A COLLABORATIVE APPROACH FOR REAL-TIME MEASUREMENTS OF HUMAN TRUST, SATISFACTION AND FRUSTRATION IN HUMAN-ROBOT TEAMING

by

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A Thesis Submitted to the Faculty of

The College of Engineering and Computer Science

in Partial Fulfillment of the Requirements for the Degree of

Master of Science

Florida Atlantic University

Boca Raton, FL

August 2018

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This thesis was prepared under the direction of the candidate's thesis advisor, Dr. Mehrdad Nojoumian, Department of Computer & Electrical Engineering & Computer Science, and has been approved by the members of his supervisory committee. It was submitted to the faculty of the College of Engineering and Computer Science and was accepted in partial fulfillment of the requirements for the degree of Master of Science.

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ACKNOWLEDGEMENTS

"I would like to thank my graduate advisor, Dr. Nojoumian for guiding and advising me through this journey of graduate studies at Florida Atlantic University. Without a doubt, Dr. Nojoumian helped me become a better professional by expanding my knowledge in Computer Science and more specifically about the field of Human Robot Interaction (HRI) and autonomous Systems.

I would also like to express my gratitude to Dr. Engeberg and Dr. Zhuang for offering their guidance through my experimental studies and also agree to review my research as my thesis committee members.

To my colleges in the BioRobotic lab at Florida Atlantic University, I would like to also express my gratitude for collaborating with me in different projects. Special thanks goes to Moaed A. Abd for assiting me in multiple projects related to this research. Finally, I would like to thank my parents, family, and friends for providing there support and motivation through my Masters.

This work was supported by the Department of Energy Minority Serving Institution Partnership Program (MSIPP) managed by the Savanah River National Laboratory under SRNS contract TOA#0000332969 in collaboration with Florida International Universitys Applied Research Center and Idaho National laboratory. This research was also supported by the NIH: NIBIB award # 1R01EB025819 and I-SENSE at FAU."

ABSTRACT

Author:	Iker Javier Gonzalez Moya
Title:	A Collaborative Approach for Real-Time Measurements of Human Trust, Satisfaction and Frustration in Human-Robot Teaming
Institution:	Florida Atlantic University
Thesis Advisor:	Dr. Mehrdad Nojoumian
Degree:	Master of Science
Year:	2018

This thesis aims at real-time measurements of human trust, satisfaction, and frustration in human-robot teaming. Recent studies suggest that humans are inclined to have a negative attitude towards using autonomous systems. These findings elevate the necessity of conducting research to better understand the key factors that affect the levels of trust, satisfaction and frustration in Human-Robot Interaction (HRI). We utilized a new sequential and collaborative approach for HRI data collection that employed trust, satisfaction and frustration as primarily evaluative metrics. We also used haptic feedback through a soft actuator armband to help our human subjects control a robotic hand for grabbing or not grabbing an object during our interaction scenarios. Three experimental studies were conducted during our research of which the first was related to the evaluation of aforementioned metrics through a collaborative approach between the Baxter robot and human subjects. The second experiment embodied the evaluation of a newly fabricated 3D-finger for the I-Limb robotic hand through a nuclear-waste glove. The third experiment was based on the two previous studies that focused on real-time measurements of trust, satisfaction and frustration in human-robot teaming with the addition of pressure feedback to the system through soft actuators. In the last case, human subjects had more controls over our robotic systems compared to earlier experiments leading to a more collaborative interaction and teaming. The results of these experiments illustrated that human subjects can rebuild their trust and also increase their satisfaction levels while lowering their frustration levels after failures or any faulty behavior. Furthermore, our analyses showed that our methods are highly effective for collecting honest and genuine data from human subjects and lays the foundation for more-involved future research in the domain of human-robot teaming.

*To my father, **Francisco**, my mother, **Enilde** and my brothers **Gabriel** and **Daniel**, with deepest love*

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CHAPTER 1

INTRODUCTION

In recent years, autonomous systems have been one of the main focus in technology research, analyzing human daily tasks that could potentially be done by robots or with a team of humans and robots. The wide range in applications of autonomous systems keeps growing, from industrial robots, military robot assistance, self-driving cars and also in home robot assistants. It has been proven in the past that the usage of robots can potentially increase the performance and efficiency of humans in the work space and in general, in humans lives. This opens the opportunity for researchers to test the limits of automation by increasing the complexity of the systems to perform more complex tasks.

We have already established that autonomous systems are here to stay but there are multiple factors such as trust, satisfaction and frustration that need to be addressed in order to understand how humans can successfully work along side with autonomous systems. Multiple studies have determined that one of the principal challenges for integrating autonomous systems and artificial intelligence in a successful manner is the management and development of mutual trust in HRI.Another potential issue that autonomous system brings to the table is the misuses and abuses that humans may have. For instance, users could become overly dependent on automation technologies or could also avoid the use of these systems. This is mainly due to trust and distrust, therefore understanding these factors that take place in the interaction is key for creating a framework that helps designing autonomous systems [1, 2].

Moreover, safety should be consider as a high priority in these systems. Since most autonomous system are designed to perform high complex tasks, users can often be unaware of what they can and cannot do. By adding certain factors and modifying some others, safety can be greatly increased withing autonomous systems. Such factors and modifications as stated in [3], can be training prior the exposure so user have a better understanding of what the system is capable of doing and simplification the overall system to avoid confusion.

In this thesis, we study how factors such as Trust, Satisfaction and Frustration (with main focus on Trust) play a crucial role in Human-Robot Interaction by evaluating the human subjects response towards an autonomous system. By instigating an active HRI team, we aim to understand how humans increase and decrease their trust on robots, and what factors affect the interaction the most to create a variation in trust levels.

The structure for this thesis is as follows: Chapter 2 embodies a literature review of major studies in the scope of HRI and trust in autonomous systems. Chapter 3 presents a study that analyzes three main factors in Human-Robot Interaction which are Trust, Satisfaction and Frustration through a passive approach of a object delivery. Chapter 4 describes a new approach for a contact detection system through pressure sensors in a humanoid robotic hand. Chapter 5 corresponds to the main experiment of this thesis utilizing a combination of the previous experiments findings to evaluate trust, satisfaction and frustration levels in an active Human-Robot interaction team with the aid contact feedback from pressure sensors. Finally, Chapter 6 covers the concluding remarks, limitation of the current approach, proposes new ideas and possible future directions of the research.

1.1 OUR MOTIVATION

Studies show that humans in general, are more inclined to have a negative reaction to the unknown. This is by nature because we like to understand what we are interacting with. This can be translated to the scenario in which humans distrust autonomous systems. We often see and hear people talking about how machines and artificial intelligence will eventually take over the world, self-driving cars are not safe or simply don't appeal to the idea of having a robotic assistant. This is due to the bridge of mutual trust between humans and autonomous system that has not been fully crossed yet but researchers are investing time and effort to achieve it.

Our main motivation for this thesis is to get a better understanding of Trust in HRI, how it can be increased, decreased and rebuilt. The increase in complexity of autonomous systems, managing the trust levels has become a crucial concept when designing new AI and autonomous systems. Different studies in the scope of AI and autonomous systems are suggesting that the primarily challenge faced in HRI will be trust management and therefore are dedicating a tremendous amount of resources to help the industry facilitate users usage of autonomous systems [22, 23]. The findings from these studies present the importance of a proper management of trust through research for a better understanding and assessment of the situation. How can an autonomous system regain the lost trust?, what factors and to what extend do these factor affect the overall interaction in a team of humans and Robots?, what assistance can we provide to users through sensors in order to facilitate a training and a successful interaction?. All these questions and many other remain unanswered to the best of our knowledge and this thesis aims to generate insightful findings and help solve some of the current issues in HRI.

1.2 NOVELTY OF OUR APPROACH

To the best of our knowledge, these are novel findings of our research methodology approach to Trust in HRI:

- The usage of a structured-and-sequential data collection approach with various Trust States: A Trust and Distrust format is commonly use in most studies to gather the human subjects responses. In this research we consider a five level system (distrust, somehow distrust, neutral, somehow trust, and trust). This approach is also used for two more metrics, Satisfaction and Frustration.

- A 3D printed finger tip called TakkTip specially design to incorporate pressure feedback for the iLimb prosthetic hand by Touch Robotics and help human subjects during the HRI.
- A new approach for detecting direction of slip through the BioTac sensor by SynTouch.

Our purpose is to construct a model of trust by experimental methods, understand principles of lost in trust levels before and after interactions with autonomous systems. In later chapters, definitions of these methods will be defined in detail with systems specifications that fitted the scope of our research.

1.3 HIGHLIGHTS OF OUR DISCOVERIES

This thesis was subdivided into 3 main experiments from which we arrived to a few interesting findings after analyzing the gathered data. The list below, describes some of the highlights of our findings (see Chapters: 3, 4, and 5 for a detail reports on each experiment).

Experiment 1 Highlights:

- Both groups showed similar patterns in the results.
- There exist some correlation between the factors of Trust, Satisfaction and Frustration when comparing them side by side.
- The impact in satisfaction for both groups was more noticeable than the other factors.

- Trust was somewhat preserve until case 6 (dropped mode) where subjects did not trust Baxter. Trust was successfully rebuilt after the experiment was concludes for both groups.

Experiment 2 Highlights:

- There exist some inherited bias when the robotic hand is in the glove.
- We managed to gather consistent data throughout 4 different trials of each mode.
- The sensing ability to the i-Limb was not substantially altered as the robotic hand performed the tasks for different modes with consistency throughout the experiment for the tested modes.
- The newly fabricated TakkTip sensor proved to detect contact with an object when compared to no object for the two studied modes, however, the sensor did not perform consistently if it was used at different contact angles.

Experiment 3 Highlights:

- A clear pattern in results for all metrics (Trust, Satisfaction, and Frustration).
- Successful rebuilt of Trust, Satisfaction and Frustration.
- Since the experiment was conducted with a 50% male and 50% female population, we evaluated a how the results deviate based on gender. Findings show that females were variate their states a lot less than males.
- The soft actuator armband utilized in the experiment successfully helped human subjects when grabbing and releasing the object.

CHAPTER 2
LITERATURE REVIEW

2.1 TRUST

In our society, the concept of trust is always present. It defines in some sense who we are and how we interact with each other daily. It can be placed in almost anyone or anything and ranges for the trust in the workspace as well as the trust we put in our friends and family. With all the advances in technology, humans are more connected than ever. The development of the Internet as well as the World Wide Web (www), has an important role in the increase of virtual communication, and the need of trust becomes more important to ensure that these virtual communication happen withing a trustworthy environment [4, 5, 6].

Trust is normally referred as the relationship between to entities, were the trustor is willing to rely on the actions performed by the trustee. This basic concept of trust can be further expanded into the relationship between individual persons, between a person and an object or action, and within social groups such as family, companies, countries, etc. From the computer science perspective, this concept of trust refers to the relationship between virtual entities. Next, we present a set of definitions from the literature to better understand the concept of trust.

Gambetta [7] defines trust as "a particular level of the subjective probability with which an agent assesses that another agent or group of agents will perform a particular action, both before it can monitor such action (or independently of his capacity ever to be able to monitor or enforce it) and in a context in which it affects his own action. From Gambetta's definition we can understand that trust is subjective, it varies from people to people because is based on the expectation from the trustor. Also, trust exists even before the action occurs based on prior behavior.

Jsong et al. [8] presents two different definitions of trust, one that relates to Gambetta's definition in [7] and a second definition inspired by McKnight and Chervany in [9]. Trust is the extent to which one party is willing to depend on something or somebody in a given situation with a feeling of relative security, even though negative consequences are possible.

The above definitions, bring to light aspects of trust that are important in order to comprehensively understand "What is trust?" The concept of reputation is crucial when placing trust withing entities. It is probably one of the most popular ways of building trust [10]. Reputation is the expectation about an agent's behavior based on information or observations from previous actions [11].

Very often, reputation can be confused with trust and although they closely connect to each other, there is a clear difference that can be illustrated in the following two scenarios:

1. A trust B because B has a good reputation. This is a clear example in which reputation can be utilized for building trust.

2. A trust B despite B's bad reputation. In this scenario, A knows that B has a bad reputation but it is more important to A the past experiences based of its private knowledge of B.

From a social science perspective, trust is the willingness of a person to become vulnerable to the actions of another person irrespective of the ability to control those actions [12]. From technical perspective, trust is determined as an expectation that an entity may have with respect to the future behavior of another party, i.e., a personal quantity measured to help the players in their future dyadic encounters [13]. The formal definition of trust can be defined as follows [14]:

Definition: Let $T_i^j(t)$ be the trust value assigned by $P_i to P_j$ in period t. Let $T_i(t)$: $N \rightarrow R$, i.e., from natural to real numbers, be the trust function that illustrates how trustworthy P_i is:

$$T_i(t) = \frac{1}{n-1} \sum_{j \neq i} T_i(t) \tag{2.1}$$

where $-1 \leq T_i(t) \leq +1$ and $T_i(0) = 0$ is the initial trust value.

As shown, upper and lower bounds should limit a trust value, and an initial value must be determined. For instance, this definition illustrates if we have a technological system that interacts with a group of people, the perceptions that all these people have regarding the trustworthiness of the system will define how reliable it is, i.e., the average of trust perceptions.

New technologies including robots playing an important role in our daily life, due to many applications of robot ranging from performing simple task like delivering object to disabled people [15], doing complex tasks like doing a surgery [3], doing military task [16] or even doing search and rescue in hazardous locations [17], it is important to study the HRI behavior and make models for different parameters like trust. As the robot developed and become more significant for our lives the demand for such model become essential to make it possible to change the trust mode of a certain human when interacting with robot especially in complex tasks. Many researchers address the trust issue for HRI [18, 19, 20].

According to recent findings by researchers at Chapman University [21], Americans expressed the second highest level of fear about technology such as artificial intelligence and robots. These fascinating discoveries highlight the necessity of conducting research to better understand the notion of trust from human reasoning perspective [22]. Indeed, the ultimate objective is to design computational models of trust [23] for technological systems that interact with humans. These computational models can be then incorporated into the controllers of such systems for reliable interactions between humans and technologies.

Trust is a parameter which usually takes time to develop and is important during interaction with any autonomous system. In general, there are many factors that might affect trust, for example, previous experiences interacting with autonomous systems. A lack of trust may negatively impact the task performance and impact the productivity of a human-robot team task.

Marsh [24] was one of the first to define trust from a computational point of view. He understood the fact that for trust usually implies some degree of uncertainty and hopefulness regarding an outcome [25]. Marsh divided trust in three groups, (1) The basic trusting disposition independently of the encountered agent. This relates to the accumulation of direct experiences. Positive direct experiences creates a greater disposition of trust and negative direct experiences will the lead to less disposition of trust. (2) The second group corresponds to General trust. This the trust that one agent has in another agent without considering any specific situation. (3) Situational trust will then be the opposite of general trust. Depending of a specific situation, the agent will trust or not another agent.

