systems, in which the human operator is the sole participant in the loop control element. The motivation for this was the need to establish predictive models for control where humans are involved, e.g., aircraft (Sheridan, 1992).

The first model viewed the human operator factor as independent from the controlled process, but soon this was found to be impractical, since the characteristics of the human operator proved to be very much dependent upon the controlled process. Following this, a proposal was made to model the human operator and the controlled process as a single element. It was assumed that there would be only minor variations of the combined human and process from application to application. The result is the simple crossover model of McRuer et al. (1965), which has the form: $\frac{X}{e} = \frac{Ke^{-j\omega T}}{j\omega}$.

This is virtually a combined pure time delay and integrator, where X is the output, e is the error and ω stands for the frequency. The variations of parameters K, the gain, and T, time delay, are well established in the literature. Figure 3 presents a comparison between McRuer's model block diagram and the simple compensatory model (Sheridan, 1992).

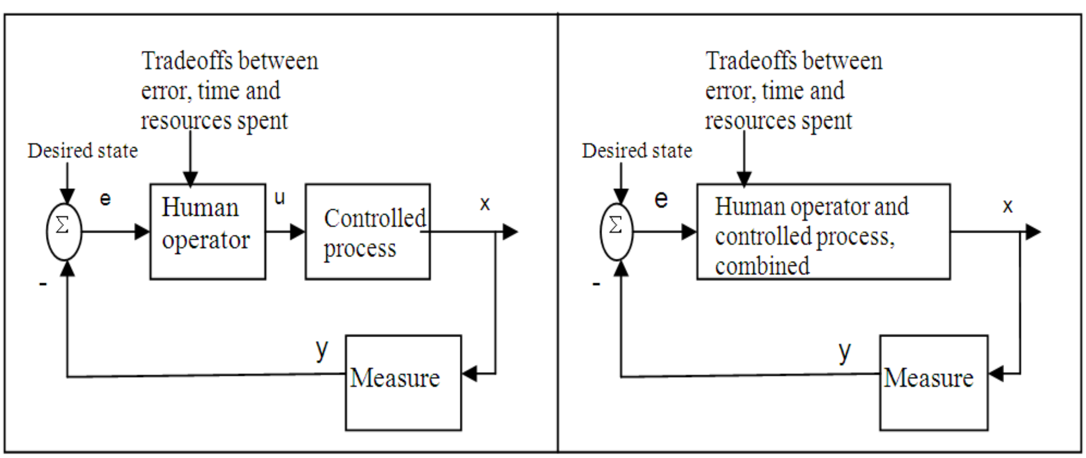

Figure 3: Simple compensatory manual control (human and controlled process are independent) vs. McRuer's simple crossover model (human and controlled process act as an invariant combination). (Sheridan, 1992).

2.2.5 Human – Robot collaboration models' complexity

According to Sheridan (1992), human-robot control involves complex and flexible systems where operators have free will in planning, setting goals, and evaluation. Setting goals and decision making seems to be the most difficult aspect of human-robot control to model (Sheridan, 1992). In addition, modeling free will seems paradoxical, since free will is determined from within the operator and not by an outside source. This is also the reason why mental events can only be inferred and cannot be directly measured.

Another difficulty in modeling arises when there is free interaction between human and computer. It is difficult to determine which behavior is a result of true human decision making and which occurs following the computer's advice.

Moreover, according to Shoval (2008), as the science of robotics advances, specifically in terms of computation capabilities, speed and availability, determining the optimal automation level is becoming more and more composite.

2.3 Quantitative model for integrated systems in target recognition tasks

Target recognition is a common task and usually an essential part of a robotic system. However, target recognition in unstructured environments, e.g., agriculture, is characterized by a low detection rate and a high false alarm rate (Bechar et al., 2006).

Bechar et al. (2006) developed a quantitative methodology for determining the optimal collaboration level of an integrated human-robot system in target recognition tasks. Based on Sheridan's scale of "action selection and automation of decision" (Table 3), Bechar et al. (2006), defined, tested and evaluated four basic levels for Human-Robot collaboration. The system objective function is designed to enable determination of the expected value of task performance, given the parameters of the system, the task, and the environment (Bechar et al., 2006).

Statistical analysis results indicate that the best system performance, the optimal performance measures values, and the best collaboration level depends on the task, the environment, human and robot parameters, and the system characteristics (Bechar et al., 2006).

3. System Objective Function (Bechar, 2006)

This chapter is based on the model developed by Bechar in his Ph.D. thesis (Bechar, 2006).

3.1 Definitions

This research evaluates the performance of an integrated human-robot system with the following definitions:

- ‘System’ refers both to the 'human' and 'robot' subsystems and indicates their overall combined performances and parameters.
- ‘Robot’ refers to an autonomous robot which calculates its outcomes based on its algorithm.
- ‘Human’ refers to a human operator who operates the system fully manually.
- 'Environment' refers to the surrounding conditions the 'system' operates in such as the target probability and number of objects.
- ‘Task’ refers to the specific parameters of the ‘system’ which are derived from the system’s objective such as the reward gained from detecting a target.

3.2 Assumptions

- The system is serial: the robot first inspects the object and then decides whether it is a target or not; subsequently, the human, which is exposed to the robot’s decision, inspects the object and makes his decision.
- The robot’s decision is independent, i.e., the human’s performance has no influence on the robot’s performance.
- The human, robot, and system performances do not influence the appearance of target and non-target objects.
- The human, robot, task, and environmental parameters are stable over time.
- Both target and non-target objects are normally distributed and have equal variance.

3.3 Operational levels

The model includes four different operational levels based on Sheridan’s (1978) scale of “action selection and automation of decision”. 1) H: The human operator detects and marks the desired target single-handed. This level is compatible to level 1 on Sheridan’s scale. 2) HR: The human marks targets, aided by recommendations from the robot, i.e., some objects are automatically marked by a robot detection algorithm, the human operator responsible enters the robot’s correct detection into the target bank and marks targets which the robot missed. This level is compatible to levels 3-4 on Sheridan’s scale. 3) HOR: The human supervises the robot. Objects are identified automatically by the robot's detection algorithm and inserted into the target bank, compatible with levels 5-7 on Sheridan's scale. The human's assignment is to cancel false detections and to mark the targets missed by the robot system. 4) R: Fully autonomous, the targets are marked automatically by the robot, compatible to level 10 on Sheridan's scale.

3.4 Objective function – Equations and Notations

The aim is to maximize the objective function. In target recognition tasks, the system has four different possible outcomes: Correct Rejection (CR) occurs when the system didn't mark a non-target object. False Alarm (FA) occurs when the system marked a non-target object. Miss (M) occurs when the system didn't mark a target object and Hit (H) occurs when the system marked a target object. Each of the possible outcomes has a weight in the objective function. The reward for detecting a target is notated as V_H. The penalty for missing a target is notated as V_M. The penalty for false alarm is notated as V_{FA} and the reward for correct rejection is notated as V_{CR}. In addition, the objective function considers the operational costs which are notated as V_T. The objective function for each object is illustrated in equation (1):

(1) $V_I = V_H - V_M - V_{FA} + V_{CR} - V_T$

Equations (2) to (5) illustrate the explicit part of each possible outcome.

(2) $V_H = N \cdot P_S \cdot p_H \cdot W_H$

(3) $V_M = N \cdot P_S \cdot p_M \cdot W_M$

(4) $V_{FA} = N \cdot (1 - P_S) \cdot p_{FA} \cdot W_{FA}$

(5) $V_{CR} = N \cdot (1 - P_S) \cdot p_{CR} \cdot W_{CR}$

All these equations are composed similarly where N is the number of objects in the analyzed image and Ps is the probability for an object to be a target and therefore (1-Ps) is the non-target probability. These parameters characterize the environment conditions. The third parameter, p_x, symbolizes the probability of the system for one of the possible outcomes, where index x can be H, M, FA or CR. This parameter considers the human and robot characteristics. The last parameter, W_X, symbolizes the weight's value for each possible outcome, where index x can be H, M, FA or CR. The value of each weight is a task parameter and is determined upon the system's mission.

The system's probability of an outcome is influenced by the serial structure of the model and is composed of the robot and the human probabilities. Equations (6), (7) illustrate the system probability for hit and false alarm.

(6) $$p_{H_S} = p_{H_r} \cdot p_{H_{rh}} + \left(1 - p_{H_r}\right) \cdot p_{H_h}$$

(7) $$p_{FA_S} = p_{FA_r} \cdot p_{FA_{rh}} + \left(1 - p_{FA_r}\right) \cdot p_{FA_h}$$

The system has two options for detecting a target. One possibility is for the robot to detect a target, p_{H_r}, and the human to confirm the robot detection, $p_{H_{rh}}$. Second is that the robot could miss, $\left(1 - p_{H_r}\right)$, but the human would detect the target, p_{H_h}. The system probability for miss is complementary to hit and therefore equal to (1- p_H). The FA probability is computed in the same way as the H probability but with the FA probabilities. The system probability for CR is complementary to FA and therefore equal to (1- p_{FA}). The system operational cost includes both costs of time (V_t) and action (V_c) as illustrated in equation (8).

(8) $$V_T = \underbrace{t_S \cdot W_t}_{V_t} + \underbrace{\overbrace{\left(N \cdot P_S \cdot p_H + N \cdot (1 - P_S) p_{FA}\right)}^{W_a} \cdot W_C}_{V_c}$$

The cost associated with time (V_t) is composed of t_S which is the system time that is required to analyze an image, and W_t which is the cost of one time unit. The cost associated with action (V_c) is influenced only by hit or false alarm outcomes (W_a), since there is an actual action of the robotic system for these outcomes only. W_c is the cost of one object recognition operation.

The system time, t_S, consists of the time for the human operator (HO) to confirm the robot hits, the time for the HO to hit additional targets, the time for the HO to correct the robot false alarms, the time for the HO to mark false alarms, and the robot time to process the image and to perform hits or false alarms. Also included in ts is the time it takes the human to decide whether an object has been correctly rejected (CR) or missed (M). Equation (9) illustrates the explicit of t_s.

(9) $$\begin{aligned} t_S = {} & N \cdot P_S \cdot p_{H_r} \cdot p_{H_{rh}} \cdot t_{H_{rh}} + N \cdot P_S \cdot \left(1 - p_{H_r}\right) \cdot p_{H_h} \cdot t_{H_h} + \\ & + N \cdot \left(1 - P_S\right) \cdot p_{FA_r} \cdot p_{FA_{rh}} \cdot t_{FA_{rh}} + N \cdot \left(1 - P_S\right) \cdot \left(1 - p_{FA_r}\right) \cdot p_{FA_h} \cdot t_{FA_h} + \\ & + N \cdot P_S \cdot p_{H_r} \cdot \left(1 - p_{H_{rh}}\right) \cdot t_{M_{rh}} + N \cdot P_S \cdot \left(1 - p_{H_r}\right) \cdot \left(1 - p_{H_h}\right) \cdot t_{M_h} + \\ & + N \cdot \left(1 - P_S\right) \cdot p_{FA_r} \cdot \left(1 - p_{FA_{rh}}\right) \cdot t_{CR_{rh}} + N \cdot \left(1 - P_S\right) \cdot \left(1 - p_{FA_r}\right) \cdot \left(1 - p_{FA_h}\right) \cdot t_{CR_h} + t_r \end{aligned}$$

t_{Hrh} is the HO time required to confirm a robot hit, t_{Hh} is the HO time required to hit a target which the robot did not hit, t_{FArh} is the HO time needed to correct a robot false alarm, t_{FAh} is the HO false alarm time, t_{Mrh} is the HO time lost when a robot hit is missed, t_{Mh} is the HO time invested when missing a target which the robot did not hit, t_{CRrh} is the HO time to correctly reject a robot false alarm, t_{CRh} is the HO correct rejection time, and t_r is the robot time. It was assumed that each of the human time variables represents a superposition of a decision time, t_d, and a motoric time, t_m, in accordance with the collaboration level. The time parameters for the H, HR and HOR collaborations are shown in equations (10), (11), and (12), respectively.

$$\begin{aligned} t_{Hh} &= t_d + t_m \\ t_{FAh} &= t_d + t_m \\ t_{Mh} &= t_d \\ t_{CRh} &= t_d \end{aligned} \tag{10}$$

$$\begin{aligned} t_{Hh} &= t_d + t_m \\ t_{FAh} &= t_d + t_m \\ t_{Mh} &= t_d \\ t_{CRh} &= t_d \\ t_{Hrh} &= t_d + t_m \\ t_{FArh} &= t_d + t_m \\ t_{Mrh} &= t_d \\ t_{CRrh} &= t_d \end{aligned} \tag{11}$$

$$\begin{aligned} t_{Hh} &= t_d + t_m \\ t_{FAh} &= t_d + t_m \\ t_{Mh} &= t_d \\ t_{CRh} &= t_d \\ t_{Hrh} &= t_d \\ t_{FArh} &= t_d \\ t_{Mrh} &= t_d + t_m \\ t_{CRrh} &= t_d + t_m \end{aligned} \tag{12}$$

Table 4 presents the objective function parameters divided into four main groups.

Table 4: Summary of the objective function parameters into four main groups

Human performance	**Robot performance**	**Task orientation**	**Environment**
p_{Hh}	p_{Hr}	W_H	N
p_{Hrh}	p_{FAr}	W_M	P_S
p_{FAh}	t_r	W_{FA}	
p_{FArh}		W_{CR}	
t_{Hh}		W_c	
t_{Hrh}		W_t	
t_{FAh}			
t_{FArh}			
t_{Mh}			
t_{Mrh}			
t_{CRh}			
t_{CRrh}			

3.5 Signal Detection Theory

To simplify the objective function and facilitate its analysis robot and human performance measures and overall system performance were described using signal detection theory parameters based on Bechar (2006).

Background

Signal detection theory (SDT) is a method of assessing the decision making process for binary categorization decisions. In detection, a detector attempts to distinguish two stimuli, *noise (N)* and *signal plus noise (S + N)*.The detector performance analyses are based on hit and false alarm rates, where a hit is an outcome when a person correctly identifies a signal when one is presented, and a false alarm is the identification of a noise. The detector's ability to distinguish between noise and signal depending on the overlap between the distributions, quantified by *d',* the normalized (by the standard deviation) difference between their means. The placement of the criteria determines both the *hits* ("yes" responses to signals) and the *false alarms* ("yes" responses to noise). When the criterion is high (i.e., conservative), the detector will result in few false alarms, but also few hits. By adopting a lower criterion (i.e., liberal), the number of hits increases, but at the expense of increasing the false alarm rate. This change in the decision strategy does not affect *d',* which is therefore a measure of *sensitivity* that is independent of the criterion placing. In this work the criterion is represented by β which is the likelihood ratio of the two distributions at the cutoff point *x*. Figure 4 illustrates an example of SDT.

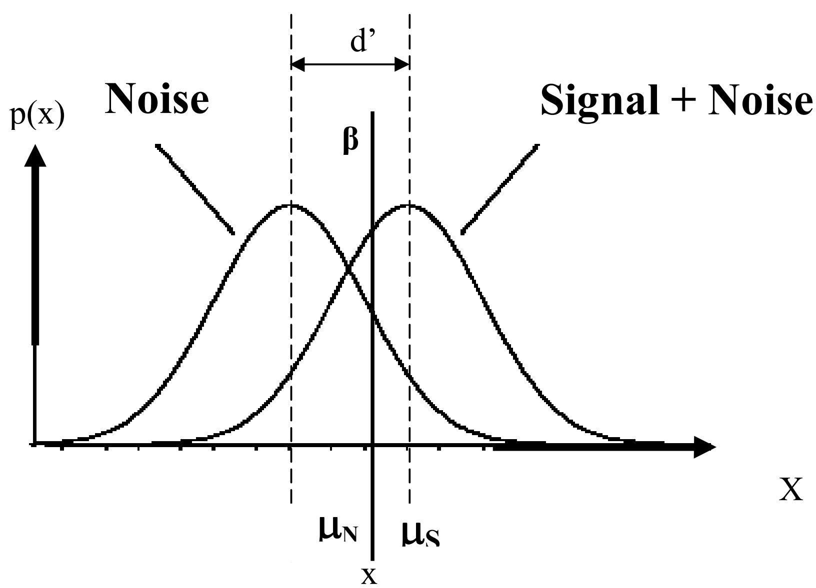

Figure 4: An example of binary decision analyzed with SDT

Signal detection theory allows to compute the probability of hit and false alarm in terms of d' and β and therefore by applying SDT to the system objective function the numbers of target identification parameters are reduced and the analysis is simplified (Appendix II).

Applying SDT into the system objective function requires the following assumptions about the human and robot target identification parameters: the targets and non-target objects are normally distributed and have identical variance even though they are independent.

Modified SDT for the model

Bechar considered the human-robot system as a system with two detectors. The performance of the first detector (robot) is determined by its sensitivity (d'_r) and it criterion (β_r). The second detector (human) uses its sensitivity (d'_h) and two criteria; one for objects already marked by the robot, β_{rh}, and one for objects unmarked by the robot, β_h (Figure 5).

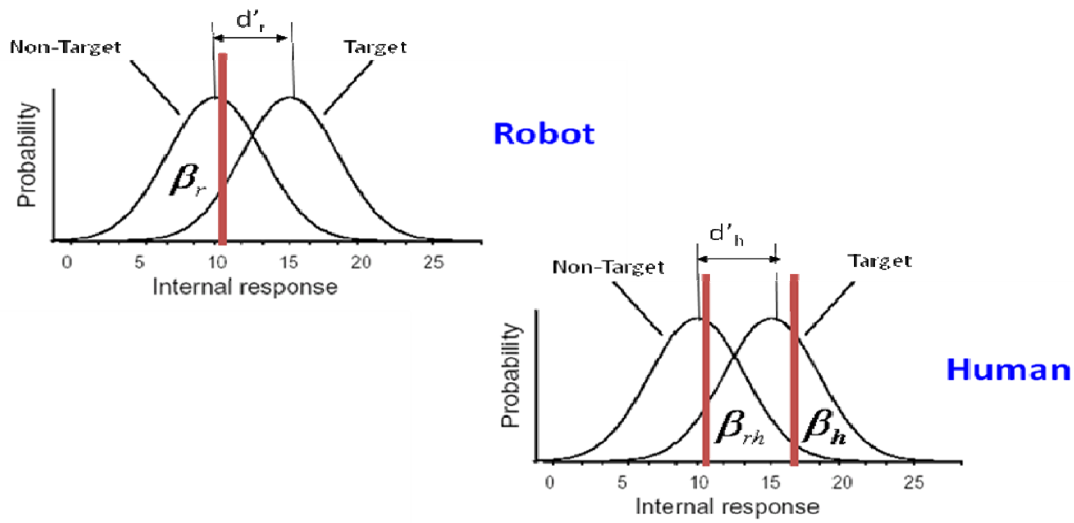

Figure 5: Application of modified SDT for the model

3.6 Model's flowchart

The model assumes that the system is serial and works in the following way: first the robot examines the object and decides if it is a target or not. Then the human operator has to make two decisions: One for the objects the robot marked and one for non marked objects. Figure 6 depicts the model's work flow.

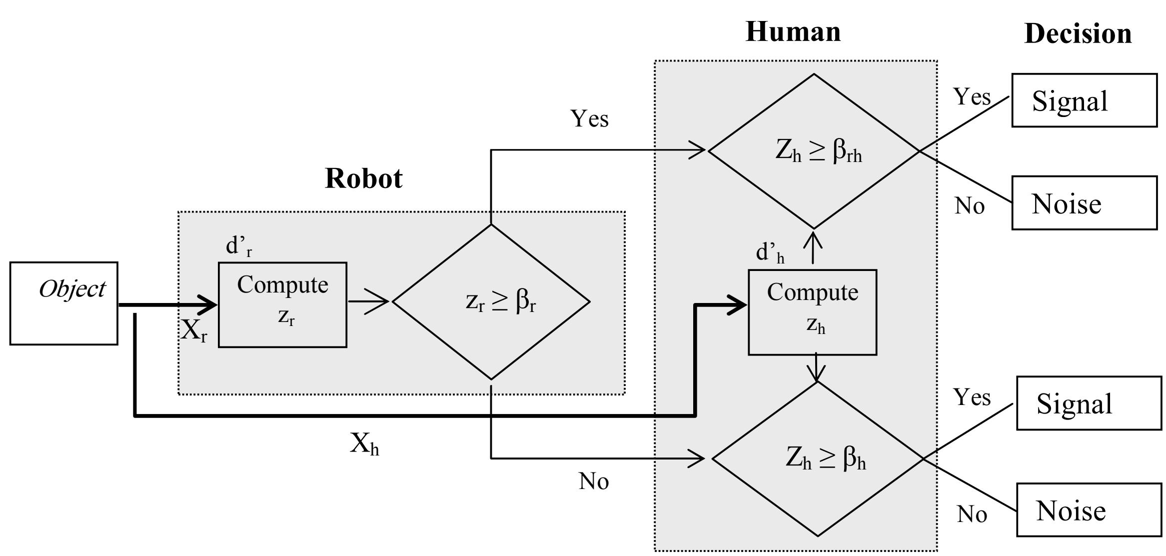

Figure 6: Flowchart of the model

4. Methodology

4.1 Overview

The objective of this work is to evaluate the performance of different integrated human-robot systems for target recognition tasks. Based on Bechar's model, a comprehensive numerical analysis was conducted by examining the influence of human, robot, environment and task parameters on different integrated systems.

The numerical analysis of the global objective function was conducted on a PC with Matlab 7.1™. Bechar (2006) analyzed the objective function excluding the parts of the reward for correct rejection (W_{CR}, t_{CRr}, t_{CRh}, t_{CRrh} equal to zero) and the penalty for miss (W_M, t_{Mr}, t_{Mh}, t_{Mrh} equal to zero). This thesis expanded Bechar's previous work by conducting a numerical analysis on the complete objective function including all parts. The analysis focused on two major objectives which were not covered in Bechar's work: determining the best operational level for various systems and investigating the operational costs. In addition, a sensitivity analysis of different parameters was conducted. The Matlab™ code is presented in Appendix III.

4.2 Best Operational Level Analysis

The analysis focused on the influence of different human and robot sensitivity combinations (d'_h and d'_r) and different target probabilities (P_S) on the best operation level of various systems.

Integrated human-robot systems have different target recognition assignments and goals, thus, they differ in their design. For example, a mine finding system is designed to prioritize detecting targets (mines), which implies a high value for the hit weight (W_H). Contrastingly, medically oriented systems prioritize minimization of false alarms, which implies a high value for the false alarm weight (W_{FA}). In this thesis we focused on analyzing the performance of various integrated systems; by setting different values for the objective function weights (W_H, W_{FA}, W_{CR}, and W_M) various systems were simulated and analyzed.

<u>Simulation parameters</u>

In order to simulate different systems with different assignments three ratio parameters between the objective function weights were set; the ratio between false alarm and hit weights, W_{FA2H}, the ratio between correct rejection and miss weights, W_{CR2M}, and the ratio between miss and hit, W_{M2H}. The values of these ratios were set for 0.1, 1 and 10 in order to create a drastic difference between the objective function weights. The value of hit weight, W_H, was set to 50 and all the other weights were determined according to the ratios. For example, if W_{FA2H} = 0.1, W_{CR2M} = 0.1 and W_{M2H} = 1 then the values of the other weights will be W_{FA} = 5, W_{CR} = 5, W_M = 50. The probability for target, P_S, ranged from 0.1 to 0.9. The human sensitivity, d'_h, and the robot sensitivity, d'_r, ranged from 0.5 to 3. The values of the different parameters of the simulation were extracted from a preliminary experiment performed by Bechar et al. (2006). The operational cost weights were constant where the cost for one system action was set to W_c= 2 and the cost for one time unit was set to W_t= 2000 hr-1. The number of objects in each task was set to N= 1000. The decision time for all human time parameters was set to t_d=5 sec/object, and the human motoric time was set to t_m=2 sec/(detected object). The robot time was set to t_r=0.01 sec/object. In addition, all analyses were performed for optimal likelihood ratios. The optimal likelihood ratios, β_r, β_h, and β_{rh}, were determined in the range between the logarithm of -4 and the logarithm of 4, in order to cover the available hit and false alarm probabilities. Table 5 presents a summary of the different variables which were used in the analysis.

Table 5: Summary of the variable parameters analyzed in the research

Parameter	Description	Range
W_{FA2H}	Ratio between the value of false alarm and hit	0.1,1,10
W_{CR2M}	Ratio between the value of correct rejection and miss	0.1,1,10
W_{M2H}	Ratio between the value of miss and hit	0.1,1,10
d'_r	The robot sensitivity	0.5 - 3
d'_h	The human sensitivity	0.5 - 3
P_S	Target probability	0.1 – 0.9

4.3 Operational Costs Analysis

A comprehensive analyses of both operational cost parts; time and action were conducted.

The operational costs influence the objective function score and therefore the best operation level map. The model's operational cost (V_T) consists of cost associated with time (V_t) and operation (V_c) and is described in chapter 3.6, equation (8). The cost as a function of time, V_t, is affected by the number of decisions which the system (robot and human) has to make, how fast these decisions are made, and the cost per time unit of system operation. The cost as a function of operation, V_c, is affected by the cost per one operation of the robotic arm (action) and the number of times an action is required. Since the robotic arm actually moves only as a result of false alarms or hit outcomes, this cost is only present when one of these results is obtained.

4.4 Sensitivity Analysis

A sensitivity analysis of the optimal criteria was conducted. Since the numerical analysis was conducted for optimal criteria, the sensitivity analysis focused on investigation of the influence of small deviations from the optimal value of each β. The sensitivity analysis was performed for the three betas: β_r, β_h and β_{rh} for a given situation. The logarithm of the analyzed beta ranged from -4 to 4 in order to cover wide range of criteria. In addition, since in real world applications the human and robot sensitivities are not constants and can be changed during a work, sensitivity analysis of these two parameters were also conducted.

5. Best Operational Level Analysis

The numerical analysis focused on the influence of different human and robot sensitivity combinations (d'_h and d'_r) and different target probabilities (P_S) on the best operational level of different systems. Figure 7 shows system performance for different human and robot sensitivities combinations. Each surface represents one of the system's possible collaboration levels. This figure illustrates the influence of the sensitivities on the objective function score (z axes) and the highest score for each sensitivities combination which is composed of the highest surface created from the surfaces intersections of the different operational levels (its perimeter is marked with a black solid line). Furthermore, each intersection in this area represents shifting between the operational levels to maintain optimal performance.

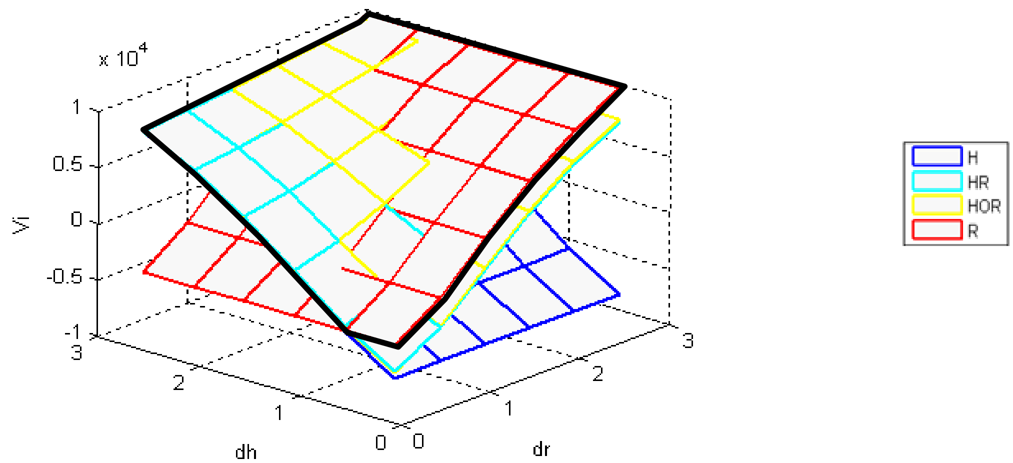

Figure 7: The influence of the human and robot sensitivities on the system's performance for each operational level – an example.

5.1 Definition

The best operational level is defined as the level which under specific task parameters, achieves the highest objective function score (V_I). Analysis was conducted on a 2D graph that illustrates the best operational level map (Figure 8) where each operational level is represented by a different color. In the case presented, HR, HOR and R levels are the best levels in different areas of the sensitivity space. This example indicates that for the same task the best operational level can change from one level to another. Different task, human, robot, or environment parameters will result in different operation level maps.

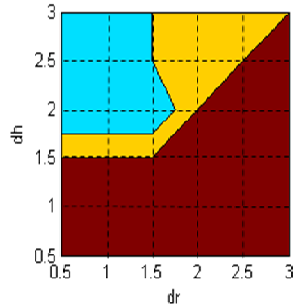

Figure 8: Best operational level map. HR – Cyan, HOR – Yellow, R – red – an example.

5.2 Results

Due to the multitude of results, the first objective was to find any common behavior between the different systems which were analyzed. After investigating all the different operational level maps which were produced by the analysis, it was found that the different maps (which represent different systems) can be classified into two main types of systems. Classification was based on the influence of the target probability on the best operational level maps. It was found that the two types have opposite tendencies as a function of the target probability, i.e., the tendency of changes in the best operational level maps as a function of the target probability is opposite for the two types. The first type, denoted hereon as *'Type 1'*, consists of systems geared towards minimizing false alarms. This goal can be reached by setting proportionately higher rewards for correct rejections and/or higher penalties for false alarms. The second type denoted hereon as *'Type 2'* consists of systems geared towards detecting targets when one is presented. This goal can be achieved by setting proportionately higher rewards for hits and/or higher penalties for misses.

Type 1: High priority to minimizing false alarms

The analyses indicated that as the target probability, P_S, increases, the area of R level, in the best operational level map, is reduced. Furthermore, results indicated that HR is the best level only when the human sensitivity, d'_h, is higher than the robot sensitivity, d'_r. It should be considered that when the target probability, P_s, is high, HOR level is preferable in most of the sensitivity space. However, when robot sensitivity is higher than human sensitivity the best level is R. The H level (human performs solely) was never the best operational level (Figure 9). Additional results are presented in Appendix IV.

