Assessment of Advanced Behaviours for Assistive Robotic Wheelchairs

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Declaration of Authorship

I, **Bojan Andonovski**, certify that the work in this thesis has not previously been submitted for a degree nor has it been submitted as part of requirements for a degree except as fully acknowledged within the text.

I also certify that the thesis has been written by me. Any help that I have received in my research work and the preparation of the thesis itself has been acknowledged. In addition, I certify that all information sources and literature used are indicated in the thesis.

Signed:

Date: 24/02/2016

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First and foremost, I would like to thank my thesis advisors, Dr. Jaime Valls Miró and Prof. Gamini Dissanayake, for offering me every opportunity to learn and grow as a researcher. Pursuing a Master wouldn't have been possible without their constant advice and support in all areas call from writing papers, doing research presentation, participating in different forums on world stage.

I would also like to thank all the bright minds who were around me at the Centre of Autonomous Systems (CAS), especially James Poon, for all the intelligent conversations, coffee breaks and "volunteering" for experiments, the results of which are collected in different chapters.

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Abbreviations

2D	Two Dimensional
ADL	Activities of Daily Living
AMCL	Adaptive Monte Carlo Localisation
ARMA	AutoRregesssive Moving-Average
AT	Assistive Technology (AT)
ATOM	Assistive Technology Outcome Measure
AR	AutoAegressie
BN	Bayesian Network
CAS	Centre of Autonomous Systems
DBN	Dynamic Bayesian Network
EKF	Extended Kalman Filter
EKG	Electrocardioraph
FIM	Functional Independence Measure
FEW-Q	Functional Evaluation in a Wheelchair Questionnaire
GUI	Graphical User Interface

HMM	Hidden Markov Model
IR	Infra Red
IPW	Intelligent Power Wheelchair
IMU	Inertial Measurement Unit
IWS	Intelligent Wheelchair System
KDD	Knowledge Discovery from Databases
KNN	K-Nearest Neighbors
MCL	Monte Carlo Localisation
MA	Moving-Average
MDP	Markov Decision Process Models
LPC	Linear Prediction Coding
OCAWUP	Obstacle Course Assessment of Wheelchair User Performance
OT	Occupational Therapist
OTFACT	Occupational Therapy Functional Assessment Compilation Tool
PCDA	Power-Mobility Community Driving Assessment
PIADs	Psychosocial Impact of Assistive Devices
PIDA	Power-Mobility Indoor Driving Assessment
PMD	Powered Mobility Devices
PoW	Prince of Wales Hospital
ROS	Robot OPerating System

POMDP	Partially Observable Markov Decision Process
PN	Probabilistic Networks
RF	Random Forest
SLAM	Simultaneous Localisation and Mapping
SVM	Support Vector Machine
UTS	University of Technology Sydney
WhOM	Wheelchair Outcome Measure
WST	Wheelchair Skills Test
WST-P	Wheelchair Skills Test Powered

Abstract

Research demonstrates that use of appropriate Assistive Technology (AT) is associated with increased independence and reduced need for ongoing care and support. Powered mobility devices (PMDs) such as power wheelchairs and scooters are proving to be useful pieces of assistive technology. This study focuses on developing and assessing the validity of a stand-alone sensor package and algorithms to help the assessment by an Occupational Therapists (OT) whether a person has the capacity to safely and efficiently operate a powered mobility device such as a wheelchair in their daily activities. This is accomplished by analysing data computed from a standalone sensor package fitted on a wheelchair platform. The proposed solution consists of a suite of sensors capable of inferring navigational features from the platform it is attached to (e.g. trajectories, map of surroundings, speeds, distance to doors, etc). The study aims to compare and contrast objective data derived from a PMD mounted sensor package with subjective data obtained using a standard Occupational Therapy assessment. The research work demonstrated that accurate, reliable objective data from a sensor package can be used to augment the Occupational Therapists subjective assessment. Furthermore, the task-specific parameters that may provide the most relevant user information for the assessment are automatically revealed through a machine learning approach. Machine learning automated assessment classification tests, with data attained from multiple runs of able clients simulating varying degrees of erraticness in their driving skills while they performed the assessment tasks, have indicated success rates in the order of 85%.

Chapter 1

Introduction

1.1 Research Problem

PMDs such as power wheelchairs and scooters have proven to be powerful tools in AT. Especially with the aging population, research has been focused on matching the technology of a PMD to user's needs. However, this is a long and complex problem due to their weight and fast-movement and usability in-and outdoors (dynamic) environments. In disability healthcare there exist multiple means for determining performance of mobility aid users and a number of variables that can be assessed. Furthermore, some tools used to assess AT are often subjective (Psychosocial Impact of Assistive Devices (PIADS), while others such as the Occupational Therapy Functional Assessment Compilation Tool (OTFACT), Assistive Technology Outcome Measure (ATOM) and the Wheelchair Outcome Measure (WhOM)) are not necessarily specific to the device being assessed. Generally, the models of practice and assessments used for selection of AT are poorly developed and concerns have been raised about the available wheelchair assessments, clearly indicating the need for further research.

A review of the literature suggests that there is a lack of evidence-based procedures for the selection of AT. There is a need to augment the existing therapist's subjective assessments of PMD use with objective and quantitative performance indicators. It therefore remains an open challenge for automated assessment based on criteria from

standard wheelchair assessment tasks, in a format that is also convenient to therapist staff overseeing patient rehabilitation.

1.2 Motivation

With the aging population increased the number of individuals who require mobility assistance. Adults aged over 50 are the most prevalent wheelchairs users [2], and it is estimated that PMD use is 3.5 times more frequent after the age of 65 [3]. The benefit they bring in maximising the independence of people in the community can be so prominent they are sometimes regarded in equal terms to the rehabilitation treatment programs. There are over 4.3 million users of powered wheelchairs in the US alone [3], and it has been reported that 10% of powered wheelchair users experience serious difficulties with the standard operation of their wheelchair [2]. Furthermore, there are many other individuals who require mobility assistance yet also have other conditions such as visual or cognitive impairments, that hamper their ability to safely operate a powered wheelchair. These factors coupled with new technologies providing a broad range of wheelchair options complicate the mobility aid prescription process [4], resulting in an increasing need for an outcome measurement to clinically quantify the necessity of mobility aids from one patient to another. The biggest challenge and therefore the highest potential value of assistive technologies relate to the most debilitated individuals (e.g. those with cognitive and mobility impairments). For these clients, the best solutions are likely to involve automated AT that match users need.

Mobility performance measures have been mostly proposed in the literature as a means to providing some form of shared control of the platform. The work presented as part of the "CanWheel" project [1] shows the outcomes of the Intelligent Wheelchair System (IWS) developed to help older adults with cognitive impairments drive a powered wheelchair safely and effectively. Past work on the profiling of wheelchair users [5] has also been done with focus on tailoring aspects of collaborative control [6], and scenario-based profiling has proven suitable for potentially long-term co-autonomy [7]. Similar mobility performance measures have also been trialled as a means for comparison with

the widely used Wheelchair Skills Test (WST) [8] with promising results. However, this may not be practical for professional classification in a clinical setting where many clients may be evaluated for wheelchair prescription, given possible limitations on both time and the quantity of available test equipment. A series of brief, easily repeated tasks draws a closer parallel to currently practiced clinical methods, as they possess a greater ease of use for therapists due to their inherent simplicity.

1.3 Research Objectives

The overall goal of the research work is to develop algorithms to aid the routine assessments carried out by OTs in their analysis of clients. The sensing platform will include a suite of sensors with a facility for data logging, whilst a set of algorithms will determine the trajectory followed by the wheeled platform and generate a map of the surrounding environment. Additionally, the task-specific parameters that may provide the most relevant user information for the assessment will be automatically revealed through a machine learning approach. Availability of such information will allow clinical staff to make a conclusive analysis on the performance of clients, presenting OTs with the capability to discern whether clients are ready to be safely deployed with mobile aids for their daily activities.

It should be noted that while the authors acknowledge that some form of anti-collision protection would be paramount for the safe deployment of any automated solution of power mobility devices when dealing with older adults, the focus of this thesis is the assessment of a person's driving skills as a first step to assess whether one such device can be safely prescribed to them. The context of collision avoidance (be that to circumvent "positive" obstacles such as walls, people, chairs, or ''negative" obstacles such as drop-offs, sidewalk curbs, stairs, or voids in general) for users with cognitive impairments is briefly addressed at the end of the thesis where future work is described.

1.4 Approach and Methodology

The research work focuses on developing and assessing the validity of a stand-alone sensor package and algorithms to aid the assessment by an OT as to whether a person has the capacity to safely and effectively operate a powered mobility device such as a wheelchair in their daily activities. In order to gain knowledge about the accuracy of the estimated pose and the sensors used for the task at hand, the estimated pose was extracted in a number of localization techniques, and then compared.

The proposed solution consists of a suite of sensors capable of inferring navigational characteristics from the platform it is attached to (e.g. trajectories, map of surroundings, speeds and distances to doors, etc). This analysis aims at gaining knowledge about the users interactions with indoor environments such as a hospital or homes, which then can be used for automatic navigation in more complex and dynamic outdoor environments.

For the early stages of the research work, a standalone package was deployed on a power wheelchair platform at the Prince of Wales Hospital (PoW) containing a laser range finder, Inertial Measurement Unit (IMU) and a camera. This preliminary analysis focused on comparisons of individual tasks, such as approaching a doorway or aligning the wheelchair with a bed from the PoW data. Healthy participants maneuvred the wheelchair while an OT assessed performances via the Power-Mobility Indoor Driving Assessment (PIDA), a standardized test for determining performance of mobility aid users. Further tests were then carried out with an instrumented wheelchair at UTS where more significant volume of data could be more easily collected.

Data logged from the sensor package was converted into topographical maps of the test area. Further quantitative measures were then extracted from the sensor data, e.g. actual or close collisions, number of tries, standard deviation of linear and angular velocity, distance to obstacles (safety), completion time, idle time, etc.

The research work hence proposed first a methodology to find correlations between therapist scores and quantitative measures that can be evaluated with a standalone sensor package. Whereas the earlier works of the project were based on environmen-

tal attributes such as alignment with a bed and other parameters recommended by a therapist, the next stage of the research proposes the use of parameters data-mined from test runs for an assessment of general user proficiency. With much more available ratings for each task from the PIDA assessment test, a machine learning approach was then proposed to *learn* which quantitative measures are most informative. This is done in order to be unrestricted to any particulars concerning the required assessment outcomes of the respective OT, allowing classification to focus solely on navigational ability. Selection of parameters based on platform movement is done through machine learning, as parameters less easy to interpret by people on-the-fly may possibly provide greater insights for classification.

The main contributions arising from this thesis work are summarised below:

- Develop and assess the validity of a a stand-alone sensor package able to be deployed on a wheeled platform such as a wheelchair. Furthermore, we made use of navigational characteristics from the platform it is attached to (e.g. trajectories, map of surroundings, speeds and distances to doors, etc) inferred from a suite of sensors.
- Develop a novel evidence-based automated utility to aid proficiency assessment by OTs via algorithms to classify the performance of the wheelchair users. Therefore, OTs scores drawn from a sub-set of PIDA and WST are compared to a range of objective parameters inferred from the measured wheelchair navigational data.
- Data mining was applied to data recorded during the execution of a series of assessment tasks from PIDA and WST by healthy volunteers, and results from three typical classifiers are presented based on learnings from the manual labeling of training data. An 85% success rate using a Random Forest (RF) classifier was obtained. This is a promising outcome that sets the scene for a potential clinical trial with a larger user pool.

1.5 Thesis Overview

This thesis is structured as follows:

Chapter 2 The detailed analysis of the sensor package with mapping and wheelchair tracking algorithms is presented in this chapter. This analysis starts by comparing the estimated pose with three methods for robot localization. Furthermore, a suite of algorithms is developed which is capable of generating a map of the surrounding environment and estimating the trajectory with associated navigational parameters followed by the wheeled platform while performing the set of given tasks in the assessment. Based on the data collected from individual laser scans and IMU data, it is shown now it becomes possible to analyze navigational parameters relevant to the assessments that OTs do manually, e.g. assessments tasks in PIDA and WST, as shown in the next chapter.

Chapter 3 This chapter describes details of analysis of parameters relevant to the assessments that OTs do manually, e.g. proximity to doors and alignment with beds, based on the data collected with the proposed sensor package. The purpose of the analysis was to gain knowledge about the users interaction with an indoor environment such as a hospital, and establish a correlation between parameters recommended by OTs and these extracted by the proposed algorithms.

Chapter 4 In this chapter, parameters were data-mined from test runs for an assessment of general user proficiency. This was done in order to be unrestricted to any particulars concerning the required assessment outcomes of the respective OT, allowing classification to focus solely on navigational ability. Selection of parameters based on platform movement is done through machine learning, as parameters less easy to be interpreted by people on-the-fly may possibly provide greater insights for classification. A simple Graphical User Interface (GUI) was developed to be able to conveniently use the system in an intuitive, repetitive and consistent manner with little need for familiarization with the underlying robotics hardware or software.

Chapter 5 In this chapter, conclusions from the work described in this thesis are given, together with the future work and a summary of the findings of this research.

1.6 Related Publications

1. J. V. Miro, R. Black, **B. Andonovski**, AND G. Dissanayake. Development of a novel evidence-based automated powered mobility device competency assessment, *ICORR'13 International Conference on Rehabilitation Robotics*, Seattle, USA, 2013, pp.1-8.

2. **B. Andonovski**, J. V. Miro, J. Poon, AND R. Black. An automated mechanism to characterize wheelchair user performance, *BioRob'13 IEEE International Conference on Biomedical Robotics and Biomechatronics*, Sao Paulo, Brazil, 2014.(to appear)

1.7 Ethical and Risk Consideration

To my knowledge there are no ethical, social or environmental implications that can be identified with accordance in the University of Technology Sydney (UTS) Human Resource Ethics Committee Policy. Furthermore, the research does not involve work with chemicals or animals. All experiments will be carried out with computer simulations or on platforms in controlled settings where relevant laboratory and site safety regulations will apply.

Chapter 2

A Sensor Package for PMDs Mapping and Tracking

2.1 Introduction

PMDs such as wheelchairs and scooters have been recognized as primary mobility aids for the aging and disabled population. One of the key factors in developing intelligent PMDs is in acquiring sufficient information from the surrounding environment. In terms of onboard navigation sensors, most systems rely on standard distance sensors, such as sonar, IR, laser range-finding, or binocular vision for mapping, localization and obstacle avoidance. Laser range-finders, which offer the best accuracy in terms of range measurements, were relatively rare until recently due to their high-cost and large form factor. However the technology has been improving in this area, making them a more viable option [9].

This chapter describes the proposed navigational sensor package of sensing and computing able to be deployed on a standard mobile platform, such as a wheelchair or a walker, and a suite of algorithms capable of generating a map of the surrounding environment and estimating the wheelchair trajectory. The purpose of this study is to provide the OT with good accurate estimated pose which is of essential importance for

Figure 2.1: The SmartWheeler robot platform

the assessment. Two techniques are presented: 2D SLAM (Simultaneous Localization and Mapping) [10] algorithm based on a Rao-Blackwellized particle filter where odometry was virtually generated, effectively learning occupancy grid maps from the 2D laser range data [11], and Hector SLAM, with significant improvement in accuracy for the latter. Furthermore, the estimated pose by three methods for robot localization were compared. This analysis is essential before starting with other parameters analysis relevant to the assessments that OTs do manually such as alignment to beds or distance to the doors, described in the next chapter.

2.2 Related Work

The integration of robotics into medical fields has become of great interest in the past twenty years. Assistance, service, rehabilitation and surgery are the areas that have benefited the most from recent advances in robotics. The emphasis in the literature review in this section is on intelligent PMD devices and the mapping of the surroundings and tracking the PMDs.

The work presented in [12] describes and evaluates an intelligent wheelchair, adapted for users with cognitive disabilities and mobility impairment, where the study focus was on a patient with celebral palsy, one of the most common disorders affecting muscle control and coordination, thereby impairing movement. In the same line the work from

Figure 2.2: NOAH wheelchair system (commercially available wheelchair equipped with stereo-vision camera and laptop)

the "CanWheel" project [13] shows the outcome of a developed prototype intelligent wheelchair that prevents collisions and provides navigation assistance through audio prompts to assist the user in reaching desired locations.

Fig. 2.1 depicts the SmartWheeler platform (built on top of a commercially available Sunrise Quickie Freestyle which was extended in-house at McGill's Centre for Intelligent Machines) [9]. The work which was presented as part of the "CanWheel" project [1] shows the outcomes of the IWS which was developed to help older adults with cognitive impairments drive a powered wheelchair safely and effectively. The (IWS) consists of a Pride Mobility wheelchair, a 4mm Bumblebee 3D stereo-vision camera mounted on the front of the wheelchair, and a laptop computer placed at the bottom of the wheelchair, as shown in Fig. 2.2.