2.2 HUMAN ROBOT INTERACTION

There are key factors that determine if the interaction is successful or not successful in HRI. One of these key factors involves trust, an imperative component for HRI. By the use of machine learning techniques, we can model, understand, and even evaluate trust in order to improve the human's relationship with the robot or autonomous system. [26] describes a study done by a group of researchers at Purdue University in which the main focus was on dynamic modeling of trust in human-machine interactions. The authors argue the importance of trust in order to integrate autonomous systems into our daily lives. The study consisted in 581 human subjects in a obstacle detection scenario in which each subject was asked to record if they trusted or distrusted the system depending on the machine's response towards the obstacles. In other words, the subjects would repeatedly evaluate the obstacle detection algorithm and choose whether or not to trust the system. They divided the experiment into two groups (Group 1 and Group 2) and the experimentally obtained trust level and the predicted values turned out to be 83.77% and 76.17% for group 1 and 2, respectively.

Another study performed from a group of researchers at Purdue University on 2017, demonstrated an experiment involving real-time sensing of trust [27]. This study consisted of 31 adults divided into two groups (Group 1 and Group 2). Using the Galvanic Skin Response (GSR) and Electroencephalogram (EEG) signals as primary source of information in order to measure trust levels from humans towards the machine. The authors proposed a real-time methodology that enable machine algorithm design and possibly improve the interaction between humans and machines. The subjects were asked to respond to a scenario (trust or distrust) in which they would be driving a car with image processing capabilities. The experiment results showed how psycho-physiological measurements can be use to sense human trust in real-time and by using the Voting Classifier, they reached a mean accuracy 71.57%. The authors argue that features such as dis-positional of trust were not taking in accountant and could potentially affect the overall accuracy of the system.

Convolutional Neural Network are used to process multiple array data, for instance, image and videos. In [28], the authors describe the problem of facial recognition by dividing it into two main categories. The first one corresponding to the less-demanding application such as online image search and family photo album organization where the agents are in favor instead of against the system. The other category falls into the mass surveillance and terrorism watch list for which the robustness of the system has to be much higher that the previously mention category. The authors stated the problem that facial recognition application often present (variations in illumination, image misalignment, and occlusion in the test image). Then, proposed an improvement to these problems by implementing a complete face recognition system that can effectively and efficiently recognize faces under different yet realistic variations. in 2015,a group of researchers study the idea of using CNNs in highway perception scenarios. They argue that the combination of deep learning and computer vision can offer an inexpensive yet robust solution to self driving cars [29].

When back-propagation was first introduced, its most exciting use was for training recurrent neural networks (RNNs), especially when the task involved sequential inputs such as speech and language. The main idea behind RNNs is to process an input sequence one element at a time, maintaining the information about the history of all the past elements in the sequence, thus recreating a short time memory behaviour [30]. In [31], the authors introduced the Long Short-Term Memory technique for recurrent neural networks. They argue how recurrent back-propagation is a time consuming task and proposed the LSTM which is now commonly used for most of the RNNs applications.

In 2008, C. Breazeal and A. Thomaz, presented a new learning mechanism for autonomous systems that correspond to socially guided learning and self exploration in which the robot's learning process is based on social interaction between the human agent and the robot as well as a self exploration aspect in which the robot is able to learn on its own [32]. This is a clear example of Recurrent Neural Network in combination with Convolutional Neural Network. Leonardo (Name of the Robot) used RNN for the most part on speech recognition and to make sense of what the socially guided instruction from the human and CNN for image recognition in order to classify different objects that the human pointed at during the experiment trials. This process can be defined as reinforced learning and it has become essential when working with robots and autonomous systems in general. In [33], the authors define a case study in which reinforced learning is the primarily focus. The TAMER (Training an Agent Manually via Evaluative Reinforcement) framework that helps the process of learning to be based on numeric human feedback. The authors taught the robot with signals of approval or disapproval depending on the task performed by the robot. Later, these signals were map to numeric values in order to be used as "human reward".

Kristin E.[34] present a novel approach for measuring trust in human robot interaction. The study consists on a $0-100\%$ rating scale with a trust score percentage based on six experiments performed in order to generate a 40 item trust scale.

Yanco H.A. et al. [35] research two methods for modeling trust between humans and intelligent systems. The first method consists on the traditional approach of surveys, were large groups of people are asked to rank factors that affect their trust towards intelligent systems. The second method proposed in this research relates to conducting experiments with different controlled factors in which human subjects use the intelligent system.

In [36], a framework that identifies methods for causing trust in automated and autonomous systems is presented. The methods are used throughout a products life cycle. The authors propose new methods that create both systems and operational trust for autonomous systems.

Floyd M.W et al. [37] present a new algorithm in which the robot agent can learn from its behavior when interacting with a human by estimating its trustworthiness and adapt itself in a attempt to improve it. This research consisted mainly on a comparison between two approaches, the one created by the authors and another approach in which the robot does not learn. Their results show that their inverse trust estimation and behavior adaptation algorithm can identify trustworthy behavior significantly faster than the second approach.

In [38], Xin Liu et al. argue how the traditional approach of evaluating trustworthiness based on the specific agent involved, derived from the history of its behavior may not be the most efficient method. The authors presented a generic method in which machine learning is utilized to extract significant features that help determine if the transaction is successful or not. It also uses the previous interactions with other agents to build the knowledge base.

Gao F. et al. in [39] conducted two experiments that investigated the impact of human robot interactions in order to design a robust and effective teamwork in HRI. Experiment 1 investigated the impact of team structure and uncertainty of task arrival processes on team coordination and performance. Experiment 2 explored the usage of information-sharing tools under different uncertainty levels.

In 2012, Munjal Desai explored trust in HRI by designing and evaluating different experiments with different variables in a controlled environment. The author asked different participants to drive a robot through an specific path as fast as they could without hitting any object while performing other tasks to increase the workload. Since the subjects were allow to choose between controlling the robot or using the fully automated robot mode, by changing the conditions for the experiment (light, reliability, increasing the amount of tasks, etc), the author was able to acquire enough data to understand how much the performance of the robot is as well as the importance of having a trustworthy robot-team can positively affect the outcome of a difficult task such as search an rescue missions [40].

In [41], a gray-box modeling approach is introduced to help autonomous system predict variations in human trust towards the systems. The authors performed an experiment in which subjects had to react to a simulated environment that recreates a self driving car by state if they trust or not the system. They also introduced the effects of demographics on trust behavior which can help the autonomous systems understand and predict the variations in human trust better.

2.3 TRUST IN HUMAN ROBOT INTERACTION

In 2010, a new model was proposed to test the acceptance of assistive social agents by elderly users. The study represents an extension of the Unified Theory of Acceptance and Use of Technology (UTAUT) by a controlled experiment data collected at homes of elders. The findings from the study supports and contributes to the understanding of how elders accept assistive social agents. In a future work, the authors mentioned modifying and addressing different factors such as age, gender, computer experience and how these factors can boost or decrease the acceptance rate [42]. Another study performed by D. Li et. al. addresses appearance as an important factor in trust. The team of researchers developed a study, analyzing different cultural backgrounds and investigated the interaction between humans and robots from a cultural perspective. The authors suggest that a study utilizing the findings from this research could help the robots design, making them more region specific in order to improve the trust metric [43].

R. E. Yagoda and D. J. Gillan, in 2012, presented two studies to identify critical considerations in the HRI in order to examine the role of trust in HRI. To this end, the authors performed the first study relating to content validity assessment of preliminary items generated which were based on previous research. The second study corresponds to the assessment of quality of each trust scale item derived from the first study. Based on the results from both studies, an HRI trust measurement tool was developed. The future work is aimed to expanding the HRI Trust scale to include a human information subscale [44].

A new approach to study the effects of robots performance and behavioral style on human trust presented by R. Van den Brule, et. al in 2014. To this end, the authors developed a set of experiments using animated robot avatars in video human robot interaction (VHRI) to clearly identify which behavioral styles affect human trust. A second experiment used immersive virtual environment (IVE) to measure behavioral interaction between humans and an animated robot equipped with the findings from the first experiment. The authors were able to reaffirm that the performance of a robot during a task influences its trustworthiness [45].

In 2015, L. Royakkers and R. van Est performed a literature review on social robotics and bring to light interesting topics that are around the corner for social robotics. Robots are starting to be developed in different areas such as home, health care, traffic, police, and the army but how far are we planning to develop the automation in these systems. The authors provide insight into social issues that new robotics can potentially arise [46]. Following the previous study, during the same year, A. Prakash and W. A. Rogers investigated the importance of humanoid robots face in HRI. The authors proposed a new method approach to identify patters of perception across different appearances and also study the reasons that influence the formation of those perceptions. The results from this study reflect how people perception of robot faces vary as a function of robot human-likeness. Another interesting finding addresses the preferences for humanoid robots depending on the task. For future work, the authors mentioned that it should tackle the weight of these different factors when forming the perceptions in both global and task specific [47].

A novel study addressing reciprocity as an important factor in Human robot interactions performed in 2016 by E. B. Sandoval et. al. An experiment was performed utilizing the Repeated Prisoners Dilemma Game and the mini Ultimatum Game. The results showed that humans were more inclined to collaborate with human agent rather than robot agents. Nevertheless, human subjects tended to be equally reciprocal with both agents. Overall, robots were perceived as less open and agreeable than humans. With these findings, the authors suggest that reciprocity applied in HRI can improve the future of robot design [48]. Another study performed in the same year by G. Charalambous, et. al. addresses human robot collaboration using Trust as a key element for a trust measurement scale. The scale was developed in two phases. The first phase explored the collection of participants opinions qualitatively, helping the process of paving the road for generating the questionnaire. For the second phase, the authors performed three trials using three different types of industrial robots in which the generated questionnaire was applied to participants. The results were analyzed in a statistical fashion from which key factors that impacted trust were derived, helping the making of a trust measurement scale for industrial HRC. In future work, the authors mentioned that the above study provide a basis for more specific studies of components such as the robots gripper reliability and mentioned that a possible study could include the investigation of the impact of human trust under varying levels of gripper reliability [49].

In 2017, C. J. Stanton and C. J. Stevens performed a study that focuses on gaze and the importance it has on social communications as well as the important role it can have on HRI. The authors describe how gaze can signify different signals such as threat, dominance and aggression but also can influence trust, likability and compliance. The research investigated three different levels of robot gaze (averted, constant, and situational). An interesting find from this research was found where gender influences how much a subject relied on the robots gaze. Females were least likely to trust a robot which stared at them. For future work the authors address the possibility of studying the limitation of the study such as gender effects on trust between humans and robots during the HRI [50]. J. Michael and A. Salice researched commitment as a fundamental factor in HRI. The study represents a starting point for designing robots with a sense of commitment. The authors identified different challenges that such system will most likely approach and also mentioned possibilities to address these challenges [51]. Y. Liang and S. A. Lee evaluated a specific form of sociological fear, which the authors named fear of autonomous robots and artificial intelligence (FARAI). The authors argue that this fear can be a crucial factor affecting how people respond to and interact with robots. The study consisted in a series of questions that helped the authors shape the results for analysis. Findings from this study showed that FARAI can also be associated with other types of fear such as loneliness, unemployment. For future work, the authors suggest exploring phobia of robots [52]. a survey on factors that have potential to influence human perception and attitudes toward non-anthropomorphic robots in public spaces performed by D. C. May et. al in 2017. Within the study, factors such as demographic, attitudinal, and contextual difference were evaluated and provided interesting findings that suggests that even though gender, age, race and contextual differences play an important role, the majority of adults showed great acceptance of mechanical-appearing robots in public environments where demographic added little to no variation to this acceptance. For future research, the authors proposed the development of a study in which two groups are designed to evaluate the acceptance. One group for adults and the second group for children and juveniles [53].

S. Whelan et. al. presented a literature review on social robots specifically design to assist older adults including people with dementia or cognitive impairment in 2018. The paper reviews different studies that have explored how acceptability plays a crucial role in these interactions. The main goal for the research is to identify key factors that improve acceptability and also to make recommendations for future research. All findings from the research were based on the Almere robot acceptance model and showed multiple interacting factors that affected acceptance. Also, it was shown that acceptance can be improved by the use of robots with humanlike communication, being personalized based on the users needs. For future research, the authors suggest focusing on different cultural groups, to investigate how different cultural factors affect the robot acceptability [54]. P. Jeri et. al. addressed the performance in collaborative HRI. The experiment consisted in a turn-takin version of the Tower of Hanoi serious game. The Geneva Emotion Wheel questionnaire was utilized to analyze the elicited emotions. From the results, the authors drew the conclusion that there is not a statistical significant difference in terms of performance between humans or robot collaborators, but human collaborators were perceived as more credible than the robot one. There are interesting findings from this study that suggests that using robot collaborators show potential on being as efficient as human collaborators [55]. V. Gonzalez-Pacheco et. al. studied social robotics and active learning. The authors developed an experiment in which they taught poses to a robot and uses a group of users to answer several questions, utilizing the answers for a feature filter in the robots learning space. The feature filter focused on three types of question, free speech queries, yes/no queries and rank queries. After the filter was developed and the robot was trained, the authors performed a comparison between a robot that was taught using an active learning approach with the above-mentioned feature filter and a passive learning (without filters). The results show some improvement in learning in certain scenarios but a decay in learning for other scenarios [56].

CHAPTER 3
PERFORMANCE OF A ROBOTIC ASSISTANT DECOUPLES HUMAN PERCEPTION OF TRUST, SATISFACTION, AND FRUSTRATION

This experiment consisted in the base line for the HRI from the passive perspective performed by two groups of 10 people each for a total of 20 human subjects selected after giving informed consent under the approved IRB protocol. The autonomous system performed a series of object deliveries to the subject. These deliveries were carefully set in different modes to create a range of scenarios which allow the investigators to evaluate the impact of three main factors on HRI. These factors are Trust, Frustration and Satisfaction [57].

3.1 METHODS

Robot operating system (ROS) was used to establish a communication channel, control the Baxter robot, and record all the subjective evaluations of trust, frustration, and satisfaction. All the recorded data was synchronized with each other and had the same time stamp (Fig.3.1).