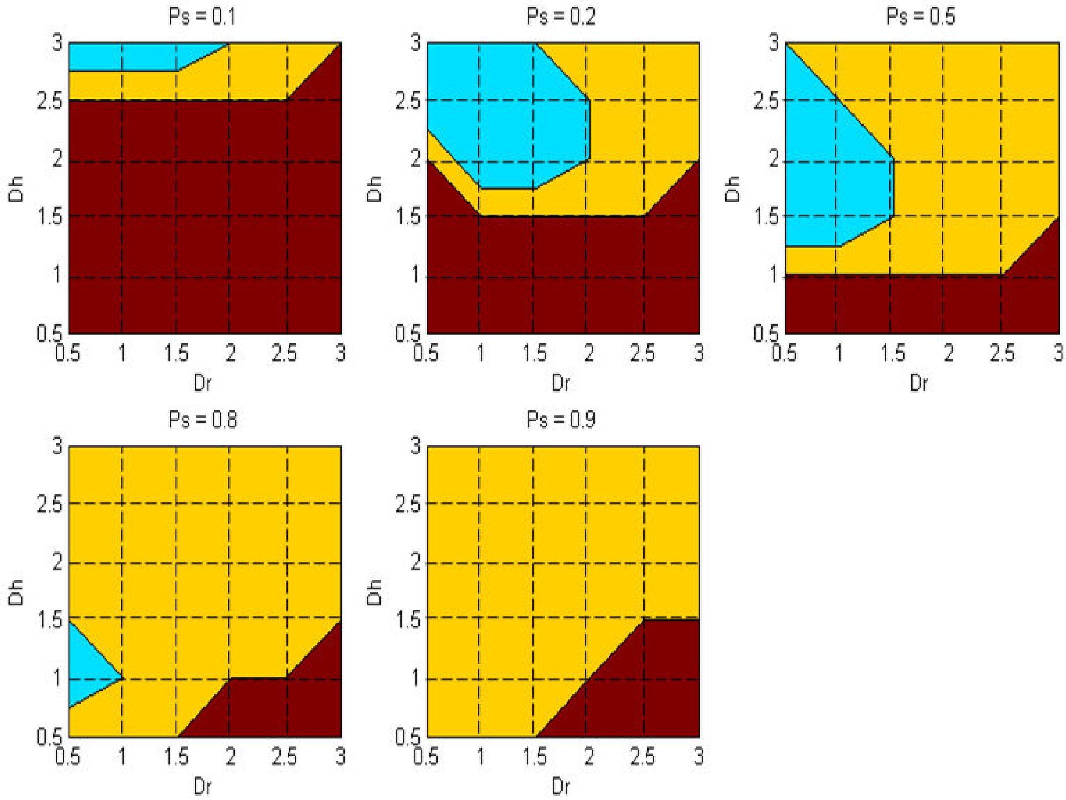

Figure 9: Example of 'Type 1' systems best operational level maps for different target probabilities. HR – Cyan, HOR - Yellow and R – Red.

Type 2: High priority to target detection

As opposed to *'Type 1'* systems, in *'Type 2'* systems, an increase in the target probability, P_S, increases the area of R level in the best operational level map. Moreover, for high and intermediate target probabilities, R was found to be the best level when the sensitivity of the robot is higher than that of the human. HR was found to be the best operational level only when the target probability was low, and the human sensitivity was higher than the robot sensitivity. For very low target probability (P_S=0.1), HR level is the best operational level in more cases than HOR, although as target probability increases HOR performs better in more cases than HR (Figure 10). Similar to the findings in *'Type 1'* systems, the *'Type 2'* systems' manual mode (H) was never the best level. Additional results are presented in Appendix V.

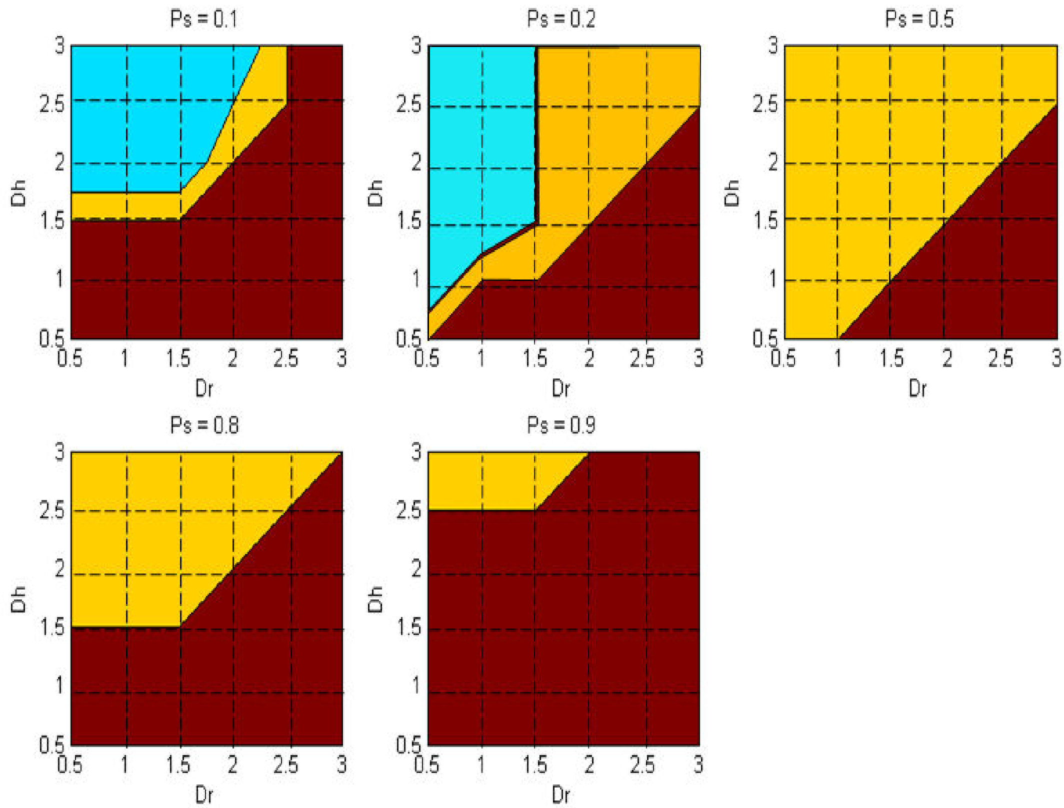

Figure 10: Example of 'Type 2' systems operational level maps for different target probabilities. HR – Cyan, HOR - Yellow and R – Red.

System Properties Analysis

The analysis of best operational level reveals symmetry between hits and false alarms ratio, W_{FA2H}, and between correct rejection and miss ratio, W_{CR2M}, i.e., the same operational level map was generated when W_{FA2H} =X, W_{CR2M} =Y and W_{FA2H} =Y, W_{CR2M} =X where X and Y are the ratios values independent of the system's type. In order to examine these findings a further analysis of the objective function score was conducted. The analysis of the objective function score was conducted by analyzing contour graphs in the human and robot sensitivity space for different target probabilities (Figure 11).

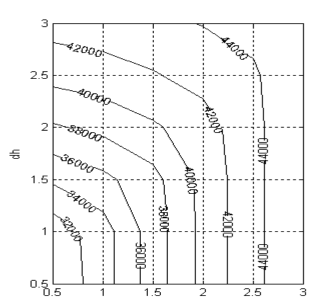

Figure 11: Objective function score, the isobar lines represent equal value score.

For both types, the symmetry discovered in the best operational level analysis revealed that different systems have identical best operational level maps. However, while there is an overlap in the best operational level maps of the systems, their objective function score is different. The difference is derived from the way these systems achieve their goal - minimizing false alarms for *'Type 1'* and detecting targets for *'Type 2'*. In *'Type 1'*, while some of the systems achieve the goal of minimizing false alarms, by giving high penalty for false alarms, other systems achieve it by giving high reward for correct rejections. In *'Type 2'*, while some of the systems achieve the goal of detecting targets, by giving high reward for hit, other systems achieve it by giving high penalty for miss.

Figures 12 and 13 present an example for these results: the objective function score maps of two different *'Type 2'* systems show an identical operational level maps, which is presented in figure 10. Additional results are presented in Appendix VI.

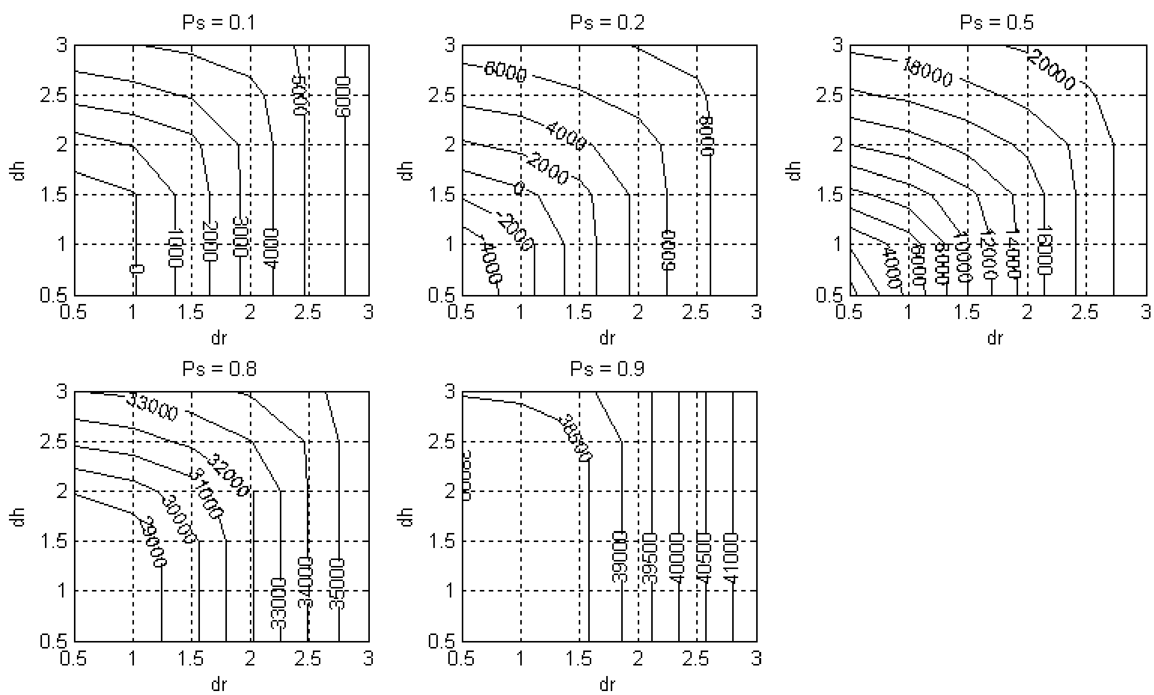

Figure 12: Example of 'Type 2' objective function graph where the system's goal achieved by giving high penalty for 'miss' proportionally to 'hit'

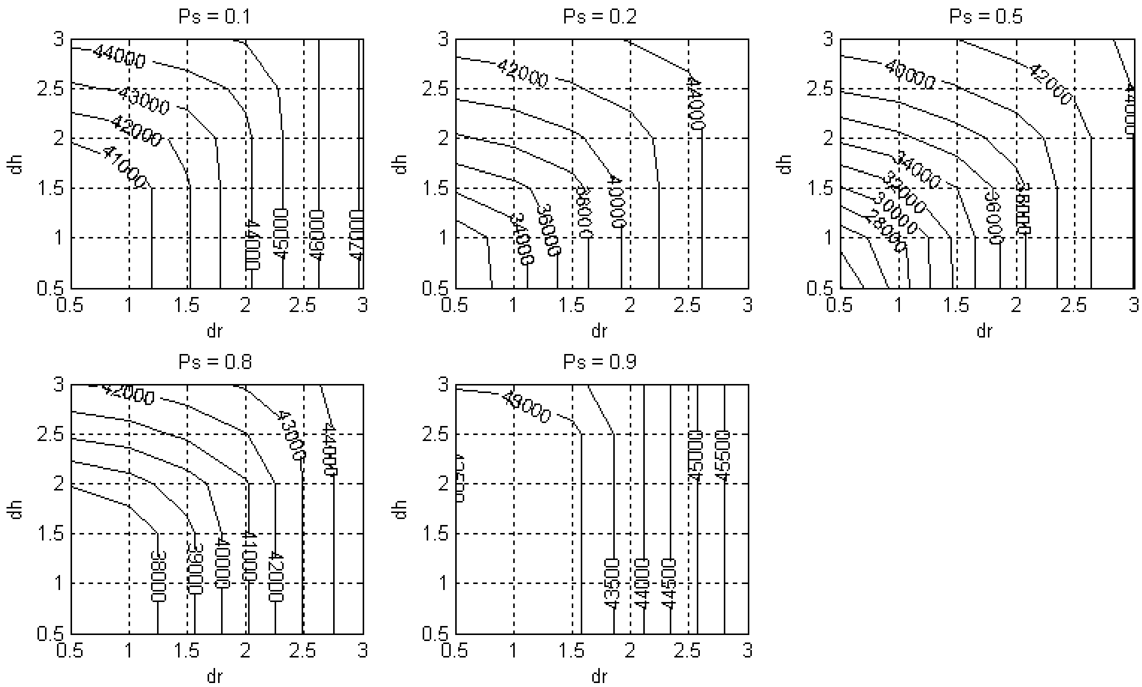

Figure 13: Example of 'Type 2' objective function graph where the system's goal achieved by giving high reward for 'hit' proportionally to 'miss'

Actually, these findings indicates that there is symmetry between hit weight (W_H) and miss weight (W_M) and symmetry between correct rejection weight (W_{CR}) and false alarm weight (W_{FA}). This yields that, if we set $\{W_H = X_1, W_M = X_2, W_{CR} = Y_1, W_{FA} = Y_2\}$, $(X_1 \neq X_2, Y_1 \neq Y_2)$, then the same best operational level maps will appear for: $\{W_H = X_2, W_M = X_1, W_{CR} = Y_1, W_{FA} = Y_2\}$, $\{W_H = X_2, W_M = X_1, W_{CR} = Y_2, W_{FA} = Y_1\}$, $\{W_H = X_1, W_M = X_2, W_{CR} = Y_2, W_{FA} = Y_1\}$. Notice that each set represents a different system. An example of the last finding is presented in Table 6.

Table 6: Example of different systems with the same best operational level maps

W_H	W_M	W_{CR}	W_{FA}
20	5	10	7
5	20	10	7
20	5	7	10
5	20	7	10

These results led to further analysis, aimed at testing the shift in the best operational level maps, which occurs in the transition between the symmetrical weights. In order to perform this analysis, a new variable, μ, was computed. μ equals to the difference between the symmetrical weights, divided by ten ($\mu = (W_H-W_M)/10$ or $\mu = (W_{CR}-W_{FA})/10$). In each of the iterations in the simulation, μ was deducted from the highest valued weight and added to the lowest valued weight. A pseudo code is presented in Appendix VII.

Last analysis revealed that for all the analyzed systems the same best operational level map was received, i.e., the symmetry attribute depends upon the difference between the weights. In fact, this further analysis extended the symmetry attribute and it was found that the system type (1 or 2) depends upon the ratio between $\Delta_1 = W_{CR}\text{-}W_{FA}$ and $\Delta_2 = W_H\text{-}W_M$. If $\Delta_1/\Delta_2 > 1$ the system classified as *'Type 1'*. If $\Delta_1/\Delta_2 < 1$ the system classified as *'Type 2'*. In cases where $\Delta_1/\Delta_2 = 1$ the system can be considered as *'Type 1'* or *'Type 2'*. This can be assumed as a new property of the objective function. Figure 14 presents these findings.

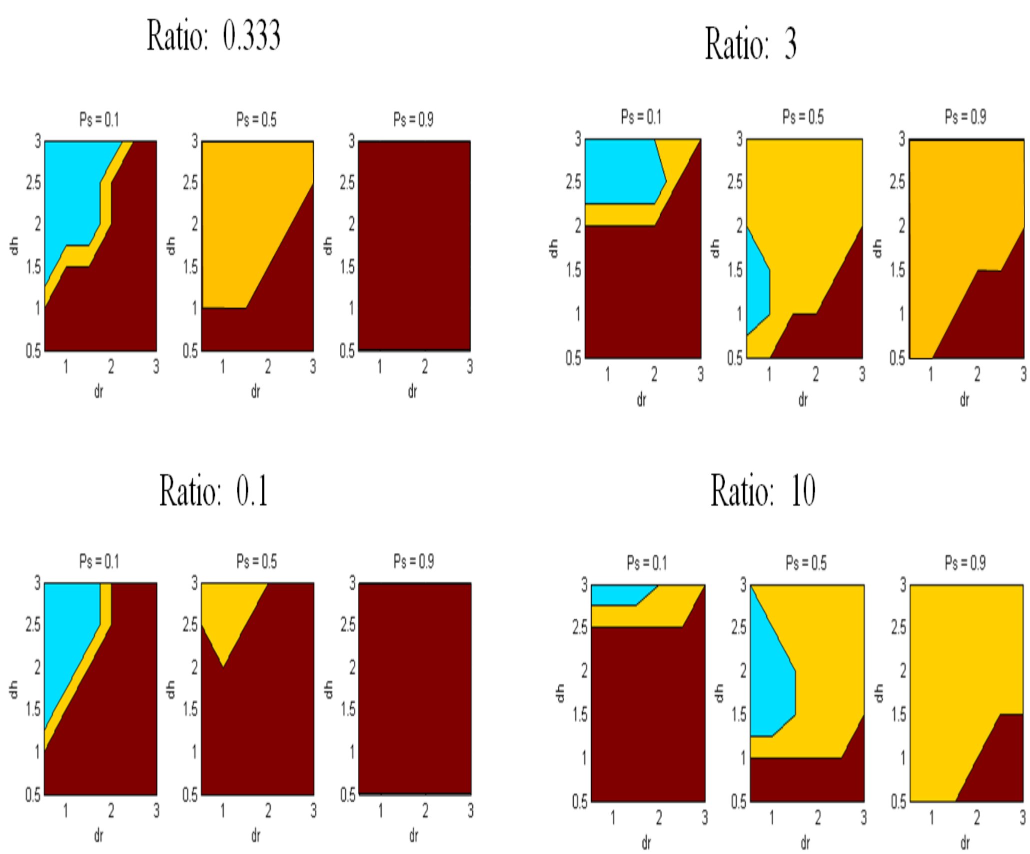

Figure 14: Example of the symmetry property. On the right graphs, $\Delta_1/\Delta_2 > 1$ and therefore, these systems are *'Type 1'*. On the left graphs, $\Delta_1/\Delta_2 > 1$ thus, these systems are considered as *'Type 2'*. Different ratios will produce different best operational level maps.

All the analyses were conducted with optimal βs. Equation 13 presents the expression for optimal β.

$$(13) \qquad \beta^* = \overbrace{\frac{(1-P_S)}{P_S}}^{\mathbf{A}} * \overbrace{\left(\frac{W_{CR}-W_{FA}}{W_H-W_M}\right)}^{\mathbf{B}}$$

From equation 13 it can be seen that the optimal β is composed of two parts: the ratio between the a-priori probabilities (noted as A) and the ratio between the weights (Δ_1/Δ_2, noted as B). From the analysis of the objective function, it was found that the two system types differ as a function of P_S and that the system's type depends on the ratio Δ_1/Δ_2. These results are related to both parts of the optimal β equation. Note that the a-priori probability (P_S) is an unknown parameter which depends on the environment and cannot be controlled by the system's designers. Thus, this parameter has not been considered as a parameter which defines the system's type but it does affect the system's performance. On the other hand, the ratio between the weights (Δ_1/Δ_2) depends on the system's tasks and can be controlled by the system's designers. Thus, this ratio defines the system's type.

6. Operational Costs Analysis

The operational costs analyses were conducted *'Type 1'* and *'Type 2'* systems where the weights' ratios were set to $\Delta 1/\Delta 2 = 10$ and $\Delta 1/\Delta 2 = 0.1$ accordingly.

6.1 Time Cost Analysis

The cost of time, V_t, is composed of the system time that required to analyze an image, t_s, multiplied by the time cost weight, W_t, which is the cost of one time unit (q.v. chapter 3.4 equation 8).

6.1.1 t_s analysis

The system time is affected by the target probability (P_S), the human's and robot's sensitivities (d'_r and d'_h), thresholds (β_s) and reaction times (q.v. chapter 3.4 equation 9). Since the robot's reaction time depends on computer hardware and algorithm complexity, it was assumed that the effect of the system situation on it can be neglected, i.e., the robot time is considered to be deterministic. On the other hand, the human decision time, t_d, cannot be assumed to be deterministic. The human operator's decision time depends on many variables, such as; the operator's skills, fatigue, image complexity. It should therefore be considered as variable.

The analysis focused on the effects of each of the parameters influencing t_s which were described above: P_S, d'_r, d'_h and t_d. Figure 15 presents *'Type 1'* analysis. These graphs demonstrate the effect of target probability and human and robot sensitivities on each of the operational levels. As previously explained, robot time is treated as a constant and therefore this level is not presented. Each surface represents a different target probability, axes x and y represent the robot and human sensitivities respectively, and the z axis is the system time (t_s).

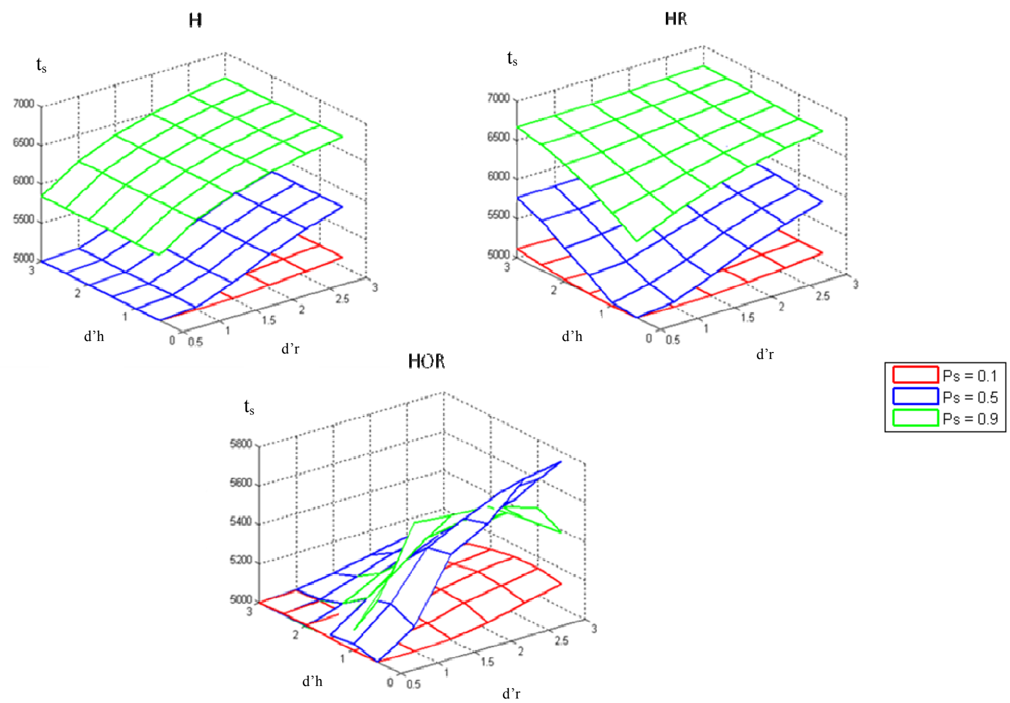

Figure 15: Time cost analysis of 'Type 1'. The effect of different sensitivities and target probabilities on the system time

In H operational level, the 'hit' and 'false alarm' outcomes are associated with longer reaction times than 'miss' and 'correct rejection', since these outcomes also involve a motoric motion (q.v. chapter 3.4 equations 10, 11, 12). Results show that for level H, as target probability and human sensitivity increases, t_s is higher. These results are supposedly counter-logical, as one would expect that as human sensitivity rises, his/her discerning ability improves, causing decision-making time to shorten, and therefore, system time to diminish. Actually, as human sensitivity improves, the probability of detecting a target (probability for hit) rises, which leads to a larger amount of longer reactions to be made, and therefore, the total amount of time the system operates is longer.

The difference between HR and HOR operational levels in the model's objective function manifests itself by the t_s value. Thus, the graphs of these operational levels are so different. In HR level, the robot first marks objects it considers as a target and then the human decides whether these objects are targets, i.e., enters the object to the target bank, or non-targets, i.e., erases the robot's mark. Thus, in HR level, similarly to H level, 'hit' and 'false alarm' outcomes are associated with longer reaction times than 'miss' and 'correct rejection'. Therefore, HR level behaves similarly to the H operational level. In HOR level, the robot first enters into the target bank objects it considers as targets, then the human enters objects the robot misses, and rejects wrong entries of the robot. Thus, in HOR operational level, contrary to H and HR levels, 'miss' and 'correct rejection' outcomes are associated with longer reaction time than 'hit' and 'false alarm'. Consequently, HOR level graph is opposite to H and HR graphs.

The results for *'Type 2'* system are presented in figure 16.

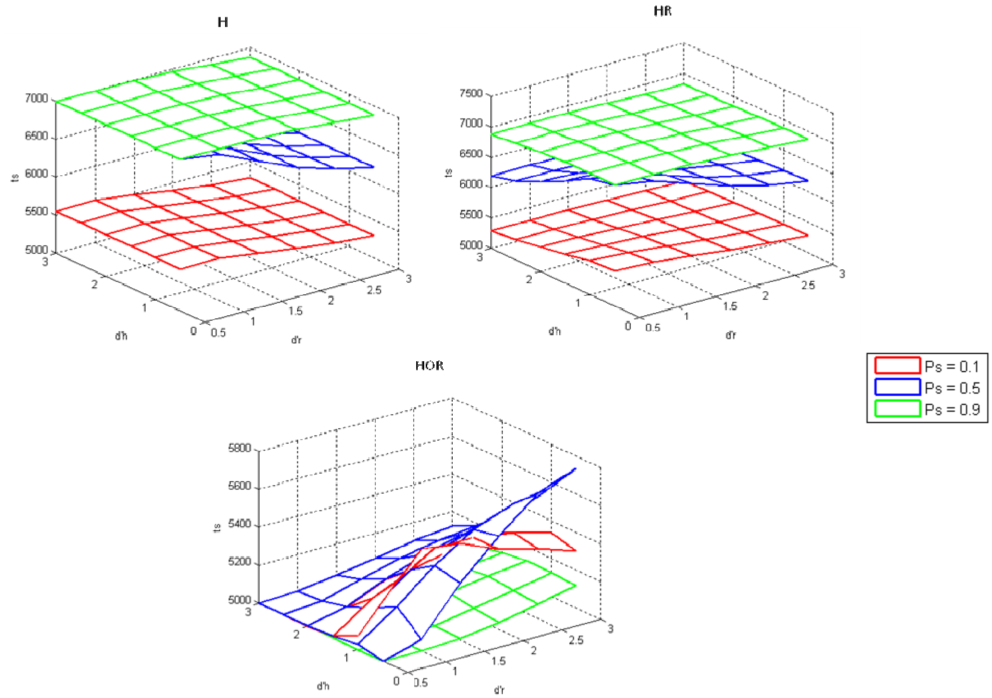

Figure 16: Time cost analysis of 'Type 2'. The effect of different sensitivities and target probabilities on the system time

Similarly to the results of *'Type 1'*, as target probability increases, the value of t_s increases in H and HR levels. However, contrary to the results of *'Type 1'*, as human and robot sensitivities increase, t_s decreases in these operational levels. This result is derived from the difference between *'Type 1'* and *'Type 2'*. In *'Type 1'* systems, an increase in the system's (human and robot) sensitivity mostly influences the number of 'hits' which increases as well and therefore t_s increases. However, in *'Type 2'* systems, an increase in the system's sensitivity mostly influences the number of false alarms which decreases, thus t_s decreases.

HOR graph behaves similarly to the graph of *'Type 1'* except that the surfaces of P_s = 0.1 (red surface) and P_s = 0.9 (green surface) are opposite. This result reflects the opposite tendency between the two types as a function of the target probability.

6.1.2 t_d analysis

In order to investigate the influence of human decision time, t_d, on the system performance, its value was ranged from 2 to 14 seconds. Figure 17 presents *'Type 1'* analysis for the best operational level maps as a function of P_s, t_d, d'_h and d'_r.

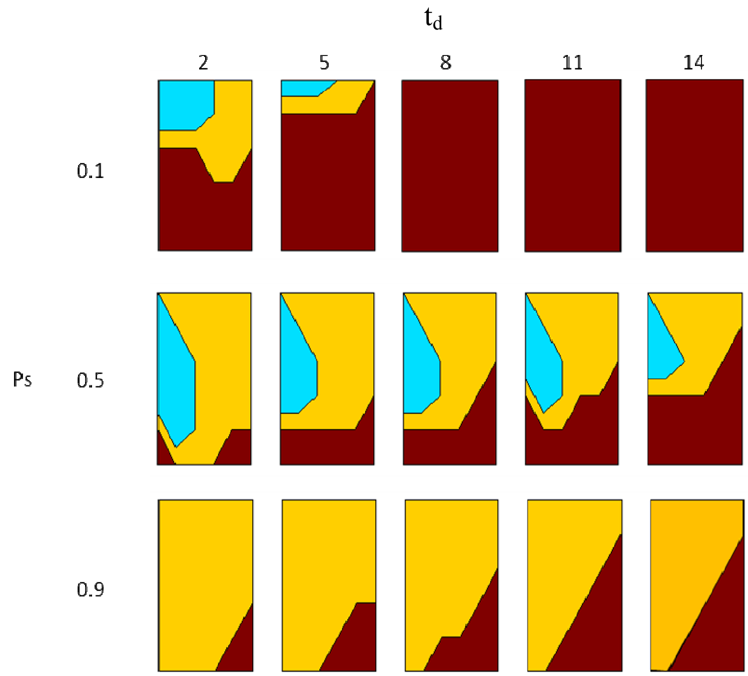

Figure 17: 'Type 1' results for analysis of best operational level maps for different t_d and P_s. Columns are for different t_d and rows for different P_s. Each map is represented in the sensitivity space where x axis is d'_r and y axis is d'_h.