One of the key factors in the process of quantitative assessment is that of mapping the surroundings and tracking the PMD platform with the sensor array mounted on it. In the work from the "CanWheel" project [13] the mobile robot platform explores the environment autonomously, collecting laser scans or images in order to create global

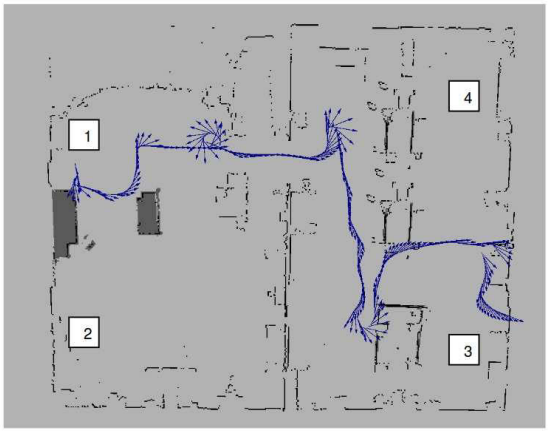


Figure 2.3: Map of laboratory as a part of the "CanWheel"project created by the mapping component.

occupancy maps. These maps were created by stitching together multiple local occupancy grids using odometry information in order to represent larger environments. This map needs only to be constructed once for each home or long-term care facility. Fig. 2.3 shows the map of the laboratory created as described above and used by subsequent components. For the localisation of the platform, landmarks from incoming stereo images are matched to previously seen landmarks. The wheelchair's position and orientation are then computed using information about the camera's geometry (visual odometry).

For the work presented in [1], the map was constructed using a Pioneer robot equipped with a SICK laser which implements SLAM based on a Rao-Blackwellized particle filter [14] as seen in Fig. 2.4. This allowed the creation of an accurate and dense map that can be used by the Route Planner module. The map is loaded in to a graphic interface in a visualization module provided by ROS called Rviz, where start and goal locations can be specified by clicking on appropriate regions.

The work of [15] provides a comprehensive overview of the design and validation of the Intelligent Power Wheelchair (IPW). Fig. 2.5 illustrates, after each map updating, the location of narrow passages determined through a low-frequency analysis of the surrounding environment, eliminating locations that are incompatible with the platform geometry.

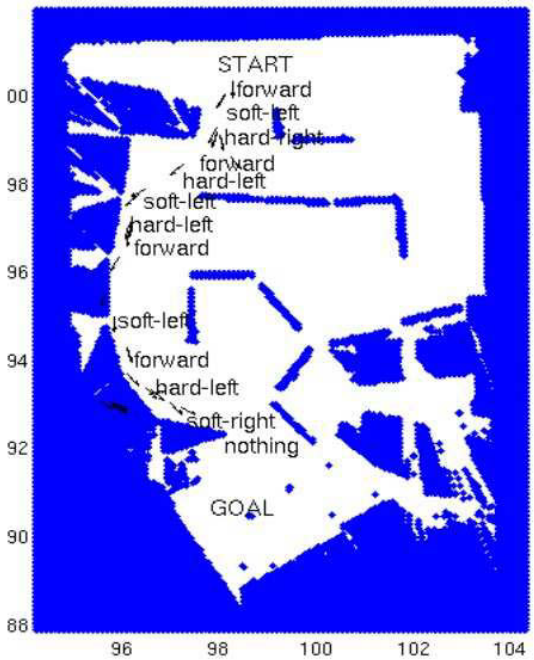


Figure 2.4: Laser map of the facility with examples of system prompts.

2.3 Sensor Package on the PMD Platform

For the initial part of this work, standalone sensor package was deployed on a wheeled platform. The sensing platform includes a suite of sensors with a facility for data logging, whilst the algorithms developed determine the trajectory followed by the wheeled platform and generate a map of the surrounding environment. Availability of such information will allow staff to make a conclusive analysis on the performance of clients, presenting occupational therapists with the capability to decide whether clients are ready to be safely deployed with mobile aids for their daily activities.

The sensor package employed at PoW consists of:

- A Hokuyo UTM-30LX/LN scanning laser range finder, able to measure distance to objects between {0.1m - 30m} in a semicircular field of 270°.
- A Point Grey Dragonfly2 Firewire camera able to capture high resolution (1032x776pixels) colour images at 30fps.
- A Xsens MTi inertial measurement unit (IMU), a low weight 3DoF attitude and

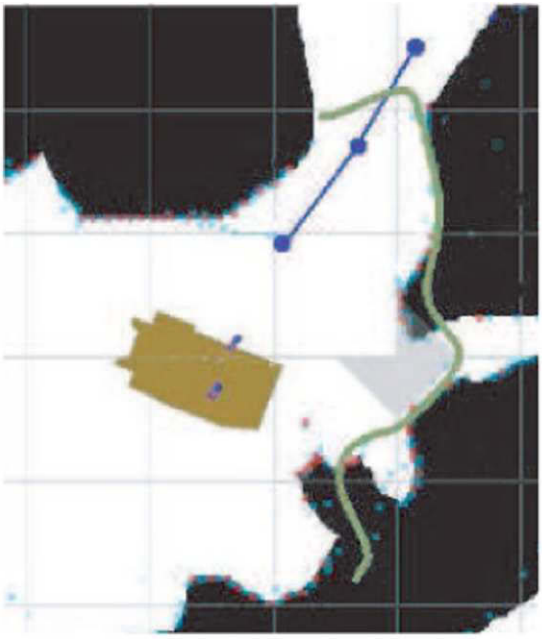


Figure 2.5: Example of narrow passage and waypoint sequence determination (blue curve)

Figure 2.6: Sensor package prototype - detail.

heading reference system capable of measuring accelerations, angular velocities and magnetic orientations.

The sensor package (Fig. 2.6) is a small size, light-weight and self-contained that can be easily mounted on most mobility aids with standard fixtures, as shown in Fig. 2.7 for the case of a standard Pride LX power wheelchair. This is one of the platforms regularly used by the occupational therapists at the PoW hospital in their routine assessments. Further to the sensor set-up, a Toshiba Libretto U100 notebook computer and a custom Lithium-Polymer battery (and power converters) are hosted outside in a separate enclosure to power and operate the sensors, and provide the data logging

Figure 2.7: Sensor enclosure mounted on PoW wheelchair

capabilities. The initial analysis of the data from PoW follows in the next sections of this work.

For the further analysis and research work at UTS due to practical reasons and the possibility to perform a larger number of experiments and extract more parameters relevant for the OTs assessments, the wheelchair platform with sensor package as shown in Fig. 2.8 was used. An instrumented wheelchair platform equipped with drive motors and wheel encoders was fitted with a modular sensor package housing an RGB-D camera (MS Kinect), a Hokuyo laser range finder and an Xsens inertial measurement unit (IMU). The sensors were all connected with a wheelchair's on-board PC controller.

2.4 Mapping and Tracking

In order to gain knowledge about the accuracy of the estimated pose and the used sensor sources, the estimated pose by three methods for robot localization were compared. These analyzes are essential for having good localization and pose estimation, before starting with other parameters analysis relevant to the assessments that OTs do manually such as alignment to beds or distance to the doors.

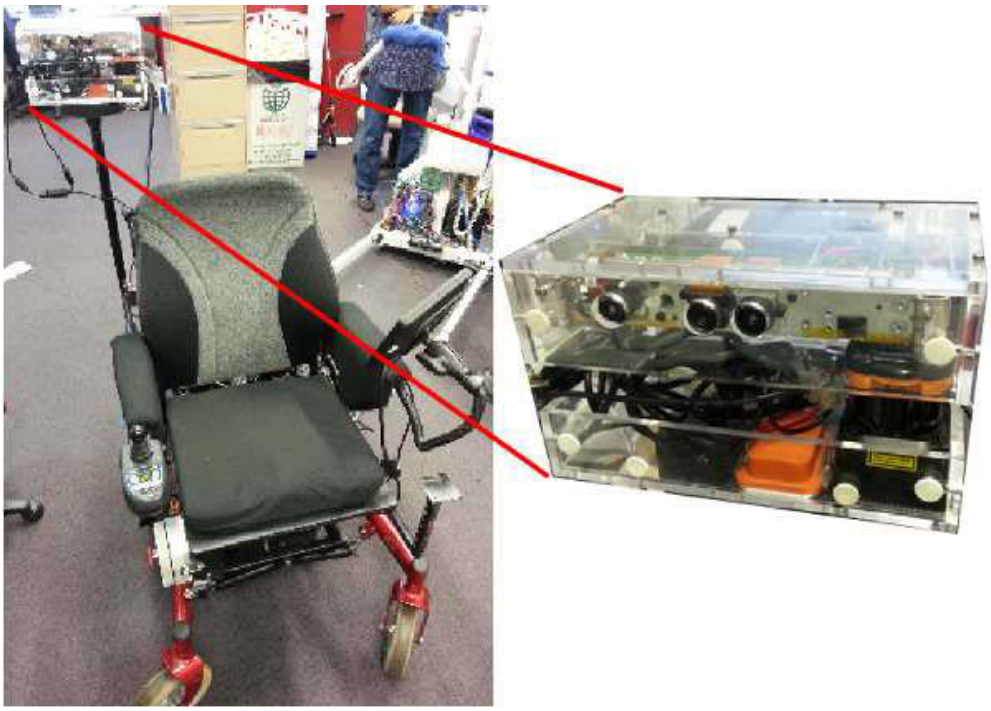


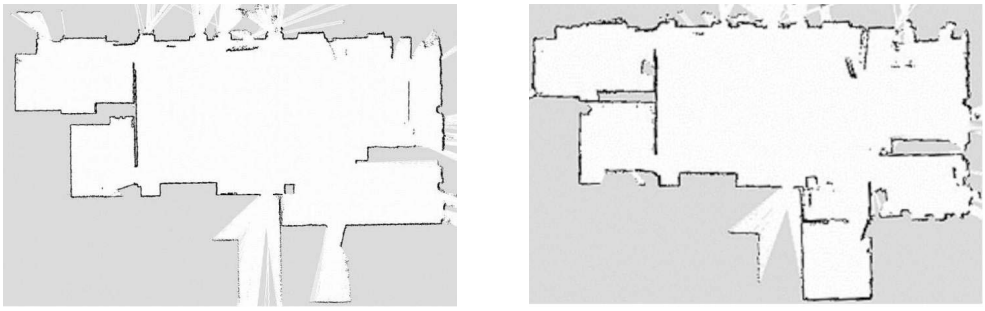
Figure 2.8: UTS wheelchair platform with closeup of sensor package

2.4.1 Map Building

Before starting with the estimators a short study of the map building was successfully done. Two methods of obtaining a map from the logged data were compared.

Firstly, this analysis was performed on the PoW platform without, odometry. Data was logged while the PoW wheelchair was driven around by users in an indoor hospital test area. Two-dimensional (top-down view) maps of the environment, could then be generated from the laser range finder and IMU data collected. Logged streaming data was not used for navigational purposes in this study, but it allowed the OT to visually replay the user runs at a latter date for further study. The software framework employed in this work is built around ROS (www.ros.org), an open source meta-operating system middleware for robotic platforms. Amongst other things, it provides a range of tools to map and localize mobile robotic platforms as they move about based on sensory feedback from the environment [16].

Initially, a 2D SLAM [10] algorithm based on a Rao-Blackwellized particle filter



(a) Hector Mappings map of the PoW indoor environment.

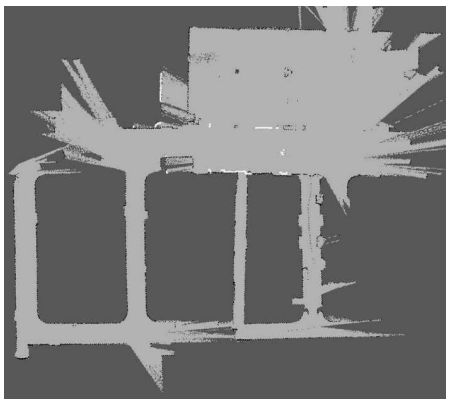
(b) Gmapping map of the PoW indoor environment

Figure 2.9: Map of the PoW indoor environment build by different methods.

(Gmapping), had been employed to effectively learn occupancy grid maps from the 2D laser range data [11]. The generated maps were then re-used to localize the platform in the learned environment producing the paths followed by the wheelchair [17]. However, this solution has got a number of drawbacks: it works best in fully planar environments, does not leverage the high update rate provided by modern sensors systems (such as laser range finders), and still relies on sufficiently accurate odometry being estimated. The end results are wheelchair trajectories highly sensitive to correct parameter settings, which impact negatively in the additional navigational metrics (described in the next chapter) proposed in this work to complete an objective assessment of the wheelchair user's driving abilities.

An alternative SLAM proposition "Hector Mapping", operates on the principle of integrating laser scans in a planar map. As scans are aligned with the existing map, the matching is implicitly performed with all preceding scans. The system is accurate enough not to need explicit loop-closure to attain accurate trajectory information in many real world scenarios, as well as being better suited for fast online learning of occupancy grid maps requiring low computational resources. It combines a robust laser scan matching approach [18] with 3D attitude estimation from the on-board inertial sensing. By using a fast approximation of map gradients and a multi-resolution grid, reliable localization and mapping capabilities in a variety of challenging environments have been reported in the literature [19]. It also integrates into the API of the the ROS navigation stack, and thus can be easily interchanged with other SLAM approaches or

(a) Gmapping map of the level 2 at the UTS building.



(b) Hector Mapping map of the level 2 at the UTS building.

Figure 2.10: Map of of the level 2 at UTS building build by diffeernt methods.

other probabilistic localisations modules available in the ROS ecosystem. Fig. 2.9(a) shows the map obtained with Hector Mapping and GMapping (Fig. 2.9(b)) methods. It is clear that the two maps differs as the process of obtaining them is different.

As mentioned before the analysis was carried out on the UTS wheelchair platform, so a short analysis of the map building by this platform with dead reckoning is presented. Firstly, two different maps of the level 2 at the UTS building where the wheelchair was driven around by users are presented. Fig. 2.10 shows the map of the level 2 at the UTS building obtained with Gmapping (Fig. 2.10(a)) and Hector Mapping (Fig. 2.10(b)) methods. These two maps can be used in the pose estimation process in the further analysis. As they are different, the estimated pose by different approaches is expected to be different as well.

An additional comparison in a hospital setting is presented. Fig. 2.11 shows the map obtained with Gmapping. Fig. 2.12 shows the Hector Mapping map. It is clear that the Hector Mapping SLAM process is more accurate than the Gmapping one and was used for robot localization in this work.

Figure 2.11: Gmapping Map of the GDS experiment environment

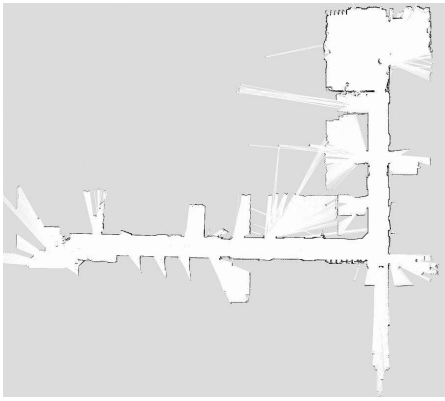


Figure 2.12: Hector Mappings Map of the GDS experiment environment

2.4.2 Pose Estimation Approaches Background

The generated maps (obtained from the approaches described before) can be re-used to localize the platform in the learned environment producing the trajectories followed by the user as she/he drives the wheelchair around. While generating these maps is a computationally expensive exercise, particularly for larger environments, localising the platform is a feasible proposition to be carried out on-line while driving around. Three different pose estimation approaches were used for this analysis, namely:

1. Adaptive Monte Carlo Localization (AMCL)
2. Hector Mapping
3. Extended Kalman Filer (EKF)

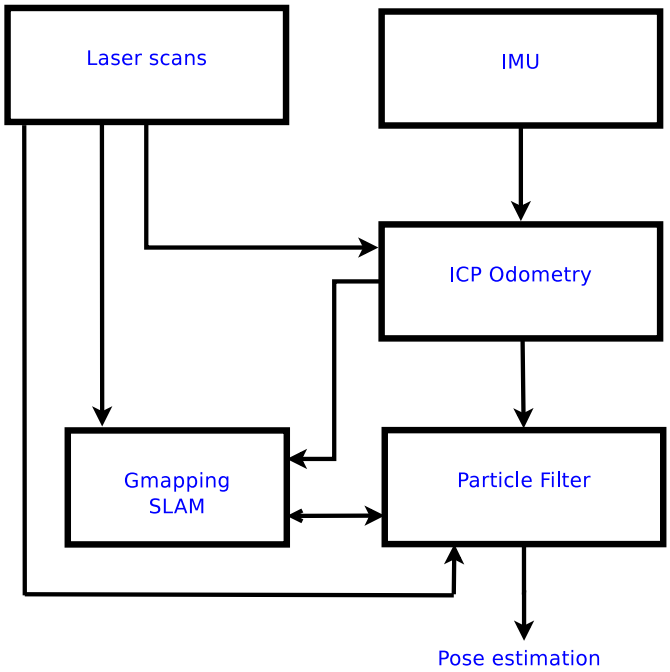


Figure 2.13: System overview of the AMCL solution.

The first method, Adaptive Monte Carlo Localization (AMCL) (Fig. 2.13) uses a particle filter for the pose estimation. The AMCL is a probabilistic localization system for a robot moving in 2D. It implements the adaptive (or KLD-sampling) Monte Carlo localization approach, which uses a particle filter to track the pose of a robot against a known map. It does not necessarily require sensors data from IMU or wheel odometry sources.

