Collaborative human-machine interfaces for mobile manipulators.

Shamsudeen Olawale Abubakar

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COLLABORATIVE HUMAN-MACHINE INTERFACES FOR MOBILE MANIPULATORS

By

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M.S., Systems and Control Engineering, 2016
B.S., Computer Engineer, 2011

A Dissertation
Submitted to the Faculty of the
J.B. Speed School of Engineering of the University of Louisville
in Partial Fulfillment of the Requirements
for the Degree of

Doctor of Philosophy
in Electrical Engineering

Department of Electrical and Computer Engineering
University of Louisville
Louisville, Kentucky

December 2021
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A Dissertation Approved On

November 11, 2021

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DEDICATION

To a better view of things.
ACKNOWLEDGEMENTS

I would like to thank Dr. Dan Popa for guiding and advising me during my PhD studies. I am grateful for the opportunities and experiences I have had at the Next Generation Systems Lab. I would also like to thank Dr. Karla Welch, Dr. Tommy Roussel, and Dr. John Naber for taking the time out of their busy schedule to serve on my thesis defense committee.

I would like to acknowledge the help of Dr. Cynthia Logsdon’s help in the design of features of the Patient Sitter feature of the ARNA robot as well as in design of experiments to evaluate its usefulness and ease of use. I am grateful for the contributions of Dr. Indika Wijayasinghe and Dr. Mohammad Nasser Saadatzi to the formulation and development of mechanisms for the state estimation method in this work and the experienced approach to hardware implementation that Doug Jackson readily offered in different areas of this work. I acknowledge the insights on Robotics (and indeed other related and unrelated areas) that I have gotten from learned discussions with Dr. Sumit Kumar Das, Chris Robinson and other folks that have spent time at the NGS Lab during my PhD studies.

Lastly, I am grateful for my friends, family and well-wishers who have been a source of support and inspiration during this PhD journey in a manner which words would never be adequate to convey. Thank you all.
ABSTRACT

COLLABORATIVE HUMAN-MACHINE INTERFACES FOR MOBILE MANIPULATORS

Shamsudeen Olawale Abubakar

November 11, 2021

The use of mobile manipulators in service industries as both agents in physical Human Robot Interaction (pHRI) and for social interactions has been on the increase in recent times due to necessities like compensating for workforce shortages and enabling safer and more efficient operations amongst other reasons. Collaborative robots, or co-bots, are robots that are developed for use with human interaction through direct contact or close proximity in a shared space with the human users. The work presented in this dissertation focuses on the design, implementation and analysis of components for the next-generation collaborative human machine interfaces (CHMI) needed for mobile manipulator co-bots that can be used in various service industries. The particular components of these CHMI’s that are considered in this dissertation include:

- Robot Control: A Neuroadaptive Controller (NAC)-based admittance control strategy for pHRI applications with a co-bot.

- Robot state estimation: A novel methodology and placement strategy for using arrays of IMUs that can be embedded in robot skin for pose estimation in complex robot mechanisms.
• User perception of co-bot CHMI's: Evaluation of human perceptions of usefulness and ease of use of a mobile manipulator co-bot in a nursing assistant application scenario.

To facilitate advanced control for the Adaptive Robotic Nursing Assistant (ARNA) mobile manipulator co-bot that was designed and developed in our lab, we describe and evaluate an admittance control strategy that features a Neuroadaptive Controller (NAC). The NAC has been specifically formulated for pHRI applications such as patient walking. The controller continuously tunes weights of a neural network to cancel robot non-linearities, including drive train backlash, kinematic or dynamic coupling, variable patient pushing effort, or slope surfaces with unknown inclines. The advantage of our control strategy consists of Lyapunov stability guarantees during interaction, less need for parameter tuning and better performance across a variety of users and operating conditions. We conduct simulations and experiments with 10 users to confirm that the NAC outperforms a classic Proportional-Derivative (PD) joint controller in terms of resulting interaction jerk, user effort, and trajectory tracking error during patient walking.

To tackle complex mechanisms of these next-gen robots wherein the use of encoder or other classic pose measuring device is not feasible, we present a study effects of design parameters on methods that use data from Inertial Measurement Units (IMU) in robot skins to provide robot state estimates. These parameters include number of sensors, their placement on the robot, as well as noise properties on the quality of robot pose estimation and its signal-to-noise Ratio (SNR). The results from that study facilitate the creation of robot skin, and in order to enable their use in complex robots, we propose a novel pose estimation method, the Generalized Common Mode Rejection (GCMR) algorithm, for estimation of joint angles in robot chains containing composite joints. The placement study and GCMR are demonstrated using both Gazebo simulation and experiments with a 3-DoF robotic arm containing 2 non-zero link lengths, 1 revolute joint and a 2-DoF composite joint.

In addition to yielding insights on the predicted usage of co-bots, the design of control and sensing mechanisms in their CHMI benefits from evaluating the perception of
the eventual users of these robots. With co-bots being only increasingly developed and used, there is a need for studies into these user perceptions using existing models that have been used in predicting usage of comparable technology. To this end, we use the Technology Acceptance Model (TAM) to evaluate the CHMI of the ARNA robot in a scenario via analysis of quantitative and questionnaire data collected during experiments with eventual uses.

The results from the works conducted in this dissertation demonstrate insightful contributions to the realization of control and sensing systems that are part of CHMI’s for next generation co-bots.
TABLE OF CONTENTS

ACKNOWLEDGEMENTS iv
ABSTRACT v
LIST OF TABLES xi
LIST OF FIGURES xii

CHAPTER 1: INTRODUCTION 1
  1.1 Challenges 4
  1.2 Contributions 6
  1.3 List of Research and Development activities 8
  1.4 Dissertation Organization 8

CHAPTER 2: BACKGROUND 10
  2.1 Control of Collaborative Robots 10
  2.2 Pose estimation for Robots and Humans in collaborative HRI. 14
  2.3 Human perception of co-bot CHMI 17
  2.4 Adaptive Robotic Nursing Assistant (ARNA) 20
    2.4.1 Hardware Platform 21
    2.4.2 Instrumentation 21
    2.4.3 Interfaces 24
  2.5 Summary 26

CHAPTER 3: NEUROADAPTIVE CONTROLLER FOR MOBILE ROBOT BASE 27
  3.1 Neuroadaptive controller 27
  3.2 Admittance control with NAC for an Omnidirectional Robot 29
  3.3 Simulated Implementation 31
    3.3.1 NAC Implementation 31
3.3.2 Simulation Experiments

3.4 Hardware Implementation

3.4.1 Considerations for Hardware Implementation of NAC on ARNA robot

3.4.2 User Experiments

3.5 Discussion

3.6 Summary

CHAPTER 4: ROBOT STATE ESTIMATION USING IMU

4.1 Method Formulation

4.1.1 DCMR

4.1.2 GCMR

4.2 Experimental Testbeds

4.2.1 Hardware Testbed

4.2.2 Simulation Setup

4.2.3 Metrics

4.3 Selection of Optimally placed IMUs

4.3.1 IMU Placement Study using DCMR

4.3.2 Magnetometer Selection for GCMR

4.3.3 Viable IMU Configurations for GCMR

4.3.4 Optimal IMU Configuration Selection for GCMR

4.4 Results and Discussion

4.4.1 Hardware Results

4.4.2 Simulation Results

4.5 Summary

CHAPTER 5: USER PERCEPTION OF CO-BOT CHMI

5.1 ARNA User Sitter

5.1.1 Tablet Interface for ARNA patient sitter
### LIST OF TABLES

<table>
<thead>
<tr>
<th>Table</th>
<th>Description</th>
<th>Page</th>
</tr>
</thead>
<tbody>
<tr>
<td>3.1</td>
<td>PARAMETERS FOR ADMITTANCE MODEL AND NAC CONTROLLER.</td>
<td>33</td>
</tr>
<tr>
<td>3.2</td>
<td>Average of metrics for HRI user experiments in Square and Slope paths.</td>
<td>44</td>
</tr>
<tr>
<td>3.3</td>
<td>Average of metrics for HRI user experiments in Counter clockwise (CCW) and Clockwise (CW) paths.</td>
<td>44</td>
</tr>
<tr>
<td>4.1</td>
<td>Results of Experiment 1. ( n = 1000 ) (i.e. ( me &lt; 0.001 )).</td>
<td>60</td>
</tr>
<tr>
<td>4.2</td>
<td>JOINT RMS ERROR WITH THE TOP 5 PLACEMENT CONFIGURATIONS,* IS OPTIMAL SELECTION.</td>
<td>67</td>
</tr>
<tr>
<td>4.3</td>
<td>EFFECT OF ADDITIVE NOISE TO IMU DATA ON GCMR ESTIMATION PERFORMANCE.</td>
<td>71</td>
</tr>
<tr>
<td>4.4</td>
<td>EFFECT OF IMU PLACEMENT ERRORS.</td>
<td>71</td>
</tr>
<tr>
<td>4.5</td>
<td>COMPARISON OF 1-DOF GCMR &amp; DCMR.</td>
<td>72</td>
</tr>
<tr>
<td>5.1</td>
<td>Time breakdown of tasks performed during patient sitter experiment.</td>
<td>91</td>
</tr>
<tr>
<td>5.2</td>
<td>ANOVA analysis results of Patient user data.</td>
<td>91</td>
</tr>
</tbody>
</table>
LIST OF FIGURES

2.1 Examples of service robots used in different applications as co-bots. (a) Baxter robot. (b) Fetch robot [1]. (c) Tiago robot. (d) Lio robot [2] (e) RIBA robot [3].

2.2 Robotic skin to facilitate pHRI. (a) On PR2 robot manipulator. (b) On custom Octocan to be used as human user input interface [4]

2.3 Impact of Fluency and other human affects on robot use and comfort as noted in literature.

2.4 ARNA robot with a user in User walker mode.

2.5 Top-view diagram of sensors placed around the ARNA robot. Physically, sensors were installed and wired to modular sensor boxes that include bump, IR, IMU, and ultrasonic units.

2.6 Architecture of a novel protocol that was implemented to interface serial readout sensors to ROS.

2.7 Packet transmission as a function of transmission period and average throughput over packet size between the bridge protocol and brute force ROS Serial.

2.8 User using tablet interface showing camera feedback, and divot controls for base and arm teleoperation.

3.1 Admittance controller including feed-forward admittance model and inner-loop Neuroadaptive Controller (NAC)

3.2 ARNA robot with a hospital bed and IV pole in Gazebo Simulation Environment.
3.3 Joint velocities and control torque in response to force applied to the handlebar in (a) longitudinal direction, i.e., $f_x = 10$N and (b) lateral direction, i.e., $f_y = 10$N (right Panel). The dashed line is the output of the admittance model for each joint. The blue trajectories are for the no-payload condition, and the red trajectories are for the with-payload condition.

3.4 ARNA handlebar used as user interface in hardware experiments.

3.5 Paths through which user with ARNA robot pHRI experiments were conducted. Square paths consist of ABCDEFGHA, Counterclockwise (CCW) and Clockwise (CW) paths consist of BDFHB and BHFDB respectively and Slope path consists IJI.

3.6 Joint velocities and control torque in response to force applied to the handlebar in a sample (a) Square path experiment and (b) Slope path experiment. The dashed line is the output of the admittance model which is reference velocity for each joint. The blue trajectories are feedback velocities for each joint.

3.7 Average Robot torque per user in different paths.

3.8 Average User Effort per user in different paths.

3.9 (a) Average Total robot Jerk in Square and Slope paths. (b) Average Total robot Jerk in CCW and CW paths.

4.1 Notations used. Joint 1 is a 1-DoF joint and Joint 2 is a 2-DoF Pitch-Roll composite joint. The link index is $i$ and the IMU index is $j$.

4.2 2 joint 3-DoF two-link arm with IMU sensors.

4.3 Custom PCB on each link of the test robot.

4.4 (Blue) Encoder values and (red) estimated values from filtered accelerometer data ($\hat{\theta}_{s,s}$) for simulations. All accelerometer data were used for the estimation.

4.5 2-link 3-DoF arm with IMU sensors in Gazebo.

4.6 Graphical illustration of sensor distribution and indexing for the configuration $[1 0 1 0 1]$. 
4.7 RMS error of pose estimation plotted against the categories for experiment/simulation
1. $n = 1000$ (i.e. $me 0.001$). (E) - experiment, (S) - simulation. 61

4.8 Average SNR of estimated pose plotted against the categories for experiment/simulation 1. $(n = 1000)$. (E) - experiment, (S) - simulation. 62

4.9 RMS error and average SNR of pose estimation plotted against the number of accelerometers for simulation 3. $(m; 0.001$ for RMS error, $n = 1000)$. 63

4.10 RMS Errors of using magnetometers to estimate 1-DoF rotations of 3 sinusoidal reference trajectories for (a) Pitch joint of Joint 1 and (b) roll Joint of Joint 2. 66

4.11 Hardware estimation results for 3-DoF 2-link arm with all joints moving simultaneously. Solid lines are joint angles $q_{id}$ measured with joint encoders, while dashed lines are GCMR estimated joint angles $q_i$. 68

4.12 Estimation results for 3-DoF 2-link arm with joints moving one at a time. 69

4.13 Simulation estimation results for 3-DoF 2-link arm with all actuators moving simultaneously. $q_{id}$ and $q_i$, $i = 1, 2, 3$, are reference and estimated Joint 1 pitch, Joint 2 pitch and Joint 2 roll angles respectively. 70

5.1 Examples of medical equipment that can be used in a Patient Sitter application (a) Digital Infrared thermometer (b) Digital Pulse Oximeter. 75

5.2 A novel surface disinfection application of ARNA in the Patient Sitter scenario. (a) ARNA driving up to surface to be disinfected with UV light. (b) ARNA in position to disinfect surface with sprayer system. 77

5.3 Architectural connection of devices that facilitate Patient Sitter implementation. 78

5.4 ARNA tablet interface for teleoperation in Patient sitter mode. 79

5.5 Controlling ARNA arm by moving the tablet. 79

5.6 Technology Acceptance Model (TAM) proposed by [5] 80

5.7 Patient sitter experiment conducted to evaluate human user perception of the ARNA’s CHMI. 82
5.8 Robot jerk for each trial during of ARNA patient sitter experiments.

5.9 Sample trajectory of the ARNA robot during patient user experiments. Blue trajectory shows trajectory to fetch box containing items for use and red trajectory shows motion to return the box. Time interval between both trajectories is time during which user used the items in the box.

5.10 Average measures of user perceived usefulness of ARNA patient sitter.

5.11 Average measures of user perceived ease of use of ARNA patient sitter.

5.12 Some questions on users’ overall beliefs about the performance of the ARNA robot in sitter scenario.
CHAPTER 1

INTRODUCTION

Collaborative robots, or co-bots, are defined by the International Federation of Robotics (IFR) as robots intended for direct human robot interaction within a shared space, or where humans and robots are in close proximity [6]. Service robots - which are co-bots capable of being used in homes and professional settings - are increasingly mobile manipulators. Co-bots generally enhance the human user’s abilities by providing speed and/or load-bearing assistance while humans are responsible for ensuring correct execution of tasks in a given scenario. As a result, co-bots such as those used for personal physical robotic assistance intelligent social assistance are capable of shared manipulation in industrial and service settings that traditional stand-alone robots do not allow.

Human Robot Interaction (HRI) is a term used to refer to the collaboration, communication, and cooperation between humans and robots. As a field of research, it leverages and builds on work in psychology, the social sciences, ergonomics, computer science/engineering, as well as robotics, and its focus includes the design and application of robots and their application scenarios for use by/increasingly with humans [7]. This increasing focus is embodied by the inclusion of modern control, sensing and human factors in the design of modern co-bots. Main sub-fields of HRI include physical Human Robot Interaction (pHRI) [8], which looks at the development of robots that feature physical interaction with humans, and Socially assistive robotics [9] which focuses more on the development of robots that affect the behaviour and feelings of humans via social interaction. Co-bots that are capable of pHRI have been applied in industrial and social services and include the collaborative robotics arms used in human mobility assistance or mobile robots for terrain exploration and agriculture [10]. Co-bots are increasingly mobile and a famous example is
the PR-2 personal robot that has been used to provide social services including waiters [11], bartenders [12] and in giving directions [13].

One particular application area that has seen a continued increase in the demand for co-bots is the healthcare industry. Some examples of medical procedures in which robots have assisted in performing include minimally invasive surgery [14] and computer-integrated surgery [15]. In general, the application areas for robots in healthcare include surgical, robotic replacement of lost function, robot-assisted rehabilitation, behavioral therapy, personalized care and health promotion [16]. Co-bots that are capable of pHRI are in high demand in healthcare industry due in part to a shortage of nurses [17] as well as such the major potential of pHRI-capable co-bots to facilitate potential solutions that assist with safe patient handling and mobility, deliver medications, monitor patients, and assist with daily hygiene in healthcare environments [18]. These tasks are some of the more mundane and routine tasks for nurses and associated healthcare staff that are a major cause of physical injuries and musculo-skeletal disorders [19]. Therefore, the use of co-bots in assisting with the performance of these tasks will enhance the productivity and efficiency of nurses, reduce their incidence of injury and result in a safer, improved healthcare delivery overall.

Collaborative Human Machine Interface (CHMI) broadly refers to the intelligent connection between novel multi-modal arrays of sensors monitoring users and the environment, and control decisions and actions taken by co-bots to assist their human users in pHRI scenarios [20]. Safety is essential for the realization of co-bots, and while there are some definition of safety standards for co-bots such as ISO/TS 15066 (entitled Robots and robotic devices - Collaborative robots), these standards are still being improved alongside the development of these robots [21]. One thing that is clear however is to facilitate safe, efficient and comfortable physical Human-Robot Interaction (pHRI) with co-bots, there is a need for robust sensing and highly-adaptive control mechanisms for robots used in such interactions. For example, as opposed to design of closed controllers whose main focus is trajectory following, control mechanisms for collaborative robots need to incorporate human user affect and perception in robot trajectory generation and control. Moreover, CHMIs
need to use feedback data from both the robot and human to curate the interaction. These control schemes must be able to work with various human-machine interfaces to allow human users of various skill or ability levels use these robots adequately. In addition to being adaptable to large number of users and scenarios, it is also desired that control strategies for co-bots can facilitate skill transfer or rapid learning during their deployment. The increased need for adaptation in co-bots improves the need for characterizing for their safety, and as such, these control formulations need to have proofs or characterization of their performance bounds wherever possible.