For low target probability (P_s = 0.1), a change in decision time is critical and for values equal and above t_d = 8 seconds the best level is only R. In contrast, for a medium (0.5) or high (0.9) target probability, a change in decision time has only low influence on the best operational level maps. In order to compare between the influences of the t_d and P_s, further analysis, which examined these parameters together, was performed (Figure 18).

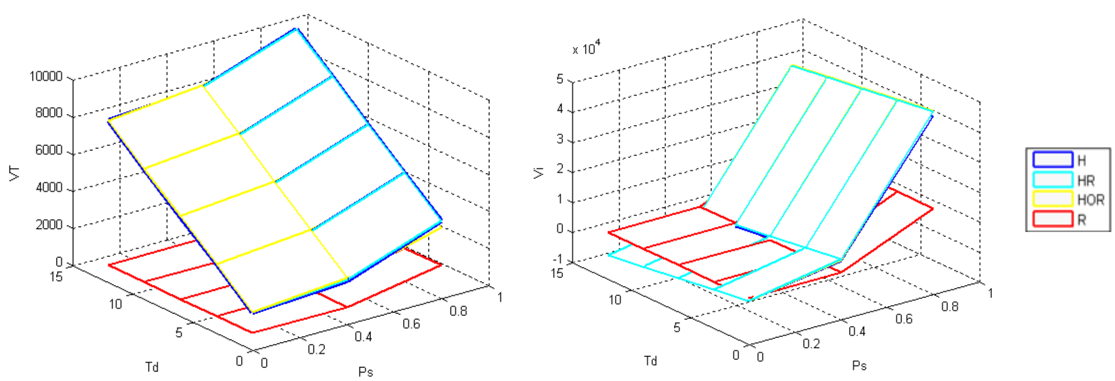

Figure 18: Decision time analysis of 'Type 1'. Effect of t_d and P_s on V_T (left graph) and V_I (right graph)

These graphs present the effect of P_S and t_d on the objective function score (V_I, right graph) and on the operational costs (V_T, left graph, values are absolute). Results show that on V_T, decision-time, t_d, has a larger effect than P_s, i.e., an increase in this parameter leads to a sharper increase in operational costs. In contrast, on the total score, V_I, the results are opposite and P_S is the parameter which has a larger effect. Thus, t_d's level of influence on the system's overall performance is depended upon the ratio V_T/V_I. As this ratio gets larger, t_d is relatively more effective than P_S. For both graphs t_d has an identical effect on levels H, HR, and HOR.

'Type 2' systems' results are presented in figures 19 and 20.

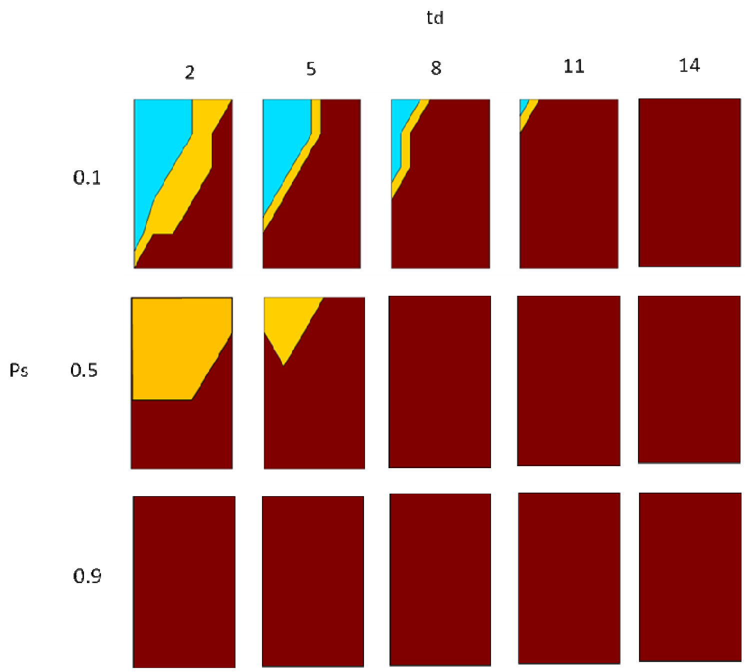

Figure 19: 'Type 2' results for analysis of best operational level maps for different t_d and P_s. Columns are for different t_d and rows for different P_s. Each map is represented in the sensitivity space where x axis is d'_r and y axis is d'_h.

For low (0.1) and medium (0.5) target probability, a change in decision time has a great influence on the best operational level maps. As t_d increases, R level is more preferable.

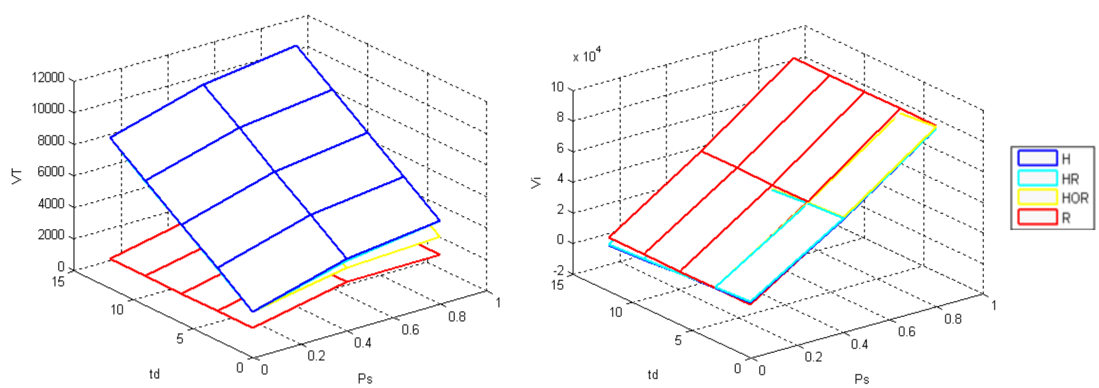

Figure 20: Decision time analysis of 'Type 2'. Effect of t_d and P_s on V_T (left graph) and V_I (right graph)

Similarly to the results of *'Type 1'*, while t_d has a larger effect than P_s on V_T, the target probability has a larger influence than t_d on the total score, V_I. Thus, t_d's effect is independent of the system's type.

6.1.3 W_t Analysis

The cost of a time unit, W_t, depends upon the type of assignments the system has to perform and the system's (human and robot) efficiency and effectiveness. In order to examine the effect of Wt, this parameter received variable values, between 2000 and 10000 hr^{-1}. Figure 21 presents *'Type 1'* analysis for best operational level maps for different values of W_t and different target probabilities.

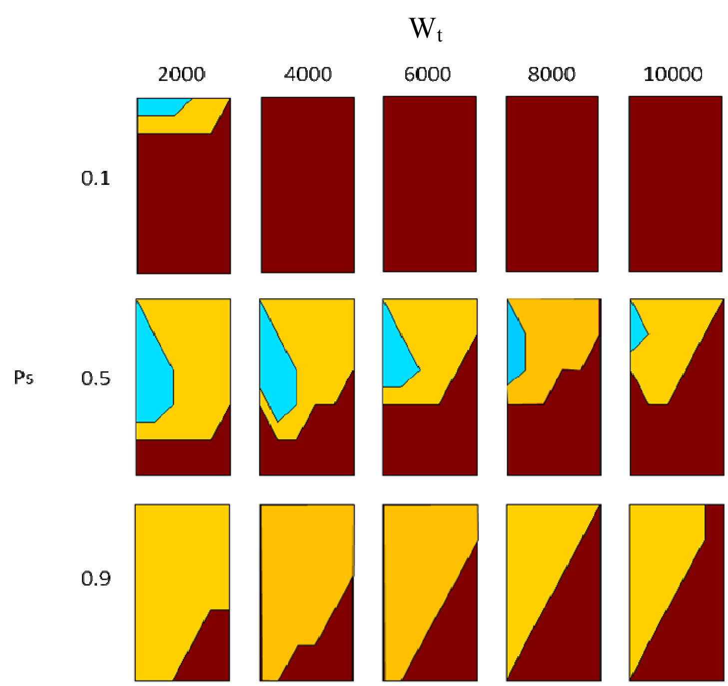

Figure 21: 'Type 1' results for analysis of best operational level maps for different W_t and P_s. Columns are for different W_t and rows for different P_s. Each map is represented in the sensitivity space where x axis is d'_r and y axis is d'_h

Results show that by increasing W_t the R level is more dominant. However, for all the target probabilities, W_t, has a low influence on the best operational level maps. In order to further examine these results, W_t's influence was compared to P_s's influence on operational costs, and on total system performance (Figure 22).

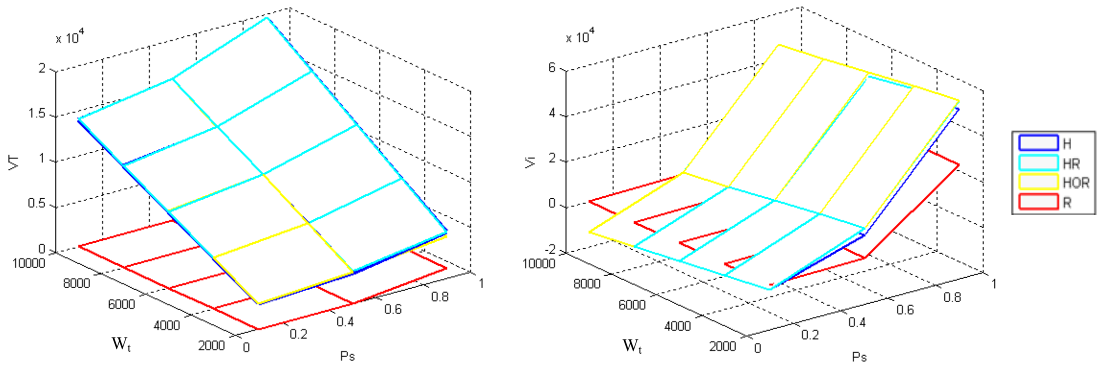

Figure 22: 'Type 1' analysis of the effect of W_t and P_s on V_T (left graph) and V_I (right graph)

A change in W_t and P_s has an almost identical effect on H, HOR, and HR levels in both graphs. On R level, a change in W_t almost does not have any effect. This finding is a result of R's reaction time being significantly lower than the other levels. Similarly to the result found from t_d analysis, while a change in W_t has a larger effect than P_S on the operational cost (figure 22, left), the change in P_S has a larger effect than W_t on the total system performance (figure 22, right). This result points to the conclusion that as the percentage of V_T out of V_I is larger, W_t is a more influential factor as compared to P_S. Thus, W_t is more influential on the best operational level map.

Figures 23 and 24 present W_t's analysis for systems of *'Type 2'*.

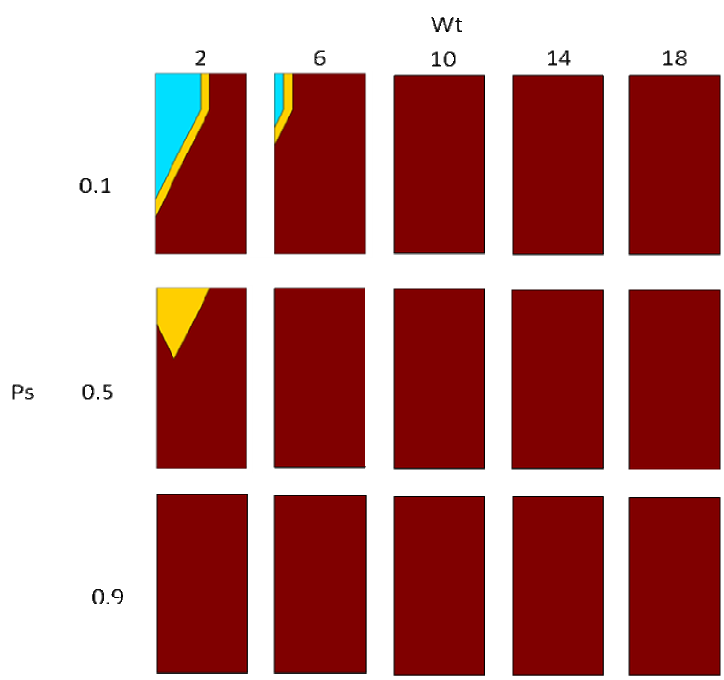

Figure 23: 'Type 2' results for analysis of best operational level maps for different W_t and P_s. Columns are for different W_t and rows for different P_s. Each map is represented in the sensitivity space where x axis is d'_r and y axis is d'_h

Correspondingly to *'Type 1'* results, as W_t increases R level becomes more dominant.

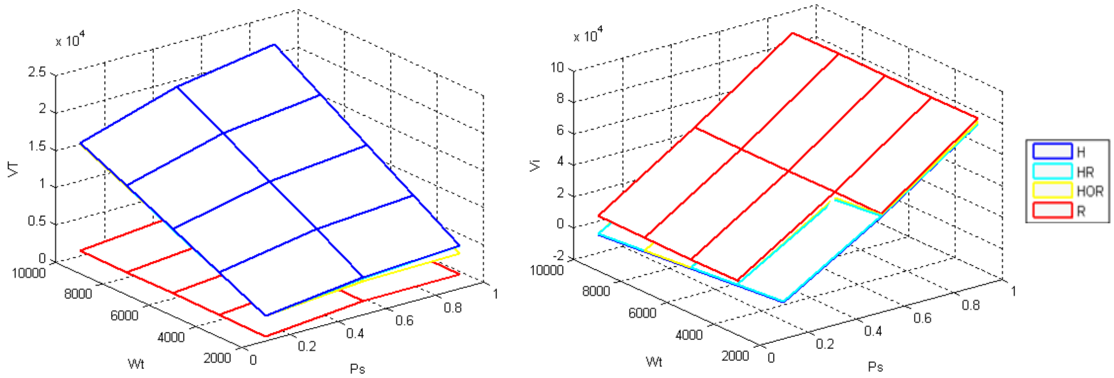

Figure 24: 'Type 2' analysis of the effect of W_t and P_s on V_T (left graph) and V_I (right graph)

These findings match *'Type 1'* systems' results. Thus, W_t's effect is independent of the system's type.

6.2 Action Cost Analysis

The cost of action, V_c, composed of the number of 'false alarms' and 'hits' outcomes (W_a) multiplied by the operation cost weight, W_c, which is the cost of one action implementation (q.v. chapter 3.4 equation 8).

6.2.1 W_a analysis

The analysis focused on the effects each of the parameters had on W_a: P_S, d'_r and d'_h. *'Type 1'* analysis is presented in figure 25. The following graphs illustrate the effect of target probability and the human and robot sensitivities, for each of the operational levels. Each surface represents a different target probability. The x and y axes represent the human and robot sensitivities, respectively, and the z axis represents the value of W_a.

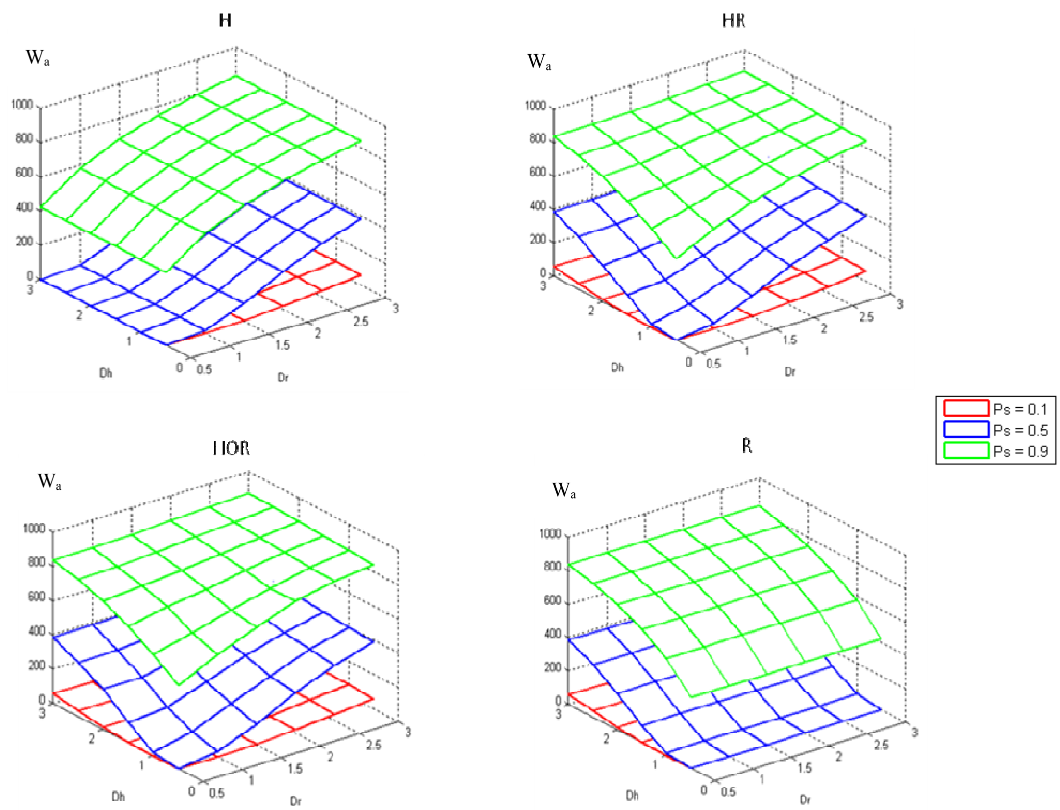

Figure 25: The effect of different sensitivities and target probabilities on W_a for each operational level of 'Type 1' systems

For all model's operational levels, increase of d'_r, d'_h and P_S leads to an increase in W_a. In addition, for low target probability ($P_S = 0.1$), changes of the sensitivities have less influence. These results are derived from the fact that W_a is the number of 'hits' and 'false alarms' outcomes; better human sensitivity, robot sensitivity and target probability increase the number of 'hits', therefore, increasing W_a.

Figure 26 presents W_a's analysis for *'Type 2'* systems.

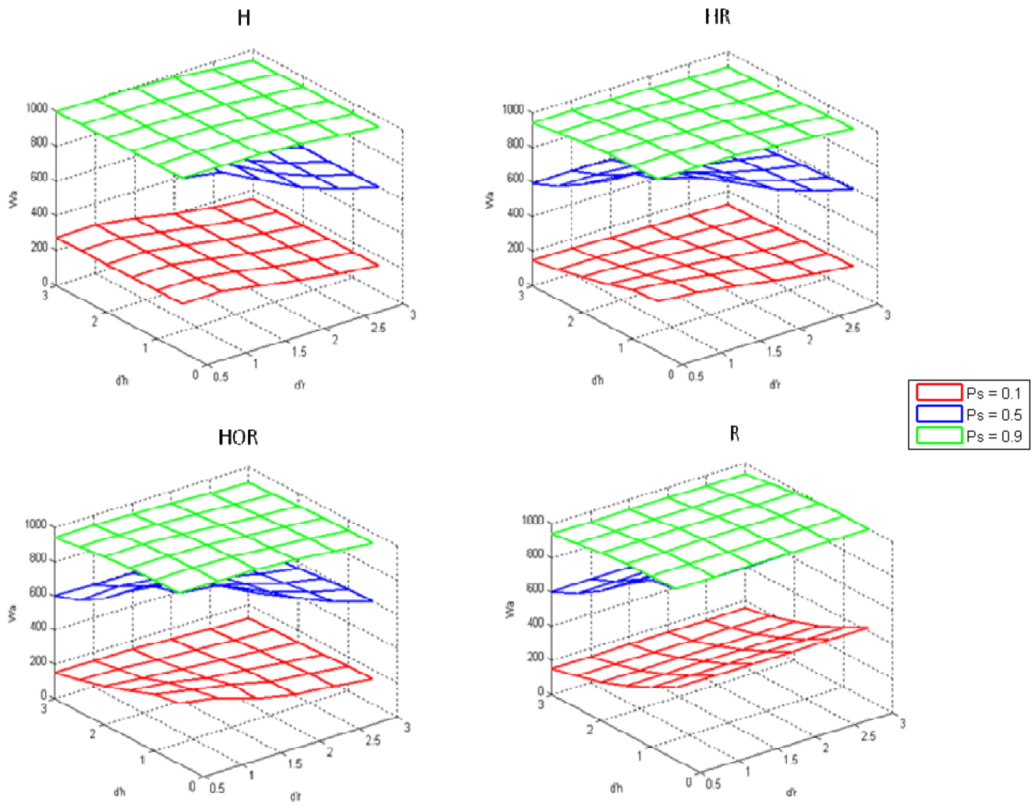

Figure 26: The effect of different sensitivities and target probabilities on W_a for each operational level of 'Type 2' systems

Results of *'Type 2'* are opposite to these of *'Type 1'*. For all model's operational levels, increase of d'_r, d'_h and P_s leads to a decrease in W_a. In addition, in *'Type 2'* systems, for high target probability ($P_S = 0.9$) changes of the sensitivities have less influence. These results demonstrate the difference between the two types. Systems of *'Type 1'* are geared towards minimizing false alarms. Thus, for low system's sensitivity (robot and human), in order to keep the false alarm ratio low the hit ratio will be low as well. As the system's sensitivity increases, the system will be able to increase the hit ratio without affecting the false alarm ratio. On the other hand, *'Type 2'* systems are geared towards detecting a target when one presented. For this type, low system's sensitivity leads to high ratio of false alarms. As the system's sensitivity increases, false alarm ratio decreases.

6.2.2 W_c Analysis

The operational cost as a function of time is a variable cost and depends, among other things, in the type of assignments the system has to perform, and the robotic system's complexity. In order to examine the effect of W_c, this parameter received variable values, ranged from 2 to 18. Figure 27 presents *'Type 1'* analysis of the best operational level maps for different values of W_c and different target probabilities.

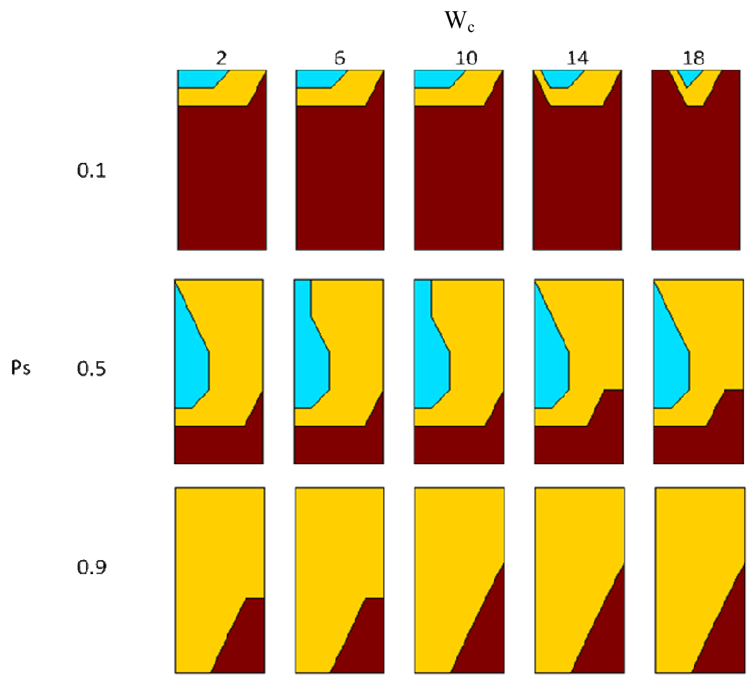

Figure 27: 'Type 1' analysis of best operational level maps for different W_c and P_s. Columns are for different W_c and rows for different P_s. Each map is represented in the sensitivity space where x axis is d'_r and y axis is d'_h

Results show that changes in W_c have a small influence on the best operational level maps for all target probabilities. Similarly to the time cost analysis, for a further examination of W_c, its influence compared to the influence of P_S on the operational costs and on the total objective function score (figure 28).

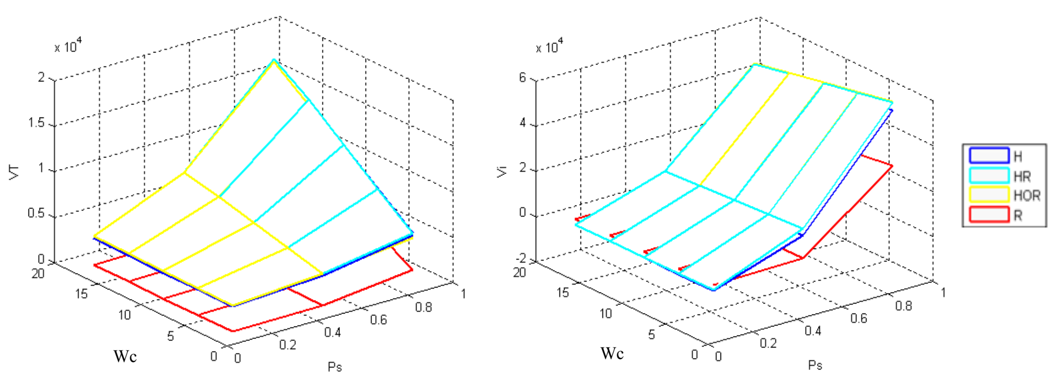

Figure 28: Effect of W_c and P_s on V_T (left graph) and V_I (right graph) of 'Type 1' systems

Increase of W_c has little influence on the operational costs (figure 28, left) and total system performance (figure 28, right) for all model's operational levels. However, combination of high P_s and high W_c dramatically increases the operational costs dramatically. Higher target probability increases W_a (number of 'hits' and 'false alarms') which is the factor that is multiplied by W_c, thus, combination of high P_s and high W_c has a great influence on the operational costs (figure 28, left).

Figures 29 and 30 present W_c's analysis for systems of *'Type 2'*.

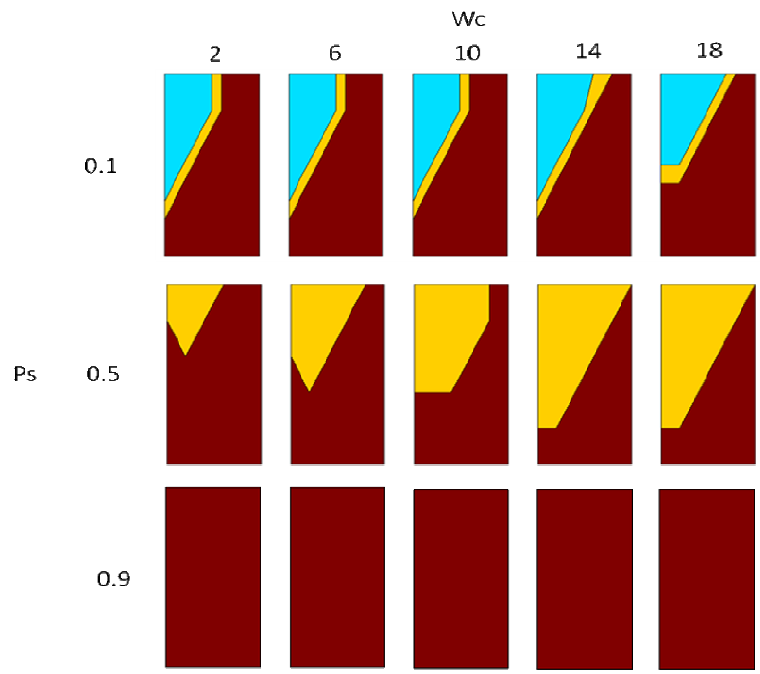

Figure 29: 'Type 2' analysis of best operational level maps for different W_c and P_s. Columns are for different W_c and rows for different P_s. Each map is represented in the sensitivity space where the x axis is d'_r and the y axis is d'_h

These results are correspondingly with *'Type 1'* systems'. Changes in W_c have only slight affect on the best operational level maps for all the target probabilities.

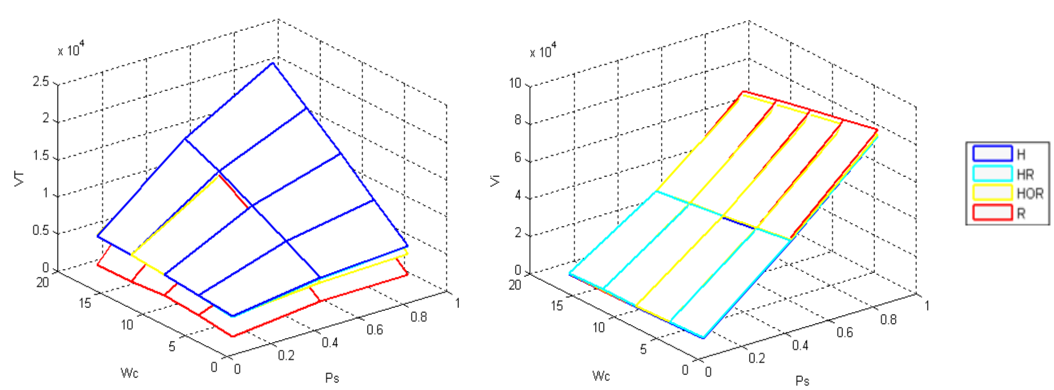

Figure 30: Effect of W_c and P_s on V_T (left graph) and V_I (right graph) of 'Type 2' systems

These findings match the results of *'Type 1'*. Thus, the influence of W_c is independent of the system's type.

7. Sensitivity Analysis

7.1 *βs analysis*

The sensitivity analysis was performed for the three betas: β_r, β_h and β_{rh} for a given situation, i.e., for a given d'_r, d'_h, P_s and outcomes weights (W_H, W_{FA}, W_{CR} and W_M). The logarithm of the analyzed beta ranged from -4 to 4 in order to cover wide range of criteria. In order to reduce the number of analysis and since we assume in this work that human perform better than robots in unstructured environments, only the cases where $d'_h \geq d'_r$ were analyzed. The analysis focused on three levels of target probability: Low (P_s = 0.1), Meduim (P_s = 0.5) and High (P_s = 0.9). The following results are for system of *'Type 1'* where Δ_1/Δ_2 = 5. Results of *'Type 2'* systems are presented in Appendix VIII. It should be noted that throughout the entire sensitivity analysis the term 'small deviations' refers to ±1 deviations from the optimal value of the examined β.

<u>General description</u>

Figure 31 presents an example of the graphs which were used for all the analysis. Each β has its own graph where β_r's analysis is on the left graph, β_h's analysis is on the middle graph and β_{rh}'s analysis is on the left. Each of the model's operational levels is presented by a different line color where H blue, HR cyan, HOR green and R red. The x axis is the value of the β and y axis is the objective function score (V_I). The optimal β and the highest possible score are marked with a black circle on the best level. In the example the best operational level in the optimal case is HOR.