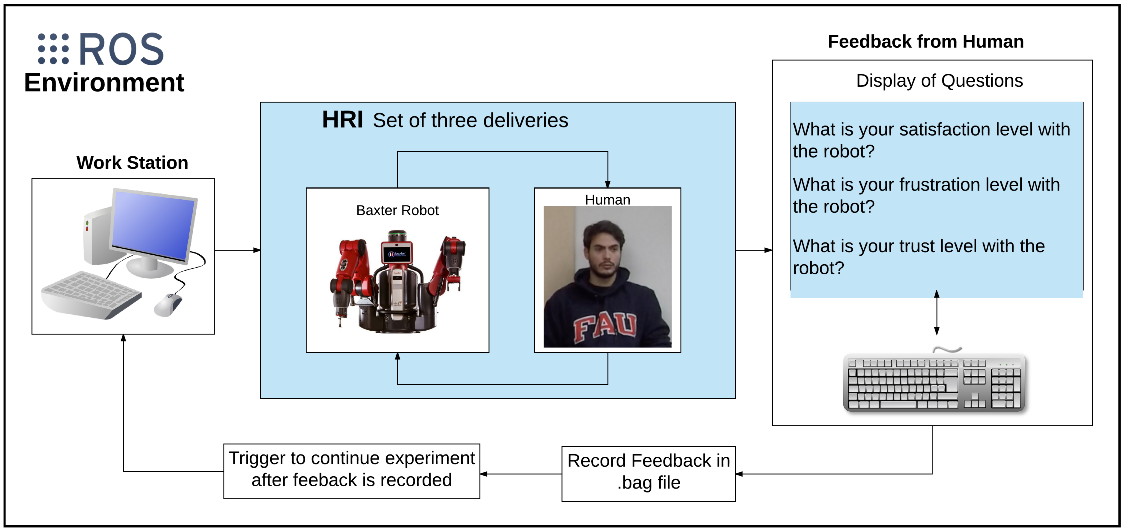

Figure 3.1: HRI Experiment Cycle.

After each set of 3 water bottle deliveries, the Baxter robot operational mode was altered among five pre-programmed modes 3.1.

1. The success mode in which the Baxter robot successfully delivered the object to the human subject with an average end effector speed of 0.3 m/s (Fig.3.2(A)).
2. Exactly the same as mode (1) except with an end effector speed of 0.1 m/s.
3. The wrong location mode: Baxter delivered the bottles to a wrong location far away from the human subject with a mean end effector speed of 0.3 m/s, forcing the person to stand up from his or her seat to take bottle from the robot (Fig.3.2(B)).
4. The dropping mode: the robot was programmed to "accidentally" drop the object before delivery with a mean end effector speed of 0.3 m/s (Fig.3.2(C-F)).
5. Exactly the same as mode (1) except with an end effector speed of 0.7 m/s.

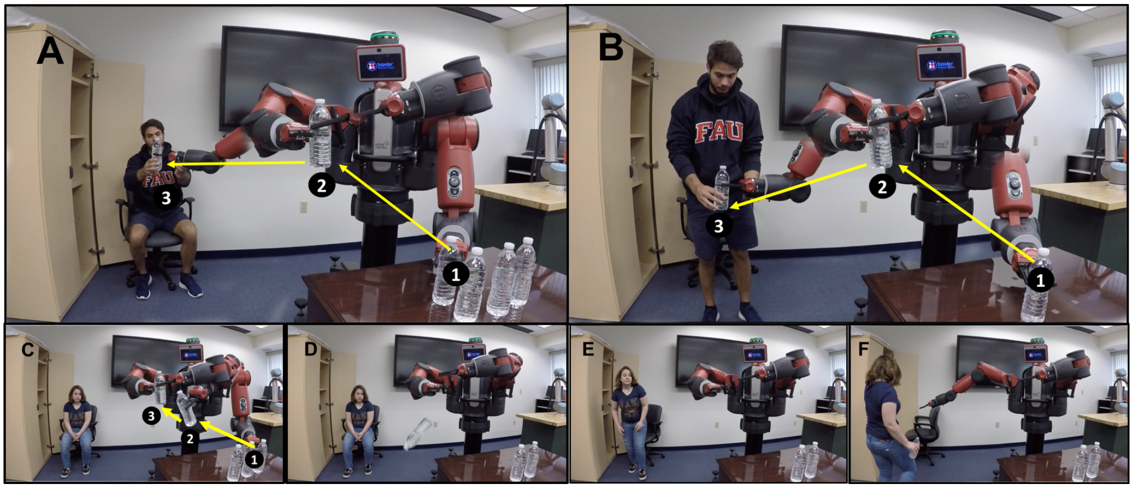

Figure 3.2: Photo Sequence: (A) Successfull Delivery, (B) Wrong Location Delivery, (C - F) Sequence for Object Dropped

Table 3.1: Group 1 & 2, Experiment Sequences

Cases	Operation Mode	Speed (m/s)
1	1 (Successful delivery)	0.3
2	2 (Slow Successful delivery)	0.1
3	3 (Wrong Location)	0.3
4	3 (Wrong Location)	0.3
5	1 (Successful delivery)	0.3
6	4 (Bottle Dropped)	0.3

After Both groups finished the first six cases, a set of 18 deliveries combining the different modes in the following sequence were performed including mode five which represents the fast speed successful delivery. For Group 1 (Modes: 2, 4, 5, 1, 1, 1) and for Group 2 (Modes: 2, 1, 1, 1, 1). The last case for these set of deliveries was set as Case 7 (see Results and Discussion) to illustrate the state of both groups after the experiment was done and to evaluate further comparisons. When each set was concluded, the subjects were asked the following questions:

- What is your Trust level with the robot?
- What is your satisfaction level with the robot?
- What is your Frustration level with the robot?

The human subjects rated each question from 1 to 5, 1 being the lowest level and 5 being the highest level. Moreover, when all data was successfully collected, each metric was analyzed using two main tools, The Mean and Standard deviation and The nonparametric Mann-Whitney U-test (Wilcoxon Rank Sum Test). The mean and standard deviation allow the evaluation of the overall impact of the different cases between the subjects and helped determine significant differences between groups. was used to statistically analyze the subjective data related to trust, satisfaction, and frustration. The Mann-Whitney U-test is a nonparametric test for two populations of independent data to test for equality of population medians of two independent samples. With the U-test, a pairwise statistical analysis was performed to determine if there was any robot operational mode that significantly impacted the subjects' trust, satisfaction, or frustration.

3.2 RESULTS

3.2.1 Trust-Trust Level Comparison

The mean and standard deviation of trust for Group 1 and Group 2 are illustrated in (Fig 3.3(a)). The dropping mode (4) substantially reduced the trust levels in comparison to the other modes across both groups. These reductions in trust due to the dropped object were statistically significant as shown by the pairwise comparisons for Group 1 is illustrated in (Fig 3.3(b)) and for Group 2 in (Fig **??**(c)), respectively. All other cases did not show a significant variation in the pairwise comparison.

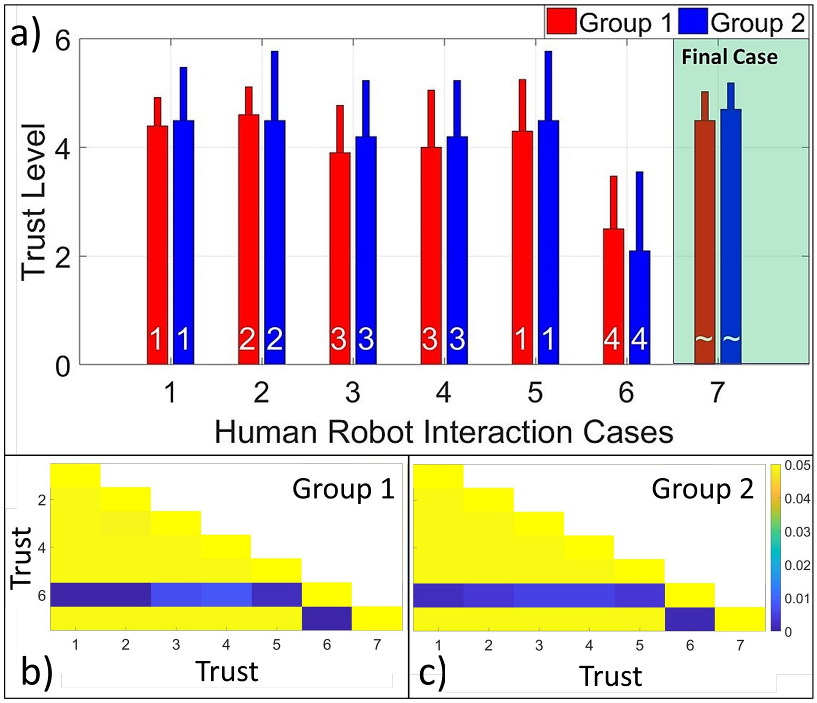

Figure 3.3: Group 1 and Group 2: Trust Level (a) Mean and Standard deviation. (b) Group 1: Wilcoxon Rank Sum Test. (c) Group 2: Wilcoxon Rank Sum Test.

3.2.2 Frustration-Frustration Level Comparison

(Fig 3.4(a)) illustrates the mean and standard deviations of frustration for Group 1 and 2. Additionally, the statistical analysis for Group 1 is illustrated in (Fig 3.4(b)) and for Group 2 in (Fig **??**(c)). Depending on the robots operation mode, the frustration levels changed but mainly case six, dropping mode, showed the greater impact. Across both groups, there exists a similar pattern when observing the pairwise comparison except for cases such as three, four and six were the human subject felt frustrated with the Robots performance.

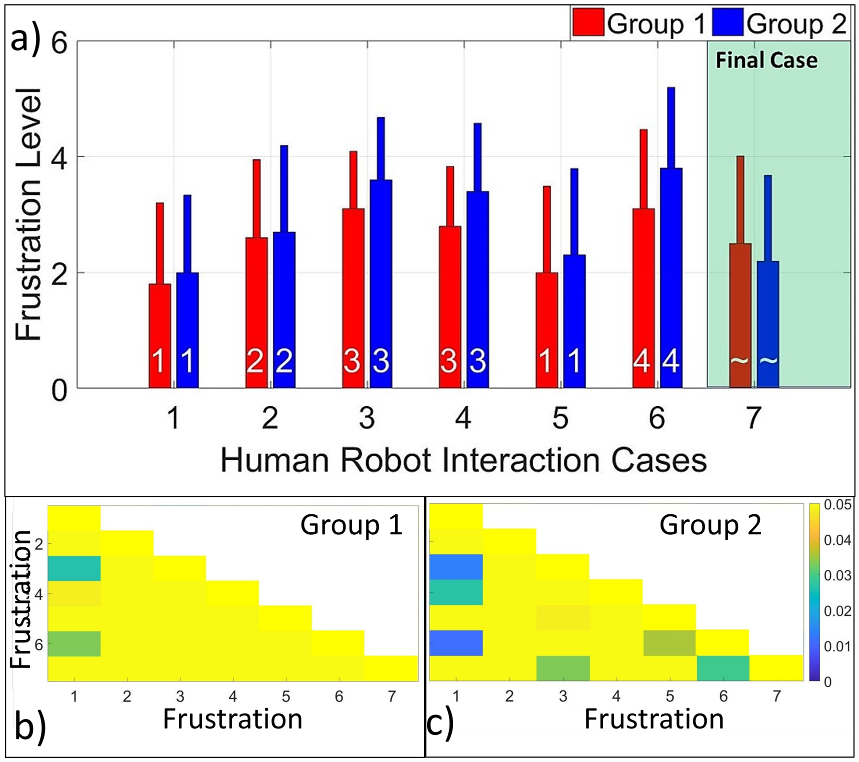

Figure 3.4: Group 1 and Group 2: Frustration Level (a) Mean and Standard deviation. (b) Group 1: Wilcoxon Rank Sum Test. (c) Group 2: Wilcoxon Rank Sum Test.

3.2.3 Satisfaction-Satisfaction Level Comparison

The mean and standard deviation of satisfaction for Group 1 and Group 2 are shown in (Fig 3.5(a)). Likewise, the statistical analysis using the Wilcoxon Rank Sum Test for Group 1 is illustrated in (Fig 3.5(b)) and for Group 2 in (Fig 3.5(c)). As illustrated, depending on the robots operation mode, the satisfaction levels changed. The dropping mode, i.e., mode 4, shows the lowest satisfaction level across both groups. The satisfaction level also decreased in both groups when Baxter delivered the object to the wrong location (mode 5).

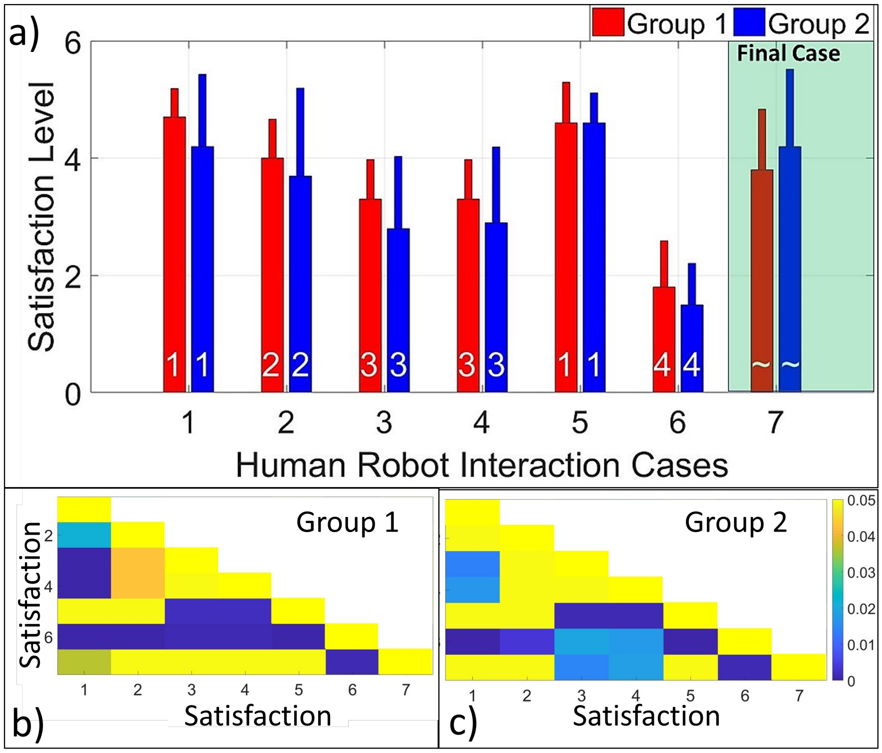

Figure 3.5: Group 1 and Group 2: Satisfaction Level (a) Mean and Standard deviation. (b) Group 1: Wilcoxon Rank Sum Test. (c) Group 2: Wilcoxon Rank Sum Test.