Similarly, sensing mechanisms and methods that enable versatile and accurate feedback of states of human and robot agents in collaborative scenarios are required for CHMIs of next-gen co-bots. These mechanisms can also be useful for providing advanced sensing for robot state for non-collaborative robot that are used for advanced applications [22] [23] as well as being usable with sensing mechanisms used by human users in a collaborative HRI scenario. Examples of such advanced sensing mechanisms include robot skins [24] [25], which are large arrays of sensors that are envisioned to conform along the surface of a robot to facilitate multi-sensory perception of humans interacting physically with machines via touch pressure, acceleration, temperature and proximity. Recently, an increasing number of studies have focused on the fabrication [4], characterization [26] and simulation [27] of these robotic skins. While more work needs to be done in these regards to efficient data processing and structural connections of such sensors, methodologies that would facilitate their functioning are also needed. These include methods that would efficiently use the data from robotic skin and similar to provide joint state estimates. An example is the formulation of novel methods that can use data from IMU and other sensors in such robotic skin for advanced sensing of the robot or human state. While these methods can be inspired by existing joint state methods used with traditional robots, their use with co-bots or other mechanisms that can be more complex than traditional robots as part of facilitating more complicated scenarios necessitates improvements in the formulation of these methods.

Advanced control and sensing mechanisms that are being designed for use with
pHRI capable co-bots require an increased integration of human factors in their design and operation. Understanding user perceptions is typically obtained through experiments that are designed to enable users provide feedback on novel systems along themes or hypothesis that are selected to investigate certain properties of the designed system. Insights from users’ perception and beliefs about novel technological device have been studied in this manner to improve the use of these systems as has been done with technological innovations in information systems deployed in different industries. This measure of user perceptions can then be used in the verification and improvement of the design of these systems, which in the case of co-bots, include the design of control and sensing systems in the CHMI for these co-bots to make them safer and more efficient than traditional robots. With the use of co-bots - especially those capable of pHRI - a relatively recent development, investigations that facilitate an understanding of the perception of potential users of these co-bots are thus necessary to enable proper design of control and sensing mechanisms as well as facilitate the widespread usage of the co-bots.

1.1 Challenges

In this section, we briefly describe some of the challenges that must be addressed to enable the creation of CHMI for co-bots that are capable of pHRI.

**Robot Dynamics:** Efficient and appropriate control of robot dynamics is central to component of the CHMI for proper operation of a co-bot. Controlling the highly non-linear dynamics of a mobile manipulator, especially one that has flexible linkages and whose payload distribution is expected to change with changes in operating conditions, needs to be performed in a manner that is safe and robust to ensure safe interaction especially in cases where the robot is in motion. High performance dynamic control is essential for the implementation of efficient navigation behavior by the robot, especially when deployed in unstructured spaces.

Traditional control methods such as Proportional Integral Derivative (PID) controllers and classical adaptive and robust control methods are often limited in their adap-
tive capability and operation limits. While their formulation usually include proofs of stability and performance, they require significant model representation in the controller formulation, and they generally treat human/environment interaction forces/torques as disturbances. Intelligent control methods such as Fuzzy Logic [28] or Genetic Algorithm [29] based controller use machine learning approaches to estimate the robot dynamic models but rarely have any structured proofs or performance characterization of the closed-loop controlled system. Some form of characterization of this closed-loop performance is desirable in the design of controllers for co-bot in order to better understand their operational safety. The robot dynamics control methods also need to incorporate forces/torques from human users as sources of user intent, and make adequate use of increased information from modern distributed multi-modal skins to facilitate high adaptation to wide class of users. The efficient use of computation resources for the controller is also an essential consideration as that would allow the resulting co-bots to quickly adapt to changes in the environments and users' needs.

**Robot State estimation:** Improved sensing of kinematic states of both human user and robot are essential in the responsive operations of CHMI for co-bots. Traditional sensing methods such as the use of encoders in robot actuators, or visual systems can either be limited or unusable in many cases due to occlusions, cost increase, etc.

To facilitate accurate and adaptive sensing in human and co-bot HRI systems, novel sensing mechanisms - such as robot skins and sensors embedded in clothing item of human users - as well as methods that use the data from such mechanisms are desirable for use with next generation co-bots. These mechanisms and methods should facilitate estimation with complex robot mechanisms like composite joints that can be found in the mechanism of these robots and human anatomy, a capability that is not common in many existing joint state estimation methods. Since robot skins and embedded sensors are also designed to house many of sensors, these novel methods are also expected to be able to incorporate sensor data from multitude sensors. An analysis of the impact of noise in sensor data on the joint state that is estimated using these methods is also essential.
User perception of co-bots: Human users’ perception of efficacy, ease of use and usefulness of technological innovations such as office productivity software [30] and health informatics systems [31]. Works that investigate user perceptions of technology along these scales do so by having users partake in experiments which are designed to evaluate the effect the users’ cognitive and affective characterization of the technology through the user responses to post-experiment questionnaires constructed according the principles of some technology acceptance model. These works have been important to wide spread adoption of these systems that is the case today and as such have been shown to be key drivers of the adoption of these innovations.

More recent works in the area of technology adoption via user perception investigation include extending the use of these approach to hardware systems. An example of this is [32] where the authors investigate the use of a model of technology acceptance for wearable technology. While there have been increasing works showing the use of co-bots in many new applications scenarios, creating measurable systems for understanding the perception of the potential users of co-bots is an area of research that is only recently receiving more focus. Models that have been used to conduct similar work in the development of other technological products evaluate beliefs, attitudes and intentions of users as well as properties of the technology under consideration such as its complexity and trialability. Drawing inspiration from these kinds of work, it is thus necessary to evaluate the user perception of the CHMI of a co-bot to not only improve the likelihood of eventual usage of these co-bots, but also because they provide a basis for the definition of robot qualities that can controlled to improve the experience of the users of these co-bots.

1.2 Contributions

In this thesis, we present novel components for the CHMI with mobile co-bots including:

1. We formulate, implement, and evaluate a Neuroadaptive Controller (NAC) based admittance control algorithm for the omni-directional mobile base of the Adaptive
Robotic Nursing Assistant (ARNA) co-bot. While the Neuroadaptive Controller (NAC) has seen increasing deployment on different robots in recent times, all previous applications have been done with robotic arms, and its use in this work is the first that would deploy and test it as part of a control strategy for a mobile manipulator. Through patient walking experiments with 10 human users and metrics on robot performance related to user safety and overall efficiency, we evaluated the performance of the NAC in pHRI capable mobile co-bot in varied operating conditions.

2. We design, develop and evaluate the Generalized Common Mode Rejection (GCMR), which is a novel algorithm for evaluating robot poses using arrays of Inertial Measurement Units (IMU). GCMR is a novel extension of the Common Mode Rejection (CMR) class of methods for robot joint estimation. However, this novel method is capable of estimating the state of composite joints that can be found on humans and complex robot mechanisms. We analyze the effects of IMU placement parameters such as the number of sensors whose data are used, their placement location on the robot, and sensors’ noise properties on the quality of robot pose estimation and its signal-to-noise Ratio (SNR). The proposed GCMR algorithm is also validated in simulations and experiments with robotic hardware.

3. We analyze users’ perception of usefulness and ease of use of ARNA via its CHMI. This analysis was done via user experiments with the ARNA robot in a hospital environment and involved 24 student nurses whose profile are very similar to those of the professional nurses that are one of the key user demographics for the robot. The task performed in the patient sitter experiments for this purpose included remote item fetching via teleoperation of the robot and is a major operation in patient sitting. The results of this analysis would be very useful in designing interventions that can drive the actual usage of co-bots as well as provide a basis of data that can be used to define metrics for improved control as part of the CHMI for co-bots.
1.3 List of Research and Development activities

1. Implemented NAC controller algorithm to work on an omni-directional robot base used with pHRI, taking into consideration the kinematics involved with such base whose dynamics can vary depending on user and environment profiles.

2. Conducted and analyzed data from human user experiments with ARNA robot in patient walking and patient sitting scenarios in outdoor and hospital environments.

3. Software and Hardware implementation of the GCMR, a novel IMU-based robot pose estimation algorithm capable of estimating states of composite joints.

4. Developed new software assets Android Tablet tele-operation of ARNA robot, PID control, Myo Control of 7-DoF collaborative robot arm.

5. Supervised multiple wholesale hardware assembly and improvements for the Adaptive Robotic Nursing Assistant (ARNA) robot Improved reassembly, reliable simulation setup, instrumentation board, skirts, gripper interface for robot arm.

6. Implemented shared control for a collaborative arm to perform Coronavirus-focused sanitization project with ARNA robot.


8. Co-authored 8 conference/journal publications. (See list in curriculum vitae section of back matter.)

1.4 Dissertation Organization

Chapter 2 provides a background and literature survey on the CHMI topics and challenges that are addressed in this dissertation. In Chapter 3, the formulation and evaluation of a Neuroadaptive control (NAC) based admittance control strategy for the control of a mobile omnidirectional robot base of the ARNA robot is presented. Results from simulation and hardware implementations with human user experiments are presented. In Chapter 4,
the formulation, analysis and evaluation of the novel Generalized Common Mode Rejection (GCMR) method that uses IMU data and mechanism kinematics to evaluate robot joint states in complex robots is presented. Chapter 5 presents work evaluating users’ perception of usefulness and ease of use of the ARNA robot via its CHMI in the Patient Sitter scenario. Further discussions of results, conclusions as well as limitations on the work done in this dissertation are presented in Chapter 6.
CHAPTER 2

BACKGROUND

In this chapter, we provide a background on dynamics and control of collaborative robots, pose estimation for robots, and using human affect in control schemes for collaborative robots. For each of these, we present the motivations for these concepts and review significant related works as a way of providing context for works that are carried out in this dissertation.

2.1 Control of Collaborative Robots

According to the International Federation for Robotics (IFR), robots that support a human in providing a service, as opposed through automation, are in high demand with an average year on-year sales growth rate of 21% between 2017 and 2021 [33]. Of the varied fields in which service robots are used, those used in manufacturing have the fastest growth with 41% and 50% increase in their sales between 2017 and 2018. Typical examples of these type of robots include manipulator systems for healthcare delivery [34] and industrial applications [35], as well as humanoid/zoomorphic robots for use in retail/hospitality [36] and elder care [37] [38]. Autonomous Guided Vehicles (AGVs) for industrial logistics [39] [40], and mobile manipulators including those for physical therapy and rehabilitation other general uses in homes and hospitals are another group of service robots with notably rising usage [41] - [2] [42].

This demand for service robots is partially driven by the need for physical Human Robot Interaction (pHRI) capabilities to autonomously complete or support human users in the completion of tasks in dynamic environments. Some collaborative robots that have been used as service robots are shown in figure 2.1 and include an object fetch and delivery...
system in a warehouse in [1], a collaborative mobile production assistant in [43] and a part-assembly arm used in [44]. In the healthcare industry, collaborative service robots have been used in the surgeries, patient monitoring and mobility; the latter tasks falling into a category of tasks for a nursing assistant robot [45] - [3] [46]. In addition to having stricter safety requirements than traditional robots, service robots also need to be effective in cluttered, unstructured spaces and task performance and safety requirements are factors that can be explicitly considered in formulating control schemes for robots.

As control strategies that take into account external forces, the stability and performance characteristics of implicit force control strategies like Admittance and impedance control have been extensively studied in literature [47] - [48]. The goal of control techniques in this class is to provide a stable contact for the robots end-effector during robot-environment contact or to regulate the mechanical compliance of the robot for a physical human-robot interaction (pHRI) that feels natural to the human user [48] - [49]. Generally, in admittance control methods, motion is controlled after a force is measured while with impedance control methods, force is controlled after motion or deviation from a set point is measured. Classical formulations of both admittance and impedance control methods however typically depend on a known dynamic model of the robot as well as the robot-environment contact characteristics [50]. In the case of collaborative service robots, such knowledge of the robot-environment characteristic might not be fully available. For example, if the robot is one capable of taking on payloads - as is often the case in pHRI capable service robots - the dynamic model of the robot is variable in a manner that makes the robot have an unknown, time-varying center of gravity and, ultimately unbalanced load and frictional forces on each actuator. Additionally, non-linearities caused by inherent flexibility/uncertainty in the robot-user linkage increase the overall models perturbations. In the presence of these inaccuracies, relying on model-based controllers lead to performance deterioration and hence safety hazards (e.g., collision), unless conservatively-high controller gains are employed.

Therefore, to realize high performance physical collaborations between human oper-
Figure 2.1: Examples of service robots used in different applications as co-bots. (a) Baxter robot. (b) Fetch robot [1]. (c) Tiago robot. (d) Lio robot [2] (e) RIBA robot [3].
ators, robots and patients, new types of interaction control algorithms are needed to take into account large variations in robot operation conditions and human preferences, while maintaining safety during interaction. Of particular interest are control strategies that are able to incorporate factors like increased information from modern distributed sensors, utilize efficient computation abilities, and have high adaptation that would allow the resulting co-bots to remain usable in dynamic applications and conditions. More recent efforts have incorporated adaptation to these approaches in order to change the interaction performance depending on the task and user preferences [51]. In the context of mobile manipulation, such control schemes generate torque and velocity commands for both the robot base and arm based on interaction forces from the robot end-effector and/or human user.

Due to the innate adaptation in their structure, using machine learning algorithms in the design of control strategies for pHRI-capable co-bots have shown promise of better performance than controllers based on classical control techniques. Examples of such works include [52] which uses an adaptive fuzzy networks for learning model uncertainties and trajectory following of a robot manipulator. While a novel activation function is used and stability analysis presented, period-delayed repetitive training is required for the learning the model uncertainties which could be limiting in dynamic applications. In [53], the authors use a model-free Neural Network (NN) based approach with a concurrent learning from I/O data from a mobile manipulator. While this approach has an improved use in dynamic cases compared with repetitive or offline learning approaches, stability analysis for the system is not presented and only simulation results are shown. In addition to some of these limitations, robot manipulators seem to have a larger focus of the available works on control for robots that are capable of pHRI than either humanoid robots [54] and mobile robot bases. This is a significant concern because the adaptation of these intelligent control techniques can be significantly impacted by their application environment.

The Neuroadaptive controller (NAC) is a NN-based control method that leverages the properties that include the functional approximation of multilayer and recurrent networks and back-propagation techniques to to control nonlinear dynamic systems. Initially
presented by Lewis et al. [55], the NAC’s features that include the availability of a Lyapunov stability proof, non-requirement of pre-training and adaptive to robots in a wide class of system. Some of the recent works that have deployed this controller in different applications include [51] wherein the controller was deployed to the manipulator of a PR2 co-bot to achieve a shared-workspace task with a human user. [56] extended this work with the introduction of an inner-loop/outer-loop structure that allowed the inclusion prescribed error dynamics in the inner-loop and adaptive task-reference and human-intent estimation modules in the outer-loop. This was also deployed with the manipulator of a PR2-robot with a task that had more challenging safety and performance specifications. Other applications of the NAC include [57] where the NAC was used to detect interaction forces during pHRI, and in [26] automated calibration of tactile sensors for improved safety performance during pHRI.

To address the challenge of realizing CHMIs that are highly adaptive, robust in order to facilitate safe, intuitive and efficient pHRI with next-gen mobile co-bots, we present an admittance control scheme that features Neuroadaptive control for an omnidirectional robot base in this work. This control scheme is formulated in a novel manner for a mobile base of co-bot and its safety, efficacy and efficiency are evaluated by quantitative and qualitative user testing.

2.2 Pose estimation for Robots and Humans in collaborative HRI.

In order to improve the proprioceptive and heteroceptive sensing capabilities of collaborative robots (co-bots), artificial skin sensors covering the exterior surface of robotic arms have long been envisioned. Inspired by their biological counterparts, multi-modal artificial skins incorporate a constellation of embedded sensing units, such as pressure sensor arrays [58] [4], temperature transducers [59] [60] , and, more recently, inertial measurement units (IMUs) [61]. A related idea is to have such sensors embedded in clothing items that can be worn by a human agent in a collaborative HRI to facilitate overall control schemes that are more aware of the human’s motion and intent in robot trajectory generation and
general robot operation [62].

The use of robot state estimation methods that work with traditional sensing mechanisms like camera sensors, embedded optical or magnetic encoders might be costly to implement [63], limited in application [64] and generally inadequate [65]. Therefore, there is a need for portable and effective joint state estimation methods that use other cost-effective sensors such as IMUs that can be placed in robot skin or embedded in human-wearable mechanisms. Application examples where the use of IMUs is particularly warranted include legged locomotion, dual arm co-manipulation, and exoskeletons.

Although inertial data from IMUs have been used to study human biomechanics and motion analysis of prostheses and rehabilitation devices, the inclusion of IMUs in artificial robot skin opens promising avenues to supplement the perception capabilities of robots and can provide encoder-free estimation of robot pose and joint coordinates. Such a configuration will allow additional flexibility during HRI, where a multi-modal robot skin will able to both sense user forces and estimate robot pose by utilizing tactile and IMU sensor respectively. Industrial-level application of joint-estimation methods that could be used in such a robot skin include [66] where an extended Kalman filter was employed for pose estimation of 6- and 7-DoF robotic arms based on the readings obtained from IMUs mounted on the robot links. Cantelli et al. [67] presented an IMU-based method for joint angle estimation and fault detection in industrial arms. Vihonen and colleagues [68] applied a sensor fusion technique to linear accelerometers and rate gyroscopes mounted on a heavy-duty mobile manipulator, and successfully estimated its joint angles. The accuracy of Kalman Filter-based methods is significantly dependent on the accuracy of the non-trivial and drift-prone estimation of a covariance matrix.

Some estimation methods that do not rely on variance matrix estimation but on the knowledge of the kinematics of the mechanism in conjunction with IMU data include Common Mode Rejection (CMR) method [69], where one accelerometer is required on adjacent links of a joint, and the Differential Common Mode Rejection (DCMR) method [70] where at least two accelerometers are needed on adjacent links of a joint. Common
Figure 2.2: Robotic skin to facilitate pHRI. (a) On PR2 robot manipulator. (b) On custom Octocan to be used as human user input interface [4]
Mode Rejection with Gyroscope Integration (CMRGI) [71] and Common Mode Rejection with Gyroscope Differentiation (CMRGD) [72] both use one accelerometer and gyroscope on adjacent links but use different estimation algorithms, with the gyroscope data used in different ways to compensate in the estimation of fast-moving joints. While theoretic and experimental validations in [73] and [74] show that the DCMR is the most stable of the CMR based methods, none of these methods is demonstrated to work with composite joints - i.e. joints with 2 or more degrees of freedom - as can be found on a human user or sophisticated robots. The authors do not however present the effect the of IMU placement properties on the accuracy of the methods.

