Communication through Physical Interaction: Robot Assistants for the Elderly

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THESIS

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LIST OF ABBREVIATIONS

ADL	Activities of Daily Living
IMU	Inertial Measurement Unit
CBDT	Clustering Based Decision Tree
DTW	Dynamic Time Warping
RISq	Recognition by Indexing and Sequencing
UIC	University of Illinois at Chicago

SUMMARY

This research work is a part of a broader research project which has the aim to build an effective and user friendly communication interface for assistive robots that can help the elderly to have an independent life at home. Such communication interface should incorporate multiple modalities of communication, since collaborative task-oriented human-human communication is inherently multimodal. For this purpose, data was collected from twenty collaborative task-oriented human-human communication sessions between a helper and an elderly person in a realistic setting (fully functional studio apartment).

My research mainly focus on collecting physical interaction data in an unobtrusive way during human-human interaction and analyzing that data to determine how it can be implemented to communication interface for assistive robots particularly in elderly care domain. Thus a pressure sensors equipped data glove was developed. Based on the data collected from this glove, communication through physical interaction during collaborative manipulation of planar objects was studied. Subsequently, an algorithm was developed based on the laboratory data analysis which can classify four different stages of collaborative manipulation of planar object. This algorithm was later successfully validated on experiments performed in a realistic setting with subjects involved in performing activities of elderly care and determining human-human hand-over of planar object in real-time. Other than understanding the communication through physical interaction, this research also presents the methods for recognizing various physical manipulation actions that take place when an elderly is helped by a care-giver in cooking and setting of dinning table. This particular work was motivated by the natural language analysis of the data collected with helper and an elderly person which showed that the knowledge of such physical manipulation actions helps to improve communication through natural language. The physical interaction based classification methods are first developed through laboratory experiments and later successfully validated on the experiments performed in a realistic setting.

CHAPTER 1

INTRODUCTION

1.1 Motivation

Personal robot assistants hold great promise for addressing pressing societal needs. One of the areas where they could potentially have an enormous impact is to support the independent living of the elderly, especially since the world's population is aging at a growing rate (1; 2; 3). However, if a robot is to help an elderly person with activities of daily living (ADLs), it needs to physically interact with the person. ADLs are activities that are essential for a person to live independently, such as getting up from a bed or chair, getting dressed, preparing dinner. While physical interaction between robots and humans has been well studied (e.g. (4; 5; 6)), the focus has been on interpreting the interaction at the control level rather than explore its communicative aspect. If the robot is to assist with daily activities it needs to respond to other types of user input such as gestures and touch. This motivates us to work towards an adaptive multi-modal user interface for robotic assistants to the elderly.

Human beings inherently communicate through multiple modalities of communication using the various senses. A multi-modal communication interface has the following advantages as compared to unimodal communication interface.

1. Expanded usability and controllability: Integration of multiple modalities capability into a human-robot interface would potentially enrich the controllability of the interface. The

user can benefit from deploying alternative communication methods under different situations and environments. Moreover, the extended communication channels can boost the interaction speed and efficiency between robot and human in two directions: from human to robot, the human can choose more efficient communication methods and from robot to human, the robot can supply multi-modal feedback to indicate how much information is understood from the user.

2. Refined adaptability and flexibility: A multi-modal human-robot interface can choose any combination from a number of potential communication methods, and customize itself to a special communication method for individual users. In other words, it provides more choices for people with severe disabilities.

3. High accuracy and robustness: Properly fusing various complementary information into a multimodal human-robot interface could improve the overall performance of the interface. By sharing the information between the modalities in a multimodal interface there is no need for highly accurate interfaces for each individual modality.

1.2 Goal

The goal of this work is to advance research in the following areas:

- Enabling a robot with the ability to communicate with a human through physical interaction. By physical interaction we intend the communicative aspect of a bi-directional exchange of forces during a direct or indirect (through an object held by the robot and the user) contact. This requires exploring how humans communicate through physical interaction.

- Establishing how physical interaction collaborates with other communication modalities and helps humans to interpret (assign meaning) to these modalities.

These are very broad research areas with myriad possible research directions. It is hoped that the findings of this work will be advanced by other researches to fully develop these research areas in the coming years.

The advancement in the human-robot interaction field requires the knowledge of how humans interact with other humans so that an easy-to-use communication interface may be realized (7; 8; 9). This general trend requires collecting data of human-human interactions and determining specific human activities in that data. Manual annotations of such activities are very time consuming. Therefore, automatic annotations have paramount value in simplifying the analysis of human activities data and consequently speeding up the research in human robot interaction. Recognition of human activities and determination of features that differentiate between various activities is also important for implementation of the same functionality on a robot. For this purpose, this research work describes a set of human studies that were designed to establish a corpus of multimodal interactions between an elderly person and a helper, placing special emphasis on the physical interaction. First, a user study involving interactions of the elderly and a caregiver in a realistic setting was conducted. This user study showed that manipulation of planar objects frequently occurs during preparing meals with a helper and assisting with setting the table. Also the processing of the collected spoken dialogues showed that knowledge of physical manipulation actions significantly improves the understanding of spoken language (10; 11). To test whether pressure sensor data is useful for recognition of these actions of interest, experiments were conducted and human physical interaction data was collected in a laboratory setting. To sense the physical interaction, a sensory glove with pressure sensors was developed. Classification methods were then developed which show that physical manipulations can be recognized from the pressure sensor data. The developed classifications methods were subsequently tested on the validation study. The validation study was performed in a realistic setting and involved pairs of subjects playing the role of care-giver and elderly person.

Hence, the specific goals of this research can be listed as:

- Develop a hardware that can collect physical interaction data in an unobtrusive way.
- Classify different stages of planar object manipulation based on pressure sensors data. Use the developed algorithm to determine the stages of human-human handing over of a planar object in real time.
- Based on pressure sensors data, recognize the physical manipulation actions that help disambiguate communication through natural language.

1.3 Related Work

Language and vision are well-established modalities of human-robot interaction (12). Information obtained from vision can further be classified as pointing gestures, hand gestures, gaze, facial expression etc. These modes of communication are studied individually as well as in combination with each other. It has been shown that incorporating the information obtained from vision disambiguates spoken language. Thus there is reasonable amount of work done on integrating language with gestures (13) and language with gaze(14; 13). However the role of physical interaction as one of the modalities of interpersonal communication has not received much attention. For example in (15) force signals are transmitted to the blind student through a glove to help her understand the gesture of a teacher. Though this work uses force signals to convey information, this work is different than our work as we are trying to interpret the communication through physical interaction rather than using it to communicate the information generated by the other modalities. More recently the relationship between grip force and load force has been studied during human-human hand-over in a very controlled experiment (16); this work stresses the importance of studying physical interaction during hand-over.

The importance of tactile information cannot be denied. For example, users find touch screen interface and touch pen interface more convenient to use than buttons. Recently humanoid robots are being equipped with tactile sensors in addition to microphone, speakers and cameras for example NAO and HERMES (17). However these sensors are very limited at present (18).

Humans sense their environment through physical interaction along with language and vision. It plays a critical role to determine the surface properties and shape of grasped items (19), to maintain a stable grasp(20; 21) and, according to our hypothesis, for collaborative manipulation. Despite its importance, physical interaction has not been given as much attention in robotics as other sensory modalities have. This may be attributed to both the complicated nature of the sense of touch and the fact that developed tactile sensors are not yet as sophisticated as the human touch sensors. Recently there are efforts made to improve the human-robot collaborative manipulation (22; 23). Particularly (23) uses an estimate of human applied wrench to change the cooperating role of robot for moving the table in a plane.

Robots have revolutionized the manufacturing industry. Automating repetitive tasks by robots has drastically reduced production cost. Recently due to advancements in computing, robots have also found various applications in many natural environments outside industry like in museums, hospitals and homes. This class of intelligent robots is instructed and used by naive users who require a human-like user friendly communication interface. Over the last decade, considerable effort has been devoted to improve assistive robots for the elderly, due to the increase in the aging population and shortage of health-care personnel in the West. Assistive robots for the elderly can be divided into two main categories 1) rehabilitation robots 2) assistive social robots. Rehabilitation robots are those which are not perceived as communicative, for example a smart wheelchair (24). Assistive social robots are those robots which communicate with the user. These can further be categorized as companion type or service type(25). There are studies which discuss the psychological and social effects of pet type companion robots like Omron's NeCoRo, Sony's AIBO and Paro(26; 27; 28). These robots help reduce the loneliness of the elderly. These companion robots use a variety of sensors to make the communication realistic, but the touch sensors they use have very limited function as discussed in (29). Robots have also been successfully developed as fitness trainers (30) and walking aids (31). In all these instances, robots mostly communicate with the elderly user through vision and language. There are also robots which utilize haptic feedback to assist in walking (32), rehabilitation (33; 34; 35) and transmitting the gesture of teacher to a visually impaired student (15). These works differ from the work herein in that we are trying to interpret interpersonal communication through haptics, rather than using it to communicate the information generated by other modalities or for rehabilitation.

1.4 Contributions

This research work identifies and explores the role physical interaction plays to improve inter-personal communication in the domain of elderly care. However, the contributions may be utilized in other areas. The specific contributions of this work can be divided into the following areas:

1.4.1 Hardware Development

I developed a portable hardware to measure and record the pressure information from human hand while someone is performing ADL without affecting the way one performs those actions. This hardware development can be used as reference for making similar hardware for other sensors.

1.4.2 Communication Through Physical Interaction During Hand-Over

The activities which require communication through physical interaction in the domain of elderly care were identified through a user study involving dyads of elderly and care-giver in a realistic setting. Analysis of physical interaction data from one of such activities, namely manipulation of planar objects, was performed. This involved performing further laboratory experiments and developing a classification algorithm. The classification algorithm was subsequently validated on data obtained from the user study during elderly care as well as for classification in real-time. The results of this work showed that pressure signals contain the information that can be used for identifying the stage of collaborative manipulation.

1.4.2.1 Applications and Broader Impact

This research may be utilized in domains of human robot interaction other than elderly care. Some of the envisioned applications and future extensions of this particular research are:

- Since the experiments were performed in an uncontrolled setting the results are easier to be generalized on different hardware platforms using different sensors. Implementation of these results on robotic hardware will improve planar object hand-over between human and robot.
- As demonstrated, these research findings may identify different stages of human-human hand-over in real-time.
- This work may be extended to hand-over of planar and non-planar objects of various shapes and weight.

1.4.3 Improving Communication Through Natural Language

It has been shown by the collaborating researchers that the information about physical manipulation actions performed during elderly care improves natural language processing by helping resolve third person pronouns and deictic words (36; 11). Deictic words are words (such as *this, that, these, those, now, then*) that point to the time, place, or situation in which the speaker is speaking. In my work, I have determined how to identify physical manipulation actions based on pressure data through experiments. The results have been validated on the data obtained from elderly care experiments in a realistic setting.

1.4.3.1 Applications and Broader Impact

Some of the envisioned applications and future extensions of this particular research are:

- Automatic human activity recognition for advancement of research in multimodal task-oriented human-human communication scenarios. Such automatic recognition would save the time-consuming manual annotations and facilitate studies involving human subjects observation. Such human activity recognition through on-body tactile sensors may also be used in any other application that requires monitoring such physical manipulation activities.

- Integrate information from vision and natural language with that of physical manipulation actions classification to improve such classification.

- Learning from pressure sensors data how humans perform the studied physical manipulation actions and implementing that knowledge on robotic platforms for executing similar physical manipulation actions and for object recognition based on tactile information.

- Integrating this work with the above mentioned work on hand-over to determine when the human/robot is manipulating a planar object and then determining the stage of hand-over of that planar object, i.e. if the robot should leave the planar object or not based on whether the pressure sensors data is indicating that the object is grasped by the other person.

1.5 Outline

The first step towards our work was to select a hardware to collect the physical interaction data when a care-giver assists an elderly person with performing ADLs. I will describe the commercially available hardware, its limitations, developed hardware and other related hardware issues in Chapter 2. After the development of hardware the next step was to perform a human study which involves ADLs taking place between elderly and care-giver dyad in a realistic living setting to determine which tasks would be suitable for studying communication through physical interaction. This is described in Chapter 3. One of the tasks which requires communication through physical interaction, namely hand-over task, is studied in more detail. Chapter 4 describes the experiments that were performed to collect more data on hand-over task, various classification methods used to analyze that data and the results obtained by using different techniques. The experiments performed and the results obtained from the recognition of physical manipulation actions based on pressure data are explained in Chapter 5. Finally, conclusions and future work is proposed in Chapter 6.

CHAPTER 2

HARDWARE

The first step towards my research was to select a hardware to collect the physical interaction data when a care-giver assists an elderly person with the ADLs. For that, I first reviewed the commercially available hardware to find a suitable hardware for collecting data and performed some initial analysis on that data. It was found from the initial analysis that the collected data from the commercial hardware was not sufficient. So I developed a data glove at Robotics Laboratory.

2.1 Tactile Sensors

Over the past two decades considerable work was done towards improving the physical interaction sensors and it still continues. As a result a variety of sensor designs have been proposed based on different transducers and made of different materials (37; 38; 39). A complete detail of these sensors can be found in the review papers (40; 41). The commercially available physical interaction sensing devices range from very precise force and torque measuring sensors to crude pressure sensors. The size and weight of 6 DOF force and torque sensors, even for recent smaller and lighter products (42), make them unsuitable for wearable devices. A fingertip mounted six-axis force sensor is described in (43), but it is not commercially available and it appears to be relatively difficult to deploy for user studies. In addition to them being bulky, force-torque sensors are expensive so it is not feasible to use several of them to cover different areas of the human hand or arm. A widely used alternative are flexible pressure sensors (44). These give a rough estimate of the pressure at the point of contact rather than a precise measurement of force and torque. The big advantage of these sensors is that they are cheap and one can deploy many of them over a larger area to get the information about physical interaction (45). These properties make flexible pressure sensors well suited to conduct studies on how humans use physical interaction in collaborative tasks.

2.2 Data Glove

In order to develop an intuitive and easy to use human-robot interface, it is necessary to understand how humans communicate while performing different tasks. It is thus important to develop experiments and equipment that can be used to collect the relevant data during collaborative activities. The ideal hardware that can measure physical interaction data when a care-giver is helping an elderly should have the following characteristics:

1. It should be able to measure pressure wherever a direct or indirect (through an object) contact between the elderly and the care-giver may occur.
2. It should not interfere with the activity.
3. It should be cost effective.