3.2.4 Trust-Frustration Level Comparison

The statistical analysis for Group 1 and 2 (Trust vs Frustration) is shown in (Fig 3.6). Depending on robots operation mode, the correlation between trust and frustration differs. The figure shows significant variation between Trust and Frustration across almost all cases. These variances could be due to the personal point of view towards frustration and trust from each human subject and also because in operation modes such as the dropping mode, trust levels are most likely going to decrease while the frustration level will potentially increase.

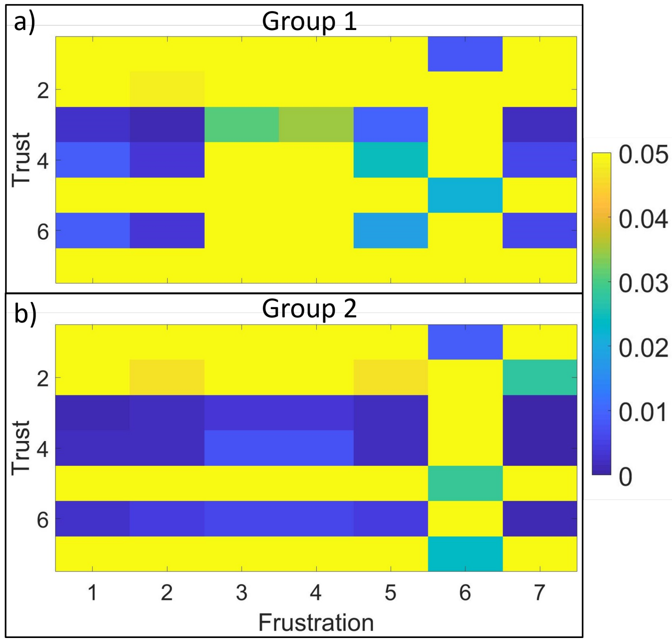

Figure 3.6: Group 1 and Group 2: The Wilcoxon Rank Sum Test for Trust Vs. Frustration.

3.2.5 Trust-Satisfaction Level Comparison

Next, a comparison between Trust and Satisfaction is made (Fig 3.7) for Group 1 and 2. This analysis showed how in some cases the levels of Trust are not statistically different than the levels of satisfaction (case 1, 2 and 5). Cases 3, 4 and 6 show the most meaningful differences due to their negative impact on the experiment since they correspond to the object being delivered to the wrong location and the object being dropped.

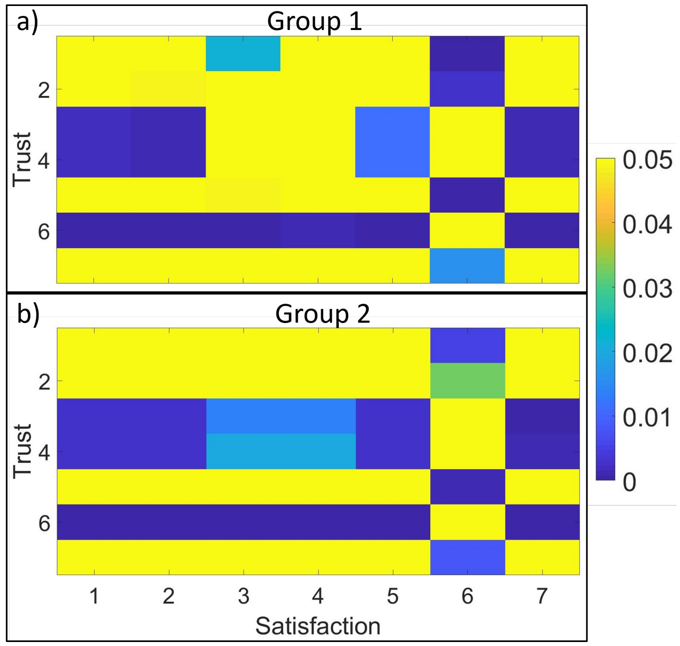

Figure 3.7: Group 1 and Group 2: The Wilcoxon Rank Sum Test for Trust Vs. Satisfaction

3.2.6 Satisfaction-Frustration Level Comparison

As analyzing the differences and similarities in the Satisfaction Vs Frustration Data (Fig 3.8) between Group 1 and 2, it came as no surprise how the dropping and wrong placement mode (case 5 and 6 for Group 1 and 2) is where most of the differences can be noticed. But it is interesting how case 5 from satisfaction (success) compared to case 3 and 4 from frustration (wrong location) showed a small difference which illustrates a neutral state from the human subjects across both groups.

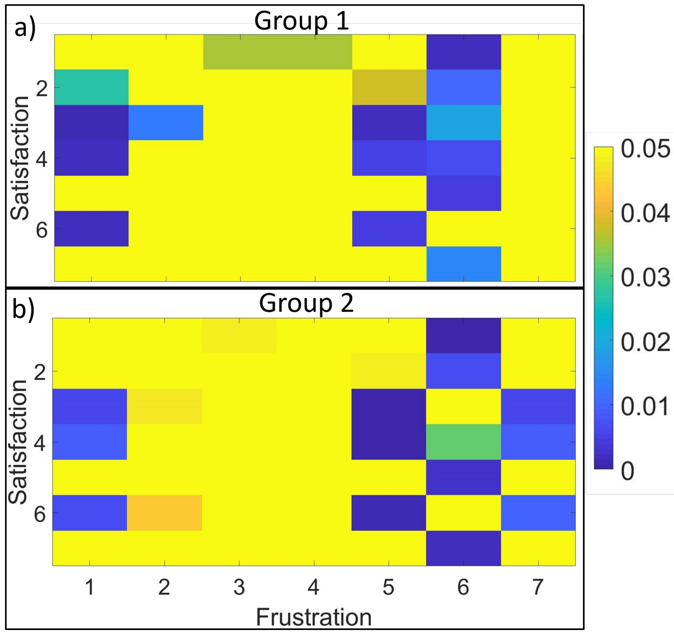

Figure 3.8: Group 1 and Group 2: The Wilcoxon Rank Sum Test for Satisfaction Vs. Frustration

As the robot become more and more involved in our environment, the demand for trust, frustration and satisfaction model is becoming necessary. Human must trust the autonomous system before a successful interaction can be achieve. This work focuses on the interaction with a robot in daily life tasks such as delivering objects to disabled or elderly people, helping them with a daily routine. In this study, the HRI feedback was measured for trust, satisfaction, and frustration after interaction with Baxter robot. The feedback was altered based on the operation mode of the robot in delivering the objects to a human. It turns out that the human trust, satisfaction and frustration level are unstable and changing according to the performance of the autonomous system. If the robot performed the delivery task without mistakes, the human would trust it, otherwise, the trust level would be different.

3.3 CONTRIBUTIONS

This work was performed with the collaboration of Moaed A. Abd, Dr. Mehrdad Nojoumian and Dr. Erik D. Engeberg. The design of the experiment was done by Moaed A. Abd while the author performed the demographic data gathering as well as the analysis and plots of the same. All results from this study were plotted by Moaed A. Abd and analyzed by both the author and Moaed Abd. After the necessary results were gathered and analyzed, the author and Moaed A. Abd, with the guidance of both Dr. Nojoumian and Dr. Engeberg, wrote the different sections that encloses the publication.

CHAPTER 4

ROBOTIC FINGER FORCE SENSOR FABRICATION AND EVALUATION THROUGH A GLOVE

This second experiment presents the effort taken to examine the effects of the glove on a robotic hand. This was done by designing a new force sensor geometry utilizing Takktile sensor and testing the sensor ability to detect force applied through various modes with and without gloves. An i-Limb Ultra Revolution prosthetic hand was used to perform the testing (Fig.4.1). A Takktile sensor from RightHand Robotics was embedded into a fingertip to be mounted onto the index finger of the i-Limb hand. This sensor was coined the TakkTip. The hand is inserted into the glove to compare the effect it has on the force. The experiment had three modes and each mode was tested with and without the glove [58]. I previously done experiment by the author and Moaed A. Abd, Thomas C. Colestock, Benjamin A. Kent, Dr. Erik D. Engeberg (2018), aimed to detect the direction of slip using a pressure sensor called Tactile by SynTouch. This research presented a machine learning approach to evaluate and detect the movement of the object after grasped [60].

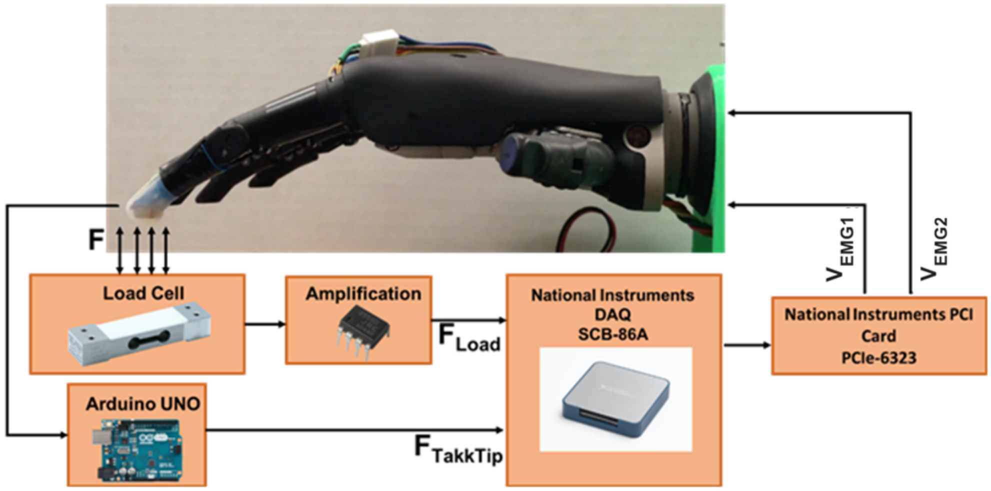

Figure 4.1: System level diagram illustrating the experimental setup. Presented is the i-Limb Ultra with a TakkTip sensor mounted at the tip of the index finger. This sensor, the i-Limb and a load cell are connected to Simulink 2016b through a PCIe-6323 from National Instruments.

4.1 METHODS

The TakkTile sensor by RightHand Robotics was used as it offers a reliable source of data at an inexpensive price. The sensor consists a MEMS barometric sensor embedded in a rubber material to not only protect the electronics but also to allow a wider area for sensing capabilities such as detecting subtle contact with objects [61].

Humans have the ability to sense the applied force on external objects despite the effects of wearing a glove. They are also able to adjust their grip accordingly to perform various tasks with the ability to sense the applied force while wearing that glove, however, the effects of the glove on a robotic hand have not been examined as deeply yet.

4.1.1 TakkTip Sensor Fabrication

This new design, called the TakkTip, is comprised of a Takktile force sensor from RightHand Robotics (Fig.4.2), and fabricated in three steps. The first step was modeling the desired geometry. The second focused on 3D printing the structure to support the sensor and the third was to embed the assembled sensor into a semi-soft rubber called DragonSkin 50.

Figure 4.2: Fabricated TakkTip sensor for measuring the forces of all experiments in this paper.

4.1.2 Modeling and 3D Printing

Solidworks 2017 was used to create the CAD model for 3D printing (Fig.4.3). This was achieved by removing the preexisting fingertip on the i-Limb Ultra robotic hand. This exposed the mounting post which allows the fingertip to be removable with minimal effort. Multiple images were taken of the post to create a 3D model of the cavity needed for mounting. This design was printed using PLA filament (Fig.4.4).

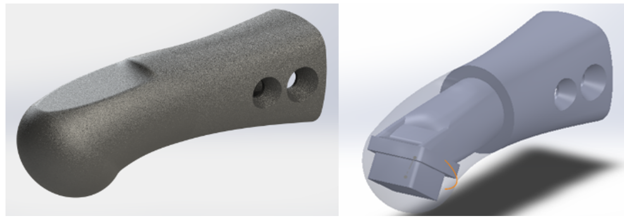

Figure 4.3: CAD model in Solidworks 2017 of the TakkTip sensor.

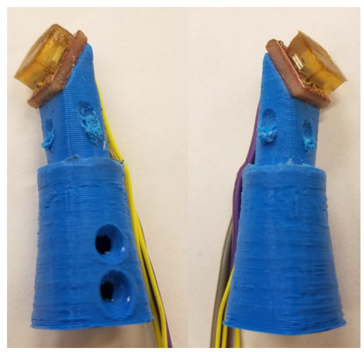

Figure 4.4: 3D printed structure used to mount the sensor to the iLimb Ultra hand.

4.1.3 Donning and Doffing the Glove

This was very important in the analysis of whether there is an effect of wearing the glove on the force that can be sensed. To minimize the variability from test to test, all measurements were gathered during the same session and all mounting hardware was marked to easily perform testing in the same location after putting the glove on and taking it off, minimizing the possibility of error.

4.1.4 Measuring the Forces

The force measurements gathered during each test were made using the load cell, FLoadCell, and TakkTip sensor, FTakkTip. The TakkTip was connected to an Arduino Uno and a library found online was used to read data from the TakkTile sensor and send it out through one of the PWM pins. There were noticeable variations in force measurements due to the sensor being temperature sensitive. This was compensated for by calibrating the voltage of the sensor with the temperature and a correlation to map the two and compensate for temperature changes.

The load cell was connected to an amplification board prior to connecting to Simulink to both amplify and filter the signals.

4.1.5 Mode 1 - Open/Close

The open/close mode was tested by starting with the hand in the open position and continuously closing and then opening the hand at a rate of 9 rad/s (Fig.4.5). The measurements were gathered with the glove on and the glove off.

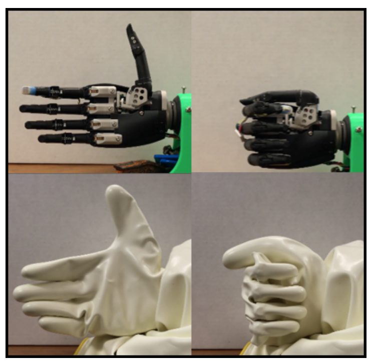

Figure 4.5: Mode 1: Fully opened hand posture cycling repeatedly to a closed posture and back

4.1.6 Mode 2 - Tapping

The second mode, shown in (Fig.4.6), measured the force applied by the i-Limb when intermittently in contact with an object. This formulated a tapping scenario. For consistency purposes, a load cell was utilized as the object in contact and also served as a way to confirm the measurements with an externally calibrated device. The reason for this is because a load cell offers a flat surface that helps with repeatability as well as a direct way of measuring the force being applied.