The second one, Hector Mapping approach is the alternative SLAM proposition described in the mapping section before. It combines a robust laser scan matching approach with 2D attitude estimation from the on-board inertial sensing. The basic idea in scan matching using a Gauss-Newton approach is inspired by work in computer vision. Using this approach, there is no need for a data association search between beam endpoints or an exhaustive pose search. Fig. 2.14 shows the block diagram of this approach.

The third method, an Extended Kalman Filter (EKF) approach fuses different sensor sources (e.g. wheel odometry, IMU, etc.). The Robot Pose EKF package in ROS is used to estimate the 3D pose of a robot, based on (partial) pose measurements coming

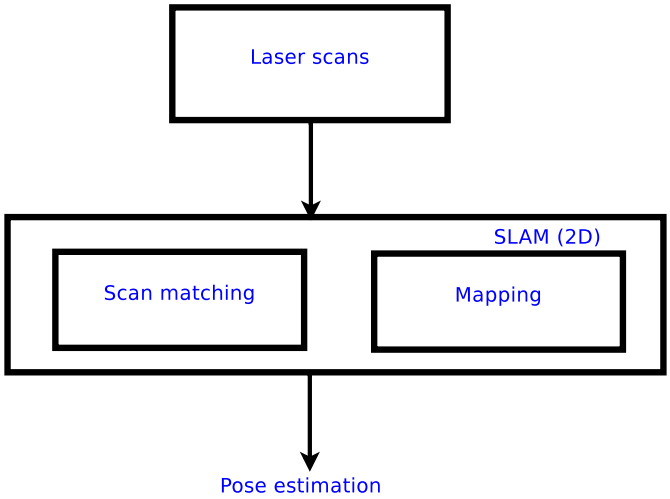


Figure 2.14: Overview of the Hector Mapping SLAM system.

from different sources. It uses an extended Kalman filter with a 6D model (3D position and 3D orientation) to combine the wheel measurements (from wheel odometry, IMU sensor and visual odometry). The basic idea is to offer loosely coupled integration with different sensors, where sensor signals are received as ROS messages.

In the case of PoW data which contains sources from IMU, laser and kinect, fusion of IMU and virtual odometry from Hector Mapping was implemented using the Robot Pose EKF package, as shown in Fig. 2.15.

It is clear that virtual odometry is just an instance of the Hector Mapping pose and this input for EKF is actually the same as the output of the Hector Mapping package. The other case of using Robot Pose EKF package is fusing the sensor information from the encoders in the sense of raw odometry and the IMU. This option is studied later in the chapter with the UTS platform which provides actual wheel odometry.

2.4.3 Comparing the Estimated Pose of Wheelchairs Platforms

After studying the three proposed methods, the estimated pose of wheelchairs platforms were compared. Fig. 2.16 shows the estimated pose of a PoW wheelchair platform when AMCL and Hector Mapping approaches were used. It is clear that the performance of the Hector Mapping approach is better than the AMCL. There is a significant improve-

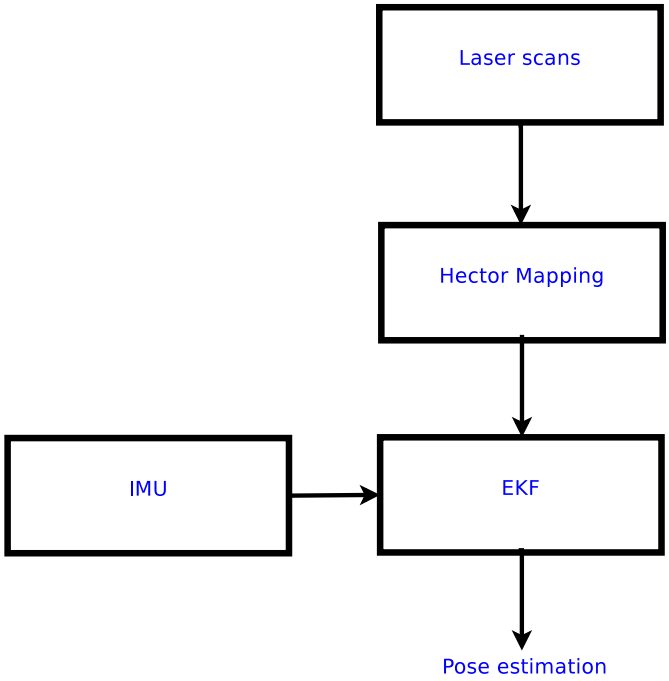


Figure 2.15: The extended Kalman filter approach fusing virtual odometry and IMU.

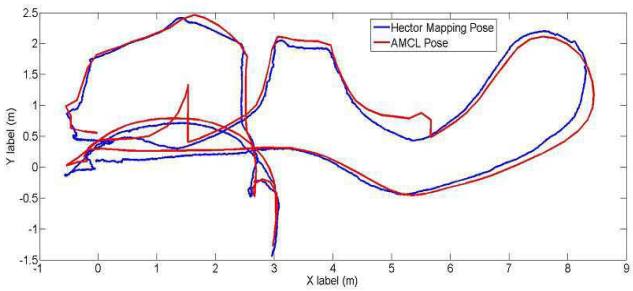


Figure 2.16: Estimated pose with AMCL and Hector Mapping by Run1 and User3.

ment of the estimated pose using the Hector mapping approach as the scan matcher is able to performs better than the AMCL approach with this type of planar data.

For the case of PoW data files that contain IMU and laser scans, the option of fusing virtual odometry using the Hector mapping and the IMU source was enabled. The wheelchair pose by one of the runs in PoW hospital was extracted using the Robot Pose Ekf package in ROS. In this case the sensor information from IMU and the Hector Mapping (in the sense of virtual odometry) were fused to obtain the pose estimation. The output of the Hector Mapping, the instances of the pose in the form of odometry

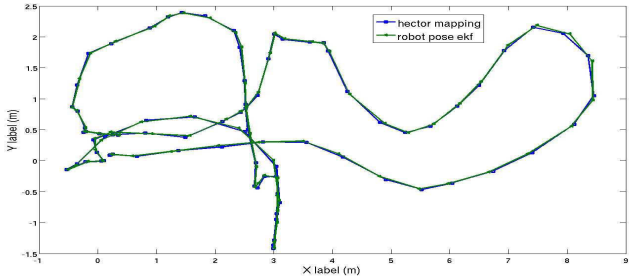


Figure 2.17: Estimated pose with Robot Pose EKF by Run1 and User3.

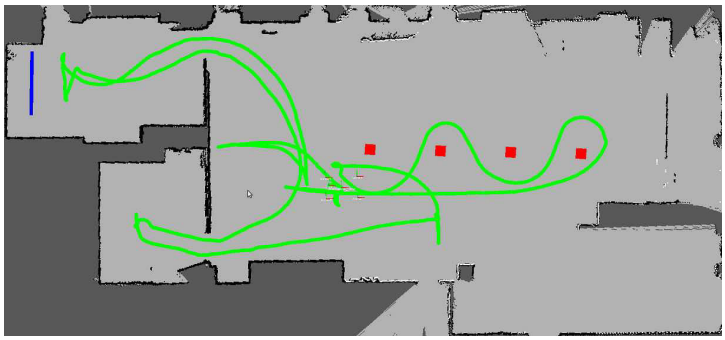


Figure 2.18: Wheelchair trajectory while performing one of the task runs in PoW. Light grey is empty space (i.e. the room), dark grey is unknown (beyond the walls), green is the trajectory followed, white/green/red icons represent the orientation and edges of the wheelchair. Pylons used during the zig-zag motion are shown in red, while the right edge of the bed in the left room is shown in blue.

were used to feed the input of the Robot Pose EKF package. Because of that there is no significant difference between the Hector Mapping pose (in blue in Fig. 2.17) and the estimated pose of Robot Pose EKF (in green in Fig. 2.17).

Two-dimensional (top-down view) maps of the environment, like the ones depicted in Figure 2.18, could then be generated from the laser range finder and IMU data collected. It shows the trajectory followed by the wheelchair platform during one of the task runs in the PoW.

A similar analysis was carried out on two UTS mobile platforms with different sensor packages. The first platform being used was a Segway robot that contained IMU, Laser, Kinect and wheel encoders as a sensor package. This platform provides odometry that is known to be unsatisfactory. Knowing this fact estimation approaches were implemented in the following analysis. Fig. 2.19 illustrates the different pose using

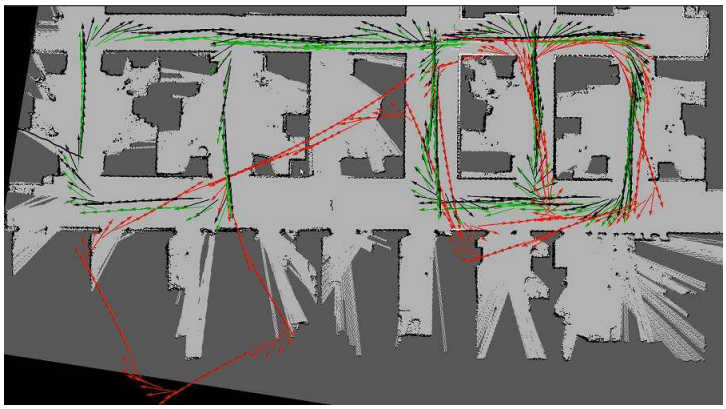


Figure 2.19: Trajectory while performing Task in CAS (Segway robot).

the EKF approach (Robot Pose EKF ROS package) of the platform during the run performed in the CAS center at UTS. Raw odometry (in red) and the outcomes from the Robot Pose EKF package (in black and green) are shown. In Fig. 2.19 virtual odometry (in black) provided by the Hector Mapping approach only slightly differs from the output of the Robot Pose EKF (in green). Both Hector Mapping and output of the EKF approach provide quite accurate pose estimation and are certainly applicable for this platform. Better performance of the EKF approach can be achieved with the appropriate tuning of the covariances values. Knowing the drifting wheel odometry the performance of the EKF and Hector Mapping approach can be recognized as satisfactory.

The real odometry suffers from drift as it does not use any feedback. As the real odometry from this platform suffers from significant drift, fusing the virtual odometry from Hector Mapping and the IMU was considered as a reasonable solution for this problem. Hector Mapping actually aligns scans in the real world and matches them against past observations, so it can greatly reduce the drift. The "localization only" mode is still not implemented in the Hector Mapping stack, so localization is achieved as a part of the overall scan process.

The second platform for this analysis is the instrumented UTS wheelchair (Fig. 2.8). Fig. 2.20 illustrates the pose of the UTS wheelchair platform using the Hector Mapping approach performing a run in level 2 at the UTS building. In blue is the Hector mapping provided pose while in red is the wheel odometry. Fig. 2.21 shows the performance of

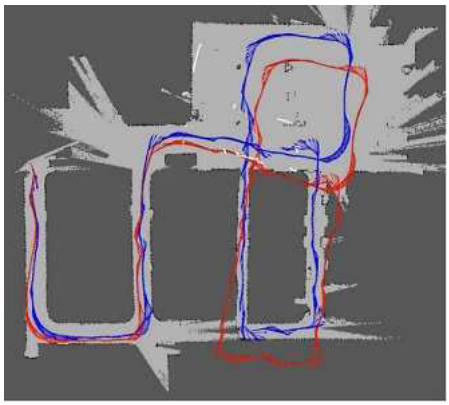
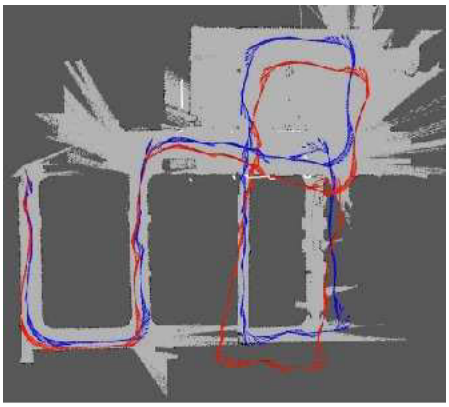
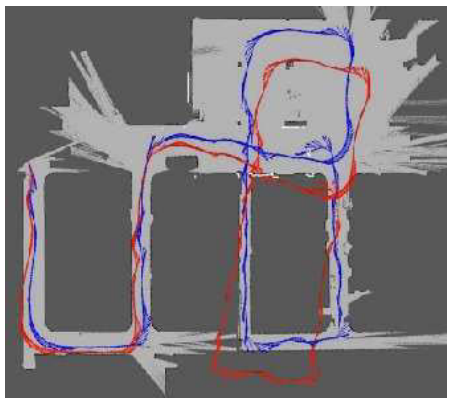


Figure 2.20: Hector Mapping pose and raw odometry (wheelchair run at level 2 UTS).



(a) AMCL using the map from Hector Mapping.



(b) AMCL using the map from Gmapping.

Figure 2.21: AMCL pose and raw odometry (wheelchair run at level 2 UTS).

the AMCL approach (in blue) when using the map from Hector Mapping (Fig. 2.21(a)) and Gmapping (Fig. 2.21(b)). The EKF approach using the Robot Pose EKF package is shown in Fig. 2.22 and Fig. 2.23. In Fig. 2.22 the EKF approach fused the IMU with the virtual odometry from Hector Mapping, while in Fig. 2.23 it used the wheel encoders as sensor information. Fig. 2.23(a) and Fig. 2.23(b) show the output of the EKF by the map from Hector Mapping and Gmapping.

In order to compare the estimated pose by all three methods, the extracted position tracking was presented in the XY coordinate frame as depicted in Fig. 2.24. It is clear that there is a significant difference between the estimated position of all three methods, and that Hector Mapping is able to produce better pose estimates. The difference

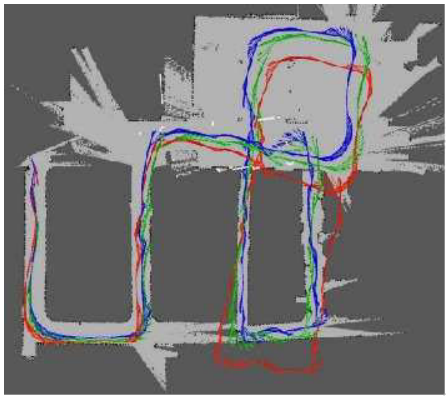
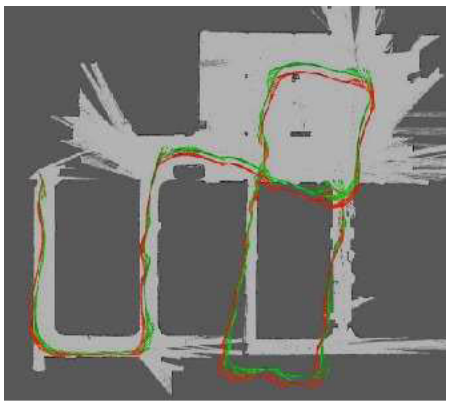
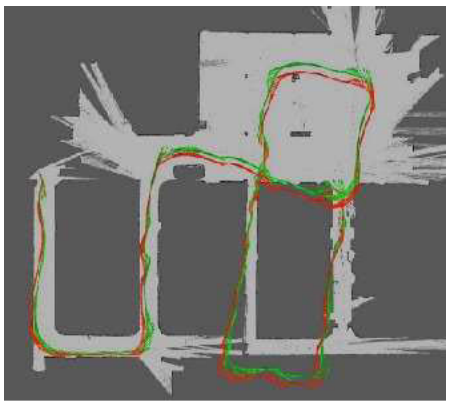


Figure 2.22: Robot Pose EKF fusing virtual odometry and IMU (wheelchair run at level 2 UTS).



(a) EKF using the map from Hector Mapping.



(b) EKF using the map from Gmapping

Figure 2.23: Robot Pose EKF fusing real odometry and IMU (wheelchair run at level 2 UTS).

in the estimated pose between AMCL and Hector Mapping coming from the better performance of the scan matcher used by Hector Mapping. Hector mapping actually aligns scans in the real world and matches them against past observations, so it can greatly reduce the drift from the real odometry. In ROS the robot pose is published to tf (as the map->odom transform) if the "pub map odom transform" parameter is set to true. It also is published as a geometry msgs/Twist message on the "slam out pose" topic. Using Hector Mapping odometry transform can be obtained, which can then be used as one of the sensors sources for the Robot Pose EKF to fuse IMU.

Robot Pose EKF package combines wheel, visual and IMU sensors information. When

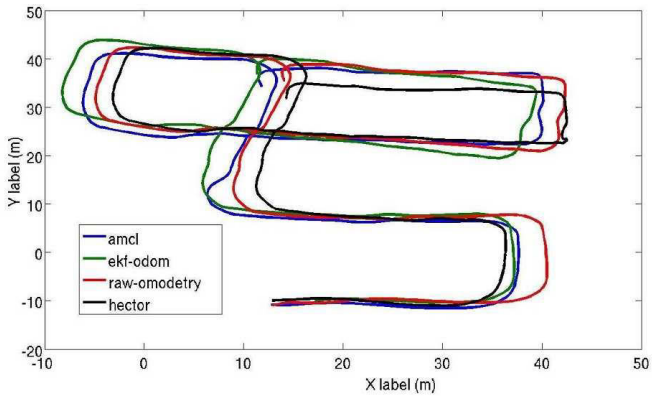


Figure 2.24: Estimated position tracking in XY coordinates frame

fusing real odometry and IMU, Robot Pose EKF do not obtain sufficient feedback from the environment to reduce the drift from the real odometry. So the accumulated error from the encoders readings and IMU can not be corrected sufficiently.