In this work, we present the Generalized Common Mode Rejection (GCMR) method as a CMR based method that uses accelerometer and magnetometer readings from IMUs placed on links of a robot to estimate states in simple or composite joints. A composite joint is one with 2 or more DoF and examples include the human shoulder joint or a spherical joint [75]. We also present a study of the effect of IMU placement properties including number of IMUs used and placement location on a link on the accuracy of the DCMR method.

2.3 Human perception of co-bot CHMI

Based on studies on the effect of human perception on the usage of technological innovation, studies on perceptions of safety, efficiency, and intuitiveness of co-bots via their CHMI are crucial factors for the wider adoption of service co-bots. This is analogous to the consideration of the impact of human perception of robot politeness [13], volume of dialogue exchange [76] and dialogue efficiency [77] in the usage of social robots. Many works that investigate these relationships usually use metrics that are defined for a particular application - for example social robots are more interested in the nature of interaction than the fluency of task execution - and with pHRI capable co-bots. Examples of work that look at the effect of human perception on the usage of a pHRI co-bot include [78] where the fluency of a operation involving human users carrying car parts to a shared workspace and
an anticipatory robot assembled them. Fluency is a major metric considered in this area [79] and the consideration of fluency of interaction between human and figure 2.3 shows the impact of fluency on several other properties that affect the usage of co-bot as drawn from literature. Findings from these fluency studies have also been essential in the formulation of adaptive control strategies for co-bots in these shared workspace handover tasks [80] [81].

Figure 2.3: Impact of Fluency and other human affects on robot use and comfort as noted in literature.

Systemic approaches that have been taken to investigating the effect of human perception on the adoption of technological devices include the Decomposed Theory of Planned Behaviour (DTPB) [82], which presents a model for understanding behavior of users with a technology based on the relationship between their beliefs, attitudes and intention. Perceived Characteristics of Innovating (PCI) theory shows how major characteristics of a technological innovation - namely relative advantage, compatibility, complexity, trialability, and observability can impact its actual usage [83] [84]. DTPB is extensive in its character-
ization of beliefs to an extent that it can be difficult for practical use, and while PCI is a less complex model but is more suitable for obtaining insights for improving the design and initial use of a technology over insights for improving the technology for widespread or long term use [85].

Another model that is practical to use and suitable for the evaluation of human perception of usefulness and ease of use through human is the Technology Acceptance Model (TAM) [5]. This model presents relationships between several human factors such as perceived usefulness and perceived ease of use - and acceptance for use of a technology. It is a model that has been widely studied for applications with different systems including immersive simulated learning and mobile learning systems in healthcare education [86] [87] and information systems in various fields [88]. Improvements on the TAM usually involve the inclusion of other factors that have been found to impact use of a given technology [89].

shortage of nursing staff availability as well as the necessity to reduce injuries from physical activities that are performed by patients and nurses in patient care. Nurses providing ambulatory support to patient during patient walking and the fetching of remote items by both nurses and patients as a patient sitting activity are two frequently occurring activities in patient care that makes significant contributions to these injuries. Some of the efforts that involve robots which have been taken to deploy robots that have been developed to assist in this regard include [90] [91]. Other efforts where robots have been used to support nurses in effective communication and task completion include [92] and can free professional nurses for more important critical thinking and caring roles [93]. While there are some works that have applied the TAM to investigating the desire for using service co-bots in healthcare applications [94] [95], the recent increase in their actual development for various uses in healthcare delivery means there is a need for conducting experiments on human user perceptions of usefulness and ease of use of these service co-bots via their CHMI. The findings of these experiments would be useful in the design of CHMI systems that would further facilitate their widespread use, including human-adaptive control and sensing strategy of these co-bots.
2.4 Adaptive Robotic Nursing Assistant (ARNA)

The Adaptive Robotic Nursing Assistant (ARNA) robot is a mobile manipulator that consists of an omnidirectional base with an instrumented handlebar, and a 7-DOF robotic arm. It is a service robot capable of providing physical assistance to a human user. Novel contributions in its developments are present in the multi-sensor instrumentation board for heteroceptive sensing, and the use of a neuroadaptive controller that provides tunable pHRI with different users.

The primary tasks which are intended to be achieved by the ARNA robot can be defined as:

- **User sitter**: This is a task wherein the robot monitors a user and responds to remote commands. In a hospital room, this can be useful for monitoring bedridden patients for their vitals or providing entertainment. Such item fetch-and-retrieve capability can be used by a bedridden patient.

- **User walker**: In this mode, the robot provides ambulatory support to a user while transporting an object. The objects are transported by holding them with the end effector of the robot’s arm (such as IV pole, part on a wheel platform) or having the object otherwise attached to it on the arm-riser platform (such as a hospital bed) - while a user controls the robot’s motion while walking behind it or riding on the footrests attached to the robot. In [96], we present user experiments that are conducted with the ARNA robot operating in this mode.

To carry out these tasks and potentially other complex tasks, the ARNA robot has been designed to perform the following functions:

- Autonomous navigation in unstructured environments.

- Pick and place of certain classes of objects in the environment.

- Heteroceptive sensing of environments and human health.
• Interface with a human user via physical and teleoperative means.

Many of the ideas presented in this Dissertation are implemented on and tested using the ARNA robot and the following subsections give a brief description of the robot’s system.

2.4.1 Hardware Platform

Fig. 2.4 shows the ARNA robot, a mobile robot equipped with a 7-DOF robotic arm. Constructed in-house and designed to be capable of transporting heavy loads, it has a base footprint of 1.14m x 1.14m and weighs 226.7 kg. The base uses 4 mecanum wheels to provide a capability for omnidirectional motion for efficient navigation of the cluttered and unstructured spaces in which the robot is envisioned to be used. Constructed internally using aluminium frames and layers, the robot base holds batteries, computing and associated devices including Nvidia Jetson TX2 and VersaLogic EPU 4562 Blackbird, and a Netgear Nighthawk AC1900 router to provide high-fidelity local network for interfacing and remote control of the robot. While the robot’s arm has a stated reach of 0.8m, a riser mechanism on the ARNA robot is used to extend the arm’s effective reach to 1.2m. Connecting platforms such as those that attach the arm to the riser, and the one that connects the handlebar to the force/torque sensor are designed to be adaptable for attaching another kind of arm or input interface. The connecting platform is also implemented to allow the connection of the ARNA robot to other objects such as a hospital bed or a tote bin for used for delivery in a hospital.

2.4.2 Instrumentation

A sensor system for environment sensing, early warning and emergency stopping is a key component of the ARNA robot. Fig. 2.5 shows the sensor suite that has been strategically installed on the robot.

This includes 12 ultrasonic sensors distributed around the robot for detecting approaching obstacles and infrared (IR) sensors that are placed close to the ground and act
as level sensors to detect changing heights of surfaces that the robot is navigating. Imaging sensors include an ASUS Xtion Pro Camera and Hokuyo URG LiDar. These sensors are used in a Simultaneous Localization and Mapping (SLAM) system that facilitates autonomous navigation of the robot. Emergency halting of the robot is implemented using bump sensors that when collided with, say by an object suddenly, causes an immediate stopping of the robot by disconnecting all motors from their power supply.

Sensors that facilitate pHRI with the robot include an ATI Axia 80 force-torque sensor that is installed under the handlebar to sense user interaction forces. The adapter for installing this sensor is modular in a way that facilitates quick change for maintenance and using another device for the user to use in interacting with the robot. Another force-torque sensor, Delta model by ATI-IA USA, is installed under the 7-DOF arm of the robot, which we used data in [15] to facilitate the estimation of external forces and torques on the robot’s arm in order to detect collisions and user interaction.
Robot Operating System (ROS) is the primary software implementation platform, and it facilitates a fundamentally modular development of software and is thus suited for leveraging useful robotics software that are open source available. A novel component of the ARNA instrumentation subsystem is the protocol for reading data from sensors with serial readouts from the IR, ultrasonic and bump sensors. These sensors connect to a microcontroller unit (MCU), which is in turn connected to the robot computing system running Robotics Operating System (ROS). A novel protocol provides a bi-directional asynchronous sensor data over the native hardware USB-Serial. Efficiently designed definition files facilitate packet parsing in both directions - to and from ROS and the MCU - and are used to create individual ROS topics for all available data streams. Fig. 2.6 below shows the architecture of this protocol and how it is interfaced with ROS through a bridge node.

In its essence, the novelty of this protocol is a firmware-level implementation of topics
used in the ROS network. By using customized structured message types that are passed as shown in 2.6, a lot of overhead is removed from the protocol while allowing a significant proportion of error rejection, increasing speed and fidelity at the same time. Fig. 2.7 shows a latency comparison of the novel bridge instrumentation protocol used on the ARNA robot and a typical implementation with the commonly used ROSSerial library. It shows that with the novel instrumentation protocol we implemented on the ARNA robot, packet losses occurring at measurable rates have a consistent local peak loss around the middle of the data rate sweep. This can be interpreted this as actual transmission time varying little between packet sizes and processing time generally being faster than transmission time—therefor, short packets are processed faster, but more frequently, while long packets have an effective transmission delay, allowing the MCU enough time to parse the data before the next packet finishes arriving.

2.4.3 Interfaces

Several devices are used to facilitate user interaction with the ARNA robot including a Bluetooth-enabled joystick for teleoperation. The robot’s 7-DoF manipulator is equipped with a web-based interface for diagnostics and control as well an X-box game controller for teleoperation while the robot’s handlebar with a force/torque sensor provides a pHRI
packet transmission as a function of transmission period and average throughput over packet size between the bridge protocol and brute force ROS Serial.

Figure 2.8: User using tablet interface showing camera feedback, and divot controls for base and arm teleoperation.

interface for the User walker scenario described earlier. An android tablet, as shown in Fig. 2.8, is used to develop and deploy apps to teleoperate the robot through on-screen buttons and voice commands and is used to facilitate the User sitter mode. Data from accelerometers, gyroscope and magnetometer sensors that are components of the tablet are used in implementing the tablet interface to yield an adaptive teleoperation experience for the user.

The ARNA robot is implemented to facilitate a relatively easy hardware and software incorporation of other interfaces like installing an array of robot skin sensors [4] on the
handlebar, or integrating the control systems with a human-located sensor interface like the Myo armband for recognizing activity of a nurse or rehabilitating patient [97]. More information on the ARNA robot interfaces and other components are contained in our work [96].

2.5 Summary

The control of collaborative robots require the use of novel control strategies because of the fundamental differences between the ways human/external forces are considered in control strategies for traditional robots and how they need to be considered in collaborative robots. This necessitates the development and user testing of such control strategies with collaborative robots capable of pHRI like the ARNA robot. These control strategies will perform better with a quality awareness of intent/pose of the human user as well as the robot, but limitations of common methods that have been used for similar applications include a need for covariance matrix estimation and being incapable of estimating states of composite joint. Combining this intent/pose information with human affect will result in an overall CHMI that is safe, efficient and intuitive which will improve the use of collaborative robot systems.
CHAPTER 3

NEUROADAPTIVE CONTROLLER FOR MOBILE ROBOT BASE

In this chapter, we present a robot-specific Neuroadaptive controller (NAC) for AR-NAAs mobile base that employs online learning to estimate the robots unknown dynamic model and nonlinearities. This control scheme relies on an inner-loop torque controller and features convergence with Lyapunov stability guarantees. The NAC forces the robot to emulate a mechanical system with prescribed admittance characteristics during patient walking exercises and bed moving tasks. The proposed admittance controller is implemented on a model of the robot in a Gazebo-ROS simulation environment, and its effectiveness is investigated in terms of online learning of robot dynamics as well as sensitivity to payload variations. Preliminary results on a hardware test setup are also presented.

3.1 Neuroadaptive controller

A robots dynamics in joint space can be stated as

\[ M(\theta) \ddot{\theta} + C(\theta, \dot{\theta}) \dot{\theta} + F(\dot{q}) + G(q) + \tau_d = \tau + \tau_h \]  

(3.1)

where \( \theta \in \mathbb{R}^n \) is the robots joint angles, \( M \) is the inertial/mass matrix, \( C \) is the Coriolis matrix, \( \tau_d \) is the disturbance vector, \( \tau \) is the control torque, \( \tau_h \) is the user input, and \( F \) summarizes the friction forces.

Assuming the reference trajectory in the joint space, \( \theta_r \), is known, the trajectory-following error, \( e \), and the sliding-mode error, \( r \), are defined as

\[ e = \theta - \theta_r \] 

(3.2)

\[ r = \dot{\theta} - \Lambda \dot{\theta}_r \] 

(3.3)
where \( L \) is a symmetric, positive-definite design matrix.  Incorporating 3.2 and 3.3 in 3.1, the sliding-mode error dynamics is achieved as

\[
M(\theta)(\ddot{\theta}_r - \dot{\theta} + \Lambda \dot{e}) + C(\theta, \dot{\theta})(\dot{\theta}_r - r - \Lambda e) + F(\dot{\theta}) + G(\theta) + \tau_d = \tau + \tau_h \quad (3.4)
\]

Setting \( x = [e^T \dot{e}^T \theta_r^T \dot{\theta}_r^T \dot{\theta}_r^T] \), equation (3.4) becomes

\[
M(\theta)\dot{r} + C(\theta, \dot{\theta})r + f(x) + \tau_d = \tau + \tau_h \quad (3.5)
\]

where

\[
f(x) = M(\theta)(\ddot{\theta}_r + \Lambda \dot{e}) + C(\theta, \dot{\theta})(\dot{\theta}_r + \Lambda e) + F(\dot{\theta}) + G(\theta) \quad (3.6)
\]

is a nonlinear function of unmodeled robot parameters.

The Neural Network (NN) that is used to obtain \( f(x) \) can be defined as

\[
f(x) = W^T \sigma(V^T x) + \epsilon \quad (3.7)
\]

where \( W \) and \( V \) are the ideal weights, \( \sigma \) is the activation function vector and \( \epsilon \) is the approximation error of the NN approximation.

Since the ideal weights are unknown a priori, a weight tuning algorithm is used to update the approximate NN weights \( \hat{W} \) and \( \hat{V} \). With the input to the NN being \( x \) and \( \hat{f}(x) \) be an approximation of the robot function \( f(x) \) that is provided by a Neural Network using its function approximation property, a control input can be defined as

\[
\tau = \hat{f}(x) + K_v r - v(t) \quad (3.8)
\]

where \( K_v r \) is the gain used to ensure PD performance of the closed loop system of the outer PD tracking loop with \( K_v \) is a positive definite, diagonal matrix. \( v(t) \) is signal that comes from the Lyapunov-approach based stability proof of the control law as presented in [98] and compensates for unmodelled and unstructured disturbances.
\[ v(t) = -K_z(\|\hat{Z}\|_F + Z_B)r \]  

(3.9)

with \( K_z \) is the robustifying term gain and

\[ \hat{Z} = \begin{pmatrix} \hat{W} & 0 \\ 0 & \hat{V} \end{pmatrix} \]  

(3.10)

\( \| \cdot \|_F \) is the norm, and \( Z_B \) is a bound on the NN weights.

Update equations for NN weights as obtained from the stability proof for the control strategy are:

\[ \dot{\hat{W}} = A\hat{\sigma}r^T - A\hat{\sigma}'\hat{V}xr^T - \kappa A\|r\|\hat{W} \]  

(3.11)

\[ \dot{\hat{V}} = Bx(\hat{\sigma}'TWr)^T - \kappa B\|r\|\hat{V} \]  

(3.12)

\[ \hat{\sigma}' = \text{diag}\{\sigma(\hat{V}^Tx)\}\left[I - \text{diag}\{\sigma(\hat{V}^Tx)\}\right] \]  

(3.13)

Using (3.8) in (3.5), the closed loop error dynamics of the controlled system is

\[ M(\theta)\ddot{r} = -C(\theta, \dot{\theta})r - K_vr + \tilde{f}(x) + \tau_d + v(t) \]  

(3.14)

where \( \tilde{f}(x) = f(x) - \hat{f}(x) \) is the function approximation error. The closer the update weights are to the ideal weights the closer \( \tilde{f}(x) \) is to 0.

### 3.2 Admittance control with NAC for an Omnidirectional Robot

In pHRI tasks like pushing, pulling and tugging with the ARNA robot, admittance control can be used to achieve an overall natural interaction by regulating the mechanical compliance of the robot. As a general approach, admittance control techniques achieve this objective by forcing the tracking error dynamics to follow a prescribed admittance model with virtual mass, stiffness, and damping coefficients, and, thereby enabling the robot to behave compliantly.
In an admittance control strategy, a compliant mechanical structure is typically represented as a transfer function, $G$, which is the ratio of the structure’s velocity to the forces/torques applied to the structure [99], as:

$$V(s) = G(s)F(s)$$  \hspace{1cm} (3.15)

where $F$ is the input forces/torques, $V$ is the reference admittance velocity, and $s$ is the complex frequency. A mechanical structure with a large admittance is easily set in motion with the application of small forces and torques, while a structure with a small admittance requires large acting forces and torques.

Admittance control techniques typically depend on a known dynamic model of the robot as well as the robot-environment contact characteristics [100] but the adaptive nature of the NAC relaxes this dependence. The relaxation of this dependence is essential in a mobile robotic walker like the ARNA robot that is designed for use with varying weight and placement of loads in the form of human users, attached hospital beds and medical equipment, as well as unmodeled uncertainties introduced by frictional forces that vary with different riding surfaces and impermanent attachment between user and handlebar. In our work, we use an admittance model in combination with user force/torque inputs and ARNA’s inverse kinematics to obtain user-desired reference trajectory that is tracked by the NAC.

Figure 3.1 shows the admittance control strategy used in this work. The admittance model, $G(s)$ that is used in this work is given by

$$G(s) = diag\left(\frac{1}{sM_x + D_x}, \frac{1}{sM_y + D_y}, \frac{1}{sM_\omega + D_\omega}\right)$$  \hspace{1cm} (3.16)

where $M_x/D_x$, $M_y/D_y$ and $M_\omega/D_\omega$ are desired mass or inertia/damping coefficients in the $x$, $y$ and $\omega$ directions respectively. A mass-damper structure is used for the admittance model because using this structure results in a better admittance tracking with low frequency pHRI applications like Patient Walking than other general admittance control structures [101].
3.3 Simulated Implementation

In this section, we describe the implementation of the NAC controller on the ARNA robot as implemented in Gazebo simulation environment that was interfaced with Robotics Operating System (ROS). Gazebo is an open-source software capable of dynamic simulation of sensors, robots, and their interaction with the environment based on multiple physics engines while ROS is a software framework for robot software development with services such as hardware abstraction, low-level device control, message-passing, and package management for a distributed and robust development of robotic software. Because of the ease of transfer of ROS-built assets between robots regardless of whether they are simulated or hardware, implementing the NAC in simulation allowed us to significantly reduce time for software development and controller tuning and testing before deploying NAC on the ARNA hardware.

