Towards quantifying false alarms for effective human robot interactions

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Towards Quantifying False Alarms for Effective Human Robot Interactions

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Summary

Human robot teams combining the complementary capabilities of robots and humans towards solving complex tasks are gaining wide spread popularity. Accomplishment of these tasks greatly depends on the quality of interaction between human and the robot thereby requiring models and metrics to evaluate human robot interactions (HRI) in relation to performance. The traditional and most popularly adopted approach to this end has been the neglect tolerance model. The major shortcoming of this traditional model is that it presumes ideal conditions in which an operator switches control between robots sequentially based on an acceptable performance level for each robot whilst ignoring any erroneous interactions.

In this thesis, the erroneous interactions that inevitably arise in HRI are identified as false alarm interactions, classified and their effects estimated. More specifically, two significant metrics that quantify the effects of false alarm interactions are defined, viz. false alarm time, and false alarm demand. In addition, the neglect tolerance model is extended to accommodate for the additional demands due to false alarm interactions. Extended neglect tolerance model is further expanded for multi-robot systems taking into account the independent or co-operating natures of robots in the team.

Traditional neglect tolerance model forms the basis for fan out metric which is adopted as a general index in predicting the maximum number of

robots a single operator can handle simultaneously while maintaining performance at acceptable levels. The fan out metric was redefined to account for additional demands due to the occurrence of false alarm interactions.

Experiments are performed with real and virtual humanoid soccer robots across tele-operation, and semi-autonomous modes of autonomy. Measured HRI metrics were largely consistent with the proposed extended neglect tolerance model predictions for simulation and real robot experiments. Through, statistical analysis of the simulation and experimental results, it is shown that extended neglect tolerance model offers more realistic estimates of robot performance, workload and fan out as compared to the traditional neglect tolerance model.

In this thesis, we put forward a new class of false alarm metrics to measure the susceptibility of robots to false alarm interactions and classify robots based on safe human robot interaction abilities. We analyse the relationship between false alarm interactions and safety in terms of occurrences of accidents. We also demonstrate the efficacy and validity of the proposed metrics by applying them to a service robot.

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1. Introduction

1.1 Motivation

Growing popularity and increasing viable application domains has contributed to greater presence of robots in the commercial marketplace especially in industrial and service space. Robots are now dominating the manufacturing industry performing repetitive manual tasks that are sometimes hazardous to humans. The demand of industrial robots is growing at a rapid pace. The industrial robots are being used for a wide variety of applications, such as automotive, food industry, pharmaceutical industry, packaging industry, etc. They are especially useful for the applications where high precision and accuracy is required. As per the data provided by the International Federation of Robotics (IFR), currently the worldwide market for industrial robots is Euro 4 Billion dollars and it is forecast to grow by 4.2 per cent per year till 2010.

The worldwide stocks of operational industrial robots are estimated to approach 1,173,300 units at the end of 2010 [1]. While industrial robots were designed and developed essentially to perform risky, repetitive and tedious tasks, a new class of service robots are gaining wide spread popularity that are designed to tackle a radically different kind of tasks such as interacting and entertaining human, performing daily chores or even healthcare in a home environment. Recent studies show that robotic systems can be of great help in treating patients who are suffered from long-term illness where therapy oversight, coach and mental motivation can

be provided with minimal or no human intervention [2] [3]. Such systems have great potential as pervasive disorders such as Autism, Anorexia Nervosa and others predominate among children today. In some parts of the world, such robot-assisted therapies are already available at affordable prices to patients covering the range of needs from rehabilitation to promoting reintegration in society or even prevention [4] [5].

With most developed world aging rapidly, several robotic technologies are being developed to help this society in everyday lives, delay the onset of dementia and provide companionship to cope with depression and lack of social interaction [6] [7]. Moreover, robotics sensing and activity modelling methods will potentially play a big role in enhancing early screening and continual assessments and providing a personalized, effective and affordable therapy. All of these efforts will help elderly, whose numbers are on the rise, to better cope with their lives and enable people with disabilities to faster recover and go (back) into the workforce thus maintaining and improving the productivity of the workforce and increasing its size.

A separate survey by world robotics predicts that there are 5.4 million service robots currently in use worldwide and this number is estimated to reach 12.1 million by 2011 [8]. These applications include rehabilitation, service, search-and-rescue, exploration, hazardous waste clean-up, and so on. Some commercial success stories include, Scooba, a domestic robot widely used in many households

for automatic floor washing and cleaning [9]. Robo-Erectus kid, the humanoid toy robot is used in many primary and secondary schools for teaching physics, mathematics and programming languages [10]. More than 1500 PackBots from iRobot are currently on station in Iraq and Afghanistan to handle situations involving potential explosives, aiming to reduce the risk of personal injury [11]. These highly evolving applications of robotics in the recent years show the importance of human robot interaction as more and more robotic products reaches consumer marketplace.

For example, in the Scooba and Robo-Erectus kid applications, the humans and the robots occupy the same physical area dynamically interacting with each other giving rise to a new dimension and a range of new research problems in the field. The interaction between a human and a robot is usually rich and multi-dimensional as the robot cohabits and interacts with a dynamically changing environment involving humans.

One significant contributor hindering the success of human robot teams in both industrial and service domains is the presence of an interaction gap between humans and robots. Several factors including limitation in robot's hardware (sensors, actuators, etc), software, human attention, awareness, cognitive capabilities and task complexities contribute towards this interaction gap. As a result of this gap, erroneous interactions occur between the human operator and the robot negatively impacting the performance of human robot teams.

For example, in a mobile robot navigation task the human operator may select an incorrect way point leading to an erroneous interaction as the mobile robot would fail to reject the interaction as erroneous or there may be a scenario where the human operator may select a correct way point but the mobile robot navigate to an incorrect destination/ignores the human operator inputs due to uncertainties in robot software/hardware leading to an erroneous interactions.

These erroneous interactions impacts the robot performance negatively and increases the workload of the robot operator as he/she has to dedicate additional time and efforts in detecting the faults and rectifying them in order to raise the performance back to pre-erroneous interaction level. However, currently there are no available metrics to quantify these erroneous interactions and traditional estimation models for key metrics including robot performance, robot attention demand and fan out ignores these erroneous interactions. The traditional and most popularly adopted approach towards performance, attention demand and fan out estimations in human robot teams has been the neglect tolerance model.

The major shortcoming of the neglect tolerance model is that it presumes ideal conditions in which an operator switches control between robots sequentially based on an acceptable performance level for each robot whilst ignoring any erroneous interactions. The zero erroneous interaction assumption in neglect tolerance model results in an optimistic estimate of robot attention demand, fan out and robot performance which not only leads to the operator's failure in

accomplishing the scheduled task and fan outs due to higher attention demands in actual situation, but also leads to operator's inability in achieving the performance level set for that task due to the drop in performance attributed to the erroneous interactions. With increasing number of applications requiring more than one robot in the team, neglect tolerance model has also been extended to accommodate multi-robot teams taking into account additional complexities arising due to dependent or independent nature of the robots in the team.

This extension of the model also presumes ideal conditions ignoring any erroneous interactions yielding an optimistic estimate of performance, attention demand and fan out. These factors indicate a real need to extend the neglect tolerance model to accommodate additional demand incurred due to erroneous interactions towards achieving a more realistic estimation of performance, attention demand and fan out.

Occurrences of these erroneous interactions have potential for accidents arising serious concerns towards establishing safe human robot interaction. But, there are no available metrics to measure the susceptibility of robots to erroneous interactions. The availability of a metric class for this purpose would enable the community to classify robots based on safe human robot interaction abilities. Traditionally, humans and robots were separated physically in industrial applications, but in the emerging service robotics domain the physical space between human and robot are rapidly shrinking involving close dynamic

interactions between the two raising new hazards and risks. With more interactions occurring in the case of service robots there are higher chances for erroneous interactions and accidents thereby increasing the need for a metric class to measure the susceptibility of robots to erroneous interactions and classify robots based on safe human robot interaction abilities.

Consequently, the ever increasing application domains for robots in diverse fields and increasing need for robots to interact closely with humans overshadowed by the above challenges inspire and motivate us to investigate and quantify erroneous interactions in human robot teams. This work focuses on extension of traditionally adopted neglect tolerance model for single and multi-robot teams to accommodate for the additional demand incurred due to erroneous interactions. Also, the work formulates a new metric class to measure susceptibility of robot to erroneous interactions and classify robots based on safe human robot interaction abilities.

1.2 Objectives

The objective of this thesis is to study, investigate and quantify the erroneous interactions that affect the estimation of robot performance, attention demand and fan out in human robot teams. In this thesis, the erroneous interactions that inevitably arise in human robot teams are identified as false alarm interactions, and classified into two categories namely; the false positive interaction wherein a robot rejects a "correct" interaction and false negative interaction wherein a robot

fails to reject an "incorrect" interaction. Two significant metrics that quantify the effects of false alarm interactions in human robot teams are defined, viz. false alarm time, and false alarm demand. In addition the neglect tolerance model is extended to accommodate the effects of false alarm interactions while estimating key metrics for both single-robot and multi-robot scenarios.

Also, we put forward a new class of false alarm metrics to measure the susceptibility of robots to false alarm interactions and classify robots based on safe human robot interaction abilities. We analyze the relationship between false alarm interactions and safety in terms of occurrences of accidents. We also demonstrate the efficacy and validity of the proposed metrics and models through extensive simulations and experiments.

1.3 Research Methodologies

This thesis focuses on investigation and quantification of the erroneous interactions that affects the estimation of HRI metrics in a traditional neglect tolerance approach. In particular, literature from the research topics of HRI metrics, HRI evaluations, HRI performance and HRI safety are investigated. The work presented in this thesis proceeds on a theoretical level and on an experimental level.

On the theoretical level, two significant metrics are put forward to quantify the effects of false alarm interactions in human robot teams, viz. false alarm time, and false alarm demand. These newly defined metrics were adopted towards

extension of the traditional neglect tolerance model and its theoretical framework in accommodating the effects of any false alarm interactions while estimating key HRI metrics. Also, this thesis presents a new class of false alarm metrics to measure the susceptibility of robots to false alarm interactions and classify robots based on safe human robot interaction abilities.

On the experimental level, this thesis validates the proposed extended neglect tolerance model and conducts statistical analysis of the simulation and experimental results to compare the extended neglect tolerance model to the traditional approach for both single and multi-robot teams. Experiments were performed with real and virtual humanoid soccer robots across tele-operation, and semi-autonomous modes of autonomy. Virtual-RE Simulator, a high-fidelity game engine based robot simulator, and Robo-Erectus Junior, a soccer playing humanoid robot, were developed for this purpose. In the experiments, the impact of autonomy levels on robot performance was also investigated. This thesis also demonstrates the efficacy and utility of the proposed HRI safety metrics by applying them to a service robot, Robo-Erectus@Home.

1.4 Organization of the thesis

An overview of the research work carried out and the structure of the thesis in concise form are outlined in this section. The rest of the thesis is organized in the following fashion.

Chapter 2 describes the state of the art in human robot interaction domain. Further, major work in evaluation of system performance, operator workload and robot performance are reviewed. This chapter theoretically investigates the traditionally adopted neglect tolerance model for robot performance, attention demand, fan out and other key metric estimations in single and multi robot teams. The short falls that arise in the neglect tolerance model due to zero erroneous interaction assumptions are analyzed.

Chapter 3 identifies and classifies the erroneous interactions and further puts forward two significant metrics namely, false alarm time and false alarm demand to quantify the additional demand incurred due to false alarm interactions in human robot teams. This chapter also presents the extension of the traditionally adopted neglect tolerance model for single robot teams to accommodate the effects of false alarm interactions through incorporation of the proposed false alarm metrics towards offering a more realistic estimate of key metrics. Chapter 3 also presents the simulation and experiments carried out to validate the extended neglect tolerance model. Further, the advantages of the proposed model are investigated in detail and their performance compared against the traditional neglect tolerance model.

Chapter 4 presents the extension of the traditionally adopted neglect tolerance model for multi robot teams to accommodate the effects of false alarm interactions through incorporation of the proposed false alarm metrics towards

offering a more realistic estimate of robot performance, attention demand and other key metrics. Chapter 4 also presents the simulation and experiments carried out to validate the extended neglect tolerance model. It is established how the extended neglect tolerance model offers more realistic estimation of performance and robot attention demand as compared to traditional neglect tolerance model for multi robot teams.

Chapter 4 also presents the redefinition of the traditionally adopted fan out metrics to accommodate the additional demand due to false alarm interactions through incorporation of the proposed false alarm metrics towards offering a more realistic estimate of maximum number of robots a single user can handle simultaneously while maintaining the performance at an acceptable level. The theoretical results are verified using extensive simulations. Experimental verification of the redefined fan out is elaborated using a team of soccer playing humanoid robots.

Chapter 5 analyzes a significant and often neglected topic related to safe human robot interaction and proposes a new class of false alarm metrics to measure the susceptibility of robots to false alarm interactions and classify robots based on safe human robot interaction abilities. Further, the experimental validation of the proposed metric with our walking assistive service robot across tele-operation and semi-autonomous modes are presented. This chapter also presents a Poisson representation of the false alarm interaction in human robot teams towards

computing probabilities of occurrence of false alarm interactions and robots requiring human attention.

Chapter 7 summarizes and concludes the work presented in the thesis and also provides recommendation for the future work.

2. Human Robot Interaction

2.1 Introduction

Rapidly increasing commercially viable applications and technological advancements are the main drivers of the development of human centred robots. Most of the present day robotics applications require frequent interactions between human and the robots. For example, in the commercial arena, the rehabilitation of elderly is an important scenario with much of the developed economy aging very rapidly. Walking assistive robot is one commercially viable solution that would help reduce the operating costs and efficiency of this rehabilitative activity [12] [13].

Walking assistive robots can also enable the elderly to have an independent lifestyle in their accustomed environments. Commercially sponsored projects such as Silbo [14], Honda's Walking Assistant [15], Lokomat [16], Nomura's Walker [17], etc are some examples of landmarks projects that have demonstrated successful implementation of the walking assistive robots for elderly. In these cases of walking assistive robots, the interaction that occurs between the human user and the robot is crucial as any incorrect interactions could lead to accidents and therefore injury to elderly user. In general, the nature of human robot interaction (HRI) is very complex due to the multi-dimensional nature of the interactions that prevail between the robot, human and the operating environment. Experiments with

trust factor in HRI have shown that the impact of operator trust on robot is far greater than the nature or mode of the interaction [18] [19].

Improvement in task performance can be achieved through optimization of robot teams, but cognitive capabilities and situation awareness of a human operator will always be required to select appropriate strategy and robots [20]-[22]. Some of the common hurdles in developing efficient HRI includes noisy sensors and actuators, lack of situation awareness in human user, limitation in communication systems, limitations in computational capabilities and so on [23] [24].

2.2 Five Principle Components of HRI Study

Categorizing HRI will aid us to define the scope and better understand the concept of HRI. [25] categorize the relationships in HRI in terms of three different taxonomies namely: numeric, spatial, and authority relationships between the human and the robot. [26, 27] proposes to include all possible classifications of HRI using 11 standard taxonomies. We propose that there are five principle components in HRI: human, robot(s), world, interaction system, and task. All the classifications mentioned above can be equated to one of these elements or relationship between two or more of these elements.

2.2.1 Human

The role of humans in human robot teams vary widely from a mere bystander who co-exist in the environment of the robot to a supervisor who oversees a number of robots. The level of personal skill possessed by the human operator can also vary drastically from beginner to an expert. Classifying these behaviours for the human operator is a critical task as it contributes significantly towards the performance of human robot teams. [28] demonstrates the importance of adopting expertise level of the end user as a HRI design parameter for successful interaction between the human and the robot. The number of humans working in a human robot team can range from one to many depending on the task. For example, in surveillance operations many security personnel control and monitor data from one robot.

2.2.2 Robot

A robot is a mechanical or virtual agent with some level of intelligence. There may be complete, partial or zero human control of robots. In this thesis, we restrict the definition of robot to an electromechanical device that directly interacts with its environment with certain degree of autonomy. In terms of locomotion capabilities, the robots can be classified as static or mobile platforms depending on their ability to move around. From robot morphology perspective, a robot can be classified based on their physical appearance as anthropomorphic (human like), zoomorphic (animal like) and functional (appearance related to robot's function)

[29]. The robots can be classified depending on the environment they operate as ground, aerial, or nautical platforms. Robot autonomy is an essential component as it relieves the human operator from the demanding decision making processes however, in most cases some human supervision will be required to provide useful information about the dynamically changing parameters towards accomplishing the goal. [30] proposes ten autonomy levels for human robot teams. Most commercial applications would require robots to work closely with the humans, and these robots would typically falls into tele-operation and shared control modes of autonomy.

Tele-operation is the basic and most mature mode of robot control. In this mode the operator has full responsibility for every action taken by the robot. This mode is suitable in complicated or unexpected situations which no algorithm can deal with [31]. The robot can be configured to take basic initiative to protect itself by assessing its status and surrounding environment to decide if the commands issued by the operator are safe [32, 33]. Tele-operation places heavy workload on the operator as he/she needs to continuously control the robot in achieving the given task. In shared control, the human and the robot control different functions of the system concurrently [34].

In most cases, the robots handles low level tasks, and the humans only provide high level control directives to accomplish a given task [35, 36]. Therefore, the workload requirements for the operator would be reduced largely in shared

control as compared to tele-operation mode. There may be situations where the robots can sense, reason and act in an unstructured environment without any human intervention and this is the class of autonomous robots [37, 38]. The number of robots deployed can range from one to many depending on the task. In case of multiple robots, they can be of the same type forming homogenous teams or involve different types of robots forming heterogeneous teams. Cooperative robotics is one of the hot research topics being explored by the robotics community, other classifications of robot teams are listed in [39, 40].

2.2.3 World

The world is the environment in which the robot is operating towards achieving the given task. Different environment offers different challenges to the human robot teams and therefore require appropriate robots and human robot interactions. [41] estimates world complexity through weighted sum of the branch and clutter complexities of the robot's environment. [42] presents three metrics for describing rough terrain robot mobility in terms of traversability, coverability and crossability. The robot and the human can be co-located in the same environment or they may be in different physical environments. Based on the environmental changes, the robot world can be classified into static or dynamic. The other features of the environment listed as light or dark, cold or hot, open or closed and clear or dusty. [43] presents the negative effects of unwanted noises in the operating

environment on human and robot performances. [44] presents the findings on the impact of the environmental conditions on the HRI during the World Trade Center rescue mission.

2.2.4 Task

In human robot teams, the robots and the humans work together towards accomplishing a given task. Some of such tasks include surveillance, search, rescue, surgery, and rehabilitation. According to [45], the task handled by human robot teams can be categorized into navigation, perception, management, manipulation, and social. Navigation involves tasks wherein the robot needs to move from one point to another. Performing these tasks requires the robot to understand where it is presently located, where it needs to go, how to navigate to the given point, and how to handle the environmental parameters like obstacles, differing terrain, etc.

Perception involves tasks wherein the robot needs to perceive and monitor a given environment. Some sample applications include surveillance, search and rescue. Performing these tasks require the robot to sense its working environment, preprocess the acquired sensor data, and decide the amount of information to be shared with other robot/human agent. Management involves tasks wherein the human or the robot coordinate and manage the activities of both towards accomplishing the given goal.

One key issue to be addressed is the optimal distribution of resources in order to achieve complete coverage. These tasks require the robot/human manager

to understand the strength and weaknesses of team members, identify and settle disputes, and monitor resource availability. Manipulation involves task wherein the robot physically interacts with the environment like manipulating objects including pulling, pushing and grasping. Some sample applications include bomb disposal, earth sampling, construction, factory automation and delivery. Performing these tasks requires the robot to understand what are the objects to be manipulated, how to manipulate and feedback on manipulation. Social involves task wherein the robot interacts with the humans in a highly social manner. Some sample applications include rehabilitation, entertainment, and service.

2.2.5 Interaction System

In human robot teams, the communication between the humans and the robots takes place through the interaction system. These systems serve as an interface medium between the humans and the robots helping them to better understand each others needs. The design of these systems has a huge impact on the success of human robot teams as lack of communication between the two leads to failure in achieving the task. In terms of modalities, an interaction system can vary from single mode where the communication between the robots and humans occur through one medium may be speech or joystick or keyboard to multi mode where more than one mode is used for communication. A multimodal interaction system is presented in [46] which mimics human model of communication and

interaction through incorporation of natural language understanding and gesture recognition for human robot interaction.