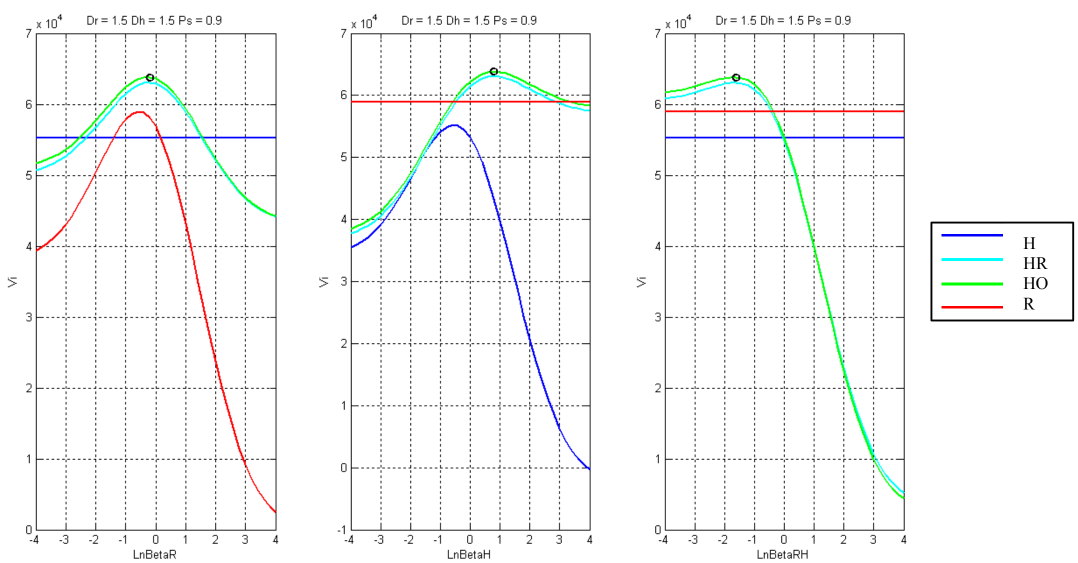

Figure 31: Example of β sensitivity graphs

The following results are common for all analyes; changes in β_r do not affect the H level (the blue line in the left graph), changes in β_h do not affect the R level (the red line in the middle graph) and changes in β_{rh} do not affect both the H and R levels (notice the red and blue lines in the right graph are straight).

The aim of this analysis is to examine if small deviations from the optimal value of each β can casue a level shifting in order to maintain optimally. In this example (figure 31), an increase in β_{rh} dramatically influences the objective function score and can cause a level shfiting from HOR to R level.

<u>Low Target Probability (P_s = 0.1)</u>

In system of *'Type 1'*, for low P_s the R level is more dominant. For all the tested cases, when the R level was the best level, small deviations from the optimal β_r did not force level shifting and the R level remained the best (Figure 32).

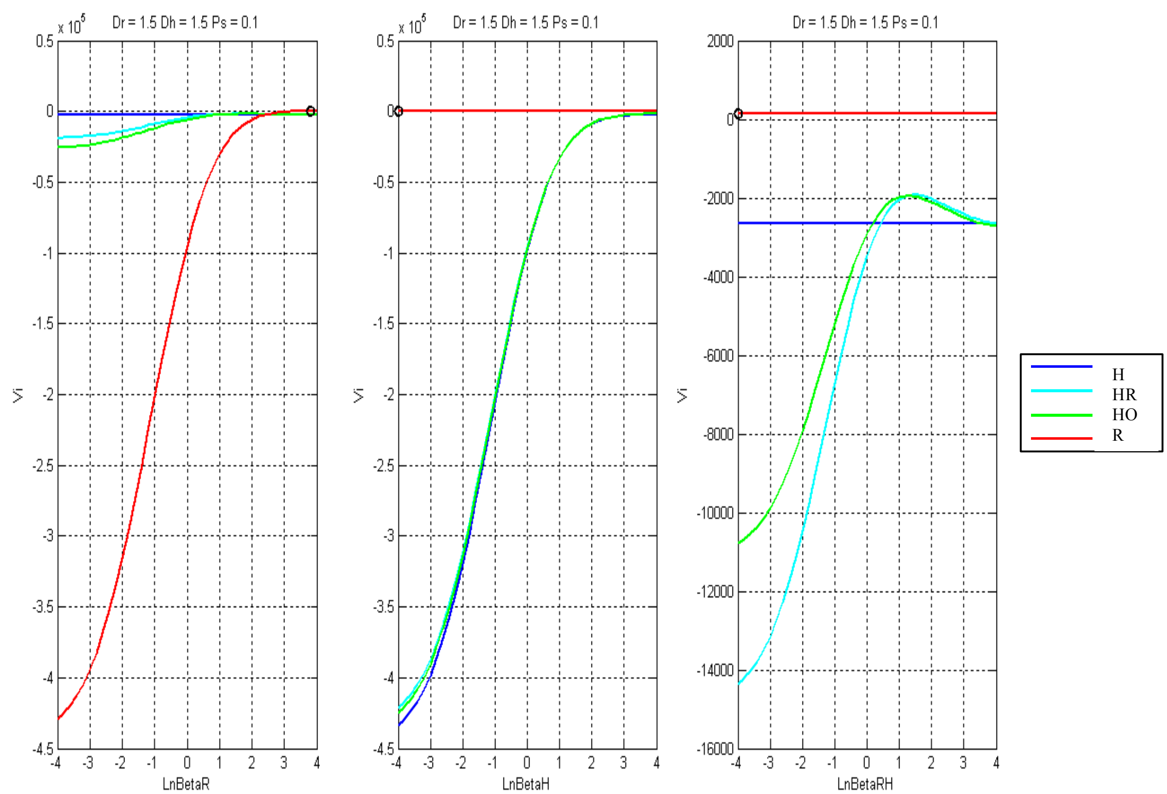

Figure 32: βs analysis – low target probability and R is the best level

Figure 33 presents a case where the target probability is low and R is not the best level.

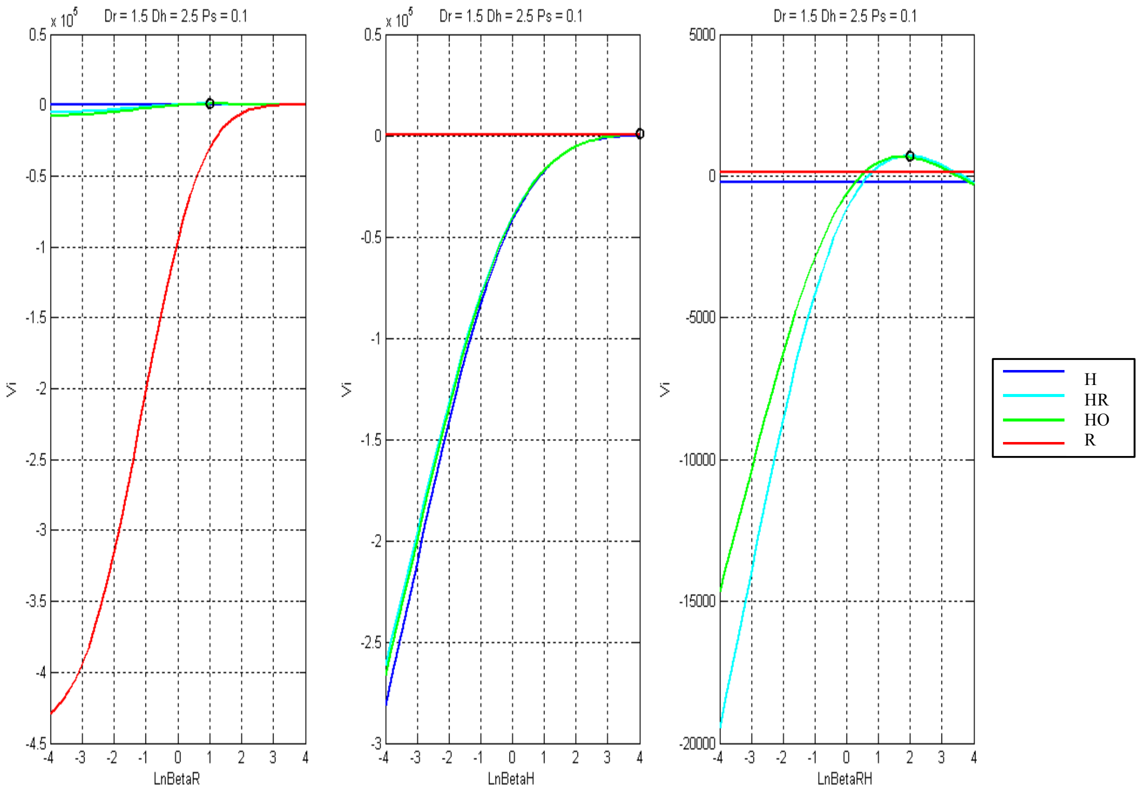

Figure 33: βs analysis – low target probability and R is not the best level

Changes in β_r has a low influence on HR and HOR levels. On the other hand, changes in β_h and β_{rh} decrease the objective function score of these levels. The value of β_h is more sensitive to deviations than the value of β_{rh} , i.e., smaller deviations are required to enforce level shifting to R level from β_h than from β_{rh} value. These results point out that for this case the human's decisions are more critical and have greater influence on the HR and HOR levels than the robot's decisions.

Medium Target Probability (P_s = 0.5)

The results for the case where P_s = 0.5 depends on the difference between d'_h and d'_r. If the difference is high (1 or more) then small deviations of β_r or β_{rh} can cause level shifting to H level (Figure 34). For low differences between d'_h and d'_r, changes in β_r anf β_{rh} affect the objective function score of the best operational level, however, small deviations from the optimal value of these βs does not force level shifting (figure 35).

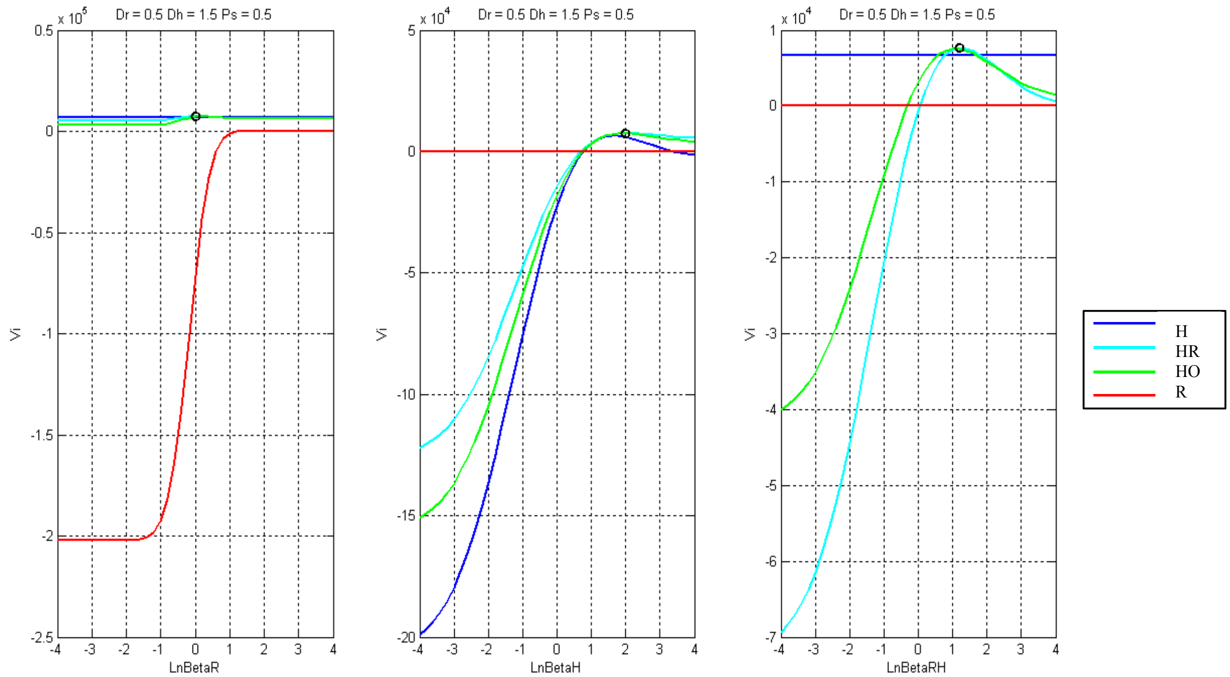

Figure 34: βs analysis – medium target probability and high difference between d'$_h$ and d'$_r$

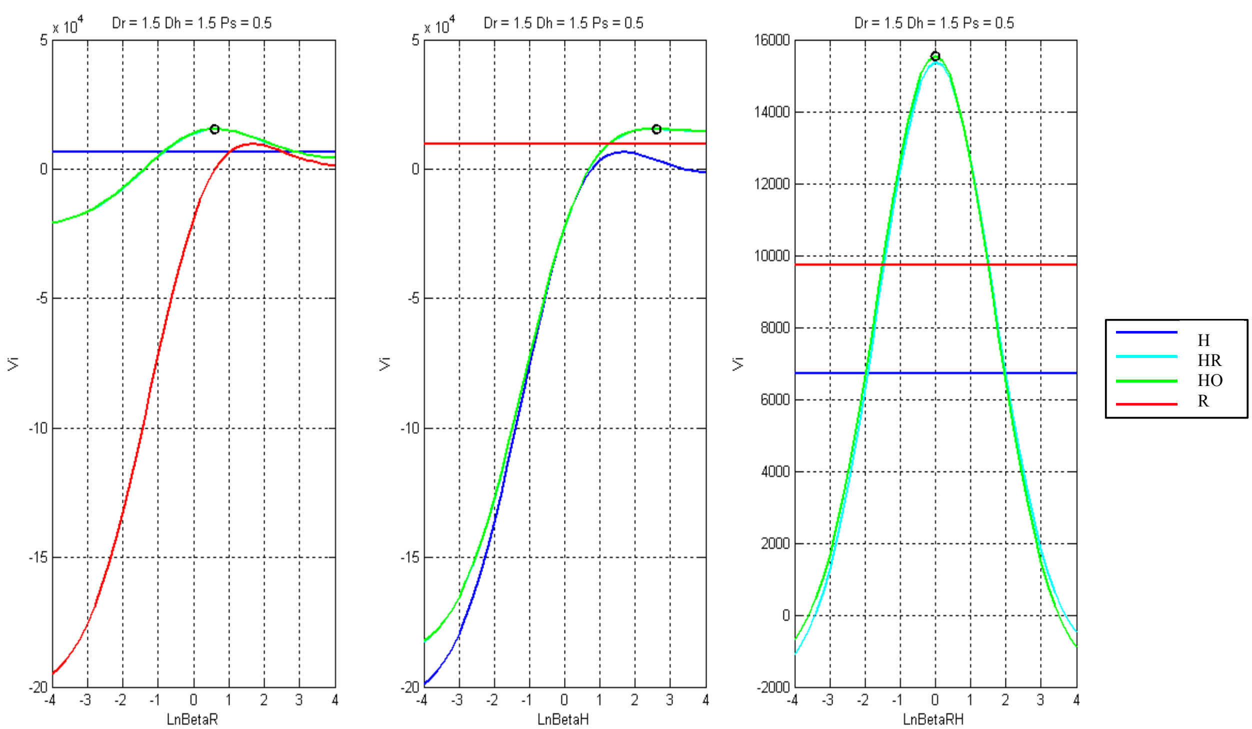

Figure 35: βs analysis – medium target probability and low difference between d'$_h$ and d'$_r$

High Target Probability (P_s = 0.9)

Similarly to the findings for P_s = 0.5, the results depends on the difference between d'_h and d'_r. Figures 36 and 37 present the results for high and low differences respectively. Results show the increase from the optimal value of β_{rh} is the most influential deviation (steepest gradient of the objective function score).

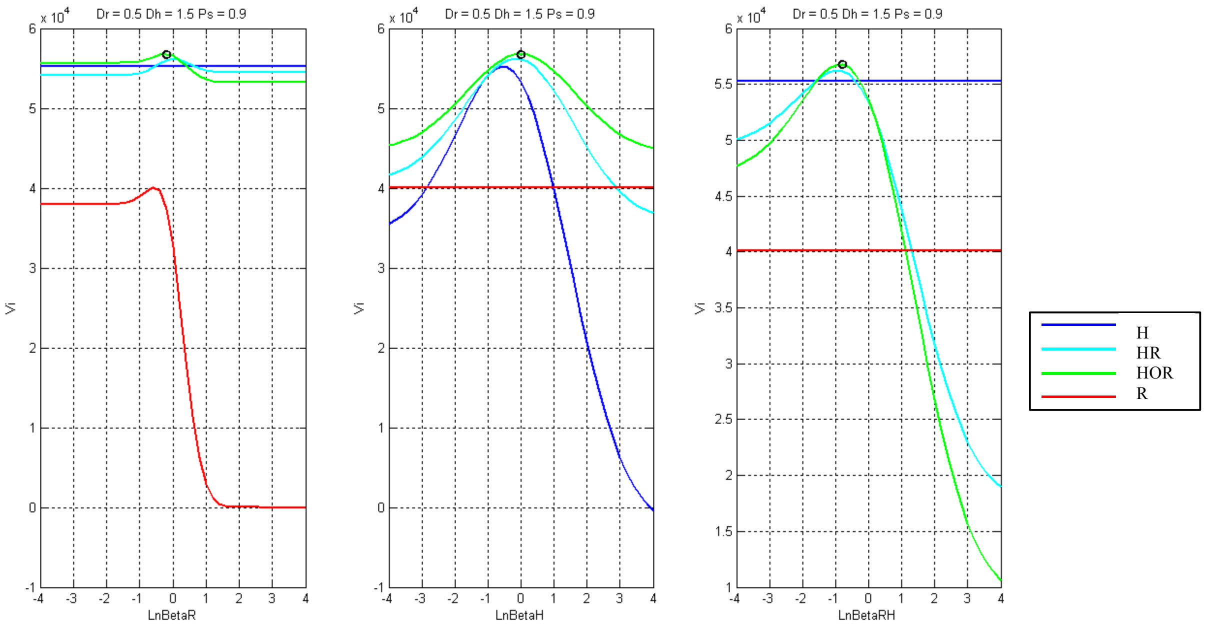

Figure 36: βs analysis – high target probability and high difference between d'_h and d'_r

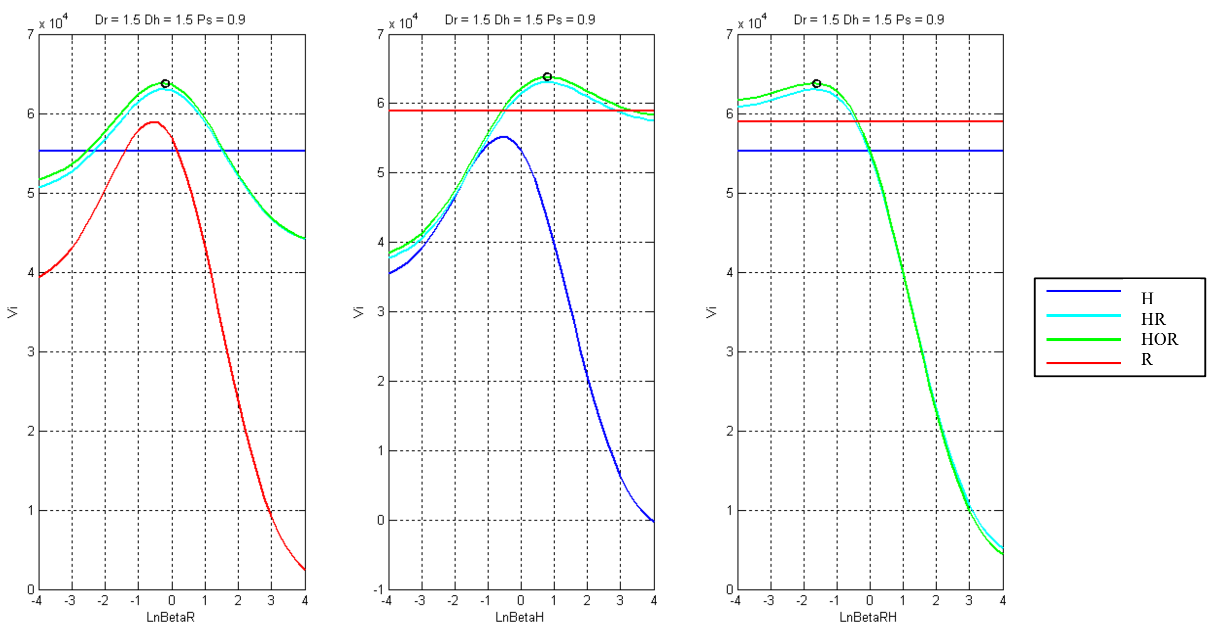

Figure 37: βs analysis – mid target probability and low difference between d'_h and d'_r

7.2 *Human's and Robot's sensitivities analysis*

The analysis was performed for both sensitivities: d'_h and d'_r. The following results are for system of *'Type 1'* where $\Delta_1/\Delta_2=5$. Results of *'Type 2'* systems are presented in Appendix IX.

<u>General description</u>

Figure 38 presents an example of the graphs which were used for all the analysis. This example is of d'_h analysis. The x axis is the value of the analyzed sensitivity (d'_h in that example) and y axis is the objective function score (V_I). The sensitivity paramter which is not analyzed (d'_r in that example) is determined for six different values (one graph for each value). Each of the model's operational levels is presented by a different line color where H blue, HR cyan, HOR green and R red. In the presented example the target probabilty set to 0.5.

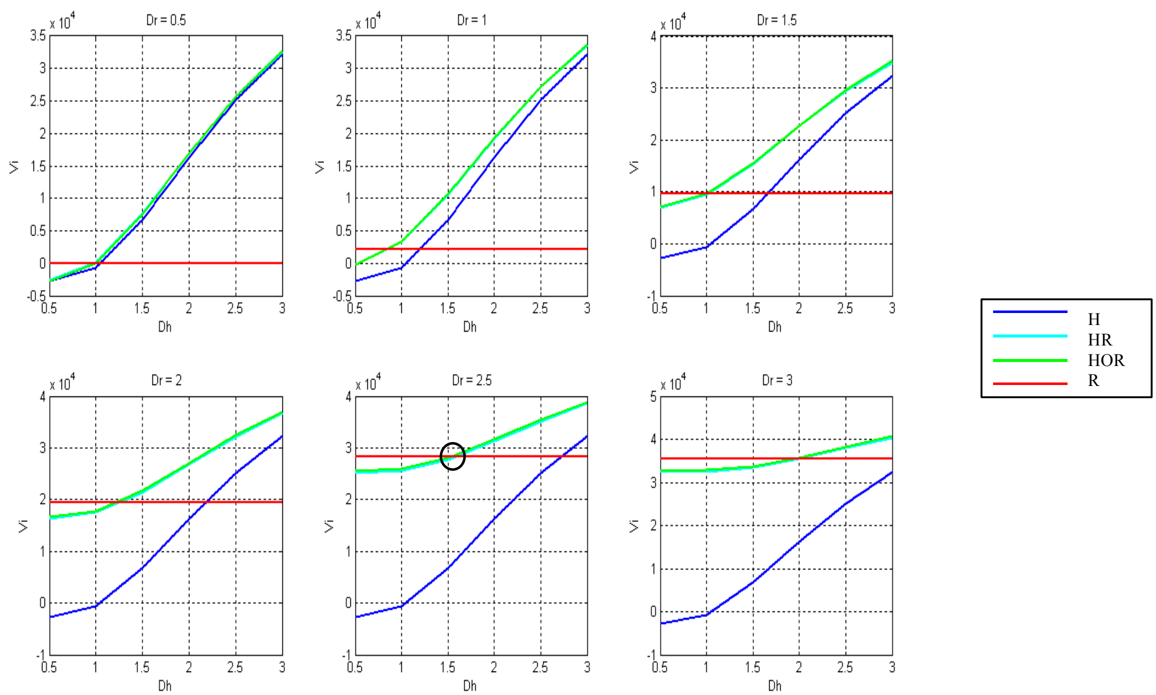

Figure 38: Example of d'_h sensitivity graphs

The top line in each graph represents the best collaboration level. Each intersection between the lines represents level shifting. The objective of this analysis is to point out *critical values*. A *critical value* is defined as a value that a small deviation from it can cause a level shifting. For example, in figure 38, when $d'_r = 2.5$ then the critical value of d'_h is 1.5 (marked with a black circle). These values are critical since we assume that in real systems the robot and especially the human sensitivities are random variables.

Figure 39 presents the robot's sensitivity (d'_r) analysis.

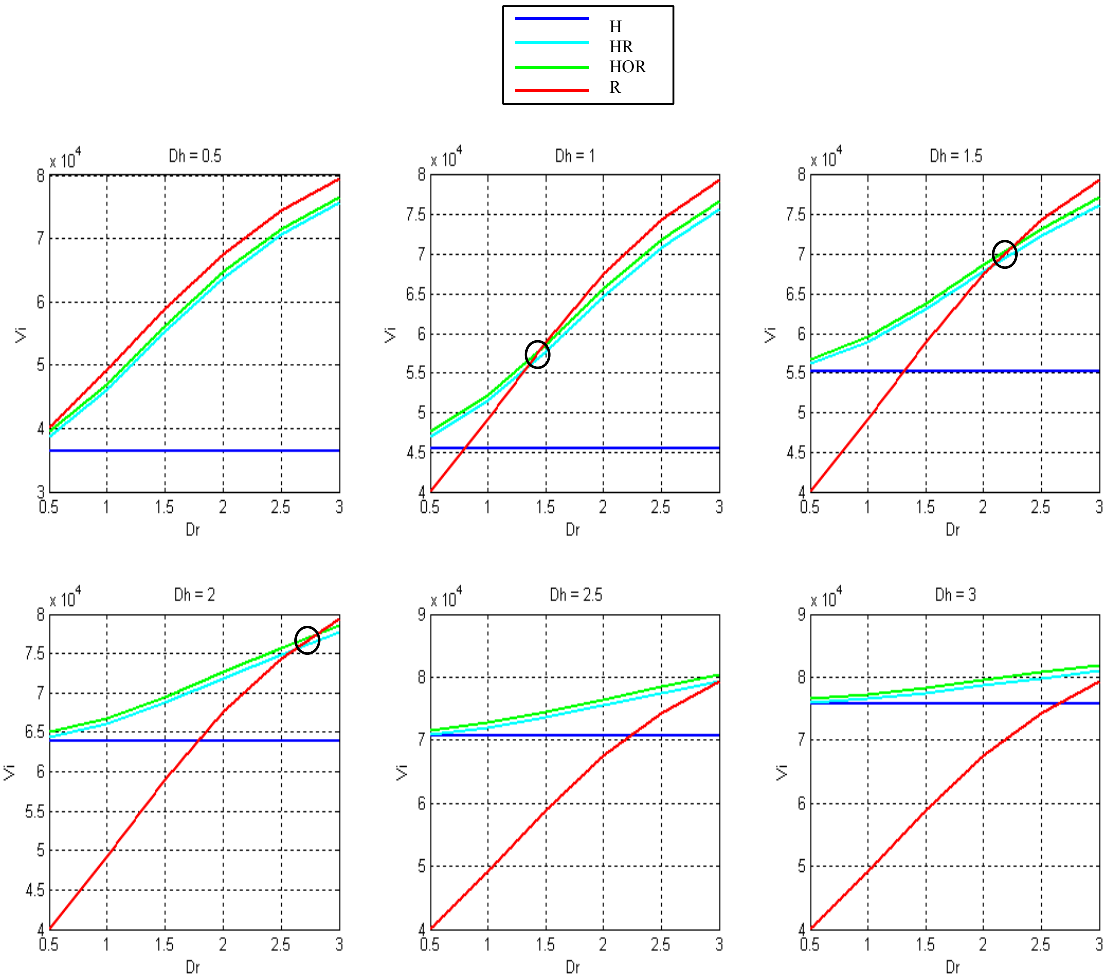

Figure 39: Sensitivity analysis of d'_r

Results show that for low d'_h (1 or less) changes in the robot sensitivity has similar effect on HR, HOR and R levels (the gradients of these levels are almost equal). However, as d'_h increases, changes in d'_r are more influential on the R level (this level has a steeper gradient). In Figure 39, there are three critical values (marked with black circles).

Figure 40 presents the human's sensitivity (d'_h) analysis.