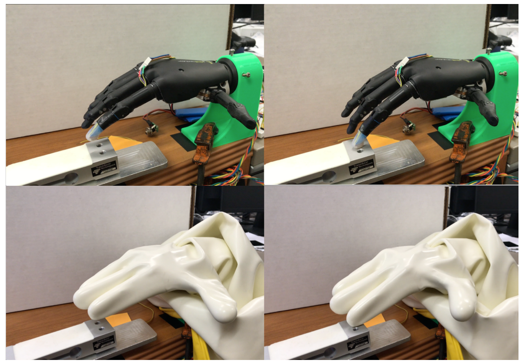

Figure 4.6: Mode 2: Intermittent tapping force

4.1.7 Mode 3 - Constant Force

The final mode (Fig.4.7) tested the ability of the sensor to apply a constant load intermittently. Actuation was similar to the tapping mode but during contact with the load cell, the finger maintained contact and no additional movement commands were initiated until the sensor values reached steady state conditions. The finger was then extended to the fully opened position and the cycle repeated. This was performed with the glove and without the glove to observe the effect of the glove on the force measurement.

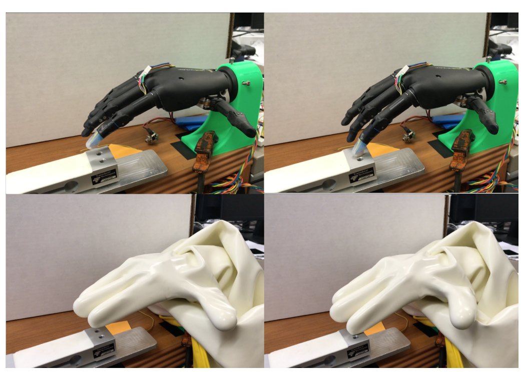

Figure 4.7: Mode 3: Constant force

4.2 RESULTS

4.2.1 Mode 1 - Open/Close

The results for opening and closing the hand are presented below and show that there is a difference in the measured force when the hand operated with and without a glove (Fig.4.8). Without a glove present the TakkTip had no observed force effects transferred from the motion of opening and closing the hand. When the glove is put onto the hand there is an inherent bias imposed on the force measurement through the TakkTip. This bias was consistently observed throughout many tests. Note that this bias varied in magnitude each time the glove was put on but once the glove was on the bias was consistent and discernable for force sensing capabilities through the glove during the opening and closing motions.

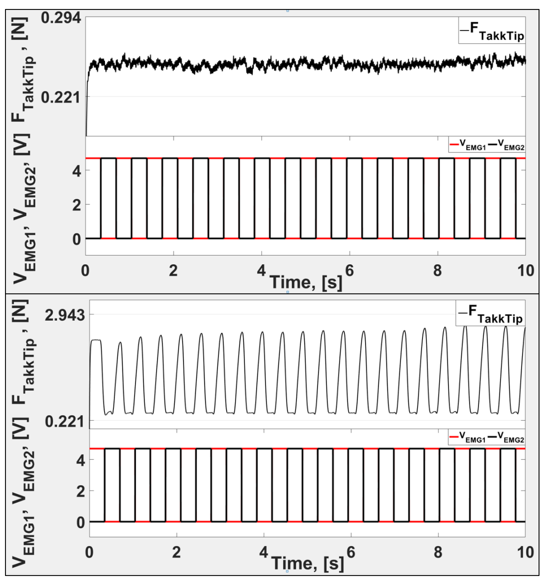

Figure 4.8: Results from opening and closing the i-Limb to the limits of its range for both no glove (top) and glove (bottom)

4.2.2 Mode 2 - Tapping

Similar to the results from opening and closing the hand, there is an inherent bias when putting the glove on. In the case of intermittent tapping the force was discernable from test to test (Fig.4.9). This justifies this sensor as able to detect an applied force through a glove for this mode. Note that the angle of contact between the TakkTip and the load cell remained consistent from test to test. This was important to obtain consistent results for determining the effect of the glove for this portion of the research.

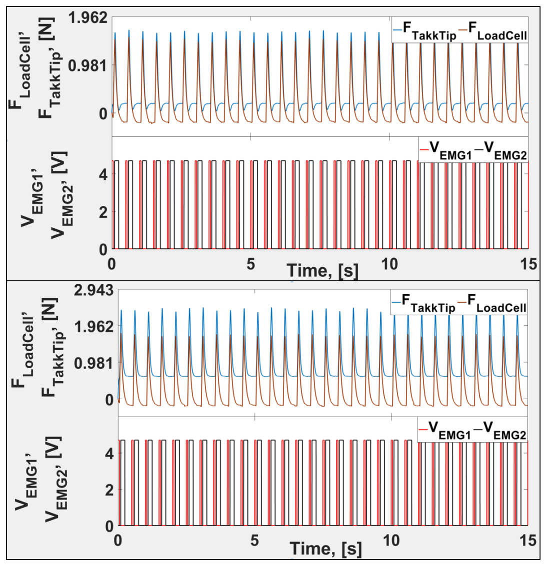

Figure 4.9: Results from intermittent tapping onto the load cell. This was done for both wearing a no glove (top) and glove (bottom)

4.2.3 Mode 3 - Constant Force

The results for this mode have similar notes to mode 2. As illustrated in (Fig.4.10), all trials produced the same results and were consistent from test to test.

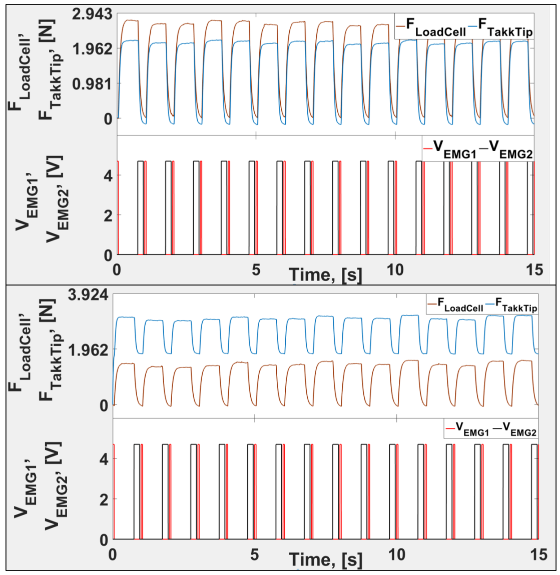

Figure 4.10: Results from intermittent constant force onto the load cell. This was done for both wearing a no glove (top) and glove (bottom)

This study found noticeable differences in tactile force sensor readings between the cases of a prosthetic hand wearing a glove and without the glove, however the force measurements from both cases were still recognizable and can be used to determine the force applied to an object. Note that an inherent bias was observed in the system when the glove was worn. Moreover, the sensing ability to the i-Limb was not substantially altered as the robotic hand performed the tasks for different modes with consistency throughout the experiment for the tested modes. The newly fabricated TakkTip sensor proved to detect contact with an object when compared to no object for the two studied modes, however, the sensor did not perform consistently if it was used at different contact angles. A future study can determine the characteristics of varied contact angles on the force sensing capabilities. Additionally, to address the inherent bias observed in all cases of force sensing through the glove, this can be compensated for by applying a zero-out calibration at the beginning of each test. Ultimately, these results suggest that the tested tactile sensor has potential to sense grasping forces in automated glovebox situations. The anthropomorphic solution afforded by a prosthetic hand offers direct application of electromyogram control methods [62, 63].

4.3 CONTRIBUTIONS

This work was performed with the collaboration of Craig Ades, Mostapha AlSaidi, Dr. Mehrdad Nojoumian, Dr. Ou Bai, Dr. Aparna Aravelli, Dr. Leonel Lagos and Dr. Erik D. Engeberg. The author, Craig, and Mostapha developed the experiment and the different modes of operation evaluated during the experiment. The Analyzing portion of the study was performed by Craig and the author while the plots were generated by Craig Ades using MATLAB. The 3D printed design of the TakkTip was performed by Craig Ades and the construction of the TakkTip Finger was done by the author. The writing portion for this study was performed by Craig Ades, Mostapha AlSaidi and the author with the guidance of Dr. Nojoumian and Dr. Engeberg.

CHAPTER 5
A COLLABORATIVE APPROACH FOR REAL-TIME MEASUREMENTS OF HUMAN TRUST, SATISFACTION AND FRUSTRATION IN HUMAN-ROBOT TEAMING

A new approach to the evaluation of Human Robot Interaction is presented. The research is based of two different experiments performed in the past to tie both ends and analyze an active interaction between a Human subject and an autonomous system. The main focus of the experiment was to evaluate the levels of trust, satisfaction and frustration in an environment in which the human subject would control the actuation of a robotic hand (iLimb) with the use of EMG signals gathered from their forearms. Also, we provided feedback to the participants when the object was grasped or release by utilizing a soft actuator armband designed in a previous experiment [59].

5.1 EXPERIMENTAL EQUIPMENT

5.1.1 Electromyography (EMG)

Electromyography (EMG) refers to the electrical activity of muscle tissue. These signals are normally gather with the use of electrodes placed on the skin of the patient. In this study, human subjects utilized two EMG sensors to control the iLimb robotic hand. This electrodes were carefully placed on the forearm of each individual. (Fig.5.1) represents the two sensors that were placed on the subject's forearm.

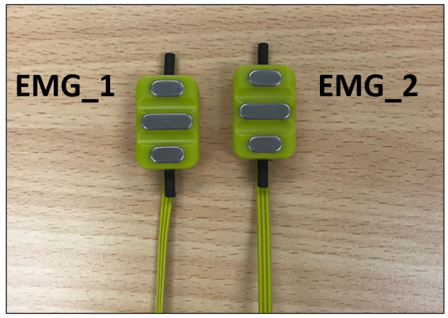

Figure 5.1: EMG Sensors: 1 and 2

5.1.2 Soft Actuators

For this study, a model performed by Moaed A. Abd of a soft actuator armband was utilized to gathered the necessary haptic feedback from the TakkTip pressure sensors allocated in the iLimb. This armband was developed using a soft rubber material called Dragon Skin 50. (Fig.5.2) illustrates the armband itself as well as how we positioned on the subjects arm. One of the goals for this experiment is to evaluate how helpful the human subject find the armband during the delivery of an object from point A to B.

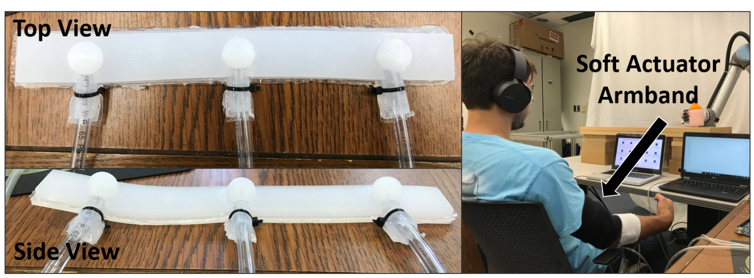

Figure 5.2: Soft Actuator Armband Top View, Side View, and positioning

5.2 METHODOLOGY

A collaborative active Human-Robot interaction task was designed where a UR10 robotic arm in junction with an iLimb Ultra (Fig. 5.3) delivered an object from point A to point B (Fig.5.4). The open/close motion of the iLimb hand was actuated by the Human with the use of Electromyography (EMG) sensors. A total of 10 human subjects participated in this study after giving informed consent under the approved IRB protocol. All the participants were between 20 and 40 years old and with a 50% male and 50% female distribution.

Figure 5.3: Robotic Hand: iLimb by Touch Bionics

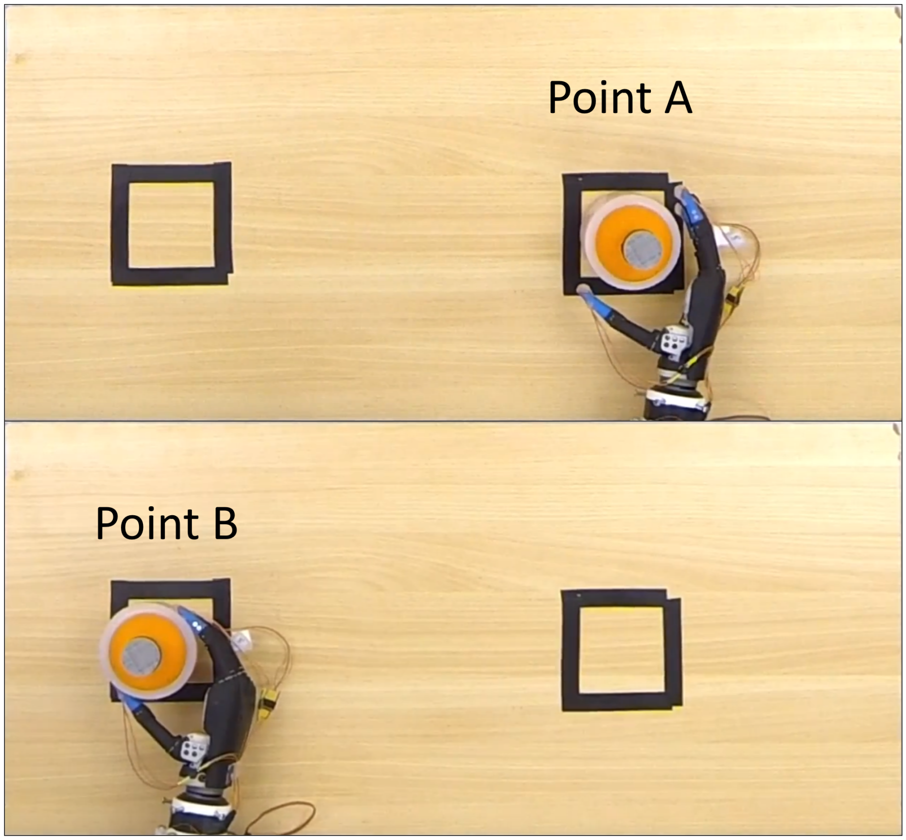

Figure 5.4: Experiment Delivery Sequence: iLimb delivering object from point A to point B

Since there is a learning curve, specifically to subjects with no prior knowledge of these types of systems, all subjects performed a training set of 5 deliveries prior the actual experiment under a normal scenario in order to get them accustomed to the feel of task. Once training was done, each participant performed 10 object deliveries. After each delivery, the self-reported levels of trust, satisfaction, frustration and the soft actuator on a scale from 1 to 5 were recorded from the human subjects who verbally rated their assessments for analysis. The subjects were not told what operational mode the robotic system would exhibit ahead of time in order to get the most honest and genuine feedback. The set of question was as follows:

- What is your Trust level with the robot?

- What is your satisfaction level with the robot?
- What is your Frustration level with the robot?
- How helpful was the soft actuator armband when delivering the object?