The interaction system may facilitate one to one, one to many, many to one and many to many channels of communication between humans and robots. [47] presents the design philosophy and practical experience with HRI systems to develop, debug, and evaluate distributed algorithms on hundreds of robots. The interaction system can be classified based on the physical medium they use as wired and wireless systems. [48] uses PDA based wireless interaction system for control of mobile robot and monitor multi-sensored environment. [49] presents a HRI system for the teleoperated Urban Search And Rescue research robot, textsfCASTER for participation in RoboCup Rescue Robot League competition. The interaction system adopts proven human computer interaction based user interface design principles to achieve interactions that were intuitive and minimised learning time while maximising effectiveness.

2.3 Evaluation of HRI

Accomplishment of all service tasks greatly depends on the quality of interaction that occurs between human and the robot thereby requiring metrics to evaluate HRI in relation to performance. While evaluating HRI, we are generally keen on measuring the effectiveness and efficiency using human robot team performance. Most of the currently existing metrics for measuring human robot

team performance are task specific evaluations. For example, in RoboCup Rescue Leagues, map quality, the number of found victims, the number of collisions and the number of operators are used as metrics for evaluating human robot team performance [50]. In USAR domain, [51, 52] adopts target and task completion as their metrics whereas in [53] uses joystick control as a metric and in [54] number of collisions is adopted as metrics for evaluating human robot team performance. For a successful evaluation of HRI, these metrics must analyze the interactions from the perspectives of each of the five components of human robot interaction briefed in Section 2.2. [45] proposes common metrics for human robot team performance measurement from three different aspects namely: system performance, robot performance and operator performance.

2.3.1 System Performance

System performance measures how well the human and the robot work as a team towards accomplishing a given task. [45] presents three metrics namely: quantitative performance, appropriate utilization of mixed initiative and subjective rating for measuring system performances for HRI. Quantitative metrics evaluates the effectiveness and efficiency of the human robot team in performing the given task. These metrics would encompass the level of autonomy of the robot under study. Effectiveness is measured as the percentage of the task accomplished with the given autonomy whereas the efficiency is measured as the time required by the

robot for accomplishing the task. Subjective metrics evaluates the quality of the interaction. For example, in a surveillance operation the human robot team locates suspicious activities in the place of interest whereas the security team gets there to perform verification and responsive action. Metrics for this task should evaluate not only the qualitative metrics but also the quality of the information supplied to the security teams. Appropriate utilization of mixed initiatives measures the ability of the human robot teams to continuously monitor and manage the right balance of human and robot autonomy.

In most scenarios, both the humans as well as the robots are capable of performing a given task therefore it becomes necessary to determine and allocate the task to the one that best performs the task of interest. [55] presents a systematic evaluation of human and robot roles using functional primitives, in order to optimize the design and performance of human-robot system architectures using well-defined performance evaluation metrics. [56] [57] presents a new metric, interaction effort for measuring the effort a human operator must put in to interact with the robot of interest at a given level of autonomy.

2.3.2 Operator performance

Operator performance measures the efficiency of the human operator towards achieving the given task. [45] presents three metrics namely: situation awareness, operator workload, and accuracy of mental models. Situation

awareness is formally defined in [58] as “the perception of the elements in the environment within a volume of time and space, the comprehension of their meaning and the projection of their status in the near future”. Situation Awareness Global Assessment Technique (SAGAT) presented in [59] is most widely used for assessing situation awareness in human robot teams. [60-62] use SAGAT to evaluate situation awareness for varying autonomy and tasks.

Operator workload measures human performances and workload for a given task and commonly evaluated using subjective workload assessment techniques. [63] elaborates the two widely adopted subjective workload assessment techniques namely, SWAT and NASA-TLX. In general, higher level of autonomy and lesser robot servicing times decreases the subjective rating of workload. Human operator mental models involving design affordability, operator requirements, and stimulus response compatibility affects human performances. Extensive research has been performed on human operator mental models in the human factors community with electronics and computer appliances which can be directly applied to HRI [64-66].

2.3.3 Robot performance

Robot performance measures the ability of the robot in accomplishing the given task. It also measures how well a human robot team completes its task. The definition of performance may vary widely. For example, there are time based

performance metrics that attempts to maximize speed of task completion, coverage based performance metrics that measure how much of the larger goal is achieved, etc. Also, the performance can be classified as overall and current. Overall performance is best measured after the task is accomplished. An example would be the time needed to complete the task. In many applications, current performance proves advantageous, which is the effectiveness of the robot at that moment. One such measure is the speed with which the robot is moving towards the final destination.

Neglect tolerance model is adopted as a general index for measuring robot performance and attention demand in relation to autonomy [67, 68]. Neglect tolerance model is used in [69] to estimate optimal solutions for autonomy mode switching problems in human robot teams. The neglect tolerance model forms the basis of the fan out metric which is used to estimate the maximum number of robots a human user can handle simultaneously while maintaining the performance at acceptable level [70]. [71] uses neglect tolerance model to evaluate human robot interfaces with special attention to the role of a collaborative workspace in enabling mixed-initiative interaction between humans and heterogeneous teams of robotic vehicles. [72] uses neglect tolerance model to derive models that approximated absolute autonomy and power in agent systems. [73] extends neglect tolerance model to investigate human interaction with cooperating robot teams within a

realistically complex environment. [74-76] show the extension of neglect tolerance model to estimate performance in multitasking and multi-robot applications.

2.3.3.1 Neglect Tolerance Model for Single Robot Teams

Single robot teams wherein one human user is dedicated towards interacting with one single robot are very common in wide ranging fields including surgery, search & rescue, industry automation, and entertainment. Neglect tolerance model for single robot teams uses two components namely: neglect tolerance and interface efficiency for estimating robot performance in human robot teams. Neglect tolerance is a measure of how the robot's current performance declines over time when the robot is neglected by the user. In general, any increase in neglect tolerance results in performance decrease. Figure 2.1 presents the relationship between neglect and robot performance for varying autonomy modes with constant world complexity. A fully autonomous robot receives no inputs from the human operator while accomplishing the task whereas in a semi-autonomous robot, the human and the robot control different functions of the system concurrently and in the case of tele-operation, the robot receives every single control from the human operator.

From the figure, it is evident that the performance of a tele-operated robot degrades rapidly with any neglect from the human operator. In the case of an

autonomous robot, the performance does not degrade upon neglect but its peak performance is not expected to be as high as the tele-operated robot.

Figure 2.1 Neglect Versus Robot Performance for varying autonomy modes with constant world complexity [102]

Interface efficiency is a measure of how the robot's performance changes during servicing with the given interaction scheme. When the human user starts interacting with a robot, the performance of the robot is expected to increase. The nature of performance change depends greatly on the deployed interaction scheme as the information delivery and control components put in place affects the situation awareness, decision making and actions of the human user. A poorly developed interaction scheme requires more time and efforts from the operator. Consider the case wherein information about the environment is presented by the

robot to the human user in the form of text messages. In this scenario, the human user must read the text and spend considerable time and efforts to create a mental representation of the environment in which the robot exists before making any decisions on the robot navigation. Similarly, the information presentation from the robot to the human can influence the performance. As an example, consider controlling a rescue robot using a mouse. It may be time consuming as the human user needs to understand how the mouse movements translate into robot navigation in uneven terrain. Figure 2.2 presents the relationship between time on task and robot performance for varying modes of autonomy.

Figure 2.2 Time on Task Versus Robot Performance for varying autonomy modes with constant world complexity [102]

An important factor that directly affects robot performance and other key metrics is the world complexity. Consider the two worlds presented in Figure 2.3. From the figure, it is evident that it would be easier for a robot to navigate in world b than in world a. Thus, the complexity of the world in which the robot exists greatly influences the robot performance and other key metrics. Any increase in world complexity generally decreases the robot performance. Thus, both neglect tolerance and interaction efficiency both depends on the estimates of world complexity.

Figure 2.3 Worlds with Varying Complexities

Figure 2.4 shows the neglect tolerance model combining the neglect tolerance and interaction efficiency across tele-operation and semi-autonomous autonomy modes. In Figure 2.4, moving from left to right along the horizontal axis,

a robot begins at zero performance. When a human operator begins interaction with the robot, the performance increases gradually and is modelled as interface efficiency curve [77]. The robot performance begins to deteriorate when the human operator terminates interaction with the robot and robot performance is modelled by neglect tolerance curve [78, 79]. Acceptable performance is the minimum level of performance that can be tolerated by the operator for a given application. Figure 2.4 also presents how acceptable interaction rates can be estimated from the neglect tolerance model. An acceptable interaction rate is a frequency and duration of interactions so that the expected robot performance does not fall below acceptable performance.

Figure 2.4. Neglect Tolerance Model for Single Robot Teams [102]

The performance of a robot using an interaction scheme, π , is defined by a random process indexed by time, t , world complexity, c , the time-off-task, NT , the

time-off-task for the previous interaction, NT_p and the time-on-task, IT . The performance is defined as,

$$p = V(\pi; t, c, NT_p) = \begin{cases} V_s(\pi; IT, c, NT_p) & \text{If being serviced} \\ V_N(\pi; NT, c) & \text{Otherwise} \end{cases} \quad (2.1)$$

Where $V_s(\pi; IT, c, NT_p)$ is a measure of interface efficiency of π and $V_N(\pi; NT, c)$ is a measure of the neglect tolerance of π . For convenience, we represent $V(\pi; IT, c, NT_p)$, $V_s(\pi; IT, c, NT_p)$ and $V_N(\pi; NT, c)$ as $V(\pi)$, $V_s(\pi)$ and $V_N(\pi)$ respectively. $V_s(\pi)$ presents the performance of the robot when the human user is interacting with the robot whereas $V_N(\pi)$ presents the robot performance when the robot is neglected by the user and $V(\pi)$ indicates the average frequency and duration of interactions that should occur between the human user and the robot so as to keep the performance above a predefined threshold.

A key aspect that greatly influences the performance is the amount of time a robot demands from an operator. Robot attention demand (RAD) is used as a metric to measure the fraction of the total time that an operator must attend to a given robot. RAD is defined as a relationship between IT and NT as follows,

$$RAD = \frac{IT}{IT + NT} \quad (2.2)$$

RAD is a unitless quantity that represents the fraction of an operator's time that is spent on interacting with the robot of interest. The numerator is the amount of time the human user must be spending interacting with the robot and the denominator is the total time including both interaction and neglect. If IT is small relative to NT then the RAD will be very small. In the case of a tele-operated robot, NT is very small and therefore RAD approaches 1. Most applications require a lower RAD so that the human user can focus on other activities besides interacting with the robot. Reducing RAD can be achieved by increasing NT or decreasing IT .

Another metric related to RAD is the available relative free time (RFT) of the human user. This is the fraction of the total time that the user can relax and does not have to interact with the robot. RFT is defined as:

$$RFT = \frac{NT}{IT + NT} = 1.0 - RAD \quad (2.3)$$

The sum of RFT and RAD should be 1. It is apparent from the representation that relative free time is maximized when neglect time is minimized.

2.2.3.2 Neglect Tolerance for Multi-Robot Teams

Many new robotics applications such as deep tunnel and underwater explorations, rehabilitation, entertainment, and defence fields involves tasks that

are difficult, if not impossible to be accomplished by a single human robot team [80] [81]. These applications require a team of robots and human operator to work together towards accomplishing the given task. These multi-robot systems offer redundancy and contribute cooperatively to accomplish the given task. For a given application these multi-robot systems are highly reliable, faster, or cheaper than a single robot [82].

[67] [68] presents the neglect tolerance model for tasks involving multiple independent robots. Figure 2.5 depicts the neglect tolerance model for an independent task involving multiple semi-autonomous robots.

Figure 2.5 Neglect Tolerance Model for Independent Multi Robot Teams [68]

Since, the tele-operation mode requires a very large (near unity) robot attend demand (RAD), thereby making it impossible for the human operator to handle a secondary robot simultaneously. Therefore, the neglect tolerance model presented in this thesis covers mainly semi-autonomous multi-robot teams.

Let π_i be an interaction scheme deployed for robot i , and let $N_i(\pi) = (NT_i, IT_i)$ denote the neglect characteristics associated with a preselected performance threshold as denoted in Equation 2.4. Suppose that we have M independent robots. Let $\pi = (\pi_1, \pi_2, \dots, \pi_M)$ denote the vector of interaction schemes, and let

$$N(\pi) = (N_1(\pi_1), N_2(\pi_2), \dots, N_M(\pi_M)) \quad (2.4)$$

denote the vector of the neglect and interaction times for the team of robots for a given interaction scheme. Associated with each $N(\pi)$ is the set of average performance levels for each robot $J_i(\pi)$. Given the average performance of each robot, the expected average performance of the independent robot team is defined as,

$$J(\pi) = \frac{1}{M} \sum_{i=1}^M \bar{J}_i(\pi_i) \quad (2.5)$$

The summation indicates the independent nature of the robots and the team performance is therefore the average of the individual performance of the robots in

the team. This analysis allows researchers to search through the set of feasible team configuration to find the set of interaction schemes and performance thresholds that maximize performance.

Jijun in [83] presents the neglect tolerance model for tasks involving multiple robots and human operator working towards dependent goals. This model has been widely adopted for estimation of robot performance, attention demand, and other multi robot specific metrics [84-86]. In the case of dependent robots, the performance curve tends to rise when the operator controls a cooperating robot to maintain the overall task performance above acceptable level. For example, when controlling two robots to push an object forward, both the left and right robots has to be periodically controlled to move the object forward. Figure 2.6 shows the neglect tolerance model for estimating performances for dependent multi-robot systems. The time spent servicing cooperating robots so as to synchronize their actions is given by occupied time (OT) [87].

Figure 2.6 depicts the scenario wherein an operator control two cooperating robots, the neglect time for robot 1 would comprise of the FT preceding the interaction with robot 2, OT for the robot 1, and FT following the interaction with robot 2. For a multi-robot system with N dependent robots, neglect time with respect to j^{th} robot is defined as [86]:

Figure 2.6 Neglect Tolerance Model for Measuring Robot
Performance in Dependent Multi-Robot Teams [83]

$$NT_j = \sum_{\substack{i=1 \\ i \neq j}}^N (FT_{ij} + OT_{ij}) + FT_T \quad (2.6)$$

Where FT_{ij} is the FT with respect to j^{th} robot after interaction with $(i-1)^{\text{th}}$ robot and before interaction with i^{th} robot, OT_{ij} is the occupation time with respect to j^{th} robot that is contributed by interaction time for $N-1$ cooperating robots, and FT_T is the FT after interaction with the N^{th} robot.

Cooperation effort (CE) is defined as the additional efforts needed to control robots that work together in accomplishing a common task. CE for a robot is the ratio between sum of the OTs for cooperating robots and the interaction time

for that robot. CE for j^{th} robot in a multi-robot system with N dependent robots is given by:

$$CE_j = \frac{\sum OT_{ij}}{IT_j} \quad (2.7)$$

Co-ordination demand (CD) is defined as the percentage of time spent on controlling cooperating robots while the operator neglects the operator neglects the j^{th} robot. For independent robots, OT will be zero making CD zero as no cooperation is necessary. CD for j^{th} robot in a multi-robot system with N dependent robots is given as,

$$CD = 1 - \frac{\sum FT}{NT} = \frac{\sum OT}{NT} \quad (2.8)$$

Robot attention demand for j^{th} robot in a multi-robot system with N dependent robots is given by,

$$RAD_j = \frac{IT_j}{NT_j + IT_j} \quad (2.9)$$

Team attention demand (TAD) is defined as the percentage of time spent on interacting with a multi-robot team. Computation of TAD involves both neglecting and servicing times for the multi-robot team. TAD is given by,

$$TAD = \frac{\sum OT_{ij} + IT_j}{NT_j + IT_j} \quad (2.10)$$

Team interaction and neglect times for the entire team of robots are defined as,

$$IT_T = \sum (FT_{ij} + OT_{ij}) + IT_j \quad (2.11)$$

$$NT_T = FT_T \quad (2.12)$$

Relative Free Time (RFT) is defined as the fraction of the task time that the operator can perform secondary task without servicing the primary robot. Sum of RFT and RAD should be one. RFT for j^{th} robot in a multi-robot system with N dependent robots is given by,

$$RFT = \frac{NT_j}{(IT_j + NT_j)} \quad (2.13)$$

2.3.3.3 Neglect Tolerance Model & Fan out Estimation

It is very much desired in wide ranging application to develop robots that allow a single human to manage multiple robots. The possibility of such multi robot teams are further fuelled by the ever increasing autonomy of robots. Fan out metric offers an estimate of the maximum number of robots a human user can operate at one time simultaneously while maintaining performance above a

predefined threshold [56]. There are physical and cognitive constraints that affect the theoretical fan out limits. Task saturation is one of the physical constraints where the task is either simple or the operating world is small and that dedicating more robots will not result in improved performance.

For example, in a rescue task, the search perimeter imposes a limit on the number of robots that can be deployed for the task. Cognitive constraints are caused by the limitation of human cognition. While controlling multiple robots, human operator has to remember the robot state information, autonomy modes, robot capabilities, etc. This places enormous working memory demands on the human operator and given that only limited information can be stored in short term memory. Neglect tolerance model forms the basis of the fan out estimation and estimates of IT and NT are used. Figure 2.7 illustrates the relationship between IT, NT and fan out.

There are two widely adopted definitions for estimating fan out. [70] and [88] proposes that fan out could be estimated for independent robots using the equation,

$$FO_I = \frac{NT}{IT} + 1 \quad (2.14)$$

Figure 2.7 Relationship between IT, NT & Fan out

[89] and [90] modified the Equation 2.14 to include wait times (WT). It also categorizes total system wait time as the sum of the interaction wait times, which are the portion of IT that occur while a vehicle is operating in a degraded state (WTI), wait times that result from queues due to near simultaneous arrival of problems (WTQ), plus wait times due to operator loss of situation awareness (WTSA).

Figure 2.8 illustrates the relationship of wait times to interaction and neglect times. Fan out for independent robots with inclusion of wait times is given by,

$$WT = \sum_{i=1}^X WTI_i + \sum_{j=1}^Y WTQ_j + \sum_{k=1}^Z WTS A_k \quad (2.15)$$

$$FO_{WT} = \frac{NT}{IT + \sum_{j=1}^Y WTQ_j + \sum_{k=1}^Z WTS A_k} + 1 \quad (2.16)$$

Since, dependent robot works together towards a common goal, fan out for dependent multi-robot systems is formulated based on Equation 2.14 defined as,

$$FO_D = \frac{\sum_{\substack{i=1 \\ i \neq j}}^N (FT_{ij} + OT_{ij}) + IT + FT_T}{\sum_{\substack{i=1 \\ i \neq j}}^N (FT_{ij} + OT_{ij}) + IT} \quad (2.17)$$

(a)

(b)

Figure 2.8 Performance Versus Time: (a) WTQ and (b) WTSA [90]

Fan out for dependent robots with inclusion of wait times is given by,

$$FO_{DWT} = \frac{\sum_{\substack{i=1 \\ i \neq j}}^N (FT_{ij} + OT_{ij}) + IT + \sum_{j=1}^Y WTQ_j + \sum_{k=1}^Z WTSA_k + FT_T}{\sum_{\substack{i=1 \\ i \neq j}}^N (FT_{ij} + OT_{ij}) + IT + \sum_{j=1}^Y WTQ_j + \sum_{k=1}^Z WTSA_k} \quad (2.18)$$

2.3.3.4 Neglect Tolerance Model & Limitations

Neglect tolerance model uses the neglect and interaction times that occur in human robot interactions to estimate the robot performances, attention demand and other key metrics in relation to autonomy. Notable neglect tolerance model adaptations discussed in this thesis are robot performance estimations in single robot teams [67] [69], robot performance estimations in multi robot teams [68] [83], and fan out estimations [89] [56]. The estimation of these parameters helps the robot operator in task/robot scheduling, appropriate interface/robot selection, and performance comparison among a set of robots. But, this traditional neglect tolerance approach assumes ideal conditions during robot operation and ignores any erroneous interactions during robot operation.