2.5 Summary

This chapter presents a standalone sensor package able to be deployed on a standard mobile platform, such as a wheelchair or a walker, and a suite of algorithms capable of generating a map of the surrounding environment and estimating the wheelchair trajectory. This work builds upon the initial results published in [16]. Probabilistic methods which implement a simultaneous localization and mapping algorithm for mapping and tracking the wheelchair platform have been presented. Furthermore, the influence of different sensor sources in the pose estimation and localization was analyzed. This work suggests an alternative SLAM proposition where instead of generating virtual odometry through scan-matching, it operates on the principle of integrating laser scans in a planar map.

Chapter 3

Automatic Analysis and Evaluation of PMDs Navigational Parameters

3.1 Introduction

In disability healthcare there exist multiple means for determining the performance of mobility aid users, such as the WST [20], and the PIDA [21] tests. The outcomes of assessments tests normally depend on the judgment of a qualified OT with recommendations [22] on the most suitable type of mobility aid, if any. Despite desirable increases to assessment consistency and efficiency there is yet to be a means for automated assessment based on criteria from standard wheelchair assessment tasks, in a format that is also convenient to therapist staff overseeing patient rehabilitation.

After the maps were created, and the paths followed by the platform during the user runs estimated, it is now clearly possible for therapists and clinicians to examine other navigational parameters that can help them to obtain an accurate assessment of the user's driving ability. There are a considerable number of quantitative registrations that can be measured using the sensor package, such as angular speeds, closest distance

(a) The wheelchair must travel along a sloped platform.

(b) The wheelchair must be aligned to the left wall.

Figure 3.1: Travel along a sloped platform and align to a wall stations of the WST, with an intelligent wheelchair.

between wheelchair and doorway when a user is asked to navigate through a door, or distance to a wall a user might be requested to follow in an exercise. The choice of parameters is limited only by the requirements of the assessing team/therapist. Speed, for example, is an important observation and needs to vary depending on the environment of use. When crossing the road a wheelchair user will need to proceed quickly. However, when surrounded by other people or when approaching a doorway speed will need to be reduced. The sensor package will allow the assessing team/therapist to determine if a wheelchair user was able to select the speed appropriate to the environment and to accurately record and analyse this parameter as the person spends more time using the device. Similarly, if a wheelchair user's average speed was found to be low, as compared with that of a skilled user in a particular environment, it might be used to indicate the need to adjust parameters on the chair such as seating or position of the wheelchair controller.

3.2 Related Work

Generally, the models of practice and assessments used for the selection of assistive technology are poorly developed and concerns have been raised about the set of available wheelchair assessments, clearly indicating the need for further research. An extensive review of the literature from 2003-2007 concluded that there is lack of evidence-based

(a) The wheelchair must move forward through a door.

(b) The wheelchair must travel through increased rolling resistance (in this case, gravel).

Figure 3.2: Move forward through a door and travel through increased rolling resistance stations of the WST, with an intelligent wheelchair.

procedures for the selection of assistive technology [23]. The need for higher levels of evidence-based practice was concluded in relation to matching mobility assistive technology in people with multiple sclerosis. Large inconsistencies have been reported between currently available manual wheelchair tests [24]. Also, commonly used standardized PMD assessments are not intended to determine whether or not a person will be a safe driver and do not assist therapists in determining when risk becomes untenable [25]. But maybe more relevantly in recent times, funding bodies in countries such as Australia are increasingly requiring more detailed and specific data about the intended uses and suitability of expensive pieces of equipment e.g. power wheelchairs and scooters, before they support therapistâs applications for these types of equipment.

Among a number of tools used by OTs to assess user acceptance of technology in general, some wheelchair user-specific questionnaires have also been developed to assess self-perceived wheelchair skills e.g. the WST [26](revised [20]), PIDA [21], and the Power-Mobility Community Driving Assessment (PCDA) [27].

PIDA is a widely used assessment tool. It was developed to determine accurately a client's competency and safety using a power mobility device. The instrument's content validity was established through a national survey of power mobility experts including consumers and OTs. The final version of the assessment has 30 items. The PIDA provides quantitative data that is helpful to OTs who prescribe power mobility devices

and implement training programmes.

Fig. 3.1 and Fig. 3.2 show an experimenter undergoing some of the skills included in the powered wheelchair version of the WST (WST-P) [9]. One pass over all tasks takes about 30 minutes. The WST (WST-P) test covers 32 skills which are considered representative for general wheelchair performance. The assumption is that a person doing well (performance and safety) on the 32 tasks included in the WST can be considered a skilled wheelchair user because the situations he/she encounters on a daily basis will resemble those tested. In other words, the WST abstracts from a real-world setting to measurable wheelchair skills.

There is clearly a pressing need to augment the existing therapist‘s subjective assessments of PMDs use with more objective and quantitative performance indicators. The use of subjective and objective assessments would provide complementary, but distinct, information allowing a more complete assessment of mobility [28]. This is an important observation: quantitative assessment does not mean a preference over subjective/qualitative assessment. There is a need to ’complement’, not to replace, one with the other. Therapists are highly skilled at combining observations with evaluation, being trained to see behaviour but also judge its quality simultaneously. Yet additional data can be interpreted by therapists and used to support and augment their observations in completing a comprehensive evidence-based evaluation of a person PMD use. This, in turn, presents OTs with the capability to factually decide whether clients are ready to be safely deployed with mobile aids for their daily activities.

3.3 Additional Navigational Parameters

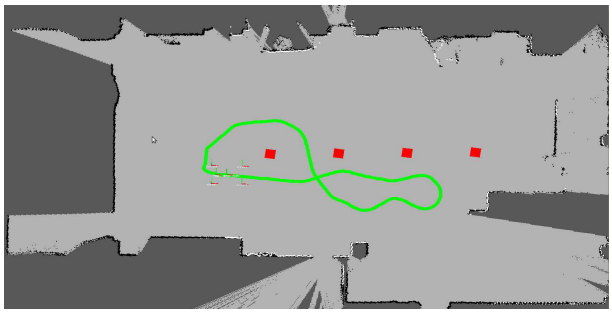
The PIDA wheelchair assessment was chosen to evaluate a set of automatically extracted navigational parameters. This is the routine commonly use at the PoW facility where the field trials were conducted, hence is also more familiar to the OT who carried out the manual assessments. Performances on test subsections are scored from 1 to 4. Optimal performance receives a score of "4" and inability to complete a task would be given a score of "1". Multiple or hesitant attempts or those in which a user bumps into objects or

people would be rated "2" or "3" depending on the liklihood of harm to the user, people or other objects. Four able users of differing abilities in operating power wheelchairs were asked to perform four runs each representing a range of tasks broadly aligned to those outlined in the PIDA assessment. For reference, these tasks have been categorized into “familiarization” (task 1), “basic” (task 2) and “advanced” (task 3) [1]:

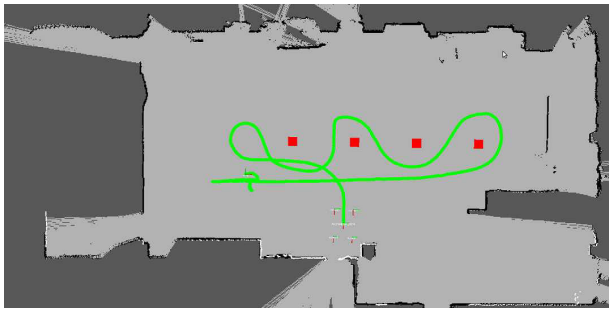
- Task 1 (Getting familiar)
  - Warm up task to get familiar with the chair. No specific tasks given.
- Task 2 (Basic control)
  - Turn 90° left and right on the spot.
  - Drive 5m in a straight line.
  - Drive the wheelchair in a zig-zag pattern around 5 pylons spaced at 1.5m.
  - Drive the wheelchair towards a closed door without driving into it, here the person driving the chair should be able to open the door.
- Task 3 (Advanced control)
  - Drive the wheelchair through a doorway without touching the sides.
  - Drive the wheelchair underneath a table, so the person driving the chair can interact with objects on the table.
  - Position the wheelchair so it is oriented sideways to a bed in preparation for a sliding-board transfer. The person should be able to touch the pillow of the bed. Ideally, the chair is parallel to the bed and as close as possible.
  - Back the wheelchair between two tables and keep the chair parallel to the tables.

The trajectories shown in Fig. 3.4, which correspond to User 4, are representative of the various tasks described above. Fig. 3.3(a) shows the result of the warm up task. Fig. 3.3(b) is the pose trajectory for task 2, whereas the more convoluted manoeuvre in

[1] An additional Task 4, combining all previous 3 in a single, sequential run, was also carried out, although could not be completed by all 4 users for logistic reasons (only 2 users could do it)



(a) Wheelchair trajectory while performing Task 1 run (User 4)

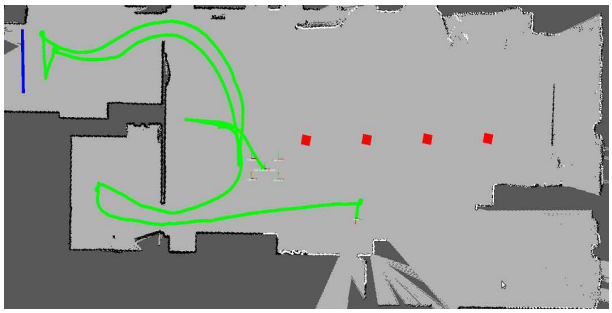


(b) Wheelchair trajectory while performing Task 2 run (User 4)

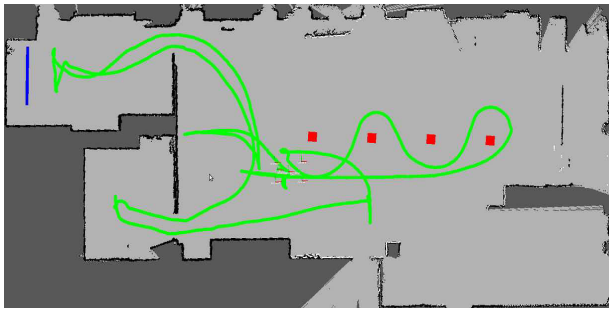
Figure 3.3: Trajectories followed by the wheelchair platform during the 1 and 2 task runs. Light grey is empty space (i.e. the room), dark grey is unknown (beyond the walls), green is the trajectory followed, white/green/red icons represent the orientation and edges of the wheelchair. Pylons used during the zig-zag motion are shown in red, while the right edge of the bed in the left room is shown in blue.

Fig. 3.4(a) correspond to the advanced task 3, where the user was asked to drive trough two open doors (shown on the left). In the room at the top he had to manoeuvre the wheelchair to align sideways in parallel with the bed, while in the room at the bottom he had to position the wheelchair underneath a table. Finally, Fig. 3.4(b) shows the last of the four runs which was a combination of all the previous ones, i.e. combining all tasks together (Task 4).

OT's scores drawn from the sub-set of PIDA tasks can then be compared to a range of objective parameters inferred from the measured wheelchair navigational data. This analysis is followed by closely comparing two individual event epochs e.g. approaching a door and aligning with a bed. While there are a considerable number of quantitative registrations that can be measured from the inferred trajectory, this work has focused



(a) Wheelchair trajectory while performing Task 3 run (User 4)



(b) Wheelchair trajectory while performing the final Task 4 run (User 4) - a combination of Tasks 1, 2 and 3

Figure 3.4: Trajectories followed by the wheelchair platform during the 3 and 4 task runs. Light grey is empty space (i.e. the room), dark grey is unknown (beyond the walls), green is the trajectory followed, white/green/red icons represent the orientation and edges of the wheelchair. Pylons used during the zig-zag motion are shown in red, while the right edge of the bed in the left room is shown in blue.

on four key metrics so that the comparison with the OT's qualitative PIDA scoring can be more effectively carried out:

1. alignment with beds (e.g. Figures 3.5 and 3.6)
2. proximity to doors (e.g. Figures 3.7 and 3.8)
3. linear velocity profile (e.g. Figure 3.9-Figure 3.10)
4. angular velocity profiles (e.g. Figure 3.11-Figure 3.12)

For that purpose, based on the data collected from individual laser scans and IMU data, further ROS nodes were developed in order to analyze parameters relevant to the assessments that OTs do manually, e.g proximity to doors and alignment with beds. The implementation considers all profile users like very experienced, skilled and

	Yaw [deg]	Distance [m]
User1	-80.96	0.54
User2	-95	0.72
User3	-108.5	0.45
User4	-94.5	0.59

Table 3.1: Yaw angle and distance to bed

unskilled ones. After that, linear and angular velocity profiles were extracted.

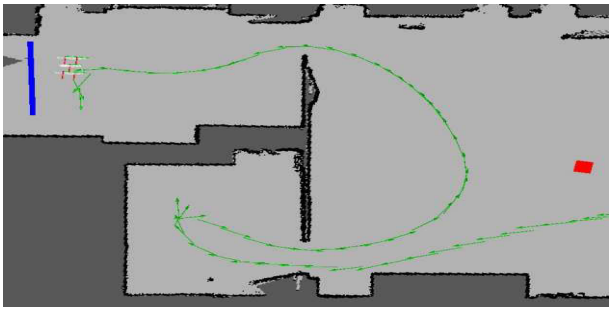
3.3.1 Alignment with Beds

The first analysis parameters relevant to the assessments that OTs do manually is alignment with beds. For that purpose, a ROS node was developed which was able to calculate the orientation and distance parameter when the wheelchair is approaching the bed. When accessing the bed from the right side, as in the test set up, the PIDA instructions call for the client to manoeuvre on the right side of the bed so that they can move directly to the bed. The distance and orientation to the bed information was used to analyse the user's ability to manoeuvre the wheelchair to access the bed for a transfer. The orientation of the wheelchair is orientation relative to a direction would be recognized as a reference. The calculated distance is the minimum distance to the bed. In this case it is in the positive direction of the X axis. As the input serve the individuals laser scans, the output of the node is the wheelchair orientation Yaw (in degrees) and the minimum distance to bed by linear velocity approx. zero.

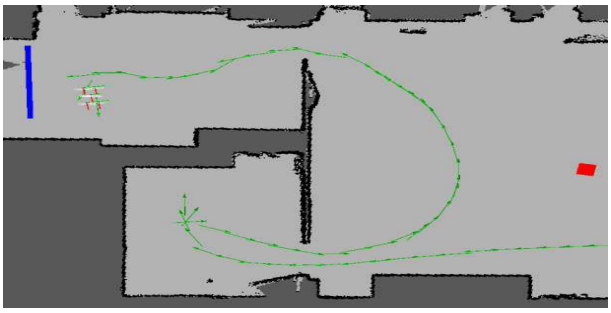
Fig. 3.5 and Fig. 3.6 illustrate the specific bed alignment component of the advanced task 3 by Users 1, 2, 3 and 4, where the right edge of the bed in the left room is shown in blue alongside the final orientation of the wheelchair.

Tab. 3.1 shows the numerical values of the Yaw angle in degree and the minimum distance to bed by linear velocity approx. zero. According to the presented information a detailed analysis of this parameter relevant to the assessments that OTs do manually, can be enclosed successfully.

The experimental evaluation of these results is presented in the next section.



(a) Alignment to bed and the base link coordinate frame by User 1.



(b) Alignment to bed and the base link coordinate frame by User 2.

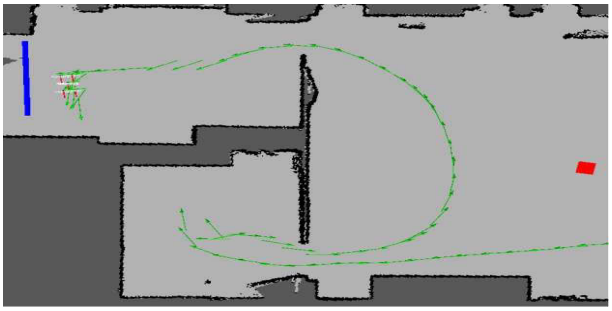
Figure 3.5: Bed alignment component of the advanced task 3 by Users 1 and 2.

3.3.2 Minimum distance to Doors

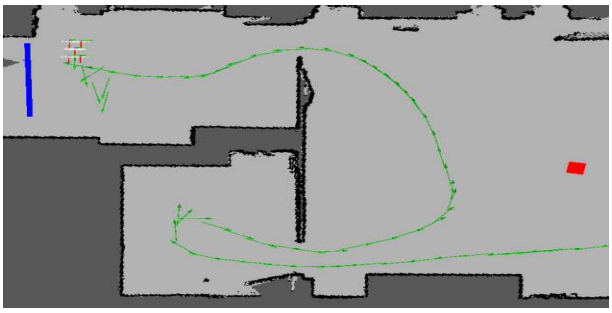
Following the first analysis of parameters relevant to the assessments, this study has focused on the next parameter namely the closest point (proximity to doors). For that purpose, a ROS node was developed that provided as an output data the minimum distance to the doors.

Similarly, distance to door is not specifically assessed in the PIDA but is a factor in determining if a user is likely to bump into the door and cause harm to themselves, other people or objects. The assumption was that the OT would possibly use these parameters in their assessment and the aim was to see if this was the case. If so, there would be a correlation between the objective and subjective scores. The OT was not specifically required to assess these parameters.