The first requirement would translate into placing sensors all over the surface of the human arm. For example, in the user study described in (46), the care-giver uses her arm to help the elderly subject. Clearly, measuring all such interactions is difficult. For practical purposes I thus restricted ourselves to the hands, as that is where the majority of communication through physical interaction takes place. To further simplify the data acquisition process I only focused on the right hand. Dictated by the need for the device not to interfere with the observed activity, I decided to use a wearable data glove, which can be worn by the care-giver. The data glove should have force sensors on the surface of the hand and the necessary electronics should be lightweight, so that the mobility of the care-giver is not affected. Also, the sensors deployed on the glove should be flexible and thin so that the sensation of the subject and the movement of the hand are not significantly affected. While investigating the data gloves available on the market that can fulfill the first two requirements, the one that was probably best is (47), however at the cost of $10,000 it is hardly cost-effective. Furthermore, even with this glove the calibration of the sensors is fairly inaccurate (48). The other option (49) is also not suitable as the conducting strips attached to the sensors are too long and they might affect how the care-giver performs activities. I found X-ist data glove with the cost of $6000 to be a reasonable trade-off between the sensors and price. The details of this glove are explained in next section.

2.2.1 Purchased Data Glove

The X-IST Data Glove used in the experiments is a product of noDNA, the designer and manufacturer of the X-IST realtime products. Electronic components and sensors are hidden inside the glove. The Data Glove carries all sensors but no sensor post processing or power supply electronics. This is done by ADBox24w, the sensor processor. The ADBox24w is a 24 channel analogue/digital converter with switchable USB/wireless output. A pair of cables connects the DataGlove with the ADBox24w.

(a) Purchased Data Glove (b) ADBox24w

Figure 1: Purchased Glove

I used the wireless option of ADBox24w during the experiments; the ADBox24w and its portable power supply was carried in a small backpack which was worn by the care-giver during the experiments. The data output of ADBox24w was sent wirelessly to the receiving computer where it is received using the wireless receiver module and software that accompany DataGlove/ADBox24w. The information of each sensor is displayed in real time by the glove software and it can also be stored in a comma separated file as shown in Figure 2.

The X-IST DataGlove captures

- FINGER or FINGER joint up/down movements, there are 15 bend sensors in total, 1/joint/finger as shown in Figure 3.
- FINGERTIP pressure,1 per finger tip as shown in Figure 4.
- HAND pitch and roll rotation i.e. hand tilt up-down and hand tilt left-right through the inertial measurement unit places at the back side of palm as shown in Figure 3.

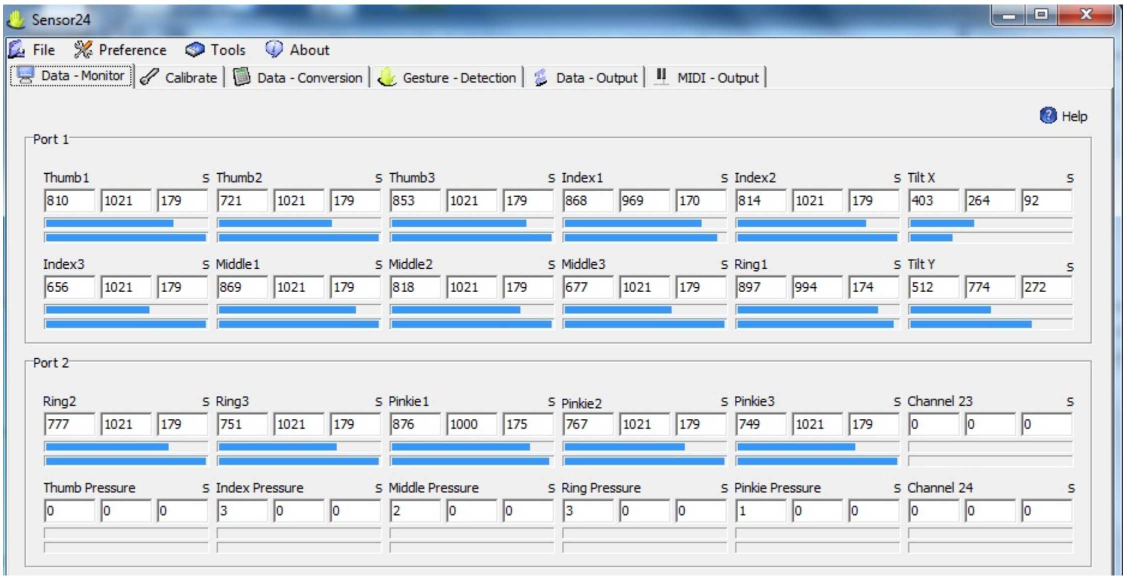

Figure 2: Purchased Glove Data

Figure 3: Purchased Glove Bend Sensors and IMU Location

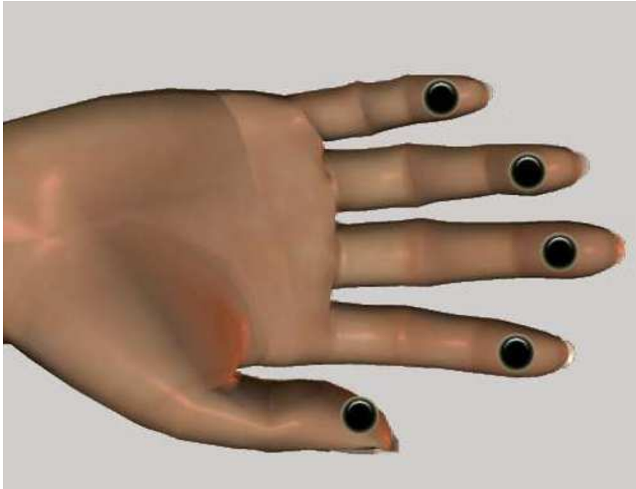

Figure 4: Purchased Glove Pressure Sensors Location

2.2.1.1 Data Analysis

The pressure data obtained during the first two pilot experiments was synchronized with the experiment videos to see how haptic data corresponds to the tasks performed. The data did indicate some useful information, for example during a pilot experiment when the helper is helping the elderly to get up from a bed the pressure signals displayed in Figure 5 are observed.

In Figure 5 the helper started helping the elderly to sit up by pulling his arm at sample 1477. It was observed that the elderly moved up but then went back at about sample 1554 at which the helper again pulled him with more force, finally helping him sit.

It was noted through episodes of this sort that the pressure signals are not observed from all the five pressure sensors when all fingers are supposed to have exerted the pressure. As in

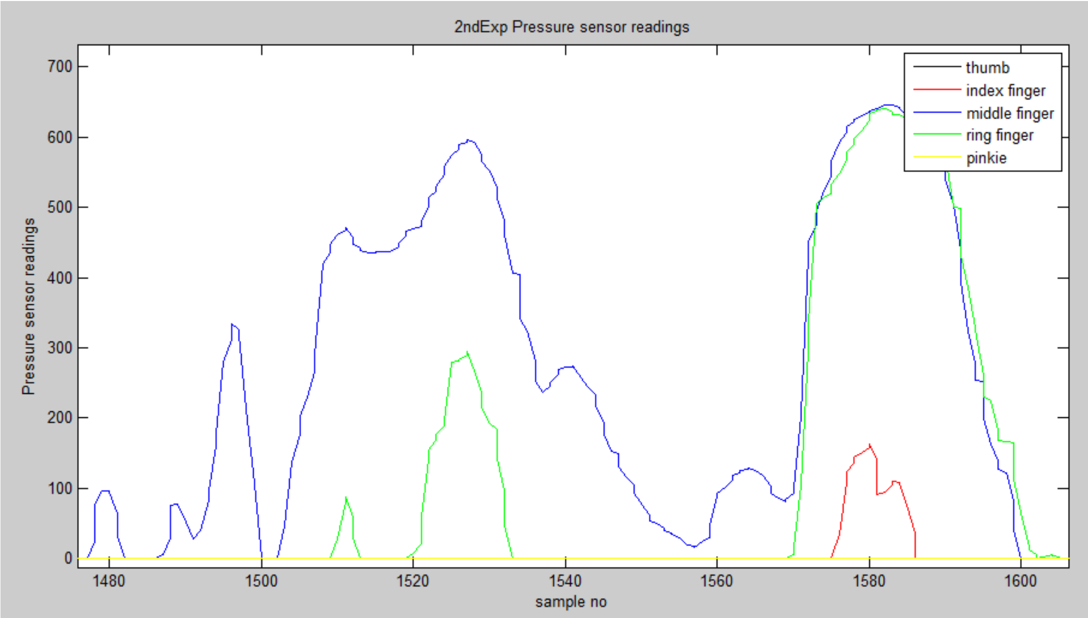

Figure 5: Pressure Data Plot

this example there are pressure signals on mainly the middle and the ring fingers whereas the thumb must also be exerting pressure when the helper is pulling on the arm of elderly.

2.2.1.2 Limitations

Although X-IST DataGlove was the found closest to our application among the data gloves available on the market, data collected with it had revealed certain issues. These issues are summarized as

- The pressure sensors were available only at the finger tips and it is observed in most of the activities finger tips were not touching the grasped objects (Appendix A).

- Palm and finger segments touched the grasped objects most of the times, but there were no pressure sensors to capture the pressure data from these areas.
- Bend sensors values decrease as one opens the hand or in other words straightens the finger joints. They increase again as one fully extends the finger as it causes the bend-sensors to bend. So I got same bend-sensor reading for the inward and outward bending of the inner-most joint of the finger.
- It is hard to generalize the training data for various users (Appendix A).

2.2.2 Developed Data Glove

Since the pressure sensors themselves are quite inexpensive, I thus decided to develop a data glove myself in Robotics Laboratory at the University of Illinois at Chicago. In this glove I used FlexiForce pressure sensors (Tekscan, USA). These sensors are thin and light. One challenge was how to attach the sensors to the glove and connect the wires to them so that these did not make the glove uncomfortable. I decided to put the pressure sensitive part on the front side of the hand, wrapping the sensor to the backside of the hand where all the wires were attached. Since the sensors could not be trimmed by the manufacturer to less than 2 inch, I trimmed the sensors myself and then used the T49 Klipwrap Terminals(Vector Electronics & Technology,INC) to connect the sensor to the wire. The sensors were stitched to the glove to hold them firmly in place. A cotton glove was used to make this data glove. Cotton was chosen since it is comfortable to wear.

The sensors were placed on every segment of each finger except for the middle segments of the thumb and the pinkie that are too small. I also placed four of the pressure sensors on

Figure 6: Developed Glove

the palm. In total, 17 pressure sensors were attached to the glove (Figure 6). In addition to the pressure sensors, a 6 DOF inertia measurement unit (ITG3200/ADXL345, SparkFun Electronics, USA) was used to capture hand tilt and acceleration. It was attached to the back of the palm. Since the pressure sensors were basically force sensitive resisters (FSR), I used a voltage divider circuit to get analog input proportional to the applied pressure as indicated in Figure 7. The glove to which the sensors were attached was covered with an outer glove during the data collection to hide the electronics and protect the sensors. The glove was connected to a processor box based on Arduino Mega microcontroller board (50) through two 20 wire cables. I used the digital outputs of the microcontroller as switches to activate and deactivate particular sensors at a given time. In this way, 5 analog signals are multiplexed into a single analog input as shown in Figure 7.

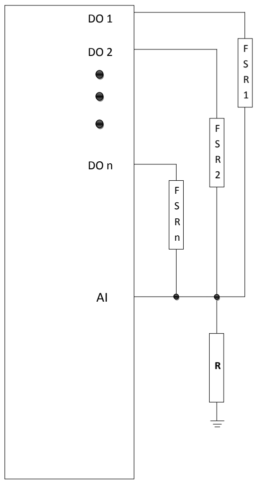

Figure 7: multiplexing

After reading sensor values, the microcontroller transmitted the data wirelessly to the computer using Xbee module. The transmission sequence is represented in Figure 8. A USB XBee receiver module received the data and verifies the size from start symbol to stop symbol, block ID and checksum and if the information was correct stored the bock otherwise discarded it. The data was sampled at around 70Hz. Every time the computer receives a data sample it was time stamped by the system clock up to a millisecond. The total equipment cost for this glove was around $600, significantly less than the cost of comparable data gloves available in the market.

Start Symbol	Block Size	Block ID	Arduino Timestamp	Sensors Data	CkeckSum	Terminator Symbol

Figure 8: Transmitted Data Sequence

2.2.2.1 Limitations

Although the sensors cover most of the hand and do not hinder the bending of fingers, the pressure sensors are sensitive to pressure from both sides so pressure is recorded even if one only bends the fingers. The sensitivity of the pressure sensors is not uniform over all the sensors. I thus calibrated each sensor based on the maximum and minimum reading obtained during the experiments. To filter out the noise the recorded data was filtered using a moving average smoothing filter. I didn't come across any literature that discussed these limitations for the commercially available gloves; so, the performance of my glove could not be compared with that of the commercial gloves.

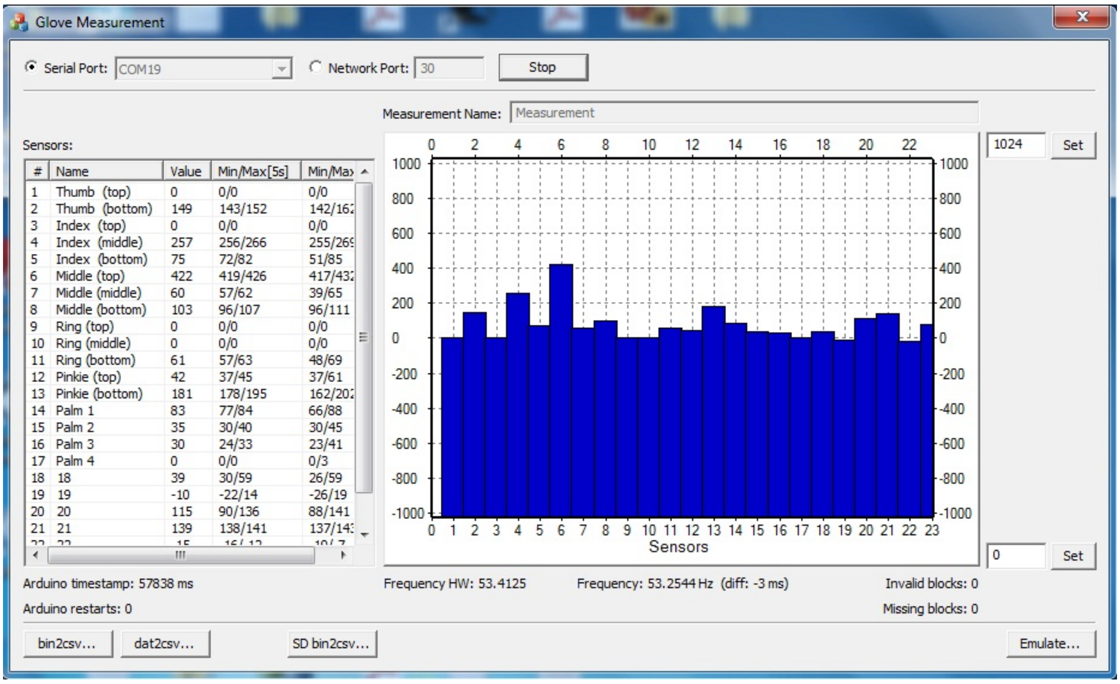

Figure 9: Graphical User Interface of Developed Glove

CHAPTER 3

USER STUDIES

In this chapter three user studies are described that were part of our investigation. Section 3.1 describes a study of different dyads between the elderly and caregivers in a realistic setting (fully functional studio apartment). This study was used to identify activities of daily living (ADL) where physical interaction plays a prominent role. Subsequently, further experiments were conducted in the laboratory setting to study these activities in detail (Section 3.2). The collected data were used to develop a set of classifiers that can determine the actions of interest based on pressure sensors data. Subsequently, additional study was performed in a realistic setting (Section 3.3) to validate the classification procedures.