In most real life applications erroneous interactions between the human and the robot are common due to uncertainties in human operators, robots, environment, task involved and the interaction system in place which are the key elements of any human robot system. For example, in a manipulator control task the human operator may select a incorrect co-ordinate points leading to a erroneous interaction as the manipulator would fail to reject the false interaction or there may be cases where the human operator select correct co-ordinate points but the robot navigate to an incorrect co-ordinate points/ignores the human operator controls due to uncertainties in robot software/hardware leading to erroneous interactions as the robot rejects a true interactions. These erroneous interactions directly results in

performance deterioration and increased workload as the human user has to spend additional time and efforts in identifying the error and rectify so as to bring the performance back to the pre-erroneous interaction level.

Therefore, the actual robot performance achieved for the task and fan out capabilities would decrease and workload demand on the operator would increase as a result of the erroneous interactions. Assumption of zero erroneous interactions in traditional neglect tolerance model results in a more optimistic estimates of robot performances, fan out, attention demand and other key metrics, which not only leads to the operator's failure in accomplishing the task as scheduled due to higher attention demands in actual situation, but also leads to operator's inability to achieve the performance level set for that task due to the drop in performance attributed to the erroneous interactions. Since the neglect tolerance model forms the basis of fan out metric, the zero erroneous interaction assumption in the former result in a higher estimate of fan out and therefore results in operator inability to handle the planned number of robots for a given task and eventually resulting in task failure.

With no available metrics, there is an immediate need to develop a new class of metrics to identify, classify and quantify these erroneous interactions and extend the neglect tolerance model to account for the additional demands imposed due to erroneous interactions while estimating robot performances, attention demand and fan out. These erroneous interactions also have the potential for

causing accidents which might result in damage to the robot and/or environment and injury to human operator involved. Therefore, additional metrics are needed to measure the susceptibility of robots to erroneous interactions and classify robots based on safe human robot interaction abilities. In summary there are several open issues in quantifying and classifying erroneous human robot interactions, in particular to the neglect tolerance model centred performance, attention demand and fan out estimations, which needs to be properly addressed in detail.

2.4 Conclusion

Although neglect tolerance model has been widely adopted in estimating robot performance, attention demand and fan out in human robot teams, this traditional model assumes ideal conditions ignoring any erroneous interactions that inevitably occurs during human robot teams. Treatment of these erroneous interactions and their influence on robot performance, attention demand and fan out estimations are not covered in the reported work in the context of neglect tolerance model. In particular, currently there are no available metrics to quantify and classify these erroneous interactions. Based on the discussion and examination of related work in neglect tolerance model the need to quantify and classify erroneous interactions is well established beyond doubt.

This thesis is mainly focused on the extension of neglect tolerance model adopted towards estimation of robot performance, attention demand and fan out

using a new class of metrics that quantify the effects of erroneous interactions. Additionally, metrics are put forward to measure the susceptibility of robots to erroneous interactions and further classify them based on safe human robot interaction abilities. We also demonstrate the efficacy and validity of the metrics and models proposed in this thesis through extensive simulations and experiments.

3. Extended Neglect Tolerance Model for Single Robot Teams

3.1 Introduction

Erroneous interactions that occurs between the human and robot is a major obstacle in deriving a realistic estimate of robot performance and attention demand using neglect tolerance model. This traditional model must be extended to incorporate the negative effects of these erroneous interactions in order to arrive at a realistic estimation of robot performance. Firstly, identification and classification of the erroneous interactions is required. Secondly, quantification of their effects and redefinition of the existing metrics within an extended neglect tolerance framework to incorporate the additional demands incurred due to these erroneous interactions is needed.

This chapter identifies two significant metrics namely, false alarm time and false alarm demand to quantify the effects of erroneous interactions in human robot teams. The traditionally adopted neglect tolerance model for single robot teams is extended to accommodate the effects of false alarms through incorporation of the proposed false alarm interaction metrics towards offering a more realistic estimate of robot performance and attention demand. Simulation and experiments were carried out to demonstrate the efficacy and utility of the extended neglect tolerance model for single robot teams. Further, the advantages of the proposed model are

investigated in detail and their performance compared against the traditional neglect tolerance model.

The concept of the extended neglect tolerance model for single robot teams is introduced in Section 3.2. Descriptions of the real and virtual Robo-Erectus Junior humanoid robot used in the experiments are presented in Section 3.3. Experimental results are presented in Section 3.4.

3.2 Extended Neglect Tolerance Model for Single Robot Team

Neglect tolerance model assumes zero erroneous interactions during robot operation while estimating robot performance and attention demand. But, in most real life applications erroneous interactions between the human operator and the robot are common due to uncertainties in human operators, robots, environment, task involved and the interaction system in place which are the key elements of any human robot system. We term these erroneous interactions as “false alarm interactions” and identified them as “*A response in which robot rejects a "correct" interaction or fails to reject an "incorrect" interaction*”.

We also classify these false alarm interactions in human robot teams into “false positive interactions” and “false negative interactions”. A “false positive interaction” is one in which the human makes an incorrect interaction and the robot fails to identify the incorrect interaction and proceeds with action whereas in a “false negative interaction” the human delivers a correct interaction and the robot

either responds with an incorrect interaction or do not respond. Table 3.1 shows the classification of interactions in human robot teams. For example, in a robot navigation task the human operator may select the wrong way point leading to a "false positive interaction" as the robot would fail to reject the false interaction. There may also be situations wherein the human operator selects correct way point but the decision making body of the robot chooses a wrong way point/ignores the human operator control due to uncertainties in robot software/hardware leading to a "false negative interaction" as the robot rejects a true interactions.

Table 3.1 Classification of Interactions in Human Robot Teams

		Human Decision	
		Correct Interaction	Incorrect Interaction
Robot Decision	Correct Interaction (Accept)	True Positive Interaction (TPI)	False Positive Interaction (FPI)
	Incorrect Interaction (Reject)	False Negative Interaction (FNI)	True Negative Interaction (TNI)

The occurrence of false alarm interactions results in performance deterioration as the robot deviates from the specified task. The human operator would be required to spend additional time and efforts to identify the false alarm interaction that occurred, plan and implement rectification measures to bring the

performance back to the pre-false alarm level. Therefore, the zero false alarm assumption in neglect tolerance model could lead to operator's inability in achieving the performance target set as he/she ignores the performance drop due to the false alarms.

To incorporate the additional demands due to false alarm interactions we have extended neglect tolerance model for single robot teams which involves one human operator and one robot by introducing the notion of false alarm time (FAT) as illustrated in Figure 3.1. FAT is defined as the time spent over false alarm identification and team performance recovery to the pre false alarm level. The scenario depicted in Figure 3.1 starts just after the operator starts to service the target robot. The robot performance increases with time and saturates at some point for both tele-operation and semi-autonomous modes.

The peak performance of the robot in both tele-operation and semi-autonomous robots depends greatly on the training, skills and situation awareness of the robot operator and interface schemes adopted. In the case of a false alarm interaction either false positive or false negative interaction, the performance drops in both the autonomy modes and upon identification by the operator the performance recovers to the pre-false alarm level. FAT, the time spent over false alarm identification and performance recovery is shown in the Figure 3.1 for both the autonomy modes. The FAT for tele-operation mode is expected to be smaller as compared to the

semi-autonomous mode due to the delay in the false alarm identification process for the latter.

Figure 3.1 Extended Neglect Tolerance Model for Single Robot Teams

In the case of tele-operation mode, the robot is continuously controlled by the robot operator and so any false alarm interactions that occur during operation of the robot are identified and the performance is brought back to the pre false alarm level in a short time. But, in the case of semi-autonomous mode the operator only specifies the way point and switches control to the secondary robot task so any false alarm interactions that occurred could only be identified and rectified during next period of service by the operator thereby increasing the FAT. False alarm demand, FAD, is then defined as:

$$FAD = \frac{\sum FAT}{IT + \sum FAT} \quad (3.1)$$

where, FAD for a robot is the ratio between the sum of the false alarm times and sum of total FAT's and interaction time. FAD in Equation 3.1 can be expanded as:

$$FAD = \frac{\sum FAT_P + \sum FAT_N}{IT + \sum FAT_P + \sum FAT_N} \quad (3.2)$$

where, FAT_P is the false alarm time contributed by false positive interactions and FAT_N is the false alarm time contributed by false negative interactions. Robot Attention Demand (RAD) defined in the Equation 2.2 as the robot's average performance over an interaction cycle assumes zero false alarm interactions, so we redefine RAD to account for the false alarms as:

$$RAD = \frac{IT + \sum FAT}{IT + NT + \sum FAT} \quad (3.3)$$

The original RAD definition in Equation 2.2 does not acknowledge and skipped the erroneous interactions and therefore considers the $IT+NT$ to be the entire time of the mission ignoring also the associated performance drop. But, the new metric redefines the total time as $(IT+NT+\sum FAT)$ taking into account any erroneous interactions as well as the related drop in robot performances. In the new representation, any increase in the $\sum FAT$ results in an increase in RAD, the

workload of robot operator as well as decrease in robot performances. A related metric to RAD is the operator's Relative Free Time (RFT) defined in Equation 2.3 as the fraction of the task time the user does not need to pay attention to the robot. This definition assumes zero false alarm interactions and is therefore redefined to encompass the effects of false alarms as:

$$RFT = 1 - \frac{IT + \sum FAT}{IT + NT + \sum FAT} \quad (3.4)$$

An increasing FAT decreases the RFT of the operator. It is desirable to have higher RFT for a given task so that the operator has more free time to dedicate for secondary tasks. In applications like surveillance with higher RFT, the operator can control more robots and therefore monitor larger area requiring lesser resources for a given task. We conducted experiments with our humanoid soccer robots, Robo-Erectus Junior to validate the extended neglect tolerance model across tele-operation and semi-autonomous autonomy modes.

3.3 Robo-Erectus Junior – A Soccer Playing Humanoid Robot

This section provides a brief description of Robo-Erectus Junior humanoid robot that was used for the experiments to validate the proposed model and metrics in this thesis. Robo-Erectus Junior is one of the foremost leading soccer playing humanoid robots in the RoboCup Humanoid Leagues. The aim of the Robo-Erectus Junior development team is to develop a low-cost humanoid platform for soccer

robotics [91, 92] and human robot interaction research [93, 94]. The development of Robo-Erectus Junior has gone through many stages either in the design of its mechanical structure, electronic control system and gait movement control. Figure 3.2 shows the physical design of Robo-Erectus Junior. Robo-Erectus Junior has been designed to cope with the complexity of a 3 versus 3 soccer game. It has three processors each for vision, artificial intelligence and control. Table 3.2 shows the specification of the processors used in Robo-Erectus Junior.

Figure 3.2 Robo-Erectus Junior, the Latest Generation of the Family Robo-Erectus

The platform is equipped with three sensors: an USB camera to capture images, a tilt sensor to detect a fall, and a compass to detect their direction [95]. The servomotors used send back the feedback data including angular positions, speed, voltage, and temperature [96] [97].

TABLE 3.2 Processor Specification of Robo-Erectus Junior

Features	Artificial Intelligence Processor	Vision Processor	Control Processor
Processor	Intel ARM XScale	Intel ARM XScale	ATMEL ATmega-128
Speed	400Mhz	400Mhz	16Mhz
Memory	16MB	32MB	4KB
Storage	16MB	16MB	132KB
Interface	RS232, WIFI	RS232, USB	RS232, RS485

To communicate with its teammates, Robo-Erectus Junior uses a wireless network connected to the artificial intelligence processor. The vision processor performs recognition and tracking of objects of interest including ball, goal, field lines, goal post teammate and the opponents based on a blob finder based algorithm [96, 97]. The further processing of detected blobs, wireless communications and

decision making are performed by the artificial intelligence processor which selects and implements the soccer skills (for example, walk to the ball, pass ball, kick ball, dive etc.) the robot is to perform. Finally, the control processor handles the low level control of motor based on the soccer skill selected by the artificial intelligence processor. Table 3.3 shows the physical specifications of Robo-Erectus Junior. It is powered by two high-current lithium polymer rechargeable batteries, which are located in each foot. Each battery cell has a weight of only 110g providing 12v which means about 15 minutes of operation.

A framework of hierarchical reactive behaviours is the core of the control module. This structure restricts interactions between the system variables and thus reduces the complexity. The control of the behaviours happens in three layers: skill, reactive, and planning layer. Figure 3.3 shows the behaviour framework of Robo-Erectus Junior. These layers respond in a different way to sensor data. The interaction of these layers produces the final behaviour of the robot.

TABLE 3.3 Physical Specification of Robo-Erectus Junior

Weight	Dimension			Speed
	Height	Width	Depth	Walking
3.2 Kg	480 mm	270 mm	150 mm	5 m/min

Besides the physical sensor data, the system employs abstract sensors, take decisions. These abstract sensors are built by merging data from different sensors

and their history records. The best example of these types of sensors is the map, which is generated with camera information, compass data, and previous positions [98] [99]. Experiments with virtual Robo-Erectus Junior humanoid robots were performed using our Virtual-RE simulator providing several possibilities of visualization and interaction with the simulated world [100]. Figure 3.3 shows the virtual Robo-Erectus Junior humanoid robot and its environment.

Figure 3.3 Robo-Erectus Junior in Virtual-RE simulator

Virtual-RE simulator uses the Open Dynamics Engine (ODE) to simulate rigid body dynamics, which has a wide variety of features and has been used successfully in many other projects [101].

The visualization as well as the computation of imaging sensor data is based on OpenGL libraries, as it standard offers the best performance with modern hardware on different platforms. The simulator is a client/server-based system, which offers the possibility of halting or stepwise executing the whole simulation without any concurrencies. It allows also a more comprehensive debugging of the executed robot software. The simulation kernel models the robots and the environment, simulates sensor readings, and executes commands given by the controller or the user.

The user interface is responsible for the display of information and for the interaction with the user. The controller implements the behavioural control. In each simulation step, the controller reads the available sensors, plans the next action, and sets the actuators to the desired states. Virtual-RE provides each robot with a set of simulated sensors, i.e. tilt, compass, gyroscopes, camera images, and motor feedback. The camera sensor generates an RGB24/YUV420 image of 320x240 pixels. The motors state are also simulated as in the real robot with feedback information that includes the joint angles as well as the velocities of motors.

3.4 Experiments & Results

3.4.1 Experimental Design

In these experiments we investigated the false alarm interactions in human robot teams by comparing the measured and extended neglect tolerance model predicted performances and attention demand for real and virtual single robot teams across two autonomy modes. We compared the results from extended neglect tolerance and traditional neglect tolerance models to study the inaccuracies in robot performance and attention demand estimations due to zero false alarm assumptions in the latter. We also validate the proposed model and establish how the extended neglect tolerance model outperforms the traditional approach towards estimating robot performance and attention demand in single robot teams across varying world complexity and minimum acceptable performance levels.

We selected the primary task to be navigating our Robo-Erectus Junior humanoid robot in the soccer field towards a randomly placed ball. The robot and ball position were randomly selected in the soccer field. The operator used the interaction scheme under test to navigate the robot to the ball position. When the robot reached the ball position, the ball was placed randomly in another location of the soccer field for the robot to navigate to. We introduced a secondary task of solving two digit arithmetic problems that imposed cognitive load on the test subject. The operator is expected to manually write the answers to the arithmetic problem in a sheet of paper. The secondary task used in this experiment is difficult

Figure 3.4 Flow Diagram for Experimental Design

because it requires response-selection attention, occupies working memory, and requires manual effort in writing the answers. Figure 3.4 shows the flow diagram for the experimental design.

We used a self-paced implementation, meaning the operator chose when a new arithmetic problem was presented. However, once the arithmetic problem was presented, the operator had only 10 seconds to answer it. This process was repeated for every operator for real and virtual robots across tele-operation and semi-autonomous modes of autonomy.

3.4.2 Interaction Scheme

In this section, we describe the interaction scheme designed for the purpose of performing the robot navigation tasks presented in this thesis. The interaction scheme has two key components namely, control interface and information interface. The information interface presents the information about the robots and its environments to human operators. Figure 3.5 shows a snap shot of the information interface used for the experiments.

The control interface allows user to control the robot in two autonomy modes with varying degrees of autonomy. While the control interfaces of the interaction schemes vary with the autonomy mode, the information interface is largely the same for the two autonomy modes. The main portion of the information interface shows a topographical map of the robots' world. On the topographical

map, the position of each robot is marked by a semi-circular objects and the ball positions are marked by a rectangle.

Figure 3.5 Information Interface

On the right hand side of the information interface various system indicators are listed, such as team performance, time-based workload, time elapsed, and number of balls kicked for both cases of primary and secondary robots. At the

bottom of the information interface, the sensory information of the robot currently being serviced is displayed.

Graphic visualization of the sonar, compass, and video camera placed on the robot were presented. The control element is located at the bottom the information interface and it presents the user inputs from the control interface which is a hardware input device like joystick, mouse, etc. At the lower right hand corner are various buttons: a locate robot button (used to help the operator locate the current robot on the global map), a locate goal button (used to help the operator locate the ball position), and a done button (used to terminate the current task and move on to another task).

The control interface in the case of tele-operation mode is a Joystick. For tele-operation, the user input supplied to the robot via the joystick was depicted graphically in the control element of the information interface. This helps the operator to understand the direction they were telling the robot to go. Tele-operation autonomy modes are potentially very complexity tolerant because the human operator makes the high level decisions (and is thus able to reason through complex situations). However, if the information interface does not provide the human operator with adequate awareness of the robot's environment, increased world complexity can lead to decreased robot performance. The control interface of semi-autonomous mode is a mouse.

The operator defines a series of way points by simply clicking on the map telling the robot what to do next. Additional buttons are also provided for control (Forward, Backward, Turn Right, Turn Left, and Stop). These buttons are placed in the control element of the information interface. As feedback, the button currently employed is made darker in colour to let the operator know what to expect from the robot. After the robot believes that it has fulfilled the current command, it notifies the operator by switching the button to back to normal state.

3.4.3 Instantaneous Performance

In this Section, we have redefined instantaneous performance given in [102] to suit the selected task of navigating the robot to the ball as ratio of the current capability of the robot at a given time for a task and the maximum capability of the robot or other objects for the same task. Instantaneous performance can take any value from 0 and +1. It is given by:

$$P_I(t) = \frac{C_c(t)}{M_c(t)} \quad (3.5)$$

where, $C_c(t)$ is the current capability of the robot at time t for a task, $M_c(t)$ is the maximum capability of the robot or other objects at time t for the same task and $P_I(t)$ is the instantaneous performance at time t . In our case, the goal for the robot is to navigate to the ball position so the maximum capability would be the

distance travelled by the robot moving optimally towards the ball position at top speed. We define maximum capability of the robot as:

$$M_c(t) = K \times \delta_t \quad (3.6)$$

where, δ_t is a small interval of time and K is the maximum speed of the robot. Since, Robo-Erectus Junior humanoid robots can travel at the speed of 8.33cm per second, K value used was 8.33. The current capability of the robot is the actual distance travelled by the robot in the time, δ_t ,

$$C_c(t) = D_t - D_{t-\delta_t} \quad (3.7)$$

where, D_t is the distance travelled by the robot at time t and $D_{t-\delta_t}$ is the distance travelled by robot at time t- δ_t . The instantaneous performance at time t is computed as:

$$P_I(t) = \frac{C_c(t)}{M_c(t)} = \frac{D_t - D_{t-\delta_t}}{K \times \delta_t} \quad (3.8)$$

In the experiments conducted, future performance and RAD estimates were obtained as average over the prior trials of the same task. The actual performance is measured using the Equation 3.8 which gives instantaneous performance measure.

3.4.4 World Complexity

World complexity is a measure of difficulty level of the world in which the

robot is operating and it remains as a key factor in deciding the robot performance level and number of occurrences of false alarm interactions. In the experiments presented, the world complexity is only a function of static obstacle density given by,

$$OD = \frac{TO}{TA} \quad (3.9)$$

Where OD is the static obstacle density, TO is the total number of obstacles in the robot workspace and TA is the total robot workspace area in m², the area used in the experiments is 24 m². Figure 3.6 shows the robot workspace utilized for the experiments presented in this paper.

Figure 3.6 Robot Workspace

The workspace was divided into a 1m x 1m grid where the obstacle was placed. Each obstacle was a static cylinder of diameter 10 cm. The obstacles were

randomly placed in any of the 24 grids and routinely changed for every experiment. But, task complexity can be further extended to include active obstacle density and terrain factors. The dotted line indicates a potential path for the robot to navigate from start to finish points. During the experiments, the operator was free to choose any path.