Fig. 3.7 and Fig. 3.8 illustrate minimum distance to the door frame when the Users 1,2,3,and 4 drives the wheelchair. To demonstrate the work of the localization, zoomed



(a) Alignment to bed and the base link coordinate frame by User 3.



(b) Alignment to bed and the base link coordinate frame by User 4.

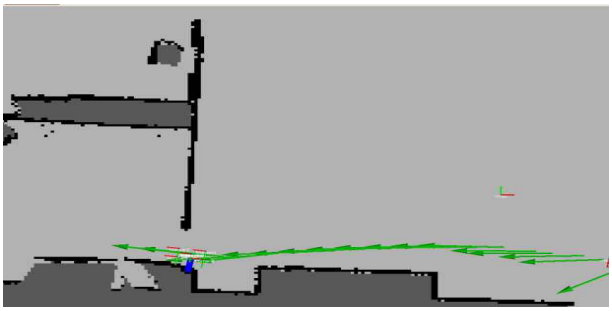
Figure 3.6: Bed alignment component of the advanced task 3 by Users 3 and 4.

figures of driving the wheelchair through the door frame are shown. Hereby the current minimum distance with the marker visualisation is illustrated.

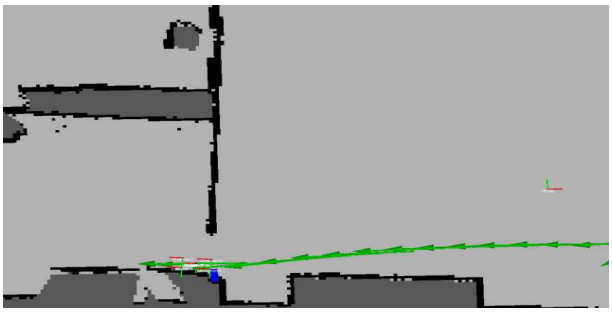
Tab. 3.2 shows the overall minimum distance to the doors in meters. Here, all profile users by run 3(task 3) were considered. The presented figures give a closer loop of the localization work. It is very obvious that the values are very small, considering the doors and wheelchair dimensions. So, it has to be analyzed if this information presented in such manner is relevant for the OTs.

	Distance [m]
User1	0.181
User2	0.184
User3	0.179
User4	0.182

Table 3.2: Minimum distance to the door



(a) Minimum distance to Doors with the visualization marker by User 1.

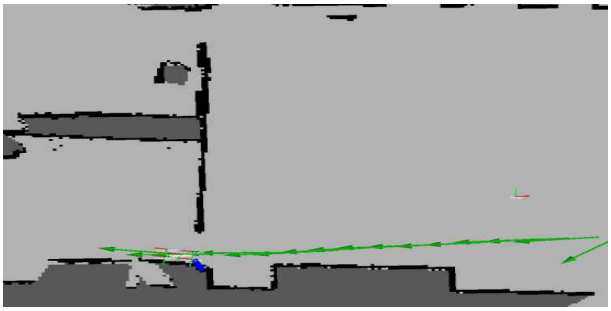


(b) Minimum distance to Doors with the visualization marker by User 2.

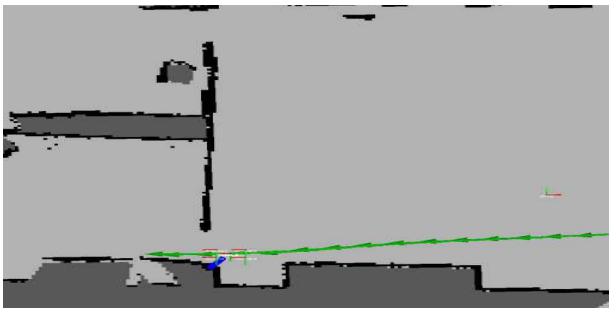
Figure 3.7: Minimum distance to Doors with the visualization marker of the advanced task 3 by Users 1 and 2.

3.3.3 Velocity Profiles

Speed is an important observation that can be used to infer a user's confidence and situational awareness. When crossing the road a wheelchair user will need to proceed quickly. However, when surrounded by other people or when approaching a doorway speed will need to be reduced. The parameters derived from the sensor package measurements may allow for instance the assessing team/therapist to determine if a wheelchair user was able to select the speed appropriate to the environment of use, and to accurately record and analyse this parameter as the person spends more time using the device. Similarly, as will be seen in the next Section, if a wheelchair user's speed profile was found to be low, as compared with that of a skilled user in a particular environment, it might be used to indicate the need to adjust parameters on the chair such as seating or position of the wheelchair controller. On the other hand, if the wheelchair was properly set up, such behaviour might suggest lack of confidence or the impact of any visual or



(a) Minimum distance to Doors with the visualization marker by User 3.



(b) Minimum distance to Doors with the visualization marker by User 4.

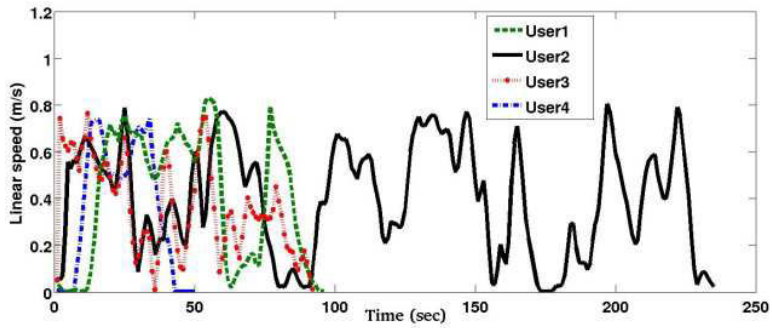
Figure 3.8: Minimum distance to Doors with the visualization marker of the advanced task 3 by Users 3 and 4.

cognitive impairment in a user and the need for further input by the therapist.

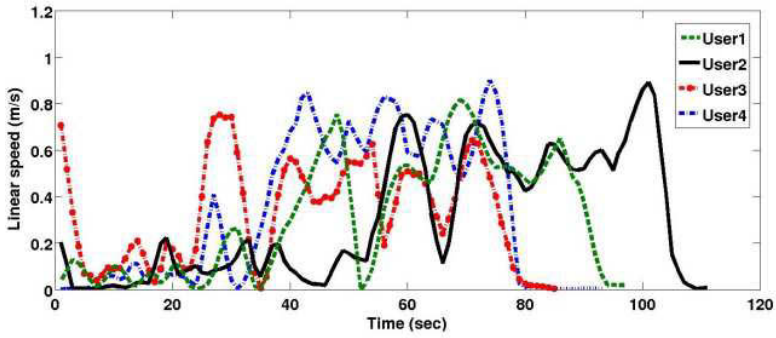
The velocity parameters were extracted based on the position and orientation values of the localizer. To be able to present successful analysis of the extracted profiles, a localizer with accurate estimated wheelchair pose is needed. As in the previous chapter successful analysis of the estimated pose and localization was done, the Hector Mapping approach being used when the velocity profiles were extracted.

Fig. 3.9 till Fig. 3.12 depict the linear and angular velocity profiles by all four users when performing each of the four task runs. The experimental evaluation of these results is presented in the next section.

A similar analysis was carried out on two UTS mobile platforms with different sensor packages. The first platform used for this analysis was the Segway platform in the CAS centre. In Fig. 3.13 the linear velocity profiles were extracted using the Hector



(a) Linear velocity profiles for all users while executing the Task 1 run.



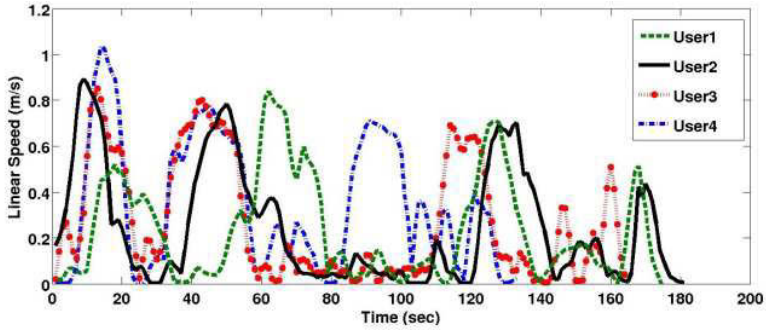
(b) Linear velocity profiles for all users while executing the Task 2 run.

Figure 3.9: Linear velocity profiles for Task 1 and 2 runs.

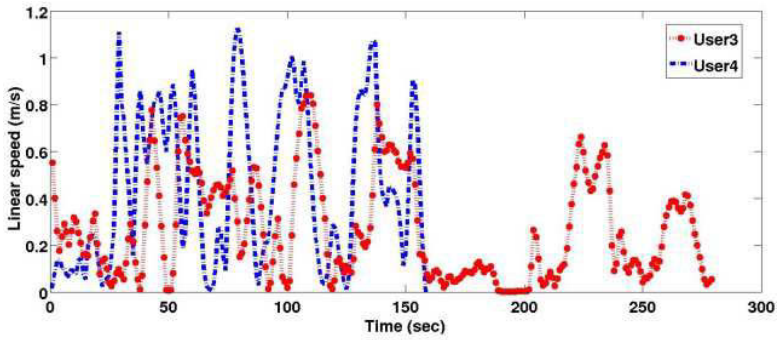
Mapping and EKF approaches. In the EKF approach first the virtual odometry from the Hector Mapping and IMU was fused, then, fusing raw odometry with the IMU. From the picture, no significant differences in all three approaches are to be seen. So, it is not trivial to recognize the role of IMU in this process. Similar to the linear velocity profiles the angular ones were extracted. Fig. 3.14 illustrates the angular velocity while the platform is performing a run in the CAS center. Here, the same comments remain as those about the linear velocity profiles.

The second platform used for this analysis was the UTS wheelchair platform with the sensor package described in the previous chapter. Fig. 3.15 illustrates the linear velocity while the UTS wheelchair platform is performing a run in level 2 of the UTS building.

In Fig. 3.15(a) the linear velocity profiles were extracted using all four approaches. Here, it is clear to see that there is a significant difference in linear velocity between any of the used methods. Also, a closer zoom (Fig. 3.15(b)) of the profiles, provides



(a) Linear velocity profiles for all users while executing the Task 3 run.



(b) Linear velocity profiles for the 2 users who undertook the Task 4 run.

Figure 3.10: Linear velocity profiles for Task 3 and 4 runs.

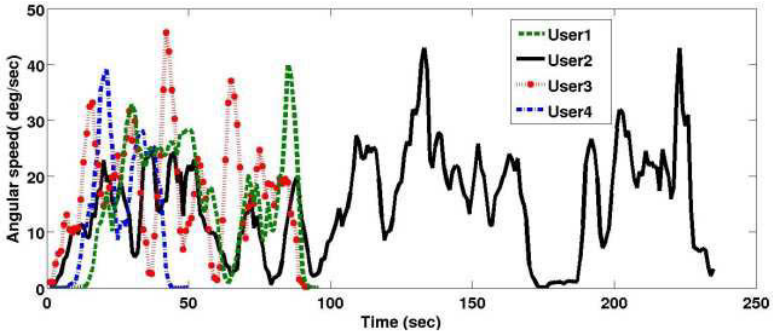
information on the significant difference.

Similar to the linear velocity profiles the angular ones were also extracted. Fig. 3.16 illustrates the angular velocity of the same run. The angular velocity profiles simular to the linear ones show significant difference between them, especially between the raw odometry of the AMCL and the other three methods.

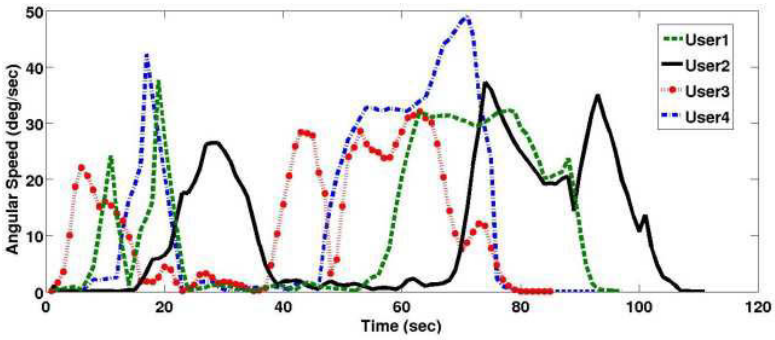
3.4 Experimental Evaluations of the Extracted Navigational Parameters

The final metric results for all the users are collected in Table 3.3 for the advanced task 3, which includes the task sub-components scored by the OT's PIDA assessment [2]. It

[2]The combination task 4 also includes these sub-components, but it could not be undertaken by all 4 users, hence was disregarded for comparison purposes



(a) Angular velocity profiles for all users while executing the Task 1 run.



(b) Angular velocity profiles for all users while executing the Task 2 run.

Figure 3.11: Angular velocity profiles for Task 1 and 2 runs.

can be seen how there is high consistency in the subjective scores and objective data in the task of assessing "Distance to door". All users received higher subjective score of "3" and "4" and all were approximately $0.14m$ from the door with little or no variation between them. A larger number of participants is needed to determine if the one point difference in PIDA scores is statistically significantly different.

The advantage of having data from the sensor array is that the possible sub-components or parameters of a task, like approaching the bed, can be studied in detail. However, it is possible that the therapist might attend to, or attribute more importance to, one particular sub-component or parameter over another. In the PIDA the task of approaching the bed is defined as "Accessing Bed - Left" or "Accessing Bed - Right". From the sensor array the subcomponents of wheelchair proximity and orientation can be determined. Users 1, 2 and 4 received subjective scores of "3" for "Accessing Bed - Right". These users were within 10 deg of the ideal orientation to the bed and were

User	Distance to door (m)	OT's score	Orientation to bed (°)	Distance to bed (m)	OT score
1	0.13	4	1	0.55	3
2	0.14	3	5	0.73	3
3	0.13	3	18	0.46	2
4	0.14	4	6	0.61	3

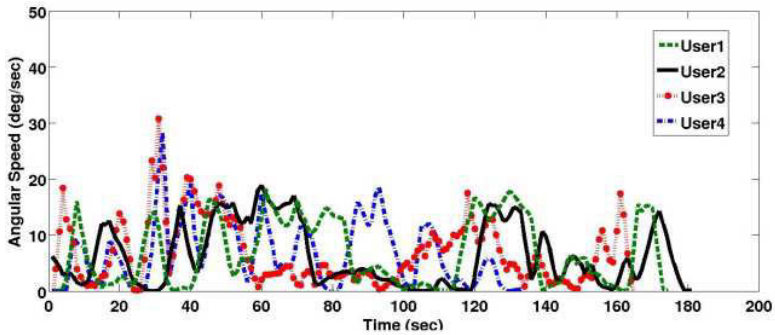
Table 3.3: Specific user performance metrics and OT scores during the "Advance task 3".

User	Task 1 speed (linear±std), (angular±std)	Task 2 speeds (linear±std), (angular±std)	Task 3 speeds (linear±std), (angular±std)	OT score for "speed"
1	(0.4±0.3), (14.5±14.6)	(0.3±0.3), (15.9±34.7)	(0.3±0.3), (7.2±7.6)	4
2	(0.4±0.3), (19.4±43.7)	(0.3±0.3), (11.5±14.5)	(0.2±0.3), (8.2±9.7)	3
3	(0.4±0.2), (17.1±15.4)	(0.3±0.3), (13.3±15.7)	(0.3±0.3), (9.1±11.2)	2
4	(0.4±0.3), (12.6±15.8)	(0.3±0.4), (15.0±19.9)	(0.3±0.3), (9.6±11.8)	4

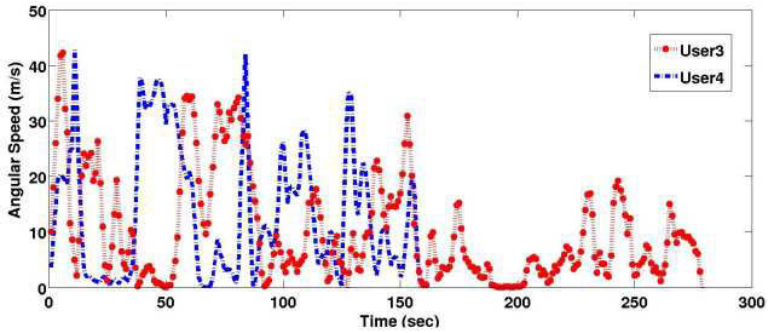
Table 3.4: Wheelchair speeds - linear (m/sec) and angular (°/sec) - and OT scores over all tasks

between $0.55m$ and $0.73m$ from the bed. In this position it was possible for them to all touch the pillow on the bed. User 3 received a lower subjective score of "2". This user was closest to the bed ($0.45m$) but exhibited significantly poorer orientation (18 deg error) with respect to the bed. Consequently, it is likely that the therapist was focusing on the perceived alignment discrepancy rather than distance to the bed in their subjective assessment of "Accessing Bed - Right".

Table 3.4 shows the mean (± standard deviation) of the linear and angular velocities for each user during each task. All of the data, in each sub-component of each task, was combined or 'lumped' into a single value. Hence, there is a single linear and angular velocity result for tasks 1, 2 and 3. T-tests were performed to compare each user's performance over all tasks. Users 1 and 2 significantly reduced their linear velocity when performing basic control tasks (task 2) as compared to their performance in the free trail/familiarization task (task 1). Users 3 and 4 did not significantly modify their



(a) Angular velocity profiles for all users while executing the Task 3 run.