3.1 First User study: Study of Dyads of Elderly and Caregivers

In order to better understand different communication modalities and types of interactions between the elderly and their care-givers, we conducted user studies in a fully functional studio apartment in the College of Nursing at Rush University. We note that no similar data is available; in particular we are not aware of any study that included collection of physical interaction data. Our experiments focused mainly on ADLs that are crucial for the independent living of the elderly, including:

- Getting up from the bed/chair.
- Ambulating in the apartment.

- Cooking a meal.
- Setting a table for a meal and subsequently cleaning up.

Each experiment session was conducted with a pair of subjects. One of them played the role of helper and the other was an elderly person, more than 70 years of age, residing in an assisted living facility. Two students in gerontological nursing played the role of the helper, one in each experiment. A total of 20 such experiments were performed. Five of those were pilot studies performed with younger subjects playing the role of the elderly and the rest were performed with real elderly subjects. All elderly subjects were highly functioning at a cognitive level and did not have any major physical impairment. During the experiments, video streams from 7 cameras were recorded to provide complementary views of the room and the subjects. The subjects also wore wireless microphones to record the audio. The size of our collected video data is shown in Table I. The number of experiments also included 5 pilot sessions, since those pilot interactions did not measurably differ from those with the real subjects. Usually one experiment lasts about 50 min.(recording starts after informed consent and after the microphones and data gloves have been put on). Further, we eliminated irrelevant content such as interruptions, e.g. by the person who accompanied the elderly subjects, and further explanations of the tasks. This resulted in about 15 minutes of what we call *effective* data for each subject (51).

The details about the tasks performed during experiments is given in Table II

To obtain the information on physical interaction, the subjects wore the data glove equipped with pressure sensors described in Section 2.2.2 on their right hand. While the data glove only provides limited information on the forces during the physical interaction, it only minimally

TABLE I: EXPERIMENTS STATISTICS

Experiments	Raw(Min)	Effective(Min)
20	482	301

interferes with the normal interaction between subjects. None of the elderly or the care-giver ever complained that they could not perform the ADLs properly because they wore the data glove.

During the pilot experiments and first few experiments with real subjects only the helper wore the purchased data glove. The initial analysis of the data collected with the purchased glove showed the limitations of that glove which motivated me to develop a data glove as described in Chapter 2. Once I had developed a glove, the helper wore the developed glove and the elderly wore the purchased glove.

The experiments confirmed our hypothesis that physical interaction plays an important role in the communication of the elderly with the care-giver as reported in (46). Out of all tasks performed, as shown in the Table II the activities that require physical interaction can be divided into the following broad categories:

- handing-over objects;
- manipulating an object together;
- supporting the elderly in walking or getting up.

TABLE II: TASK MATRIX

	In Bed		Find								Set					Unset	Cooking			
Session No.	get up	put shoes	book	soup	pot	salad bowl	drink	clips	others	tray	plates	bowls	glasses	silverware	napkin	table	drain pasta	fill water in pot	put pot on stove	open salad bowl
1					✓						✓	✓		✓			✓	✓	✓	
2	✓								✓											
3	✓		✓		✓	✓		✓	✓		✓			✓	✓			✓	✓	✓
4		✓		✓	✓	✓	✓			✓	✓		✓	✓		✓		✓	✓	✓
5	✓	✓	✓	✓	✓	✓	✓	✓				✓	✓	✓		✓		✓	✓	✓
6	✓	✓	✓	✓	✓	✓		✓	✓	✓	✓		✓	✓	✓	✓	✓	✓	✓	✓
7	✓	✓	✓		✓	✓		✓	✓	✓	✓		✓	✓		✓		✓	✓	✓
8	✓	✓	✓		✓	✓	✓			✓	✓			✓			✓	✓	✓	✓
9	✓	✓	✓	✓	✓	✓				✓	✓		✓	✓		✓	✓	✓	✓	✓
10	✓	✓	✓	✓	✓	✓	✓		✓		✓			✓			✓	✓	✓	✓
11	✓	✓	✓		✓	✓	✓			✓	✓		✓	✓	✓	✓		✓		
12	✓				✓	✓	✓		✓	✓		✓		✓		✓	✓	✓	✓	
13		✓	✓		✓	✓					✓		✓	✓		✓		✓	✓	
14	✓	✓	✓	✓	✓	1				✓	✓			✓		✓	✓	✓	✓	
15	✓	✓	✓	✓	✓	✓	✓			✓	✓			✓	✓	✓	✓	✓	✓	
16		✓	✓	✓	✓	✓				✓		✓		✓	✓	✓		✓	✓	✓
17	✓	✓	✓		✓	✓	✓			✓	✓			✓	✓	✓				✓
18		✓	✓	✓		✓	✓			✓			✓	✓		✓				✓
19	✓	✓	✓	✓	✓	✓	✓			✓	✓		✓	✓	✓	✓		✓	✓	✓
20		✓		✓	✓	✓			✓		✓		✓	✓	✓	✓	✓	✓	✓	✓

Figure 10: Data collection in a mock-up apartment

3.2 Second User study: Data Collection in a Laboratory Setting

The first user study in a realistic scenario indicated that handing-over objects and manipulating an object together are actions that require inter-personal communication through physical interaction (Section 3.1). It was also observed that both handing-over objects and manipulating objects together often involved planar objects, e.g. handing over plates or a tray while setting and cleaning the table. This was the case for 15 subjects out of a total of 20 subjects that participated in this user study. Cooking and setting of table activities was performed by 19 out of the total 20 participating subjects. I thus decided to further investigate collaborative manipulation of planar objects. User study data also suggested that collaborative manipulation of planar objects mainly consists of the following actions:

1. Holding an object alone with one hand.
2. Holding an object alone with both hands.
3. Holding an object with another person.
4. Not holding anything.

Hence, four experiments were conducted in the laboratory to collect more data of these manipulation actions. Each experiment involved a pair of subjects, with one subject wearing the data glove described in the Section 2.2.2 and performing the mentioned actions in collaboration with the other subject. The experiments were video taped. The time stamp of the glove data was used to synchronize the pressure data with the video. The details of these experiments are given in Chapter 5.

Since natural language analysis of the motivational user study had also indicated that manipulation actions help to understand spoken language (36; 11), these actions were studied in more detail through laboratory experiments. These experiments were performed with UIC students as subjects. For each task, the subject wearing the data glove (Section 2.2.2) held the object for several seconds and then released the object or opened/closed a drawer or cabinet and then rested for a few seconds. This was repeated around ten times for each action. The continuous stream of data was stored in a comma separated file. Experiments were videotaped. The video was then synchronized with the glove data using the data glove time stamps. Each data glove sample was annotated for actions based on the video. These annotations were used for verification of classification results. A total of four such experiments were performed with three different subjects. The first three experiments included a subset of the actions of interest and in the last experiment most of the actions were combined. The results of these experiments are explained in Chapter 6.

3.3 Third User study: Validation

From the analysis of data collected in laboratory setting (Section 3.2), I developed classification methods to identify physical manipulation actions and classify different stages of planar object manipulation. To validate whether the classification methods can be applied to the data collected during experiments that mimic the realistic scenario a validation user study was conducted. The experiments performed as a part of this user study involving caregiver helping the elderly with ADLs were largely unscripted and took place in a completely natural setting. Therefore, if my findings can be applied on that data as well, it would be evidence that these capture the haptic collaboration during manipulation of planar objects and recognize the physical manipulation actions.

These experiments were conducted at the same location as the first motivational user study and involved the same ADLs with the exception of "getting up from chair/bed" as that activity did not contain data of interest. The validation study was performed with dyads of UIC students playing the roles of the elderly person and caregiver. A total of four such experiments were performed.

CHAPTER 4

CLASSIFICATION METHODS OVERVIEW

This Chapter describes the various classification methods that were used to classify various haptic actions of interest.

4.1 Supervised Classification

Supervised classification algorithms require training data for which the output class has been labeled and classify the testing data based on the knowledge obtained from training data (52). The classification was performed in MATLAB.

4.1.1 k-Nearest Neighbor

k-Nearest Neighbor (*k-NN*) is an instance-based supervised learning classification method which predicts the task class of a testing instance by finding the k closest neighbors of the testing instance in the training set. The testing instance is assigned the class of majority of its k closest neighbors (53).

Figure 11 shows how *k-NN* works. For example, the triangles represent data points of class 1, circles represent data points of class 2 and diamonds represent data points of class 3. All these data points belong to the training data set. The black square represents a test data point, which needs to be classified based on *k-NN*. If k is one, then the one closest neighbor of the test data point belongs to class 3 represented by diamonds and the test data point is classified as class 3. However, if k is four, then the test data point is classified as class 2 because the two

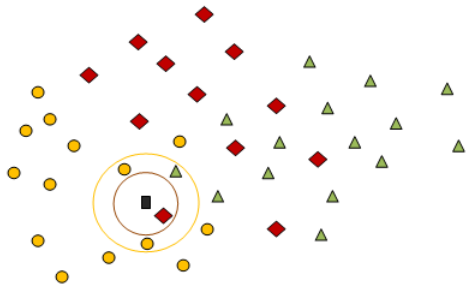

Figure 11: k-Nearest Neighbor Example

data points that belong to that class are among the two closest neighbors whereas one data point each belongs to the other two classes.

4.1.2 Linear Discriminant Analysis

Linear Discriminant Analysis (*LDA*) classifies the data from k classes by defining *k-1* partitions (52). These partitions are defined in a such a way that they separate data from different classes as much as possible.

Figure 12 shows how *LDA* defines a partitioning magenta line that separates the data from two classes represented by blue and red dots.

4.1.3 Dynamic Time Warping (DTW)

DTW is used for classification of temporal data sequences. For two given sequences, *DTW* provides a distance which reflects similarity between the given sequences. Smaller distance indicates more similarity between the given sequences. It measures the similarity even if two sequences are of different frequency. For example, for the action of opening a cabinet it does

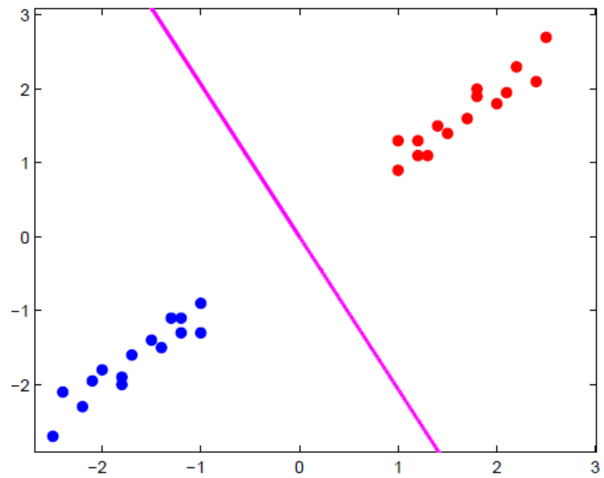

Figure 12: Linear Discriminant Analysis Based Data Classification

not matter whether one person has done it fast and the other has done it slow as far as pattern of pressure data variation is samilar, DTW will indicate them as similar actions.

For classification purpose, an instance of test data is compared with every instance of training data using DTW. The class or label of the training data instance for which the distance is minimum is selected as a winning class. Test Data instance is classified as belonging to winning class (54).

I implemented the DTW algorithm in MATLAB for classification.

4.1.4 Recognition by Indexing and Sequencing (RISq)

RISq is a method for temporal data sequence data classification. *RISq* index each sample of test data determines the closest neighbors for it in the training data and assign a vote to the selected nearest neighbors based on their distance from the indexed test data sample. After this *indexing* phase, an optimal sequence path of votes is selected for each class that minimize the distance or in other words maximize the sum of votes between the test sequence and training sequences for each class. This phase is called sequencing *sequencing*; hence, the name of the algorithm is Recognition by Indexing and Sequencing (*RISq*). The class for which the distance is minimum is selected as a winning class and the test data sequence is classified as belonging to the winning class (55).

It should be noted that *RISq* combines samples from multiple examples of the same class to determine the optimal sequence for a particular class. So, distance measure between each test data sequence and training data sequence does not need to be computed separately. Also, indexing can be performed in parallel for every sample of test data which can make the classification faster. *RISq* also correctly determines the similarity between two actions irrespective of any difference in the speed of actions performed (e.g., closing cabinet doors quickly or slowly).

4.2 Dimentionality Reduction Methods

4.2.1 Linear Discriminant Analysis (LDA)

LDA transforms the data to a lower dimension space such that the data from various classes may be best separated. In the reduced dimensional space each dimension represents a linear combination of features in the original space (52). Figure 13 represents *LDA* data transformation from 2D data points onto a 1D line.

4.2.2 Principal Component Analysis (PCA)

PCA transforms data defined on certain dimensions to some other dimensions called "principal components." These principal components are orthogonal to each other and defined such

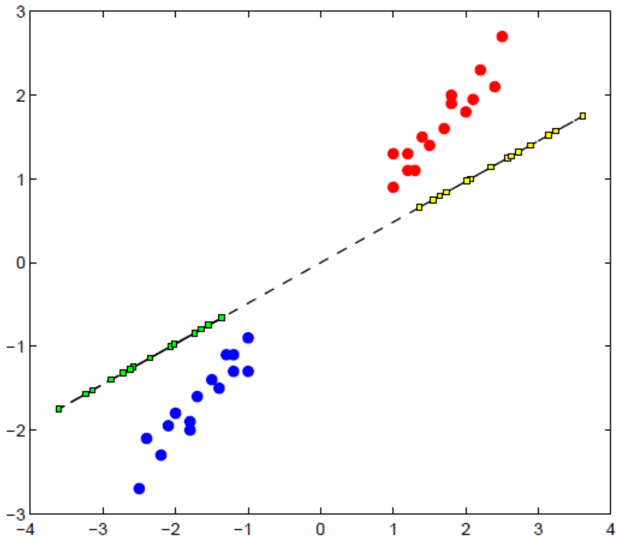

Figure 13: Linear Discriminant Analysis Based Data Transformation

that the first principal component covers most of the information presented in the data, then the second principal component and so on. Hence, the principal components that come at the last contain very little information and may be ignored to reduce the dimensions of the data(56).