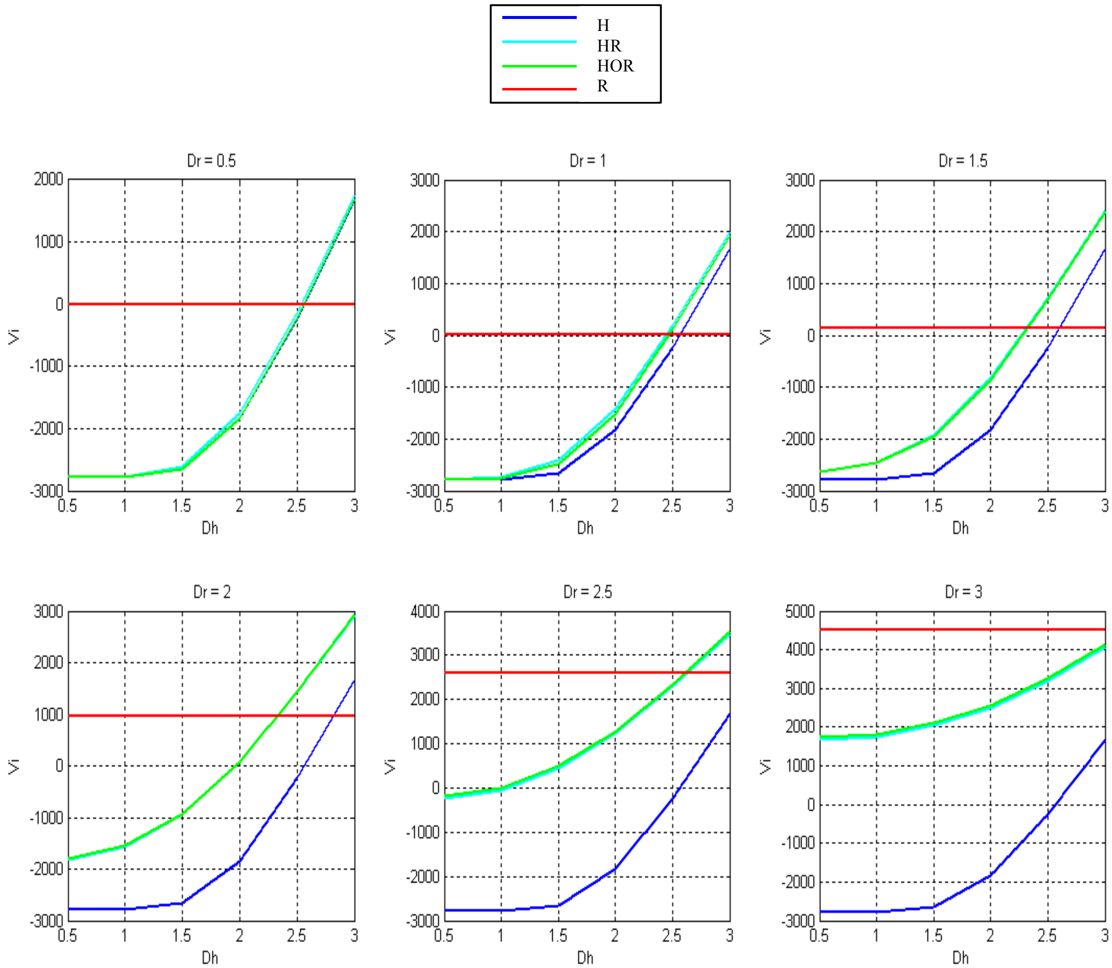

Figure 40: Sensitivity analysis of d'_h

For all the cases, d'_h has a very similar effect on the performance of H, HR and HOR levels (almost identical gradients in all graphs). This finding leads to the conclusion that changes in d'_h will not enforce level shifting between these levels. In addition, as human sensitivity rises, small changes in d'_h are more influential on these levels' performance. In all the graphs except one (where R level is the best for all d'_h values) there are critical values. In all the critical values, an increase from the critical value leads one of the collaboration levels to become the best (HR or HOR) while a decrease leads the R level to become the best level.

8. Conclusions

The numeric analysis exposed two different behavior types; *'Type 1'*, geared towards minimizing false alarms and *'Type 2'* geared towards detecting targets. Results indicate that an increase in the human or robot sensitivities led to an increase in the objective function score for both types of systems, since higher sensitivity increased the discrimination ability between target and noise (no target object). Better sensitivity leads to more target detections and less false alarms and thus regardless of the system's type or method of reward or penalty the objective function score increases. Furthermore, the manual level (H) was never the best level for the optimal cases; this may be the result of high operational costs and a relatively low detection rate. This implies that collaboration between human and robot in target recognition tasks, with similar conditions, will always improve system performance. It appears that the improvement in detection rate and hence rise in profits gained by this collaboration outweighs the rise in operational cost attributable to adding the robot to the system.

Results showed opposite tendencies between the two types of systems found. In systems of *'Type 1'* as target probability increased R level was preferable in more cases, and as a result other collaboration levels were less preferable. In systems of *'Type 2'* the trend was reversed: as target probability increased collaboration levels were preferable in more cases. *'Type 1'* systems greatly value not committing errors; that is to say, they place high importance on results in situations where no target is present, or target probability is low. In turn, *'Type 2'* systems greatly value results in which a target is present. Even though very different tendencies were discovered by the function analysis, several important similarities found between them should be pointed out: in both systems as the probability of the prominent object (non target in *'Type 1'* and target in *'Type 2'*) increases, the R level will be preferable in more cases and, as the probability of the prominent object decreases, collaboration between human and robot is preferable. It can be assumed that this trend stems from the reciprocation between operational costs and recognition profits.

Symmetry between the 'hit' weight, W_H, and the 'miss' weight, W_M and between the 'correct rejection' weight, W_{CR}, and the 'false alarm' weight, W_{FA} was revealed. The symmetry is expressed by the fact that different systems have identical best operational level maps. This finding lead to a further investigation which indicated that only the ratio Δ_1/Δ_2, where $\Delta_1 = W_{CR}-W_{FA}$ and $\Delta_2 = W_H-W_M$, determines the classification of the system ('*Type 1*' or '*Type 2*'). The last finding served to generalize the results which were found for specific systems in this work to any system with the same ratio. Moreover, this finding can be assumed as a new property of the objective function score and assist in the understanding of further analysis.

The results from this work point out that the two types differ as a function of the target's probability (P_S) and that the system's type depends on the ratio Δ_1/Δ_2. These results are related to both parts of the optimal β equation (q.v. chapter 5.2 equation 13). The a-priori probability (P_S) is an unknown parameter which depends on the environment and cannot be controlled by the system's designers. Thus, this parameter has not been considered as a parameter which defines the system's type but it does affect the system's performance. The ratio between the weights (Δ_1/Δ_2) depends on the system's tasks and can be controlled by the system's designers. Thus, this ratio defines the system's type.

The operational costs analysis reveals that changes in the time cost parameters have a high influence on the system performance. However, the action cost has a lower influence on the system performance. This result was obtained since the action cost depends upon the number of 'hits' and 'false alarms'. Since the analysis was conducted for optimal thresholds, it is reasonable to assume that the system will have more 'hits'. Thus, more actions (hits or false alarms) will further lead to higher action cost but also to higher reward. This is the reason why the influence of the action cost is diminished. From all the analyzed parameters, the human operator decision time was found to be the most influential parameter on the best operational level map. Improvement in the human decision time (i.e., shortening) leads to the collaboration levels HR and HOR to become preferable over R level. In addition, the operational costs analysis reveals that except for two parameters, t_s and W_a, all the analyzed parameters had a similar effect on both types of systems. The system time, t_s, and the number of actions, W_a, are depended upon the value of the target probability. Since *'Type 1'* and *'Type 2'* have opposite tendencies as a function of the target probability, these parameters have a different effect on each type.

Sensitivity analysis of βs revealed that in many cases, a small deviation from the optimal value required the system to switch to another operational level in order to stay at optimum performance. In addition, the sensitivity analysis of d'_h and d'_r indicates that while the influence of d'_h depends on its value (i.e., deviations from high value has different effects on the system performance than deviations from low value of d'_h), in which the influence of d'_r is not depended upon its value.

Results from this research can aid in designing new integrated systems and controlling various human-robot systems by mapping the influence of different parameters on the system state.

9. Discussion and future research

This study aimed to investigate the performance of human-robot collaboration systems through a model developed by Bechar et al.(2006).

The literature review suggested two main issues. First, the limitations of autonomous robots, especially in dynamic environments, lead to the vast interest and speedy development in human – robot collaboration research. Second, most human-robot collaboration studies use qualitative methods to examine human-robot system with the main goal to further advance the system development and to answer questions such as how the different parts should be appointed between human and robot.

This study used a quantitative model, which has several significant advantages. Its results supply quantitative indexes for the system's performance and it can support the initial part of designing the system as well as be used as an algorithm in an existing system. One drawback is that in order to model a collaboration system and to quantify the different parameters several variance assumptions must to be made, which diminishes from the generality of the model.

The model was especially designed for target recognition tasks. However, with some modifications it can be customized for any task of integrated human-robot system which requires binary decision making. Future research may focus on modifications and implementations of Bechar's model for different human-robot applications such as navigation.

The numerical analysis was conducted with constant time parameters. In reality, these parameters, especially, the human's time parameters are variables with a certain distribution. They depend on numerous factors such as: operator's skills and fatigue, environmental conditions, image quality. Since these parameters affect the operational cost, the weight of the operational cost proportionately to the other objective function weights will determine the degree of their effect. In real life, each system has its own operational costs which depend on the system's mission. In cases where the weight of the operational cost has a significant influence on the system's objective function score and the time parameters have high variance, the results using time parameters as constants will not be adequate and the influence of these parameters should be investigated. Future research should focus on developing models that include variable time parameters and their analyses.

This study presumes that robots do not function well in unstructured environments and therefore, collaboration is preferred. The analysis reveals that the changes in the human sensitivity and human decision time have great influence on the performance of the collaboration level. That is to say, amelioration of the operator's capabilities would be reflected in better sensitivity (i.e., better ability to distinguish between signal and noise) which would lead to better performance. Moreover, better sensitivity will lead to a faster decision making process and to a minimization of the time cost. Another direction for future research may focus on examining the influence of operator's skills improvement on the overall system performance.

In order to apply Bechar's model on a real system, some assumptions and estimations have to be made. It should be assumed that both target and non-target objects are normally distributed and have equal variance. This assumption will be acceptable for most environments. If the following assumption is not valid, the model can be applied but its objective function cannot be analyzed with the modified SDT method. In addition, the sensitivities of the system (d'_h and d'_r) and the a-priori probability (P_s) should be estimated. The accuracy and the effectiveness of the model are dependent on these estimations.

Bechar's model and its analysis resulting from this work can be used to control the operational level of a human-robot system in real time. In dynamic and unstructured environments, the value of the model's parameters is not constant and can change very fast. This situation can lead to different operational levels becoming optimal in a relatively short time interval. That is, based on the model's objective function, in order to maintain optimum, the system has to shift between its operational levels. In real systems, each shifting between the operational levels is associated with some costs, thus, the decision of level shifting cannot be based on the value of the objective function per se. The value of the objective function will be the main factor for that decision. However, we have to consider other aspects such as: *Who decides on the level shifting, the robot or the human? What is the minimal time interval between level shifting?* (the human's fatigue and his/her learning curve should be considered). Future research should examine these questions and develop a transfer function (perhaps as a new part of the existing function or as a new function) which will consider the costs that are involved in level shifting.

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11. Appendixes

LIST OF APPENDIXES

Appendix I: PAPER: Performance Analysis of Human-Robot Collaboration in Target Recognition Tasks

Performance Analysis of Human-Robot Collaboration in Target Recognition Tasks

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***Abstract* — Application of autonomous robots in dynamic and unstructured environments still produces inadequate results. Integrating human perception skills with the autonomous systems' accuracy and consistency can result in improved performance. This paper presents an in-depth performance evaluation of an integrated human-robot system for target recognition tasks based on quantitative analysis of an objective function developed in previous work. The system's model is composed of four human-robot collaboration levels fitted for target recognition tasks. The objective function quantifies the influence of the robot, human, environment and task parameters through a weighted sum of performance measures, and enables it to determine the best level of collaboration based on these parameters. Numerical analysis of the objective function was performed for different objective function weights. In addition, sensitivity analysis of the influencing variables was performed on the optimum values. Results reveal two types of systems. The first type consists of systems geared towards minimizing false alarms. The second type consists of systems geared towards detecting a target when one is presented. In addition, it was found that the manual level is never the best collaboration level.**

***Index Terms* — collaboration levels, human-robot collaboration, objective function, performance analysis.**

I. INTRODUCTION

Application of autonomous robots in real world, dynamic and unstructured environments still produces inadequate results [1]. Having an automated system handle all conceivable scenarios is extremely difficult [2], [3]. Inadequacies of sensor technologies further impair the capabilities of autonomous robotics [4]. Therefore, the promise of automatic and efficient autonomous operations has fallen short of expectations in unstructured and complex environments [5], [6]. Complexity is increased when dealing with natural objects such as in medical and agricultural environments due to the object's high degree of variability in shape, texture, color, size, orientation and position. Consequently, the robotic systems become increasingly cumbersome, thereby creating a complicated system which is expensive to develop and operate [7] and not robust enough.

Humans' acute perception capabilities enable them to deal with a flexible, vague, changing, and wide scope of definitions [8]. Moreover, humans have superior recognition capabilities and can easily adapt to changing environmental and object conditions [9]. However, a human operator is not consistent, tends to fatigue, and suffers from distraction [10]. By taking advantage of human perception skills and the accuracy and consistency of the autonomous system, the combined human-robotic system can be simplified, resulting in improved performance [11].

The introduction of robots into everyday tasks such as surgery, therapy, service and entertainment domains requires development of methods that enable easy and effective communication between robots and humans [12]. Human-robot collaboration research has addressed the issue of how the human-robot association affects automation in aspects of data acquisition, data and information analysis, decision making, action selection, and action implementation [11], in accordance with specific task or sub-task goals and parameters. Types and levels of automation are evaluated by examining their associated human performance consequences such as mental workload, situation awareness, complacency, and skill degradation [3]. Sheridan [13] divides automation into ten levels, from fully autonomous, with no human intervention to fully manual. Tsuji and Tanaka [14] investigated a tracking task where the human and the machine act simultaneously. Hughes and Lewis [15] developed different automation levels for a human-robot vehicle in an indoor exploration task. Graves and Czarnecki [16] described a scale of five human-robot interaction levels for a telerobotic behavior based system.

Four human-robot collaboration levels for target recognition tasks in unstructured environments were developed in previous research [17]. An objective function was developed to determine the expected value of task performance in a target recognition task, given the parameters of the system, the task, and the environment [18]. To simplify the analysis of the function a modified signal detection theory was applied [19]. Numerical analysis of a simple form of the objective function was done [17]; the analysis excluded the miss and correct rejection parts. In this paper we complement previous analyses by including an in-depth analysis that evaluates the affects of rewards for correct rejection and penalties for missing targets.

II. METHODOLOGY

a. Collaboration Levels

Four basic Human-Robot collaboration levels for target recognition tasks were defined, tested and evaluated based on Sheridan's scale of "action selection and automation of decision" [13]- 1) H: The human detects and marks the desired target manually. 2) HR: The human detects targets, aided by recommendations from the robot, *i.e.*, objects are marked by a robot detection algorithm, the human inserts into the targets database, targets which marked by the robot and targets which the robot missed. 3) HOR: The human supervises the robot. Objects are identified by the robot's detection algorithm and inserted into the targets database. The human removes false detections from the targets database and inserts targets missed by the robot. 4) R: Fully autonomous, the targets are marked automatically by the robot.

b. System Objective Function

The objective function is designed to enable determination of the expected value of task performance and the best collaboration level given the system parameters. The objective function [20] considers four major groups of parameters - human, robot, environment, and task. Each parameter influences the system's situation and therefore the system's performance. The objective function (V_{Is}, equation 1, [21]) is composed of five parts; one for each of the four possible outcomes: correct detection (hit), false alarm, miss, correct rejection, and the fifth for the operational costs. The operational costs part includes the costs related to operational time and the action costs associated to the detected objects, whether they are hits or false alarms.

$$
\begin{aligned}
V_{I_S} &= N \cdot P_S \cdot \left[p_{H_r} \cdot p_{H_{rh}} \cdot \left(V_H + V_C + t_{H_{rh}} \cdot V_t\right) + \right. \\
&+ \left. \left(1 - p_{H_r}\right) \cdot p_{H_h} \cdot \left(V_H + V_C + t_{H_h} \cdot V_t\right)\right] + \\
&+ N \cdot P_S \cdot \left[p_{H_r} \cdot \left(1 - p_{H_{rh}}\right) \cdot \left(V_M + t_{M_{rh}} \cdot V_t\right) + \right. \\
&+ \left. \left(1 - p_{H_r}\right) \cdot \left(1 - p_{H_h}\right) \cdot \left(V_M + t_{M_h} \cdot V_t\right)\right] + \\
&+ N \cdot \left(1 - P_S\right) \cdot \left[p_{FA_r} \cdot p_{FA_{rh}} \cdot \left(V_{FA} + V_C + t_{FA_{rh}} \cdot V_t\right) + \right. \\
&+ \left. \left(1 - p_{FA_r}\right) \cdot p_{FA_h} \cdot \left(V_{FA} + V_C + t_{FA_h} \cdot V_t\right)\right] + \\
&+ N \cdot \left(1 - P_S\right) \cdot \left[p_{FA_r} \cdot \left(1 - p_{FA_{rh}}\right) \cdot \left(V_{CR} + t_{CR_{rh}} \cdot V_t\right) + \right. \\
&+ \left. \left(1 - p_{FA_r}\right) \cdot \left(1 - p_{FA_h}\right) \cdot \left(V_{CR} + t_{CR_h} \cdot V_t\right)\right] + t_r \cdot V_t
\end{aligned}
\qquad (1)
$$

where N is the number of objects in the image, P_S is the probability of an object becoming a target, V_H is the gain of a single hit, p_{Hr} is the robot probability of a hit, p_{Hrh} is the human probability of confirming a robot hit, and p_{Hh} is the human probability of detecting a target which the robot did not detect, V_M is the cost of a single miss, V_{FA} is the damage of a single false alarm, p_{FAr} is the robot false alarm probability, p_{FArh} is the human probability of not correcting the robot false alarm, and p_{FAh} is the human false alarm probability, V_{CR} is the benefit of a single correct rejection, V_t is the cost of one time unit, and V_C is the cost of one object recognition operation (hit or false alarm), t_{Hrh} is the human time required to confirm a robot hit, t_{Hh} is the human time required to hit a target which the robot miss, t_{FArh} is the human time needed to correct a robot false alarm, t_{FAh} is the human false alarm time, t_{Mrh} is the human time lost when a robot hit is missed, t_{Mh} is the human time invested when missing a target which the robot did not detect, t_{CRrh} is the human correct rejection time of robot false alarm, t_{CRh} is the human correct rejection time, and t_r is the robot time.

c. Signal Detection Theory

To simplify the analysis of the objective function, a modified version of Signal Detection Theory (SDT) was applied [17]. The classic SDT for a single detector considers four performance measures: hit, false alarm, correct rejection and miss that can be computed by two variables; the sensitivity, d', and the likelihood ratio criteria, β. In previous work [19] we modified SDT for two detectors, human and robot, where the performance of the first detector (robot) is determined by its sensitivity, d'_r, and its criterion, β_r. The second detector (human) uses its sensitivity, d'_h, and two criteria; one for objects already marked by the robot, β_{rh}, and one for objects unmarked by the robot, β_h.

Figure 1 represents a flowchart diagram of the target recognition process in an integrated human-robot system. The system is serial; each object is at first analyzed by the robot and then by the human operator. The robot analysis is exposed to the human operator.

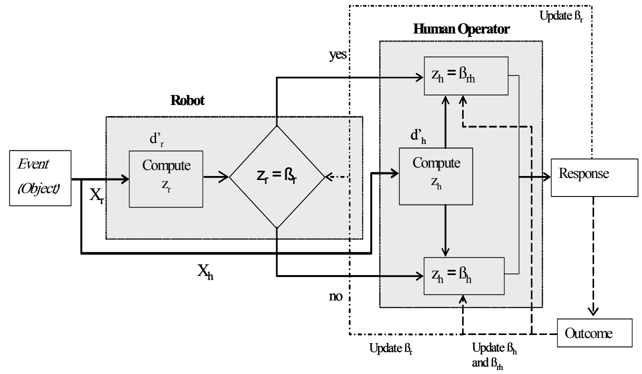

Fig. 1. Flowchart of the target recognition process in an integrated human-robot system.

III. Numerical Analysis

A numerical analysis of the objective function was conducted on a PC with Matlab 7.1™. The analysis determined the best collaboration level and the objective function score for a given human sensitivity, robot sensitivity, target probability and different objective function weights [17]. All analyses were performed for the optimal likelihood ratios, β_r, β_h, and β_{rh}. For every analyzed set of parameters the optimal likelihood ratios were determined in the range between the logarithm of -4 and the logarithm of 4, in order to cover the available hit and false alarm probabilities.

As aforementioned, previous work [17] analyzed the objective function excluding the parts of the reward for correct rejection (V_{CR}, t_{CRr}, t_{CRh}, t_{CRrh} equal to zero) and the penalty for miss (V_M, t_{Mr}, t_{Mh}, t_{Mrh} equal to zero). In this paper the numerical analysis was conducted on the complete objective function. Systems differ in the way they are designed and in their assignments, *e.g.,* a mine finding system is designed to prioritize detecting targets (mines), which implies a high value for the hit weight (V_H). In turn, medically oriented systems prioritize minimization of false alarms, which imply a high value for the false alarm weight (V_{FA}). In the current analysis, different systems were simulated by giving different values for the objective function weights ($V_{H,}$ V_{FA}, V_{CR}, and VM). The current numerical analysis (Figure 2) focused on the influence of different human and robot sensitivity combinations (d'_h and d'_r) and different target probabilities (P_S) on the best collaboration level and the objective function score of different systems. Each surface in Figure 2 represents one of the system's possible collaboration levels. This figure illustrates the influence of the sensitivities on the objective function score (z axes) and the highest score for each sensitivities combination which is composed of the highest surface created from the surfaces intersections of the different collaboration levels (its perimeter is marked with a black solid line). Furthermore, each intersection in this area represents shifting between the collaboration levels to maintain optimum performance.

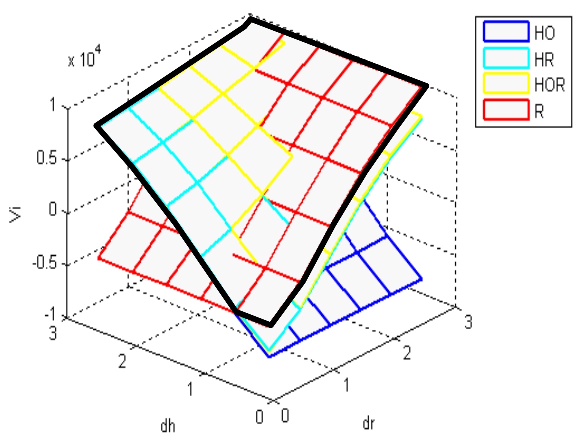

Fig. 2. The influence of the human and robot sensitivities on the system performance for each collaboration level.

a. Task Parameters

Three ratio parameters between the objective function weights were set; the ratio between false alarm and hit weights, V_{FA2H}, the ratio between correct rejection and miss weights, V_{CR2M}, and the ratio between miss and hit, V_{M2H}. The V_{FA2H} and V_{CR2M} values were set for 0.1, 1 and 10 in order to create a drastic difference between the objective function weights and to simulate different systems with different assignments. The ratio between miss and hit, V_{M2H}, was set to 1. The value of hit weight, V_H, was set to +50 and all the other weights were determined according to the ratios. For example, if $V_{FA2H} = 0.1$ and $V_{CR2M} = 0.1$ then the values of the other weights will be $V_{FA} = -5$, $V_{CR} = +5$, $V_M = -50$.

The target probability, Ps, ranged from 0.1 to 0.9. The human sensitivity, d'_h, and the robot sensitivity, d'_r, ranged from 0.5 to 3. The operational cost for one object recognition operation was set to V_C=-2 and the cost for one time unit was set to V_t=-2000 hr^{-1}. The number of objects in each task was set to N= 1000. The values of the different parameters of the simulation were extracted from a preliminary experiment performed by Bechar et al. [18].

b. Best Collaboration Level

The best collaboration level is defined as the level which under specific task parameters, achieves the highest objective function score (V_{Is}). The analysis was conducted on a 2D graph that illustrates the best collaboration regions (Figure 3) where each collaboration level is represented by a different color. In the case presented, HR, HOR and R collaboration levels are the best collaboration level in different areas of the sensitivity space. This example indicates that for the same task the best collaboration level can change from one collaboration level to another. Different task, human, robot, or environment parameters will result in different collaboration maps.

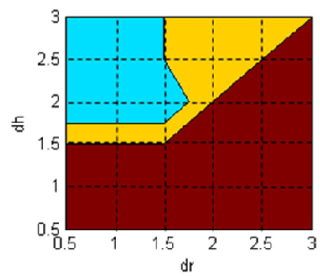

Fig. 3. Best collaboration level map. HR – Cyan, HOR – Yellow, R – Red.

The analysis revealed two main types of systems. The first type, denoted hereon as 'Type 1', consists of systems geared towards minimizing false alarms. This goal can be reached by setting proportionately higher rewards for correct rejections and/or higher penalties for false alarms. The second type denoted hereon as 'Type 2' consists of systems geared towards detecting targets when one is presented. This goal can be achieved by setting proportionately higher rewards for hits and/or higher penalties for misses.

For both system types, analysis of the collaboration map reveals symmetry between hits and false alarms ratio, V_{FA2H}, and between correct rejection and miss ratio, V_{CR2M}, *i.e.*, the same collaboration map was generated when V_{FA2H} =10, V_{CR2M} =0.1 and V_{FA2H} =0.1, V_{CR2M} =10.

Type 1: High priority to minimizing false alarms

The analyses indicated that as the target probability, Ps, increases, the area of the R collaboration level, in the best collaboration level map, is reduced. Furthermore, results indicated that HR is the best collaboration level only when the human sensitivity, d'_h, is higher than the robot sensitivity, d'_r. It should be considered that when the target probability, Ps, is high, the HOR collaboration level is preferable in most of the sensitivity space. However, when robot sensitivity is higher than human sensitivity the best collaboration is R. The H collaboration level (human performs solely) was never the best collaboration level (Figure 4).

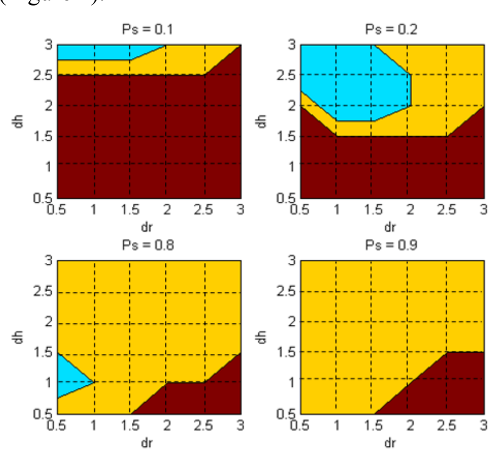

Fig 4. Example of ‘Type 1’ systems collaboration map where V_{FA2H} = 10, V_{CR2M} = 10. HR – Cyan, HOR - Yellow and R – Red.

Type 2: High priority to target detection

As opposed to 'Type 1' systems, in 'Type 2' systems, an increase in the target probability, P_S, increases the area of the

R collaboration level in the best collaboration level map. Moreover, for high and intermediate target probabilities, R was found to be the best collaboration level when the sensitivity of the robot is higher than that of the human. HR was found to be the best collaboration level only when the target probability was low, and the human sensitivity was higher than the robot sensitivity. For very low target probability (Ps=0.1), the HR collaboration level performed better than HOR, although as target probability increased HOR performed better than HR (Figure 5). Similar to the findings in 'Type 1' systems, the 'Type 2' systems' manual mode (H) was never the best collaboration level.

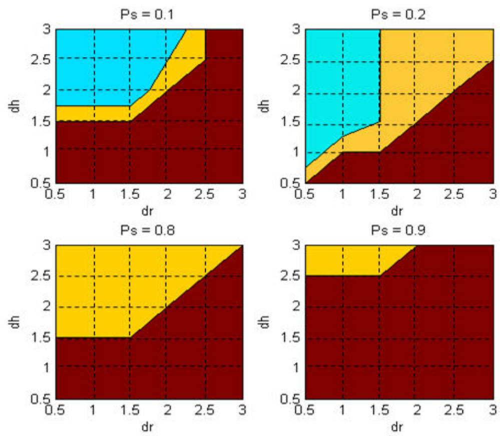

Fig.5. Example of 'Type 2' systems collaboration map where $V_{FA2H} = 1$, $V_{CR2M} = 0.1$. HR – Cyan, HOR - Yellow and R – Red.

c. Objective function score

The objective function score reflects system profit. The analysis investigated the influence of the system and the tasks' parameters on the objective function score where the system operates optimally, *i.e.*, when the system uses the optimal likelihood ratios and the best collaboration level. While the symmetry which was found in the best collaboration level analysis revealed identical collaboration maps, the objective function score maps were not found to be equal. Similarly to the collaboration level analysis, the objective function score was analyzed in the human and robot sensitivity space for different target probabilities (Figure 6).

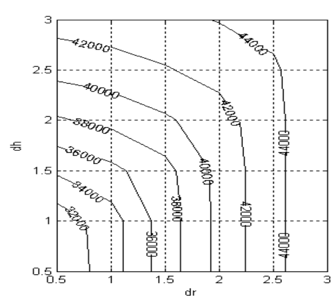

Fig.6. Objective function score, the isobar lines represent equal value score.

For both types, the symmetry discovered in the best collaboration analysis revealed that different systems have identical best collaboration maps. However, while there is an overlapping in the best collaboration level maps of the systems, their objective function score is different. The difference is derived from the way these systems achieve their goal - minimizing false alarms for 'Type 1' and detecting targets for 'Type 2'.

Type 1

While some of the systems achieve the goal of minimizing false alarms, by giving high penalty for false alarms, other systems achieve it by giving high reward for correct rejections. The value of the objective function score of 'Type 1' systems depends on both target probability and on the ratio between the reward for correct rejection and the penalty for false alarm.

When the goal is achieved by giving high reward for correct rejection the objective function score decreases as the target probability increases (Figure 7).

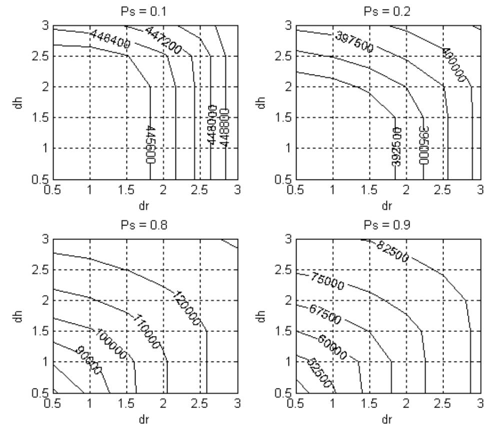

Fig.7. The system’s goal is achieved by giving high reward for correct rejection

The value of each of the objective function parts (V_H, V_{FA}, V_M, V_{CR}) depends on the probability for this part and the weight of the part. Since the analyses were performed for optimal βs, it is reasonable to assume that the probability of correct rejections would be higher than the probability of false alarms (these probabilities are complementary). Consequently, when the goal is achieved by giving high penalty for false alarms the tendency of the objective function can be changed depending on the ratio between V_{FA} and V_{CR}; for low ratios (when V_{FA} is not much larger than V_{CR}), the objective function score decreases as the target probability increases. For higher ratios, changes in the target probability hardly affect the objective function score (Figure 8) probably due to the tradeoff between the value of the probability and the value of the weight. When the ratio is high enough, the objective function score increases as the target probability increases.