The human subjects rated each question from 1 to 5, 1 being the lowest level and 5 being the highest level. Moreover, when all data was successfully collected, each metric was analyzed using two main tools, The Mean and Standard deviation and the nonparametric Mann-Whitney U-test (Wilcoxon Rank Sum Test). The mean and standard deviation allow the evaluation of the overall impact of the different cases between the subjects and helped determine significant differences between groups. was used to statistically analyze the subjective data related to trust, satisfaction, frustration and the soft actuator feedback. The Mann-Whitney U-test is a nonparametric test for two populations of independent data to test for equality of population medians of two independent samples. With the U-test, a pairwise statistical analysis was performed to determine if there was any robot operational mode that significantly impacted the subjects' trust, satisfaction, frustration, or the soft actuator feedback.

The experiment architecture illustrated in (Fig.5.5) represents the communication between all the components of the experiment including the human subject.

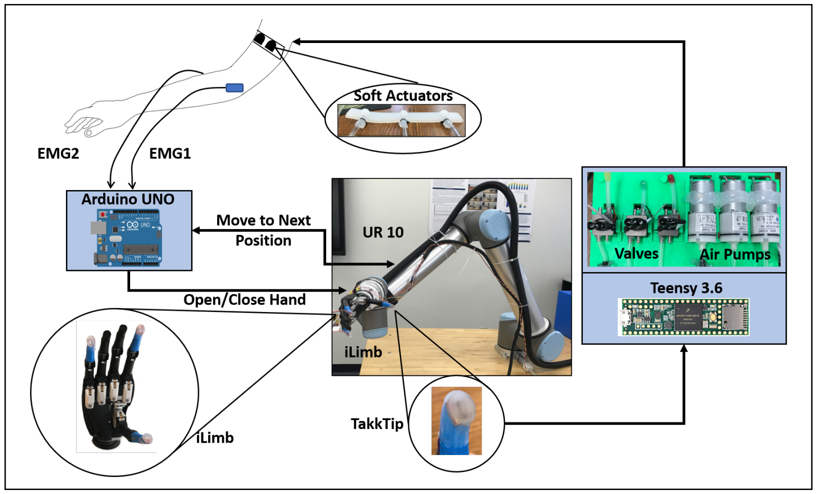

Figure 5.5: Experiment Architecture

After each delivery, the operational mode of the robotic system was altered among three pre-program modes. A description of these different operational modes for the system are:

1. Normal: The robot behaves as intended, delivering the object from point A to B without any problems as long as the subject successfully grasps the object

2. Abnormal: The EMG signals are swapped. Opening acts as Closing but if the object is properly grasped, the soft actuator gives the expected feedback to the user.

3. Extremely Abnormal: The EMG signals are swapped. Opening acts as Closing. Also, no feedback from the soft actuators.

The following photo sequences represent the scenarios utilized for these experiment. (Fig.5.6) represents the Normal Scenario. In (a), the subject is relax and ready to grab the object. (b) represents the human subject flexing the forearm to send the signal through the EMG sensors and close the hand. In (c), the robotic arm is delivering the object to position B and in (d) the human subject extends in order

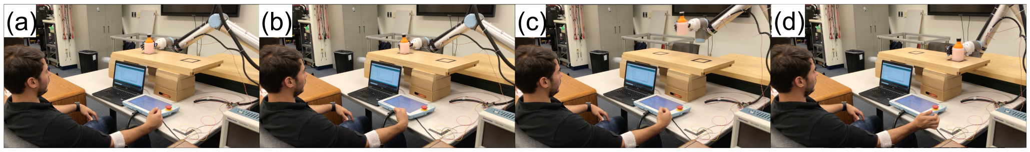

Figure 5.6: Normal Scenario Photo Sequence

to release the object and finalize the delivery. (Fig.5.7) represents the Abnormal and Extreme Abnormal scenarios. It is worth noting that in the abnormal scenario the soft actuator system was working but in the extreme abnormal scenario, the soft actuators were disabled. In (a) the subject flexes in order to grab the object but the arm does not move. In (b) the subject is told to release the object to continue the experiment. (c) and (d) represent the end of that trial where the object could not be delivered to position B.

The sequence of deliveries was carefully selected to clearly demonstrate the impact of the different modes in the three metrics evaluated as well as the feedback on how helpful the soft actuator served during the experiment. (Table 5.1) illustrated the sequence of deliveries performed by each subject.

5.3 RESULTS

The following section represents the analyzed results of all subjects. First, we asked the human subjects to give the level of trust, satisfaction and frustration towards an autonomous system such as a robotic assistant. This allowed us to create a base

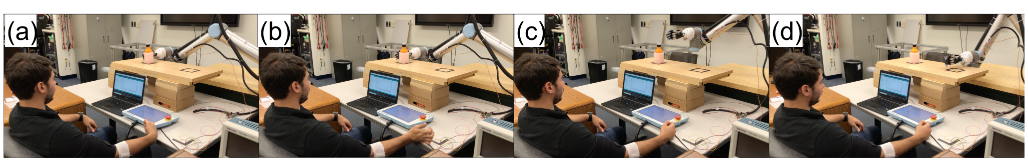

Figure 5.7: Abnormal and Extreme Abnormal Scenarios Photo Sequence

Table 5.1: Experiment Sequences

Trial Number	Mode
1	Normal (N)
2	Abnormal (A)
3	Abnormal (A)
4	Extreme Abnormal (EA)
5	Normal (N)
6	Normal (N)
7	Normal (N)
8	Abnormal (A)
9	Extreme Abnormal (EA)
10	Normal (N)

line for the experiment by knowing were the overall levels are prior conducting any interaction with the system (Fig.5.8). Second, a comparison between the same metric in order to understand the correlation between trials. The third part of the results represents a comparison between metrics in order to understand the correlation between metrics. The last part of the results illustrated the analysis of the feedback from the soft actuator armband.

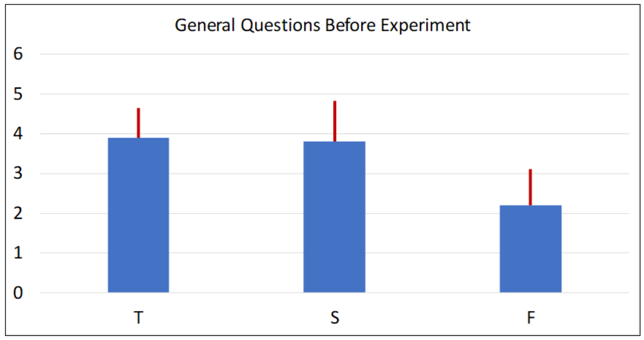

Figure 5.8: General Baseline Questions: Trust, Satisfaction and Frustration Level. Mean and Standard deviation (Trusts is represented as T, Satisfaction is represented as S and Frustration is represented as F

5.3.1 Trust-Trust Level Comparison

The mean and standard deviation of trust for all subjects is illustrated in (Fig.5.9(a)) and the Wilcoxon Rank Sum Test for the statistical analysis is illustrated in (Fig.5.9(b)). Throughout the experiment, a trend line was generated in which trust was depleted for the abnormal and extreme abnormal cases but was successfully rebuilt to its original value for the next three normal cases. This was also observed in the next cases in which the robot behaved abnormal and extreme abnormal followed by the last case of a normal behavior. For the statistical analysis, comparison between cases 5, 6, and 7 (normal) with case 4 (extreme abnormal), shows a significant different as expected. All other cases did not show a significant variation in the pairwise comparison.

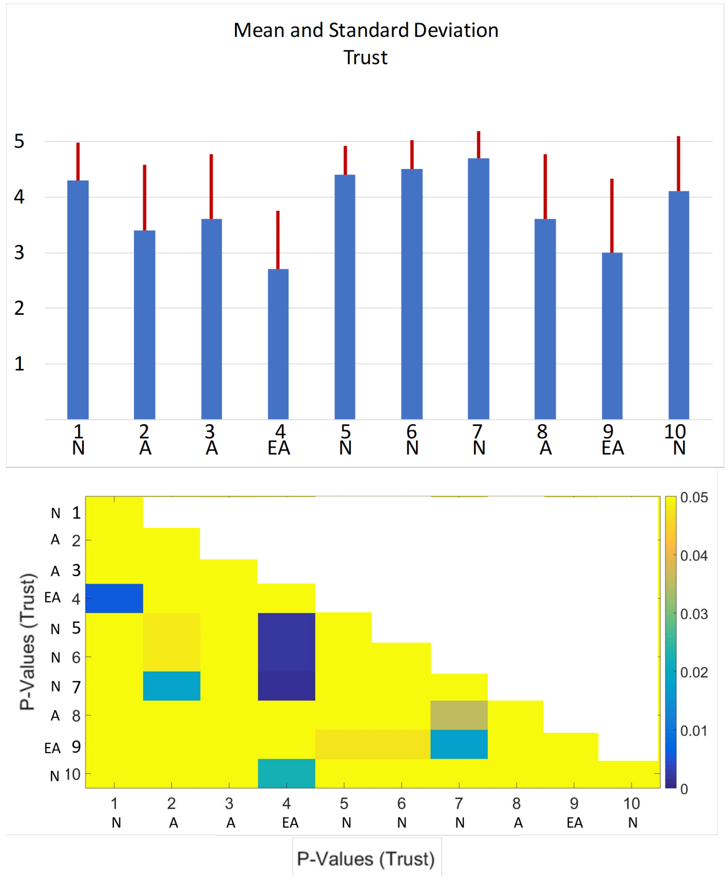

Figure 5.9: Trust Level (a) Mean and Standard deviation (Normal is represented by N, Abnormal is represented as AB, and Extreme Abnormal is represented by EA). (b) Wilcoxon Rank Sum Test.

5.3.2 Satisfaction-Satisfaction Level Comparison

The mean and standard deviation of trust for all subjects is illustrated in (Fig.5.10(a)) and the Wilcoxon Rank Sum Test for the statistical analysis is illustrated in (Fig.5.10(b)). Throughout the experiment, a trend line was generated in which satisfaction was depleted for the abnormal and extreme abnormal cases but was regained close to its original value for the next three normal cases. This was also observed in the next cases in which the robot behaved abnormal and extreme abnormal followed by the last case of a normal behavior. For the statistical analysis, comparison between normal cases and extreme normal cases showed the significant differences within the figure.

All other cases did not show a significant variation in the pairwise comparison.

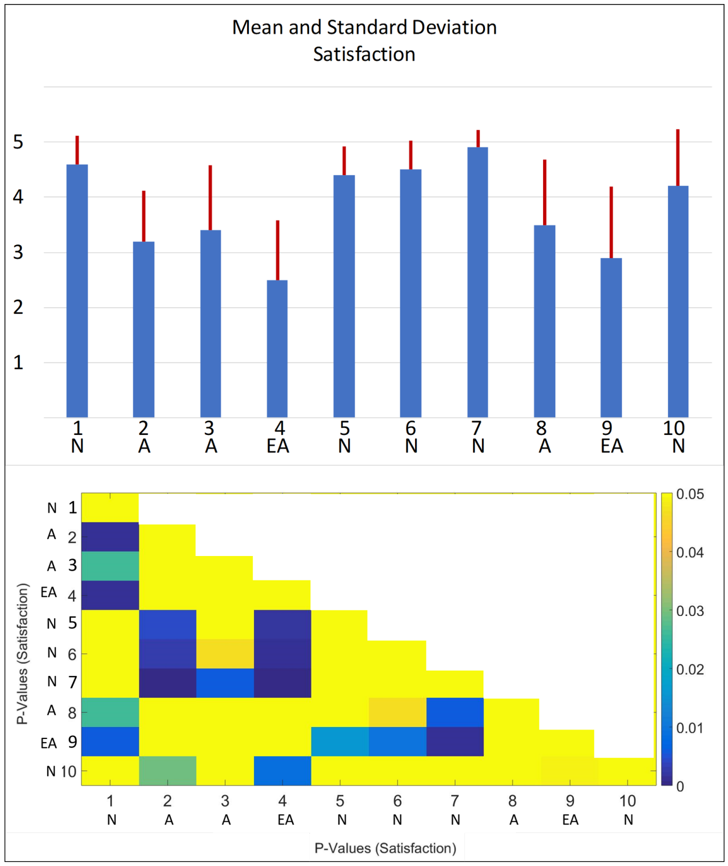

Figure 5.10: Satisfaction Level (a) Mean and Standard deviation (Normal is represented by N, Abnormal is represented as AB, and Extreme Abnormal is represented by EA). (b) Wilcoxon Rank Sum Test.

5.3.3 Frustration-Frustration Level Comparison

The mean and standard deviation of trust for all subjects is represented in (Fig.5.11(a)) and the Wilcoxon Rank Sum Test for the statistical analysis is illustrated in (Fig.5.11(b)). Throughout the experiment, an inverse trend line was generated in which frustration was increased for the abnormal and extreme abnormal cases but lowered close to its original value for the next three normal cases. Towards the end, even though the experiment was not longer than 20 min, subject showed an increase in frustration. This could be due to the abnormal and extreme abnormal cases. For the statistical analysis, comparison between normal cases and extreme normal cases showed the significant differences within the figure. A good example of the steadiness of frustration level is case 10. When compared to all other cases, is noticeable how the extreme abnormal case is the only significant variation. This proposes that frustration levels were maintained throughout the experiment. All other cases did not show a significant variation in the pairwise comparison.

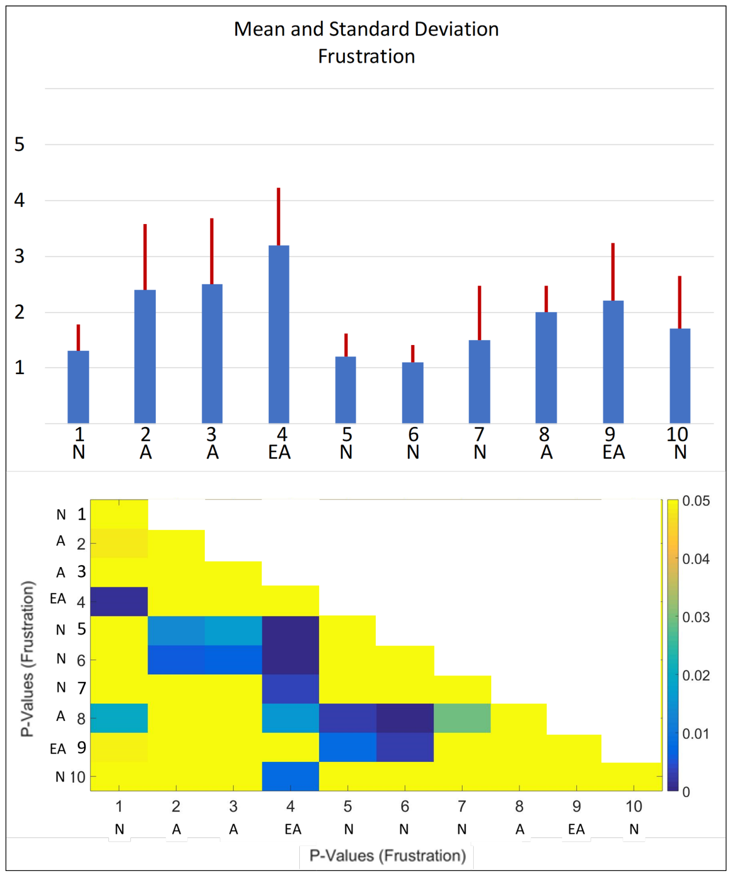

Figure 5.11: Frustration Level (a) Mean and Standard deviation (Normal is represented by N, Abnormal is represented as AB, and Extreme Abnormal is represented by EA). (b) Wilcoxon Rank Sum Test.