Figure 14 represents PCA data transformation from 2D data points onto a 1D line. It should be noted that PCA does not require class labels for the data points. It just finds the dimensions along which most of the data information can be presented. Also note the difference between LDA and PCA transformation for the same set of data.

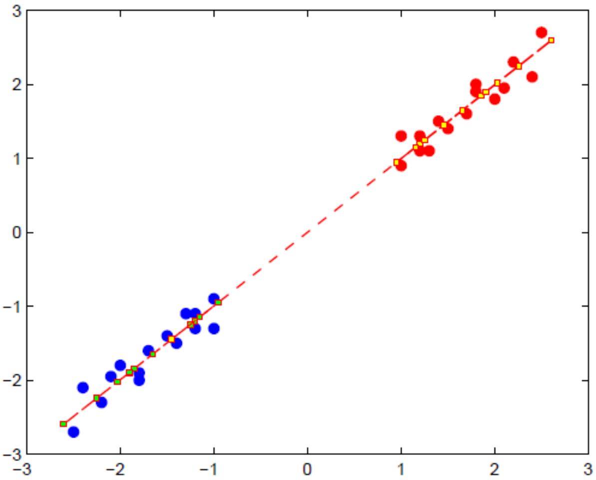

Figure 14: Principal Component Analysis Based Data Transformation

4.3 Classification Results Evaluation Metrics

The results of classification are presented in a confusion matrix. It represents what is the actual class and what is the classified class for all the instances which are classified (57). For example, the results of classification of four classes namely "open closet," "open drawer," "grasp plate," and "grasp glass" may be represented by the confusion matrix given in Table III.

TABLE III: EXAMPLE CONFUSION MATRIX

		Predicted Class			
		open closet	open drawer	grasp plate	grasp glass
Actual Class	open closet	**7**	0	1	2
	open drawer	2	**6**	1	1
	grasp plate	0	1	**8**	0
	grasp glass	2	0	0	**9**

Row three of Table III represents eight instances in the “grasp plate” class are correctly predicted (true positive) as “grasp plate;” whereas, one instance is wrongly predicted (false negative) as “open drawer.”

How well a particular classification algorithm has performed is determined through precision, recall, F1-score and accuracy. In a classification task, the precision for a class is that portion of predicted instances for that class which is correct (57).

$$Precision = \frac{CorrectlyPredictedInstances}{TotalPredictedInstances} = \frac{TruePositive(TP)}{TruePositive(TP)+FalsePositive(FP)}$$

False positive (FP) refers to instances which do not belong to a particular class but are wrongly predicted as belonging to that class; for example, for the classification of the “grasp plate” class, one instance of “open closet” and one instance of “open drawer” are wrongly predicted as “grasp plate” furthermore one instance is wrongly predicted (false negative) as “open drawer”and FP = 1+1 = 2. So, the precision of “grasp plate” class may be given as:

$$Precision_{\text{(grasp plate)}} = \frac{TruePositive(TP)}{TruePositive(TP)+FalsePositive(FP)} = \frac{8}{8+2} = 0.8$$

Recall of a classification method is the portion of total actual instances for a specific class which is correctly identified (57).

$$Recall = \frac{CorrectlyPredictedInstances}{TotalActualInstances} = \frac{TruePositive(TP)}{TruePositive(TP)+FalseNegative(FN)}$$

False negative (FN) refers to instances, which are wrongly predicted as belonging to a class different than the actual class. For example, for the classification of the “grasp plate” class, one instance is wrongly predicted as “open drawer” and FN = 1. So, the recall of “grasp plate” is given as:

$$Recall_{\text{(grasp plate)}} = \frac{TruePositive(TP)}{TruePositive(TP)+FalseNegative(FN)} = \frac{8}{8+1} = 0.89$$

The harmonic mean of precision and recall is call F1-score (57) and it is expressed as:

F1-score $= \frac{2.Precision.Recall}{Precision+Recall}$

For example, F1-score of "grasp plate" is given as:

F1-score $_{\text{(grasp plate)}} = \frac{2.Precision.Recall}{Precision+Recall} = \frac{2.(0.8).(0.89)}{0.8+0.89} = \frac{1.424}{1.69} = 0.84$

Accuracy of a classification method is the correctly predicted portion of total instances for all classes. For example for the confusion matrix presented in Table III the accuracy is given as:

$Accuracy = \frac{SumofTP}{SumofAllInstances} = \frac{7+6+8+9}{7+1+2+2+6+1+1+1+8+2+9} = \frac{30}{40} = 0.75$

CHAPTER 5

COLLABORATIVE MANIPULATION OF PLANAR OBJECT

5.1 Related Work

Over the last decade there is some research work done towards studying haptic collaboration. Very recently, based on the results of experiments performed on shared manipulation of virtual object, Groten et al. (58) strongly suggests that communication though haptics take place for the integration of intentions in shared task execution. Research has also been done towards enabling companion robots with recognition of touch gestures (59; 60; 29). Reed et al. designed an experimental setup for 1 degree of freedom (DOF) human-human haptic collaboration during target acquisition (61; 62). They have observed that human partners perform the task faster than they do it individually by specializing the roles. However they couldn't achieve such improvement in performance when one of the partners is replaced by a robot although human partners believed that they were working with a human rather than a robot. Bakar et al. (63) studied the motion characteristics during human-human collaborative displacement of an object along 1 DOF horizontal direction. The impedance characteristics of human arm for collaboration with robots is presented by Rahman et at. (64). More recently the relationship between grip force and load force has been studied during human-human hand-over in a very controlled experiment (16). In (23), an estimate of human applied wrench is used to change the cooperating role of a robot for moving the table in a 2D plane. Although all these research studies are valuable for understanding haptic collaboration our work is quite different than all these. Rather than designing an experiment for human-human haptic interaction we have observed haptic collaboration during assisting elderly with ADLs and studied one of the activities that took place frequently: collaborative manipulation of planar object.

5.2 Laboratory Experiments

5.2.1 Data Collection

The preliminary data collection confirmed our hypothesis that haptic interaction plays an important role in the communication of the elderly with the care-giver as reported in (46). The activities that require haptic interaction can be divided into the following broad categories:

- handing-over objects
- manipulating an object together
- supporting the elderly in walking or getting up

Figure 15: Data Collection in a Laboratory Experiment

TABLE IV: OBJECTS HANDED OVER DURING SETTING THE TABLE

	plates	bowls	glasses	silverware	napkins
Subject 1	✓	✓		✓	
Subject 2	✓			✓	✓
Subject 3	✓		✓	✓	
Subject 4		✓	✓	✓	
Subject 5	✓		✓	✓	✓
Subject 6	✓		✓	✓	
Subject 7	✓			✓	
Subject 8	✓		✓	✓	
Subject 9	✓			✓	
Subject 10	✓		✓	✓	✓
Subject 11		✓		✓	
Subject 12	✓		✓	✓	
Subject 13	✓			✓	
Subject 14	✓			✓	✓
Subject 15		✓		✓	✓
Subject 16	✓			✓	✓
Subject 17			✓	✓	
Subject 18	✓		✓	✓	✓
Subject 19	✓		✓	✓	✓
Subject 20	Did not perform the cooking and setting table experiment				

Since the preliminary data collection was largely unscripted and took place in a completely natural setting, additional data was collected in a laboratory setting. The experiments consisted of one person wearing the data glove and performing different instances of the planar manipulation task in collaboration with another person in whatever order they prefer. The object that was manipulated was a dinner plate (Figure 15). For example, the subject wearing the glove held the plate alone for some time with the gloved hand, then for some time held it with the collaborating subject, and so on. We performed each of the four actions mentioned earlier in a completely random order for more than ten times for each action. Since these actions were random, certain actions could be performed for a longer duration than others, and some actions may be repeated more than others. In any case, we get more than ten instances of each action.

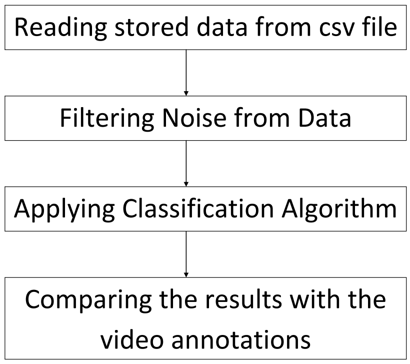

Figure 16: Sequence of steps in processing of the collected data

5.2.1.1 Data Processing

Although each received data sample was time stamped but these samples are not uniformly spaced in time and the frequency of receiving data varies. To get data at a uniform frequency we thus interpolated the received data. Since the received data is time-stamped up to milliseconds, it is plotted on a 1000 Hz frequency scale and the missing samples are defined by linear interpolation of obtained values. The interpolated data is subsequently down-sampled to 20 Hz. To filter out the noise, the data was filtered using a moving average smoothing filter.

The data was collected from 4 experiments. 3 subjects performed the experiments where one subject participated in two experiments on different days. Experiments were videotaped. The video was then synchronized with the glove data using the time stamps of glove data. Each sample of glove data was annotated for actions listed above based on the video. These annotations were used for verification of predicted results. Figure 16 describes the steps involved in the data processing. For each action, each sample was considered as a separate data point. For example, if an instance of a particular action occurred for 3 seconds, there were $20 \times 3 = 60$ data points for that instance. In the classification experiments each of these data points was classified individually.

5.2.2 Classification of Data

To test whether all of the actions performed as a part of collaborative manipulation of the planar object could be identified from the pressure data different classification methods were used. This Section describes these methods and their result. We again remind the reader that we classified each data sample rather than the whole instance of each action.

5.2.2.1 Supervised Classification

The data was first classified based on supervised classification. Supervised classification algorithms requires training data for which the output class has been labeled and classifies the testing data based on the knowledge obtained from training data (52). The classification was performed in Matlab.

5.2.2.1.1 Within Subject Classification

In this classification task both the training and test data belonged to the experiment performed by one subject. From the plot of the data from each sensor it was observed that the data did not vary much during each instance of performing a particular action. In addition to annotating the data with the action, it was also annotated with the instance number of each action e.g. the first time an action of holding a plate with both hands was performed the instance number was marked as 1 and after holding it with another person and with one hand the next time when the plate was held by both hands the data was marked with instance number 2. Data was partitioned into 10 parts such that the samples with the instance number modulo 10 equaled to 1 were placed in partition 1 and so on. 10-fold cross-validation was performed on the data, namely, each of these partitions were then used as a testing data one by one and the remaining 9 partitions were used as a training data. The results from these 10 runs of classification were combined to report the final evaluation results. This way test data was 10% of the total data and the remaining 90% of the data was used as training data.

5.2.2.1.1.1 k-Nearest Neighbor Results

k-Nearest Neighbor (*k-NN*) is an instance-based supervised learning classification method which predicts the task class of a testing instance by finding the k closest neighbors of the testing instance in the training set. The testing instance is assigned the class of majority of its k closest neighbors (53). *k-NN* was applied on each subject data for various values of k. It was observed that average F1-score (the harmonic mean of precision and recall) improved as the value of k was increased from 1 to 100 then for k=100 to k = 1000 the results improved for some subjects and deteriorated for others such that the average F1-score for all the subjects did not vary much and stayed around 66% to 68%. In a classification task, the precision for a class is the portion of predicted instances for that class which is correct. Recall in this context is the portion of total actual instances for a specific class which is correctly identified (57). The average *k-NN* results with $k = 1000$ for all the subjects is given in Table V.

TABLE V: AVERAGE WITHIN SUBJECT *K-NN* RESULTS

	Precision	Recall	F1-Score
Another Person	61.829%	61.023%	61.423%
One Hand	70.787%	57.472%	63.438%
Empty Hand	83.793%	83.851%	83.822%
Both Hands	63.492%	66.632%	65.025%
Average F1-score: 68.427%			

5.2.2.1.1.2 Linear Discriminant Analysis Results

Linear Discriminant Analysis (*LDA*) classify the data from *k* classes by defining *k-1* hyperplanes (52). The average *LDA* results for all the subjects is given in Table VI. The average F1-score for these result is 73.98%. These results are significantly better than *k-NN* ($p<0.05$, χ^2) for the most appropriate value of *k* (1000), it was expected as *LDA* defines hyperplanes such that the data from various classes are as well separated as possible.

TABLE VI: AVERAGE WITHIN SUBJECT *LDA* RESULTS

	Precision	Recall	F1-Score
Another Person	66.002%	67.808%	66.893%
One Hand	66.19%	59.434%	62.63%
Empty Hand	91.96%	92.55%	92.26%
Both Hands	71.13%	77.44%	74.15%
Average F1-score: 73.98%			

5.2.2.1.2 Across Subject Classification

Since within class classification was successful with the results significantly better than the random guess ($p<0.05$, χ^2), next it was tested whether the earlier mentioned supervised classification techniques could be generalized among different subjects. For this purpose, the test data from each subject was classified using the classification algorithms trained with training data from remaining three subjects.

5.2.2.1.2.1 k-Nearest Neighbor Results

It was observed that average F1-score improved as the value of k was increased from 1 to 800 then declined for $k = 1000$. The combined across subject *k-NN* results for all the subjects for $k = 800$ is given in Table VII. The average F1-score for these results is 56.93%. It should be noted that though these results are significantly better than the random guess ($p<0.05$, χ^2), these have significantly declined as compare to within class classification with *k-NN*.

TABLE VII: COMBINED ACROSS SUBJECT *K-NN* RESULTS FOR ALL THE SUBJECTS

	Precision	Recall	F1-Score
Another Person	46.90%	50.36%	48.56%
One Hand	62.18%	55.25%	58.51%
Empty Hand	73.50%	94.19%	82.57%
Both Hands	50.93%	30.39%	38.07%
Average F1-score: 56.93%			

5.2.2.1.2.2 Linear Discriminant Analysis Results

The average F1-score for across subject for classification with *LDA* also declined significantly to 52.15% from the within subject result of 73.98% ($p<0.05$, χ^2). The combined *LDA* results for all the subjects is given in Table VIII.