3.4.5 Participants and Procedure

The experiment started with training of the test subjects on how to control the robots using the interaction schemes for real and virtual robots across tele-operation and semi-autonomous modes of autonomy. The training session continued until the test subject was confident in using the interaction scheme which was followed by test sessions. We recruited 20 test subjects aged between 18 and 51 and each of them took part in two ten minute session with real and virtual robots, so a total of 80 test sessions were performed. Of these sessions, 40 were dedicated to the tele-operation mode and remaining 40 to the semi-autonomous mode. In the test session, the operator first serviced a robot to accomplish the task of navigating to the ball. After servicing the first robot, he/she switches to the secondary task of solving two digit arithmetic problems. The operator was instructed to navigate to the ball as many times as possible during each ten minutes test session. The instantaneous performance measurements together with the time, operator controls, and robot state information were recorded for each test session.

3.5 Results

3.5.1 Extended Neglect Tolerance Model Validation

Figure 3.7 shows the performance of the real and virtual robots in accomplishing the given task across tele-operation and semi-autonomous modes for all the twenty test subjects. The world complexity was set to 0.75. The plots closely resemble the extended neglect tolerance model proposed earlier in this chapter. False alarm interactions were witnessed in all the 80 test sessions. A total of 143 false alarm interactions were recorded in the 80 test sessions out of which 105 were false positive interactions and 38 were false negative interactions.

(a)

(b)

(c)

Figure 3.7 Robot Performance in Single Robot Teams for a constant world complexity of 0.75: (a) Real Robot in Tele-operation Mode, (b) Virtual Robot in Tele-operation Mode, (c) Real Robot in Semi-autonomous Mode and (d) Virtual Robot in Semi-autonomous Mode.

The false negatives were mainly due to errors in the graphic user interaction scheme, software faults in robot's control and artificial intelligence modules, and hardware failures in sensor/actuator systems. The false positives were mainly due to the human error pertaining to lack of understanding of the interaction scheme, and the task of interest.

The performance results for real and virtual robots were found to follow similar pattern for both tele-operation and semi-autonomous autonomy modes. As postulated, the FADs for tele-operation were found to be shorter than those for semi-autonomous experiments. For the given task, tele-operation mode is more efficient in increasing the performance of the robot upon servicing after a neglect period as compared to semi-autonomous mode. This is mainly attributed to the continuous control of robots by the operator in the tele-operation mode.

The robot performance dropped abruptly to zero within three seconds of the neglect period for all the tele-operation experiments attributed to the lack of any intelligence in robots whereas the performance drop during neglect period was more gradual for semi-autonomous experiments. For both the autonomy modes, the occurrence of false alarm interactions decreases the performance as the operator has to spend a considerable amount of time in identifying and rectifying the false alarm interactions. The performance loss due false alarm interactions are more significant in semi-autonomous mode as compared to tele-operation mode as the performance recovery rate to the pre-false alarm level is faster in the tele-operation mode. The trend of the graphs in Figure 3.7, validate the extended neglect tolerance model proposed in this thesis.

Figure 3.8 show the average interactions required by the interaction scheme for minimum acceptable performance level (MAPL) of 50% of the peak value for real and virtual robots across the two autonomy mode. From Figure 3.8, it

is evident that the tele-operation mode requires the operator to interact continuously with the robot as in the case of neglect the robot performance drops rapidly to zero whereas semi-autonomous mode offers operator sufficient time to perform secondary task.

In semi-autonomous mode, it is interesting to note that neglect times in some operators are larger than the servicing times indicating that the operator spent more time performing secondary task as compared to the primary task maintaining the performance at 50% of the peak value. Thus, the human robot interaction using semi-autonomous autonomy mode requires less operator workload than tele-operation mode. RAD can be derived using Equation 3.3 from the robot neglecting and servicing times.

(a)

(b)

(c)

(d)

Figure 3.8 Average Interactions required by the interaction scheme for MAPL of 50% of peak value for real and virtual robots across the two autonomy modes: (a) Real Robot in Tele-operation Mode, (b) Virtual Robot in Tele-operation Mode, (c) Real Robot in Semi-autonomous Mode and (d) Virtual Robot in Semi-autonomous Mode.

Figure 3.9 shows the RAD plotted against the robot performance for virtual and real robot experiments across tele-operation and semi-autonomous modes of autonomy using the extended neglect tolerance model. Figure 3.9 presents the robot performance plotted against the RAD for all twenty operators. From Figure 3.9, it is evident that tele-operation and semi-autonomous modes have similar performance results but tele-operation requires much higher RAD as

compared to semi-autonomous mode. The results for the twenty operators were consistent across tele-operation and semi-autonomous autonomy modes for both real and virtual robot experiments.

We recomputed the performance and RAD data for the traditional neglect tolerance model ignoring all the false alarm interactions. Figure 3.10 show the RAD plotted against the robot performance for experiments with real and virtual humanoid robots across tele-operation and semi-autonomous modes of autonomy using the traditionally adopted neglect tolerance model ignoring all the false alarm interactions. Significant differences were found between the two sets of robot performances with and without false alarm interactions while operating the robot in tele-operation mode for both real robot, $t(19)=13.51$, $p<0.0001$ and virtual robot, $t(19)=12.32$, $p<0.0001$ experiments.

Results for the semi-autonomous mode also showed significant difference in the two data sets for robot performances with and without false alarms in both real robot, $t(19)=16.98$, $p<0.0001$ and virtual robot, $t(19)=18.34$, $p<0.0001$ experiments. In statistical t-test, the p-value is the probability of obtaining a test statistic atleast as extreme as the one that was actually observed, assuming that the null hypothesis is true. One often “rejects the null hypothesis” when the p-value is less than 0.05 or 0.01. When the null hypothesis is rejected, the result is said to be statistically significant [103].

(a)

(b)

Figure 3.9 RAD plotted against the robot performance for (a) Real Robot and (b) Virtual Robot experiments using extended neglect tolerance model.

(a)

(b)

Figure 3.10 RAD plotted against the robot performance for (a) Real Robot and (b) Virtual Robot experiments using traditional neglect tolerance model.

Also, significant differences were found between the two sets of RAD estimations with and without false alarms while operating the robot in tele-operation mode for both real robot, $t(19)=10.39$, $p<0.0001$ and virtual robot, $t(19)=10.66$, $p<0.0001$ experiments. Results for the semi-autonomous mode also showed significant difference in the two data sets for RADs with and without false alarms in both real robot, $t(19)=58.11$, $p<0.0001$ and virtual robot, $t(19)=50.75$, $p<0.0001$ experiments.

From the t-test results and Fig. 3.9 & 3.10, it is evident that significant differences exist in robot performance and RAD estimations offered by the traditional approach and the proposed extended neglect tolerance model. Also, the traditional approach renders an optimistic estimate of robot performance and RAD as compared to the proposed extended neglect tolerance model due to the zero false alarm interaction assumptions.

We conducted statistical experiments to compare the predicted robot performance and RAD from the first group with and without FATs to the observed robot performance from the second group. Another group of twenty test subjects with same age profile performed the same experiments as the first group. Figure 3.11 shows the average robot performance plotted against the RAD with FATs taken accounted as in actual real world scenarios for the second group of test subjects. We assumed the results from the second group as measured reference data for further comparative analysis against the predictions from the first group.

Significant differences in robot performance were found between the predictions from first group without FATs using traditional approach and the observation from second group while operating the robot in a semi-autonomous mode for both real robot, $t(38) = 9.83$, $p < 0.0001$ and a virtual robot, $t(38) = 8.07$, $p < 0.0001$ experiments.

Results for tele-operation mode also showed significant differences in robot performance between the predictions from first group ignoring FATs using traditional approach and the observations from second group in both real robots, $t(38)=14.44$, $p < 0.0001$ and virtual robots, $t(38)=7.75$, $p < 0.0001$ experiments.

(a)

(b)

Figure 3.11 Robot Performance plotted against the RAD incorporating the FATs across the two autonomy modes for second group: (a) Real Robot, (b) Virtual Robot.

But, no significant differences were found between the predictions from first group taking FATs into account using the proposed extended neglect tolerance approach and the observations from second group while operating the robots in semi-autonomous mode for both real robots, $t(38) = 0.67$, $p=0.511$ and virtual robot, $t(38) = 1.24$, $p=0.231$ experiments. Results for tele-operation mode also showed no significant differences in average robot performances between the predictions from first group with FATs accounted using proposed extended neglect

tolerance approach and the observations from second group in both real robot, $t(38)=0.78$, $p=0.443$ and virtual robot, $t(38)=0.84$, $p=0.41$ experiments.

Significant differences in RAD were also found between the predictions from first group without FATs using traditional approach and the observations from second group while operating the robot in a semi-autonomous mode for both real robot, $t(38) = 6.17$, $p<0.0001$ and a virtual robot, $t(38) = 6.59$, $p<0.0001$ experiments. Results for tele-operation mode also showed significant differences in RAD between the predictions from first group ignoring FATs using traditional approach and the observations from second group in both real robots, $t(38)=2.49$, $p=0.0221$ and virtual robots, $t(38)=9.99$, $p<0.0001$ experiments.

But, no significant differences were found between the predictions from first group taking FATs into account using the proposed extended neglect tolerance approach and the observations from second group while operating the robots in semi-autonomous mode for both real robots, $t(38) = 0.36$, $p=0.722$ and virtual robot, $t(38) = 1.46$, $p=0.1595$ experiments. Results for tele-operation mode also showed no significant differences in average robot performances between the predictions from first group with FATs accounted using proposed extended neglect tolerance approach and the observations from second group in both real robot, $t(38)=1.42$, $p=0.1627$ and virtual robot, $t(38)=0.89$, $p=0.3847$ experiments.

The statistical t tests that were performed further validated the extended neglect tolerance model and the need for the inclusion of additional demands

incurred due to occurrences of false alarm interaction. The observed robot performance and RAD for the second group showed significant differences when compared to predictions from first group without FADs for all experimental cases thereby proving the critical shortfalls that exists in the traditional neglect tolerance approach when applied to real world experiments. No significant differences were found while comparing the observed robot performance and RAD estimations from the second to predictions from first group with FADs accounted for all experimental cases indicating the robustness of the proposed extended neglect tolerance model in estimating robot performances.

The results derived from the experiments offers significant impact as the assumption of zero false alarm interactions in the traditional approach leads to an optimistic robot performance prediction thereby contributing towards operator's inability in accomplishing the performance goal set for the task. Since, the occurrences of false alarm interactions in actual situation result in performance loss that are not accounted in the former whereas inclusion of false alarm demand as proposed in the extended neglect tolerance model offers a more realistic robot performance predictions. Also from these results, it is clear that ignoring false alarm interactions results in a lower estimate of RADs which may result in operator's failure in accomplishing the task in actual situation as additional efforts are required from the operator towards identifying and rectifying false alarm interactions whereas the RAD estimations using extended neglect tolerance model

are realistic and in close agreement with the second group.

3.5.2 Results for Varying World Complexities

World complexity is a key parameter that directly impacts the robot performance and attention demand as well as the occurrences of false alarm interactions. We next validate the extended neglect tolerance model for varying world complexities. Figure 3.12 shows the average interactions required for a constant world complexity of 0.5. Comparing Figure 3.12 to the Figure 3.8 where the world complexity is set to 0.75, it is evident that with any decrease in world complexity, IT decreases and NT increases for both tele-operation and semi-autonomous modes. In the tele-operation mode, IT decreased by 7.15% for real experiments and 3.72% for virtual experiments.

(a)

(b)

(c)

(d)

Figure 3.12 Average Interactions required by the interaction scheme for constant world complexity of 0.5: (a) Real Robot in Tele-operation Mode, (b) Virtual Robot in Tele-operation Mode, (c) Real Robot in Semi-autonomous Mode and (d) Virtual Robot in Semi-autonomous Mode.

Also, NT increased by 36.4% for real experiments and 78.72% for virtual experiments. In the semi-autonomous mode, IT decreased by 0.8% for real experiments and 4.96% for virtual experiments. Also, NT increased by 5.82% for experiments and 3.61% for virtual experiments. Figure 3.13 shows the RAD plotted against the average performance for all experimental cases using the extended neglect tolerance model for world complexity at 0.5. Figure 3.13 illustrates the trade-off between robot performance and operator workload in terms

(a)

(b)

Figure 3.13 RAD plotted against robot performance for world complexity of 0.5 (a) real and (b) virtual robot experiments using extended neglect tolerance model.

of RAD for all the ten operators involved in the experiments for world complexity of 0.5. Comparing Figure 3.13 to the Figure 3.9 where the world complexity is set to 0.75, it is evident that any increase in world complexity result in a proportional increase in the RAD as the human operator has to spend more time interacting with the robot that is operating in a more complex environment.

We recomputed the performance data for the traditional neglect tolerance model ignoring all the false alarm interactions. Figure 3.14 show the RAD plotted against the average performance for all experimental cases using the traditionally adopted neglect tolerance model ignoring all the false alarm interactions with a world complexity of 0.5.

(a)

(b)

Figure 3.14 RAD plotted against the average performance for (a) real and (b) virtual robot experiments using traditional neglect tolerance model.

Significant differences were found between the two sets of robot performances with and without false alarms while operating the robot in tele-operation mode for both real robot, $t(19)=10.47$, $p<0.0001$ and virtual robot, $t(19)=10.26$, $p<0.0001$ experiments. Results for the semi-autonomous mode also showed significant difference in the two data sets for robot performances with and without false alarms in both real robot, $t(19)=26.81$, $p<0.0001$ and virtual robot, $t(19)=10.99$, $p<0.0001$ experiments.

Also, significant differences were found between the two sets of RAD estimations with and without false alarms while operating the robot in tele-

operation mode for both real robot, $t(19)=11.5$, $p<0.0001$ and virtual robot, $t(19)=16.48$, $p<0.0001$ experiments. Results for the semi-autonomous mode also showed significant difference in the two data sets for RADs with and without false alarms in both real robot, $t(19)=14.12$, $p<0.0001$ and virtual robot, $t(19)=33.67$, $p<0.0001$ experiments.

From the t-test results and Figure 3.13 & 3.14, it is evident that significant differences exist in robot performance and RAD estimations offered by the traditional approach and the proposed extended neglect tolerance model. Also, the traditional approach renders an optimistic estimate of robot performance and RAD as compared to the proposed extended neglect tolerance model due to the zero false alarm interaction assumptions in the former across varying world complexities.

(a)

(b)

Figure 3.15 Robot Performance plotted against the RAD incorporating the FADs across the two autonomy modes for second group with world complexity of 0.5: (a) Real Robot, (b) Virtual Robot.

We conducted statistical experiments to compare the predicted robot performance from the first group with and without FADs to the observed robot performance from the second group. A second group of twenty test subjects aged between 20 and 45 were asked to perform the same robot navigating task as the first group of subjects. Figure 3.15 shows the average robot performance plotted against the RAD with FADs taken into account using extended neglect tolerance model as in actual real world scenarios for the second group of test subjects.

As assumed earlier, we considered the second group as measured reference

data. Significant differences in robot performance were found between the predictions from first group without FATs using traditional approach and the observations from second group while operating the robot in a semi-autonomous mode for both real robot, $t(38) = 26.81$, $p < 0.0001$ and a virtual robot, $t(38) = 10.99$, $p < 0.0001$ experiments. Results for tele-operation mode also showed significant differences in robot performance between the predictions from first group ignoring FATs using traditional approach and the observations from second group in both real robots, $t(38) = 10.47$, $p < 0.0001$ and virtual robots, $t(38) = 10.26$, $p < 0.0001$ experiments.

But, no significant differences were found between the predictions from first group that takes FATs into account using the proposed extended neglect tolerance approach and the observations from second group while operating the robots in semi-autonomous mode for both real robots, $t(38) = 0.3$, $p = 0.7654$ and virtual robot, $t(38) = 0.15$, $p = 0.8805$ experiments. Results for tele-operation mode also showed no significant differences in average robot performances between the predictions from first group with FATs accounted using proposed extended neglect tolerance approach and the observations from second group in both real robot, $t(38) = 0.96$, $p = 0.3548$ and virtual robot, $t(38) = 0.0221$, $p = 0.9826$ experiments.

Significant differences in RAD were found between the predictions from first group without FATs using traditional approach and the observations from second group while operating the robot in a semi-autonomous mode for both real

robot, $t(38) = 11.81$, $p < 0.0001$ and a virtual robot, $t(38) = 6.72$, $p < 0.0001$ experiments. Results for tele-operation mode also showed significant differences in RAD between the predictions from first group ignoring FATs using traditional approach and the observations from second group in both real robots, $t(38)=7.43$, $p < 0.0001$ and virtual robots, $t(38)=6.39$, $p < 0.0001$ experiments.

But, no significant differences were found between the predictions from first group taking FATs into account using the proposed extended neglect tolerance approach and the observations from second group while operating the robots in semi-autonomous mode for both real robots, $t(38) = 1.29$, $p=0.214$ and virtual robot, $t(38) = 0.072$, $p=0.9434$ experiments. Results for tele-operation mode also showed no significant differences in average robot performances between the predictions from first group with FATs accounted using proposed extended neglect tolerance approach and the observations from second group in both real robot, $t(38)=0.4$, $p=0.6966$ and virtual robot, $t(38)=0.44$, $p=0.666$ experiments.

The statistical t tests that were performed validated the extended neglect tolerance model and the need for inclusion of additional demand incurred due to false alarm interactions into the model across varying world complexities of 0.5 and 0.75. The observed average robot performance and RAD for the second group showed significant differences when compared to predictions from first group without FATs for all experimental cases thereby proving the shortfalls that exists in the traditional neglect tolerance approach when applied to real world applications.

No significant differences were found while comparing the observed robot performance and RAD from the second to predictions from first group with FATS accounted for all experimental cases indicating the robustness of the proposed extended neglect tolerance model in estimating robot performances across varying world complexities.

Also, the experiments with varying world complexities presented in this section, showed the correspondence between the RAD and the varying world complexities. Results indicated drop in RAD for all experimental cases as the world complexity was increased from 0.5 to 0.75. The RAD data for real robot tele-operation witnessed 3.18% drop whereas for semi-autonomous the drop was at 2.21% for world complexity increase of 0.25. In the case of virtual robot experiments, the drop in RAD stood at 5.01% for tele-operated robots as compared to 4.35% for semi-autonomous robots. Experimental results indicated no predictive correspondence between the RAD and the performance. The RAD value in isolation would be useful for a robot operator in understanding the difficulty in handling a given task and comparing the nature of varying tasks in terms of workload requirements.

3.5.3 Results for Varying MAPLs

We next validate the extended neglect tolerance model for varying MAPLs based on experiments presented in Figure 3.7. Figure 3.16 shows the average

interactions required for a MAPL of 70% of the peak value using extended neglect tolerance model.

(a)

(b)

(c)

(d)

Figure 3.16 Average Interaction required for MAPL of 70% of peak value: (a) Real Robot in Tele-operation Mode, (b) Virtual Robot in Tele-operation Mode, (c) Real Robot in Semi-autonomous Mode (d) Virtual Robot in Semi-autonomous Mode.

Comparing Figure 3.16 to the Figure 3.8 with MAPL set to 50%, it is obvious that any increase in MAPL, the IT increases and NT decreases as the operator now has to spend more time interacting with the robot to maintain a higher performance and NT decreases as with higher performance requirement the operator cannot afford to neglect the robot for longer durations. In the tele-operation mode, IT increased by 16.12% for real experiments and 17.61% for virtual experiments. Also, NT decreased by 65.79% for real experiments and 37.87% for virtual experiments. In the semi-autonomous mode, IT increased by 4.87% for real experiments and 1.72% for virtual experiments. Also, NT decreased by 23.9% for experiments and 13.4% for virtual experiments.

Figure 3.17 show the RAD plotted against the average performance for all experimental cases using the extended neglect tolerance model considering the additional demands due to false alarm interactions for a MAPL of 70%. Figure 3.17 illustrates the trade-off between robot performance and operator workload in terms of RAD for all the twenty operators involved in the experiments. Comparing Figure 3.17 to the Figure 3.9 where the MAPL is set to 50%, it is evident that with any increase in MAPL, the RAD increases as the operator is now required to maintain a higher performance level. We recomputed the average performance and RAD data for the traditional neglect tolerance model ignoring all the false alarm interactions.

(a)

(b)

Figure 3.17 RAD plotted against the average performance for MAPL at 70% (a) real and (b) virtual robot experiments using extended neglect tolerance model.