3.3.1 NAC Implementation

To develop the Gazebo model of the ARNA robot, we first created ARNA’s CAD model in SolidWorks and utilized a plugin to convert it to a URDF format. In this model, the Mecanum wheels were simulated using Gazebo’s planar move plugin. To obtain realistic dynamic behavior of the model, we tuned its physical parameters including mass/inertia.
of different elements, coefficients of joint viscous/coulomb frictions, as well as the friction between the Mecanum wheels and the ground. We also included the model of a hospital bed and a IV pole in the simulation environment which are examples of payload that can be added to the ARNA robot in the Patient Walking scenario. The NAC controller for the ARNA was then implemented in a ROS node that interfaced with the Gazebo simulator. Figure 3.2 depicts ARNA’s model in Gazebo simulator.

![Figure 3.2: ARNA robot with a hospital bed and IV pole in Gazebo Simulation Environment.](image)

Gazebo 8.6 with ODE physics engine and ROS Kinetic on Ubuntu 16.0 were used for the simulation implementation. The Gazebo-ROS control plugin was utilized to facilitate communication between ROS packages by providing interfaces for robot joint actuation and robot data feedback. A controller update frequency of 1 KHz was used in The Gazebo-ROS simulation.

The NN used had 2 layers, 21 inputs including bias, sigmoid activation functions, 15 neurons in the hidden layer, 4 outputs, and the weight matrices initialized with small random entries. For the sake of safety, the velocity of the ARNA mobile platform is limited to 0.4 m/s, 0.4 m/s, and 0.2 rad/s, in the $x$ (longitudinal), $y$ (lateral), and $\omega$ (rotational)
directions respectively. The nature of the Patient Walking task being conducted as well as considerations to ensure that the robot can start and stop gently while needing only moderate user torques to reach desired maximum steady-state velocities in the respective directions resulted in the selection of inertia coefficients - $M_x, M_y$ and $M_\omega$ - and damping coefficients $D_x, D_y$ and $D_\omega$ - for the admittance model as defined in Table 3.1. For example, with 15 N force applied by the user in the longitudinal direction, the robot gently reaches the steady-state longitudinal velocity of 0.4 m/s in 2.5 s. Table 3.1 also show the PD and NAC gains used in these experiments.

**TABLE 3.1**

PARAMETERS FOR ADMITTANCE MODEL AND NAC CONTROLLER.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>$M_x, M_y$</td>
<td>18.75 Kg</td>
</tr>
<tr>
<td>$D_x, D_y$</td>
<td>37.5 Ns/m</td>
</tr>
<tr>
<td>$M_\omega$</td>
<td>3 kgm$^2$</td>
</tr>
<tr>
<td>$D_\omega$</td>
<td>6 Nm/rad</td>
</tr>
<tr>
<td>$K_v$</td>
<td>5 $I_4^*$</td>
</tr>
<tr>
<td>$K_z$</td>
<td>0.005</td>
</tr>
<tr>
<td>$\kappa$</td>
<td>0.07</td>
</tr>
<tr>
<td>$Z_B$</td>
<td>100</td>
</tr>
<tr>
<td>$A$</td>
<td>100 $I_4^*$</td>
</tr>
<tr>
<td>$B$</td>
<td>50 $I_4^*$</td>
</tr>
</tbody>
</table>

**3.3.2 Simulation Experiments**

Two sets of experiments that emulate the Patient Walking scenario were carried out with this simulation setup. In the first set of experiments, the ARNA robot moved with no payload and in the second experiment, ARNA robot moved with a payload in the form of 250-kg hospital bed that was fastened to the front panel of the robot base and a 5kg IV pole that connected to the robot arm. The first scenario simulates a Patient Walking
scenario or when a nurse operator docks the robot to a corner, while the second set simulates
the robot being used to transport heavy objects in Patient Walking mode, which are both
activities for which nursing assistant robots are suited [102]. In all simulations, the robot
was commanded to move starting from a standstill condition and Fig. 3.3 shows velocity
tracking results from these experiments.

Figure 3.3 shows reference and actual velocities as well as control torques in joint
space for each wheel actuator in the no-load and loaded experiments conducted with the sim-
ulation setup. Both velocity tracking results show a generally stable tracking performance.
In the with-payload scenario, there are oscillations that settle within the first second of
motion from rest and do not reoccur in the rest of the trajectory. Because these oscillations
do not occur in the no-payload scenario and are more pronounced on the front wheels of the
robot where the payload is connected than on those at the back of the robot (wheel 3 and
wheel 4), we note that these oscillations are due to the added inertia caused by the attached
payload and the roller-induced slipping of the wheels at low initial speeds. However, due to
the robustness of the mechanism of the ARNA robot, these low-amplitude, short-duration
oscillations barely transfer to the rear wheels and thus, a smooth overall user experience is
achieved in both no-payload and with-payload Patient Walking scenarios.

3.4 Hardware Implementation

In this section, we discuss considerations made for porting the NAC implementation
for software experiments described in Sec. 3.3 to the ARNA hardware for user experiments
and describe the set of experiments that we conducted to evaluate the NAC for ARNA base
in hardware.

3.4.1 Considerations for Hardware Implementation of NAC on ARNA robot

While implementing the NAC with a Gazebo-ROS setup of the ARNA robot signif-
ically reduce development time, practical considerations that are present in a hardware
setup necessitate some extra considerations. For example, while we can apply forces directly
Figure 3.3: Joint velocities and control torque in response to force applied to the handlebar in (a) longitudinal direction, i.e., $f_x = 10N$ and (b) lateral direction, i.e., $f_y = 10N$ (right Panel). The dashed line is the output of the admittance model for each joint. The blue trajectories are for the no-payload condition, and the red trajectories are for the with-payload condition.
to the admittance model in simulation, with the ARNA hardware, it is more user friendly to read user torques as they are a less noisy representation of the human user effort. Figure 3.4 shows the handle bar and F/T sensor connection on the ARNA robot with the direction of forces and torques. So although there are force readings available from the handlebar F/T sensor, in the hardware experiments, \( f_x \) and \( f_y \) are derived from \( \tau_x \) and \( \tau_y \) respectively.

\[
\begin{align*}
\tau_x & \quad f_x \\
\tau_y & \quad f_y
\end{align*}
\]

Figure 3.4: ARNA handlebar used as user interface in hardware experiments.

As stated earlier, the NAC controller was tuned in simulation and the gains obtained there were used in hardware experiments due to the high fidelity of the dynamic properties of our simulation model. The overall compliance behavior of the robot, however, depends on the bandwidth of both the prescribed admittance model and the Neuroadaptive controller. Therefore, parameters of the inner loop NAC and PD controllers were tuned such that their bandwidth was at least twice that of the admittance model, and hence, it could respond to the user input. Due to reliability considerations of the computational resources on the ARNA robot, for the hardware implementation the set update rate of the inner loop was 333 Hz compared with 125 Hz for the admittance control loop.

### 3.4.2 User Experiments

Using data from these experiments with human users of varying weights and heights acting as users in these experiments, we evaluate the pHRI performance of the robot in Patient Walking scenarios along different paths. The evaluation of the NAC-based admittance controller is done by comparing its performance in a human-robot collaborative motion of the ARNA robots through four paths against the performance of an admittance control
Figure 3.5: Paths through which user with ARNA robot pHRI experiments were conducted. Square paths consist of ABCDEFGHA, Counterclockwise (CCW) and Clockwise (CW) paths consist of BDFHB and BHFDDB respectively and Slope path consists IJI strategy with a PD controller whose gains are optimally tuned used in place of the NAC. The four paths are Square, Counterclockwise (CCW), Clockwise (CW) and Slope and shown in Fig. 3.5.

These paths were chosen to enable us evaluate the controllers’ performance in all 3 directions of motion of the omnidirectional ARNA base. In the square path, there are no rotations i.e. moving from C to E and G to A in path for square experiments shown in Fig. 3.5 are performed with the user and robot moving sideways. Clockwise and counter clockwise paths are chosen evaluate differences in performances might result from different profile of the non-rigid connection between user and robot in the Square path. The Slope
path is a 5.87° incline used to evaluate the performance of the NAC in a sample challenging environment.

At the start of a session of experiments with each user, the objective and procedure of the experiments, the potential risks, robot safety measures were verbally explained to each user with the aid of the Informed consent form as part of University of Louisville IRB number 17.0609. A demonstration of using the ARNA robot in Patient Walking mode was then shown to the user and they were allowed to move it around for 2 minutes in order to get familiar with the robot, after which the experiments commenced. The experiments consisted of each user moving the robot between markers along the stated path as quickly as was comfortable for them. Movement through each path was conducted twice, once using the NAC controller and once using the PD controller in the inner loop of the admittance controller, leading to eight data collection sessions per each user. The order of the path and controller setting were randomized to reduce carryover of user bias about the robot performance between experiments. Figure 3.6 shows a sample run of the an Patient Walker scenario user experiment in Square and Slope paths.

3.5 Discussion

While the development of the simulation environment allowed us to extensively tune the developed PD and NAC controllers, human user experiments were required to obtain the performance of the control strategy using real-life forces/torques from actual human users in real world environments. We conducted these user experiments with 10 users who had no experience using the ARNA robot before the experiments were conducted.

For objective evaluation of the accuracy, safety and efficiency of the NAC and PD controllers in an admittance control strategy in pHRI scenario, we use the following metrics:

1. Velocity tracking error: This metric is defined as

   \[
   \| V_e \|_2 = \frac{1}{N} \sum_{k=1}^{N} \| \dot{V}_r(kT) - V(kT) \|_2
   \]  

   where \( \dot{V}_r \) is the reference cartesian-space velocity vector for the robot set from the
Figure 3.6: Joint velocities and control torque in response to force applied to the handlebar in a sample (a) Square path experiment and (b) Slope path experiment. The dashed line is the output of the admittance model which is reference velocity for each joint. The blue trajectories are feedback velocities for each joint.
admittance model and $V$ is velocity feedback vector from the robot. $N$ is the number of
data samples over the experiment run being evaluated and $T = 0.02$ seconds represents the data update period.

2. User torque norm: We define this as

$$\|\tau_u\|_2 = \frac{1}{N} \sum_{k=1}^{N} \|\tau_h(kT)\|_2$$

(3.18)

to measure the effective physical effort applied by the human user to control the robot in a Patient Walking scenario and $\tau_h = [\tau_x; \tau_y; \tau_z]^T$.

3. Robot torque norm: Formulated like the user torque norm, this gives a measure of the average effort applied the wheel actuators. It is defined as

$$\|\tau_{ro}\|_2 = \frac{1}{N} \sum_{k=1}^{N} \|\tau_w(kT)\|_2$$

(3.19)

and $\tau_w = [\tau_{w1}; \tau_{w2}; \tau_{w3}; \tau_{w4}]^T$ is the wheel torque vector.

4. Jerk: This is defined as

$$J_\alpha = \int_{t_s}^{t_f} \dddot{p}(t)^2 dt \frac{(t_f - t_s)^5}{A^2}$$

(3.20)

and is a dimensionless quantity that measures the smoothness of the pHRI operations used in works like [56]. $A$ is the total length of path $p(t)$ taken by the human-robot system from start time $t_s$ to finish time $t_f$. For closer evaluation of the experiments, we also refer to $J_{\alpha x}$ and $J_{\alpha y}$ as the Jerk in X and Y directions respectively.

5. Total time: Time taken to complete a drive through a path.

Jerk gives an indication of safety of HRI while a user navigates a path with the robot, Velocity tracking error is used to compare the accuracy of the controllers while User Torque and Robot torque can be used evaluate the efficiency of the robot. These metrics have been used to evaluate control strategies for robot and HMI in [103] and [56]. The average of metrics from analyzing results from these experiments are summarized in tables 3.2 and 3.3 below.
From Table 3.2, we can see that in the Square Path scenario, the NAC has a velocity tracking performance that is up to 32% better than PD tracking performance. For the Clockwise and Counterclockwise paths, there is +1% and -8% between the average velocity error in NAC vs PD, while in the slope ground scenario, the NAC is up to 18% better. The results over different users show that the NAC is more accurate in the formulated admittance control strategy than the PD controller.

![Figure 3.7: Average Robot torque per user in different paths.](image)

![Figure 3.8: Average User Effort per user in different paths](image)

With respect to user and robot torques in the walker scenario in the experiments, the results show that the NAC controller requires up to 10% lower effort from the user.
than the PD controller. This effort is made up for by the controller where the NAC uses controller effects up to 13% more effort than the PD controller. This suggests that the NAC is more intuitive than the PD controller i.e. the NAC requires lesser effort from the user as a cue to move the robot more effectively and this intuitiveness is largest in the square path scenario.

Figure 3.9: (a) Average Total robot Jerk in Square and Slope paths. (b) Average Total robot Jerk in CCW and CW paths.

Comparing the jerk of the robot when the NAC controller is used with that experienced when the PD controller is used, there is up to a 52% less jerk in the X direction and
up to 43% less jerk in the Y direction across all 4 paths in the experiment. The biggest jerk difference between the controllers occurs in the the square path scenario and looking closer, both $J_{ax}$ and $J_{ay}$ are most significant during sideways motion - i.e. during CDE and GHA segments in the path shown in Fig. 3.5. This makes sense as sideways walk is not a natural style of motion for the human users, so there are periods where the effort exerted via the users hands changes quicker than the user can keep up with their feet, which triggers a quick corrective action to correct for this rapid change. In these situations, because the NAC is more intuitive, it is able to adjust to change the and using the more intuitive than the PD and thus able to keep up better with the human.

The combination of the NAC controller being more effective, more intuitive and resulting in less jerk of the robot leads to an average time saving of up to 6% when navigating flat ground in all directions.

3.6 Summary

In this chapter, we present a novel Neural network-based admittance control strategy for the pHRI control of ARNA, an omnidirectional nursing assistant robot. The formulation of the control strategy and its implementation on the ARNA are presented. Results of simulated implementation and user testing of the control strategy in a Patient Walking task in different scenarios with the ARNA robot are presented, and used to compare the NAC based admittance control strategy with a classical PD based admittance control strategy. These results indicate that the NAC based admittance control strategy results in a pHRI that is more accurate, responsive and requires less user effort than a classical PD based admittance control strategy.

In addition to robot control strategy of co-bots, another essential component of CHMI’s for co-bots is their sensing capability. In the next chapter, we present a novel sensing methodology that facilitates robot state estimation in complex robots and the creation of novel sensing mechanisms for next-generation co-bots.
TABLE 3.2: Average of metrics for HRI user experiments in Square and Slope paths.

<table>
<thead>
<tr>
<th>Metric</th>
<th>Square</th>
<th>PD</th>
<th>Slope</th>
<th>PD</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>NAC</td>
<td>Mean</td>
<td>std dev</td>
<td>Mean</td>
</tr>
<tr>
<td>Velocity error m/s</td>
<td></td>
<td>0.0002</td>
<td>4.7140e-05</td>
<td>0.0003</td>
</tr>
<tr>
<td>User torque norm Nm</td>
<td></td>
<td>0.4832</td>
<td>0.1527</td>
<td>0.5388</td>
</tr>
<tr>
<td>Robot torque norm Nm (Jax)</td>
<td></td>
<td>5.8062</td>
<td>0.7947</td>
<td>5.0990</td>
</tr>
<tr>
<td>Robot torque norm Nm (Jay)</td>
<td>10^12</td>
<td>0.2393</td>
<td>0.2270</td>
<td>0.5018</td>
</tr>
<tr>
<td>Robot torque norm Nm (Jxy)</td>
<td>10^12</td>
<td>0.4030</td>
<td>0.4498</td>
<td>0.7054</td>
</tr>
<tr>
<td>Total time s</td>
<td></td>
<td>95.7946</td>
<td>21.0663</td>
<td>101.8362</td>
</tr>
</tbody>
</table>

TABLE 3.3: Average of metrics for HRI user experiments in Counter clockwise (CCW) and Clockwise (CW) paths.

<table>
<thead>
<tr>
<th>Metric</th>
<th>CCW</th>
<th>PD</th>
<th>CW</th>
<th>PD</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>NAC</td>
<td>Mean</td>
<td>std dev</td>
<td>Mean</td>
</tr>
<tr>
<td>Velocity error m/s</td>
<td></td>
<td>0.0006</td>
<td>0.0003</td>
<td>0.0004</td>
</tr>
<tr>
<td>User torque norm Nm</td>
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<td>0.5575</td>
<td>0.1717</td>
<td>0.5610</td>
</tr>
<tr>
<td>Robot torque norm Nm (Jax)</td>
<td></td>
<td>6.2616</td>
<td>0.9266</td>
<td>5.4892</td>
</tr>
<tr>
<td>Robot torque norm Nm (Jay)</td>
<td>10^12</td>
<td>0.0141</td>
<td>0.0248</td>
<td>0.0123</td>
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<tr>
<td>Robot torque norm Nm (Jxy)</td>
<td>10^12</td>
<td>0.0332</td>
<td>0.0579</td>
<td>0.0322</td>
</tr>
</tbody>
</table>
CHAPTER 4

ROBOT STATE ESTIMATION USING IMU

Most modern robots are equipped with joint angle encoders for pose estimation. However, in some situations, it is not possible or not desirable to introduce encoders on all joints. To tackle such situations, one solution is to embed inertial measurement units (IMUs) into artificial skin patches placed on the robot. In this chapter, we present our work on using IMUs for estimating the pose of robot joints which had two objectives: first, we analyze the effects of design parameters such as the number of sensors, their placement on the robot, and noise properties on the quality of robot pose estimation and its signal-to-noise Ratio (SNR). In particular, we study the benefits of using large numbers of IMUs, which is possible due to the proliferation of inexpensive micro-machined sensors. This study was conducted with the Differential Common-Mode Rejection method (DCMR), which works in limited kinematic situations, for example in the case of serial 1-DoF revolute joints with non-zero link lengths. Secondly, we propose a novel pose estimation method, the Generalized Common Mode Rejection (GCMR) algorithm, for estimation of joint angles in robot chains containing composite joints.

4.1 Method Formulation

In this section, we present the DCMR formulation used to conduct a placement study with insights relevant to the use large IMU sensor arrays. We then extend DCMR to the GCMR method, a novel CMR-variant that uses robot kinematics, and arrays of accelerometers and magnetometers from IMUs on the links of the robot to estimate the pose of robot chains with arbitrary joint kinematics.
4.1.1 DCMR

This method for estimation of rotational joint angles uses kinematic constraints and a transformation of coordinates with the fundamental premise that the acceleration of the joint center can be estimated using data of accelerations and displacements of (at least) two other points on the connected links.