TABLE VIII: COMBINED ACROSS SUBJECT *LDA* RESULTS FOR ALL THE SUBJECTS

	Precision	Recall	F1-Score
Another Person	38.824%	55.051%	45.535%
One Hand	56.651%	39.732%	46.707%
Empty Hand	73.434%	73.83%	73.632%
Both Hands	46.837%	39.255%	42.712%
Average F1-score: 52.15%			

Across subject classification results are similar for both *k-NN* and *LDA* ($p>0.05$, χ^2). *LDA* had performed better than *k-NN* for within subject classification however it seems that the data processing done by *LDA* to capture most of the differences among various classes for a particular subject does not work that well across subjects.

5.2.2.1.3 Dimension Reduction Based on Linear Discriminant Analysis

In order to interpret the features that helped in successful classification of actions of interest we tried to reduce the dimensionality of the input data from 17 to lower than 5. For this purpose again Linear Discriminant Analysis (*LDA*) was used but this time to reduce the dimensionality rather than classification of data. *LDA* projects the data onto a lower dimension space by seeking the projections that best separates the data. In the reduced dimensional space each dimension represents a linear combination of features in the original space (52).

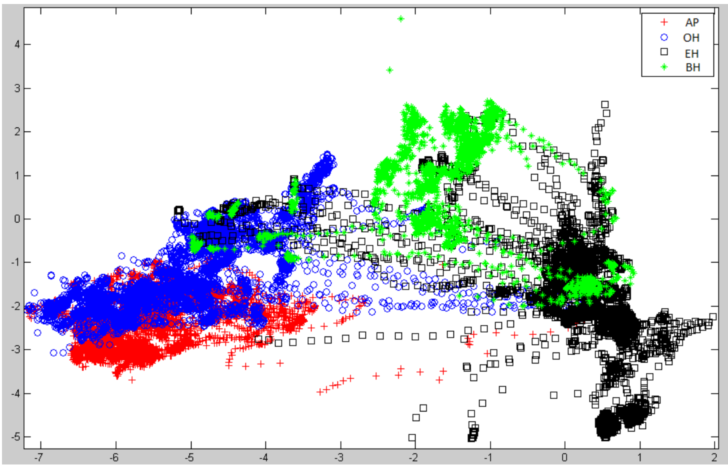

Figure 17: Subject 1 Data Plot in 2D (95.6% information)

The information from the combined data from all the four subjects was transformed into three dimensions using *LDA* where 86.6% of the total information was represented by the first data dimension. However, this most informative vector was formed by assigning comparable weights to 15 out of 17 sensor data in the original data space. This indicated that the information from a small subset of the sensors could not be interpreted to classify different classes under consideration. *LDA* was also applied for dimension reduction on one subject's data at a time to see whether a small subset of pressure sensors which were more important for classification within the data of that subject can be identified. Again it was found that more than 70% of the information was presented by a vector in reduced 3-dimensional space that assigned comparable weights to at least 9 sensors for each subject. It was also observed that the sensors which were given high weight in the reduced dimension space were also not same across different subjects.

5.2.2.2 Unsupervised Classification

We next wanted to get insight into the properties of the data that helped to classify different classes of interest. For this purpose data classification based on unsupervised classification technique of clustering was used. Unsupervised classification doesn't require any training data before classification. Clustering is the task of assigning a set of objects into groups (called clusters) so that the objects in the same cluster are more closely related to each other than to those in other clusters (53). Clustering of the 17 dimensional data did not give good results. The dimensionality of the data was thus reduced by applying principal component analysis (PCA) (56).

The results of PCA showed that more than 50% of the total information was concentrated in the first two principal components. Figure 18 gives the plot of data of two leading principal components for subject 3. This plot helps to visualize how the data from different actions was clustered.

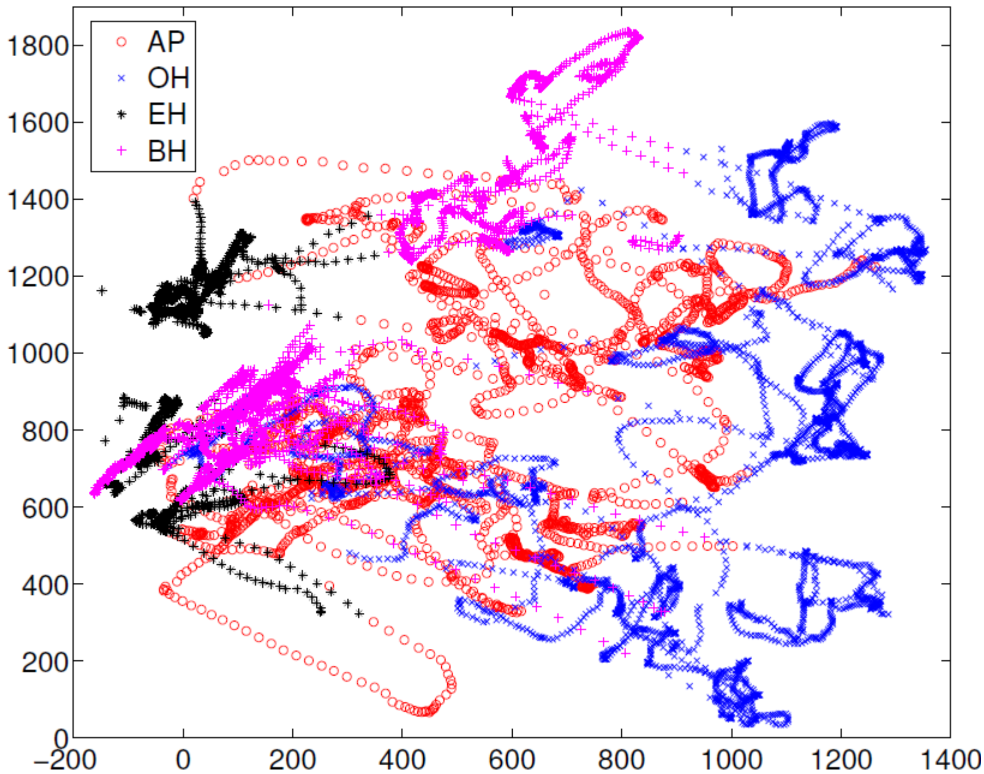

Figure 18: Data Plot of Two Leading Principal Components for Subject 3

TABLE IX: DATA COMPOSITION OF 12 CLUSTERS FOR SUBJECT 3

-	1	2	3	4	5	6	7	8	9	10	11	12
Another Person	2	571	68	142	289	234	29	241	0	429	2	526
One Hand	2	279	0	650	981	145	84	18	0	517	699	197
Empty Hand	0	21	231	0	0	4	808	330	1459	0	0	0
Both Hands	458	83	1	12	1	1094	573	130	1	31	0	445

The k-mean clustering (53) of the first two principal components yielded clusters that helped identify different actions to some extent, but at times confused two actions. The results of clustering for the experiment performed by subject 3 are given in Table IX. Here the data is split into 12 clusters for 4 classes instead of 4, as the mean silhouette value for all data points was highest for 12 clusters. Mean silhouette value for data determines how well the data points have been clustered (65).

TABLE X: CLUSTERING RESULTS FOR SUBJECT 3

	Precision	Recall
With Another Person	59.853%	22.542%
One Hand	83.933%	65.23%
Empty Hand	96.023%	59.236%
Both Hands	80.041%	54.860%

Note in Table IX that the clusters 1-6, 9 and 11 contained most of the data samples from only one particular action whereas the clusters 7, 8, 10 and 12 confused two actions. The numbers in Table IX represent individual data samples that is why these numbers are very high as there were 20 samples for each second of the experiment.Table Table X gives the precision and recall for the well separated clusters (1-6, 9 and 11).

TABLE XI: AVERAGE CLUSTERING RESULTS FOR ALL THE SUBJECTS

	Precision	Recall
Another Person	77.018%	54.187%
One Hand	76.711%	48.339%
Empty Hand	90.024%	81.789%
Both Hands	76.124%	60.269%

The average of the clustering results obtained from all the experiments is given in Table XI. Recall is low, as those clusters that were shared by two or more actions were not considered. F1-score is also not given in Table X and Table XI as staistics are presented for only well separated clusters (1-6, 9 and 11) which has caused recall to be low.

5.2.2.3 Clustering Based Decision Tree

Clustering using PCA gave satisfactory results across subjects, but it unfortunately provided little insight into what physical features of the data distinguished different classes. To interpret the rules that resulted in placing the data samples from different actions in separate clusters, we

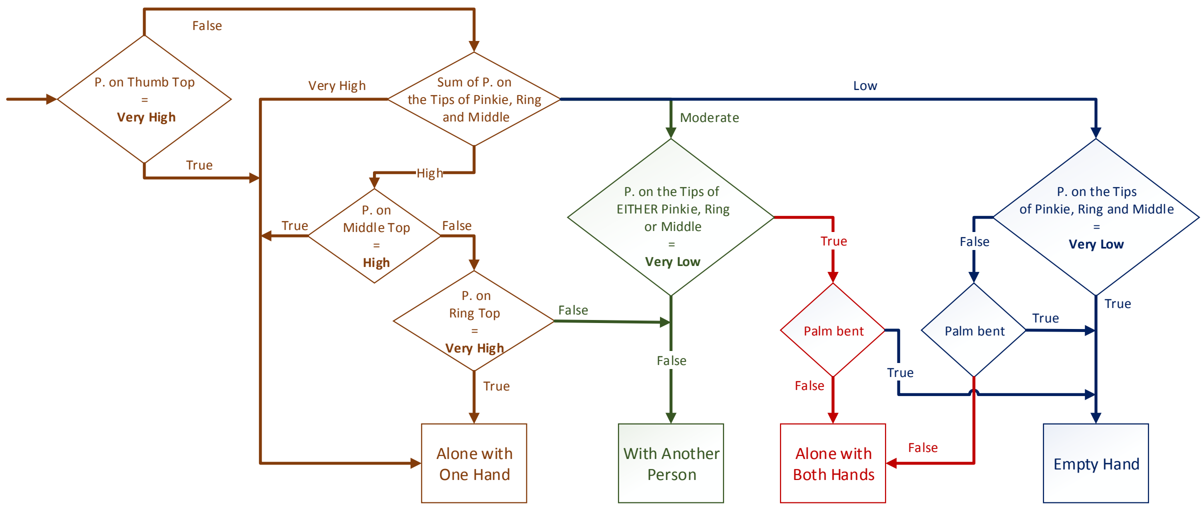

Figure 19: Clustering Based Decision Tree

thus tried to physically interpret the first principal component. More specifically, the sensors that were given more weight in the leading principal component were identified. The first principal component carried 30%-60% of total information for the four experiments' data. Our observation was that the leading principal component gave high weight to fingertip sensors excluding the index finger for all the subjects. Observing the common characteristics of the important sensors in well separated clusters, a decision tree which is shown in Figure 19 was built. Please refer to Table XII for explanation of different pressure levels.

The logical interpretation of these rules can be easily made. For example, to classify a point as *empty hand* in case the pressure on the fingertips is not high enough to classify it otherwise, palm middle sensor pressure is checked. The reason is that empty hand is often closed slightly which causes the palm middle sensor to bend. In turn this results in high pressure on that sensor

TABLE XII: PRESSURE LEVEL DEFINITIONS

	Very High	High	Moderate	Low
Sum of pinkie, ring and middle finger top	greater than 2100	greater than 1800	less than 1800 and greater than 700	less than 700

	Very High	High	Very Low
Pinkie Top	NA[1]	NA[1]	less than 150
Ring Top	greater than 900	NA[1]	less than 300
Middle Top	greater than 900	greater than 700	less than 300
Thumb Top	greater than 750	NA[1]	less than 300
Palm Middle	NA[1]	greater than 700	less than 300

while the finger-tips are not touching anything, which means that the cumulative pressure on the finger-tips should be low.

If the pressure on only one or two of pinkie, ring finger and middle finger is very low whereas either the sum of pressure on these three fingertips is not low or pressure on the palm middle sensor is not high, it is the action of holding the plate alone with both hands. The reason may be that when one is holding the plate alone with both hands one may relax the pressure on one or two of the fingers as one knows that the other hand is holding the plate with sufficient force.

Table XIII gives the confusion matrix (57) for the results obtained by using the derived decision tree, and Table XIV gives the recognition statistics of different actions. In the confusion matrix, each column of the matrix represents the instances in a predicted class, while each row represents the instances in an actual class.

TABLE XIII: CONFUSION MATRIX FOR CLUSTERING BASED DECISION TREE

	Another Person	One Hand	Empty Hand	Both Hands
Another Person	**11064**	3158	627	1419
One Hand	6599	**9530**	231	1225
Empty Hand	163	64	**15219**	1665
Both Hands	1502	512	1115	**7576**

TABLE XIV: EVENT RECOGNITION RESULTS FOR CLUSTERING BASED DECISION TREE

	Precision	Recall	F1score
Another Person	57.24%	68.01%	62.16%
One Hand	71.85%	54.19%	61.78%
Empty Hand	88.52%	88.94%	88.73%
Both Hands	63.74%	70.77%	67.07%
Average F1-score: 69.94%			

The average F1-score for the classification with the derived decision tree is 69.94%. We thus conclude that the decision tree successfully distinguishes different actions during human collaborative manipulation. It is especially interesting that it is possible to recognize from the pressure data whether an object is held with two hands by a single person, or with two hands but by two different people.

[1] "Clustering Based Decision Tree" does not mention this pressure level.

The results of classification based on "Clustering Based Decision Tree" across all subjects with average F1-score of 69.94% are quite comparable (p>0.05, χ^2) with the results of *LDA* for within subject classification (average F1-score 73.98%). This implies that the inferred physical interpretation of the data and the derived decision tree captures the information remarkably well.

5.3 Naturalistic Setting Data Classification

After developing a generalized algorithm that successfully classified different stages of collaborative manipulation performed by different subjects at the laboratory, the next step was to test whether these results could be applied to the data collected during the first user study (Section 3.1). The experiments performed as a part of the first user study were largely unscripted and took place in a completely natural setting so if CBDT could be applied on that data as well, it would provide evidence that it can classify various stages of planar objects manipulation using haptic data. Such analysis would also identify the challenges towards application of this work in a scenario where many ADLs are involved in addition to the collaborative manipulation of planar objects. Unfortunately, the haptic data collected during the user study, turned out to be corrupt. The *a posteriori* analysis identified that the pressure sensor data was corrupted due to an outer glove that was worn over the fabricated glove to help the video processing performed by the vision group collaborating in this project (see the yellow gloves on the helper's hands in Figure 10). Thus additional data had to be collected to verify CBDT in a natural setting during elderly care (Section 3.3). This *Naturalistic Validation (NatVal)* data was collected in the same mock apartment at Rush University where we had performed the first user study, and involved the same ADLs. These *NatVal* experiments were performed with dyads of UIC students playing the roles of elderly person and care-giver. A total of four such experiments were performed.