Figure 3.18 show the RAD plotted against the average performance for experiments with real and virtual humanoid robots across tele-operation and semi-autonomous modes of autonomy using the traditionally adopted neglect tolerance model ignoring all the false alarm interactions for MAPL at 70%. Significant differences were found between the two sets of RAD estimations with and without false alarms while operating the robot in tele-operation mode for both real robot, $t(19)=5.06$, $p<0.0001$ and virtual robot, $t(19)=4.3$, $p<0.0001$ experiments. Results for the semi-autonomous mode also showed significant difference in the two data sets for RADs with and without false alarms in both real robot, $t(19)=72.47$, $p<0.0001$ and virtual robot, $t(19)=46.42$, $p<0.0001$ experiments.

(a)

real and (b) virtual robot experiments using traditional neglect tolerance model.

Since, the robot performance data used in this section have been extracted from Figure 3.7 and the statistical analysis for the same was already performed in Section 3.5.1, the analysis in this section focussed only on the RAD estimations.

From the t-test results and Fig. 3.17 & 3.18, it is evident that significant differences exist in RAD estimations offered by the traditional approach and the proposed extended neglect tolerance model for MAPL at 70%. Also, the traditional approach renders an optimistic estimate of RAD as compared to the proposed extended neglect tolerance model due to the zero false alarm interaction assumptions.

We conducted statistical experiments to compare the predicted RAD from the first group with and without FATs to the observed robot performance from the second group with MAPL at 70%. A second group of ten test subjects aged between 20 and 45 were asked to perform the same robot navigating task as the first group of subjects. Figure 3.19 shows the average robot performance plotted against the RAD with FATs accounted as in actual real world scenarios for the second group of test subjects. As done earlier for further comparative studies, we assumed results from the second group as reference. Significant differences in RAD were also found between the predictions from first group without FATs using traditional approach and the observations from second group while operating the

(a)

(b)

Figure 3.19 Robot Performance plotted against the RAD incorporating the FATs across the two autonomy modes for second group with MAPL at 70%: (a) Real Robot, (b) Virtual Robot.

robot in a semi-autonomous mode for both real robot, $t(38) = 3.59$, $p < 0.0001$ and a virtual robot, $t(38) = 2.55$, $p < 0.0001$ experiments.

Results for tele-operation mode also showed significant differences in RAD between the predictions from first group ignoring FATs using traditional approach and the observations from second group in both real robots, $t(38)=6.25$, $p < 0.0001$ and virtual robots, $t(38)=9.87$, $p < 0.0001$ experiments. But, no significant

differences were found between the predictions from first group taking FATs into account using the proposed extended neglect tolerance approach and the observations from second group while operating the robots in semi-autonomous mode for both real robots, $t(38) = 0.02$, $p=0.9819$ and virtual robot, $t(38) = 0.384$, $p=0.705$ experiments. Results for tele-operation mode also showed no significant differences in RAD between the predictions from first group with FATs accounted using proposed extended neglect tolerance approach and the observations from second group in both real robot, $t(38)=1.74$, $p=0.0976$ and virtual robot, $t(38)=1.6$, $p=0.1253$ experiments.

The statistical t tests that were performed validated the extended neglect tolerance model and the need for inclusion of false alarm demand into the model across varying MAPLs of 50% and 70% of peak performance levels. The observed RAD for the second group showed significant differences when compared to predictions from first group without FATs for all experimental cases thereby indicating the shortfalls in the traditional neglect tolerance approach. No significant differences were found while comparing the observed RAD from the second to predictions from first group with FATs accounted for all experimental cases indicating the robustness of the proposed extended neglect tolerance model in estimating RAD across varying MAPLs.

We also computed and compared the FATs for real and virtual robot experiments presented in Figure 3.7. Figure 3.20 shows the average FATs for all

experimental cases. The mean FATs for semi-autonomous mode were higher as compared to tele-operation mode and the real and virtual robot experiments yielded similar results. These FATs can be used as a performance metric in identifying optimal robot platform/autonomy mode for a given application as FATs are directly proportional to the net performance of the robot. In the experiments performed, FAT was higher for semi-autonomous mode as compared to tele-operation mode thereby implying that latter offers higher performance for the task involved as compared to the semi-autonomous mode. These experiments can be further extended to compare performance of different interaction schemes and robot platforms for a given task.

3.6 Conclusions

This chapter has introduced the concept of the false alarm interactions with the purpose of identifying and classifying the erroneous interactions that occurs in single robot teams. We presented two new metrics, the false alarm time (FAT) and false alarm demand (FAD), for measuring effects of false alarm interactions on human robot teams and extend the neglect tolerance model to situations in which false positives and false negatives are present. We conducted experiments with virtual and real humanoid soccer robots across tele-operated and semi-autonomous

modes of autonomy to demonstrate the efficacy and utility of the proposed metrics and the extended neglect tolerance model for single robot teams.

Figure 3.20 Average FADs for all experimental cases

Results of our experiments with virtual and real robots were largely consistent with the proposed extended neglect tolerance model predictions for the two autonomy modes. False alarm interactions occurred in all experimental cases and impacted performance negatively. Statistical experiments performed showed significant differences in robot performance and RAD predictions between the target population with and without inclusion of false alarm interactions across varying world complexities. From the results, it was also evident that the tele-operation and semi-autonomous modes offered similar performance results for the same task but the latter requires lower RAD and offers better performance

deterioration rate during neglect times. FADs were found to be higher in semi-autonomous mode as compared to tele-operation mode for experiments with both real and virtual robots.

Statistical experiments were conducted to compare the predicted robot performances from the first group with and without FATs to the observed robot performance from a second group. Results showed substantial differences in the robot performances and RAD for all experimental cases for the predictions from first group with zero false alarms assumption in comparison to the observed results from the second group. However, the experimental results using extended neglect tolerance model from the first group were in close agreement with the observed results from the second group. Extended neglect tolerance model offers a more realistic estimation of robot performance and RAD thereby helping the operator to plan a more realistic scheduling of robot tasks. Use of extended neglect tolerance model also helps in improving the overall task performance as compared to the traditional approach as the latter offers a more optimistic estimation of performance and RAD which are unachievable in actual situations due to additional false alarm demands.

The experiments have demonstrated a very important phenomenon that the proposed extended neglect tolerance model offers a more realistic estimate of robot performance, and RAD in single robot teams as compared to the traditionally adopted neglect tolerance model. This also implies that false alarm interactions that

occur between human and robot if ignored as in traditional approach may lead to task failure as the operator may not be able to meet both time and performance criteria set for the task due to additional false alarm interaction demands in real world scenarios.

4. Extended Neglect Tolerance Model for Multi Robot Teams

4.1 Introduction

Although, neglect tolerance model have been widely adopted for estimation of robot performances, attention demand and other key metrics in multi-robot teams wherein a single operator handle multiple robots towards accomplishing dependent or independent tasks. No systematic studies or theoretical analyses have been carried out to estimate the impact of zero false alarm interaction assumptions in this traditional model while estimating key metrics. In Chapter 3, we proved that the assumption of zero false alarm interactions in traditional neglect tolerance model for single robot team is a major obstacle in deriving a realistic estimate of robot performance and RAD. We also put forward and validated an extension of the traditional approach that accounts for the false alarm interactions.

In this chapter, we make use of the two false alarms metrics identified in Chapter 3 that quantifies the effects of false alarm interactions to extend the neglect tolerance model for multi-robot system towards obtaining a realistic estimation of robot performances, attention demand and other key metrics. While working with multi-robot teams, it is always preferred for an operator to manage large number of robots. Fan out is adopted as a general index among human robot interaction researchers in predicting the maximum number of robots a single operator can

handle simultaneously while maintaining performance at acceptable levels. But, the traditional neglect tolerance forms the basis of the fan out metric and therefore assumes zero erroneous interactions. In this Chapter, we redefine the fan out metric to account for any additional demands due to the occurrence of false alarm interactions. Simulation and experiments were carried out to demonstrate the efficacy and utility of the extended neglect tolerance model for both independent and dependent multi-robot teams.

Further, the advantages of the proposed model are investigated in detail and their performance compared against the traditional neglect tolerance model for multi-robot teams. The impact of false alarm interactions on estimation of multi-robot team specific metrics including fan out, co-operation effort, co-ordination demand, and team attention demand are studied.

The concept of extended neglect tolerance model for both independent and dependent multi-robot teams are introduced in Section 4.2. Experimental validation of the proposed model for independent multi-robot teams is presented in Section 4.3 and experimental validation for the extended model involving dependent multi-robot teams is presented in Section 4.4.

4.2 Extended Neglect Tolerance Model for Multi-Robot Team

Neglect tolerance model for multi-robot teams assumes zero false alarm interactions during robot operation while estimating robot performance and fan out

for both dependent and independent tasks. But, in most real life applications false alarm interactions between the human operator and the robot are common due to uncertainties in human operators, robots, environment, task involved and the interaction system in place which are the key elements of any human robot system.

To incorporate the additional demands due to false alarm interactions we have extended neglect tolerance model for both dependent and independent multi-robot teams by introducing the notion of false alarm time (FAT) defined in Chapter 3. As noted in the Chapter 3, the tele-operation mode requires a very large (near unity) robot attend demand (RAD), thereby making it much difficult for the human operator to handle a secondary robot. Therefore, in this thesis we focus on multi-robot systems operating in semi-autonomous mode of autonomy.

4.2.1 Independent Multi-Robot Teams

Figure 4.1 depicts the extended neglect tolerance model for an independent task involving multiple semi-autonomous robots with inclusion of FATs. The scenario depicted in Figure 4.1 starts just after the operator starts to service the target robot. The robot performance increases with time and saturates at some point in time. In the case of a false alarm interaction either false positive or false negative, the performance drops in both the autonomy modes and upon identification by the operator the performance recovers to the pre-false alarm level.

FAT, the time spent over false alarm identification and performance recovery is shown in the Figure 4.1.

Figure 4.1 Extended Neglect Tolerance Model for Semi-Autonomous Independent Multi-Robot Teams

Let π_i be an interaction scheme deployed for the i^{th} robot, and let $N_i(\pi) = (NT_i, FAT_i, IT_i)$ denote the neglect characteristics associated with a preselected performance threshold with inclusion of FATs. As indicated in Section 2.2.3.2, the performance can then be computed as weighted average of $J_i(\pi)$ associated with each $N_i(\pi)$.

Two widely adopted definitions of fan out for independent multi-robot teams are presented in Equation 2.14 and 2.16. But, these traditional metrics uses neglect tolerance model as basis and therefore ignores false alarm interactions that

occur in human robot interaction. We redefined the fan out metrics presented in Equation 2.14 and Equation 2.16 to account for the additional demand due to false alarm interactions as,

$$FO_{IF} = \frac{NT}{(IT + FAT)} + 1 \quad (4.1)$$

$$FO_{IFWT} = \frac{NT}{IT + FAT + \sum_{j=1}^Y WTQ_j + \sum_{k=1}^Z WTSA_k} + 1 \quad (4.2)$$

4.2.2 Dependent Multi-Robot Teams

Figure 4.2 depicts the extended neglect tolerance model for a dependent task involving multiple semi-autonomous robots with inclusion of FATs. The scenario depicted in Figure 4.2 starts just after the operator starts to service the first robot. The robot performance increases with time and saturates at some point. In the case of a false alarm interaction either false positive or false negative, the performance drops in both the autonomy modes and upon identification by the operator the performance recovers to the pre-false alarm level. FAT, the time spent over false alarm identification and performance recovery is shown in the Figure 4.2. When the operator neglects the first robot, the performance drops but increases once he/she starts to interact with the dependent second robot. The performance increases even during the neglect time of the first robot as the operator is

dedicating this time towards interacting with a dependent second robot towards accomplishing a common task. OT quantifies the additional efforts needed from the operator towards synchronizing the two dependent robots.

Figure 4.2 Extended Neglect Tolerance Model for Dependent Multi Robot Teams

FATs for co-operating robots were incorporated into the model. Metrics including neglect time (NT_j in Equation 2.6), Co-operation effort (CE in Equation 2.7), Co-ordination demand (CD in Equation 2.8), Robot attention demand (RAD in Equation 2.9), Team attention demand (TAD in Equation 2.10), Team interaction time (IT_T in Equation 2.11), Team neglect times (NT_T in Equation 2.12), and relative free time (RFT in Equation 2.13) defined earlier were redefined to accommodate for the effects of false alarm interactions,

$$NT_j = \sum_{\substack{i=1 \\ i \neq j}}^N (FT_{ij} + OT_{ij} + FAT_{ij}) + FT_T \quad (4.3)$$

$$CE_j = \frac{\sum OT_{ij} + FAT_{ij}}{IT_j} \quad (4.4)$$

$$CD = \frac{\sum (OT + FAT)}{NT} \quad (4.5)$$

$$RAD_j = \frac{IT_j + FAT_j}{NT_j + IT_j + FAT_j} \quad (4.6)$$

$$TAD = \frac{\sum (OT_{ij} + FAT_{ij}) + IT_j + FAT_j}{NT_j + IT_j} \quad (4.7)$$

$$IT_T = \sum (FT_{ij} + OT_{ij} + FAT_{ij}) + IT_j + FAT_j \quad (4.8)$$

$$NT_T = FT_T \quad (4.9)$$

$$RFT = \frac{NT_j}{(IT_j + FAT_j + NT_j)} \quad (4.10)$$

Two widely adopted definitions of fan out for independent multi-robot teams are presented in Equation 2.17 and 2.18. But, these traditional metrics uses neglect tolerance model as basis and therefore ignores false alarm interactions that

occur in human robot interaction. We redefined the fan out metrics presented in Equation 2.17 and Equation 2.18 to account for the additional demand due to false alarm interactions as,

$$FO_{DF} = \frac{\sum_{\substack{i=1 \\ i \neq j}}^N (FT_{ij} + OT_{ij}) + IT + FAT + FT_T}{\sum_{\substack{i=1 \\ i \neq j}}^N (FT_{ij} + OT_{ij}) + FAT + IT} \quad (4.11)$$

$$FO_{DFWT} = \frac{\sum_{\substack{i=1 \\ i \neq j}}^N (FT_{ij} + OT_{ij}) + IT + FAT + \sum_{j=1}^Y WTQ_j + \sum_{k=1}^Z WTSA_k + FT_T}{\sum_{\substack{i=1 \\ i \neq j}}^N (FT_{ij} + OT_{ij}) + IT + FAT + \sum_{j=1}^Y WTQ_j + \sum_{k=1}^Z WTSA_k} \quad (4.12)$$

We conducted experiments with our humanoid soccer robots, Robo-Erectus Junior described in Section 3.3 to validate the extended neglect tolerance model for both independent and dependent semi-autonomous multi-robot teams towards estimating robot performance and attention demand. We also analyzed the impact of false alarm interactions on estimation of multi-robot team specific metrics like fan out, co-operation effort, co-ordination demand, and team attention demand.

4.3 Independent Multi-Robot Teams - Experiments & Results

4.3.1 Experimental Design

In these experiments we investigated the false alarm interactions by comparing the measured and extended neglect tolerance model predicted performances and attention demand for real and virtual independent semi-autonomous multi-robot teams. We compared the results from extended neglect tolerance to the traditional neglect tolerance approach for independent multi-robot teams to study the inaccuracies in robot performance estimations due to zero false alarm assumptions in the latter. We also validate the proposed model and establish how the extended neglect tolerance model outperforms the traditional approach towards estimating robot performance in independent semi-autonomous multi-robot teams. Figure 4.3 shows the flow diagram for the experimental design.

We selected the task of navigating two independent Robo-Erectus Junior humanoid robots towards a randomly placed ball with varying world complexities. The robots and ball positions were randomly selected in the environment. Towards distinguishing the experiments, we termed the robots as primary and secondary. The primary robot was operated in an environment with world complexity measure of 0.5 whereas the secondary robot was operated in an environment with world complexity measure of 0.75. The world complexity is computed based on the definition presented in Equation 3.9. The operator used the interaction scheme

Figure 4.3 Flow Diagram for Experimental Design

under test to navigate the primary robot to the ball position. When the primary robot reached the ball position, the ball was placed randomly in another location for the robot to navigate to. We used the interaction scheme presented in Section 3.4.2 for these experiments. We introduced a secondary task of navigating a second robot during the neglect time of the target robot. This process was repeated for every operator for both real and virtual robots. Computation of instantaneous performance followed the definition presented in Section 3.4.3.

4.3.2 Participants and Procedure

Sufficient training was provided for the test subjects until confidence was gained towards controlling the robots using the interaction schemes involved for both real and virtual experiments. We recruited 20 test subjects aged between 18 and 51 and each of them took part in a ten minute session with real and virtual robots, so a total of 40 test sessions were performed. In the test session, the operator first serviced the primary robot to accomplish the task of navigating to the ball. After servicing the primary robot, he/she switches to the secondary task of navigating the secondary robot to the ball. The operator was instructed to navigate to the ball as many times as possible with the two robots during each ten minutes test session. Key parameters including performance, time, operator controls and robot state information were logged for experimental analysis.

4.3.3 Results

Figure 4.4 shows the performance of primary and secondary robots for all experimental cases. The plots closely resemble the extended neglect tolerance model for independent multi-robot teams proposed earlier in this chapter. False alarm interactions were witnessed in all the 40 test sessions. A total of 57 false alarms were recorded in the 40 test sessions out of which 38 were false positives and 19 were false negatives.

(a)

(b)

Figure 4.4 Robot Performance in Independent Multi-Robot Teams: (a) Real Robot in Semi-autonomous Mode and (b) Virtual Robot in Semi-autonomous Mode.

(a)

(b)

Figure 4.5 Average Robot Performances in Independent Multi-Robot Teams: (a) Real Robot in Semi-autonomous Mode and (b) Virtual Robot in Semi-autonomous Mode.

As in the case of our experiments with single robot teams, the false negatives interactions were mainly due to errors in the graphic user interaction scheme, software faults in robot's control and artificial intelligence modules, and hardware failures in sensor/actuator systems. The false positive interactions were mainly due to the human error pertaining to lack of understanding of the interaction scheme, and the task of interest.

Due to the differences in world complexity, the performance results for secondary robots were better than the primary robots for all experimental cases.

Similarity in performance results has been observed for both real and virtual experiments. The trend of the graphs in Figure 4.4, validate the extended neglect tolerance model proposed for independent multi-robot systems in this thesis. Figure 4.5 presents the average performance computed from the primary and secondary robots using Equation 2.5. Considering the independent nature of the robots in the team, the net performance was computed as an average of individual robot performances.

Figure 4.6 show the average interactions required by the interaction scheme for minimum acceptable performance level (MAPL) of 50% of the peak value for real and virtual semi-autonomous robots. From the figure, it is evident that the neglect time is larger than the interaction time as the operator in the semi-autonomous mode only has to provide the way points and the robot is capable of handling low level control tasks. Therefore, the operator can devote the neglect time of the primary robot to handle secondary robot.

Figure 4.7 presents the RAD versus the average performance results for extended neglect tolerance model. RAD can be derived using Equation 3.3 from the robot neglecting and servicing times. Both real and virtual experiments presented consistent results across all operators involved.

(a)

(b)

Figure 4.6 Average Interaction required for MAPL of 50% of peak value for real and virtual robots: (a) Real Robot in Semi-autonomous Mode and (d) Virtual Robot in Semi-autonomous Mode.

We ignored the false alarm interactions and recalculated the performance using the traditional neglect tolerance model. Figure 4.8 show the RAD plotted against the average performance for experiments with real and virtual humanoid robots using the traditionally adopted neglect tolerance model for multi-robot teams ignoring all the false alarm interactions.

Figure 4.7 RAD plotted against the average performance for using extended neglect tolerance model.

Significant differences were found between the two sets of robot performances with and without false alarms while operating the robot in semi-autonomous mode for both real robot, $t(19)=21.81$, $p<0.0001$ and virtual robot, $t(19)=25.02$, $p<0.0001$ experiments. Also, significant differences were found between the two sets of RAD estimations with and without false alarms while

operating the robot in semi-autonomous mode for both real robot, $t(19)=26.36$, $p<0.0001$ and virtual robot, $t(19)=27.48$, $p<0.0001$ experiments.

From the t-test results and Figure 4.7 & 4.8, it is evident that significant differences exist in robot performance and RAD estimations offered by the traditional approach and the proposed extended neglect tolerance model. Also, the traditional approach renders an optimistic estimate of robot performance and RAD as compared to the proposed extended neglect tolerance model due to the zero false alarm interaction assumptions.

Figure 4.8 RAD plotted against the average performance for real and virtual robot experiments using traditional neglect tolerance model.