(b) Angular velocity profiles for the 2 users who undertook the Task 4 run.

Figure 3.12: Angular velocity profiles for Task 3 and 4 runs.

linear velocities between tasks 1 and 2. No user made significant changes to the angular velocity of the wheelchair between tasks 1 and 2. User 1, 2 and 3 significantly reduced their linear and angular velocities when performing advanced control tasks (task 3) as compared to their performance in the free trail/familiarization task (task 1). User 4 did not significantly reduce either linear or angular velocity between tasks 1 and 3. All users significantly reduced their angular velocities between tasks 2 and 3. Only User 2 also significantly reduced their linear velocities between tasks 2 and 3. Task 2 was a series of basic control activities but task 3 involved more angular movements of the wheelchair. Hence it is possible that users responded to the greater need for turns in task 3 by uniformly reducing their angular velocities.

In the PIDA, the assessor has to allocate a single score for a number of sub-components and so give an "average" score across quite different sub-components. This is especially true of "speed selection" in which the therapist is not overtly assessing either linear or

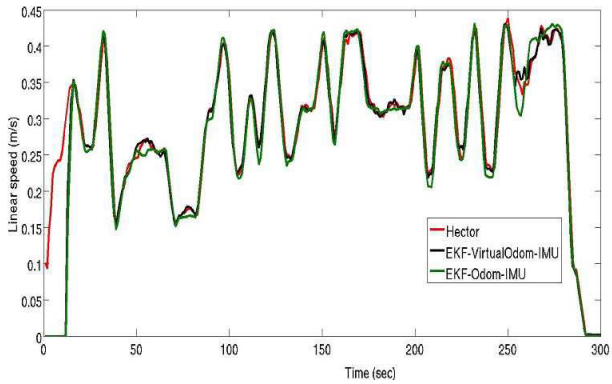


Figure 3.13: Linear velocity profiles (segway robot).

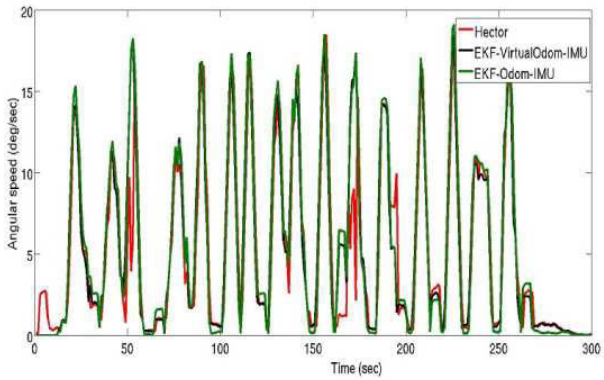
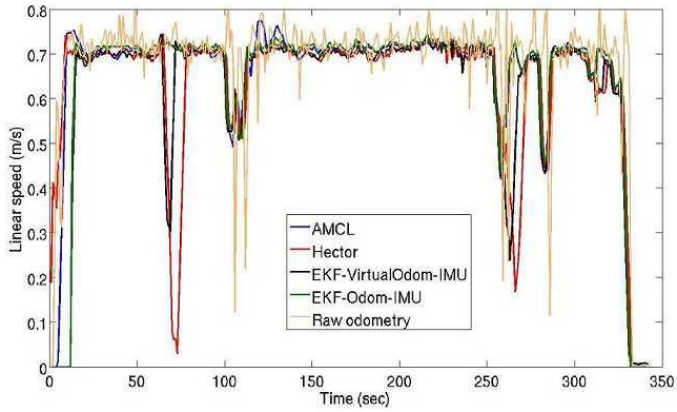


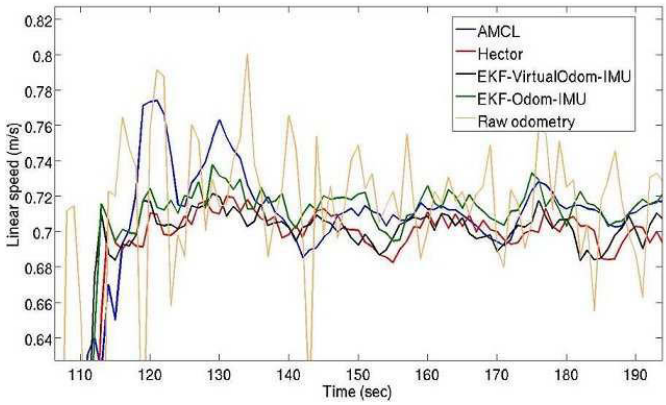
Figure 3.14: Angular velocity profiles (segway robot).

angular velocity but is giving a single "average" or "integrated" value for speed linear and angular speed selection over all sub-components. User 3 perhaps responded the most appropriately by reducing speed with increasing complexity of the task and received a reasonably high subjective score of "3" for "speed selection". User 2 was the most naive wheelchair user. They significantly reduced their linear and angular velocities only in the most complex tasks (task 3) and received the lowest subjective score of "2". User 1 generally adopted strategies of reducing velocity with increasing complexity of task, as did User 3, but was allocated a higher subjective score of "4".

Users 1 and 4 received the highest subjective score of "4" for speed selection. However, the speed selection strategies of each user were quite different. User 1 tended to reduce their linear and angular speed with increasing task complexity i.e. from task 1 to 3. User 4 was the most experienced wheelchair user and only significantly reduced their



(a) Linear velocity profiles.



(b) Zoomed linear velocity profiles.

Figure 3.15: Linear velocity profiles (UTS wheelchair platform).

angular velocity between tasks 2 and 3. Otherwise, they did not significantly modify linear or angular speed with increasing complexity of tasks. It is difficult to determine which sub-component(s) or parameter(s) the therapist was attending to when allocating the subjective score for "speed selection" in the PIDA.

Generally the therapist seems to have awarded higher subjective scores to users that significantly changed linear or angular velocity with increasing complexity of task. However, it is uncertain as to which parameters the therapist was attending to when awarding a score to User 4. This user did not appear to significantly reduce linear or angular velocity with increasing complexity of task but still received the highest subjective rating.

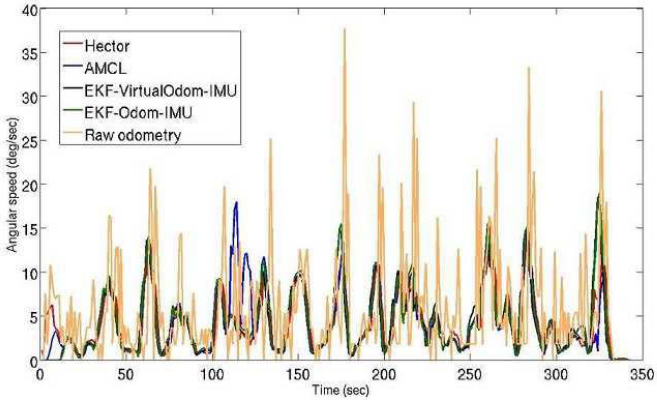


Figure 3.16: Angular velocity profiles (UTS wheelchair platform).

3.5 Summary

In this chapter additional navigational parameters were presented that can help therapists and clinicians to obtain a qualitative assessment of the user's driving ability. Among a considerable number of quantitative registrations that can be measured using the sensor package this study focuses on four key metrics so that the comparison with the OT's qualitative PIDA scoring can be more effectively carried out, namely: alignment with beds, proximity to doors, linear and angular velocity profiles. Even with these four straightforward variables inferred from the automatically revealed data, this study was able to demonstrate consistency and agreement between objective data acquired from the sensing array and the subjective assessments of a therapist analysing a user's wheelchair skills. In the next chapter we take this a step further to include data mining techniques in the process.

Chapter 4

Machine Learning for Performance Classification

4.1 Introduction

After establishing most simple navigational parameters such as alignment to beds, proximity to doors, linear and angular velocities, can help OTs in their qualitative assessment, this chapter focus is on more advanced quantitative measures captured by the sensor data, such as actual or close collisions, completion time, idle time, etc. With much more available ratings for each task from the PIDA assessment test, the reasonable preposition is on turning to machine learning to *learn* which quantitative measures are most informative for the OT assessments. Results from three typical classifiers are presented based on learnings from manual labeling of the training data.

4.2 Related Work

There is much work in the literature covering the use of machine learning algorithms in a vast range of classification applications from vocational assistance [29] and forecasting water supply losses [30], cancer diagnosis criteria [31] to the analysis of soccer videos [32].

Classification analysis through data mining techniques is also becoming widely adopted for healthcare applications given the large bodies of data to decide what information is most relevant to improve quality of patient care. However, little has been done to study whether a machine learning engine could provide support to therapists in determining what the most appropriate PMD for a client could be, a judgment in itself compounded by the lack of agreement in the tests to be carried out to decipher such an outcome.

Machine learning techniques are now being used extensively in biomedical applications. There has been less use in support of clinical decision-making and prediction, but these applications are increasing. There has been limited investigation of machine learning techniques in predicting rehabilitation outcomes. Although some of these results have been ambiguous, continued exploration in rehabilitation seems warranted given the importance and challenges of predicting rehabilitation potential or outcomes. Also, large databases are becoming available in rehabilitation settings, such as those based on the Functional Independence Measure (FIM, property of Uniform Data System for Medical Rehabilitation, a division of UB Foundation Activities, Inc) or the interRAI assessment systems, that could be used for this purpose [33].

The work presented in [34] shows the outcomes of application of machine learning techniques for the detection of one of the Arboviral disease-Dengue. They make use of SVM and RF techniques for the prognostic study of the Arboviral disease. Furthermore, it gives a brief overview of the data mining process with the goal of to predict, generalize a pattern to other data. The process itself typically involves three major steps namely: exploration, model building and validation and finally deployment. The process of knowledge discovery from databases (KDD) includes several steps, such as understanding the problem domain, selecting data sources, data cleaning and pre-processing, data reduction and projection, task selection, algorithm or model selection, model evaluation and deployment [34].

SVM and KNN have been compared to guide rehabilitation planning for home care clients [33]. KNN was chosen by these authors as it was considered to be analogous to clinical reasoning and SVM in that it that could potentially identify prototypical cases that could aid interpretation. A small number of support vectors would possibly produce

a more interpretable and parsimonious model for therapists to use. This research work aims to compare and contrast the outputs of machine learning systems that are widely used, in other fields, but have not yet been applied, in a novel way, to analyse the skill of a PMD user.

The work of [1] reports a decision-theoretic method called a Partially Observable Markov Decision Process (POMDP) to model the user's behavior and cognitive state, as well as the wheelchair's status along the route, using noisy visual observations received from the Route Planner. The Prompter tries to estimate whether the user needs help, and then issues an appropriate prompt.

Intention recognition, as defined in Heinze's doctoral thesis [35], is the process of becoming aware of the intention of another agent (the user in this case) or as the problem of inferring an agent's intention through their actions and its effects in the environment. Due to partial observations the communication of intentions between the user and agent becomes an important issue. Intention recognition has found its application in many research areas such as user assistance in aviation monitoring [35], human robot co-operation [36] and many others.

Probabilistic Networks (PN), also known as Belief Networks, has become a popular tool in the AI community as they can represent a complex system using graphical models [37]. Due to the amount of uncertainty involved in designing user assistive systems, researchers have explored the possibility of using various stochastic models like Markov Decision Process Models (MDP)/Partially Observable Markov Decision Process Models (POMDPs) [38], [39], Hidden Markov Models (HMM), Bayesian Network (BN) [40] and Dynamic Bayesian Network (DBN) [41]. The typical temporal dynamics of an assistive system consists of a sensorial system and an engine which, after learning, infers the user behaviour from the newly acquired data.

Machine learning approaches have therefore the potential to serve as a clinical assessment tool, and the work in this chapter sets at to analyze its viability to replace the judgment of a therapist in efficient and consistent mobility aid performance classification.

4.3 Background in Machine Learning and Data Mining

The work in this thesis draws on the foundation of work in robotics, machine learning and data mining techniques. Here, a short background of the data mining process and machine learning techniques is given.

Data mining is the intelligent computational analysis of large data by using a combination of machine learning, statistical analysis and database technology, with the objective to discover patterns and rules helpful for guiding decisions about feature activities. This analytical process primarily involves searching throughout vast amounts of data to spot useful, but initially undiscovered patterns.

Machine learning involves computer programs that use experience gained from exploration of a dataset to improve performance or predictive ability. These techniques are now being used extensively in biomedical applications, for example in predicting the role of genes and proteins.

In the first stage of the classification process a Support Vector Machine (SVM) [42] technique was used as a tool to process high dimensional data. SVMs, a global classification model are supervised learning methods used for classification and regression tasks that originated from statistical learning theory. This training algorithm, one of the most well-known of a class of performing methods for bio-data analysis uses the idea of kernel substitution for classifying the data in a high dimensional feature space. SVMs are based on the structural risk minimization principle, closely related to regularization theory [34]. SVMs are capable of classifying high dimensional data with high accuracy.

The RF, a classification method, is essentially a data mining package, based fundamentally on regression tree analysis and feature importance [43]. RFs are an ensemble learning method for classification (and regression) that operate by constructing a multitude of decision trees at training time and outputting the class that is the mode of the classes output by individual trees. This method uses a number of generated decision maps or ”trees”, that branch from a random set of features at each decision point. This classifier attempts to minimize both its own bias and the spread of data, making it

well-suited for classification with a limited number of features and datasets, as is the case in these experiments.

The RF is anincreasingly used statistical method for classification and regression problems introduced by Leo Breiman in 2001 [43]. RFs investigate two classical issues of variable selection. The first one is to find important variables for interpretation and the second one is more restrictive and tries to design a good cost-conscious prediction model. The main contribution is twofold: to provide some experimental insights about the behavior of the variable importance index based on RFs and to propose a strategy involving a ranking of explanatory variables using the RFs score of importance and a stepwise ascending variable introduction strategy. Developed originally for medical applications, RF has been applied as an effective statistical tool for biological and ecological research [34].

Parametric modeling is a technique for time series analysis in which a mathematical model is fitted to a sampled signal. If the model forms a good approximation to the signal's observed behaviour it can then be used in a wide range of applications, such as spectral estimation, linear prediction coding (LPC) for data compression, speech synthesis, and feature extraction for pattern recognition classification problems. The mathematical model that is most widely used is rational transfer function, the exact form of which is determined by estimating suitable values for its free parameters. If all of these parameters lie in the transfer function's denominator then the model is termed an all-pole or autoregressive (AR) model, while an all-zero or moving-average (MA) model has all of its free parameters in the numerator. A model with free parameters in both the numerator and denominator is then termed a pole-zero autoregressive moving-average (ARMA) model. The AR modelling technique can be formulated either in the frequency domain as a spectral matching problem or in the time domain as a linear prediction problem [44].

Parametric transformations use orders of autoregression, a magnitude of derived weighted sum of previous to current values. In that way the data representation (domain) is changed into specific time windows, to see if they can provide greater information compared to a dataset in its entirety. As the data is interpreted through a different

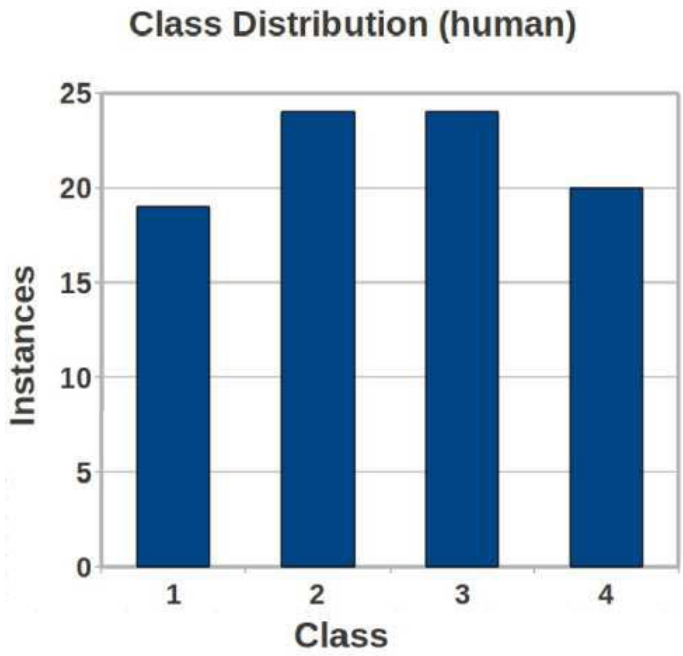


Figure 4.1: Recorded data distribution for 10m runs.

representation, a new set of parameters is also obtained which may be more beneficial to classification compared to their time-domain counterparts. Burg, covariance and modified covariance methods are all autoregression processes with different approaches for estimating data strength [45].