5.3.4 Trust-Satisfaction Level Comparison

Next, a comparison between Trust and Satisfaction is made (Fig.5.12). This analysis showed how these two metrics in some cases can be very related in terms of the levels of Trust and satisfaction. Also, there are some cases in which they deviate from each other, showing a significant difference in the graphs. Case 4 compared to cases 5, 6 and 7 show the most meaningful differences due to the negative impact from the extreme abnormal scenario on the experiment since it correspond to the robotic assistant not performing as intended.

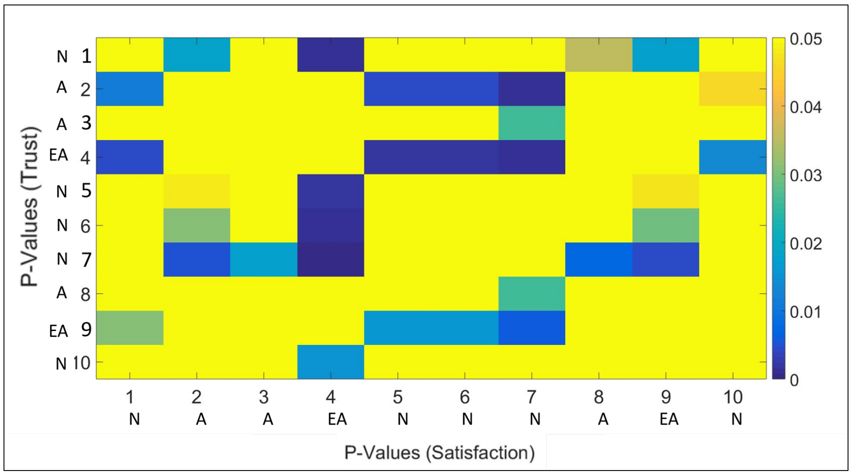

Figure 5.12: Trust VS Satisfaction Wilcoxon Rank Sum Test.

5.3.5 Trust-Frustration Level Comparison

The statistical analysis for trust vs frustration is shown in (Fig.5.13). This analysis showed how these two metrics can be related in terms of the levels of Trust and frustration. Also, there are some cases in which they deviate from each other, showing a significant difference in the graphs. For instance, when comparing case 6 (trust) with case 6 (frustration), the rank sum outputs a 0.03 p value stating that the metrics in this scenario are somewhat different. This is interesting since the subjects overall felt they could trust the system but were somewhat frustrated due to the past history cases.

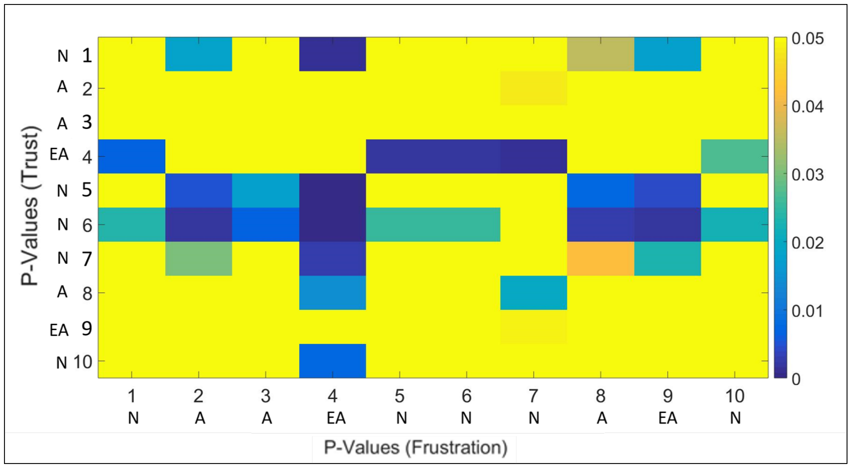

Figure 5.13: Trust VS Frustration Wilcoxon Rank Sum Test.

5.3.6 Satisfaction-Frustration Level Comparison

As analyzing the differences and similarities in the satisfaction and frustration Data (Fig.5.14), it came as no surprise how the abnormal and extreme abnormal cases is where most of the differences can be noticed. But it is interesting how case 5 from frustration compared to case 6 from satisfaction (both normal scenarios) showed a small difference (approximate 0.03 p) which illustrates that humans increased their satisfaction levels faster than how they dropped their frustration levels.

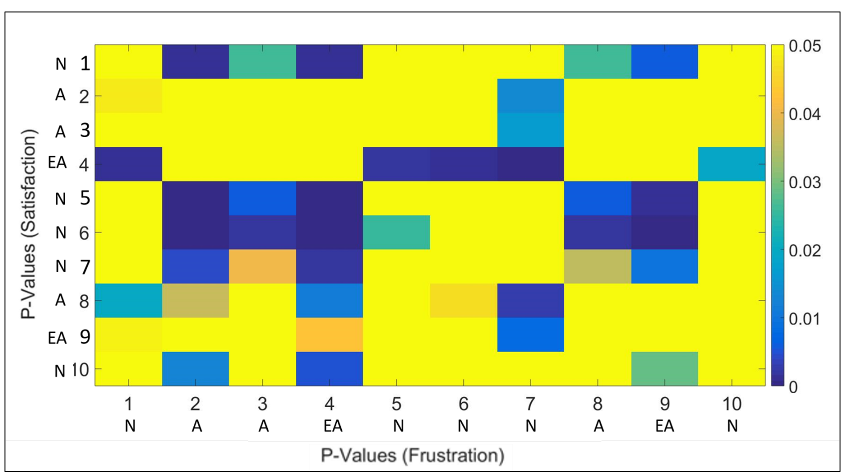

Figure 5.14: Satisfaction VS Frustration Wilcoxon Rank Sum Test.

5.3.7 Soft Actuator Results

This next subsection illustrates the overall response from humans towards the soft actuator (Fig.5.15). It appears that subjects found it very helpful specially during normal cases. But is interesting how in abnormal cases, they also found it helpful. This is due to the fact that the hand was able to grab the object but the arm would not move. Therefore they mentioned that they found the soft actuator feedback helpful since it let them know that the object was grasped but were also confused since the arm did not move.

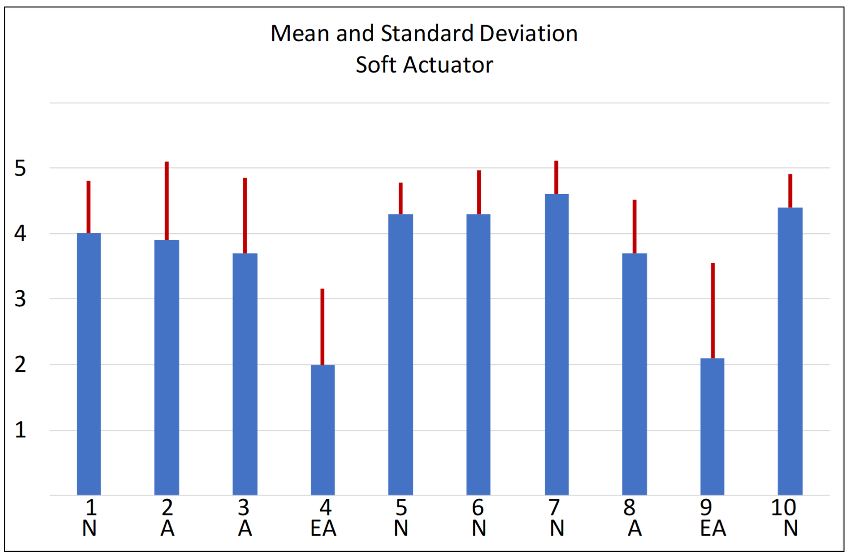

Figure 5.15: Mean and Standard Deviation: Soft Actuators

5.4 DEMOGRAPHICS RESULTS

In this section, the author wanted to create a comparison between males and females. Since we had a 50% males and 50% females population, this allowed us to evaluate how they performed in each scenario concerning trust, satisfaction, and frustration.

5.4.1 Trust between Females and Males

(Fig.5.16) demonstrated the difference in responses from the two groups with a mean and standard deviation plot. Females in general, trusted more the autonomous system even in scenarios such as abnormal and extreme abnormal. Extreme abnormal cases still showed a depletion in trust but not as pronounced as male responses.

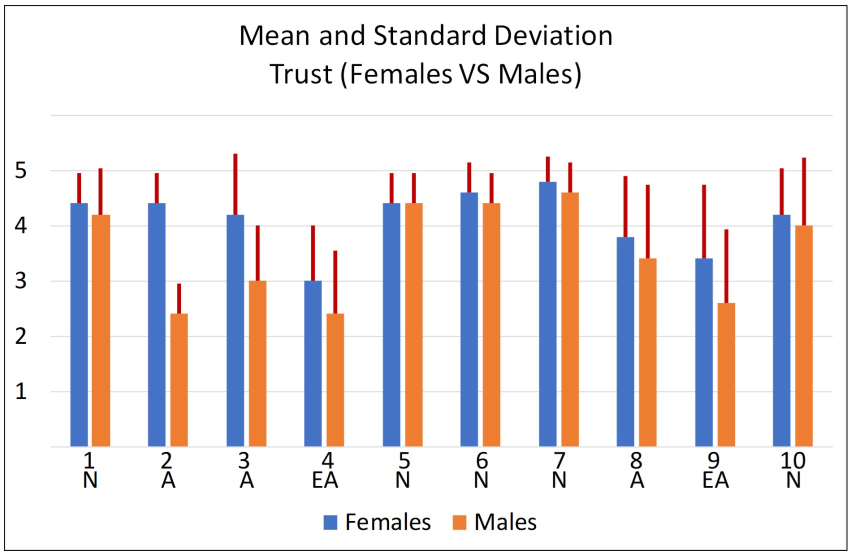

Figure 5.16: Mean and Standard Deviation: Females VS Males Trust level

5.4.2 Satisfaction between Females and Males

Again, a similar trend from both groups is shown in (Fig.5.17). Women generally show more satisfaction towards the robot except in extreme abnormal cases. Males, on the other hand, dropped their satisfaction levels significantly faster than females but showed great recovery in normal scenarios.

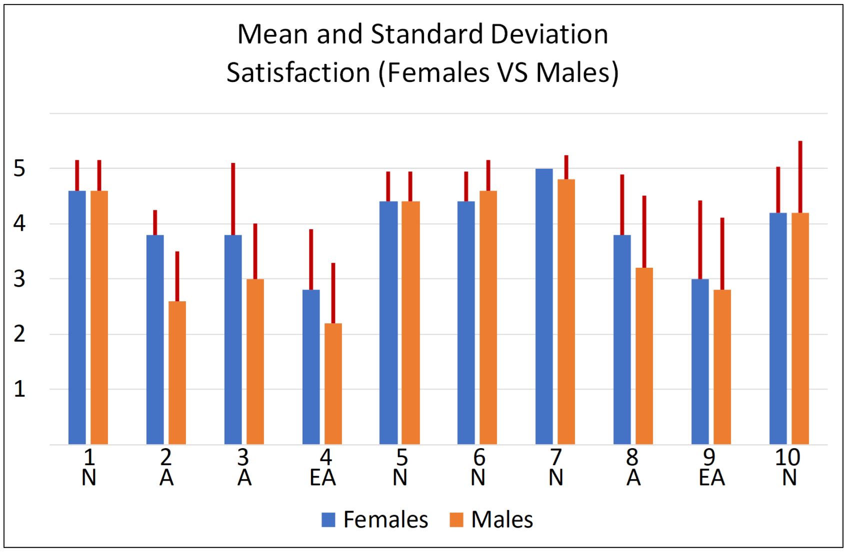

Figure 5.17: Mean and Standard Deviation: Females VS Males Satisfaction level

5.4.3 Frustration between Females and Males

Lastly, frustration level comparison utilizing the mean and standard deviation plot (Fig.5.18). Again, women demonstrated lower levels of frustration throughout the experiment except in extreme abnormal cases. On the other hand, men frustration levels spiked during the first two abnormal cases and the extreme cases. Males also showed greater signals of frustration during the last four cases of the experiment.

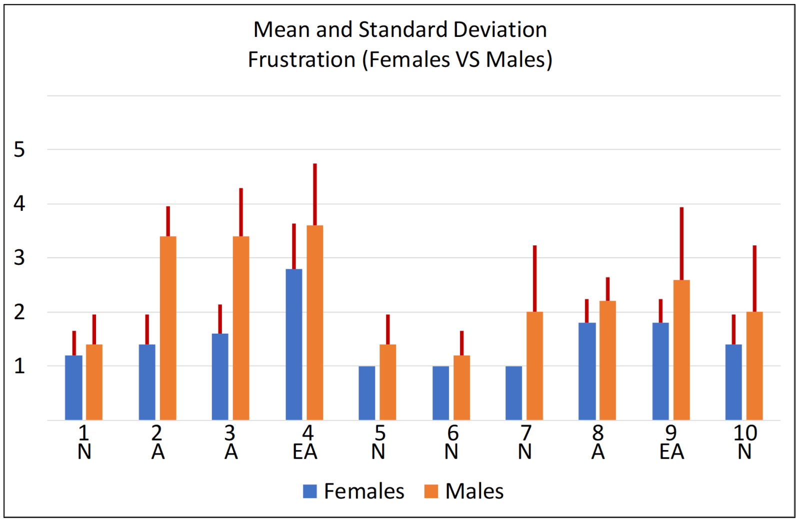

Figure 5.18: Mean and Standard Deviation: Females VS Males Frustration level

5.5 SOFT ACTUATORS RESULTS

The following section illustrates the results of the soft actuator system (EMG, Sensors, Pressure, Pump and valves). This results are separated in two main categories. The first category corresponds to Normal and Abnormal since both scenarios offered haptic feedback after grabbing or releasing the object. The second category corresponds to the Extreme Abnormal scenario.