Statistical experiments were carried out to compare the predicted robot

performance and attention demand from the first group with and without FATs to the observed robot performance from the second group. A second group of twenty test subjects aged between 20 and 45 were asked to perform the same robot navigating task as the first group of subjects. Figure 4.9 shows the robot performance plotted against the RAD with FATs taken into account as in actual real world scenarios for the second group of test subjects. As assumed earlier in Chapter 3 experiments, we considered the second group as measured reference data.

Figure 4.9 Robot Performance plotted against the RAD incorporating the FATs for real and virtual robots for second group

Significant differences in robot performance estimations were found

between the predictions from first group without FATs using traditional approach and the observations from second group while operating the robot in a semi-autonomous mode for both real robot, $t(38) = 12.87$, $p < 0.0001$ and a virtual robot, $t(38) = 12.24$, $p < 0.0001$ experiments. Experiments suggested no significant differences among the predictions from first group adopting extended neglect tolerance model and the observations from second group for both for both real semi-autonomous robots, $t(38) = 0.96$, $p = 0.3511$ and virtual semi-autonomous robot, $t(38) = 0.029$, $p = 0.9768$ experiments.

Significant differences in RAD estimations were also found between the predictions from first group without FATs using traditional approach and the observations from second group while operating the robot in a semi-autonomous mode for both real robot, $t(38) = 4.83$, $p < 0.0001$ and a virtual robot, $t(38) = 4.35$, $p < 0.0001$ experiments. Both real experiments, $t(38) = 1.15$, $p = 0.2629$ and virtual experiments, $t(38) = 0.0895$, $p = 0.9296$ presented no significant differences between the predictions from first group taking FATs into account using the proposed extended neglect tolerance and the observations from second group while operating the robots in semi-autonomous mode.

We computed and compared the two widely adopted definitions of fan outs for independent multi-robot teams presented in Equation 2.14 & 2.16 which adopts neglects tolerance model assuming zero false alarm interactions. The redefinitions of traditional equations are put forward in Equation 4.1 & 4.2 that adopts extended

neglect tolerance model taking into account additional demand due to occurrences of false alarms through real and virtual robot experiments. Figure 4.10 shows the fan outs computed using Equation 2.14 which assumes zero wait and false alarm times and its redefinition accommodating false alarms presented in Equation 4.1 for all 20 operators. Significant differences were found between the two sets of fan outs with and without false alarms for both real robot, $t(19)=20.62$, $p<0.0001$ and virtual robot, $t(19)=23.44$, $p<0.0001$ experiments. Figure 4.11 shows the fan outs computed using Equation 2.16 which accounts for wait times but assumes zero false alarm times and its redefinition accommodating for both wait and false alarm times presented in Equation 4.2. Significant differences were found between the two sets of fan outs with and without false alarms for both real robot, $t(19)=18.87$, $p<0.0001$ and virtual robot, $t(19)=22.45$, $p<0.0001$ experiments.

(a)

(b)

Figure 4.10 Fan out for real and virtual experiments
(a) FO_I ignoring FATs (b) FO_{IF} accommodating FATs

(a)

(b)

Figure 4.11 Fan out for real and virtual experiments
(a) FO_{IWT} ignoring FATs (b) FO_{IFWT} accommodating FATs

Statistical experiments were undertaken towards comparing the predicted fan out using both well accepted definitions from the predictions from first group with and without zero false alarm interactions assumption to the observed fan outs from the second group.

Figure 4.12 shows the fan out plotted against operators with FATs taken into account as in actual real world scenarios for the second group of test subjects. Significant differences in fan out estimations were found between the predictions from first group using definition presented in Equation 2.14 and the observations from second group used as reference for both real robot, $t(38) = 5.051$, $p < 0.0001$

and a virtual robot, $t(38) = 7.602$, $p < 0.0001$ experiments. Significant differences in fan out were also found between the predictions from first group using definition presented in Equation 2.16 and the observations from second group for both real robot, $t(38) = 2.7719$, $p < 0.0001$ and a virtual robot, $t(38) = 4.368$, $p < 0.0001$ experiments.

Figure 4.12 Fan out for real and virtual experiments with second group

Significant differences in fan out estimations were also found between the predictions from first group using definition presented in Equation 4.1 and the observations from second group for both real robot, $t(38) = 2.839$, $p < 0.0001$ and a virtual robot, $t(38) = 2.729$, $p < 0.0001$ experiments. But, no significant differences were found between the predictions from first group using the definition presented in Equation 4.2 taking into account both false alarm interaction and wait times

using the proposed extended neglect tolerance approach and the observations from second group for both real robots, $t(38) = 0.0004$, $p=0.9997$ and virtual robot, $t(38) = 0.0079$, $p=0.9937$ experiments. This indicates that the fan outs estimated using extended neglected tolerance model accounting for both false alarm and wait times offers a more realistic estimation as compared to the conventional approaches that assumes zero false alarm interactions for both well accepted definitions.

The statistical t tests that were performed further validated the extended neglect tolerance model for independent multi-robot teams and the need for inclusion of false alarm demand into the model. The robot performance, RAD and fan out estimations for the observations from second group showed significant differences when compared to predictions from first group without FATs for all experimental cases thereby indicating the shortfalls in the traditional neglect tolerance approach for independent multi-robot teams when applied to real world experiments. No significant differences were found while comparing the robot performance, RAD and fan out from the observations in second to predictions in first group with FATs indicating the robustness of the proposed extended neglect tolerance model for independent multi-robot teams in estimating robot performances, RAD, and fan out.

The results derived from the experiments offers significant impact as the assumption of zero false alarm interactions in the traditional approach leads to an optimistic robot performance predictions thereby contributing towards operator's

inability in accomplishing the performance goal set for the task as the occurrences of false alarm interactions in actual situation result in performance loss that are not accounted in the former. But, with the inclusion of false alarm demand as proposed in the extended neglect tolerance model for multi-robot teams offers a more realistic robot performance predictions is obtained. Results involving the traditional approach suggest that ignoring false alarms interactions results in a lower estimate of RADs which may lead the operator to schedule unachievable workload in actual situations. The results also presents a higher estimate of fan out which may gain lead the operator to schedule unachievable fan out targets in actual situations. In both these cases, additional efforts are required in actual situations from the operator towards identifying and rectifying false alarm interactions whereas the RAD and fan out estimations using extended neglect tolerance model are realistic and in close agreement with the observations from the second group.

4.4 Dependent Multi-Robot Teams - Experiments & Results

4.4.1 Experimental Design

In these experiments we investigated false alarm interactions by comparing the measured and extended neglect tolerance model predicted performances, attention demand and other key metrics for real and virtual dependent semi-autonomous multi-robot teams. We compared the results from extended neglect tolerance and the traditionally adopted neglect tolerance approach to study the

inaccuracies in robot performance estimations due to zero false alarm assumptions in the latter. We also validate the proposed model and establish how the extended neglect tolerance model outperforms the traditional approach towards estimating robot performances, attention demand and other key metrics in dependent multi-robot teams. We selected the task of pushing a paper box in the soccer field across locations of interest using two Robo-Erectus Junior humanoid robots. The locations of interest were randomly selected and provided to the operator. We labelled the robots as primary and secondary for identification purposes. The operator used the interaction scheme presented in Section 3.4.2 to control robots one by one to push the box forward. When the robots reached the location, the operator was given a new location to proceed. This process was repeated for every operator for real and virtual semi-autonomous robots. Definition presented in Section 3.4.3 was adopted to compute instantaneous performances for primary and secondary robot experiments.

4.4.2 Participants and Procedure

As in the case of previous experiments, the test subjects were trained until confidence was gained to control the robots using the interaction scheme involved. We recruited 20 test subjects aged between 18 and 51 and each of them took part in two ten minute session with real and virtual robots, so a total of 40 test sessions were performed. The operator switches between the robots interacting continuously with one of the robots as neglecting any over prolonged period would affect the

movement of the box. We recorded the key parameters including instantaneous performance measurements together with the time, operator controls, and robot state information for each test session.

4.4.3 Results

Figure 4.13 shows the robot performance of the dependent multi-robot team for all experimental cases. The robots were operated in an environment with a world complexity measure of 0.5. The plots closely resemble the extended neglect tolerance model for dependent multi-robot teams proposed earlier in this report.

(a)

(b)

Figure 4.13 Robot Performance in Dependent Multi-Robot Teams for a constant world complexity of 0.5: (a) Real Robot in Semi-autonomous Mode and (d) Virtual Robot in Semi-autonomous Mode.

False alarms were witnessed in all the 40 test sessions. A total of 53 false alarms were recorded in the 40 test sessions out of which 36 were false positives and 17 were false negatives. Experiments showcased close similarity between performance results from real and virtual robots experiments. The trend of the graphs in Figure 4.13, validate the extended neglect tolerance model for dependent multi-robot teams proposed in this thesis.

(a)

(b)

Figure 4.14 Average Interaction required of 50% of peak value for real and virtual robots: (a) Real Robot in Semi-autonomous Mode, (b) Virtual Robot in Semi-autonomous Mode.

Figure 4.14 show the average interactions required by the interaction scheme for minimum acceptable performance level (MAPL) of 50% of the peak value for real and virtual robots. Figure 4.15 presents the extended neglect tolerance results for RAD plotted against average performance. RAD can be derived using Equation 4.6 from the robot neglecting and servicing times. Real and virtual robot experimental results were found to be consistent following a similar trend.

We recalculated the robot performance data for the traditional neglect tolerance model ignoring all the false alarm interactions. Figure 4.16 show the RAD plotted against the average performance for experiments with real and virtual humanoid robots using the traditionally adopted neglect tolerance model ignoring all the false alarm interactions. Significant differences were found between the two sets of robot performances with and without false alarms while operating the robot in semi-autonomous mode for both real robot, $t(19)=32.16$, $p<0.0001$ and virtual robot, $t(19)=24.19$, $p<0.0001$ experiments. Also, significant differences were found between the two sets of RAD estimations with and without false alarms while operating the robot in semi-autonomous mode for both real robot, $t(19)=28.32$, $p<0.0001$ and virtual robot, $t(19)=20.71$, $p<0.0001$ experiments.

From the t-test results and Figure 4.15 & 4.16, it is evident that significant differences exist in robot performance and RAD estimations offered by the traditional approach and the proposed extended neglect tolerance model.

Figure 4.15 RAD plotted against the robot performance for real and virtual robot experiments using extended neglect tolerance model.

Figure 4.16 RAD plotted against the robot performance for real and virtual robot experiments using traditional neglect tolerance model.

Also, the traditional approach renders an optimistic estimate of robot

performance and RAD as compared to the proposed extended neglect tolerance model for dependent multi-robot teams due to the zero false alarm interaction assumptions. The predicted robot performance from the first group with and without FATs was compared to the observed robot performance from the second group using statistical experiments. A second group of twenty test subjects aged between 20 and 45 were asked to perform the same task as the first group of subjects. Figure 4.17 shows the robot performance plotted against the RAD with FATs taken into account as in actual real world scenarios for the second group of test subjects.

Figure 4.17 Robot Performance plotted against the RAD incorporating the FATs for real and virtual robots for second group

Significant differences in robot performance estimations were found

between the predictions from first group without FATs using traditional approach and the observations from second group while operating the robot in a semi-autonomous mode for both real robot, $t(38) = 32.15$, $p < 0.0001$ and a virtual robot, $t(38) = 17.29$, $p < 0.0001$ experiments. Experiments presented no significant differences for both real robots, $t(38) = 0.1626$, $p = 0.8726$ and virtual robot, $t(38) = 0.9503$, $p = 0.3539$ semi-autonomous experiments between the predictions from first group adopting extended neglect tolerance approach and the observations from second group.

Significant differences in RAD estimations were also found between the predictions from first group without FATs using traditional approach and the observations from second group while operating the robot in a semi-autonomous mode for both real robot, $t(38) = 14.79$, $p < 0.0001$ and a virtual robot, $t(38) = 6.776$, $p < 0.0001$ experiments. But, no significant differences were found for both real semi-autonomous robots, $t(38) = 0.0413$, $p = 0.9675$ and virtual semi-autonomous robot, $t(38) = 1.97$, $p = 0.0631$ experiments involving the predictions from first group adopting extended neglect tolerance model and the observations from second group. We also computed and compared the CDs, CEs, and TADs for real and virtual robot experiments presented in Figure 4.13. Figure 4.18 shows the average CDs for all experimental cases. The mean CDs for experiments accounting for the FATs were higher as compared to the traditional case wherein false alarm interactions were ignored.

Figure 4.18 Average CDs for all experimental cases

Significant differences were found between the two sets of CDs with and without false alarms for both real robot, $t(19)=25.16$, $p<0.0001$ and virtual robot, $t(19)=6.56$, $p<0.0001$ experiments. Also, significant differences in CD estimations were also found between the predictions from first group ignoring FATs using the traditional approach, and the observations from second group while operating the robot in a semi-autonomous mode for both real robot, $t(38) = 4.82$, $p<0.0001$ and a virtual robot, $t(38) = 4.834$, $p<0.0001$ experiments. Experiments also suggested no significant differences between the predictions from first group using the extended neglect tolerance approach and the observations from second group for both real robots, $t(38) = 0.52$, $p=0.6091$ and virtual robot, $t(38) = 0.21$, $p=0.8359$ semi-autonomous experiments. This indicates that the CDs estimated using extended

neglected tolerance mode offers a more realistic estimation as compared to the conventional approach that assumes zero false alarm interactions.

Figure 4.19 shows the average CEs for all experimental cases. The mean CEs for experiments accounting for the FAT were higher as compared to the traditional case wherein false alarm interactions were ignored. The absence of excess demand required for identifying and rectifying false alarm interactions in the traditional approach paves way for a more optimistic estimations. Significant differences were found between the two sets of CEs with and without false alarms for both real robot, $t(19)=26.56$, $p<0.0001$ and virtual robot, $t(19)=17.1$, $p<0.0001$ experiments.

Also, significant differences in CE estimations were also found between the predictions from first group ignoring FATs using the traditional approach and the observations from second group while operating the robot in a semi-autonomous mode for both real robot, $t(38) = 7.65$, $p<0.0001$ and a virtual robot, $t(38) = 6.53$, $p<0.0001$ experiments. The results also presented no significant differences between predictions from first group accommodating FATs using the proposed extended neglect tolerance approach and the observations from second group for both real robots, $t(38) = 0.289$, $p=0.7759$ and virtual robot, $t(38) = 0.2825$, $p=0.7791$ experiments in semi-autonomous mode. This indicates that the CEs estimated using extended neglected tolerance mode accommodating false alarm interactions offers a more realistic estimation as compared to the

conventional approach that assumes zero false alarm interactions.

Figure 4.19 Average CEs for all experimental cases

Figure 4.20 shows the average TADs for all experimental cases. The mean TADs for experiments accounting for the FAT were higher as compared to the traditional case wherein false alarm interactions were ignored. Significant differences were found between the two sets of TADs with and without false alarms for both real robot, $t(19)=28.46$, $p<0.0001$ and virtual robot, $t(19)=3.41$, $p<0.0001$ experiments. Also, significant differences in TAD estimations were also found between the predictions from first group ignoring FATs using traditional approach and the observations from second group while operating the robot in a semi-autonomous mode for both real robot, $t(38) = 3.19$, $p<0.0001$ and a virtual robot, $t(38) = 3.14$, $p<0.0001$ experiments.

But, no significant differences were found between the predictions from first group accounting for FATs using the proposed extended neglect tolerance approach and the observations from second group while operating the robots in semi-autonomous mode for both real robots, $t(38) = 0.69$, $p=0.5016$ and virtual robot, $t(38) = 0.6172$, $p=0.5408$ experiments. This indicates that the TADs estimated using extended neglected tolerance mode accommodating false alarm interactions offers a more realistic estimation as compared to the conventional approach that assumes zero false alarm interactions.

Figure 4.20 Average TADs for all experimental cases

We computed and compared the two widely adopted definitions of fan outs for dependent multi-robot teams presented in Equation 2.17 & 2.18 which adopts neglects tolerance model assuming zero false alarm interactions and their

redefinitions put forward in Equation 4.11 & 4.12 that adopts extended neglect

(a)

(b)

Figure 4.21 Fan out for real and virtual experiments
(a) FO_D ignoring FATs (b) FO_{DF} accommodating FATs

tolerance model taking into account additional demand due to occurrences of false alarms through real and virtual robot experiments.

Figure 4.22 shows the fan outs computed using Equation 2.17 which assumes zero wait and false alarm times and its redefinition accommodating false alarms presented in Equation 4.11. Significant differences were found between the two sets of fan outs with and without false alarms for both real robot, $t(19)=25.16$, $p<0.0001$ and virtual robot, $t(19)=6.56$, $p<0.0001$ experiments. Figure 4.21 shows the fan outs computed using Equation 2.18 which accounts for wait times but assumes zero false alarm times and its redefinition accommodating for both wait and false alarm times presented in Equation 4.12. Significant differences were found between the two sets of fan outs with and without false alarms for both real robot, $t(19)=25.16$, $p<0.0001$ and virtual robot, $t(19)=6.56$, $p<0.0001$ experiments.

(a)

(b)

Figure 4.22 Fan out for real and virtual experiments
(a) FO_{DWT} ignoring FATs (b) FO_{DWT} accommodating FATs

Figure 4.23 Fan out for real and virtual experiments with second group

Figure 4.23 shows the fan out plotted against operators accounting for the FATs as in actual real world scenarios for the second group of test subjects. Significant differences in fan out estimations were found between the predictions from first group using definition presented in Equation 2.17 and the observations from second group used as reference for both real robot, $t(38) = 12.87$, $p < 0.0001$ and a virtual robot, $t(38) = 12.24$, $p < 0.0001$ experiments. Significant differences in fan out estimations were also found between the predictions from first group using definition presented in Equation 2.18 and the observations from second group for both real robot, $t(38) = 12.87$, $p < 0.0001$ and a virtual robot, $t(38) = 12.24$, $p < 0.0001$ experiments.

Significant differences in fan out were also found between the predictions from first group using definition presented in Equation 4.11 and the observations from second group for both real robot, $t(38) = 12.87$, $p < 0.0001$ and a virtual robot, $t(38) = 12.24$, $p < 0.0001$ experiments. But, no significant differences were found between the predictions from first group using the definition presented in Equation 4.12 taking into account both false alarm interaction and wait times using the proposed extended neglect tolerance approach and the observations from second group for both real robots, $t(38) = 0.96$, $p = 0.3511$ and virtual robot, $t(38) = 0.029$, $p = 0.9768$ experiments. This indicates that the fan outs estimated using extended neglected tolerance model accounting for both false alarm and wait times offers a more realistic estimation as compared to the conventional approach that assumes

zero false alarm interactions.

We also computed and compared the FADs for real and virtual robot experiments presented in Figure 4.4 and Figure 4.13. Figure 4.24 shows the average FADs for different experimental cases. The mean FADs for both the dependent and independent experiments were substantial accounting for more than 15% of the total operator demand. If unaccounted, it could result in an optimistic estimation of key metrics results in task failure.

The statistical t tests that were performed further validated the extended neglect tolerance model for dependent multi-robot teams and the need for inclusion of false alarm demand into the model. The robot performance, RAD, fan out, CD, CE and TAD for the observations from second group showed significant differences when compared to predictions from first group ignoring FATs for all experimental cases thereby indicating the shortfalls in the traditional neglect tolerance approach for dependent multi-robot teams when applied to real world experiments. No significant differences were found while comparing the average robot performance, fan out, RAD, CD, CE and TAD from the observations in second to predictions in first group accommodating FATs for all experimental cases indicating the robustness of the proposed extended neglect tolerance model for dependent multi-robot teams.

Figure 4.24 Average FADs for all experimental cases

The results derived from the experiments offers significant impact as the assumption of zero false alarm interactions in the traditional approach leads to an optimistic robot performance prediction. These optimistic results contribute towards operator's inability in accomplishing the performance goal set for the task as the occurrences of false alarm interactions in actual situation result in performance loss that are not accounted in the former. Inclusion of false alarm time as proposed in the extended neglect tolerance model offers more realistic robot performance predictions. Also from these results, it is clear that ignoring false alarm interactions results in a lower estimate of RADs and higher estimate of fan out which may result in operator's failure in accomplishing the task and managing planned number of robots in actual situation as additional efforts are required from

the operator towards identifying and rectifying false alarm interactions whereas the RAD and fan out estimations using extended neglect tolerance model are realistic and in close agreement with the observations from the second group.