The results from the analysis of *NatVal* experiments provided significant information about the strengths and weaknesses of the developed classification algorithm and the hardware under use. The first challenge was that *NatVal* experiments had data from many actions other than those involved in collaborative manipulation of planar object. Second, in some of the experiments there were no instances of some of the four actions of interest. In principle, that should not affect our classification. However, as mentioned in the limitations of data glove, the pressure sensor readings were calibrated based on the maximum and minimum of each experiment to account for the non-uniform sensitivity of our sensors. This means that when there was a subset of four actions of interest available, as well as data from many other actions, calibration would be greatly affected and so the pressure threshold levels defined for CBDT might need to be adjusted. However, the relative pressure variation in sensors readings for the actions of interest would follow the CBDT rules developed through analysis of laboratory experiments.

To overcome the problem of calibration, only the data from the four studied actions was considered for each experiment and then this data was calibrated based upon the maximum and minimum sensor readings during each experiment. Each sample of this calibrated data was classified based on CBDT using the same pressure level thresholds as mentioned in Table XII. We again remind the reader that CBDT classified each data sample rather than the whole instance of each action.

TABLE XV: CONFUSION MATRIX OF *NATVAL* EXPERIMENTS DATA CLASSIFICATION

	Confusion Matrix				Recognition Rates		
	Another Person	**One Hand**	**Empty Hand**	**Both Hands**	**Precision**	**Recall**	**F1-score**
With Another Person	**172**	11	52	56	18.20%	59.11%	27.83%
One Hand	685	**1172**	0	66	95.13%	60.95%	74.29%
Empty Hand	88	49	**3204**	251	94.40%	89.20%	91.73%
Both Hands	0	0	138	**570**	60.44%	80.51%	69.05%
Average F1score = 65.73% ; Accuracy: 78.56%							

The combined results for all the four *NatVal* experiments are presented in Table XV. These results with classification accuracy of 78.57% show that the classification algorithm works quite reliably.Average F1-score is significantly lower than accuracy because the action of ”holding the plate with another person” has much lower number of samples as compare to other actions and this has caused the precision of this action to be very low, which in turn affected the F1-score of this action to be low and consequently low average F1-score.

Section 5.3.1 gives the details about each *NatVal* experiment results. For the classification of realistic setting that only CBDT is applied as it is not only an unsupervised classification method that performs as well as the supervised classification methods but also it can be easily implemented on other sensors and hardware and provides physical interpretation of the decision rules.

These validation results are very promising and strongly suggest that these findings should be incorporated into robotic platforms. In particular, the human-robot handover can be improved if the physical interaction information is used. Like in this work, the information on whether the plate is held with another person or alone is important in determining the next action, i.e., releasing the plate if the robot is playing the role of a giver or be ready to hold the plate with greater strength if the robot is a receiver. It should also be noted that the plate involved during the validation study is different than the one used for the lab. experiments, which suggests the developed algorithm is generalizable.

5.3.1 Individual Experiments Results

5.3.1.1 *NatVal* Experiment No. 1

During *NatVal* Experiment No. 1 only the actions of holding the plate with one hand and empty hand occurred. Since, according to CBDT and the pressure thresholds (Figure 19 and Table XII) these two actions covered the range of pressure variations, calibration was performed based on the maximum and minimum readings of the pressure sensors obtained during these actions. Classification of calibrated samples based on CBDT correctly classified 79.05% of the samples and average F1-score of the results was 85.42%. Table XVI states the results of NatVal experiment no. 1 classification results.

5.3.1.2 *NatVal* Experiment No. 2

During *NatVal* experiment no. 2, the actions of holding the plate with another person, holding the plate with one hand and empty hand occurred. Since, according to CBDT and the pressure thresholds (Figure 19 and Table XII) these actions covered the range of pressure

TABLE XVI: CONFUSION MATRIX OF *NATVAL* EXPERIMENT NO. 1 DATA CLASSIFICATION

	Another Person	**One Hand**	**Empty Hand**	**Both Hands**	**Total**
Another Person	0	0	0	0	0
One Hand	94	**330**	0	0	424
Empty Hand	87	49	**715**	47	898
Both Hands	0	0	0	0	0

variations, calibration was performed based on the maximum and minimum readings of the pressure sensors obtained during these actions. Classification of calibrated samples based on CBDT correctly classified 88.04% of the samples and average F1-score of the results was 82.59%. Table XVII states the results of NatVal experiment no. 2 classification results.

TABLE XVII: CONFUSION MATRIX OF *NATVAL* EXPERIMENT NO. 2 DATA CLASSIFICATION

	Another Person	**One Hand**	**Empty Hand**	**Both Hands**	**Total**
Another Person	**38**	10	36	5	89
One Hand	0	**362**	0	4	366
Empty Hand	1	0	**447**	59	507
Both Hands	0	0	0	0	0

Table XVII indicates that the action of "holding with another person" does not have as good recognition rate as the other two actions. The video of the experiment for the data samples which belonged to the misclassification of action "holding with another person" explained the reason. During this time the care-giver who was asked to bring a plate picked the plate from a high shelf, and while getting the plate down from the shelf held it in a way such that her fingers were on the top of the plate and thumb was at the bottom. She then handed-over the plate to the elderly while holding it in the same way. During experiments at the laboratory subjects never had to pick the plate from some high place and they never held the plate this way. It turned out that when the subject was holding plate alone in this configuration the pressure on the finger tips was very high so that action of "holding with one hand" was rightly classified. However when the care-giver was handing over the plate while holding it in this inverted fashion, the action "holding with another person" was classified for half of the time as "holding alone with one hand" as the care-giver was having firm grip and then for the latter half when the fingers were bit relaxed the data samples were classified as "empty hand".

While the care-giver was receiving the plate from the elderly she picked the plate the way it was done by all subjects in laboratory experiments i.e. with fingers under the plate and thumb on top as shown in Figure 15. In that case we got very good results with all the data samples from the short duration of time while the care-giver was holding the plate were classified correctly.

5.3.1.3 *NatVal* Experiment No. 3

The analysis of pressure sensors data of this experiment indicated that ring top and thumb top sensors were unplugged during the experiment. So, only three out of five sensors readings based on which CBDT classified the data. Due to this reduced information, CBDT was adjusted accordingly by making decision only on the basis of available sensors' readings and scaling the threshold of "sum of pinkie, middle and ring finger top sensors" by 2/3 as for this particular experiment only 2 out of three sensors which were contributing to the sum were available. Since, according to CBDT and the pressure thresholds (Figure 19 and Table XII) the actions performed during this experiment covered the range of pressure variations, calibration was performed based on the maximum and minimum readings of the pressure sensors obtained during these actions. Table XVIII states the results of NatVal experiment no. 3 classification results. Not surprisingly with the reduction in information the classification results of calibrated samples based on CBDT dropped significantly to 71.96% accuracy and 61.21% F1-score. Although even these deteriorated results are quite comparable to the results of laboratory experiments, these results indicate that thumb top and ring top pressure readings are important in improving the classification of planar object manipulation stages.

5.3.1.4 *NatVal* Experiment No. 4

During *NatVal* experiment no. 2, the actions of holding the plate alone with both hands and empty hand occurred. These actions only produce low and very low pressure readings according to CBDT. Hence for calibrating these readings, the maximum and minimum values of the five pressure sensor readings were selected such that the resulting calibrated values compared as close

TABLE XVIII: CONFUSION MATRIX OF *NATVAL* EXPERIMENT NO. 3 DATA CLASSIFICATION

	Another Person	**One Hand**	**Empty Hand**	**Both Hands**	**Total**
Another Person	**134**	1	16	51	202
One Hand	591	**480**	0	62	1133
Empty Hand	0	0	**1608**	258	3088
Both Hands	0	0	0	0	0

as possible to one of the laboratory experiments readings for these two actions. Classification of calibrated samples was then performed through CBDT. Table XIX states the results of NatVal experiment no. 4 classification which have accuracy of 87.91% and average F1-score of 87.74%.

5.4 Application of Clustering Based Decision Tree for Real-Time Classification of Hand-Over Stages

CBDT was also applied in real-time to classify the data obtained during hand-over of planar object. This real time classification was performed in ROS which is an open source Robot operating System API (66). ROS has become the most popular platform for developing robotic software as most of the present day robots are ROS compatible.

ROS implementation read the data coming from data glove, calibrated it, classified it based on CBDT and finally output the classified stage of hand-over e.g. empty hand or holding with another person in real-time. The input data and the output result was also stored in a file with time stamp. These ROS implementation steps are outlined in the Figure 20. The

TABLE XIX: CONFUSION MATRIX OF *NATVAL* EXPERIMENT NO. 4 DATA CLASSIFICATION

	Another Person	**One Hand**	**Empty Hand**	**Both Hands**	**Total**
Another Person	0	0	0	0	0
One Hand	0	0	0	0	0
Empty Hand	0	0	**434**	0	434
Both Hands	0	0	138	**570**	708

calibration of sensor values require the minimum and maximum reading of sensor that occur during performing manipulation of planar object. Therefore, before real-time classification, a brief initial experiment was performed for 2-3 minutes covering all the manipulation actions. The data from this initial experiment was used to determine the maximum and minimum sensor readings. These minimum and maximum readings are then fed into the ROS code which is designed for real-time data classification and the experiment to classify real-time was performed. During the real-time classification experiment the two subjects handing-over the planar object held it for few seconds with the other partner before releasing it so that the data samples from the action of "handing with another person" may not be very few as it happened during the hand-over in naturalistic setting (Table XV).

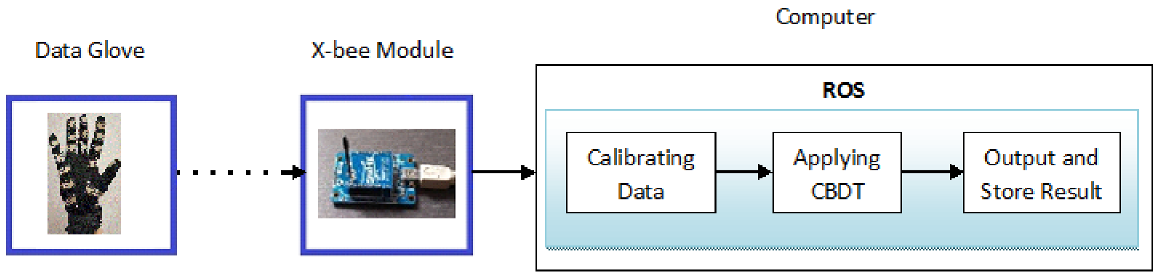

Figure 20: Real-Time CBDT Implementation Steps

For the real-time data classification based on CBDT, Table XX provides performance and the confusion matrix. These results provide a strong evidence of CBDT usability to classify various stages of hand-over of a planar object.

5.5 Summary

This chapter investigates how humans communicate haptically. The work was motivated by the need to understand human behavior before a similar functionality can be replicated on the robots. The task that was studied in detail was collaborative manipulation of a planar object. The data analysis from the laboratory experiments was used to derive a decision tree that used the rules which only depend on direct physical interpretation of the data (fingertip pressure). Different actions which seemed alike from the forces required for manipulation of the object (holding with two hands by a single person rather than holding by two people) were successfully recognized as distinct events using the derived CBDT. Since the rules in the decision tree only

TABLE XX: RECOGNITION RESULTS FOR REAL-TIME HAND-OVER DATA CLASSIFICATION BASED ON CBDT

	Confusion Matrix				Recognition Rates		
	Another Person	**One Hand**	**Empty Hand**	**Both Hands**	**Precision**	**Recall**	**F1-score**
Another Person	1470	206	18	0	63.2%	86.78%	73.13%
One Hand	808	2752	0	0	93.04%	77.30%	84.4%
Empty Hand	48	0	1270	284	98.60%	79.28%	87.89%
Both Hands	0	0	0	0	N.A	N.A	N.A
Average F1score = 81.82% ; Accuracy: 80.10%							

use relative pressure to distinguish between different actions, they can be easily adapted for different hardware platforms.

The findings in this chapter can be directly used to improve the ability of the robots to haptically interact with humans. In particular, using the work herein, the robots can better understand the human intent during haptic interaction, and can convey their intent to the human.

We also propose that this work can be particularly utilized to improve human-robot hand-over of planar objects. As in analysis of elderly care experiments and real-time hand-over experiments, it was found that different stages of hand-over can be identified using the formulated rules. It should also be noted that that the plates used in the elderly care experiments were not same as the one used in laboratory. Since we classify different actions of collaborative manipulation of planar object in terms of the relative pressure changes that occur between these actions, we also suggest that these findings remain valid for planar objects of different weight and to some extent different shape as far as the sensors used to measure the pressure can capture the variation in pressure. However the prove of this hypothesis can be one of many extensions of this work. The CBDT is successfully utilized to classify different stages of plate hand-over in real-time.

It should also be noted that in this research work each sample of glove data was classified individually irrespective of the adjacent readings. Incorporating the information from the adjacent readings to improve classification results is also a future work.

Implementation on a robotic platform is part of our future work. It should also be noted that the actions studied in this paper all involved power planar grasp. Generalizing the results to more complex manipulation tasks also remains for the future.

CHAPTER 6

RECOGNITION OF PHYSICAL MANIPULATION ACTIONS

During human studies (Section 3.1), it was observed that when an elderly subject and a helper prepared a meal together, there were many instances of the subjects grasping kitchen items, passing the items from one person to another, and moving items collaboratively. For example, imagine cooking a pot of pasta. The helper might grab a pot and fill it with water. After that the helper might encourage the elderly to help move the pot to the stove. The helper might then hand a salt container to the elderly. To achieve our main goal of understanding physical interaction, each of these events needs to be recognized, similarly to how phonemes are recognized in speech processing. The natural language processing of the first user study (Section 3.1), by collaborating researchers, highlight the role played by physical manipulation actions (10; 11). However, that research study was based on annotations of physical manipulation actions by humans using the video recordings of the experiments. It is obvious that for those models to be usable in human-robot interaction, physical manipulation actions need to be automatically recognized in the haptic data stream. Recognizing physical manipulation actions from the haptic signals is one way of grounding the high-level, Natural Language component of the RoboHelper system (46) we envision, in the physical world.