5.5.1 Normal and Abnormal

The next three figures illustrates the action and cause of the Normal case which represents the same response as the Abnormal scenarios (for the soft actuators). Each figure is represented by the three fingers utilized for the data collection of the soft actuators. (Fig.5.19) illustrated the response of the Index finger, (Fig.5.20) corresponds to the response of the Little finger and finally, (Fig.5.21), shows the response from the Thumb. All signals show consistent results in terms of activation, stability and deactivation. The EMG signals as illustrated in the top portion of the figures activates the hand for the closing and opening position. As soon as the object is properly grasped by the robotic hand, the sensors gather a consistent grip of approximately 35KPa except for the Index figure which deviates a small portion due to the grasps position and the movement of the object. When the the soft actuator systems senses the pressure changed within the system, it open or closes the valve in order to match the current pressure as illustrated in the bottom portion of the figures. There exist some delay for the soft actuator armband to deflate as expected.

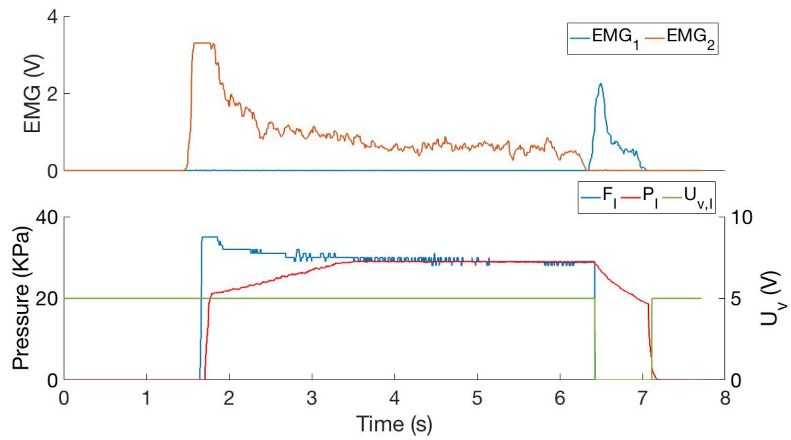

Figure 5.19: Normal Scenario Response from Index

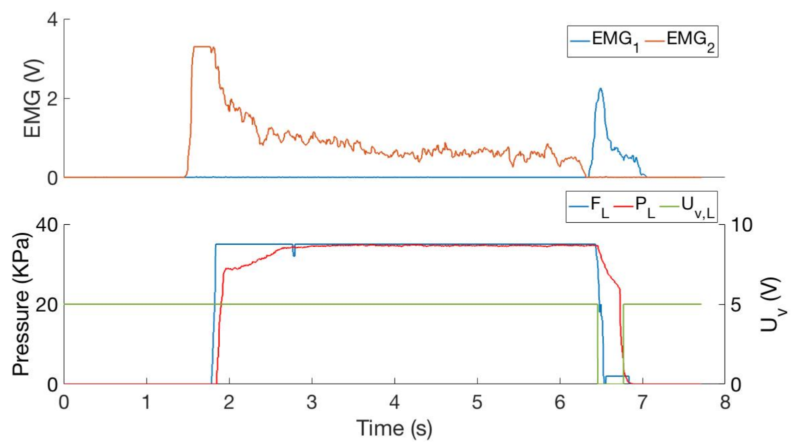

Figure 5.20: Normal Scenario Response from Little

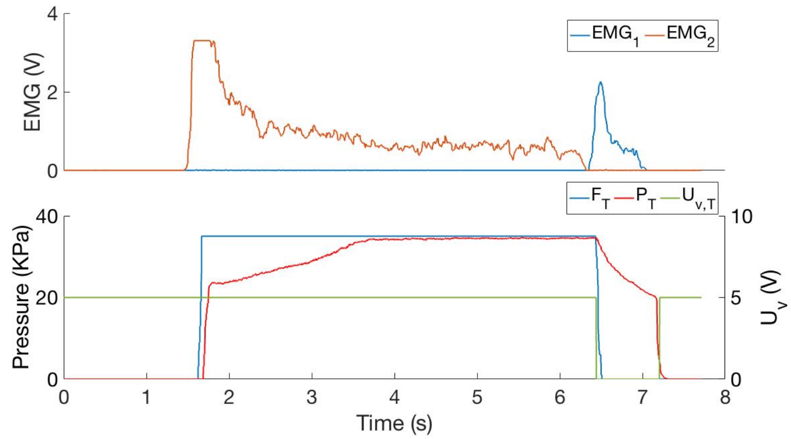

Figure 5.21: Normal Scenario Response from Thumb

5.5.2 Extreme Abnormal Results

The next three figures illustrates the action and cause of the Extreme Abnormal case. Each figure is represented by the three fingers utilized for the data collection of the soft actuators. (Fig.5.22) illustrated the response of the Index finger, (Fig.5.23) corresponds to the response of the Little finger and finally, (Fig.5.24), shows the response from the Thumb. Since the scenario is meant for the human subject to loose the haptic feedback, the figures represent the activation of the robotic hand without any movement in the soft actuators. These were disable for the duration of the extreme abnormal scenario to understand the impact over the main three metrics evaluated in this thesis. The pressure sensors on the other hand still activate when the EMG signals is triggered but without response from the pumps.

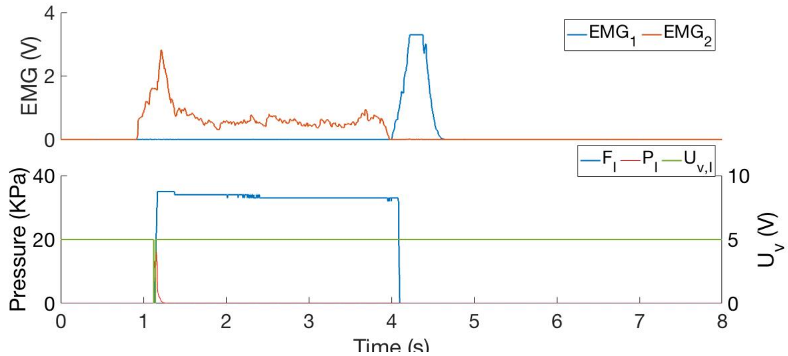

Figure 5.22: Extreme Abnormal Scenario Response from Index

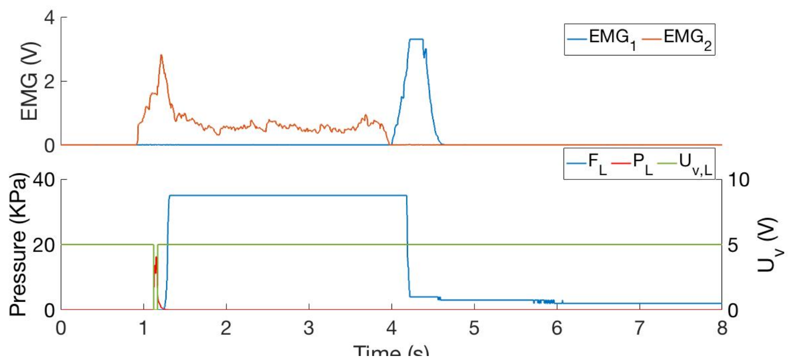

Figure 5.23: Extreme Abnormal Scenario Response from Little

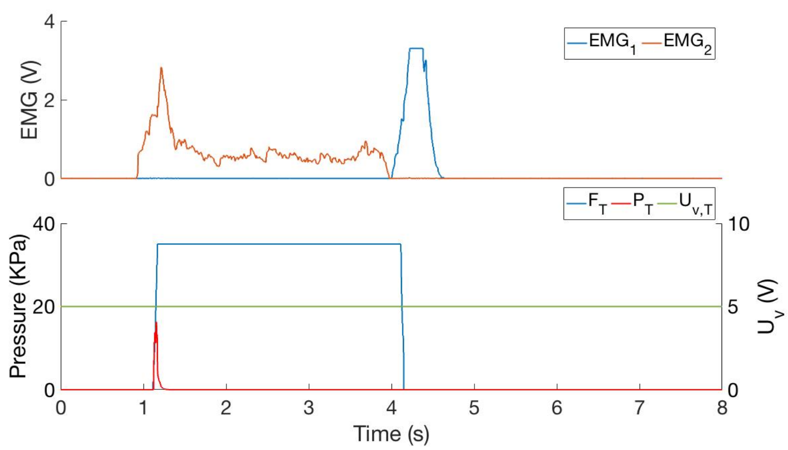

Figure 5.24: Extreme Abnormal Scenario Response from Thumb

5.6 CONTRIBUTIONS

This work was performed with the collaboration of Craig Ades, Mostapha AlSaidi, Moaed A. Abd, Dr. Mehrdad Nojoumian and Dr. Erik D. Engeberg. The author designed the experiment and the different modes of operation evaluated during the experiment. The plotting and analyzing portion of the study was performed by the author. The soft actuator system was designed by Moaed A. Abd and the arduino code for controlling the iLimb and UR 10 was performed by the author, Craig Ades and Mostapha AlSaidi. The writing portion for this study was performed by author with the guidance of Dr. Nojoumian and Dr. Engeberg.

CHAPTER 6

CONCLUDING REMARKS AND FUTURE DIRECTIONS

In this thesis a new approach was introduced for measuring trust, satisfaction and frustration levels in an active Human-Robot interaction team with the aid contact feedback from pressure sensors called TakkTips allocated on the robotic hand (iLimb). The new structured data collection method utilizing self reported feedback helped the analysis of variation in trust satisfaction and frustration during the experiment. To test this approach, an empirical experiment was designed and conducted on 10 human subjects (5 males and 5 females) all from ages between 20 and 40 years. The analysis of the experimental results indicated that humans are normally predisposed to have a negative level of trustworthiness towards autonomous system prior any interaction. This level can be improve by allowing humans to interact with these system and get familiarized with them. Also, we discovered that the results from this experiment indicate that an abnormal or extreme abnormal behavior decreases the levels of trust and satisfaction and increases the level of frustration in male subjects more than females. Furthermore, this levels can be brought to a more stable and suitable state with a series of normal scenarios performed by the robots. Since the experiment consisted in an active human robot interaction team, human subjects commented that they saw the autonomous system as a partner rather than just a robotic arm. This helped significantly in the rebuilding of broken trust, low satisfaction and high frustration.

The results of our experiment matched our initial expectations and therefore we can consider this data collection approach an adequate and reliable technique to measure subjects' levels of trust, satisfaction and frustration and also analyze their psychological responses when presented to different scenarios such as normal, abnormal and extreme abnormal. We believe that the presented approach in this thesis is novel, and can potentially be consider as a baseline for evaluating said metrics. Everyday the field of robotics and autonomous system keep growing and all this questions, concerns and issues need to be addressed.

Within the scope of HRI teams, we are highly interested in further research that involves more participants and perhaps different scenarios that would help refine our current approach. The use of non-invasive EEG signals to observe and analyze the brain response when presented with different scenarios could help gather more information that could potentially be affecting the fluctuation in the evaluated metrics.

APPENDICES

APPENDIX A

DEMOGRAPHIC QUESTIONS

Please do not provide any personal information on this form (such as your first and last names, date of birth, student or social security numbers) so that we can keep your identity anonymous.

(1) What is your gender?

❑ Male ❑ Female

(2) What is your age?

❑ 18-24 ❑ 25-30 ❑ 31-40 ❑ 41-50 ❑ 51-60 ❑ older than 60

(3) What is your ethnicity origin/race?

❑ White ❑ Hispanic/Latino ❑ Black/African American
❑ Asian ❑ Native (American) Indian ❑ Other

(4) What is your education?

❑ None ❑ High School/College Deg. ❑ Bachelor's Degree
❑ Master's Degree ❑ Doctorate Degree ❑ Postdoctoral/Professional (MD)

(5) What is your marital status?

❑ Single, Never Married ❑ Married or Domestic Partnership
❑ Widowed ❑ Divorced ❑ Separated

(6) What is your employment status?

❑ Unemployed ❑ Employed ❑ Self-Employed
❑ Student ❑ Household ❑ Unable to Work ❑ Retired

(7) In general, how do you categorize yourself?

❑ Unhappy/Depressed ❑ Happy/Pleased ❑ Anxious/Nervous

(8) How do you categorize yourself in terms of trusting people that you already know?

❑ Fully Trusting ❑ Trusting with Caution ❑ Not Trusting ❑ Neutral

(9) How do you categorize yourself in terms of trusting new people/strangers?

❑ Fully Trusting ❑ Trusting with Caution ❑ Not Trusting ❑ Neutral

(10) How influential are you? (i.e., being able to change attitude/mood or decisions of others)

❑ Not Influential ❑ Influential ❑ Very Influential

(11) Is it easy for family members/friends/people to change your attitude/mood/decisions?

❑ Never ❑ Some Times ❑ Always

(12) If you lose your trust in someone, how hard is it for that person to rebuild your trust?

❑ Very Hard ❑ Hard ❑ Average

(13) Everyone has bad experiences in trusting people. How long ago did you have such a bad experience? And for how many times in your life?

❑ Recently ❑ During Last Year ❑ Long Time Ago

❑ A Few Times ❑ Many Times ❑ Numerous Times

APPENDIX B

PUBLICATIONS

The results of this research appear in the following publications:

[1] M. A. Abd, I. Gonzalez, M. Nojoumian, and E. D. Engeberg, "Trust , Satisfaction and Frustration Measurements During Human-Robot Interaction," in 30th Florida Conference on Recent Advances in Robotics (FCRAR), no. May, pp. 89-93, (2017)

[2] Moaed A. Abd, Iker Gonzalez, Mehrdad Nojoumian and Erik D. Engeberg. Trust, Satisfaction and Frustration Measurements for Real-Time Human-Robot Interaction. Robotics: Science and Systems Workshop Morality and Social Trust in Autonomous Robots (2017).

[3] M. Abd, I. Gonzalez, M. Nojoumian and E. D. Engeberg. (2018) Performance of a Robotic Assistant Decouples Human Perception of Trust, Satisfaction, and Frustration. (Unpublished).

[4] C. Ades, I. Gonzalez, M. AlSaidi, Dr. M. Nojoumian, Dr. O. Bai, Dr. A. Aravelli, Dr. L. Lagos and Dr. E. D. Engeberg. (2018) Robotic Finger Force Sensor Fabrication and Evaluation Through a Glove. Florida Conference on Recent Advances in Robotics FCRAR. (Best Paper Award).

[5] Moaed A. Abd, Iker J. Gonzalez, Thomas C. Colestock, Benjamin A. Kent, Dr. Erik D. Engeberg (2018). Direction of Slip Detection for Adaptive Grasp Force Control with a Dexterous Robotic Hand. International Conference on Advanced Intelligent Mechatronics (AIM 2018) .

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