4.5 Conclusions

We utilized the two new metrics, the false alarm time (FAT) and false alarm demand (FAD), presented in Chapter 3 towards measuring the additional demand incurred due to false alarm interactions and extend the neglect tolerance model for independent and dependent multi-robot teams. We conducted experiments with semi-autonomous virtual and real humanoid soccer robots to demonstrate the efficacy and utility of the proposed metrics and the extended neglect tolerance model for independent and dependent multi-robot teams.

Results of our experiments with virtual and real robots for both independent and dependent multi-robot teams were largely consistent with the proposed extended neglect tolerance model predictions. False alarm interactions occurred in all experimental cases and impacted performance negatively. Statistical analyses performed showed significant differences in robot performance, RAD and fan out predictions between the target population with and without inclusion of false alarm interactions for all experimental cases.

We performed statistical experiments to compare the predicted robot performances, RAD and fan out from the first group with and without FATs to the

observed robot performance from a second group. For both independent and dependent multi-robot teams, the results showed substantial differences in the predicted robot performances, RAD and fan out for all experimental cases for the first group ignoring false alarms in comparison to the observed results from the second group. However, the experimental results using extended neglect tolerance model from the predictions in first group were in close agreement with the observed results from the second group. Extended neglect tolerance model for multi-robot teams with its more realistic estimations of average robot performance, RAD and fan out can help operators to optimize time scheduling of robot tasks and improve task performance. In addition, in the case of dependent multi-robot teams the estimations of TAD, CD and CE using extended neglect tolerance model from the first group were in close agreement with the observed results from the second group whereas the estimations using the traditional approach resulted in significant difference compared to the second group.

The experiments have demonstrated a very important phenomenon that the proposed extended neglect tolerance model offers a more realistic estimate of robot performance and other related metrics for multi-robot robot teams as compared to the traditionally adopted neglect tolerance model. This also implies that false alarm interactions that occur between human and robot if ignored as in traditional approach may lead to task failure as the operator may not be able to meet time, fan out and performance criteria set for the task due to additional false alarm

interaction demands in real world scenarios.

5. False Alarm Metric Class for Safe Human Robot Interactions

5.1 Introduction

In the recent years, there is an increasing interest in service robots that are able to assist and interact with human in a natural way. These robots are expected to provide day-to-day support in the home and the workplace, doing laundry or dishes, assisting in the care of the elderly, or acting as a caretaker for individuals within a home or institution. Many of these tasks will involve close interactions between the robot and the people it serves thereby making safety a key parameter. The term “safety” in service robots can be interpreted as prevention of any accidents that negatively impacts any human or other objects in the environment and itself.

The development of safety standards for industry robots has gone through many stages with those robots entering the marketplace in 1960s. The first industry robot safety standard, ISO 10218:1992 manipulating industry robots was published in 1992 and harmonized under the European Machinery Directive. With rapid advancement in robotic technologies, a revised part 1 version, ISO 10218-1 robot for industrial environments – safety requirements was published in 2006. The second part, ISO 10218-2, robot for industrial environments – safety requirements towards integrating robots into complete cells or lines is being developed by an

international working group (WG3) to be published in 2010. The upcoming second part is set to replace other regional and national industrial robot safety standards [104] [105]. But, these standards are more focused on robotic manipulators (hardware and software) and its end effectors applied for industrial usage that involves repetitive task without much human intervention or interaction.

Safety in service robots has been neglected by the robotics researchers for over many years as they were only prototypes in laboratories. With more and more service robots entering the commercial market place, there is an increasing demand in addressing safety issues in service robots. Recently, a working group (ISO/TC 184/SC 2/WG 8) has been formed to handle the development of standards for robots in service domain. Key parameters that are considered include degree of autonomy, safeguarding, and object of operation with applications in health care, rehabilitation, entertainment and inspection [106] [107]. Most applications in service robotics field are expected to involve close human robot interaction. Traditionally, humans and robots were separated physically in industrial applications, so the human robot physical closeness in service robots raises new hazards and risks.

Active research is being undertaken in many universities and research institutes around the world towards developing human robot interaction metrics for safety. Takashi et al in [108] puts forward a critical hazard metric for service robots and validated the same with seven service robots from different manufacturers.

The critical hazard is defined as a measure of the residual risk associated using the as low as reasonable practicable (ALARP) principle commonly adopted in the standard on functional safety IEC61508 and standards on the risk management of medical devices, ISO14971. Kim et al in [109] proposed a safety ensuring systematic design procedure that allows service robots to be designed to perform predefined task in which safety is guaranteed.

The predefined safety target was validated using a care-providing robot for physically disabled people with risk reduction measures incorporated in all steps of robot design. Through the use of the proposed design procedure, it is shown as an example that a care-providing robot for physically disabled people can be designed. Guiochet et al in [110] presented a deductive method for safety analysis and integration in service robots based on fault tolerance metrics which has been commonly adopted by industrial robots. The results were validated with a tele-robotic system for ultrasound examination. A unified modeling language (UML) based model used to identify and analyze human errors in tele-robotic systems towards determining the consequences and implications in the system safety. Extensive work has been performed in defining common metrics for task oriented human robot interaction systems [26, 45, 57, 70].

But, these current research works ignores erroneous interactions in human robot teams. In Chapters 3 and 4, we identified the erroneous interactions that occur inevitably in human robot teams as false alarm interactions and noted their

presence in all experimental cases. Occurrences of these erroneous interactions have potential for accidents arising serious concerns towards establishing safe human robot interaction. But, there are no available metrics to measure the susceptibility of robots to false alarm interactions and classify robots based on safe human robot interaction abilities. In this chapter, we put forward a new class of false alarm metrics to measure the susceptibility of robots to false alarm interactions and classify robots based on safe human robot interaction abilities. We analyze the relationship between false alarm interactions and safety in terms of occurrences of accidents. We also demonstrate the efficacy and utility of the proposed metrics by applying them to a service robot, Robo-Erectus@Home.

In this chapter, we will first discuss the proposed false alarm metric class to measure the susceptibility of robots to false alarm interactions and classify robots based on safe human robot interaction abilities. In Section 5.3, we will present a brief description of the Robo-Erectus@Home robot used in our experiments. In Section 5.4, we will present the experiments involving 20 test subjects to demonstrate the utility and efficacy of the proposed false alarm metrics towards measuring the susceptibility of robots to false alarm interactions and classify robots based on safe human robot interaction abilities. Finally, Section 5.5 presents some concluding ideas.

5.2 False Alarm Metric Class for Safe Human Robot Interaction

In most real life service robotic applications erroneous interactions between the human user and the robot are common due to uncertainties in both human user as well as the robots. In Chapter 3, we redefined false alarms in specific for human robot interactions as “A response in which robot rejects a "correct" interaction or fails to reject an "incorrect" interaction”.

We also classify the false alarms as false negative interaction, wherein a robot rejects a “correct” interaction and false positive interaction, wherein a robot fails to rejects an “incorrect” interaction. For example, in a robot navigation task the human user may select the wrong way point leading to a “false positive interaction” as the robot would fail to reject the false interaction. There may also be situations wherein the human user selects correct way point but the decision making body of the robot chooses a wrong way point/ignores the human user control due to uncertainties in robot software/hardware leading to a “false negative interaction” as the robot rejects a true interactions.

We observed from our experiments in chapter 3 and 4 that any occurrences of false alarm interactions negatively impact the performance of the robot and have potential for accidents putting at risk the human user, environment and the robot. False alarm metrics namely, true positive rate, true negative rate, false positive rate, false negative rate, accuracy, positive prediction value, and negative prediction value are commonly used in statistics [111], medicine [112], and signal processing [113] communities towards measuring system susceptibility

to false alarms. In this chapter, we redefine these metrics in the context of human robot interaction to measure the susceptibility of robots to false alarm interactions both false positives and negatives. True positive rate is used to measure the proportion of actual positives which are correctly identified. We redefine true positive interaction rate (TPIR) for human robot interaction as the percentage of correct interactions from human identified as correct by robot. TPIR for human robot interaction is given by,

$$TPIR = \frac{\sum TPI}{\sum TPI + \sum FNI} \quad (5.1)$$

For any experiment, 100% TPIR indicates that all interactions between human and the robot were correct.

True negative rate is commonly used as a measure to indicate the proportion of negatives that are correctly identified. We redefine true negative interaction rate (TNIR) for human robot interactions as the percentage of incorrect interactions from human identified as incorrect by the robot. TNIR for human robot interactions is given by,

$$TNIR = \frac{\sum TNI}{\sum TNI + \sum FPI} \quad (5.2)$$

For any experiment, 100% TNIR indicates that the robot recognizes all incorrect interactions from human as incorrect.

False positive rate is commonly used as a measure to indicate the proportion of negatives that are incorrectly identified. We redefine false positive interaction rate (FPIR) for human robot interactions as the percentage of incorrect interactions from human identified as correct by the robot. FPIR for human robot interactions is given by,

$$FPIR = \frac{\sum FPI}{\sum FPI + \sum TNI} \quad (5.3)$$

False negative rate is commonly used as a measure to indicate the proportion of negatives that are incorrectly identified by the robot. We redefine false negative interaction rate (FNIR) for human robot interactions as the percentage of correct interactions from human identified as incorrect by the robot. FNIR for human robot interactions is given by,

$$FNIR = \frac{\sum FNI}{\sum FNI + \sum TPI} \quad (5.4)$$

Accuracy is commonly used as a measure the proportion of true results both true positives and true negatives in the target population. We redefine interaction accuracy (IA) as the ratio of the number of correct interaction between the human and robot to total number of interactions between the two. IA for human robot interactions is given by,

$$IA = \frac{\sum TPI + \sum TNI}{\sum FNI + \sum TPI + \sum FPI + \sum TNI} \quad (5.5)$$

Positive predictive value is a proportion of true positives against all the positives results both true positives and false positives. We redefine positive predictive interaction value (PPIV) for human robot interaction as the ratio of correct interactions from human identified as correct by robot to all interactions identified by the robot as correct. PPIV for human robot interaction is given by,

$$PPIV = \frac{\sum TPI}{\sum TPI + \sum FPI} \quad (5.6)$$

Negative predictive value is a proportion of true negatives that are correctly identified. We redefine negative predictive interaction value (NPIV) for human robot interaction as the ratio of incorrect interactions from human identified as incorrect by robot to all interactions identified by the robot as incorrect. NPIV for human robot interaction is given by,

$$NPIV = \frac{\sum TNI}{\sum TNI + \sum FNI} \quad (5.7)$$

ROC space is widely adopted in signal processing and medicine communities for classification of noises and desired signals [114] [115]. Figure 5.1 shows the ROC space with FPIR defined on the x axis and TPIR defined on the y axis, thereby presenting a relative tradeoff between TPI (benefits) and FPI (costs). We utilize the ROC space to classify robots based on safe human robot interaction abilities. Since, any increase in susceptibility to false alarm interactions results in an increased risk to safety, the ROC space offers a framework for classifying robots based on safe human robot interaction. An ideal service robot would yield a

point in the upper left corner of the ROC space at (0,1), representing 100% TPIR and TNIR.

We segment the ROC space into four regions based on the false alarm interaction risks. Very high risk region has higher false positive interaction rates and lower true positive interaction rates. There are two high risk regions; the upper right region has higher false positive and true positive interaction rates whereas the lower left region has lower false positive and true positive interaction rates.

Figure 5.1. False alarm metrics & ROC space for safe human robot interaction

Low risk region has higher true positive rate and lower false positive rates. False alarm susceptibility risks associated with any robot can be determined by its false positive and true positive interaction rate pair. Considering that the application under study is for rehabilitation, we set passing criteria for same human

robot interaction to be at least 75% of all TPIR and FPIR pairs in the low risk zone and none in the very high risk zone of the ROC space. Otherwise, the system fails the criteria for safe human robot interaction.

5.3 Robo-Erectus@Home – A Service Robot

This section provides a brief description of Robo-Erectus@Home robot that we used for our experiments in this thesis.

Figure 5.2 Robo-Erectus@Home, the Latest Generation of the Family Robo-Erectus

Robo-Erectus@Home is one of the foremost service robotic players at the RoboCup@Home Leagues where the robot is required to undertake a series of challenges in a home environment interacting with a human in a natural way through speech and/or gestures [116]. The aim of the Robo-Erectus@Home development team is to develop a service robot for application in smart homes, and rehabilitation. The development of Robo-Erectus@Home has gone through many stages either in the design of its mechanical structure, electronic control system and software architecture. Figure 5.2 shows the physical design of Robo-Erectus@Home. It has three processors each for perception, artificial intelligence and control. The platform is equipped with a range of sensors including an USB camera to capture images, an onboard microphone to capture the speech commands from human, force sensors for force based robot control, sonar and ultrasonic sensors to identify and locate obstacles [117]. The robot uses fusion of encoder, sonar and vision information for localization. The perception processor acquire all sensory information and perform pre-processing, filtering and passes key information to the artificial intelligence processor for further processing and decision making. The vision sensor performs recognition and tracking of objects of interest including human face, gestures, and coloured cups based on a blob finder based algorithm. The further processing of detected blobs, wireless communications and decision making are performed by the artificial intelligence processor which selects and implements the behaviour skills (like walk to the

human, manipulate the cup, express specific emotion....) the robot is to perform. The force sensors are fitted to the handles of the robot towards assisting the human in walking especially for the elderly and in rehabilitation process. The combined force information from the handles is processed using a fuzzy logic based algorithm to convey the user's intention about walking to the service robot, for example to continue walking or not, turn right, walking speed and so on. A graphical user interface is also developed and mounted on the rear of the robot offering the human multiple modalities for interaction. Another channel of interaction implemented was speech controls, Robo-Erectus@Home is capable of interacting with human in a natural way through speech (go to the television, carry the cup,). The user had the option of switching between the interaction modes during robot operation. Finally, the control processor handles the low level control of motor based on the behavioral skill selected by the artificial intelligence processor.

5.4 Experiments

5.4.1 Experimental Design

In these experiments we demonstrated the utility and efficacy of the false alarm metrics proposed in this chapter to measure the susceptibility of robots to false alarm interactions and classify robots based on safe human robot interaction

abilities. We selected the task of a walking assistant for our service robot wherein the robot is expected to aid in walking exercises towards elderly or rehabilitation. The human user can choose between three modes of interaction namely, speech, graphical user interface, and force sensors.

The human user holds onto the handle bar fitted to the rear side of the robot, and uses one of the three interaction modes available to control the robot towards performing their walking exercises. When the robot reached the finish position, the robot has to be turned around and navigate back to the start position. The total distance of the route was about 400 m. The start and finish lines were clearly defined for the convenience of the user.

5.4.2 Participants and Procedure

We recruited 20 test subjects aged between 18 and 57 for this study. The test subjects selected did not have any prior training or experience in using the walking assistant platform used for our experiments. The users were asked to learn the operation of the system by themselves through trial and error procedures while using the system. Each of them took part in two twenty minute session with the service robot, so a total of 40 test sessions were performed. Of these sessions, 20 were dedicated to the tele-operation mode and remaining 20 to the semi-autonomous mode. In the test session, the human user completed a 400 m walk along a given route with the assistance of the robot.

The human user was instructed to walk along the route as many times as

possible with the assistive robot during each twenty minutes test session. Towards validating the metrics, we conducted between subject experiments with a second group of 20 inexperienced and untrained test subjects across the two autonomy modes for the same task to compare the FPIRs and TPIRs from the first group to the second group. Without training, we expect the TPIR and FPIR pairs from both first and second group to fail the criteria for safe human robot interaction as the human users lack the understanding of the system.

We then conducted intensive training sessions on the system usage and a de-briefing session on the false alarm interactions to the test subjects from both the first and second groups. We then compared the FPIRs and TPIRs from the post training experiments to the pre-training experiments for both first and the second groups. We expect the FPIRs from the post-training to be better than the pre-training results from first and second group as the user gain sufficient knowledge and understanding of the system upon training and debriefing on false alarm interactions.

We also expect the TPIR and FPIR pairs from the post-training group to pass the criteria for safe human robot interaction. In tele-operation mode, the human user continuously interacts with the robot providing every detailed control whereas in semi-autonomous mode, the human user provides the way points along the walking route. Any false alarm interactions together with the time, operator controls, and robot state information were recorded for each test session.

5.4.3 Results

False alarm interactions were witnessed in all the 40 test sessions for the experiments with the first group of untrained test subjects. A total of 212 false alarm interactions were recorded out of which 166 were FPI and 46 were FNI. The FNIs were mainly due to errors in the multimodal interaction scheme, software faults in robot's control and artificial intelligence modules, and hardware failures in sensor/actuator systems. The FPIs were mainly due to the human error pertaining to lack of understanding of the interaction scheme, and the task of interest. A total of 57 accident were witnessed where an accidents is defined as the occurrence of any collision between robot and/or human with any objects in the surrounding environment. All accidents were contributed as a result of false alarm interactions both FPIs and FNIs implying direct relationship between false alarms and accidents in human robot interactions.

Figure 5.3 shows the number of false alarm interactions and accidents associated with each of the 20 human users for both autonomy modes. A total of 568 interactions were recorded for all 20 tele-operation experiments and a total of 183 interactions were recorded for all 20 semi-autonomous experiments. From the figure, it is evident that the number of false alarms was relatively higher in tele-operation mode as compared to semi-autonomous mode. The false alarms in tele-operation mode was 147 out of which 112 were FPIs and 35 were FNIs whereas the false alarms in semi-autonomous mode was 65 out of which 54 were FPIs and

11 were FNIs.

(a)

(b)

Figure 5.3 False Alarms & Accidents versus Human User:

(a) Tele-operation Mode, (b) Semi-Autonomous Mode

The increased false alarm interactions in tele-operation mode were contributed mainly due to the increased interaction from human user. As for the accidents, the semi-autonomous experiments presents relatively increased accidents of 45 as compared to tele-operation experiments where there were only 12 accidents.

Lesser number of accidents in tele-operation mode is mainly attributed to the increased human awareness and interaction, as presence of any risk is immediately noticed by the human user and rectified whereas in semi-autonomous mode presence of any risk in the period between two way point nomination is less noticed by the human user due to the increased autonomous nature of the mode.

Figure 5.4 shows the TPIR in percentage plotted against the human user for both autonomy modes. TPIR for all experimental cases were above the 75% level implying that the robot was able to identify most correct interactions from human as correct. The TPIR in some semi-autonomous experimental cases reached 100% level indicating all correct interactions from robot were identified correctly by the robot. The average TPIR for tele-operation experiments stood at 91.80% whereas for semi-autonomous experiments was slightly lower at 90.54%.

Figure 5.5 shows the FPIR in percentage plotted against the human users for both autonomy modes. From the figure, it is evident that the robot was not very efficient in recognizing incorrect interactions from human as incorrect as the FPIs were relatively higher as compared to FNIs for most tele-operation and semi-

autonomous experiments.

Figure 5.4 TPIR versus Human User

Figure 5.5 FPIR versus Human User

The TNIs were not present in some tele-operation and semi-autonomous experiments yielding a 100% level for FPIR. The average FPIR for tele-operation experiments stood at 71.28% whereas for semi-autonomous experiments was higher at 82.45%. Figure 5.6 shows the IA in percentage plotted against the human users for both autonomy modes. From the figure, it is evident that the robot was able to recognize majority of both correct and incorrect interactions from human with the IA of all experimental cases standing on or above 50% mark.

Figure 5.6 IA versus Human User

The average TPIR for tele-operation experiments stood at 75.39% whereas for semi-autonomous experiments were lower at 64.96%, this was mainly attributed to the increased false alarms especially FPIs in semi-autonomous modes. IA can be used as criteria for evaluating the interaction system put in place between

the human and the robot.

Figure 5.7 shows the PPIV in percentage plotted against the human users for both autonomy modes. From the figure, it is evident that the robot was able to detect most correct interactions from human user with PPIV exceeding 50% level for all experiments except one. The average PPIV for tele-operation experiments stood at 79.29% whereas for semi-autonomous experiments were lower at 67.22%.

Figure 5.7 PPIV versus Human User

Figure 5.8 shows the NPIV in percentage plotted against the human users for both autonomy modes. From the figure, it is evident that the robot achieved mixed results towards detecting incorrect interactions from human user. The average NPIV for tele-operation experiments stood at 46.50% whereas for semi-autonomous experiments were higher at 50%.