6.1 Related Work

Grasp recognition is the primary focus of several studies on physical manipulation of objects. In (67; 68), an object with embedded sensors was used as a user interface to virtual environment. The work done in "programming by demonstration" is more relevant as there the grasp is determined based on the glove data worn by the demonstrator (69). A different problem is studied in (70), where a set of toys was recognized by autonomously probing them with a flat tactile sensor array mounted on the end-effector of a Unimation Puma 260 6-DOF manipulator. In (71), finger joint angles of a robotic hand are used to identify a set of 25 different objects whereas (72) uses the information from 45 pressure sensors mounted on Lucs Haptic Hand II to classify six objects of different shapes. All these works stress the importance of object identification through tactile data. When vision is occluded object identification can only be done through tactile sensing. Tactile identification can also verify the information obtained from vision. Our work is different from these studies in two respects. First, we are not interested in recognizing objects, our focus is information (objects or actions) that can be used in communication—either directly or to disambiguate other modalities such as speech. And second, we are interested in how the information from physical interaction is used for communication in everyday scenarios, and how such communication can be unobtrusively studied.

6.2 Laboratory Experiments

Experiments were performed in the laboratory with the developed glove (Section 2.2.2) to determine whether the actions of physical manipulation of objects, that help understanding natural language communication (10; 11) can be identified from pressure data. Since the haptic data was not uniformly sampled, it was sub-sampled at 50 Hz after removing outliers. The data was subsequently filtered with a moving average filter using a one-second window to remove noise.

6.2.1 *Grasp* Actions Recognition

To identify the actions of grasping different kitchen objects an experiment was performed. The data obtained from this experiment indicated that the pressure sensor readings do not change much during each object grasping action as indicated in Figure 21. So, for each action, each data sample is considered as a separate data point. For example, if an instance of a particular action lasts for 3 seconds, we have $50 \times 3 = 150$ data points for that instance. In our classification experiment, we classified each of these data points individually.

Table XXI summarizes the results obtained by the classification method kNN(53). Before applying kNN, the dimensionality of the data is reduced by applying principal component analysis (PCA) (56). kNN is then applied only on the first 3-5 principal components which contain 80% of the total data information. Half of the data from experiments is stored as training data and the remaining half is identified using the stored instances.

Table XXI represents the results obtained by kNN after using PCA with k=5. It is observed that varying the value of k from 1-10 does not affect the results much.

Figure 22 shows the objects used to collect grasp action data during laboratory experiments.

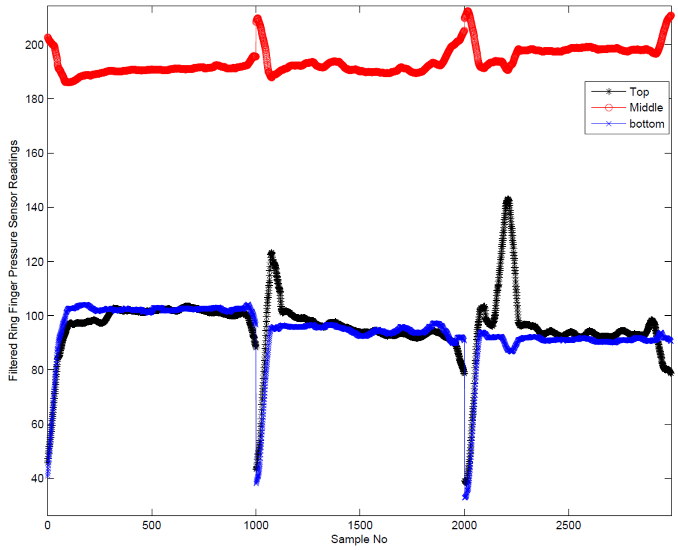

Figure 21: Ring Finger Readings During Grasping of a Food Can

6.2.2 Open/Close Actions Recognition

The annotation of first user study data (Section 3.1) indicated that in addition to grasping different kitchen items the actions of opening and closing cabinets and drawers occur very frequently when a helper assists an elderly in ADLs. Again, in order to recognize these actions, experiments were performed in the laboratory involving opening and closing drawers and cabinets. The data obtained from these experiments indicated that unlike grabbing kitchen items, these actions of opening and closing have a time varying sequence of pressure sensor readings as shown in Figure 23. Since the data was a temporal sequence, it could not be recognized using the classification methods like kNN and decision trees. Therefore, classification methods which are designed specifically for temporal data namely Recognition by Indexing and Sequencing

TABLE XXI: *GRASP* ACTIONS RECOGNITION RESULTS USING KNN

	Empty Hand	**Mug**	**Empty Container**	**Food Can**	**Pot**	**Tray (grasping with both Hands)**
Empty Hand	**656**	282	93	3	7	386
Mug	47	**87**	105	11	0	0
Empty Container	268	0	**36**	0	0	9
Food Can	29	0	0	**230**	14	2
Pot	20	0	0	4	**185**	4
Tray (grasping with both Hands)	60	0	1	0	2	**132**

(RISq) (55) and Dynamic Time Warping (DTW) (54) algorithms were implemented to identify different actions in the pressure sensors' data stream. These experiments were performed by two subjects, and the added results from both experiments are given in Table XXII.

Note that the numbers in Table XXII represent actions, unlike the data samples in Table XXI, and hence, are much smaller than numbers in the previous table. In the present classification procedure, 90% of the data is used for training, and the rest as test data (both training and test data came from the same subject). The experiments were repeated 10 times and the combined results are reported in Table XXII. The results obtained by RISq and DTW were not significantly different ($p>0.05$, χ^2). Table XXII presents results obtained by DTW.

While not shown in Table XXIIa, opening and closing of cabinet doors were at times confused with each other but these actions are well separated from the other actions; the same is true for opening/closing of drawers as these actions are similar as far as pressure signals are

Figure 22: Objects Used For *Grasp* Actions Recognition

concerned. As mentioned in Section 2.2.2, a six degrees of freedom inertial measurement unit (IMU) was attached to the back of the data glove. Table XXIIb shows that open and close actions can be recognized separately if the signals provided by the IMU are used. For IMU based classification, only the open/close actions of cabinet or drawer are classified at a time and DTW or RISq separates open actions with those of close actions. The training and test data selection and classification procedure is the same as that with pressure sensors data based classification.

6.2.3 *Grasp* and Open/Close Actions Recognition

Note that from a haptic data point of view, *Grasp* actions and *Open/Close* actions are inherently different: the former are static while the latter are dynamic. In other words, after contact with the object has been established, the different samples that are part of a *Grasp* action are very similar (the sensor readings do not change much). *Open/Close* actions are

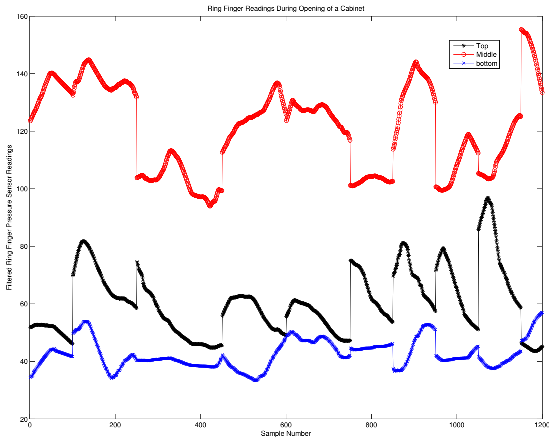

Figure 23: Ring Finger Readings During Opening of Cabinet

better seen as a time varying sequence of pressure sensor readings, as shown in Figure 21 and Figure 23. After successfully recognizing these actions separately, another experiment was performed in the laboratory where both the actions of grasping items and the actions of opening/closing of drawer/cabinet were performed in random order. The pressure data from the experiment were classified using RISq and DTW techniques of time sequence data classification. The results obtained by DTW are summarized in the Table XXIII. For this particular experiment DTW had better results than RISq ($p<0.05$, χ^2).

6.3 Naturalistic Setting Data Classification

Preferably, our methodology to automatically recognize the physical manipulation actions would be demonstrated directly on the haptic data collected via the glove from the first user study (3.1), as that data was used for natural language processing (10; 11). Unfortunately, this

TABLE XXII: OPEN/CLOSE ACTIONS RECOGNITION RESULTS

(a) Classification Based on Pressure Sensors Data

	Open/Close Cabinet	**Open/Close Drawer**	**Empty Hand**	**Total**
Open/Close Cabinet	**39**	1	4	44
Open/Close Drawer	3	**46**	0	49
Empty Hand	0	0	**77**	77

(b) Classification of Open-Close Actions Based on the IMU Data

	Cabinet		**Drawer**	
	Open	Close	Open	Close
Open	**20**	0	**23**	0
Close	0	**19**	0	**23**

was not possible because the collected haptic data turned out to be corrupt. The *a posteriori* analysis identified that the pressure sensor data was corrupted due to an outer glove that was worn over the fabricated glove to help with the computer vision algorithms (see the yellow gloves on the helper's hands in Figure 10). We thus had to collect additional data to develop the automatic recognition algorithms for physical manipulation actions. We collected data in the same mock apartment at Rush University where we had collected the first user study data driven by two goals: (1) to collect naturalistic data as similar as possible to the user study data (same environment, same tasks) with coherent haptic signals, on which to evaluate the recognition algorithms; and (2) to collect additional haptic data that would involve multiple repetitions of the same action in a naturalistic setting. The problem with completely naturalistic data is that in practice the same haptic action is never repeated: even when subjects open or close the same cabinet, their body position with respect to the cabinet subtly varies from one instance to the next, and affects the haptic signals. Since various actions in the naturalistic setting are rather sparse, such variability would pose a challenge for automatic recognition. In particular, we need at least two instances of an action in order to perform recognition experiment so that one instance can be used for training, while the other is used as a test data (please note that each action is a time series of samples). After our subjects were done with the experiments mirroring the user study experiments, we thus asked them to repeat certain actions. As a result, the experiments produced two additional sets of data: the naturalistic data mirroring the user study experiments, that we call *Naturalistic Validation* (NatVal) set; and data with forced repetitions, which we call *ForcedRep* set.

For our experiments, four pairs of subjects wear the same equipment as in the user study data collection, and perform the same ADLs (Section 3.3). Our subjects were young adults (UIC students); one subject played the role of the helper, and one the role of the elderly person. Additionally, at the end of the naturalistic tasks, we asked three helpers to grasp kitchen items and open/close cabinets/drawers multiple times. The helper wore the data glove described in Section 2.2.2. Video of the experiments was recorded through cameras installed in the mock apartment. This video was then synchronized with the glove data using the time stamps of glove data. Since the haptic data was not uniformly sampled, we subsampled it at 50Hz after removing outliers. The data was subsequently filtered with a moving average filter using a 1 second window to remove noise.

Table XXIV presents the frequency distribution of actions among the four HELper subjects, in the *NatVal* set. Table XXV presents the frequency distribution of physical manipulation actions in the *ForcedRep* set.

We performed three classification experiments: (1) using cross-validation on *NatVal* set; (2) using cross-validation on *ForcedRep* set; and (3) using the *ForcedRep* set to train a model, which was in turn used to classify the *NatVal* set. In all cases, the classification was performed within a subject. In other words, the training data and the test data in each experiment came from the same subject. For clarity, we report the recognition results for actions which are similar with respect to the pressure sensor readings as one action; in the experiments these actions were treated as distinct. In particular, *Grasp Plate* groups holding plate with one hand, holding a plate with one hand and another person, holding a plate with both hands, holding a plate with both hands and another person, and holding three plates with both hands; *Grasp Pot* groups holding a pot with one hand, holding a pot with two hands, and holding a pot with one hand and another person; and *Grasp Small Items* groups holding a spoon, holding a ladle, holding an ice-cube tray, holding a glass, holding a soda can and holding an empty jar.

6.3.1 Cross-validation on NatVal set

Table XXVI shows the recognition frequencies for the DTW algorithm when both training data and test data came from the *NatVal* set. The results obtained with RISq algorithm were similar to those obtained with DTW algorithm ($p>0.05$, χ^2). We used between 50% and 90% of the data for training (depending on whether we had at least 10 instances of the action or not), and the rest as test data (both training and test data came from the same subject).

The experiments were repeated 10 times or until each data combination could be used for testing, whichever was lower. While not shown in Table XXVI, opening and closing of cabinet were at times confused with each other but these actions are well separated from the other actions; the same is true for opening/closing of drawers. Overall 67.9% of the total of 183 physical manipulation actions are correctly classified to the right group. In our earlier work, we also demonstrated successful classification of different physical manipulation actions within one group (Chapter 5: manipulation of planar object).

6.3.2 Cross-validation on ForcedRep set

Table XXVII shows the recognition results for the DTW algorithm when both training data and test data came from the *ForcedRep* set. RISq algorithm produced similar results ($p>0.05$, χ^2). As above, we used between 50% and 90% of the data for training, and the rest as test data. Training and test data came from the same subject. Again, the experiments were repeated 10 times or until each data combination could be used for testing, whichever was lower. Similarly as above, opening and closing actions (Cabinet, Drawer and Fridge) are at times confused with each other but they are well separated from the other actions. In this case, the recognition is even better than before as 94.8% of the actions are classified into the right group.

6.3.3 Across Sets: ForcedRep used to recognize NatVal

In our final experiment we used the data from the *ForcedRep* set as training data and the data from the *NatVal* set as testing data. In a sense, this is the most logical experiment: we collected repeated instances of the actions of interest performed in the natural environment; we then use those actions to classify the actions occurring during unstructured interaction, which introduces much greater variability.

The recognition frequencies are shown in Table XXVIII. These results are obtained by DTW algorithm, RISq algorithm had similar recognition results ($p>0.05$, χ^2). Note that as before, the training data and the test data were always from the same subject. The number of actions is reduced to 102 from 183 because *ForcedRep* data was not collected for HEL 1; and, for HEL 3, repeated *Open/Close Cabinet* data was not collected. In this case, 58.8% of the 102 physical manipulation actions are classified as belonging to the right group. Not surprisingly, performance is worse than for cross-validation on the *ForcedRep* set, but it is comparable to the performance for cross-validation on the *NatVal* set.

6.3.4 Classification of Open/Close Actions Based on IMU Data

Open and *Close* are marked as separate physical manipulation actions for natural language processing (36; 11). However, the recognition algorithms used for the experiments in Section 6.3.3 were not able to distinguish between them, as these actions are similar as far as pressure signals are concerned. As mentioned in Section 2.2.2, a 6 degree of freedom inertial measurement unit (IMU) is attached to the back of the data glove. Table XXIX shows that open and close actions can be recognized if the signals provided by the IMU are used. The classification results obtained with DTW algorithm are reported, the results obtained with RISq algorithm were also similar ($p>0.05$, χ^2).

6.4 Summary

The motivational user study showed that physical manipulation actions play a crucial role in multimodal interaction. Hence, further data collection was performed in the laboratory to study whether physical manipulation actions can be automatically recognized from the haptic data collected through a sensory data glove instrumented with pressure sensors. Machine learning experiments were conducted that showed that the physical manipulation actions of interest can be recognized even though pressure sensors are relatively imprecise and the data provided by the sensory glove is noisy. Finally, we demonstrated that *Open* and *Close* actions that are difficult to distinguish from pressure sensor signals can be recognized using inertial measurement unit (IMU) readings.