The DCMR method applies to robot kinematics containing 1-DOF rotational joints with non-zero link lengths, such as the one depicted in Figure 4.1 where the third rotational DOF, \( q_3 \) is held constant. As a result, the reference mechanism depicted for DCMR is a simple two-link manipulator.

Referring to the diagram in Figure 4.1 with link index \( i \) and IMU index \( j \), let \( R_{i,j} \in SO(3) \) and \( \tilde{R}_{i,j} \in SO(3) \) represent clockwise and anticlockwise rotations of \( \alpha_{i,j} \) and \( \tilde{\alpha}_{i,j} \) respectively to align an accelerometer in IMU sensor \( S_{i,j} \) to the axis attached to the

Figure 4.1: Notations used. Joint 1 is a 1-DoF joint and Joint 2 is a 2-DoF Pitch-Roll composite joint. The link index is \( i \) and the IMU index is \( j \).
link on which it is fixed. For each of the $s_i$ number of sensors on link $i$, let $\ddot{x}_{i,j} \in \mathbb{R}^3$ be the linear acceleration measured by the IMU sensor $S_{i,j}$ expressed in the $XYZ$ frame attached to the link. $r_{i,j} \in \mathbb{R}^3$ is the position vector of IMU $j$ on link $i$ with $l_{i,j}$ the link length to accelerometer $j$ on link $i$. $\ddot{x}_k \in \mathbb{R}^3$ is the acceleration at joint $k$ with respect to the frame attached to link $i$. Bold fonts are used to indicate vector quantities while scalar quantities and matrices are printed in regular font.

Fixing $q_3$ to yield a 2-DoF 2-link robot with $i = 1, 2$, $j = 1, 2$ and $k = 1$, for accelerometers on IMU sensors $S_{2,1}$ and $S_{2,2}$ on link 2, we can write:

$$R_{2,1} \ddot{x}_{2,1} = R_{2,2} \ddot{x}_2 - l_{2,2} \begin{pmatrix} \ddot{q}_1 + \ddot{q}_2 \\ (\dot{q}_1 + \dot{q}_2)^2 \end{pmatrix}$$

(4.1)

$$R_{2,2} \ddot{x}_{2,2} = R_{2,1} \ddot{x}_2 - l_{2,2} \begin{pmatrix} \ddot{q}_1 + \ddot{q}_2 \\ (\dot{q}_1 + \dot{q}_2)^2 \end{pmatrix}$$

(4.2)

Consequently, the acceleration of joint 1 measured in link 2 attached frame can be expressed in terms of measured accelerometer readings from link 2 as:

$$\ddot{x}_2 = (l_{2,2} R_{2,1} - l_{2,1} R_{2,2})^{-1}(l_{2,2} R_{2,1} \ddot{x}_{2,1} - l_{2,1} R_{2,2} \ddot{x}_{2,2})$$

(4.3)

Similarly, following the same approach for link 1 we can write:

$$\tilde{R}_{2,1} \ddot{x}_{2,1} = \tilde{R}_{2,2} \ddot{x}_2 - \tilde{l}_{2,2} \begin{pmatrix} \ddot{q}_1 + \ddot{q}_2 \\ (\dot{q}_1 + \dot{q}_2)^2 \end{pmatrix}$$

(4.4)

$$\tilde{R}_{2,2} \ddot{x}_{2,2} = \tilde{R}_{2,1} \ddot{x}_2 - \tilde{l}_{2,2} \begin{pmatrix} \ddot{q}_1 + \ddot{q}_2 \\ (\dot{q}_1 + \dot{q}_2)^2 \end{pmatrix}$$

(4.5)

Similar to derivation of (4.3), the acceleration of joint 1 measured in link 1 attached frame can be expressed in terms of measured accelerometer readings from link 1 as:

$$\ddot{x}_1 = (\tilde{l}_{1,2} \tilde{R}_{1,1} - \tilde{l}_{1,1} \tilde{R}_{1,2})^{-1}(\tilde{l}_{1,2} \tilde{R}_{1,1} \ddot{x}_{1,1} - \tilde{l}_{1,1} \tilde{R}_{1,2} \ddot{x}_{1,2})$$

(4.6)
Accelerations \( \ddot{x}_2^{1} \) and \( \ddot{x}_2^{2} \) are, however, the same acceleration measured in two coordinate frames rotated by an angle \( q_2 \) with respect to each other. Denoting the rotation matrix for a clockwise rotation of \( q_2 \) by \( R_{q_2} \), we can write

\[
\ddot{x}_2^{2} = R(q_2)\ddot{x}_2^{1}
\] (4.7)

Denoting appropriate components in the 2-D acceleration vectors with superscript \( x \) and \( z \), by geometry, we can derive

\[
q_2 = \tan^{-1}\left( \frac{\dddot{x}_2^{2,x}}{\dddot{x}_2^{2,z}} \right) - \tan^{-1}\left( \frac{\dddot{x}_2^{1,x}}{\dddot{x}_2^{1,z}} \right)
\] (4.8)

In general form for 1-DoF joints of the the joint 0 or joint 1 with \( q_3 \) fixed, we can write the DCMR method as:

\[
q_k = \tan^{-1}\left( \frac{\dddot{x}_k^{i+1,x}}{\dddot{x}_k^{i+1,z}} \right) - \tan^{-1}\left( \frac{\dddot{x}_k^{x}}{\dddot{x}_k^{z}} \right)
\] (4.9)

### 4.1.2 GCMR

The fundamental premise of the GCMR method is that the generalized rotation of a joint in a kinematic chain can be derived with data from at least 2 unique IMUs on links that are adjacent to the joint and from the structure of the matrix that encapsulates a rotation between frames attached to each link.

In addition to the definitions listed in 4.1.1, let \( \mathbf{w}_i \in \mathbb{R}^3 \) and \( \dot{\mathbf{w}}_i \in \mathbb{R}^3 \) respectively be angular velocity and angular acceleration measured by the IMU sensor \( S_{i,j} \) expressed in the \( XYZ \) frame attached to the link, and \( \mathbf{m}_i \in \mathbb{R}^3 \) is magnetometer data from an IMU sensor on link \( i \).

**Theorem 1 (Generalized Common Mode Rejection [GCMR]):** The rotation matrix, \( \mathcal{R}(\theta_k) \in SO(3) \), between two frames attached to link \( i \) and link \( i + 1 \) connected by a joint \( k \) is given by
$$R(\theta_k) = \left[ \ddot{x}_k \ m_i \ \ddot{x}_k \times m_i \right].$$

$$\left[ \ddot{x}_{k+1} \ m_{i+1} \ \ddot{x}_{k+1} \times m_{i+1} \right]^{-T}$$  \hspace{1cm} (4.10)

**Proof.** Using the notations above and noting that the effective acceleration measured at a point on a rotating link is the resultant sum of the linear acceleration of the joint to which the link is attached and the tangential acceleration experienced at that point, we can write

$$\tilde{R}_{i,j} \ddot{x}_{i,j} = \ddot{x}_i + w_i \times (w_i \times r_{i,j}) + (\dot{w}_i \times r_{i,j})$$  \hspace{1cm} (4.11)

$$R_{i+1,j} \ddot{x}_{i+1,j} = \ddot{x}_{i+1} + w_{i+1} \times (w_{i+1} \times r_{i+1,j})$$

$$+ (w_{i+1} \times r_{i+1,j})$$  \hspace{1cm} (4.12)

For link $i$, let us call a group of $s$ sensors - with $2 \leq s \leq s_i$ - an IMU configuration $c_n$, where $n$ is an IMU configuration index. We can then define $M^i_{c_n} \in \mathbb{R}^{3 \times s}$, a sensor placement matrix for IMU configuration $c_n$, as:

$$M^i_{c_n} = \left[ r_{i,1}, r_{i,2}, \ldots, r_{i,s} \right]$$  \hspace{1cm} (4.13)

For any $M^i_{c_n}$, if we select a vector in its null space, $\Lambda^i_{c_n} \in \text{null}(M^i_{c_n})$ and $\Lambda^i_{c_n} = [\lambda_{i,1}, \lambda_{i,2}, \ldots, \lambda_{i,s}]^T \in \mathbb{R}^s$, then

$$\sum_j \lambda_{i,j} r_{i,j} = M^i_{c_n} \cdot \Lambda^i_{c_n} = 0$$  \hspace{1cm} (4.14)

Multiplying equation (4.11) by $\Lambda^i_{c_n}$ yields

$$\sum_j \lambda_{i,j} \tilde{R}_{i,j} \ddot{x}_{i,j} = (\sum_j \lambda_{i,j}) \ddot{x}_k + w_i \times (w_i \times \sum_j \lambda_{i,j} r_{i,j})$$

$$+ \dot{w}_i \times (\sum_j \lambda_{i,j} r_{i,j})$$  \hspace{1cm} (4.15)

Simplifying (4.15) yields

49
\[ \ddot{x}_k^i = \frac{\sum_j \lambda_{i,j} \ddot{R}_{i,j} \cdot \ddot{x}_{i,j}}{\sum_j \lambda_{i,j}} \quad (4.16) \]

Similarly,

\[ \ddot{x}_{k}^{i+1} = \frac{\sum_j \lambda_{i+1,j} \ddot{R}_{i+1,j} \cdot \ddot{x}_{i+1,j}}{\sum_j \lambda_{i+1,j}} \quad (4.17) \]

Then, if \( \mathcal{R}(\theta_k) \in SO(3) \) is the rotation matrix between the frames attached to links \( i \) and \( i + 1 \), we can write the relationship between accelerations \( \ddot{x}_k^i \) and \( \ddot{x}_{k}^{i+1} \) as

\[ \ddot{x}_{k}^{i+1} = \mathcal{R}^T(\theta_k) \cdot \ddot{x}_k^i \quad (4.18) \]

Furthermore, for magnetometer readings \( m_i \) and \( m_{i+1} \) we can also write

\[ m_{i+1} = \mathcal{R}^T(\theta_k) \cdot m_i \quad (4.19) \]

Finally, combining equations (4.18) and (4.19) yields

\[
\begin{bmatrix}
\ddot{x}_{k}^{i+1} & m_{i+1} & \ddot{x}_{k}^{i+1} \times m_{i+1}
\end{bmatrix} = \\
\mathcal{R}^T(\theta_k) \cdot 
\begin{bmatrix}
\ddot{x}_k^i & m_i & \ddot{x}_k^i \times m_i
\end{bmatrix}
\]

which yields the resulting rotation matrix \( \mathcal{R}(\theta_k) \) in equation (4.10).

\[ \square \]

Theorem 1 indicates that the relative rotation matrix \( \mathcal{R} \) between links \( i + 1 \) and \( i \) can be estimated from magnetometers and IMU measurements on these links using equations (4.16) and (4.17). In particular, to estimate \( \mathcal{R}(\theta_k) \) we need at least one magnetometer and two accelerometers per link, so that the null-space of the sensor placement matrix is not empty. The structure of \( \mathcal{R}(\theta_k) \) with respect to the robot joint coordinates can be defined from knowledge of the robot kinematics, and then inverse kinematics solutions can be used to recover the robot pose for both 2-DoF and 3-DoF composite joints. For example, for the 2-DoF composite joint \( k \) in Fig. 4.1, \( \theta_k = [q_2, q_3] \) where \( q_2 \) is a pitch angle and \( q_3 \) is a roll angle, we can write \( \mathcal{R}(\theta_k) \) as:
\[ \mathcal{R}(\theta_k) = \mathcal{R}(q_2, q_3) = \]
\[
\begin{pmatrix}
\cos(q_2) & -\sin(q_2)\cos(q_3) & -\sin(q_2)\sin(q_3) \\
\sin(q_2) & \cos(q_2)\cos(q_3) & -\cos(q_2)\sin(q_3) \\
0 & \sin(q_3) & \cos(q_3)
\end{pmatrix}
\] (4.21)

The GCMR can be contrasted with the DCMR method. Essentially, the DCMR is capable of estimating only 1-DoF joints which could necessitate significant changes for the method to work in certain cases. For example, to estimate the state of the 1-DOF joint \( k - 1 \) in Fig. 4.1, the DCMR requires a modification wherein gravity vector measured in while the joint is in it’s zero position is used. With the GCMR method in this case, the magnetometer data already incorporated in the method in would suffice. However, due to the prototypical representation of other CMR-based methods that the DCMR represents, we use a DCMR implementation in this work to conduct an IMU placement study to obtain insights that are applicable for placement of IMU in CMR methods.

4.2 Experimental Testbeds

In this section, we describe both hardware and simulation testbeds used to test and study both the DCMR and GCMR methods for joint angle estimation. The hardware setup was also used to demonstrate the practical application of the GCMR method given electromagnetic motor interference with magnetometer readings. The simulation setups are used to conduct a IMU placement study as well as test the performance of the GCMR method under varying conditions such as additive sensor noise, and placement errors.

4.2.1 Hardware Testbed

A 3-DoF robotic arm used for the experiments in this work is shown in Fig. 4.2. It comprises of three (3) Dynamixel MX-106T permanent magnet servo motors that facilitate a simple pitch joint and a composite pitch-roll joint, placement positions for up to sixteen (16) Adafruit breakouts for LSM9DSO IMU sensors by ST Electronics, and a customized Printed
Circuit Board (PCB) to facilitate mounting and connecting the sensors and associated electronic components.

The LSM9DS0 IMU features a 3-axis accelerometer, a 3 axis-magnetometer and 3-axis gyroscope. In the ±2g linear acceleration range for which the IMUs are used in these experiments, the accelerometers are rated to have an average SNR of 26dB, sensitivity of 0.06mg/LSB and temperature drift of ±1.5 percent over -40°C to +85°C. Under the same use conditions, the magnetometers have a dynamically canceled zero-gauss level drift, magnetic sensitivity of 0.08 mgauss/LSB and ±3 percent temperature drift. This IMU has found application in several works including [104] and [105], and its performance has been evaluated in [104].

Figure 4.3 shows one of the links of the robotic arm used in this work. Each link has a
length of 0.1651m and consists of a main wooden part and a custom PCB that connects the IMUs and other electronics including 2 multiplexers and Teensy 3.2 ARM Microcontroller. Wood was chosen as a material for the links because it does not cause soft-iron distortions in the magnetic field measured by the magnetometers and it also contributes to the dampening of high-frequency vibrations. The Teensy microcontroller was programmed to provide reference trajectories to the actuating Dynamixel motors as well as to read accelerometer and magnetometer data from up to 16 IMUs at a precise 100 Hz sampling rate.

Figure 4.3: Custom PCB on each link of the test robot.

4.2.1.1 Accelerometer Calibration

Before using IMU data, the IMUs need to be calibrated to remove measurement offsets caused default transducer settings and IMU installation imperfections. The accelerometer calibration procedure aims to zero out measurement differences between IMUs placed on the same link when there is no motion. In this subsection, we describe a least-squares accelerometer calibration procedure for use with the low-g accelerometers.

For a given 3-axes accelerometer, let $A_{xm}$, $A_{ym}$ and $A_{zm}$ be measured raw data and $A_{xc}$, $A_{yc}$ and $A_{zc}$ be calibrated data. If $CP_m$ represents a calibration parameter with $m = 1, 2, ..., 16$, we denote the matrix $X \in R^{4 \times 3}$ of calibration parameters that capture
offset and axis sensitivity as:

\[
X = \begin{pmatrix}
CP_1 & CP_2 & CP_3 \\
CP_4 & CP_5 & CP_6 \\
CP_7 & CP_8 & CP_9 \\
CP_{10} & CP_{11} & CP_{12}
\end{pmatrix}
\quad (4.22)
\]

Then, we can define the calibrated acceleration measurement of each IMU as:

\[
\begin{bmatrix}
A_{xc} \\
A_{yc} \\
A_{zc}
\end{bmatrix} = \begin{bmatrix}
A_{xm} & A_{ym} & A_{zm} & 1
\end{bmatrix} \cdot X
\quad (4.23)
\]

To estimate \(X\), consider \(n_p\) number of stationary robot poses \(p\) where we take IMU data for calibration. For each \(p\), we can construct a vector of normalized accelerometer data, \(v_p\). For example, if \(p = z_{down}\), e.g. the IMU reference Z-axis pointing down as shown in Fig. 4.5, \(v_p = [0 0 1]\). Defining \(w_p\) as a 1-padded vector of raw measurements from the IMU at pose \(p\), we can then define:

\[
Y_{n_p \times 3} = \begin{bmatrix}
v_1 \\
v_2 \\
\vdots \\
v_{n_p}
\end{bmatrix}^T
\quad (4.24)
\]

\[
W_{n_p \times 4} = \begin{bmatrix}
w_1 \\
w_2 \\
\vdots \\
w_{n_p}
\end{bmatrix}^T
\quad (4.25)
\]

This allows us to estimate \(X\) as a least squares fit:

\[
Y_{n_p \times 3} = W_{n_p \times 4} \cdot X
\quad (4.26)
\]

\[
X = [W^T \cdot W]^{-1} \cdot W^T \cdot Y
\quad (4.27)
\]

In the experimental work presented in this chapter, we used \(n_p = 6\) where

\[p \in \{x_{up}, y_{up}, z_{up}, x_{down}, y_{down}, z_{down}\}\]

### 4.2.1.2 Magnetometer hard and soft iron distortion removal

Depending on the environment in which they are deployed, the magnetometers might also require calibration. Because some of the IMUs used in this work were placed in close
proximity to the Dynamixel joint actuators - which have permanent magnets - a hard iron distortion removal process [106] was implemented. This distortion removal consists of a least square procedure similar to the one described for the accelerometer calibration previously discussed.

A soft-iron calibration procedure which will correct for variations in sensitivity axes can also be applied [106]. Since links in the experimental setup for this work are made of wood however, a soft iron calibration was found to have little to no effect on the quality of the data from the magnetometers.

Please note that for higher fidelity measurements it might be necessary to deploy more complex magnetometer data pre-processing methods like magnetic anomaly detection algorithms [107] and/or calibration methods that correct temperature change effects on magnetic sensor reading [108].

4.2.2 Simulation Setup

4.2.2.1 IMU Placement Simulation setup

To conduct a study for accelerometer placement in the DCMR method, we designed a simulation setup wherein the virtual accelerometer readings were generated from the actual encoder data from the experimental data. First velocities and accelerations of the robot during these runs, $\dot{q}_s$ and $\ddot{q}_s$, were calculated as:

$$\dot{q}_s(k) = \frac{q_s(k + 1) - q_s(k - 1)}{2h} \quad (4.28)$$

$$\ddot{q}_s(k) = \frac{q_s(k + 1) - 2q_s(k) + q_s(k - 1)}{h^2} \quad (4.29)$$

where $k$ is the index of the time step and $h$ is the time step.