We put forward false alarm demand metric in Equation 3.2 to quantify the additional demand needed due to the occurrences of false alarm interactions. Figure 5.9 shows the FAD plotted for all 20 human users across tele-operation and semi-autonomous modes for these experiments.

Figure 5.8 NPIV versus Human User

From the figure, it is evident that the demands due to false alarm interactions were lesser in comparison to the total interaction period with FADs for all experimental cases standing on or below 20% mark. The average FAD for tele-operation experiments stood at 8.15% whereas for semi-autonomous experiments were higher at 12.33%, this was mainly attributed to the increased interaction in tele-operation mode where the false alarms are detected and corrected early. FAD can be used as criteria for evaluating the interaction system put in place between

the human and the robot.

Figure 5.9 FAD versus Human User

Figure 5.10 shows the ROC space with pre-training TPIR and FPIR pairs plotted for all 20 human users from the first group across tele-operation and semi-autonomous experiments. From the figure, it is evident that all TPIR and FPIR pairs for semi-autonomous experiments with our robot fall in the high risk zone of the ROC space whereas for tele-operation experiments two TPIR and FPIR pairs fall in the low risk zone and all others fall in the high risk zone. For those results falling in the high risk zone, TPIR rates were higher with mean at 91.8% for tele-operation and 90.54% for semi-autonomous experiments. This is preferable as the

robot is capable of identifying correct interactions from human. At the same time our experiments also yielded higher FPIR with mean at 71.28% for tele-operation and 82.45% for semi-autonomous experiments which implies that the robot has problems classifying incorrect interactions from human user.

The very high risk zone was clear of any FPIR and TPIR pairs. But, 95% of the TPIR and FPIR pairs fall in the high risk zone, and therefore the system fails the criteria of below 25% in high risk zone for safe human robot interaction.

Figure 5.10 ROC space with TPIR and FPIR pairs for untrained first group

Experiments were performed with a second group of 20 test subjects whom

were also inexperienced and untrained on the same task towards comparing the FPIRs and TPIRs the two groups involved. Figure 5.11 shows the ROC space with pre-training TPIR and FPIR pairs plotted for the second group of 20 inexperienced and untrained test subjects across the two autonomy modes for the same task. From the figure, it is evident that except three TPIR and FPIR pairs all others for both semi-autonomous and tele-operation experiments falls in the high risk zone of the ROC space.

Figure 5.11 ROC space with TPIR and FPIR pairs for untrained second group

Following the trend in the first set of experiments, TPIR rates were higher with mean at 91.72% for tele-operation and 89.93% for semi-autonomous experiments at the same time our experiments also yielded higher FPIR with mean

at 66.87% for tele-operation and 72.02% for semi-autonomous experiments. No FPIR and TPIR pairs were found in the very high risk zone. But, 85% of the TPIR and FPIR pairs fall in the high risk zone, and therefore the system fails the criteria of below 25% in high risk zone for safe human robot interaction.

To validate the proposed false alarm metrics, within and between subjects statistical analysis were undertaken. As expected, no significant differences were found between the two sets of FPIRs between the untrained first and second group while operating the robot in semi-autonomous mode, $t(38)=1.5176$, $p=0.1370$ and tele-operation mode, $t(38)=0.612$, $p<0.5442$.

(a)

Figure 5.12 ROC space with TPIR and FPIR pairs for trained

(a) First group (b) Second group

Also, no significant differences were found between the two sets of TPIRs between the untrained first and second group while operating the robot in semi-autonomous mode, $t(38)=0.2675$, $p=0.7905$ and tele-operation mode, $t(38)=0.0611$, $p=0.9516$. We then conducted intensive training and de-briefing session on the false alarm interactions to the test subjects from the first group and second group towards better control robots using the given multimodal interaction scheme.

Figure 5.12 shows the ROC space with TPIR and FPIR pairs plotted for the post-training experiments with first and second group for the same task. For the post-training experiments with the first group, the TPIR rates yielded results similar to pre-training experiments with mean at 92.82% for tele-operation and 91.17% for semi-autonomous experiments but yielded much lower FPIR than the pre-training experiments with mean at 28.29% for tele-operation and 37.88% for semi-autonomous experiments. Similar results were observed in the post-training results from the second group with TPIR mean at 91.58% resembling the pre-training experiments for tele-operation and 88.71% for semi-autonomous experiments. But, the experiments yielded much lower FPIR than the pre-training experiments with mean at 23.25% for tele-operation and 37.18% for semi-autonomous experiments.

Results from post training experiments, indicated that 82.5% of the TPIR and FPIR pairs from the first group fall in the low risk zone and 80% of the TPIR and FPIR pairs from the second group fall in the low risk zone with no very high risk cases in both groups thereby satisfying the criteria set for safe human robot interaction.

As expected, significant differences were found between the two sets of FPIRs between the pre-training and post-training experiments with the first group while operating the robot in semi-autonomous mode, $t(19)=6.9252$, $p<0.0001$ and tele-operation mode, $t(19)=6.2792$, $p<0.0001$. But, no significant differences were

found between the two sets of TPIRs between the pre-training and post-training experiments with the first group while operating the robot in semi-autonomous mode, $t(19)=0.2941$, $p=0.77$ and tele-operation mode, $t(19)=0.7196$, $p=0.4762$. As expected, significant differences were found between the two sets of FPIRs between the pre-training and post-training experiments with the second group while operating the robot in semi-autonomous mode, $t(19)=3.8814$, $p<0.0001$ and tele-operation mode, $t(19)=6.1446$, $p<0.0001$. But, no significant differences were found between the two sets of TPIRs between the pre-training and post-training experiments with the second group while operating the robot in semi-autonomous mode, $t(19)=0.6924$, $p=0.4927$ and tele-operation mode, $t(19)=0.0959$, $p=0.9241$.

The indifferences in TPIRs between the pre-training and post-training for both groups is expected as no additional efforts was made towards this end as the TPIRs were high and well above the safe human robot interaction criteria set even in the pre-training experiments. Comparing the FPIRs in pre-training and post-training experiments for both groups, significant decrease was observed in FPIRs mainly attributed to the intensive training on system usage and debriefing on the false alarm interactions which equipped the robot operators with right skillset and knowledge to handle the robot for safe human robot interaction.

But, no significant differences were found between the two sets of FPIRs between the trained first and second group while operating the robot in semi-autonomous mode, $t(38)=0.1642$, $p=0.8704$ and tele-operation mode, $t(38)=0.6848$,

$p=0.4976$. Also, no significant differences were found between the two sets of TPIRs between the trained first and second group while operating the robot in semi-autonomous mode, $t(38)=1.5967$, $p=0.1182$ and tele-operation mode, $t(38)=0.8493$, $p=0.401$.

The statistical t tests that were performed validated the proposed false alarm metrics towards measuring the susceptibility of robots to false alarm interactions and classifying robots based on safe human robot interaction abilities.

5.4.3.1 False Alarm Interactions in Human Robot Teams – A Poisson Representation

The false alarm interactions in human robot teams occur at random in time. Therefore, in an H human and R robot system, the occurrence of false alarm interactions could be assumed to follow a Poisson process. Then, the probability of occurrence of x false alarm interactions over an interaction routine over a defined time interval t, could be presented as,

$$P_{FAI}(x; \mu_{FAI}) = \frac{e^{-\mu_{FAI}} \mu_{FAI}^x}{x!} \quad (5.8)$$

where x is the number of false alarm interactions in an interaction routine and μ_{FAI} is the mean number of false alarm interactions in an interaction routine for a H human and R robot teams. Then, the expected frequency for x false alarm interactions can be obtained as,

$$E_{FAI}(x; \mu_{FAI}) = P_{FAI}(x; \mu_{FAI}) * N \quad (5.9)$$

where N is the total number of interaction routines involved.

For the single human and single robot semi-autonomous experiment presented in Section 5.4.3, we computed the expected frequencies for false alarm interactions using the Poisson distribution. Table 5.1 shows the table of expected frequencies for the semi-autonomous experiments. We repeated the same Poisson representation for tele-operation experiments presented in Section 5.4.3. The expected and observed frequencies for both semi-autonomous and tele-operation experiments are plotted as a bar chart in Figure 5.13. No significant differences were found between the expected and observed frequencies for false alarm interactions for both semi-autonomous, $t(12) = 0.2982$, $p=0.7707$ and tele-operation, $t(4) = 0.0021$, $p=0.9984$ experiments. This shows excellent agreement between observed and expected frequencies of false alarm interactions in an interaction routine.

Since, the number of robots requiring human attention also occurs at random in a multi-human robot teams. We assumed a Poisson distribution for the robots requiring human attention in a H human and R robot system. Then, the probability of y robots requiring attention over an interaction phase over a defined time interval, T within which the human operators completes interaction with all the robots under his/her charge could be presented as,

$$P_{RRA}(y; \mu_{RRA}) = \frac{e^{-\mu_{RRA}} \mu_{RRA}^y}{y!} \quad (5.10)$$

where y is the number of robots requiring human attention in an interaction phase and μ_{RRA} is the mean number of robots requiring attention in an interaction phase for a H human and R robot team.

Table 5.1 Expected and Observed Frequencies of False Alarm Interactions

False Alarm Interactions per Interaction Cycle	Observed Frequency	Poisson Probability, $P(x; \mu_{FAI})$	Expected Frequency $E_{FAI}(x; \mu_{FAI})$
0	0	0.002	0.04
1	4	0.126	2.52
2	3	0.2045	4.09
3	4	0.222	4.44
4	4	0.18	3.6
5	3	0.117	2.34
6	2	0.0635	1.27

Then, the expected frequency for y robots requiring attention can be obtained as,

$$E_{RRA}(y; \mu_{RRA}) = P_{RRA}(y; \mu_{RRA}) * M \quad (5.10)$$

where M is the total number of interaction phases involved.

(a)

(b)

Figure 5.13 Expected and Observed Frequencies for False Alarm Interactions in (a) Semi-autonomous and (b) Tele-operation Experiments

For the independent multi-robot experiment presented in Section 4.3, we computed the expected frequencies for robots requiring attention using the Poisson distribution. Figure 5.14 shows the expected and observed frequencies for robots requiring human attention.

Figure 5.14 Expected and Observed Frequencies for Robots Requiring Attention in Multi-Robot Teams

No significant differences were found between the expected and observed frequencies for robots requiring attention, $t(4) = 0.1387$, $p=0.8964$. This again shows excellent agreement between observed and expected frequencies of robots requiring attention in an interaction phase. Closer agreement in expected and

observed results validates the assumption of Poisson distribution for the false alarm interactions and robots requiring human attention.

5.5 Conclusion

In this chapter, we proposed and validated a new class of false alarm metrics to measure the susceptibility of robots to false alarm interactions and classify robots based on safe human robot interaction abilities. We conducted assistive walking experiments with our Robo-Erectus@Home service robot across tele-operation and semi-autonomous modes of autonomy to demonstrate the efficacy and utility of the proposed false metrics.

Results of our experiments were largely consistent with the expected outcome. False alarm interactions occurred in all experimental cases and all accidents were contributed as a result of false alarm interactions both FPIs and FNIs implying direct relationship between false alarms and accidents in human robot interactions. We performed within and between subjects statistical analysis to validate the proposed false alarm metrics.

Between subject experiments performed showed no significant differences in TPIR and FPIR pairs between the first and second group for both pre-training and post-training scenarios. Also, the TPIR and FPIR pairs from both untrained first and second group failed the criteria for safe human robot interaction mainly attributed to the lack of user understanding of the system. Within subject

experiments performed showed significant differences in FPIRs between the pre-training and post-training results for both first and second group.

Also, the TPIR and FPIR pairs from both trained first and second group passed the criteria for safe human robot interaction mainly attributed to the intensive training and debriefing sessions that equipped the robot operators with right skillset and knowledge to handle the robot. The results derived from the experiments offers significant impact as the proposed false alarm metrics could be used by industry to compare market available robot platforms for safe human robot interaction abilities and identify appropriate system for operation. A Poisson representation was also put forward in this chapter towards computing probabilities of occurrence of false alarm interactions and robots requiring human attention.

6. Conclusions and Recommendations

6.1 Conclusions

In the recent years, great deal of research has been done towards evaluating human robot interaction in relation to performance. As a result, many researchers have concluded somewhat prematurely that these traditional models offers realistic estimates of key human robot interaction metrics. In truth however, these models assumes zero erroneous interactions in human robot teams which contributes towards an optimistic estimates of the key metrics.

After intensive analysis and a detailed review of traditional approaches, the erroneous interactions that inevitably arise in human robot teams are identified as false alarm interactions, and classified into two categories. The theoretical analysis indicated the need for the inclusion of the additional demand incurred due to occurrences of false alarm interactions and identified two new metrics that quantify these additional demands. The traditionally adopted neglect tolerance model is extended using the proposed false alarm interaction metrics as a consequence of these theoretical findings for both single and multi-robot team.

Key human robot interaction metrics namely robot attention demand, team attention demand, fan out, co-operation effort, co-ordination demand, and free time were redefined to this end. Results of the simulation, experimentation and statistical analyses carried out has shown that extended neglect tolerance model offers a more realistic estimates of performance, attention demand, fan out and

other key metrics as compared to the traditional neglect tolerance model that assumes zero false alarm interactions for both single and multi-robot teams. This also implies that false alarm interactions that occur between human and robot if ignored as in traditional approach may lead to task failure as the operator may not be able to meet time, fan out and performance criteria set for the task due to additional demand incurred due to false alarm interactions in real world scenarios. The results also demonstrated the efficacy and utility of the redefined metrics. Thus, the study shows that incorporating additional demand due to false alarm interactions in the traditionally adopted neglect tolerance model significantly improves the estimation results.

A new false alarm interaction metric class is also put forward in this thesis to measure the susceptibility of robots to false alarm interactions and classify robots based on safe human robot interaction abilities. Simulation and experiments carried out validated the proposed false alarm interaction metric class. The results derived from the experiments offers significant impact as the proposed false alarm metrics offers researchers a robust and effective means towards comparing robot platforms, autonomy modes and interaction schemes in the context of safe human robot interaction abilities and identify appropriate system for operation.

6.2 Major Contribution of the Thesis

The core model and metrics proposed in this thesis are based on well-founded theoretical formulations. An overview of the key contributions as follows:

- In this thesis, the erroneous interactions that inevitably arise in human robot teams are identified as false alarm interactions, and are classified into two categories. A new false alarm interaction metric class is put forward to measure the susceptibility of robots to false alarm interactions and classify robots based on safe human robot interaction abilities. Simulation and experiments were conducted to demonstrate the efficacy and validity of the proposed false alarm interaction metric class.
- A rigorous and comprehensive analysis of the traditionally adopted neglect tolerance model for performance and attention demand estimations in single robot teams is carried out and its shortfalls identified. Neglect tolerance model for single robot teams is extended to accommodate the additional demands due to false alarms interactions through incorporation of the proposed false alarm metrics. Simulation and experiments were conducted to establish how the extended neglect tolerance model outperforms the traditional approach towards estimating robot performance and attention demand in single robot teams. Virtual-RE Simulator, a high-fidelity game

engine based robot simulator, and Robo-Erectus Junior, a soccer playing humanoid robot, were developed for this purpose.

- Neglect tolerance model for multi robot teams that takes into account dependent and independent nature of participating robots are elaborated. The major short comings of the model in estimations of key metrics due to zero false alarm interaction assumption are presented. Neglect tolerance model for multi robot teams is extended to accommodate the additional demands due to false alarms interactions through incorporation of the proposed false alarm metrics. It is shown that the extended neglect tolerance for multi robot teams offers more realistic estimates of performance, attention demand and other key metrics as compared to the traditional neglect tolerance model that assumes zero false alarm interactions.
- Traditionally adopted fan out metrics in predicting maximum number of robots a single operator can handle is investigated. The negative issues arising due to zero false alarm interaction assumption in fan out metric are elaborated. The fan out metric is redefined to account for any additional demands due to false alarm interactions. Simulations and experiments were performed to verify the performance gains of the redefined fan out metric over the conventional approaches.

6.3 Recommendations for Future Work

Although the work presented in this thesis offers a clear insight into some of the important issues in evaluating human robot interaction and proposed efficient and effective solutions, it also opened up new issues that need further attention and research at the same time.

Future work would include means of identifying how various choices made when designing the robot's autonomy affect performance, false alarm interactions and workload. Efforts would be made towards constructing a "toolbox" of autonomy and interface choices that are known to be appropriate for a given set of performance and workload constraints for a given task. A second possibility for future work would include formulation of a framework to select performance threshold.

The current work uses average performance as the basis for determining the performance threshold. While this may be appropriate, alternatives such as being "90% confident that the robot won't fail" can also be used to select thresholds. The question of how the performance threshold should be selected when no underlying models exists remains unanswered. Further research and experiments across multiple domains is needed before an efficient system is put in place towards appropriate selection of performance threshold. A third possibility of future work is to adopt the false alarm metric class proposed and validated in this

thesis as a tool to compare suitability of robot platforms, autonomy modes and interaction schemes for tasks of varying complexities.

Author's Publications

Journal Papers:

1. **R.E. Mohan**, W.S. Wijesoma, C.A. Acosta Calderon, C. Zhou, False Alarm Metrics for Safe Human Robot Interactions in Service Robots, *Advanced Robotics*, 24(13), 1841-1859, October 2010.
2. **R.E. Mohan**, W.S. Wijesoma, C.A. Acosta Calderon, C. Zhou, Validating Extended Neglect Tolerance Model for Human Robot Interactions in Humanoid Soccer Robots, *Robotica*, Cambridge Press, 28(02), 1-12, July 2010. [DOI:10.1017/S0263574710000251]
3. **R.E. Mohan**, W.S. Wijesoma, C.A. Acosta Calderon, C. Zhou, "Experimenting False Alarm Demand for Human Robot Interactions in Humanoid Soccer Robots" *International Journal of Social Robotics*, 1(2), 171-180, March 2009.[DOI: 10.1007/s12369-009-0017-3]
4. **R.E. Mohan**, W.S. Wijesoma, C.A. Acosta Calderon, C. Zhou, On the Redefinition of Fan Out Metric for Human Robot Interactions with Humanoid Soccer Robots, *International Journal of Humanoid Robotics*, 7(4), 565-586, May 2010.

5. **R.E. Mohan**, W.S. Wijesoma, C.A. Acosta Calderon, C. Zhou, Extended Neglect Tolerance Model for Multi-Robot Teams, *IEEE Transactions on Systems, Man, and Cybernetics – Part A*, 2010. [Submitted]

Conferences Papers:

6. **R.E. Mohan**, W.S. Wijesoma, C.A. Acosta Calderon, C. Zhou, "Experimenting Extended Neglect Tolerance Model for Human Robot Interactions in Service Missions" in *Proceedings of the IEEE International Conference on Control, Automation, Robotics and Vision (ICARCV)*, pg. 2024 – 2029, Singapore, December 2010.
7. **R.E. Mohan**, W.S. Wijesoma, C.A. Acosta Calderon, C. Zhou, "False Alarm Metrics: Evaluating Safety in Human Robot Interactions" in *Proceedings of the IEEE International Conference on Robotics, Automation and Mechatronics (RAM)*, pg. 230 - 236 , Singapore, June 2010.
8. **R.E. Mohan**, W.S. Wijesoma, C.A. Acosta Calderon, C. Zhou, "Validating Extended Neglected Tolerance Model with Humanoid Soccer Robots for Varying Task Complexities" in *Proceedings of the NIST's Performance Metrics For Intelligent Systems Workshop (PerMIS)*, National Institute of

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9. **R.E. Mohan**, W.S. Wijesoma, C.A. Acosta Calderon, C. Zhou, "Redefining Fan Out Metric: Estimating Human Capability in Controlling Multiple Robots" in *Proceedings of the IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)*, St. Louis, USA, October 2009
10. **R.E. Mohan**, W.S. Wijesoma, C.A. Acosta Calderon, C. Zhou, "Validating Extended Neglect Tolerance Model for Human Robot Interactions in Search & Rescue Missions" in *Proceedings of the IEEE International Conference on Robotics and Automation (ICRA)*, Kobe, Japan, May 2009
11. **R.E. Mohan**, W.S. Wijesoma, C.A. Acosta Calderon, C. Zhou, "False Alarm Demand: A New Metric for Measuring Robot Performance in Human Robot Teams" in *Proceedings of the IEEE International Conference on Autonomous Robots and Agents (ICARA)*, 436 - 441 Wellington New Zealand, February 2009.

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