Future work includes testing the developed methodology on a robotic platform. A preliminary implementation is underway in ROS, including a real-time implementation of the physical manipulation action recognition algorithms, and we are planning experiments with a Nao robot.

TABLE XXIII: GRASP AND OPEN/CLOSE ACTIONS RECOGNITION RESULTS

(a) Classification Based on Pressure Sensors Data

	***Open/Close* Actions**		***Grasp* Actions**						**Total**
	Cabinet	Drawer	Empty bottle	Empty Container	Mug	Pot	Stuffed Toy	Food Can	
***Open/Close* Actions**									
Cabinet	**10**	2	0	0	0	0	0	0	12
Drawer	1	**10**	0	1	0	0	0	0	12
***Grasp* Actions**									
Empty Bottle	0	0	**3**	0	0	0	1	1	5
Empty Container	0	0	1	**4**	0	0	0	0	5
Mug	1	0	2	1	**1**	0	0	0	5
Pot	1	0	0	0	0	**4**	1	0	6
Stuffed Toy	0	1	0	0	0	0	**5**	0	6
Food Can	0	0	0	4	0	0	0	**1**	5

(b) Classification Among Open-Close Actions Based on IMU Data

	Cabinet		**Drawer**	
	Open	Close	Open	Close
Open	5	0	4	0
Close	1	4	1	5

TABLE XXIV: FREQUENCY DISTRIBUTION OF ACTIONS IN THE *NATVAL* SET

	HEL 1	**HEL 2**	**HEL 3**	**HEL 4**	**Total**
Open/Close Cabinet	13	13	24	17	**67**
Open/Close Drawer	16	0	17	4	**37**
Grasp Plate	3	4	2	8	**17**
Grasp Pot	8	6	5	4	**23**
Grasp Small Items	3	6	4	4	**17**
Idle Hand	8	4	8	2	**22**
Total	**51**	**33**	**60**	**39**	**183**

TABLE XXV: FREQUENCY DISTRIBUTION OF ACTIONS IN THE *FORCEDREP* SET

	HEL 2	**HEL 3**	**HEL 4**	**Total**
Open/Close Cabinet	3	0	15	**18**
Open/Close Drawer	20	11	8	**39**
Open/Close Fridge	6	0	0	**6**
Grasp Plate	11	23	9	**43**
Grasp Pot	0	0	31	**31**
Grasp Small Items	8	14	0	**22**
Idle Hand	0	4	30	**34**
Total	**48**	**52**	**93**	**193**

TABLE XXVI: CONFUSION MATRIX FOR CROSS-VALIDATION ON THE *NATVAL* SET

	Open/ Close Cabinet	**Open/ Close Drawer**	**Grasp Plate**	**Grasp Pot**	**Grasp Small Items**	**Idle Hand**	**Total**
Open/Close Cabinet	**53**	5	3	1	0	5	**67**
Open/Close Drawer	2	**28**	0	0	3	4	**37**
Grasp Plate	4	2	**6**	0	3	2	**17**
Grasp Pot	4	1	1	**17**	0	0	**23**
Grasp Small Items	5	2	2	2	**5**	1	**17**
Idle Hand	1	4	1	0	1	**13**	**20**
Total	**69**	**42**	**13**	**20**	**12**	**25**	**183**

TABLE XXVII: CONFUSION MATRIX FOR CROSS-VALIDATION ON THE *FORCEDREP* SET

	Open/ Close Cabinet	**Open/ Close drawer**	**Open/ Close Fridge**	**Grasp Plate**	**Grasp Pot**	**Grasp Small Items**	**Idle Hand**	**Total**
Open/Close Cabinet	**18**	0	0	0	0	0	0	**18**
Open/Close Drawer	0	**38**	0	0	1	0	0	**39**
Open/Close Fridge	0	0	**6**	0	0	0	0	**6**
Grasp Plate	0	0	0	**42**	1	0	0	**43**
Grasp Pot	0	0	0	0	**31**	0	0	**31**
Grasp Small Items	5	0	0	0	3	**44**	0	**52**
Idle Hand	0	0	0	0	0	0	**4**	**4**
Total	**23**	**38**	**6**	**42**	**36**	**44**	**4**	**193**

TABLE XXVIII: CONFUSION MATRIX WHEN *NATVAL* DATA IS RECOGNIZED USING *FORCEDREP* SET

	Open/ Close Cabinet	**Open/ Close drawer**	**Open/ Close Fridge**	**Grasp Plate**	**Grasp Pot**	**Grasp Small Items**	**Idle Hand**	**Total**
Open/Close Cabinet	**20**	4	0	5	1	0	0	**30**
Open/Close Drawer	0	**26**	0	1	0	3	0	**30**
Open/Close Fridge	0	1	**3**	0	0	0	0	**4**
Grasp Plate	0	5	0	**4**	3	5	0	**17**
Grasp Pot	0	0	0	0	**2**	2	0	**4**
Grasp Small Items	0	2	0	0	0	**5**	0	**7**
Idle Hand	0	7	0	0	1	2	**0**	**10**
Total	**20**	**45**	**3**	**10**	**7**	**17**	**0**	**102**

TABLE XXIX: CLASSIFICATION AMONG OPEN/CLOSE ACTIONS

	Cross-validation on *ForcedRep.*						**Cross-validation on *NatVal.***				***ForcedRep* used to predict *NatVal.***			
	Drawer		Cabinet		Fridge		Drawer		Cabinet		Drawer		Cabinet	
	Open	Close	Open	Close	Open	Close	Open	Close	Open	Close	Open	Close	Open	Close
Open	18	1	6	2	3	0	12	1	16	7	9	1	11	2
Close	1	18	0	7	0	3	4	11	11	19	4	6	5	8
Accuracy	94.74%		86.67%		100%		82.14%		66.04%		75.00%		73.08%	

CHAPTER 7

CONCLUSIONS AND FUTURE WORK

This research work identifies and explores the role physical interaction plays to improve inter-personal communication in the domain of elderly care. However, the contributions may be utilized in other areas. One particular aspect of this research is that it can have many future extensions. Such future research will realize a user friendly communication interface for robot assistants and explore the potential of physical interaction as a mode of communication. The specific contributions of this work can be divided into following areas:

7.0.1 Hardware Development

A portable hardware to measure and record the pressure information from human hand while someone is performing ADL without affecting the way one performs those actions was developed. This hardware development can be used as reference for making similar hardware for other sensors.

7.0.2 Communication Through Physical Interaction During Hand-Over

The activities which require communication through physical interaction in the domain of elderly care were identified through user study involving dyads of elderly and care-giver in a realistic setting. Analysis of physical interaction data from one of such activities, namely manipulation of planar object, was performed. This involved performing further laboratory experiment and developing classification algorithm. The classification algorithm was subsequently validated on data obtained from user study during elderly care as well as for classification in real-time. The results of this work not only prove that pressure signals contain the information that can be used for identifying the stage of collaborative manipulation.

7.0.2.1 Applications and Future Work

This research may be utilized in domains of human robot interaction other than elderly care. Some of the envisioned applications and future extensions of this particular research may be following:

- Since the experiments were performed in an uncontrolled setting the results are easier to be generalized on different hardware platforms using different sensors. Implementation of these results on robotic hardware will improve planar object hand-over between human and robot.
- As demonstrated these research findings may identify different stages of human-human hand-over in real-time.
- It may be explored how this work may be extended to hand-over of planar and non-planar objects of various shapes and weight.

7.0.3 Improving Communication Through Natural Language

It has been shown by the collaborating researchers that the information about physical manipulation actions performed during elderly care improves natural language processing by resolving third person pronouns and deictic words (36; 11). Third person pronouns and deictic words are words (such as this, that, these, those, now, then) that point to the time, place, or situation in which the speaker is speaking. In my work, I have determined how to identify physical manipulation actions based on pressure data through experiments. The results have been validated on the data obtained from elderly care experiments in a realistic setting.

7.0.3.1 Applications and Future Work

Some of the envisioned applications and future extensions of this particular research may be:

- Automatic human activity recognition for advancement of research in multimodal task-oriented human-human communication scenarios. Such automatic recognition would save the time-consuming manual annotations and facilitate the studies involving human subjects observation. Such human activity recognition through on-body tactile sensors may also be used in any other application that requires monitoring such physical manipulation activities .
- Integrate information from vision and natural language with that of physical manipulation actions classification to improve such classification.
- Learning from the pressure sensors data that how humans perform the studied physical manipulation actions and implementing that knowledge on robotic platforms for executing similar physical manipulation actions and also for object recognition based on tactile information.
- Integrating this work with the above mentioned work on hand-over to determine when the human/robot is manipulating a planar object and then determining the stage of hand-

over of that planar object, i.e. if the robot should leave the planar object or not based on whether the pressure sensors data is indicating that the object is grasped by other person.

APPENDICES

Appendix A

LABORATORY EXPERIMENTS WITH PURCHASED GLOVE

In order to understand the quality of data obtained from the purchased glove and to determine if physical manipulation actions can be recognized using the purchased glove, experiments were performed at the Robotics Laboratory of UIC.

The actions performed were grabbing of

1. small-medicine bottle.
2. cooking spray.
3. mug.
4. empty-container.
5. tomato-can
6. cooking pot

For each task, the person wearing the glove held the object for a few seconds and then released the object. This is repeated ten times for each object. The continuous stream of data was stored in a file for each object. Each data file thus consisted of sequences of alternating grasping event and idle hand event. There was one such file for each grasping action.

To classify these actions based on glove data Recognition by Indexing and Sequencing (RISq) was used which is a non-parametric technique that takes a classical pattern recognition approach modified for vector sequencing (73). RISq was trained with one instance of each of the above mentioned tasks. RISq is used for classification of discrete events whereas in our application we needed to identify the events in a continuous data stream. To achieve this goal a date window was slid over the data stream. The segments defined by the window were then the input to RISq. Since an event may be missed if the input window cuts it in the middle, the successive windows were overlapped.

TABLE XXX: EVENT RECOGNITION RESULTS

Classes	Object Holding	Idle handle Position
Medicine Bottle	32.258%	98.521 %
Cooking Spray	42.342%	66.956 %
Mug	90.26%	99.55%
Tray	91.617%	86.628%
Empty-Container	99.468%	100%
Tomato-Can	85.714%	100%
Cooking-pot	94.22%	46.358%

These results indicate that the success rate for all events identification with the exception of medicine-bottle and cooking spray grasping are quite high. However, almost no pressure signals were observed during all these events and excluding the information from pressure sensors did not affect the results. It should be noted that this recognition rate is obtained when the training and test data belong to the same subject.

As a next step towards the automatic recognition of these grasp events we tried to recognize test data from different subject than the subject for whom the training data is obtained and the results deteriorated greatly. The reason for that was the difficulties to calibrate the bend sensors of the purchased glove. We had calibrated the bend sensor readings based on the maximum and minimum values of sensors obtained during hand movement. That is when the hand is in its relaxed position each bend sensor is least bent while when the hand is made in a fist the sensors have maximum bending. So for relaxed hand we get minimum value of bend sensor and for fist we obtain the maximum value.

Due to the absence of pressure readings with the purchased glove, we did not proceed with getting more experimental data from it, as the goal of our project was to

- Determine the information obtained from pressure data.
- There are many actions during which bending of fingers does not change however the pressure applied does change. For example, holding an empty glass versus a glass full of water, opening/closing of drawer versus holding the drawer handle etc.

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	M. Javaid, M. Zefran, and B. Di Eugenio, "Communication Through Haptics: A Study of Human Collaborative Manipulation," (manuscript ready for submission).

VITA (Continued)

M. Javaid, M. Zefran, and B. Di Eugenio, "Using Pressure Sensors to Identify User Actions During Physical Interaction," (manuscript ready for submission).

B. Di Eugenio, M. Zefran, J. Ben-Arie, M. Foreman, L. Chen, S. Franzini, S. Jagadeesan, M. Javaid, and K. Ma, "Towards Effective Communication with Robotic Assistants for the Elderly: Integrating Speech, Vision and Haptics," in 2010 AAAI Fall Symposium Series, 2010.

M. Javaid, K. Hasan, and T. Izhar,"Simulation of a Fuzzy Logic controller based chasing robot," Third International Conference in Electrical Engineering (ICEE09), 2009.IEEE, pp. 1-4.

PRESENTATIONS: M. Javaid, A. Steinberg, M. Zefran, "Game-like 3-D Simulation Self-Training in Identifying and Guiding Correct Adult Teeth Placement," in techTeach@UIC Conference, October 2013 (poster).

"Communication Interface for Assistive Robot for Elderly: Integrating Haptics, Speech and Vision" at LSAMP Spring Symposium and Research conference in STEM, February 2012 (poster).

"Haptics Technology" at the Annual Conference for Women Engineers (WE13). October 2013.

"Communication Interface for Assistive Robot for Elderly: Integrating Haptics, Speech and Vision" at Committee on the Status of Women in Computing (CRA-W) Graduate Cohort 2011 Workshop. April 2011 (poster).

"Interpreting Communication through Physical Interaction during Hand-Over Task" at Graduate Student Research Forum, UIC. April 2011 (poster).

A. Steinberg, M. Javaid, M. Zefran, "Interactive CD Using Game-like 3-D Simulation for Novice Student Self-Training in Identifying and Guiding Correct Adult Teeth Placement," in ADEA Annual Session & Exhibition, September 2010.

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AWARDS AND ACHIEVEMENTS:	Selected by the Teaching & Learning Center (TLC) and Graduate College, UIC as an exemplary TA to participate as a Peer Facilitator in Campus-Wide TA Orientation for years 2012, 2013 and 2014.
	Received Chancellor's Student Service Leadership Award (CSSLA), UIC for years 2011, 2012 and 2013.
	First woman lecturer at Electrical Engineering Department of UET, Lahore.
	First woman engineer at Intech Process Automation (Pvt.) Ltd.
	Merit Scholarship holder in 1st year and 4th term of B.Sc.
	Image of developed data glove was selected as a finalist in the 2013 UIC Image of Research contest.
TEACHING EXPERIENCE:	Teaching Assistant, University of Illinois at Chicago, Chicago *Jan 2009 - May 2014* Lecturer, University of Engineering and Technology, Lahore *Dec 2005-July 2008*
SERVICE AND LEADERSHIP:	Member of Women in Science and Engineering (WISE) organization since the time of joining UIC in Fall 2008.
	Member of Society of Women Engineers (SWE) since 2012.