4.4 Extracting Parameters for an Assessment

The incipient results in this research point to the fact that machine learning approaches have the potential to serve as a clinical assessment tool to replicate the judgment of a therapist in efficient and consistent mobility aid performance classification. To that end, a methodology is proposed to find correlations between therapist scores and quantitative measures that can be evaluated with a standalone sensor package. Whereas the researchers earlier works [16; 46] were based on environmental attributes such as alignment with a bed and other parameters recommended by a therapist, the work hereby presented proposes the use of parameters data-mined from test runs for an assessment of general user proficiency. This is done in order to be unrestricted to any particulars

Table 4.1: Task Datasets

Experiment	Number of Datasets	Number of Test Users
10m drive	78	4
180° turn	78	5
Ramp drive	61	4

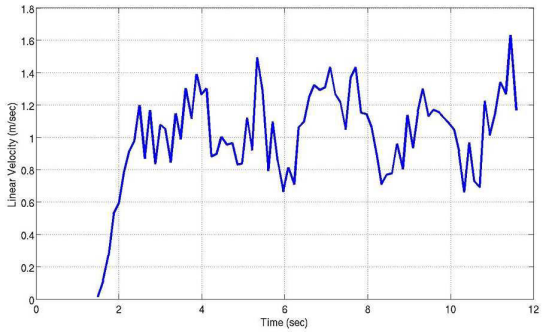


Figure 4.2: Raw data signals of instances class 1. Linear velocity over time

concerning the required assessment outcomes of the respective OT, allowing classification to focus solely on navigational ability. Selection of parameters based on platform movement is done through machine learning, as parameters possibly less intuitive to interpret may possibly provide greater insights for classification. After this pre-processing step, a number of discriminative classifiers are studied to analyse the skill of a PMD user.

4.4.1 Experiment Setup and Data Collection

This research work is primarily concerned with parameters gathered from short driving activities as a way to assess the validity of the proposed scheme. As such, three representative tasks were selected out of PIDA's available 35, namely "180 degree turn", "driving on an indoors incline" and "10m forward driving" tasks.

An instrumented wheelchair platform (Fig 2.8) as already described in the Chapter 2 was fitted with a modular sensor package. Multiple runs were then recorded from five able users while they performed the tasks under controlled environmental conditions. Details are collected in Table 4.1. The use of naive able bodied users and limited data sets to demonstrate proof-of-concept are considered a necessary first step before seeking

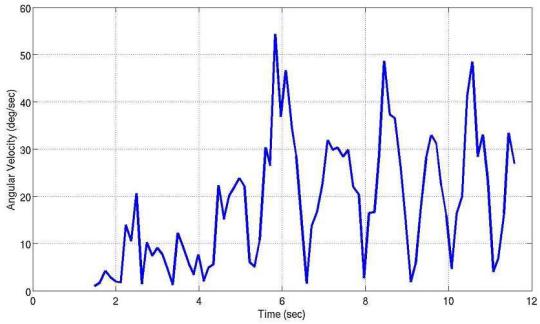


Figure 4.3: Raw data signals of instances class 1. Angular velocity over time

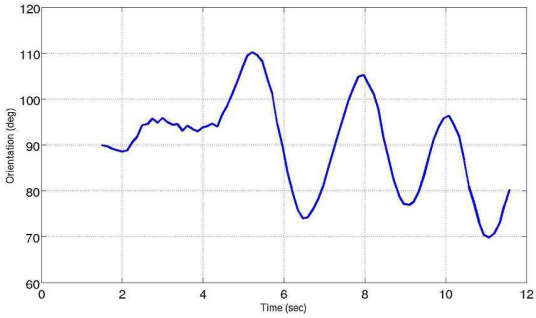


Figure 4.4: Raw data signals of instances class 1. Orientation over time

to apply the methods to those with a disability. Able bodied users will, like those with a disability, exhibit a range of skill levels that, while necessarily different from those with a disability, can still potentially be identified using the proposed machine learning techniques. Nonetheless, to align the skill set with those of the intended audience, users were asked to simulate varying degrees of erraticness in their driving, and were labelled accordingly. This is of course rather subjective, but in essence so is the task at hand, as what makes a "proficient ' or "bad" driver of a power mobility device is hard to discern in itself. But it is precisely the capacity of the proposed techniques to capture and model variability in the data trends, particularly given the associated inherent noise in the measurements, that this work is trying to capture.

As per the PIDA scale, the four classes range from poor (1) to proficient (4). Figure 4.1 shows the spread of the datasets collected, with classes distributed roughly equally and a slightly lesser number of runs deemed to be very poor or very good. Two samples of one of the extracted parameters from the 10m run task, in this case the linear velocity profile, are shown in Figures 4.2 til 4.7 for class 1 and 4 respectively (further details

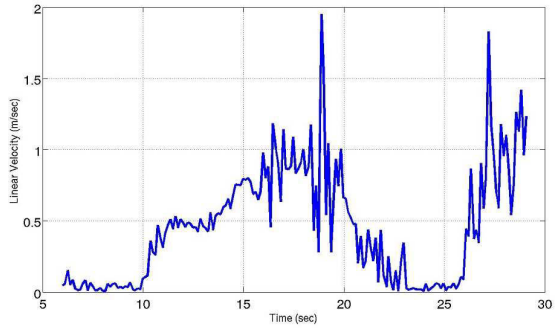


Figure 4.5: Raw data signals of instances class 4. Linear velocity over time

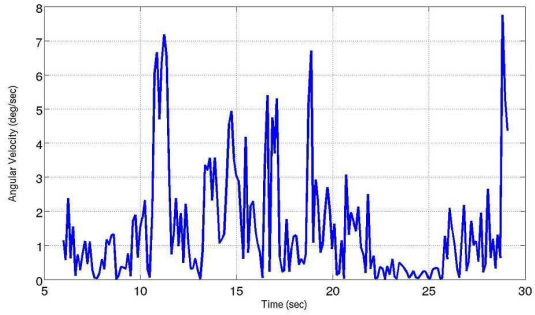


Figure 4.6: Raw data signals of instances class 4. Angular velocity over time

about the parameters analysed will be given in Section 4.4.3). It can be observed how the class 4 profile is relatively smoother despite some peaks towards the end of the run, whereas the class 1 profile appears more erratic throughout.

All the development was done in the ROS software environment. Laser scanner, odometry and IMU data was fused to map and provide wheelchair localization during the runs via the Hector mapping package [19]. Additional ROS support was developed for each of the tasks and time-stamped parameters (e.g. linear and angular velocity, proximity to obstacles, etc) were recorded during the user trials. Figure 4.8 shows the retrieved turn (Figure 4.8(b)) and pitch angle (Figure 4.8(a)) from the 180 degree and ramp tasks respectively. Figure 4.9 depicts trajectories followed by the wheelchair platform during the assessment task runs. Where Figure 4.9(b) and 4.9(a) depict a sample wheelchair trajectory from a run recorded for the 10m and 180 deg task respectively. The arrows indicate platform position and orientation, with points identified to be solid objects by the laser scanner (such as walls) shown in black. Light-grey areas represent known empty space, and the remaining dark-grey space are the unknown regions beyond

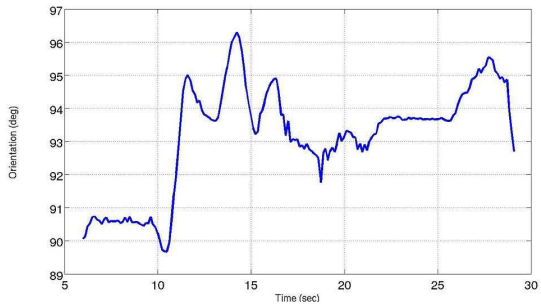
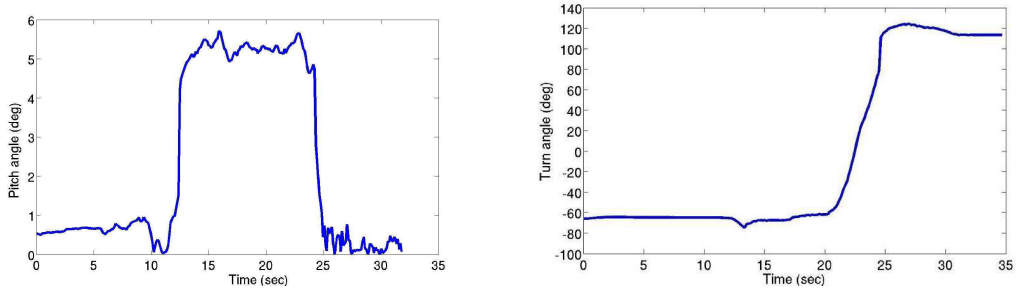


Figure 4.7: Raw data signals of instances class 4. Orientation over time



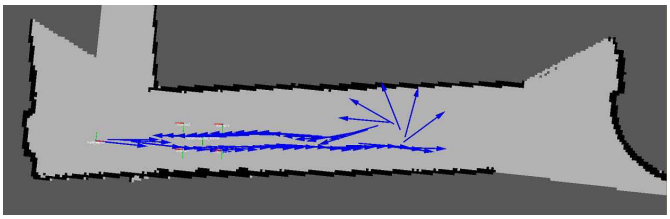
(a) Ramp Angle (b) Turn Angle

Figure 4.8: Ramp and Turn Angle by ramp up and 180° turn tasks

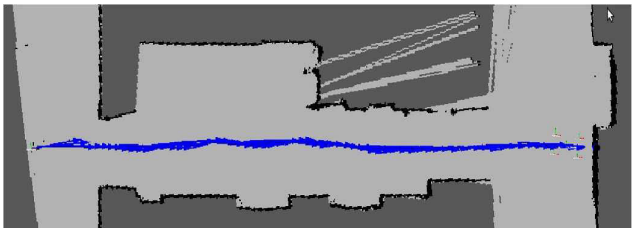
the environment sensed by the scanner. Figure 4.10 shows the ramp used for ramp task simply for illustration.

4.4.2 Graphical User Interface

Figure 4.11 depicts the simple GUI developed with the future assessing staff in mind to be able to conveniently use the system in an intuitive, repetitive and consistent manner with little need for familiarization with the underlying robotics hardware or software. This was done with the intention to allow for more tests to be conducted efficiently in a clinical setting. The interface is Qt-based and uses a MATLAB pipeline behind-the-scenes for classification based on incoming data bridged from the ROS sensor drivers. Figure 4.12 shows the graphical representation of some of the selected parameters for 10m forward task.



(a) Sample 180° turn



(b) Sample 10m run

Figure 4.9: Trajectories followed by the wheelchair platform during the assessment task runs.

Figure 4.10: Test ramp (6° gradient)

4.4.3 Parameter Selection

Feature selection on high-dimensional data reduces dimensionality, removes irrelevant or redundant features, reduces the amount of data needed for learning and improves the predictive accuracy of an algorithm. The advantage to therapy practice is that a person's care can be achieved more efficiently with a minimum number of features or minimum data set. Feature selection gives a method of reducing the number of measures and assessments and still maintaining or even enhancing accuracy [34].

Various features were extracted from the sensor data and used as an input to the classifier to perform the assessments. Parameter selection was carried out using the At-

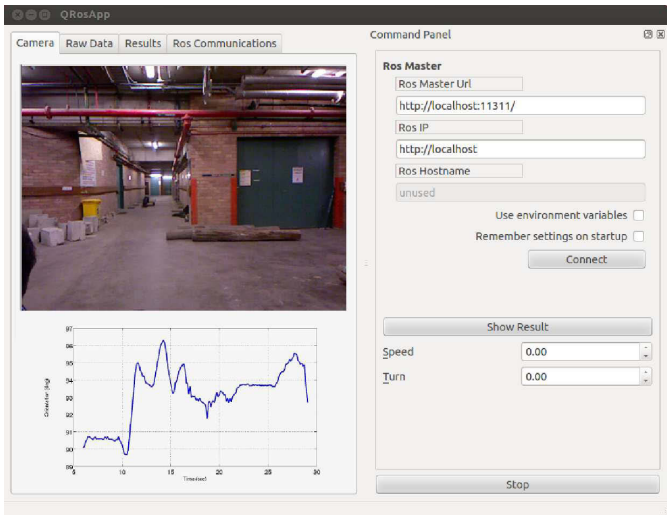


Figure 4.11: Assessment GUI.

tribute Selection feature within the WEKA(Waikato Environment for Knowledge Analysis) toolkit [47] to find the most informative attributes first. The evaluator approach computes the intrinsic value of a subset of attributes by considering the individual predictive ability of each feature, along with the degree of redundancy between them. Among the considerable number of quantitative measurements which could be derived from the sensor package data, a number of key metrics were selected as most representative for each of the tasks. Hence, for the 10m driving task the following parameters were used:

1. Average linear velocity
2. Standard deviation of linear velocity (*)
3. Average angular velocity
4. Standard deviation of anguCanwheel11lar velocity (*)
5. Time to accomplish the task

Seven metrics were selected for the 180 degree turning task:

1. Average linear velocity
2. Standard deviation of linear velocity

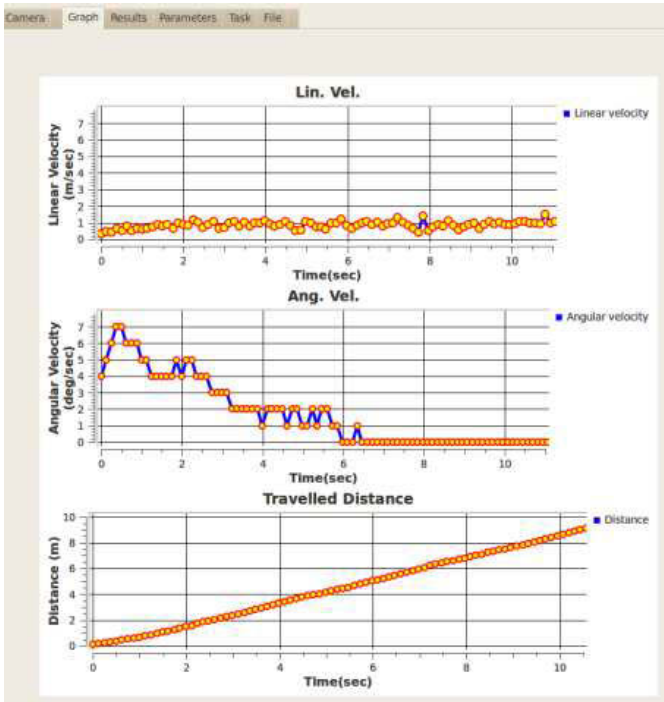


Figure 4.12: Graphical representation of the linear and angular velocity and travelled distance for 10m forward task.

3. Average angular velocity
4. Standard deviation of angular velocity (*)
5. Time to accomplish the task
6. Idle time
7. Minimum distance to obstacle

And a further seven metrics were selected for the ramp driving task:

1. Average linear velocity
2. Standard deviation of linear velocity
3. Average angular velocity
4. Standard deviation of angular velocity (*)
5. Time to accomplish the task

Table 4.2: 10m Task Parameter Statistics

	Parameter				
	1	2	3	4	5
Min	0.36	0.17	0.02	0.01	5.77
Max	1.72	4.16	0.72	0.33	27.89
Mean	0.72	1.02	0.27	0.12	15.68
Std Dev.	0.30	0.65	0.19	0.08	4.85

Table 4.3: 180deg Task Parameter Statistics

	Parameter						
	1	2	3	4	5	6	7
Min	0.07	0.15	0.03	0.07	7.36	5.05	0.04
Max	0.82	0.72	0.63	0.32	45.13	39.0	0.35
Mean	0.38	0.37	0.24	0.14	19.83	16.02	0.11
Std Dev.	0.17	0.13	0.17	0.07	9.73	8.78	0.09

Table 4.4: Ramp Task Parameter Statistics

	Parameter						
	1	2	3	4	5	6	7
Min	0.13	0.11	0.04	0.02	3.19	0.03	3.66
Max	1.74	2.63	0.71	0.68	26.89	0.26	7.69
Mean	0.82	0.45	0.25	0.19	10.66	0.08	4.69
Std Dev.	0.36	0.38	0.20	0.14	4.46	0.04	1.82

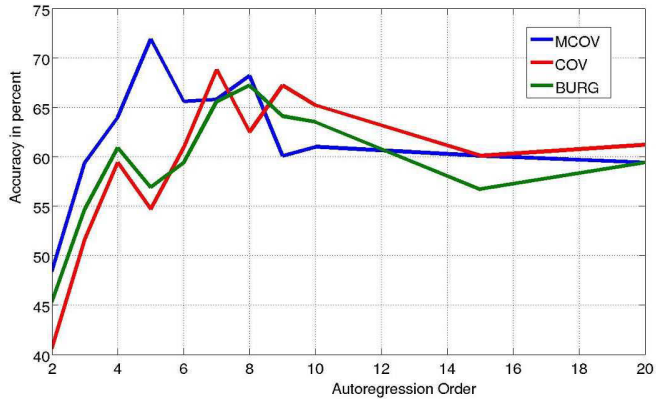
6. Minimum distance to obstacle

7. Gradient of incline

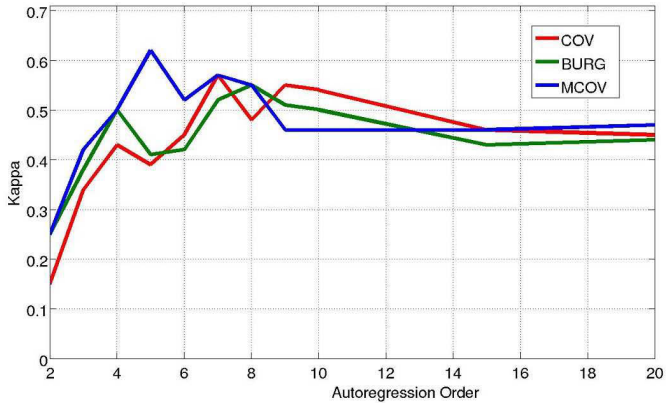
Tables 4.2-4.4 provide a breakdown of each tasks' parameters. (*) denotes the most informative parameters identified for each of the tasks. The standard deviation of angular velocity was the most informative parameter identified for all three tasks, being the sole parameter for the ramp and 180 degree tasks. The 10m driving task also had the standard deviation of linear velocity as an additional distinctive metric.