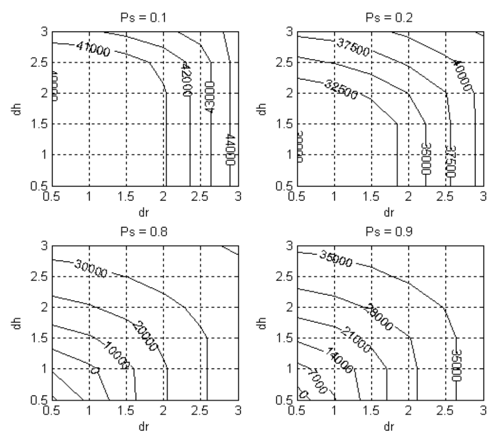

Fig.8. The system’s goal is achieved by giving high penalty for false alarm

Type 2

While some of the systems achieve the goal of detecting targets, by giving high reward for hit, other systems achieve it by giving high penalty for miss. The tendency of the objective function score depends on target probability and the ratio between hit and miss weights.

When the goal is achieved by giving high reward for hit the objective function score increases as the target probability increases. When the goal is achieved by giving high penalty for misses, similarly to ‘Type 1’, the tendency of the objective function can be changed depending on the ratio between VM and VH; for low ratios the objective function will increase as the target probability increases, for higher ratios changes in target probability will be reflected in small changes in the objective function score. When the ratio is high enough the objective function score decrease as the target probability increases.

For all the systems analyzed (Type 1 and 2), an increase in human or robot sensitivity leads to an increase in the objective function score.

IV. SENSITIVITY ANALYSIS

Sensitivity analysis was performed for β_r, β_h and β_{rh} for a given system, task and environment parameters. Figure 9 shows the influence of each β on the objective function score in all collaboration levels. In this example the analysis was performed for 'Type 2' systems where the ratios V_{FA2H} and V_{CR2M} was set to 0.1, the robot sensitivity was set to 1, the human sensitivity was set to 2.5, and the target probability was set to 0.1. Deviations in β_r were found to influence R, HOR and HR collaboration levels. Deviations in β_h were found to affect the HO, HR and HOR collaboration levels. Deviations in β_{rh} were found to influence only HOR and HR collaboration levels. For example, small decrease in β_{rh} will cause level shifting from HR to HOR to maintain optimal performance (Figure 9).

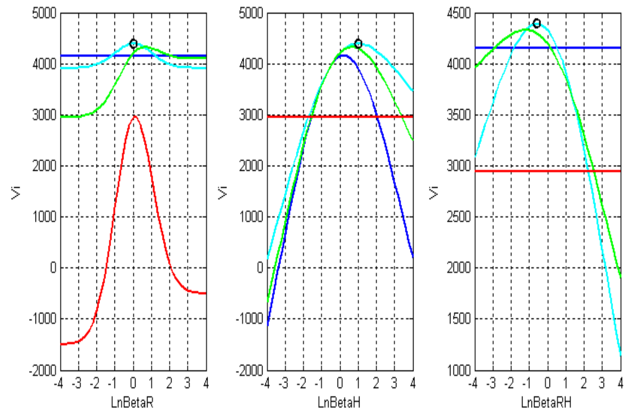

Fig.9. Influence of β_r, β_h and β_{rh} on each of the collaboration levels. Each line represents a collaboration level: R- Red, HR – Cyan, HOR- Green, H – Blue. The optimal β (X axis) and the highest score (Y axis) are marked with a black circle. The highest line represents the best collaboration level. In this example, for optimal β's, the best collaboration level is HR.

Figure 10 presents another example in which the best collaboration level is R, hence, only deviations in βr can cause level shifting to maintain optimal performance.

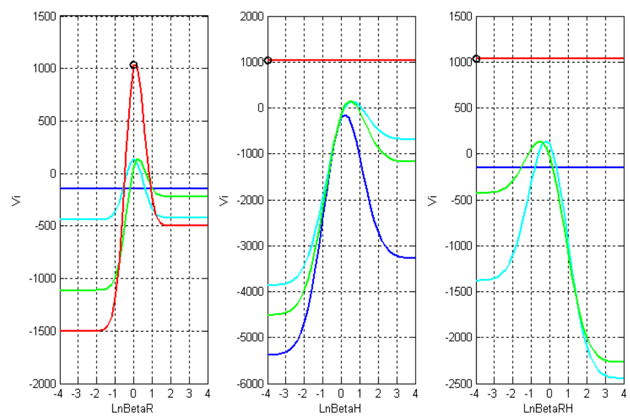

Fig.10. Small deviations in βr drastically affect the objective function score and cause level shifting from R to H to maintain optimal performance.

V. SUMMARY AND CONCLUSIONS

The numeric analysis exposed two different behavior types; 'Type 1', geared towards minimizing false alarms and 'Type 2' geared towards detecting targets. Results indicate that an increase in the human or robot sensitivities led to an increase in the objective function score for both types, since higher sensitivity increase the discrimination ability between target and noise (no target object). Better sensitivity leads to more target detections and less false alarms and thus regardless of the system's type or method of reward or penalty the objective function score increases. Furthermore, the manual collaboration mode (H) was never the best collaboration level; this may be the result of high operational costs and a relatively low detection rate. This implies that collaboration between human and robot in target recognition tasks will always improve system performance. It appears that the improvement in detection rate and hence rise in profits gained by this collaboration outweighs the rise in operational cost attributable to adding the robot to the system.

Results showed opposite tendencies between the two types of systems found. In systems of 'Type 1' as target probability increased R level was preferable in more cases, and as a result collaboration levels were less preferable. In systems of 'Type 2' the trend was reversed: as target probability increased collaboration levels were preferable in more cases. 'Type 1' systems greatly value not committing errors; that is to say, they place high importance on results in situations where no target is present, or target probability is low. In turn, 'Type 2' systems greatly value results in which a target is present. Even though very different tendencies were discovered by the function analysis, several important similarities found between them should be pointed out: in both systems as the probability of the prominent object (non target in 'Type 1' and target in 'Type 2') increases, the R collaboration level will be preferable in more cases and, as the probability of the prominent object decreases, collaboration between human and robot is preferable. It can be assumed that this trend stems from the reciprocation between operational costs and recognition profits.

In addition, sensitivity analysis of the βs indicated that while R collaboration level was only found to be affected by the position of β_r, the two collaboration levels, HOR and HR, were found to be affected by all the three betas. This analysis revealed that in many cases, a small deviation from the optimal value required the system to switch to another collaboration level in order to stay at optimum performance.

Results from this paper can aid in designing new integrated systems and controlling various human-robot systems by mapping the influence of different parameters on the system state. The findings will serve as a foundation for further analysis, which will focus on developing a dynamic model for shifting between collaboration levels based on the system's situation, as shown by the objective function.

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Appendix II: Expression of Z as a function of β and d' (Bechar, 2006)

The standard deviation unit, Z, can be expressed by the likelihood ratio, β, between the signal and noise density functions in the cutoff point x, and the distance between the means of the signal and noise distributions, which is the sensitivity parameter, d'.

i) $d' = Z_N - Z_S$

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

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

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

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

$$\Rightarrow \quad \begin{aligned} Z_N &= \frac{\ln(\beta)}{d'} + \frac{d'}{2} \\ Z_S &= \frac{\ln(\beta)}{d'} - \frac{d'}{2} \end{aligned}$$

Appendix III: Matlab™ code

Creation of initial objective function database

```
% This program create the Objective function database
% for all the following combinations :
% 3. Ps - [0.1,0.5,0.9]         4. d'h and d'r [-0.5:-0.5:3]
% 4. All 3 ln(betas) range is [-4:0.2:4]
% All time parameters are CONSTANTS.
% For each itteration the program saves a file with all the information.


clear
clc
close all


tic
N=1000; % # of objects
Nstr=num2str(N);
             VC=2:4:18;% the cost of one object recognition operation (Hit or False)
%
             for i=1:length(VC)
                  Vcstr=num2str(VC(i));
% Loop 1 : Vfa/Vh aspect ratio
VFA2H=[10];
 for VAR=1:length(VFA2H)
    VARstr=num2str(VFA2H(VAR));

% Loop 2 : Probability for object to be target
    Psvector=[0.1,0.5,0.9];
    for Pscount=1:length(Psvector)
        Ps=Psvector(Pscount);
        Psstr=num2str(Ps);

% Loop 3 : The range of d' for human (second detector)
% the operator sensativity

        dhvector=[-0.5:-0.5:-3];
        for dh=1:length(dhvector)
            dtagH=dhvector(dh);
            Dh=num2str(-dtagH);
% Loop 4 : The range of d' for robot
% the robot sensativity
            drvector=[-0.5:-0.5:-3];
            for dr=1:length(drvector)
                dtagR=drvector(dr);
                Dr=num2str(-dtagR);
  % The constants
         %    for Vfa=10:10:40
                VM=10; % the gain from hit
                VH=20; %-VM*VFA2H(VAR); % the panelty for miss
                VCR=10; % the gain from correct rejection
                VHstr=num2str(VH);
                VMstr=num2str(VM);
                VFA=-VFA2H(VAR)*VH;%VM*VFA2H(VAR); % the panelty for false alarm
                VFAstr=num2str(VFA);
                VCRstr=num2str(VCR);
                Vc=-VC(i);% the cost of one object recognition operation (Hit or False)
               % VCstr = num2str(-Vc);
%                 Vt=-VT(i)/3600; % the cost of one time unit
               Vt=-2000/3600;
               Vtstr=num2str(-Vt*3600);

                tr=0.01; % The robot time.  sec/object on average
                tmotor=2;    %(Tm - motoric time = 2)

                 Td =5;%Td - desicion time ;

            Br=0;
        % Loop 5 : beta r
                for lnbetar=-4:0.2:4
                    Br=Br+1;
```

```
                    Bh=0;
            % Loop 6 : beta h
                    for lnbetah=-4:0.2:4
                        Bh=Bh+1;
                        Brh=0;
            % Loop 7 : beta rh
                        for lnbetarh=-4:0.2:4
                            Brh=Brh+1;


                   tHh(Brh,Bh,Br)=Td;
                   tFAh(Brh,Bh,Br)=Td;
                   tMh(Brh,Bh,Br)=Td;
                   tCRh(Brh,Bh,Br)=Td;

                   tHrh(Brh,Bh,Br)=Td;
                   tFArh(Brh,Bh,Br)=Td;
                   tMrh(Brh,Bh,Br)=Td;
                   tCRrh(Brh,Bh,Br)=Td;

       % the probabilities of the robot
                            Zsr(Brh,Bh,Br)=(-2.*lnbetar+dtagR.^2)./(2.*dtagR); % R's Z of signal
                            Znr(Brh,Bh,Br)=(-2.*lnbetar-dtagR.^2)./(2.*dtagR); % R's Z of noise
                            phr(Brh,Bh,Br)=1-normcdf(Zsr(Brh,Bh,Br)); % R's probability for HIT
                            pfar(Brh,Bh,Br)=1-normcdf(Znr(Brh,Bh,Br)); % R's probability for FALSE


        %the probabilities of the HO (second detector) for object that the
        %robot didn't detect (The desicion is based on Bh)
                            ZsH(Brh,Bh,Br)=(-2.*lnbetah+dtagH.^2)./(2.*dtagH);  % HO's Z for signal
                            ZnH(Brh,Bh,Br)=(-2.*lnbetah-dtagH.^2)./(2.*dtagH);  % HO's Z for noise
                            phh(Brh,Bh,Br)=1-normcdf(ZsH(Brh,Bh,Br)); % HO's probability for HIT
                            pfah(Brh,Bh,Br)=1-normcdf(ZnH(Brh,Bh,Br)); % HO's probability for FALSE

  %the probabilities of the HO (second detector) for object that the robot
  %already detected (The desicion is based on Brh)
                            ZsRH(Brh,Bh,Br)=(-2.*lnbetarh+dtagH.^2)./(2.*dtagH); % HO-R's Z for
signal
                            ZnRH(Brh,Bh,Br)=(-2.*lnbetarh-dtagH.^2)./(2.*dtagH); % HO-R's Z for
noise
                            phrh(Brh,Bh,Br)=1-normcdf(ZsRH(Brh,Bh,Br)); % HO-R's probability for HIT
                            pfarh(Brh,Bh,Br)=1-normcdf(ZnRH(Brh,Bh,Br)); % HO-R's probability for
FALSE

     % HO-R and HO-Rr probabilities and score
                         % probability for HIT
                            PHs(Brh,Bh,Br)=phr(Brh,Bh,Br).*phrh(Brh,Bh,Br)+(1-
phr(Brh,Bh,Br)).*phh(Brh,Bh,Br);
                         % gain from HIT
                            VHs(Brh,Bh,Br)=N.*Ps.*PHs(Brh,Bh,Br).*VH;
                         % System probability for MISS
                            PMs(Brh,Bh,Br)=1-PHs(Brh,Bh,Br);
                         %  penalty from MISS
                            VMs(Brh,Bh,Br)=N.*Ps.*PMs(Brh,Bh,Br).*VM;
                        %  probability for false alarm
                            PFAs(Brh,Bh,Br)=pfar(Brh,Bh,Br).*pfarh(Brh,Bh,Br)+(1-
pfar(Brh,Bh,Br)).*pfah(Brh,Bh,Br);
                         %  penalty from false alarm
                            VFAs(Brh,Bh,Br)=N.*(1-Ps).*PFAs(Brh,Bh,Br).*VFA;
                         %  probability for correct rejection
                            PCRs(Brh,Bh,Br)=1-PFAs(Brh,Bh,Br);
                         %  gain from correct rejection
                            VCRs(Brh,Bh,Br)=N.*(1-Ps).*PCRs(Brh,Bh,Br).*VCR;

       % calculate time parameters

      % HO-Rr CL
                            tsHORr(Brh,Bh,Br)=
N.*Ps.*phr(Brh,Bh,Br).*phrh(Brh,Bh,Br).*(tHrh(Brh,Bh,Br)+tmotor)+N.*Ps.*(1-
phr(Brh,Bh,Br)).*phh(Brh,Bh,Br).*(tHh(Brh,Bh,Br)+tmotor)+N.*(1-
Ps).*pfar(Brh,Bh,Br).*pfarh(Brh,Bh,Br).*(tFArh(Brh,Bh,Br)+tmotor)+N.*(1-Ps).*(1-
pfar(Brh,Bh,Br)).*pfah(Brh,Bh,Br).*(tFAh(Brh,Bh,Br)+tmotor)...
                                     +N.*Ps.*phr(Brh,Bh,Br).*(1-
phrh(Brh,Bh,Br)).*tMrh(Brh,Bh,Br)+N.*Ps.*(1-phr(Brh,Bh,Br)).*(1-
phh(Brh,Bh,Br)).*tMh(Brh,Bh,Br)+N.*(1-Ps).*pfar(Brh,Bh,Br).*(1-
pfarh(Brh,Bh,Br)).*tCRrh(Brh,Bh,Br)+N.*(1-Ps).*(1-pfar(Brh,Bh,Br)).*(1-
pfah(Brh,Bh,Br)).*tCRh(Brh,Bh,Br)+tr;
    % HO-R CL
```

```
                            tsHOR(Brh,Bh,Br)=
N.*Ps.*phr(Brh,Bh,Br).*phrh(Brh,Bh,Br).*tHrh(Brh,Bh,Br)+N.*Ps.*(1-
phr(Brh,Bh,Br)).*phh(Brh,Bh,Br).*(tHh(Brh,Bh,Br)+tmotor)+N.*(1-
Ps).*pfar(Brh,Bh,Br).*pfarh(Brh,Bh,Br).*tFArh(Brh,Bh,Br)+N.*(1-Ps).*(1-
pfar(Brh,Bh,Br)).*pfah(Brh,Bh,Br).*(tFAh(Brh,Bh,Br)+tmotor)...
                                             +N.*Ps.*phr(Brh,Bh,Br).*(1-
phrh(Brh,Bh,Br)).*(tMrh(Brh,Bh,Br)+tmotor)+N.*Ps.*(1-phr(Brh,Bh,Br)).*(1-
phh(Brh,Bh,Br)).*tMh(Brh,Bh,Br)+N.*(1-Ps).*pfar(Brh,Bh,Br).*(1-
pfarh(Brh,Bh,Br)).*(tCRrh(Brh,Bh,Br)+tmotor)+N.*(1-Ps).*(1-pfar(Brh,Bh,Br)).*(1-
pfah(Brh,Bh,Br)).*tCRh(Brh,Bh,Br)+tr;

                            VcHORr(Brh,Bh,Br) = (N.*Ps.*phr(Brh,Bh,Br).*phrh(Brh,Bh,Br)+N.*Ps.*(1-
phr(Brh,Bh,Br)).*phh(Brh,Bh,Br)+N.*(1-Ps).*pfar(Brh,Bh,Br).*pfarh(Brh,Bh,Br)+N.*(1-Ps).*(1-
pfar(Brh,Bh,Br)).*pfah(Brh,Bh,Br)).*Vc;

                            VcHOR(Brh,Bh,Br) = (N.*Ps.*phr(Brh,Bh,Br).*phrh(Brh,Bh,Br)+N.*Ps.*(1-
phr(Brh,Bh,Br)).*phh(Brh,Bh,Br)+N.*(1-Ps).*pfar(Brh,Bh,Br).*pfarh(Brh,Bh,Br)+N.*(1-Ps).*(1-
pfar(Brh,Bh,Br)).*pfah(Brh,Bh,Br)).*Vc;
    % Operational cost (the only different between the levels is the time parameter (first
argument))

                            VTsHORr(Brh,Bh,Br)=tsHORr(Brh,Bh,Br).*Vt+ VcHORr(Brh,Bh,Br);

                            VTsHOR(Brh,Bh,Br)=tsHOR(Brh,Bh,Br).*Vt+VcHOR(Brh,Bh,Br);

    % the objective function for HO-R and HO-Rr

VIsHORr(Brh,Bh,Br)=VHs(Brh,Bh,Br)+VMs(Brh,Bh,Br)+VFAs(Brh,Bh,Br)+VCRs(Brh,Bh,Br)+VTsHORr(Brh,Bh,Br);


VIsHOR(Brh,Bh,Br)=VHs(Brh,Bh,Br)+VMs(Brh,Bh,Br)+VFAs(Brh,Bh,Br)+VCRs(Brh,Bh,Br)+VTsHOR(Brh,Bh,Br);

    % calculating the R level
                            PHsR(Brh,Bh,Br)=phr(Brh,Bh,Br);
                            VHsR(Brh,Bh,Br)=N.*Ps.*PHsR(Brh,Bh,Br).*VH;
                            PFAsR(Brh,Bh,Br)=pfar(Brh,Bh,Br);
                            VFAsR(Brh,Bh,Br)=N.*(1-Ps).*PFAsR(Brh,Bh,Br).*VFA;
                            PMsR(Brh,Bh,Br)=1-PHsR(Brh,Bh,Br);
                            VMsR(Brh,Bh,Br) = N.*Ps.*(PMsR(Brh,Bh,Br)).*VM;
                            PCRsR(Brh,Bh,Br) = 1-PFAsR(Brh,Bh,Br);
                            VCRsR(Brh,Bh,Br) = N.*(1-Ps).*PCRsR(Brh,Bh,Br).*VCR;
   % Operational cost
                            tsR(Brh,Bh,Br)=tr;
                            VcR(Brh,Bh,Br) = (N.*Ps.*PHsR(Brh,Bh,Br)+N.*(1-
Ps).*PFAsR(Brh,Bh,Br)).*Vc;
                            VTsR(Brh,Bh,Br)=tsR(Brh,Bh,Br).*Vt+VcR(Brh,Bh,Br);

    % The objective function for R

VIsR(Brh,Bh,Br)=VHsR(Brh,Bh,Br)+VMsR(Brh,Bh,Br)+VFAsR(Brh,Bh,Br)+VCRsR(Brh,Bh,Br)+VTsR(Brh,Bh,Br);

    % calculating the HO level
                             PHsHO(Brh,Bh,Br)=phh(Brh,Bh,Br);
                             VHsHO(Brh,Bh,Br)=N.*Ps.*PHsHO(Brh,Bh,Br).*VH;
                             PFAsHO(Brh,Bh,Br)=pfah(Brh,Bh,Br);
                             VFAsHO(Brh,Bh,Br)=N.*(1-Ps).*PFAsHO(Brh,Bh,Br).*VFA;
                             PMsHO(Brh,Bh,Br)=1-PHsHO(Brh,Bh,Br);
                             VMsHO(Brh,Bh,Br) = N.*Ps.*PMsHO(Brh,Bh,Br).*VM;
                             PCRsHO(Brh,Bh,Br) = 1-PFAsHO(Brh,Bh,Br);
                             VCRsHO(Brh,Bh,Br) = N.*(1-Ps).*PCRsHO(Brh,Bh,Br).*VCR;
     % Operational cost
                             tsHO(Brh,Bh,Br)=
N.*Ps.*PHsHO(Brh,Bh,Br).*(tHh(Brh,Bh,Br)+tmotor)+N.*(1-
Ps).*PFAsHO(Brh,Bh,Br).*(tFAh(Brh,Bh,Br)+tmotor)...
                                             +N.*Ps.*(1-PHsHO(Brh,Bh,Br)).*tMh(Brh,Bh,Br)+N.*(1-
Ps).*(1-pfah(Brh,Bh,Br)).*tCRh(Brh,Bh,Br);
                             VcHO(Brh,Bh,Br)= (N.*Ps.*phh(Brh,Bh,Br)+N.*(1-
Ps).*pfah(Brh,Bh,Br)).*Vc;

                             VTsHO(Brh,Bh,Br)=tsHO(Brh,Bh,Br).*Vt+VcHO(Brh,Bh,Br);

     % The objective function for HO

VIsHO(Brh,Bh,Br)=VHsHO(Brh,Bh,Br)+VMsHO(Brh,Bh,Br)+VFAsHO(Brh,Bh,Br)+VCRsHO(Brh,Bh,Br)+VTsHO(Brh,Bh,
Br);


                        end % beta r (loop 7) (Br)
                    end % beta h (loop 6) (Bh)
```

```
                end % beta rh (loop 5) (Brh)


fn=['OF_dh_',Dh,'_dr_',Dr,'_Ratio_',VARstr,'_Vc_',Vcstr,'_Vt_',Vtstr,'_Ps_',Psstr,'.mat']


                eval(['save e:\work\db\vc\hit20\',fn]) % allvariables])

              end
             end    %dr (loop 4)
        end    % dh  (loop 3)
        Pscount
    end    % Pscount  (loop 2)
%     VAR
 end   % VAR  (loop 1)
```

Creation of database for optimal betas

```
% Based on the data created in "Database.m" this program finds the optimal Beta for a given:
%  1. dr'     2.dh'     3.Ps    4.Ratio
% and based on the optimal Beta calculate the parameters  for all the collaboration levels

clear
clc
close all

tic


 dhvector=[-0.5:-0.5:-3];
 drvector=[-0.5:-0.5:-3];
 Ps=[0.1,0.5,0.9]     %probability for object to be target



   VFA2H=10; %[0.2,0.3333,3,5];%VFA/VH aspect ratio range
    for VAR=1:length(VFA2H)
        VARstr=num2str(VFA2H(VAR));

     % The constants
                VH=50; % the gain from hit
                VM=10; % the panelty for miss
                VCR=10; % the gain from correct rejection
                VHstr=num2str(VH);
                VMstr=num2str(VM);
                VFA=-VFA2H(VAR)*VH; % the panelty for false alarm
                VFAstr=num2str(VFA);
                VCRstr=num2str(VCR);
                Vc=-2; % the cost of one object recognition operation (Hit or False)
                VCstr=num2str(-Vc);
                Vt=-2000/3600; % the cost of one time unit
                Vtstr=num2str(-Vt*3600);
                tr=0.01; % The robot time.  sec/object on average
                Td = 5;
                td = num2str(Td);

        for P=1:length(Ps)
            Psstr=num2str(Ps(P));

            for dh=1:length(dhvector)       % the range of d' for human (second detector)
                dtag=dhvector(dh);
                Dh=num2str(-dtag);

                for dr=1:length(drvector)      % the range of d' for robot (first detector)
                    dtagR=drvector(dr) ;
                    Dr=num2str(-dtagR);
                    %load the data was created with Database.m

fn=['OF_dh_',Dh,'_dr_',Dr,'_Ratio_',VARstr,'_Vc_',VCstr,'_Vt_',Vtstr,'_Ps_',Psstr,'_td_',td,'.mat']
                    var =[' VIsHO PHsHO tsHO  VcHO VcR VcHOR VcHORr VTsHO PFAsHO VIsR PHsR tsR VTsR
PFAsR VIsHOR PHs tsHOR VTsHOR PFAs VIsHORr tsHORr VTsHORr'];
                    eval(['load e:\work\db\td\hit20\',fn var])

         % Calculate the parmeters with optimal Beta for the HO level ***

                 % Find index of optimal Beta
                    HOVIs(dr,dh,P)=max(VIsHO(:)); % find the max value of VIsHO
                    [x y]=find(VIsHO==HOVIs(dr,dh,P)); % find the indexes of Max(VIsHO)
```

```
                    brhs_VIsHO(dr,dh,P)=x(1); % X index
                    brs_VIsHO(dr,dh,P)=ceil(y(1)./41); % Z index
                    bhs_VIsHO(dr,dh,P)=y(1)-41*(brs_VIsHO(dr,dh,P)-1); % Y index

                  % create the HO optimal data metrix based on  optimal Beta
                    HOPHs(dr,dh,P)=PHsHO(brhs_VIsHO(dr,dh,P),bhs_VIsHO(dr,dh,P),brs_VIsHO(dr,dh,P));

HOPfa(dr,dh,P)=PFAsHO(brhs_VIsHO(dr,dh,P),bhs_VIsHO(dr,dh,P),brs_VIsHO(dr,dh,P));

HOVts(dr,dh,P)=tsHO(brhs_VIsHO(dr,dh,P),bhs_VIsHO(dr,dh,P),brs_VIsHO(dr,dh,P)).*Vt;
                    HOVcs(dr,dh,P)=VcHO(brhs_VIsHO(dr,dh,P),bhs_VIsHO(dr,dh,P),brs_VIsHO(dr,dh,P));
                    HOVTs(dr,dh,P)=VTsHO(brhs_VIsHO(dr,dh,P),bhs_VIsHO(dr,dh,P),brs_VIsHO(dr,dh,P));


          % Calculate the parmeters with optimal Beta for the R level
                 % Find index of optimal Beta
                    RVIs(dr,dh,P)=max(VIsR(:));
                    [x y]=find(VIsR==RVIs(dr,dh,P));
                    brhs_VIsR(dr,dh,P)=x(1);% X index
                    brs_VIsR(dr,dh,P)=ceil(y(1)./41); % Z index
                    bhs_VIsR(dr,dh,P)=y(1)-41*(brs_VIsR(dr,dh,P)-1); % Y index

                % create the R data metrix based on  optimal Beta
                    RPHs(dr,dh,P)=PHsR(brhs_VIsR(dr,dh,P),bhs_VIsR(dr,dh,P),brs_VIsR(dr,dh,P));
                    RPfa(dr,dh,P)=PFAsR(brhs_VIsR(dr,dh,P),bhs_VIsR(dr,dh,P),brs_VIsR(dr,dh,P));
                    RVts(dr,dh,P)=tsR(brhs_VIsR(dr,dh,P),bhs_VIsR(dr,dh,P),brs_VIsR(dr,dh,P)).*Vt;
                    RVcs(dr,dh,P)=VcR(brhs_VIsR(dr,dh,P),bhs_VIsR(dr,dh,P),brs_VIsR(dr,dh,P));
                    RVTs(dr,dh,P)=VTsR(brhs_VIsR(dr,dh,P),bhs_VIsR(dr,dh,P),brs_VIsR(dr,dh,P));


              % Calculate the parmeters with optimal Beta for the HO-R level
                 % Find index of optimal Beta
                    HORVIs(dr,dh,P)=max(VIsHOR(:));
                    [x y]=find(VIsHOR==HORVIs(dr,dh,P));
                    brhs_VIsHOR(dr,dh,P)=x(1); % X index
                    brs_VIsHOR(dr,dh,P)=ceil(y(1)./41); % Z index
                    bhs_VIsHOR(dr,dh,P)=y(1)-41*(brs_VIsHOR(dr,dh,P)-1);% Y index

                % create the HO-R data metrix based on  optimal Beta

HORPHs(dr,dh,P)=PHs(brhs_VIsHOR(dr,dh,P),bhs_VIsHOR(dr,dh,P),brs_VIsHOR(dr,dh,P));

HORPfa(dr,dh,P)=PFAs(brhs_VIsHOR(dr,dh,P),bhs_VIsHOR(dr,dh,P),brs_VIsHOR(dr,dh,P));

HORVts(dr,dh,P)=tsHOR(brhs_VIsHOR(dr,dh,P),bhs_VIsHOR(dr,dh,P),brs_VIsHOR(dr,dh,P)).*Vt;

HORVcs(dr,dh,P)=VcHOR(brhs_VIsHOR(dr,dh,P),bhs_VIsHOR(dr,dh,P),brs_VIsHOR(dr,dh,P));

HORVTs(dr,dh,P)=VTsHOR(brhs_VIsHOR(dr,dh,P),bhs_VIsHOR(dr,dh,P),brs_VIsHOR(dr,dh,P));


                % Calculate the parmeters with optimal Beta for the HO-Rr level
                 % Find optimal Beta
                    HORrVIs(dr,dh,P)=max((VIsHORr(:)));
                    [x y]=find(VIsHORr==HORrVIs(dr,dh,P));
                    brhs_VIsHORr(dr,dh,P)=x(1);
                    brs_VIsHORr(dr,dh,P)=ceil(y(1)./41);
                    bhs_VIsHORr(dr,dh,P)=y(1)-41*(brs_VIsHORr(dr,dh,P)-1);

                % create the HO-Rr data metrix based on  optimal Beta

HORrPHs(dr,dh,P)=PHs(brhs_VIsHORr(dr,dh,P),bhs_VIsHORr(dr,dh,P),brs_VIsHORr(dr,dh,P));

HORrPfa(dr,dh,P)=PFAs(brhs_VIsHORr(dr,dh,P),bhs_VIsHORr(dr,dh,P),brs_VIsHORr(dr,dh,P));

HORrVts(dr,dh,P)=tsHORr(brhs_VIsHORr(dr,dh,P),bhs_VIsHORr(dr,dh,P),brs_VIsHORr(dr,dh,P)).*Vt;

HORrVcs(dr,dh,P)=VcHORr(brhs_VIsHORr(dr,dh,P),bhs_VIsHORr(dr,dh,P),brs_VIsHORr(dr,dh,P));

HORrVTs(dr,dh,P)=VTsHORr(brhs_VIsHORr(dr,dh,P),bhs_VIsHORr(dr,dh,P),brs_VIsHORr(dr,dh,P));


                %find Max objective function
                    Vi_Temp=[HOVIs(dr,dh,P),HORrVIs(dr,dh,P),HORVIs(dr,dh,P),RVIs(dr,dh,P)];
                    Vi_max(dr,dh,P)=max(Vi_Temp);

                %find best CL based on Max objective function
                    Temp_CL=find(Vi_Temp==Vi_max(dr,dh,P));
                    BestCL(dr,dh,P)=Temp_CL(1);
```

```
                PH_Temp=[HOPHs(dr,dh,P),HORrPHs(dr,dh,P),HORPHs(dr,dh,P),RPHs(dr,dh,P)];
                PFA_Temp=[HOPfa(dr,dh,P),HORrPfa(dr,dh,P),HORPfa(dr,dh,P),RPfa(dr,dh,P)];

                BestZss(dr,dh,P)=norminv(PH_Temp(Temp_CL(1)));
                BestZns(dr,dh,P)=norminv(PFA_Temp(Temp_CL(1)));

         % find best drtag of the overall system        (Which dtag ? R or H)
                Bestdtag(dr,dh,P)=BestZns(dr,dh,P)-BestZss(dr,dh,P);
                Bestlnbeta(dr,dh,P)=-0.5.*(BestZss(dr,dh,P).^2-BestZns(dr,dh,P).^2);

                if Temp_CL(1)==4 %If the best CL is R
                    Bestdtagsys(dr,dh,P)=drvector(dr);
                    Bestlnbetasys(dr,dh,P)=-4+(brs_VIsR(dr,dh,P)-1).*0.2;
                end

            end     % dr
        end         % dh
        toc
    end             % P

 % Calculate the ratio between the:
 %   1. objective function and the time for recognize.
 %   2. objective function and the operation cost.
    HOVc2Vt=HOVcs./HOVts; % ratio between Vc and Vt
    HOVT2VI=(-1)*HOVTs./(HOVIs-HOVTs); % the Cost precentage
    HO_Vt = (HOVts./Vt);
    HO_Vc = (HOVcs./Vc);
    HO_P_Ratio = HOPfa./HOPHs;

    RVc2Vt=RVcs./RVts;
    RVT2VI=RVTs./(RVIs-RVTs)*(-1);
    R_Vt = (RVts./Vt);
    R_Vc = (RVcs./Vc);
    R_P_Ratio = RPfa./RPHs;

    HORVc2Vt=HORVcs./HORVts;
    HORVT2VI=HORVTs./(HORVIs-HORVTs)*(-1);
    HOR_Vt = (HORVts./Vt);
    HOR_Vc = (HORVcs./Vc);
    HOR_P_Ratio = HORPfa./HORPHs;

    HORrVc2Vt=HORrVcs./HORrVts;
    HORrVT2VI=HORrVTs./(HORrVIs-HORrVTs)*(-1);
    HORr_Vt = (HORrVts./Vt);
    HORr_Vc = (HORrVcs./Vc);
    HORr_P_Ratio = HORrPfa./HORrPHs;

% Calculate the optimal beta based on the indices found for each CL
    beta_rhHO=-4+(brhs_VIsHO-1).*0.2;
    beta_rhR=-4+(brhs_VIsR-1).*0.2;
    beta_rhHORr=-4+(brhs_VIsHORr-1).*0.2;
    beta_rhHOR=-4+(brhs_VIsHOR-1).*0.2;

    beta_hHO=-4+(bhs_VIsHO-1).*0.2;
    beta_hR=-4+(bhs_VIsR-1).*0.2;
    beta_hHORr=-4+(bhs_VIsHORr-1).*0.2;
    beta_hHOR=-4+(bhs_VIsHOR-1).*0.2;

    beta_rHO=-4+(brs_VIsHO-1).*0.2;
    beta_rR=-4+(brs_VIsR-1).*0.2;
    beta_rHORr=-4+(brs_VIsHORr-1).*0.2;
    beta_rHOR=-4+(brs_VIsHOR-1).*0.2;


  %  Create matrix for each Beta (rh , h , r)

    Allbeta_rh(:,:,:,1)=beta_rhHO;
    Allbeta_rh(:,:,:,2)=beta_rhHORr;
    Allbeta_rh(:,:,:,3)=beta_rhHOR;
    Allbeta_rh(:,:,:,4)=beta_rhR;

    Allbeta_h(:,:,:,1)=beta_hHO;
    Allbeta_h(:,:,:,2)=beta_hHORr;
    Allbeta_h(:,:,:,3)=beta_hHOR;
    Allbeta_h(:,:,:,4)=beta_hR;

    Allbeta_r(:,:,:,1)=beta_rHO;
    Allbeta_r(:,:,:,2)=beta_rHORr;
```

```
        Allbeta_r(:,:,:,3)=beta_rHOR;
        Allbeta_r(:,:,:,4)=beta_rR;

       % save e:\work\analysis\OF_optBeta_data2
        tmp=['OF_optBeta_Ratio_',VARstr,'_td_',td,'.mat']
        eval(['save e:\work\analysis\td\',tmp])
        beep


   end         % VAR1
```