Then the linear acceleration $\ddot{X}_S$ measured at the center of $S$ is then given by:

$$\ddot{X}_S = R_S(\Theta) \left( J_S \ddot{\Theta} + \dot{J}_S \dot{\Theta} \right) \quad (4.30)$$

where $R_S(\Theta)$ is the rotation matrix that represents the transformation from the base coordinate accelerations to the accelerometer attached coordinate frame. To simulate the effect of sensor noise, white Gaussian noise was added to the accelerometer data as:
\[ \ddot{X}_{S,s}(k) = \ddot{X}_{S,s}(k) (1 + \kappa Y) \quad (4.31) \]
\[ Y \sim \mathcal{N}(0, 1) \quad (4.32) \]

where \( \kappa \) was adjusted so that the Signal-to-Noise (SNR) ratio of the estimated encoder values from the simulation match that of the actual experiment 20 dB. Fig. shows side-by-side, the actual accelerometer data (left) from the experiment and the simulated accelerometer data (right) in one run.

![Figure 4.4: (Blue) Encoder values and (red) estimated values from filtered accelerometer data (\( \hat{\theta}_{s,s} \)) for simulations. All accelerometer data were used for the estimation.](image)

For the placement study simulation experiments, each experiment was repeated 1000 times, i.e. \( n = 1000 \).

### 4.2.2.2 Simulation testbed

Using kinematic and inertia specifications of components of the hardware robot in Section 4.2.1, we also built a Gazebo 7.1 and ROS Kinetic simulation setup of the hardware setup described above. This simulation test-bed allows us to run the GCMR method with the mechanism moving in different trajectories that might not be feasible with the hardware.
setup. IMUs in the simulation setup were implemented using Gazebo-ROS Accelerometer and Magnetometer sensor plugins. Data from the sensors were recorded at 100Hz and re-sampled to minimize the effect of non-real time operation of Gazebo. GCMR method computations were carried out using MATLAB. While the IMUs could be placed anywhere on the links in the Gazebo simulation setup, eight (8) IMU placement positions, A to H, as used in the hardware setup are used in the Gazebo simulation setup, and are shown in Fig. 4.5.

![Figure 4.5: 2-link 3-DoF arm with IMU sensors in Gazebo.](image)

### 4.2.3 Metrics

In IMU placement study simulations, we use a SNR metric to compare the efficacy of different IMU placement configurations. For run $r$ of a 2-DoF arm with IMU placement configuration indexed $p$ and estimated joint states $\hat{q}_1$ and $\hat{q}_2$, we define a SNR measure as:

$$snr^{r,p} = 10 \log \left( \frac{\sum_{k=1}^{n_r} (\hat{q}_1^2(k) + \hat{q}_2^2(k))}{\sum_{k=1}^{n_r} (\hat{q}_1^2(k) + \hat{q}_2^2(k))} \right)$$

(4.33)
where $\hat{q}_{s,n}$ is the amplitude of the useful signal, $\hat{q}_{s,n}$ is the amplitude of the noise, and $n_r$ is the number of time steps for trial $r$. Then the mean SNR value for each configuration $p$ calculated over the trials is given as:

$$\bar{SNR}^p = \frac{1}{n_m} \sum_{r=1}^{n_m} SNR^{r,p}$$

(4.34)

where $n_m$ is the total number of trials.

Finally, in both experimentation and simulation, to evaluate the performance of the GCMR method we define the RMS error, $e_d$, for DoF $d$ as

$$e_d = \sqrt{\frac{1}{n_r} \sum_{t_i=1}^{n_r} [\hat{q}_d(t_i) - q_d(t_i)]^2}$$

(4.35)

where $\hat{q}_d$ is the estimated joint angle and $q_d$ is the reference joint angle from the encoder at time sample $t_i$. This metric has also been used in [74] and [109], and thus gives us a basis to compare results obtained in this work with results reported by others.

4.3 Selection of Optimally placed IMUs

In this section, we an IMU placement study which yielded insights that are used in an algorithm to select locations of IMUs on robot links - one magnetometer and a group of accelerometers per link - in order to minimize the pose estimation error in conjunction with the GCMR method. These errors depend on noise on the accelerometers and electromagnetic noise and interference on the magnetometers, and as such the these sensors must be experimentally evaluated prior to use with our selection method.

Using the notations defined in Section 4.1, consider $s_i$ the number of IMU sensors on link $i$. Each of these sensors, $S_{i,j}$, can be placed on link $i$ in as many 3D locations as practical. In order to select those IMU sensors on the links whose data yield the best results when used with the GCMR method, we propose the following methodology:
4.3.1 IMU Placement Study using DCMR

Due to the generally small footprint of IMU sensors, depending on the mechanism used to hold these sensors on the links of robot, there are many placement options for IMU sensors used with CMR methods for placement sensing. This situation necessitates a placement study that gives insights for IMU placement and number in order to obtain optimal estimation results with this method. In this section, we present two experiments that were conducted with the simulation setup described in Sec. 4.2.2.1 and use insights from these experiments in the implementation of the GCMR method.

In the first of these IMU placement experiment, we study the effect of placement of accelerometers on each link by considering accelerometers on each link for a 2-DOF 2-link arm and varying the the gap between the sensors and the relative placement of the pair on a link. Figure 4.6 shows a sample configuration gap and the results of experiments and simulations for several configurations are presented in Table 4.1, and Figures 4.7 and 4.8.

![Graphical illustration of sensor distribution and indexing for the configuration [1 0 1 0 1].](image)

From the trends in Fig. 4.7, we can see that it is beneficial to increase the gap between the two accelerometers for minimal pose estimation error. We also notice that given that the gap between the two accelerometers is kept constant, it is slightly more beneficial to place them closer to the end of the link. From Fig. 4.8, it can be seen that for the best resultant SNR of the estimated pose, the gap between the two accelerometers has
TABLE 4.1

Results of Experiment 1. \( n = 1000 \) (i.e. \( me < 0.001 \)).

<table>
<thead>
<tr>
<th>Gap</th>
<th>Configuration</th>
<th>Real</th>
<th>Simulation</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>( \hat{e}^p )</td>
<td>( s\text{SNR}^p )</td>
</tr>
<tr>
<td>1</td>
<td>C1: [0 0 0 1 1]</td>
<td>0.1287</td>
<td>6.81</td>
</tr>
<tr>
<td></td>
<td>C2: [0 0 1 1 0]</td>
<td>0.0938</td>
<td>9.89</td>
</tr>
<tr>
<td></td>
<td>C3: [0 1 1 0 0]</td>
<td>0.1414</td>
<td>10.07</td>
</tr>
<tr>
<td></td>
<td>C4: [1 1 0 0 0]</td>
<td>0.2168</td>
<td>12.91</td>
</tr>
<tr>
<td>2</td>
<td>C5: [0 0 1 0 1]</td>
<td>0.0659</td>
<td>13.78</td>
</tr>
<tr>
<td></td>
<td>C6: [0 1 0 1 0]</td>
<td>0.0770</td>
<td>15.92</td>
</tr>
<tr>
<td></td>
<td>C7: [1 0 1 0 0]</td>
<td>0.0882</td>
<td>16.36</td>
</tr>
<tr>
<td>3</td>
<td>C8: [0 1 0 0 1]</td>
<td>0.0810</td>
<td>17.39</td>
</tr>
<tr>
<td></td>
<td>C9: [1 0 0 1 0]</td>
<td>0.0771</td>
<td>19.15</td>
</tr>
<tr>
<td>4</td>
<td>C10: [1 0 0 0 1]</td>
<td>0.0636</td>
<td>19.79</td>
</tr>
</tbody>
</table>

To be maximized.

In a second set of experiments, we analyze the effect of the number of sensors per link on the pose estimation error and the resultant SNR. To estimate the pose of a a 2-link 2-DoF robot using DCMR in this experiment, we fuse data from \( n_1 > 2 \) and \( n_2 > 2 \) accelerometers on link 1 and link 2 respectively to obtain \( \tilde{x}_k^i \) and \( \tilde{x}_{k+1}^i \) in (4.18) by defining:

\[
A_{j_2,j_2}^1 = (l_{1,j_2}R_{1,j_2} - l_{1,j_2}R_{1,j_2})
\]

\[
A_{j_1,j_1}^2 = (l_{2,j_1}R_{2,j_1} - l_{2,j_1}R_{2,j_1})
\]

\[
\tilde{A}_{j_2,j_2}^1 = \left( \tilde{l}_{1,j_2}R_{1,j_2}^T - \tilde{l}_{1,j_2}R_{1,j_2}^T \right)
\]

\[
B_{j_1,j_1}^2 = (l_{2,j_1}R_{2,j_1} \tilde{x}_{2,j_1} - l_{2,j_1}R_{2,j_1} \tilde{x}_{2,j_1})
\]

\[
\tilde{B}_{j_2,j_2}^1 = \left( \tilde{l}_{1,j_2}R_{1,j_2}^T \tilde{x}_{1,j_2} - \tilde{l}_{1,j_2}R_{1,j_2}^T \tilde{x}_{1,j_2} \right)
\]

where \((j_1, j_1)\) and \((j_2, j_2)\) represent generalized accelerometer pairs for link 1 and link 2 respectively. Then considering all possible accelerometer pairs on link 1 and link 2, can
Figure 4.7: RMS error of pose estimation plotted against the categories for experiment/simulation 1. \( n = 1000 \) (i.e. \( \epsilon = 0.001 \)). (E) - experiment, (S) - simulation.

Define

\[
A_1 = 
\begin{pmatrix}
A_{1,1}^1 \\
\vdots \\
A_{i,i+1}^1 \\
\vdots \\
A_{i,n_2}^1 \\
\vdots \\
A_{n_2-1,n_2}^1
\end{pmatrix}
, \quad
A_2 = 
\begin{pmatrix}
A_{1,1}^2 \\
\vdots \\
A_{i,i+1}^2 \\
\vdots \\
A_{i,n_2}^2 \\
\vdots \\
A_{n_2-1,n_2}^2
\end{pmatrix}
, \quad
\tilde{A}_1 = 
\begin{pmatrix}
\tilde{A}_{1,1} \\
\vdots \\
\tilde{A}_{i,i+1} \\
\vdots \\
\tilde{A}_{i,n_2} \\
\vdots \\
\tilde{A}_{n_2-1,n_2}
\end{pmatrix}
\]

\[
B_1 = 
\begin{pmatrix}
B_{1,1}^1 \\
\vdots \\
B_{i,i+1}^1 \\
\vdots \\
B_{i,n_2}^1 \\
\vdots \\
B_{n_2-1,n_2}^1
\end{pmatrix}
, \quad
\tilde{B}_1 = 
\begin{pmatrix}
\tilde{B}_{1,1} \\
\vdots \\
\tilde{B}_{i,i+1} \\
\vdots \\
\tilde{B}_{i,n_2} \\
\vdots \\
\tilde{B}_{n_2-1,n_2}
\end{pmatrix}
\]

The corresponding least squares minimized estimates of \( \ddot{x}_2^2 \), \( \ddot{x}_2^1 \), and \( \ddot{x}_1^1 \) are then
Figure 4.8: Average SNR of estimated pose plotted against the categories for experiment/simulation 1. (n = 1000). (E) - experiment, (S) - simulation.

given as:

\[
\hat{x}_1 = (A_1^T A_1)^{-1} A_1^T B_1 \\
\hat{x}_2 = (A_1^T \tilde{A}_1)^{-1} \tilde{A}_1^T \tilde{B}_1 \\
\hat{x}_2 = (A_2^T A_2)^{-1} A_2^T B_2
\]  

which are then used in (4.18) to obtain the joint states \(q_1\) and \(q_2\).

Using this least-squares minimization over all combinations of accelerometer pairs with 2 to 101 accelerometers on each link, we perform a simulation experiment using the setup described in 4.2.2.1, with resulting SNR and pose estimation error shown in Fig. 4.9. The results show that that the improvements gained by increasing the number of accelerometers were not linear. Hence the required increase in the number of accelerometers for a certain improvement in the performance metrics seems to be an exponential relationship. Therefore, increasing the number of accelerometers to improve the pose estimation accuracy seems to offer diminishing returns.
Figure 4.9: RMS error and average SNR of pose estimation plotted against the number of accelerometers for simulation 3. (me $\geq$ 0.001 for RMS error, n = 1000).

4.3.2 Magnetometer Selection for GCMR

Since the GCMR method requires one magnetometer per link, we would like to select the one with the best performance while rotating the link through its full motion range. For each link of the mechanism, we conducted 1-DOF rotation experiments while collecting data from all magnetometers placed on that link. Following each rotation, we removed hard and/or soft iron distortion by pre-processing the magnetometer data using method(s) discussed in Section 4.2.1.1 and then estimated the rotation angle of the link. By comparing the trajectory estimation with the reference trajectory measured by a reference sensor such as an encoder or camera, we can select the optimal magnetometer, $m_{oi}$, that has the least RMS error in equation (4.35). For a link that follows a composite joint, like link 2 in our experimental setup, this step was done using the motion of each DoF of the joint separately, and the magnetometer with the lowest aggregate estimation error was selected.
4.3.3 Viable IMU Configurations for GCMR

The GCMR method requires data from a group of \( s \) accelerometers where \( 2 \leq s \leq s_i \) for each link \( i \) and we call each of this possible IMU groups an IMU configuration \( c_n \) with placement matrix \( M^i_{c_n} \) where \( n \) is IMU configuration index. To select optimal IMU configurations for accelerometer sensors, for each link \( i \), we compute the nullspace basis of all \( M^i_{c_n} \) and discard those IMU configurations with an empty basis. For the viable IMU configurations, we select linear combinations of vectors in the basis of nullspace \( M^i_{c_n} \) to form \( N^i_{c_n} \), which is an extended set of vectors. In forming \( N^i_{c_n} \), we only consider addition and subtraction combinations of the nullspace basis vectors, and do not need to consider scalar multiples of each of the basis vectors, since using such multiples with the GCMR method in equations (4.16) and (4.17) yield the same results as the basis vector from which they are derived. For a given link, there are a total of \( 2^{s_i} - s_i - 1 \) possible IMU configurations to search, thus providing an exponential complexity for our search algorithm.

4.3.4 Optimal IMU Configuration Selection for GCMR

To select the best IMU configurations, we move the joints of the mechanism through a sufficiently exciting reference trajectory, and run the GCMR method using magnetometer data from \( m^i_o \) that was selected in the "Magnetometer selection" step and accelerometer data from all possible pairs of viable IMU configurations - one from link \( i \) preceding each joint and the other from link \( i + 1 \) succeeding the joint. For each viable IMU configuration pair, we run the GCMR algorithm using all possible vector pairs from \( N^i_{c_n} \)'s from links \( i \) and \( i + 1 \), and compute the RMS error according to equation (4.35). The optimal IMU configuration is the one that yields the smallest RMS error. Table 4.1 summarizes the resulting Optimal IMU selection algorithm for use with the GCMR method.
Algorithm 4.1 Optimal IMU Selection Algorithm

Require: Best magnetometers $m^i_o$, Best null vector pair $(\Lambda^i_o, \Lambda^{i+1}_o)$ from Optimal IMU configuration pair $(c^i_o, c^{i+1}_o)$ IMU location matrices $M^i_{c_n}$ from all possible $c_n$ configurations using $s_i$ IMUs on link $i$
1: for $i$ do
2: \hspace{1cm} compute $e_m$ with $m^i_j$ under 1 DoF rotation
3: \hspace{1cm} end for
4: \hspace{1cm} $m^i_o = m^i_j$ with least $e_m$
5: \hspace{1cm} Repeat 1 - 4 for all links
6: \hspace{1cm} for all IMU configuration $c_n$ on link $i$ do
7: \hspace{2cm} if $\text{null}(M^i_{c_n}) = 0$ then
8: \hspace{3cm} discard $c_n$
9: \hspace{2cm} else
10: \hspace{3cm} compute $N^i_{c_n}$
11: \hspace{2cm} end if
12: \hspace{1cm} end for
13: \hspace{1cm} Repeat 6 - 12 for all links
14: \hspace{1cm} for all $(N^i_{c_n}, N^{i+1}_{c_n})$ do
15: \hspace{2cm} for all possible $p$ pairs of $(\Lambda^i_{c}, \Lambda^{i+1}_{c})$ do
16: \hspace{3cm} from $(N^i_{c_n}, N^{i+1}_{c_n})$ run GCMR with reference trajectory compute $e_p$
17: \hspace{2cm} end for
18: \hspace{1cm} end for
19: \hspace{1cm} $(\Lambda^i_o, \Lambda^{i+1}_o) = (\Lambda^i_c, \Lambda^{i+1}_c)$ that yield least $e_p$

4.4 Results and Discussion

4.4.1 Hardware Results

To illustrate the procedure for selection of optimal IMUs, we applied it to our hardware testbed presented in Sec. 4.2.1. To select the magnetometer with the best performance on each link, we commanded the robot arm to follow three chosen sinusoidal reference trajectories with mid-points and amplitudes that divide the entire operating range of the joint so that we can better characterize the magnetometers around different operating regions. For example for Joint 1 with an operation range of $\pi/2$ rad, we used three sinusoidal trajectories centered at $\pi/6$ rad, $\pi/4$ rad, and $5\pi/12$ rad. Each had an amplitude of $\pi/12$ rad, so that the whole operating range was covered, and a period of 2s. Fig. 4.10 show magnetometer estimation RMS error for individual 1-DOF pitch rotation of both links and roll rotation of link 2, and the results indicate that the magnetometers on the IMU sensors located in position G on link 1 and position H on link 2 have the best performance over the
rotating range of the joints. The RMS trends shown for the three trajectories are consistent with what is expected given the location of permanent magnets of the Dynamixel MX-106T motors.

![Figure 4.10: RMS Errors of using magnetometers to estimate 1-DoF rotations of 3 sinusoidal reference trajectories for (a) Pitch joint of Joint 1 and (b) roll Joint of Joint 2.](image)

For our setup described in Sec. 4.2.1, given IMU placement vectors from 8 different positions, there will be 246 possible IMU combinations. Of these combinations, we found that there are 101 viable IMU placement configurations, i.e., those with a non-empty nullspace. For all of the viable configurations, we computed the extended nullspace of their placement matrices and then use all possible pairs of nullspace vectors for each possible pair of viable placement configurations with calibrated data from IMUs placed in these configurations and magnetometers in IMU located in position G on link 1 and H on link 2 in
the GCMR method. Table 4.5 shows the joint estimation errors calculated using equation (4.35) for the best 5 viable IMU configurations, with * indicating the optimum selection of 5 IMU’s on each link at locations BCFGH-BCFGH. Fig. 4.11 shows the estimation of poses from several reference trajectories found using the optimal IMU configuration.