4.5 Classification Methodology

Classification analysis is a widely adopted data mining technique for healthcare applications to improve quality of patient care. Classification analysis may produce less



(a) Accuracy of the classification with parametric methods



(b) Kappa values from Parametric transformations

Figure 4.13: Results of the Parametric transformations

accurate results if training datasets contain irrelevant features. Two methods were attempted to classify data: the first relied on time-dependent features such as velocities and derivations thereof such as mean and standard deviation. The second approach was to change the domain of the data via parametric transformations. As shown in Fig. 4.14 the minimum range of sample is 48 and the maximum 234. Also, it is obvious that 75% of the data is in the range of between 75 and 175 samples. The process is shown in Fig. 4.15. It is to consider the parametric transformations for feature matrices of burg, covariance and modified covariance [45] between autoregression orders 2 to 20 (Fig. 4.13). The upper limit of the autoregression range was manually determined due to the convergence of kappa values following order 15, which would provide less useful information. Parametric transformations use orders of autoregression, a magnitude of

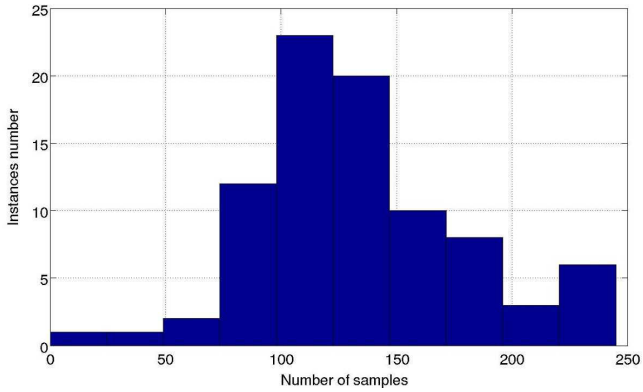


Figure 4.14: Samples distribution

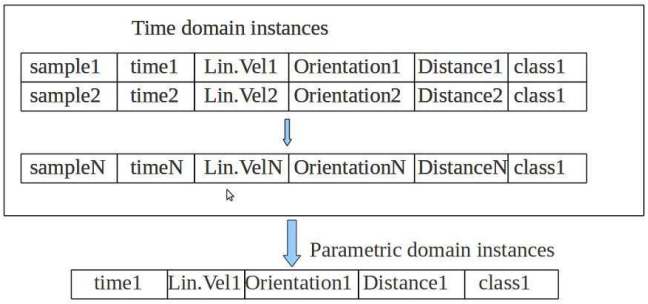


Figure 4.15: Transformation of one instance from time domain using Autoregression

derived weighted sum of previous to current values. In that way the data representation (domain) is changed into specific time windows, to see if they can provide greater information compared to a dataset in its entirety. As the data is interpreted through a different representation, a new set of parameters is also obtained which may be more beneficial to classification compared to their time-domain counterparts. Burg, covariance and modified covariance methods are all autoregression processes with different approaches for estimating data strength.

All available classifiers within WEKA were trained with datasets randomly selected from all 4 classes and were compared using both time-dependent features and feature matrices from parametric transformations for two approaches to analysis. Each classifier was tested using cross-validation in WEKA utilizing six "folds": all available data for a task is divided into six sets, and a classifier is trained from five sets and applied to the remaining one. This is repeated for each set, resulting in six classifiers whose results are

Table 4.5: Time-domain RF

	10m task				180° task				Ramp task			
	1	2	3	4	1	2	3	4	1	2	3	4
1	16	1	0	0	17	1	0	0	12	1	1	0
2	1	21	0	0	1	19	1	1	2	10	1	1
3	0	1	19	1	0	1	19	1	2	1	18	2
4	1	2	1	14	1	0	2	14	0	0	0	10

Table 4.6: Time-domain Support Vector Machine

	10m task				180° task				Ramp task			
	1	2	3	4	1	2	3	4	1	2	3	4
1	15	2	0	0	16	1	1	0	11	2	1	0
2	2	18	1	1	2	15	2	3	2	9	1	2
3	0	3	16	2	0	1	19	1	1	2	18	2
4	1	1	3	13	0	2	2	13	0	0	0	10

Table 4.7: Parametric RF

	10m task				180° task				Ramp task			
	1	2	3	4	1	2	3	4	1	2	3	4
1	14	1	1	0	15	1	1	1	10	2	2	0
2	1	21	0	0	1	17	2	2	2	10	1	1
3	1	4	14	2	1	2	17	1	2	1	18	2
4	2	2	3	12	1	1	3	12	0	0	0	10

aggregated for the overall performance of the classifier encompassing the task's available data pool.

4.5.1 Classification Results

The comparison of different classification methods is of essential meaning for this research work. Whereas machine learning has been applied to a number of different areas there is not yet agreement on which machine learning system will provide the best support for therapists in determining the most appropriate PMD for a client.

RF and SVM yielded the best results using time-dependent data, and their confusion matrices are shown in Tables 4.5 and 4.6 with the best classifier's results graphically represented in Figure 4.16. RF classification uses a number of generated decision maps or 'trees', that branch from a random set of features at each decision point. This classifier

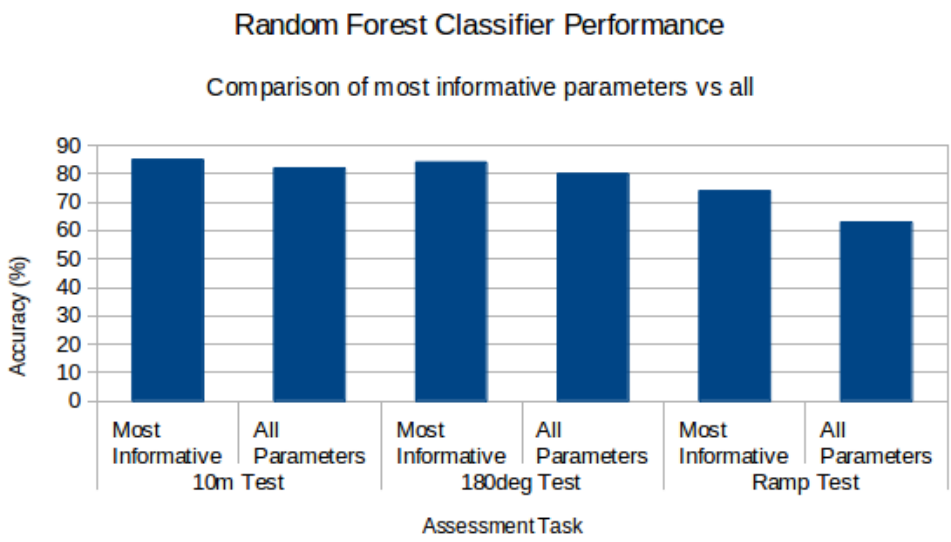


Figure 4.16: Summary of results for best classifier on 3 tasks

attempts to minimize both its own bias and the spread of data, making it well-suited for classification with a limited number of features and datasets, as is the case in the experiments. SVM is a widely-used classifier that requires manual classification of some data before automatic classification can proceed. Training results in a set of data that is 'learned', which can then be used as the basis of a statistical model for assigning the remaining data into classes. Table 4.7 shows resultant confusion matrices from the best of the parametric transformations approaches: a RF classifier on Modified Covariance with autoregression order 5.

Table 4.8 displays percentage accuracies for each method using the most evaluated parameters in comparison with all available parameters, for the approaches from the confusion matrices. Table 4.9 shows values for Cohen's Kappa [48], a measurement of inter-rater agreement for qualitative attributes. This value provides an indication of how far a classifier varies from the diagonal in a confusion matrix between 0 (poor) and 1 (perfect). It can be seen that overall the RF on time-domain data was the most successful classification method for the three assessment tasks, by achieving an averaged 81% classification rate compared to 75% and 72% for the SVM and parametric RF methods respectively. The parametric transformations approach did not perform as well as the time-domain classification due to the narrow distribution of data based on

Table 4.8: Accuracies (%)

		RF (time)	SVM	RF (parametric)
10m	Most Inf.	85	83	72
	All Param.	82	82	68
180°	Most Inf.	84	73	73
	All Param.	80	70	71
Ramp	Most Inf.	74	70	70
	All Param.	63	61	60

Table 4.9: Cohen's Kappa

		RF (time)	SVM	RF (parametric)
10m	Most Inf.	0.71	0.62	0.62
	All Param.	0.67	0.59	0.6
180°	Most Inf.	0.69	0.6	0.61
	All Param.	0.68	0.57	0.6
Ramp	Most Inf.	0.6	0.59	0.58
	All Param.	0.51	0.5	0.49

time-domain parameters. Similarly the SVM's performance was inferior to that of the time-domain RF, owing to the limited number of features for learning. It is also shown in Table 4.8 that resultant accuracies by only selecting the most informative criteria were unanimously higher than when all parameters were used. This outcome is reinforced with an averaged Cohen's Kappa of 0.67 from the RF method on time-domain data, indicating a strong relevance.

Resulting confusion matrices of a comparison with the researchers earlier work [46] are collected in Table 4.10. In this case the "Speed Selection" of the PIDA test was the task of interest. For this scenario, the ability of the user to select the appropriate speed with respect to the environment as observed throught the PIDA test is the OT's primary subjective criteria in their assessment. The task was restricted in that work to navigating through a large room, opening a door and parking alongside a bed. To establish the correlation with the methodology hereby proposed, the three tasks were combined into 61 longer, amalgamated runs and labelled based on an overall score of speed selection for each of the runs. Table 4.11 depicts obtained accuracy and Cohen's Kappa of the speed selection classifiers for amalgamated runs. There are only slightly differences between speed selection classifiers values on accuracies and kappa. The

use of most informative parameters to classify the whole performance of the users run outperformed the accuracy when using only speed selection for classification. This point out that the identified parameters may indeed be helpful to OT staff.

Despite the shortcoming of a limited set of experiments conducted on able bodies, the results obtained appear promising to address a clear need. Selecting the most appropriate PMD for a client is a time intensive and financially costly process. If therapists can have access to a critical or minimum data set a client will still obtain the most appropriate PMD, spend less time in therapy and give the therapist an opportunity to target those parameters which are critical for a person's success in operating the PMD. Novice therapists using machine learning systems could potentially function at the same level as expert therapists using conventional techniques. Future work will focus on comparing use of machine learning systems and current assessment techniques. In addition, therapists would have an opportunity to examine user's performance "in silico" to determine their skill level and if their skill is improving in response to the therapistâs input. Machine learning systems could assist therapists to extend the evidence-base of their practice, reduce the amount of time taken to learn and perform mobility aid assessments, improve the quality of assessments and reflect on the quality of their assessment techniques and tools. The professional and financial benefits would be considerable.

In this work the initial subset of parameters has been chosen to be more aligned with those currently/usually/readily/typically assessed by therapists in their tests such as velocity and time taken to accomplish a task. It would be however very useful to assess others, e.g. trajectory profile, acceleration, or the derivative of acceleration (jerk) which is generally understood to determine comfort in driving. Interestingly, by studying for instance the relevance of a parameters such as jerk, one would be able to gain an insight into whether PMD users drive their chairs in such a way as to reduce jerk. If so, it underlines the use of machine learning systems and use of a stand-alone sensor package as no therapist is going to be able to determine chair jerk during a subjective observation and pencil and paper recording of results. This study has been left for future work.

Table 4.10: Speed selection for combined tasks

	RF (time)				SVM				RF (parametric)			
	1	2	3	4	1	2	3	4	1	2	3	4
1	1	4	0	0	2	3	0	0	2	2	1	0
2	1	9	5	2	1	12	2	2	2	11	2	2
3	0	4	14	4	0	3	14	5	1	1	15	5
4	0	0	5	12	0	0	7	10	1	1	9	6

Table 4.11: Accuracy and Cohen's Kappa for speed selection classification

	RF (time)	SVM	RF (parametric)
Accuracy (%)	59	62	56
Cohen's Kappa	0.41	0.46	0.4

4.6 Summary

In this chapter a machine learning approach was presented to automatically reveal the task-specific parameters that may provide the most relevant user information for the assessment. Data mining techniques are used to reveal the most informative parameters, and results from three typical classifiers are presented based on learnings from manual labeling of the training data. The study showed that RF method applied on time domain data is possibly the most analogous to therapist's reasoning in determining skill levels of PMD users achieving classification rates of up to 85%.

Despite these promising results, the experiments conducted are not without their shortcomings. The researchers are optimistic of the system's ability to work with human training, however the labeling in these experiments was carried out by the author and may not follow a similar distribution by a qualified professional. Secondly,there were only three assessments tasks utilized in these experiments and the pool of experimental data was gathered from healthy volunteers simulating various levels of driving proficiency, causing the datasets to feature behaviours likely to deffer across the four classes from those of the less able users population the work is intended for. Nevertheless, the work is intended to show the capability of the proposed methodology to capture and learn relevant parameters with the aid of robotics sensing unit and advanced data mining algorithms as a grounding step to facilitate clinical trials on larger scale.

Chapter 5

Conclusion and Future Work

The objective of this thesis was to develop a strategy to aid the routine assessments carried out by OTs in their analysis of clients. This chapter summarizes the contributions of this thesis and several directions in which to extend the work.

5.1 Conclusions

The major theoretical and practical achievements of this thesis are:

- Proposing a solution in the form of a standalone package of sensing and computing able to be deployed on a standard mobile platform such as a powered wheelchair. Furthermore, the validity of the proposed solution for inferring navigation and environmental characteristics, e.g. trajectories, map of surroundings, speeds or proximity to doors was successful assessed.
- A novel, evidence-based, automated assessment tool methodology to derive quantitative descriptions of wheelchair usage, computed from the standalone sensor package, as a tool to aid OTs with their manual performance assessment of mobility platform users. OTs scores drawn from a sub-set of PIDA and WST tasks have been compared to a range of objective parameters inferred from the measured wheelchair navigational data to asses the validity of the extracted variables when

compared with those proposed by OT's.

- Machine learning tools were proposed as a novel method of mining data derived from the stand-alone sensor package mounted on an power wheelchair (or PMD). The technique is of potential use to OTs, as it would allow them to critically analyze objective data obtained from the sensor package during an assessment. Data mining techniques have been investigated to establish correlations across three standard assessment tasks with experimental data, achieving up to 85% accuracy with a Random Forest classifier.

- We considered it necessary to demonstrate proof-of-concept with limited data sets and to identify appropriate machine learning techniques with naive able-bodied users before seeking to apply the methods to those with a disability. Able-bodied users, like those with a disability, have a range of skill levels that can be potentially identified using machine learning techniques. A GUI was also developed for the convenience of the OT staff. The interface is Qt-based and uses a MATLAB pipeline behind-the-scenes for classification based on incoming data bridged from the ROS sensor drivers. The outcomes of the experiments have demonstrated consistent agreement between the objective data acquired from the sensing array and the subjective assessments of a human in analysing the driving skills of a wheelchair user. These outcomes present occupational therapists with additional utilities to help discern whether clients are ready to be safely deployed with mobility aids for their daily activities.

5.2 Future Work

There are several potential directions to extend the work presented in this thesis for future work:

- Despite the shortcomings of the experiments, we believe the results remain relevant in the context of this research, and a straightforward avenue for future work would be to conduct a clinical trials involving a broader user base of disabled individuals,

over a greater variety of assessment tasks along with the insight of qualified OT staff. Therapists would have an opportunity to examine user's performance "in silico" to determine their skill level and if their skill is improving in response to the therapist's input. In addition, machine learning systems have shown the potential to assist therapists in extending the evidence-base of their practice, reduce the amount of time taken to learn and perform mobility aid assessments, improve the quality of assessments and reflect on the quality of their assessment techniques and tools. The professional and financial benefits would be considerable.

- The work researched in this thesis deals with the assessment of driving skills for the safe prescription of power mobility devices. However, it is clear that anti-collision protection should be paramount when dealing with older adults using any form of automated power mobility devices. Collision avoidance technology has the capacity to facilitate safer mobility for users with physical, sensory and cognitive impairments, thus enabling independence for more users. The research work in [4] describes quantitative and qualitative results obtained from a user study of a novel vision-based collision avoidance and wayfinding system for powered wheelchair users with cognitive impairment. The target participants were older adults who have limited mobility due to lack of strength to operate manual wheelchairs, and face difficulties in safe and independent navigation due to cognitive impairment. It was shown that the collision avoidance module of the system successfully decreases the number of collisions for all participants, and the wayfinding module was proven able in assisting users with memory and vision impairments. Hence, for future work, it appears an interesting proposition to study the impact that these collision avoidance techniques could have not only in the assessment process developed in this research work, as they effectively appear capable of augmenting the driving skills of the users, but also on the usage of these intelligent power mobility devices to carry out activities of daily living in general.

- A study of how the algorithms developed above can be integrated into higher-level

capabilities in an assisted mobility tool is also of interest: developing suitable and flexible interaction procedures to fulfill users needs in a way that is both achievable and a within the users abilities. Possible extensions of the work in dynamic outdoors environment should also be considered.

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