Sensitivity analysis of the betas

```
% Sensitivity analysis of the betas

clear
clc
close all

tic


 dhvector= [-0.5:-0.5:-3];
 drvector= [-0.5:-0.5:-3];
 Ps=[0.1,0.5,0.9];     %probability for object to be target
beta=-4:0.2:4;

 VFA2H=0.2; %5
        VARstr=num2str(VFA2H);

                     % The constants

                Vc=-2; % the cost of one object recognition operation (Hit or False)
                VCstr=num2str(-Vc);
                Vt=-2000/3600; % the cost of one time unit
                Vtstr=num2str(-Vt*3600);
                tr=0.01; % The robot time.  sec/object on average


          fn1=['OF_optBeta_Ratio_',VARstr,'.mat'];
        var1 = (' Allbeta_r Allbeta_h Allbeta_rh BestCL Vi_max brhs_VIsHO brs_VIsHO bhs_VIsHO
brhs_VIsR brs_VIsR bhs_VIsR brhs_VIsHOR brs_VIsHOR bhs_VIsHOR brhs_VIsHORr brs_VIsHORr
bhs_VIsHORr');
        eval(['load e:\work\analysis\',fn1 var1])


            P = 3; % This is for the index of Ps
            Psstr=num2str(Ps(P));

                dh=1      % the index of d' for human (second detector)
                h=-dhvector(dh);
                Dh=num2str(h);

                 dr=1        % the index of d' for robot (first detector)
                        r=-drvector(dr) ;
                    Dr=num2str(r);
                    figure('Name',['Dr =',Dr,'  Dh =',Dh,'  Ps
=',Psstr],'NumberTitle','off','color','white');

                    %load the data was created with Database.m

fn=['OF_dh_',Dh,'_dr_',Dr,'_Ratio_',VARstr,'_Vc_',VCstr,'_Vt_',Vtstr,'_Ps_',Psstr,'.mat']
                    var =[' VIsHO VIsR VIsHOR VIsHORr'];
                    eval(['load e:\work\db\',fn var])
   % Sens of Br
                    Bcl = BestCL(dr,dh,P); % Saving the best CL
                    Vmax = Vi_max(dr,dh,P); % Saving the max value of the objective function
                    Bmax = Allbeta_r(dr,dh,P,Bcl);
                    ViHO = VIsHO(brhs_VIsHO(dr,dh,P),bhs_VIsHO(dr,dh,P),:);
                    ViHOR = VIsHOR(brhs_VIsHOR(dr,dh,P),bhs_VIsHOR(dr,dh,P),:);
                    ViHORr = VIsHORr(brhs_VIsHORr(dr,dh,P),bhs_VIsHORr(dr,dh,P),:);
                    ViR = VIsR(brhs_VIsR(dr,dh,P),bhs_VIsR(dr,dh,P),:);
                    subplot(1,3,1);
                    f1=plot
(beta,ViHO(:),'b',beta,ViHORr(:),'c',beta,ViHOR(:),'g',beta,ViR(:),'r',Bmax,Vmax,'ok')
                    set(f1,'LineWidth',1.5);
                    set(gca,'XTick',-4:1:4);
                    title(['Dr = ',Dr,' Dh = ',Dh,' Ps = ',Psstr]);
                    xlabel ('LnBetaR');
```

```
                    ylabel ('Vi');
                    grid on;

        % Sens of Bh
                    Bmax = Allbeta_h(dr,dh,P,Bcl);
                    ViHO = VIsHO(brhs_VIsHO(dr,dh,P),:,brs_VIsHO(dr,dh,P));
                    ViHOR = VIsHOR(brhs_VIsHOR(dr,dh,P),:,brs_VIsHOR(dr,dh,P));
                    ViHORr = VIsHORr(brhs_VIsHORr(dr,dh,P),:,brs_VIsHORr(dr,dh,P));
                    ViR = VIsR(brhs_VIsR(dr,dh,P),:,brs_VIsR(dr,dh,P));
                    subplot(1,3,2);
                    f2=plot
(beta,ViHO(:),'b',beta,ViHORr(:),'c',beta,ViHOR(:),'g',beta,ViR(:),'r',Bmax,Vmax,'ok')
                    set(f2,'LineWidth',1.5);
                    set(gca,'XTick',-4:1:4);
                    title(['Dr = ',Dr,' Dh = ',Dh,' Ps = ',Psstr]);
                    xlabel ('LnBetaH');
                    ylabel ('Vi');
                    grid on;

       % Sens of Brh
                    Bmax = Allbeta_rh(dr,dh,P,Bcl);
                    ViHO = VIsHO(:,bhs_VIsHO(dr,dh,P),brs_VIsHO(dr,dh,P));
                    ViHOR = VIsHOR(:,bhs_VIsHOR(dr,dh,P),brs_VIsHOR(dr,dh,P));
                    ViHORr = VIsHORr(:,bhs_VIsHORr(dr,dh,P),brs_VIsHORr(dr,dh,P));
                    ViR = VIsR(:,bhs_VIsR(dr,dh,P),brs_VIsR(dr,dh,P));
                    subplot(1,3,3);
                    f3=plot
(beta,ViHO(:),'b',beta,ViHORr(:),'c',beta,ViHOR(:),'g',beta,ViR(:),'r',Bmax,Vmax,'ok')
                    set(f3,'LineWidth',1.5);
                    set(gca,'XTick',-4:1:4);
                    title(['Dr = ',Dr,' Dh = ',Dh,' Ps = ',Psstr]);
                    xlabel ('LnBetaRH');
                    ylabel ('Vi');
                    grid on;
```

Sensitivity analysis of d'r

```
% Sensitivity analysis of the Dr

clear
clc
close all

tic


 dhvector= [-0.5:-0.5:-3];
 drvector= [-0.5:-0.5:-3];
 Ps=[0.1,0.5,0.9];      %probability for object to be target


    Ratio=0.2; %5

        VARstr=num2str(Ratio);


        fn1 =['OF_optBeta_Ratio_',VARstr,'.mat'];
        var1 = (' Vi_max HOVIs HORrVIs HORVIs RVIs');
        eval(['load e:\work\analysis\',fn1 var1])



        for P=1:length(Ps)
            Psstr=num2str(Ps(P));
            figure('Name',['Ratio',VARstr,'  Ps =',Psstr],'NumberTitle','off','color','white');

            for dh=1:length(dhvector)
                h=-dhvector(dh);
                Dh=num2str(h);


                    subplot(2,3,dh);
                   f1=plot
(dhvector,HOVIs(:,dh,P),'b',dhvector,HORrVIs(:,dh,P),'c',dhvector,HORVIs(:,dh,P),'g',dhvector,RVIs(:
,dh,P),'r')
                    set(f1,'LineWidth',1.5);
                    set(gca,'XTick',-4:1:4);
                    title([' Dh = ',Dh]);
                    xlabel ('Dr');
```

```
                    ylabel ('Vi');
                    grid on;

            end         % dh
            toc
        end             % P
```

Sensitivity analysis of d'h

```
% Sensitivity analysis of  Dh


clear
clc
close all

tic


 dhvector= [-0.5:-0.5:-3];
 drvector= [-0.5:-0.5:-3];
 Ps=[0.1,0.5,0.9];     %probability for object to be target


    Ratio=0.2; %5   %The ratio == (Wcr-Wfa)/(Wh-Wm)

        VARstr=num2str(Ratio)

      % Load the Data files

         fn1 =['OF_optBeta_Ratio_',VARstr,'.mat'];
        var1 = (' Vi_max HOVIs HORrVIs HORVIs RVIs');
        eval(['load e:\work\analysis\',fn1 var1])


        for P=1:length(Ps)
            Psstr=num2str(Ps(P));
            figure('Name',['Ratio',VARstr,'  Ps =',Psstr],'NumberTitle','off','color','white');

                for dr=1:length(drvector)      % the range of d' for robot (first detector)
                    r=-drvector(dr) ;
                    Dr=num2str(r);

                    subplot(2,3,dr);

              % Graph properties
                    f1=plot
(dhvector,HOVIs(dr,:,P),'b',dhvector,HORrVIs(dr,:,P),'c',dhvector,HORVIs(dr,:,P),'g',dhvector,RVIs(d
r,:,P),'r')
                    set(f1,'LineWidth',1.5);
                    set(gca,'XTick',-3:0.5:-0.5);
                    title([' Dr = ',Dr]);
                    xlabel ('Dh');
                    ylabel ('Vi');
                    grid on;


  %              end     % dr
            end         % dh
            toc
        end             % P
```

Appendix IV: Additional results of *'Type 1'* systems

Figure A-1 presents additional results of *'Type 1'* systems. In the following results (figure A-1) the ratios between the objective function weights (W_{FA2H}, W_{CR2M} and W_{M2H}) were set with different values than the results presented in the work. Therefore, these results reflect different systems with different assignments.

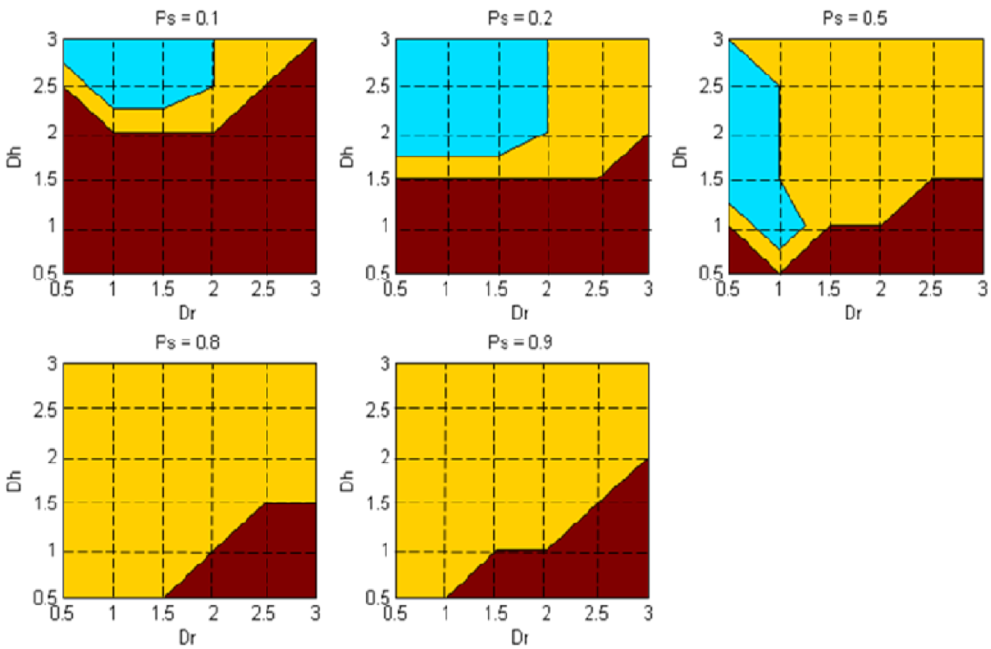

Figure A-1: Example of 'Type 1' systems best operational level maps for different target probabilities. HR – Cyan, HOR - Yellow and R – Red.

The tendency of the best operational level maps as a function of the target probability match the behavior of *'Type 1'*. As target probability increases, the HR and HOR levels become more dominant as the best levels. Notice that in this example (Figure A-1), as well, the human operator by himself (H level) is not the best level for any case.

Appendix V: Additional results of *'Type 2'* systems

Figure A-2 presents additional results of *'Type 2'* systems. In the following results (figure A-2) the ratios between the objective function weights (W_{FA2H}, W_{CR2M} and W_{M2H}) were set with different values than the results presented in the work. Therefore, these results reflect different systems with different assignments.

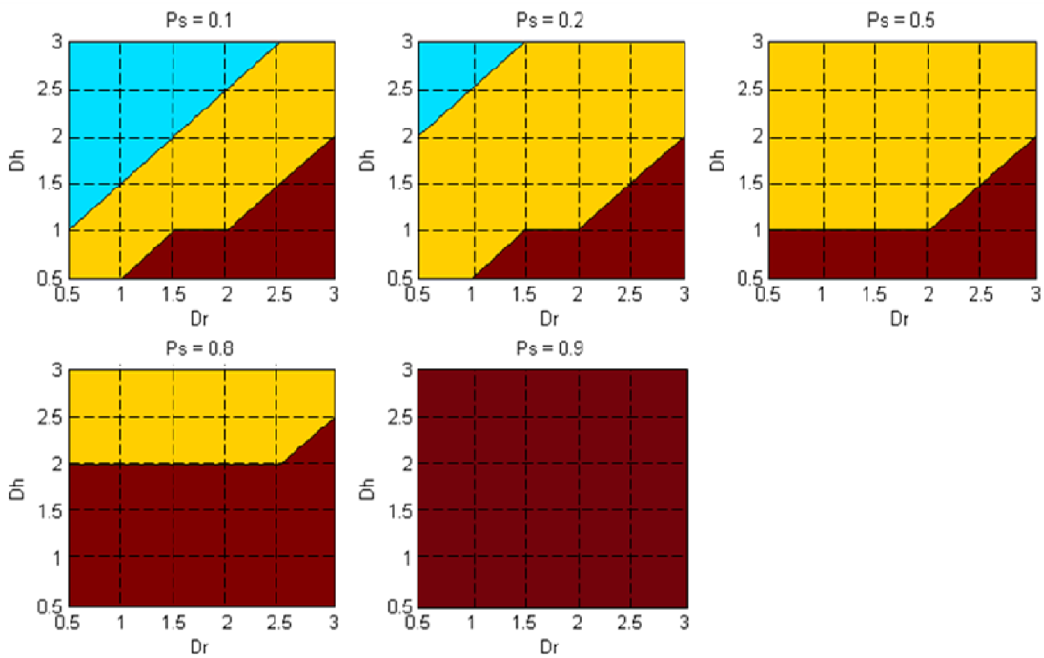

Figure A-2: Example of 'Type 2' systems best operational level maps for different target probabilities. HR – Cyan, HOR - Yellow and R – Red.

The results are different than the results which are presented in the work. However, the tendency of the best operational level maps as a function of the target probability is the same and matches to the definition of *'Type 2'* behaviour. As target probability increases, the R level becomes more dominant.

Appendix VI: Additional results of the symmetry property

Figures A-3 and A-4 present an example of the symmetry property for ‘*Type 1*’ systems. The objective function score maps of two different *‘Type 1’* systems show an identical operational level maps, which is presented in figure A-1.

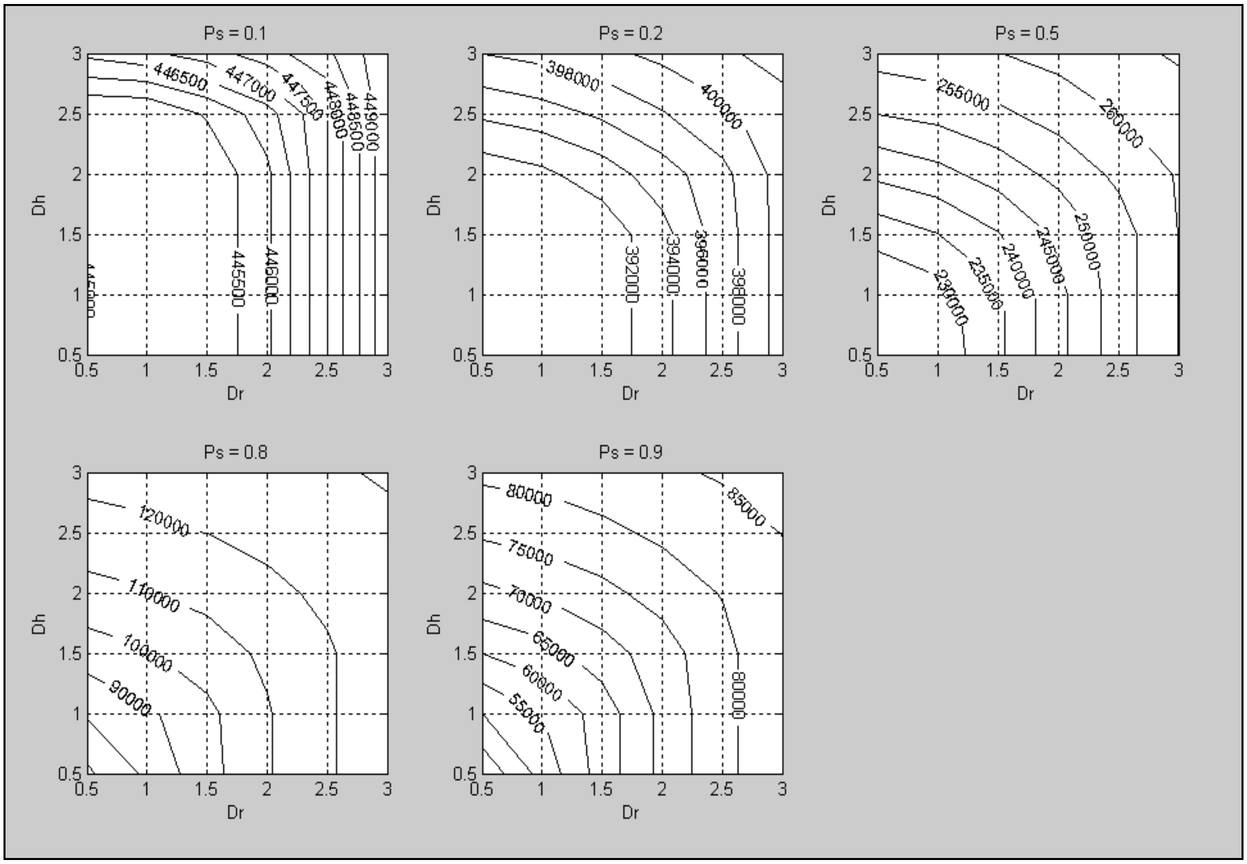

Figure A-3: Example of *‘Type 1’* objective function graph where the system’s goal is achieved by giving high reward for ‘correct rejection’ proportionally to ‘false alarm’

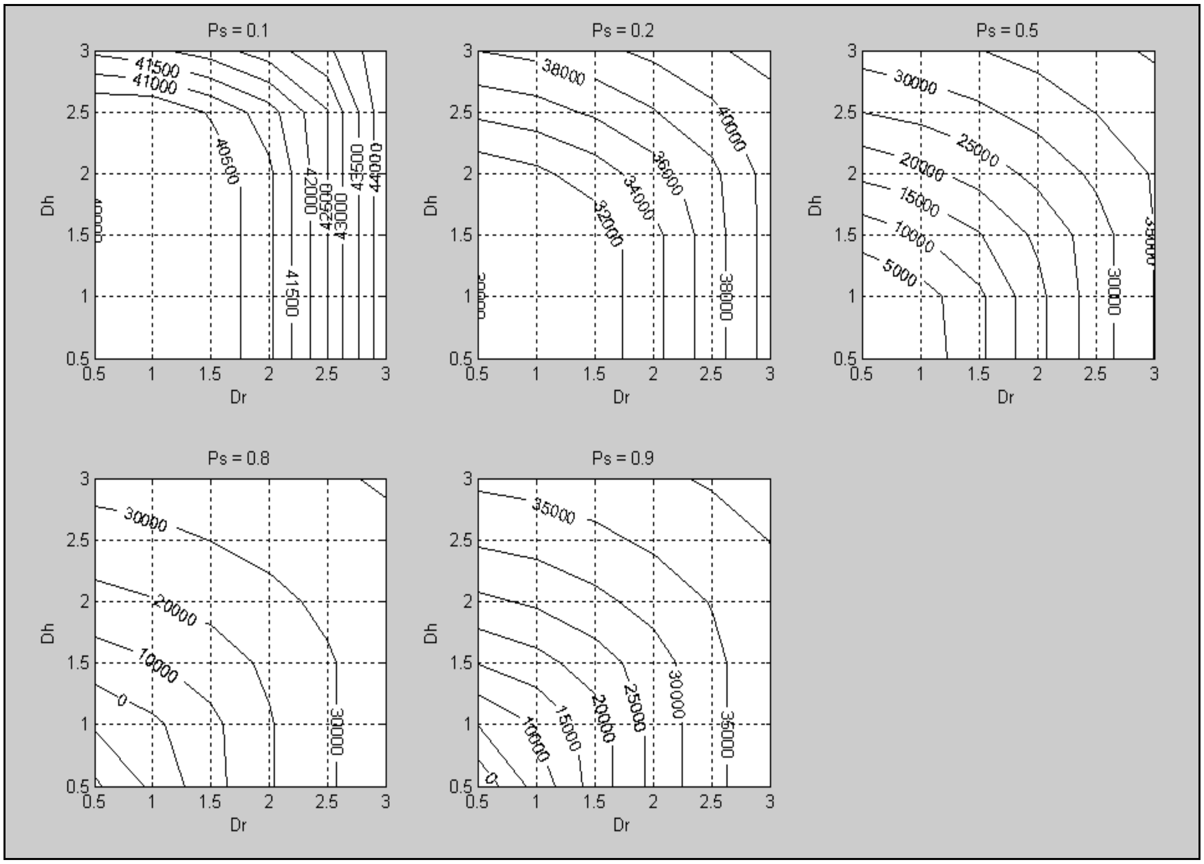

Figure A-4: Example of '*Type 1'* objective function graph where the system's goal is achieved by giving high penalty for 'false alarm' proportionally to 'correct rejection'

Appendix VII: Pseudo code of testing the shift in the best operational level maps

In order to examine the symmetry which was found, a new simulation was conducted which aimed to examine the behaviour of the best operational level maps in the transition between the symmetric weights. The following code presents the analysis between hit weight (W_H) and miss weight (W_M). The same logic was implied for the analysis between correct rejection weight (W_{CR}) and false alarm weight (W_{FA}).

```
W_H = 20
W_M = 5
Δ = |W_H – W_M| = 15
μ = Δ/10 = 1.5
for i=0 to 10
W_H = W_H – i*μ
W_M = W_M + i*μ
.
.
.
```

Appendix VIII: Results of *'Type 2'* sensitivity analysis of βs

The analysis focused on three levels of target probability: Low (P_s = 0.1), Meduim (P_s = 0.5) and High (P_s = 0.9) and the cases where $d'_h > d'_r$. The following results are for system of *'Type 2'* where Δ_1/Δ_2 = 1/5. It should be noted that throughout the entire sensitivity analysis the term 'small deviations' refers to ±1 deviations from the optimal value of the examined β.

<u>Low Target Probability (0.1)</u>

Contrary to the results of *'Type 1'*, for cases where R level was the best level, small deviations (decreasing) from optimal βr force level shifting to one of the collaboration levels: HR or HOR (Figure A-13).

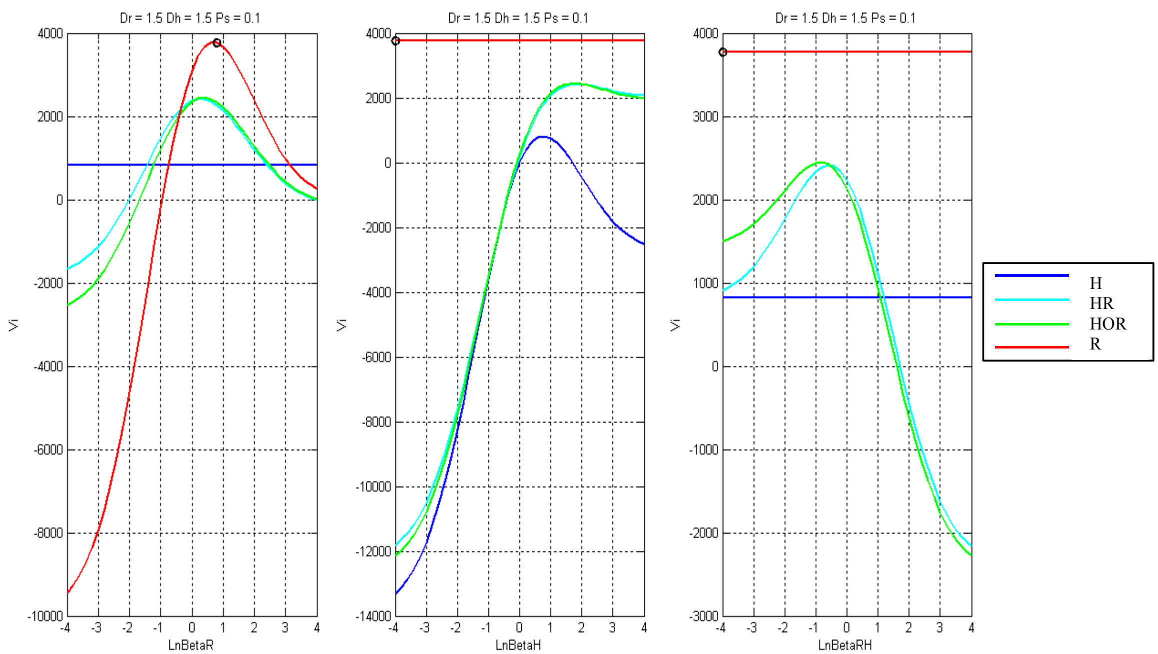

Figure A-5: βs analysis – low target probability and R is the best level

Figure A-14 presents a case where the target probability is low and R is not the best level.