### Table 4.2

<table>
<thead>
<tr>
<th>IMU Configuration with locations shown in Fig. 4.5</th>
<th>RMS error (rad)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Joint 1</td>
</tr>
<tr>
<td>BCFGH-BFGH</td>
<td>0.0054</td>
</tr>
<tr>
<td>BCFH-BCFH</td>
<td>0.0989</td>
</tr>
<tr>
<td>BCGH-ABGH</td>
<td>0.0064</td>
</tr>
<tr>
<td>BFGH-BFGH</td>
<td>0.0131</td>
</tr>
<tr>
<td>CFGH-CDFG</td>
<td>0.0192</td>
</tr>
<tr>
<td>BCFGH-BCFGH *</td>
<td>0.0055</td>
</tr>
</tbody>
</table>

GCMR estimation results from separate experiments with only 1-DoF moving at time and using the optimal IMU BCFGH-BCFGH configuration are presented in Fig. 4.12. In choosing the reference trajectories for the experiments reported in Figures 4.11 and 4.12, namely the varying periods of 18s, 8s and 4s triangular or sinusoidal shapes for links 1, 2 and 3, respectively, we balanced a desire to test the method with different reference trajectory profiles with a need to ensure the physical integrity of the hardware setup over many experiment runs. In particular, the links have physical restrictions of range of motion and cable/fastener connections that will deteriorate at high frequencies and contributes to small undershoots or overshoots at points of directions changes in the movement of the links.

In both Fig. 4.11 and Fig. 4.12, we see good tracking of the actuator reference trajectories, \( q_{id} \), by the trajectories estimated using GCMR, \( q_i \). Relative to the general
trend, there are more pronounced estimation errors at points where the direction of the reference trajectories change, due to the presence of the 100th-order 0.1 Hz low-pass FIR filter used to post-process the estimation results.

### 4.4.2 Simulation Results

Fig. 4.13 shows the estimated joint angles $q_i$, $i = 1, 2, 3$, using GCMR theorem, and reference trajectories $q_{id}$ to the joint actuators in our Gezebo simulation setup. The reference trajectories were sinusoids defined as $q_{id}(t) = A_{id} \sin(w_{id}t)$ with amplitudes $A_{id}$ and angular frequencies $w_{id}$, specifically, $A_{1d} = A_{2d} = 1.4078$ rad, $A_{3d} = 1.3502$ rad, and $w_{1d} = w_{2d} = w_{3d} = 1.5708$ rad/s.
Figure 4.12: Estimation results for 3-DoF 2-link arm with joints moving one at a time.

The results in Fig. 4.13 were obtained with the same optimal IMU configuration and magnetometers that were used in hardware experiments whose results are presented in Fig. 4.11 and were used to validate our simulation setup and conduct further studies of algorithm robustness.

Table 4.3 shows results that demonstrate the GCMR’s robustness to noisy sensor data. The experiments that yield the results in this table consist of using the same reference trajectories and IMUs in the BCFGH-BCFGH IMU placement configuration that was used to obtain the results in Fig. 4.13, but with noise added to the accelerometer and magnetometer data from the IMUs. The noise that was added to the data from the sensors is additive white gaussian noise with the specified SNR. The reported RMS errors are the average of 100 simulation runs. It should be noted that the IMUs used in the hardware
Figure 4.13: Simulation estimation results for 3-DoF 2-link arm with all actuators moving simultaneously. $q_{id}$ and $q_i$, $i = 1, 2, 3$, are reference and estimated Joint 1 pitch, Joint 2 pitch and Joint 2 roll angles respectively.

Experiments are found to operate with an average SNR of 26dB.

The GCMR method is also robust to IMU placement errors. We tested the robustness of the GCMR method to such placement errors by placing the IMUs in the simulation environment at locations given by the optimal configuration’s placement position plus and some randomly assigned placement error. The results of these experiments are presented in Table 4.4 and show the robustness of the GCMR method to IMU placement errors. The reported RMS errors are the average of 100 simulation runs.

The robustness of the GCMR method to placement errors is particularly useful in applications where it might be impractical or too expensive to ensure perfect placement of the IMU sensors on links of the mechanism in positions that are optimal for GCMR.
TABLE 4.3
EFFECT OF ADDITIVE NOISE TO IMU DATA ON GCMR ESTIMATION PERFORMANCE.

| SNR (dB) | RMS error (rad) |  |  |  |
| --- | --- | --- | --- |
|  | Joint 1 | Joint 2 (Pitch) | Joint 2 (Roll) |  |
| 40 | 0.0090 | 0.0749 | 0.0834 |  |
| 35 | 0.0110 | 0.0624 | 0.0836 |  |
| 30 | 0.0097 | 0.0740 | 0.0895 |  |
| 25 | 0.0230 | 0.0664 | 0.1304 |  |
| 20 | 0.0574 | 0.0857 | 0.1493 |  |

TABLE 4.4
EFFECT OF IMU PLACEMENT ERRORS.

| Range of random placement error (mm) | RMS error (rad) |  |  |  |
| --- | --- | --- | --- |
|  | Joint 1 | Joint 2 (Pitch) | Joint 2 (Roll) |  |
| ±0 | 0.0040 | 0.0520 | 0.0563 |  |
| ±1 | 0.0052 | 0.0549 | 0.0656 |  |
| ±2 | 0.0055 | 0.0519 | 0.0880 |  |
| ±3 | 0.0057 | 0.0483 | 0.0662 |  |
| ±4 | 0.0074 | 0.0604 | 0.0888 |  |

estimation of joint angles for that mechanism. Having an estimation RMS error for Joint 2 (Pitch) angle with an added ±3mm placement error that is better than the RMS error obtained for the same estimation with no added placement error indicates that better estimation results might be obtainable by using placement coordinates in the neighborhood of a chosen placement position.

Furthermore, GCMR’s use of magnetometer data in addition to acceleration data
allows for additional rotation angle information relative to the vertical direction that makes the GCMR method more accurate than the DCMR method. Table 4.5 shows that the GCMR method applied to 1-DoF joints yields pose estimate with errors that are up to one order of magnitude lesser than pose estimate errors using DCMR to estimate pose of a 2 link arm moving with sinusoidal trajectories described in [74].

**TABLE 4.5**

**COMPARISON OF 1-DOF GCMR & DCMR.**

<table>
<thead>
<tr>
<th>Experiment</th>
<th>DCMR [74] RMS error (rad)</th>
<th>GCMR RMS error (rad)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Simulation</td>
<td>0.0167</td>
<td>0.0055</td>
</tr>
<tr>
<td>Hardware</td>
<td>0.0636</td>
<td>0.0344</td>
</tr>
</tbody>
</table>

### 4.5 Summary

In this chapter, we proposed the Generalized Common Rejection Mode (GCMR) algorithm for robot pose estimation using IMU data. Simulations and experiments demonstrate that the method is capable of estimating angles of both composite joints and single DoF joints using data from at least two accelerometers and a magnetometer placed on links of a mechanism with a known kinematic structure. Experiments also show the GCMR method’s robustness to IMU position errors and noisy sensor data. We also presented a simulation study of the effect of IMU placement parameters on pose estimation results of CMR methods like the GCMR. This work would be particularly useful in robots with wide areas for IMU placement such as robot skins. Using insights from this study, a RMS-based algorithm for searching for the optimal IMU configuration for use with GCMR is presented as part of the steps to implementing the GCMR algorithm on a robot.

The work presented in this chapter would facilitate advanced sensing as part of CHMI for next generation collaborative robots especially in pHRI scenarios like the patient walker scenario with which experiments are conducted in Chapter 2. The co-bots can however be
used in teleoperation mode and the user perception of their CHMI in these modes are just as important as in pHRI scenarios if they are going to gain widespread adoption. In the next chapter, we present an investigation of user perception of the ARNA robot which was performed using data from patient sitter experiments conducted via the robot’s CHMI.
CHAPTER 5

USER PERCEPTION OF CO-BOT CHMI

The evaluation of co-bots with CHMIs is essential in the design and implementation of these cobots in a way that would facilitate their eventual use. There are several models that have been used to do similar evaluations in the adoption of technological innovations in by skilled professionals [110] and general public [111].

In this chapter, we present the evaluation of the CHMI of the ARNA co-bot in a patient sitter scenario. We start by describing the patient sitter scenario and then describing the experiments that were conducted to evaluate the PEOU and PU of the ARNA robot in this scenario and then discuss the findings from these experiments.

5.1 ARNA User Sitter

The sitter scenario describes the routine tasks that are performed while a patient is resting in a hospital room. This is known as a sitter task because as of now hospitals hire people to sit in the same room as the patient and monitor their vitals. They are responsible for alerting the nursing staff in case of emergencies. The personnel themselves cannot administer any medications as they are not certified for it. The required tasks come under the purview of non-physical HRI as the robot is not supposed to be in contact with the patient during this scenario.

One archetypal use of ARNA in a patient sitting scenario is the use of the robot to make and record periodic measurements of vitals of a recuperating patient that is admitted in the hospital in order to track the progress of their health. To accomplish this, sensors that allow the ARNA robot to collect these readings without making direct physical contact with the patient are practical. Digital and non-intrusive medical equipment were chosen to
Figure 5.1: Examples of medical equipment that can be used in a Patient Sitter application (a) Digital Infrared thermometer (b) Digital Pulse Oximeter.

The equipment used to equip the ARNA robot include the digital IR thermometer and Pulse Oximeter shown in figure 5.1. The thermometer is used to take temperature readings of a patient from a safe distance while the pulse oximeter collects information that include blood oxygen saturation as well of frequency of heartbeat and breathing. Through APIs provided by the sensor manufacturers, data from the sensor is transferred to the tablet via a bluetooth connection. These APIs can also be used for control of the use of the devices such as triggering the start or stop of a data collection session in more autonomous use scenarios.

Another application use of ARNA in Patient sitter mode is to use it in monitoring bed-admitted hospital patient and detecting if they are getting off of the bed. This would require maintaining continuous visual contact with the patient which is achieved through the use of RGB-D cameras on the ARNA robot. With the cameras oriented in the general field of view of the patient, the depth information from these cameras can be used for skeletal tracking to provide a more reliable motion detection system than would be achieved with RGB cameras. Upon detection of unsafe motion of a patient, the robot can then alert the
nursing staff and issue verbal commands to the patient.

While admitted in a hospital room, patient might desire objects within the room that are not within their reach. The ARNA robot can be used to fetch these objects and safely place them near the patient. These commands can be issued through a tablet interface as part of the CHMI. The commands can be issued verbally as well as though on-screen buttons. Upon the issuance of the command, the ARNA robot has to navigate the room and locate the requested item and then a pick-and-place task is performed.

The patient sitter task examples described so far are adaptable for use in other environment. For example, the object fetching task can be used in industrial spaces to fetch items for human workers while the patient monitoring tasks can be used in homes to monitor kids while at play. These tasks can be performed with varying levels of autonomy and to perform them in a teleoperation mode, we add a tablet interface as part of the CHMI system for the ARNA robot.

A novel use of the ARNA robot in patient sitter mode is the disinfection of surfaces. This was an application developed as a contribution to efforts at fighting the Coronavirus epidemic. In this task, the ARNA robot base is teleoperated to move in areas that require cleaning. The human operator uses the camera feedback to localization of the robot. Upon reaching a surface that requires cleaning, the robot arm can then be teleoperated to manipulate an ultraviolet lamp or a sanitizing fluid sprayer that has been affixed to the gripper of the arm over the surface that requires cleaning. Figure 5.2 shows the ARNA robot performing this surface disinfection using CHMI developed for the Patient sitter mode.

To summarize, the list of tasks that can be performed using the tablet interface to teleoperate the ARNA robot in a sitter scenario include:

- Visual monitoring of patient and alerting nurses in case the patient is getting out of the bed or about to fall.
- Taking vital readings periodically.
- Fetching items requested by the patient in the room.
Figure 5.2: A novel surface disinfection application of ARNA in the Patient Sitter scenario. (a) ARNA driving up to surface to be disinfected with UV light. (b) ARNA in position to disinfect surface with sprayer system.
• Ability to have a conversation with the patient.

• Other teleportation tasks such as remote disinfection of surfaces.

5.1.1 Tablet Interface for ARNA patient sitter

The tablet interface was built in Android Studio with the inclusion of ROS-Java libraries. The tablet hardware is a Google Pixel C with Android 8.1. Architecturally, the main connection between the tablet and the rest of ARNA’s computing and control system is facilitated by a wireless network provided by a Netgear Nighthawk router as shown in figure 5.3. The tablet application works by launching a ROS node that connects to the ROS master node on the ARNA robot via a wireless network provided by the router which allows the tablet node to publish and subscribe to necessary topics on the ROS network.

![Figure 5.3: Architectural connection of devices that facilitate Patient Sitter implementation.](image)

Graphically, the layout of the tablet app shown in figure 5.4 was designed with considerations for use by different users. For example, it can function in both portrait and landscape modes, and buttons are placed in locations on the screen that are reachable with relative ease and to ensure smoothness of operation. Functionally, the custom-built joystick buttons are used to control the base, while the arm is controlled by moving the tablet itself in order to use data from the gravity-compensated accelerometer data from the
accelerometer sensor in the tablet. Figure 5.5 shows a control of the arm by moving the tablet. This separation of the controls of the arm and base is used to reduce mental workload for the user. As an added safety feature, there is a mode control button included in the tablet app to switch between control of the arm and base, and while on it is being controlled, the other is held stationary.

Figure 5.4: ARNA tablet interface for teleoperation in Patient sitter mode.

Figure 5.5: Controlling ARNA arm by moving the tablet.
5.2 Technology Acceptance Model

To facilitate their effective and widespread use, it is important to evaluate the user perception of the usefulness and ease of use of a co-bot via its CHMI. In this work, we use the Technology Acceptance Model (TAM) to evaluate the usefulness and ease of use of the ARNA robot in a Patient sitter scenario in order to evaluate its predicated usage with its developed CHMI.

Developed in 1989, the original TAM [5] was formulated to predict and explain a user's acceptance of information technology (IT) resource. In the original TAM, perceived usefulness and perceived ease of use are presented as two fundamental constructs that impact user acceptance of a technological resource. Using the Theory of Reasoned Action as a theoretical framework of explanation, the relationships between perceived usefulness and perceived ease of use as well as users' attitudes, intentions, and resulting use behavior are described in the TAM. Figure 5.6 shows this TAM model. External variables refer to properties of the technology being considered for adoption - such as its design and usage processes - as well as existing characteristics of the users with similar technologies such as their knowledge, usage frequency and enjoyment of such systems. The arrows are used to indicate the dependency of components.

![Technology Acceptance Model (TAM) proposed by [5]](image)

Building on its application in research works over the years that focus on adoption of technology in work environments, external variables related to social change, human processes, and boundary-related conditions have been suggested for addition to the original
TAM model [88] [112]. An example of this is TAM2 wherein the attitudes that were considered in the original TAM were re-formulated into cognitive instrumental processes (job relevance, output quality, result demonstrability) and social influence processes (image, subjective norm, volunteering, experience) [113]. TAM3 [114] was first proposed in 2008 and presents an integrated model that combines the TAM2 with determinants of perceived ease of use into a framework that facilitates intervention for improving technology adoption. The TAM3 was composed of four constructs: perceived ease of use, perceived usefulness, use behavior, and behavior intention but while it is the most recent formulation, it is yet to see significant adoption in works of literature.

In this work, we use the original TAM to design experiments for evaluating human perception of ARNA’s usefulness and ease of use via its CHMI due to the model’s widespread use over the years, its focus on analysing voluntary and individual actions like those performed by a human user when using ARNA in patient sitter mode, and overall compatibility with the ARNA patient sitter scenario.

5.3 Patient Sitter experiments with ARNA

In the patient sitter experiments for this work, the task was performed by teleoperation of the robot base and arm through a tablet interface in the simulated hospital room. The teleoperation mode is a useful one - as feedback from the users show - and is also a versatile one as in addition to a hospital environment, it can be applicable in a home or industry. This kind of usefulness in multiple environments was in mind during the design and development of the ARNA robot.

The users (n=24) that participated in the experiments were all undergraduate and masters entry accelerated second-degree students in the nursing program at University of Louisville. Activities in which they are involved as part of their program include patient care in hospitals and they were recruited via in-class invitations by nursing faculty that were part of the organising team for these experiments. The students received credit for clinical/research hours for an undergraduate research course or capstone clinical course as
compensation for participating in the experiments.

While the participants were required to have no major disability (e.g. have full use of all fingers on both hands) they were also found to have limited to no experience with teleoperating robots, which we assume to be the kind of profile of many patients and nurses that would be using the ARNA robot in a patient sitter scenario. Approval to conduct the study was obtained from the Institutional Review Board at University of Louisville under IRB no. 17.0609. Each volunteer gave informed consent by signing an informed consent form whose content was explained to them prior to the start of their experiment session.

Figure 5.7: Patient sitter experiment conducted to evaluate human user perception of the ARNA’s CHMI.

As illustrated in figure 5.7, the sitter task in these experiments is divided into 5 (five) parts:

1. Using tablet interface, a user teleoperates the ARNA robot to the location of item to be fetched. In the experiments in this work, the item to be picked up is a box containing instruments used to measure human vitals which are shown in figure 5.1.

2. With the robot at the location of the item, the tablet interface is used to teleoperate
the arm to fetch the item.

3. The user teleoperates the ARNA robot to within arms reach of the user. Then the user collects the item, uses it, and returns the item to robot.

4. The user teleoperates the ARNA robot base to the location where the item was originally picked and then teleoperates the arm to place the object properly.

5. The user teleoperates the ARNA robot back to experiment start location.

Each participant conducts the experiments in three trials so that we can evaluate any improvement with the use of the robot that might come with increased exposure. While the users teleoperate the robot from a distance and are thus safe from any physical danger from the robot, all safety measures and features of ARNA’s CHM - including collision detection sensors and emergency stop buttons in the tablet interface - are active during these experiments. Wheel ticks data were collected via encoder during motion of the base, and at the end of the experiments, the user fills out a 5-point Likert scaled questionnaire from which Perceived Usefulness (PU) and Perceived Ease Of Use (PEOU) of the sitter use of the ARNA robot are evaluated. The questions and the evaluation of the response are modeled to be in keeping with the themes that were found to drive PU and PEOU in the TAM model presented in [5].

For Perceived Usefulness (PU) of the Patient Sitter function, we asked:

1. How quickly does the robot arrive at its destination using the tablet interface? (Slow (1)/Fast (5))

2. How safe do you think the robot is while you are controlling it with the tablet interface? (Unsafe (1)/Safe (5))

3. What would you say the speed of the robot is when moving around the room? (Slow (1)/Fast (5))

4. How stably did the robot gripper grasp the item? (Stable (1)/Unstable (5))
5. How safe do you think the robot arm is when it hands over the fetched items? (Unsafe (1)/Safe (5))

For Perceived Ease of Use, the questionnaire consisted of:

1. How convenient is it to drive the robot with the tablet interface? (Not convenient (1)/Very convenient (5))

2. How much attention does it take to drive the robot to the desired place while avoiding obstacles? (High (1)/Low (5))

3. How easy is it to drive the robot to the desired place while avoiding obstacles? (Difficult (1)/Easy (5))

4. How convenient is it to tell the robot where to go using the interface? (Not convenient (1)/Very convenient (5))

5. How easy is it to grab items with the robot arm using the tablet interface? (Difficult (1)/Easy (5))

5.4 Results

5.4.1 Quantitative measures

Using the wheel encoder data, we evaluate the smoothness of motion of the ARNA robot base using a Jerk metric. The Jerk metric is a safety indicator in pHRI scenarios like the patient walker but since the sitter operation would be carried out in cluttered spaces, a smooth motion of the robot while being teleoperated is desirable. Causes of delayed motion can be due to network communication issues and user difficulty in smoothly using tablet interface.

The jerk metric used here is similar to that used to evaluate the Neuroadaptive Controller for pHRI in Chapter 3. Here, it is defined as:

\[ J_{sitter} = \int_{t_s}^{t_f} \dddot{p}(t)^2 dt \frac{(t_f - t_s)^5}{A^2} \]  

(5.1)
where \( A \) is the total length of reference path laid out for the user to teleoperate the robot through, \( p(t) \) is the path taken during the teleoperation from start time \( t_s \) to finish time \( t_f \). Figure 5.8 shows this jerk for each of the trials in the patient sitter experiments conducted and figure 5.9 shows the trajectory of a sample run of the experiment.

![Figure 5.8: Robot jerk for each trial during of ARNA patient sitter experiments.](image)

We also record the time taken to perform the experiments. This time was broken into base travel time which is the time to drive to and fro the patient and the object to be picked and arm teleoperation time which is the time taken to teleoperate the arm to pick up the box. Table 5.1 shows the average measured time for each of the trials performed by the participants in the experiments. Total time includes time taken to for a user to drive to the box to pick it up, time to teleoperate arm to pick up box, time to use the medical equipment in the box and then drive back to return the box at the original pickup spot.
5.4.2 Qualitative measures: TAM

Using responses from the questionnaires, figures 5.10 and 5.11 shows a box plot of calculated average measures of usefulness and ease of use per trial.

We also performed analysis of variance (ANOVA) test to evaluate the effects of Perceived Ease of Use (PEOU) on Perceived Usefulness (PU) as hypothesized by the TAM model used in this work. The result of this analysis is presented in table 5.2.

In addition to the TAM questions for PU and PEOU, we also asked several questions about the general belief of the performance of the robot. These 7 Likert-scale questions were used to investigate overall beliefs and attitudes the users about the ARNA robot and were useful in the inspiration of useful anecdotal comments from the users on the "feel" of the various components of the robot. Figure 5.12 shows a divergent stacked bar chat with
some of these questions and a full list is shown in Appendix A.

### 5.4.3 Discussion of results

From the jerk results in figure 5.8, we can see that the motion of the robot is smooth along the marked trajectory. With such low jerk numbers indicating minimal vibrations from the robot as it moves, the robot can be used to move objects that are somewhat fragile which is a need that can be expected in a hospital environment. Compared with results in the pHRI Patient Walker scenario presented in tables 3.3 and 3.2, the mean jerk values shows that the motion of the ARNA robot base is much smoother when it is being teleoperated than while being operated with the handle bar. Low standard deviation of the jerk values with the patient sitter experiments also indicate that both users that have some familiarity with using tablet interfaces for similar teleoperation task and those who do not have such experience are comparable in their ability to use the CHMI of the ARNA robot in patient sitter scenario.
Figure 5.11: Average measures of user perceived ease of use of ARNA patient sitter.

From table 5.1, the average total time taken to execute the entire patient scenario tested was 209.52s. This is time saving for a nurse in which they would otherwise have had to come down to the patient’s room to fetch an item for a patient, assist them in its use and return of the object. With vital measurement like the kind simulated in these experiments being a routine activity that can be performed multiple times in a day, the ARNA robot can indeed offer significant time and effort savings to nurses that would otherwise have to perform the kind of patient sitting tasks taken by the robot in this experiment.

The ANOVA results presented in Table 5.2 is performed over data from all the trials and point to the illustrate the relationship of the PU and PEOU irrespective of trial number for a user. The R-squared value is .141 which means that the effect of PEOU on PU is 14%. This dependency of PEOU on PU is consistent with the TAM model on which the questionnaires for these experiments were designed and as such indicates that these measures can be used as a basis for evaluating eventual patient use of the ARNA robot in patient sitting mode. The questions on users attitude shown in figure 5.12 indicate an
overall belief by the student nurses that were users in these experiments that the ARNA robot would useful in the performance of their job. The responses to these questions can inform a good preliminary test for the design of a questionnaire based on TAM2 which focuses on examining user beliefs [113].

5.5 Summary

In this chapter, we present the CHMI of the ARNA robot involved in the facilitation of its Patient Sitter function. We discuss the tablet interface that is the main HMI that the human uses here (compared with the handlebar for the Patient Walker function in Chapter 2) and also describe experiments that were conducted at the University of Louisville School of Nursing with a cohort of nursing students. Using the TAM model to analysis the responses to questionnaires designed to investigate the users’ perception of the usefulness and ease of use of the ARNA robot via its CHMI in this scenario, we find that the users find the robot to highly usable and easy to use and indicate that overall, they would use the robot in performing their duties.

Some improvements to the work presented in this chapter includes conducting more longitudinal studies, using other technology acceptance frameworks and investigating the
benefits, if any, of more advanced controls - like the NAC presented in Chapter 2 - in teleoperation of co-bots like ARNA. This analysis provides a basis for gauging future improvements of the ARNA.
TABLE 5.1

Time breakdown of tasks performed during patient sitter experiment.

<table>
<thead>
<tr>
<th></th>
<th>Item pickup time (s)</th>
<th>Item use time (s)</th>
<th>Total trial time (s)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Mean</td>
<td>Std dev</td>
<td>Mean</td>
</tr>
<tr>
<td>Trial 1</td>
<td>53.12</td>
<td>11.41</td>
<td>72.47</td>
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<td>Trial 2</td>
<td>48.36</td>
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<tr>
<td>Trial 3</td>
<td>49.50</td>
<td>11.01</td>
<td>63.18</td>
</tr>
</tbody>
</table>

TABLE 5.2

ANOVA analysis results of Patient user data.

<table>
<thead>
<tr>
<th>Independent variable</th>
<th>Dependent variable</th>
<th>SumSq</th>
<th>DF</th>
<th>F</th>
<th>pValue</th>
<th>R-Square</th>
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<tbody>
<tr>
<td>PEOU</td>
<td>PU</td>
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<td>1</td>
<td>7.05</td>
<td>0.011</td>
<td>0.141</td>
</tr>
</tbody>
</table>
CHAPTER 6

CONCLUSION AND FUTURE WORK

For collaborative robots to be safe, effective, and intuitive and thus find a widespread use with different users in varying applications, CHMIs for these robots need to incorporate human intent and affect through multi-modal sensing and use this information to better control the human-robot system. Towards this objective, components for a CHMI of next generation pHRI-capable co-bot that we have presented in this dissertation include:

- An on-line Neuroadaptive Controller (NAC)-based admittance control strategy for pHRI with a nursing assistant robot in dynamic user and operation operating conditions,

- Generalized Common Mode Rejection (GCMR) - a novel algorithm that uses data from multiple inertial measurement units (IMUs) to estimate pose of robot mechanisms including those that feature composite joints, and

- Evaluations of user perceptions of usefulness and ease of use of Patient sitter application of a nursing assistant robot

For the Neuroadaptive controller based admittance control strategy, our work consisted of formulating the control strategy for use with an omnidirectional mobile base. This is a novel effort as previous uses of the Neuroadaptive controller have been on robotic manipulators and this is a first implementation on a robotic base. Our implementation of the algorithm for the ARNA robot base was carried out in both a ROS/Gazebo simulation environment [115] as well as hardware implementation. Using the hardware implementation, we conducted an evaluation of the proposed control strategy by comparing it with a PD-controller based control strategy that was also deployed on the ARNA robot for the
same Patient Walker pHRI task with a cohort of 10 human users and metrics that was used to evaluate the controllers include trajectory reference velocity, jerk, as well as robot and human efforts.

With up to 50% less jerk of the robot during operation using the NAC compared with the PD controller as well as reduced human effort required and task completion time, results from these experiments show that the NAC based admittance control strategy results in a pHRI that is more accurate, responsive and requires less user effort than a classical PD based admittance control strategy. These results add to the theoretical benefits of using the NAC in an admittance control strategy for CHMI which include increased adaptation to varying robot dynamics due to varied human user and operating environment profiles, ability to incorporate input data from varied sources, as well as adaptation to implementation characteristics like the production of correct PWM commands even though the method is conventionally presented as a torque control method.

The GCMR method proposed in this dissertation for robot pose estimation in a CHMI is a novel method for estimating joint angles robot mechanisms containing composite joints. The method uses knowledge of the mechanism’s kinematics and accelerometer and magnetometer data from IMUs to estimate joint angles. By evaluating factors of IMU placement that affect the accuracy of the GCMR and other CMR methods, we present results and insights that would facilitate the use of the method with robot skins, a next-generation sensing mechanism with the potential to give co-bots more accurate and multi-modal sensing capabilities. GCMR is also useful in robotic applications for which joint encoder measurements, or other visual markers are not available such as medical robots, flexible robots [116].

We implemented the GCMR for a 3-DOF 2-link robot in both ROS-Gazebo simulations as well as hardware implementations. This implementation includes a procedure for the selection of optimal magnetometer and accelerometers for use with the GCMR method given placement locations on a robot with which GCMR would be used. Results from simulation and hardware experiments show the efficacy of the GCMR method with estimation
accuracy up to one order of magnitude better than those of comparable CMR methods. These results add to the capability of the method to estimate the pose of composite joints, which is not a feature of other IMU-based estimation methods including Kalman filter based methods.

In our past work, a preliminary differential CMR algorithm was formulated and validated on a [74]. This study also looked at factors that affect optimal joint angle estimation - such as choosing the number and placement locations of the IMUs. Currently, we are completing a journal paper in which the novel GCMR method will be introduced [117]. As part of the remaining work for this dissertation, a use case of the GCMR method being employed to estimate human-intent using sensors on the forearm, hand and/or tablet will be formulated. The estimated pose information will then be used as a measurement of human intent to teleoperate the end-effector the ARNA robot during object fetch operations. The algorithm will be validated and evaluated using simulations in our ROS/Gazebo environment and grasp performance comparisons between GCMR and naive estimation methods based solely on tablet IMUs will be done. Results will be communicated in a future conference paper [118].

While the NAC-based admittance control strategy presented in Chapter 3 facilitates the incorporation of human factors to robot control, the user perception of the overall HRI that is facilitated by the CHMI is also an important factor in the adoption of next-gen co-bots. Measures of fluency, usefulness, and ease of use can be used to predict eventual usage of the robot, and used to evaluate the impact of functional features that can be added to the robot in the design and development stages [81] [79]. These measures are usually based on questionnaires and include the TAM [5] and [83]. In order to incorporate these measures in dynamic control of the co-bots via their CHMI, there is also increasing research focused on formulating measures based on measurable states of the robot that are analogous to the questionnaire-based user perception measures by the human users in the manner presented in [78].

In Chapter 5 of this dissertation, we present the evaluation of user perception of
the usefulness and ease of use of the ARNA robot via its CHMI in experiments of Patient Sitter use scenario. In addition to the results of average measures of quantitative measures of the experiments, the average measures of the users’ perceptions of usefulness and ease of use of the ARNA robot shows a high usefulness and ease of use of the robot. An analysis of the variance of the questionnaire scores validated our designed experiment as being in keeping with the widely researched Technology Acceptance Model (TAM) by showing the dependence of perceived ease of use on perceived usefulness of the robot. These results provide a solid basis for the development of control and other algorithms that use these results in formulating quantitative measures of human perception of the HRI like the work presented in [79].

6.1 Challenges and Future Work

While the Patient Walker user experiments designed to evaluate the ARNA CHMI NAC-based admittance control strategy in every direction of motion of the robot base, more challenging scenarios like steeper inclines and different surfaces can be included in future experiments as part of more robust tests of the adaptation of the control strategy. From a user perspective, while the experiments were conducted with able-bodied users with little familiarity with the robot, experiments conducted with users of varying classes like nurses and convalescent users would be useful in getting a better idea of the performance of the robot in the real world. This will allow the use of different reference admittance models to facilitate a better characterization of the robot’s performance in the real world.

One potential drawback of the GCMR method as currently presented is the errors in joint state estimation that can result from magnetometer data affected by stray additive magnetic fields of AC or DC motors. Depending on a given application, taking measures such as using data from magnetic data sensors that are far from the magnetic field sources and calibrating the magnetometers can improve the GCMR estimation accuracy. We believe finding one magnetometer per link with relatively consistent performance is reasonably feasible through experimentation. In general, while the GCMR is usable in the presence
of additive magnetic fields, it might be even more suited for use with non-actuated bio-
mechanical devices, or with non-electromagnetic robotic mechanisms. Directions for future 
work include formulating a more computationally efficient approach for searching the set of 
feasible IMU placement locations for an optimum - which could be quite large in instances 
like robot skins. Additional future work includes testing the GCMR method with robots 
with composite joints that allow prismatic motion and with bio-mechanical devices.

As stated earlier, the results of user perception of usefulness and ease of use of the 
Patient Sitter mode of the ARNA robot in Chapter 6 present a solid evaluation of the usage 
of the robot via its CHMI using the TAM model. Future work in this regard would include 
conducting longitudinal studies with actual potential users - as opposed to nursing students 
as is the current case - and also in different environment - such as factories or homes - as 
the Patient Sitter scenario is adaptable to these environment. These studies would be done 
with a goal of performing a more complete TAM analysis of the ARNA robot by using 
improved TAM models such as those in [89] [119], as well as other models for explaining or 
influencing users adoption of technologies. This is because the use of different models can 
yield better generalizations of different situations, and a multi-model approach to studying 
users perceptions of the robot is more likely to lead to a more robust prediction of its 
usage in different scenarios [120]. Another improvement would be leveraging these results 
in formulating measures that can be incorporated into dynamic control algorithm as part 
of the CHMI for the ARNA robot. While there is currently more work in literature in this 
regard that are focused on the fluency metric in shared workspace HRI scenarios [121] [122], 
we believe the results presented in this works forms a solid background for the consideration 
of such development for usefulness and ease of use for controller/scenario design in the CHMI 
of a mobile co-bot.
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USER ATTITUDE QUESTIONNAIRE

1. My job would be more difficult without the robot.

2. Using the robot gives me greater control over work.

3. Using the robot improves my performance.

4. The robot addresses my work-related needs.

5. The robot saves me time.

6. Robot enables me to accomplish tasks more quickly.

7. Robot accomplishes more work than possible otherwise.

8. Robot enhances effectiveness of job.

9. Improves quality of work I do.

10. The robot increases my productivity.

11. The robot makes it easier to do my job.

12. I find ARNA useful overall.

13. I am often confused when I use ARNA.

14. I make frequent errors when using ARNA.

15. Interacting with ARNA is often frustrating.

16. I need to consult the user manual often when using ARNA.

17. Interacting with ARNA requires a lot of my mental effort.

18. I find it easy to recover from errors using ARNA.

19. The system is rigid and inflexible to work with.

20. I find it easy to get ARNA to do what I want it to do.
21. The robot often behaves in unexpected ways.

22. I find it cumbersome to use ARNA.

23. My interaction with ARNA is easy to understand.

24. It is easy for me to remember how to perform tasks while using ARNA.

25. ARNA provides helpful guidance in performing tasks.

26. Overall, I find ARNA easy to use.
CURRICULUM VITAE

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Education

• M.Sc. Systems and Control Engineering.
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Patent

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U.S PROVISIONAL PATENT APPLICATION serial no. 62/834,689.

Papers

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Academic Positions

Graduate Teaching Assistant in

- ECE 211 Logic Design Laboratory. Fall 2018; Spring 2019.
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- ECE 334 Electronics I Laboratory. Spring 2019.

Honors, Awards and Involvement

- Speed School of Engineering, University of Louisville Grosscurth Fellowship (2016-2020)
- Graduate Student Member, Institute of Electrical and Electronics Engineers (IEEE).
- Collegiate Member, National Society of Black Engineers (NSBE).
- Collegiate Member, American Society of Mechanical Engineers (ASME).
Industrial Experience

HUawei

Radio Frequency Network Planning & Optimization Engineer.


- Passed HUAWEI GUL RF Wireless Product Training on the fundamentals of GSM, WCDMA, HSDPA, HSUPA, HSPA, HSPA+ and LTE Technology and devices.
- Carried out 2G KPI Optimization which involved TCH Drop, TCH Congestion, SD-CCH Drop Congestion, Drive test and OG HOSR Optimization.

Daniel Agbande Automobile Lagos, Nigeria

Trainee Automobile Mechanic.


- Contributed significantly to the execution of major repair and maintenance tasks such as complete engine replacement, replacing oil rings in Pistons, general engine servicing, etc.
- Supported other automobile service technicians in auto-body and automotive air-conditioning repair.
- Upgraded existing Health and Safety operating procedures.

University College Hospital

Information Technology Officer.


- Executed maintenance activities, software testing that improved performance of the hospitals website.
• Developed assets for the creation of an improved backend for the in-house web application for record management using ASP.NET.

• Carried out installations, configurations of different ICT tools as support for hospital staff.

Nestlé (Factory)

Trainee Electrical, Instrumentation and Automation Engineer.


• Executed upgrade and maintenance tasks on PLCs of different OEMs including Allen-Bradley, Rockwell and Siemens.

• Installed and recalibrated SCADA devices and systems as part of routine maintenance tasks which involved the use of application packages such as RSNetworx, FlexLogix, etc. in routine backup, modification of production software.

• Performed numerous troubleshooting tasks on various production processes (including Malt extraction, Milo production and packaging, Cereal production and packaging, EHP-5 production, WWTP, Boiler, etc.) as part of a cross-functional team of engineers, technicians and QA experts.