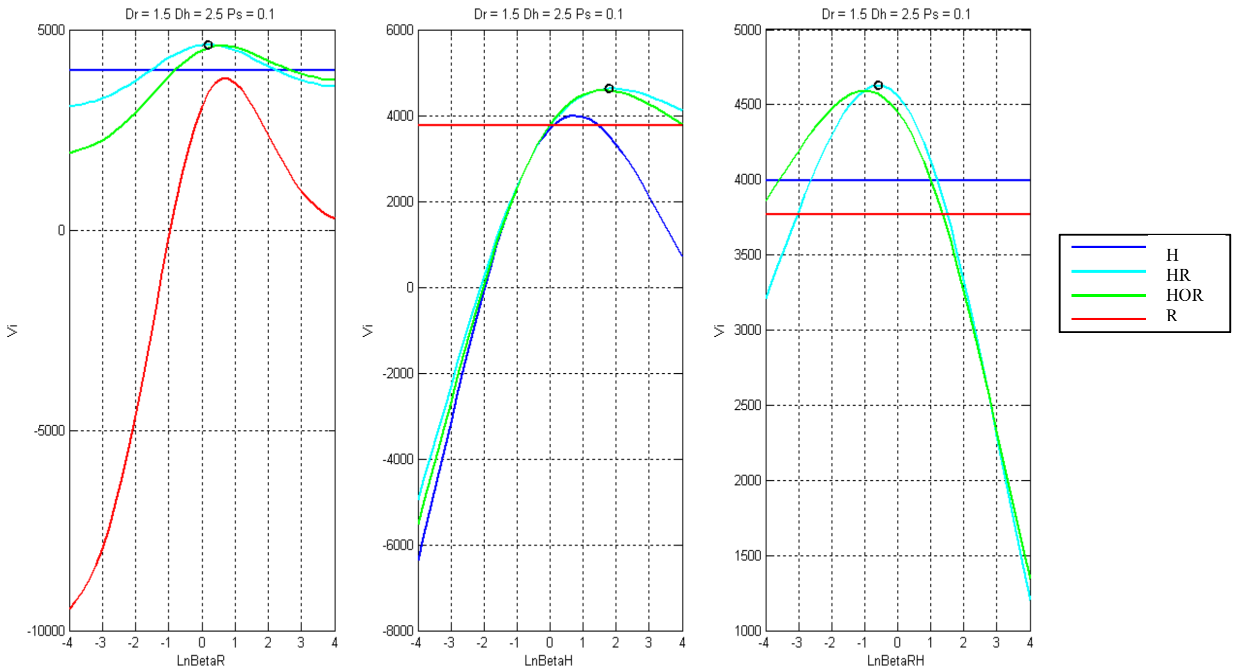

Figure A-6: βs analysis – low target probability and R is not the best level

Results show that small deviations from each of the three βs can cause level shifting between the collaboration levels (HR and HOR). However, for any small deviation, the best operation level will remain HR or HOR. The difference between the results of the two types is derived from the fact that in *'Type 2'*, when the target probability is low, the collaboration levels (HR and HOR) are the most dominant best levels.

Medium Target Probability (P_s = 0.5)

The results for the case where P_s = 0.5 depends on the value of d'$_h$. Figure A-15 presents a case where d'h is low (1.5).

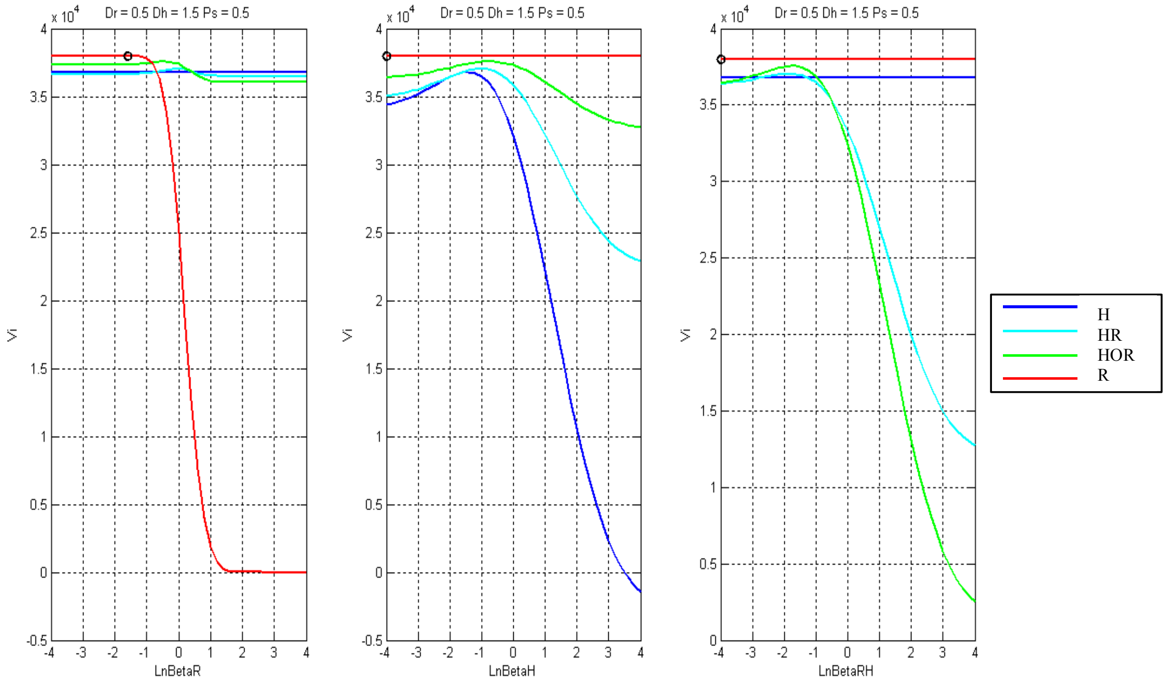

Figure A-7: βs analysis – medium target probability and low d'$_h$

In all the cases where d'$_h$ is low (1.5 or less), the best level in the optimal case is R (the red line). For these cases, small deviations of β_r (increasing) will enforce level shifting to one of the collaboration levels (HR or HOR) in order to maintain optimum.

Figure A-16 presents a case where d'$_h$ is high (above 1.5), thus, the optimal operation level is HOR.

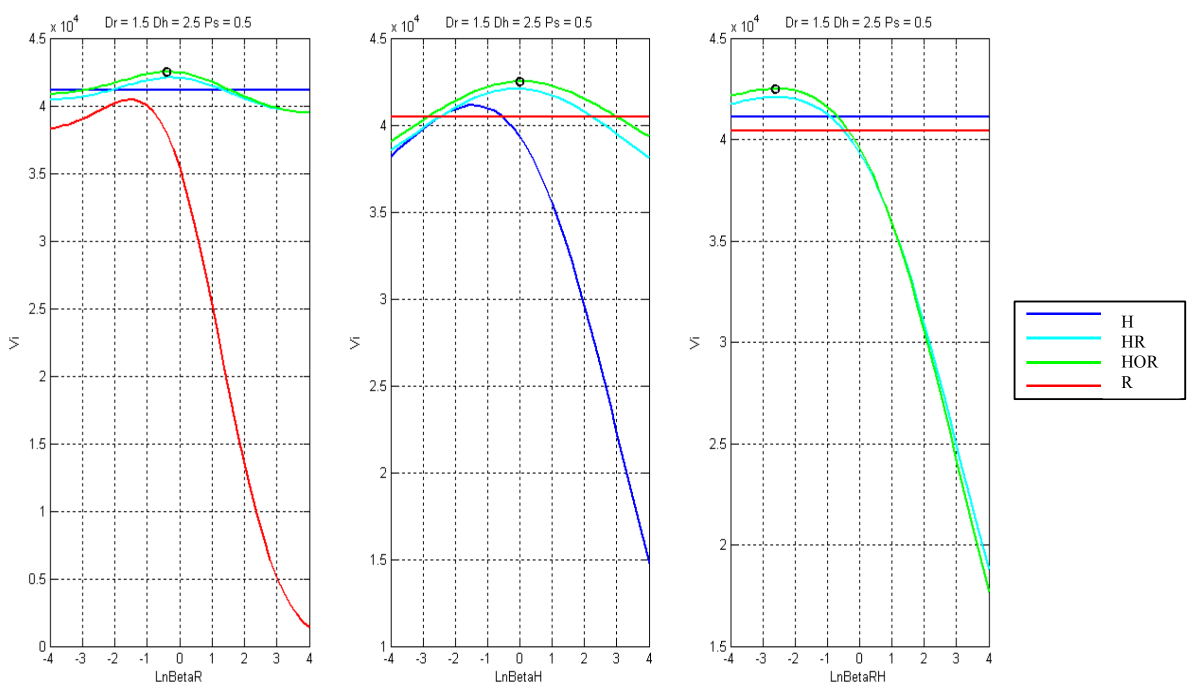

Figure A-8: βs analysis - medium target probability and high d'$_h$

Results show that small deviations from any β will not affect the best operation level.

High Target Probability (P_s = 0.9)

In 'Type 2' systems, when the target probability is high, R level is the most dominant operational level. For all the tested cases, when the R level was the best level, small deviations from the optimal β_r did not force level shifting and the R level remained the best (Figure A-17).

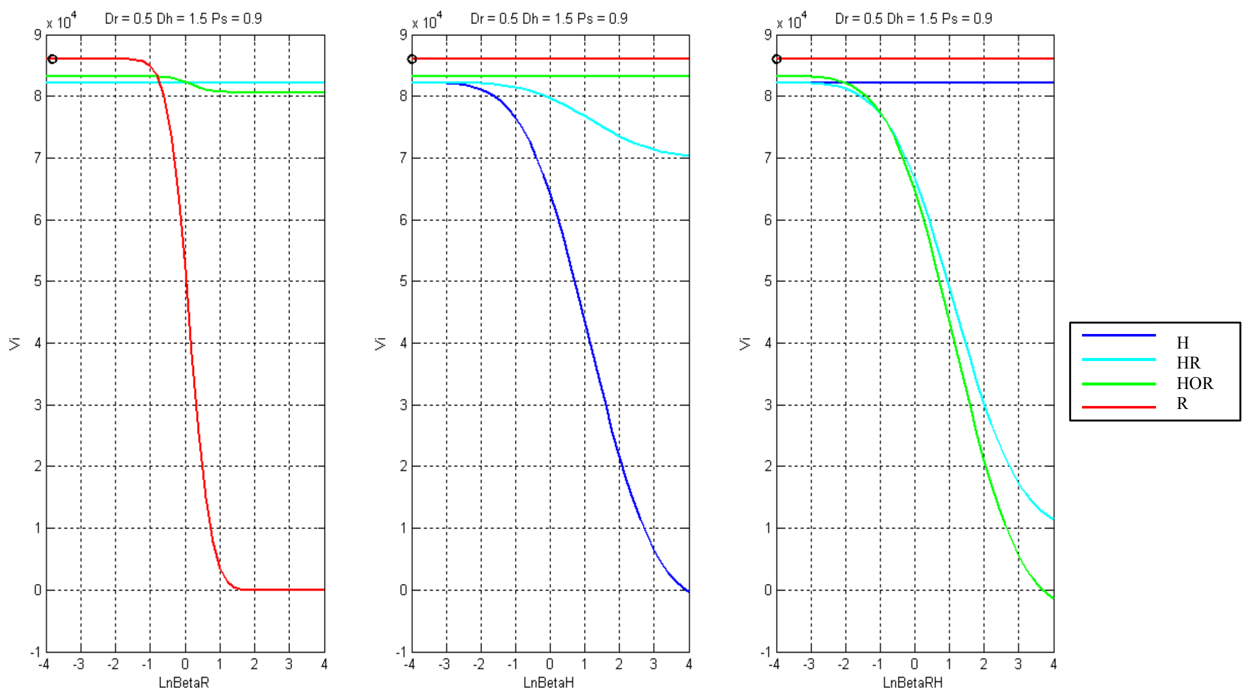

Figure A-9: βs analysis – high target probability

Appendix IX: Results of *'Type 2'* sensitivity analysis of d'$_r$ and d'$_h$

The analysis was performed for both sensitivities: d'$_h$ and d'$_r$. The following results are for system of *'Type 2'* where $\frac{\Delta_1}{\Delta_2} = \frac{1}{5}$.

<u>d'$_r$ Analysis</u>

Figures A-18, A-19 and A-20 present d'$_r$ analysis for: low, medium and high target probabilities respectively.

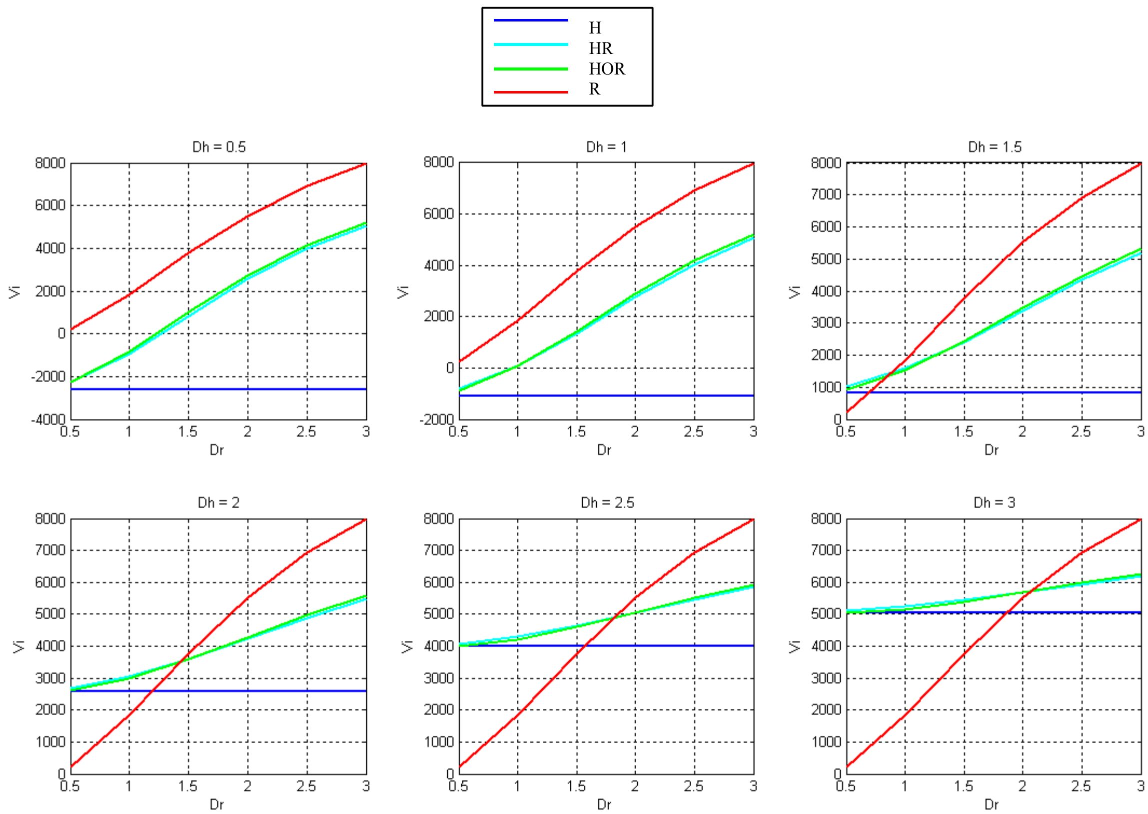

Figure A-10: Sensitivity analysis of d'$_r$ – P_S = 0.1

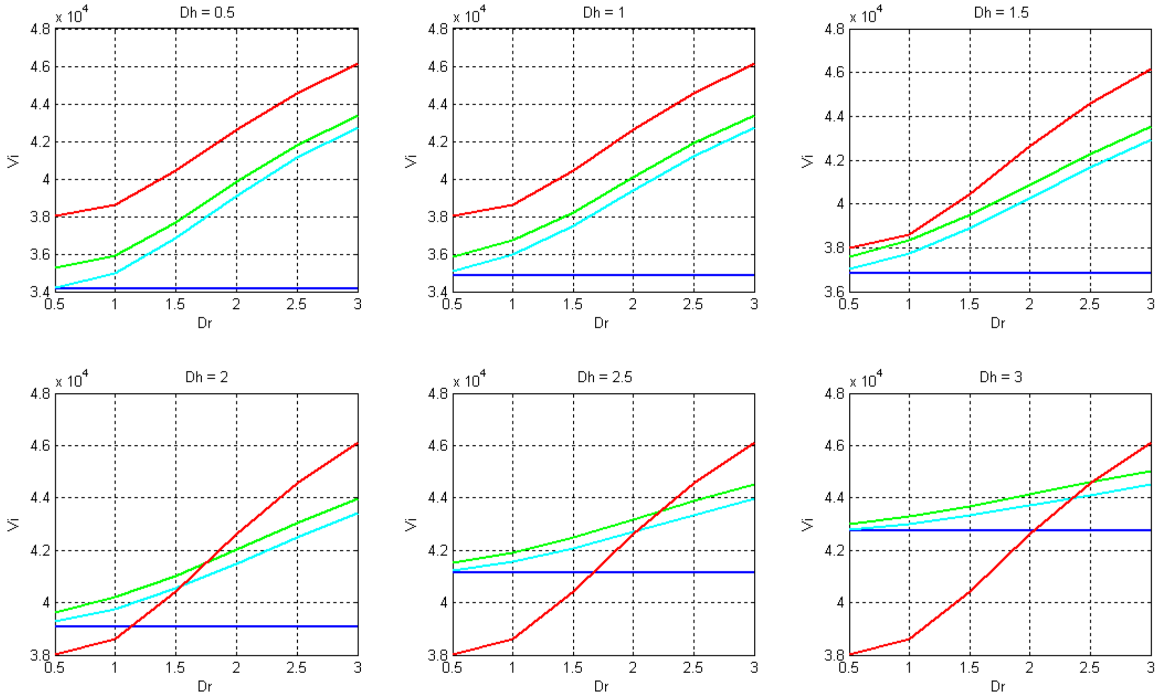

Figure A-11: Sensitivity analysis of d'$_r$ – P$_S$ = 0.5

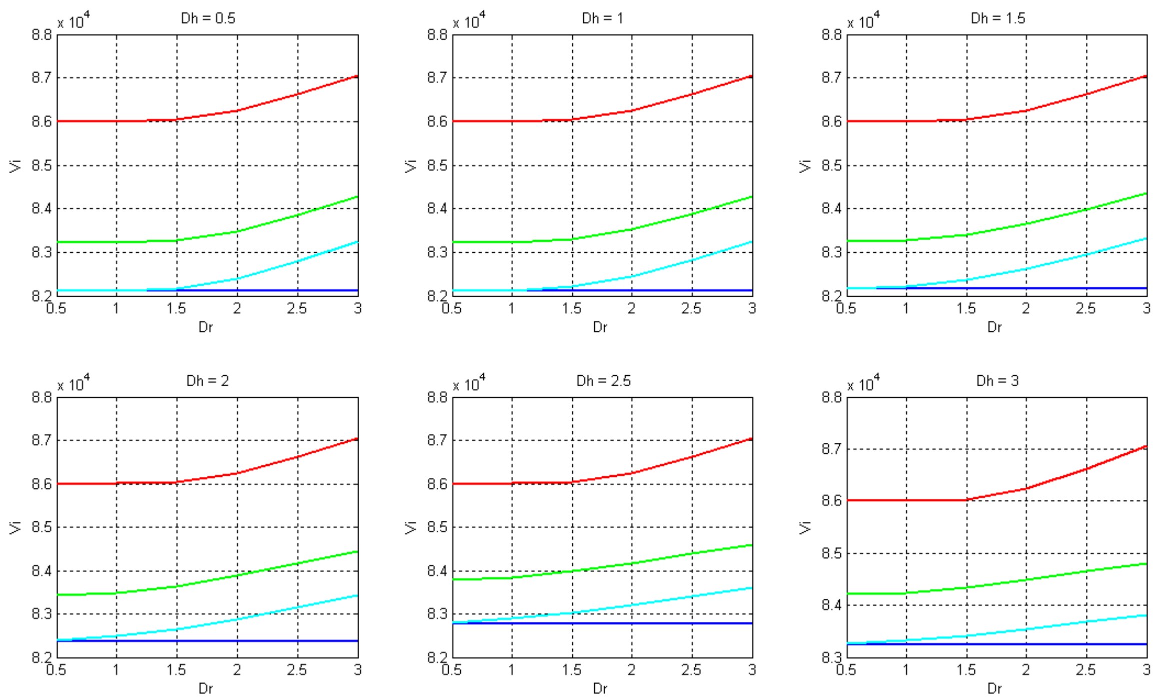

Figure A-12: Sensitivity analysis of d'$_r$– P$_S$ = 0.5

Results show that the influence of d'$_r$ on R level depends on the target probability. As target probability increases, changes in d'$_r$ have less influence on R level (notice that the gradient of R level where P_S = 0.1 is steeper for the case where P_S = 0.9). In addition, as d'_h increases, the influence of d'_r on HR and HOR level decreases.

d'_h analysis

Figures A-21, A-22 and A-23 present d'_h analysis for: low, medium and high target probabilities, respectively.

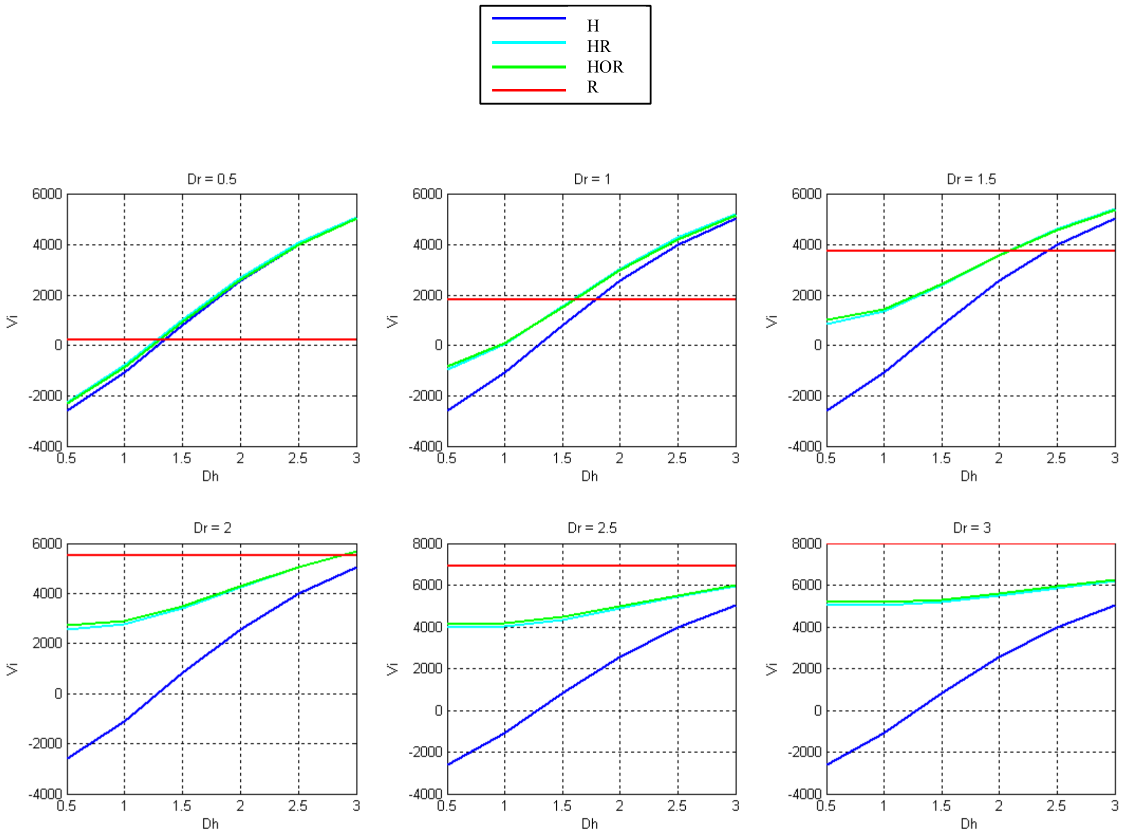

Figure A-13: Sensitivity analysis of d'_h – P_S = 0.1

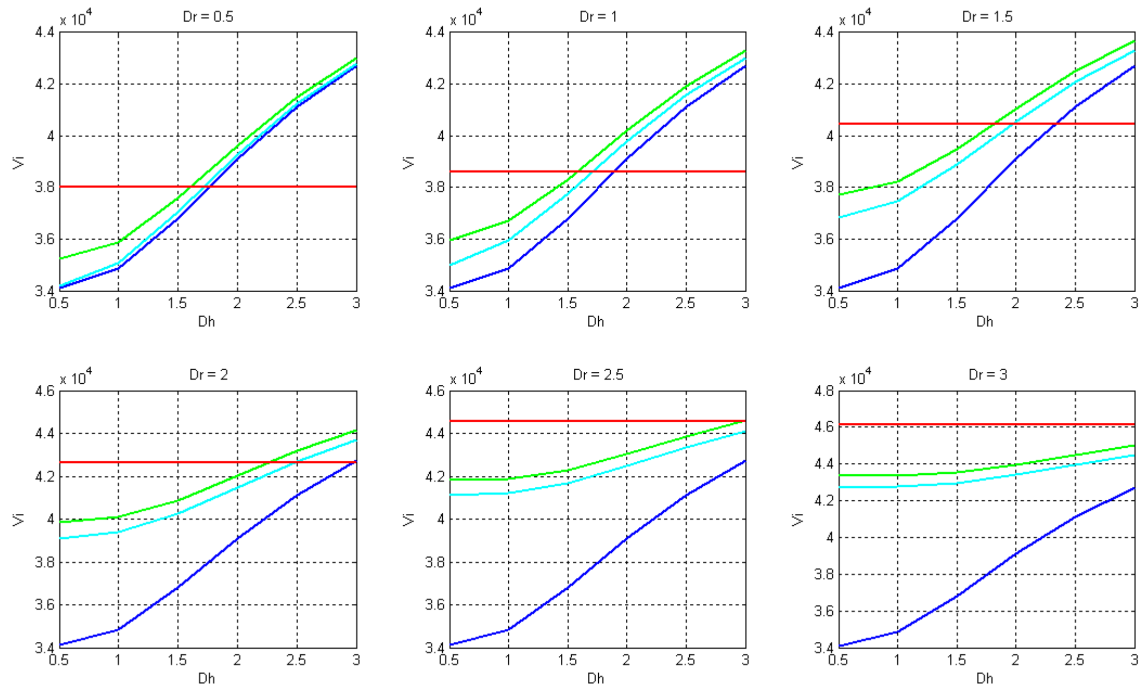

Figure A-14: Sensitivity analysis of d'$_h$ – P_S = 0.5

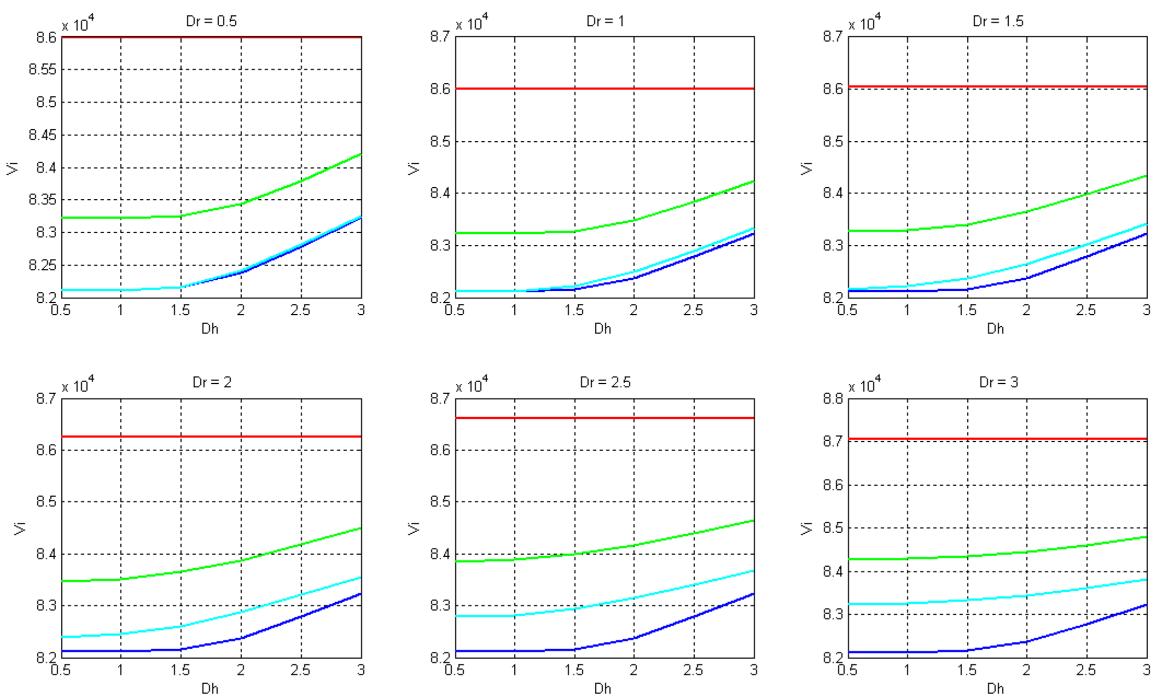

Figure A-15: Sensitivity analysis of d'$_h$ – P_S = 0.9

Results show that the influence of d'$_h$ on H, HR and HOR levels depends on the target probability. As target probability increases, changes in d'$_h$ have less influence on these levels. In addition, as d'$_r$ increases, the influence of d'$_h$ on HR and HOR level decreases.