Learning Human Navigational Skill for Smart Wheelchair

By

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A Thesis

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Abstract

Nowadays, electrically powered wheelchair is the most commonly adopted mobility assistance device utilizing modern electrical and electronic technologies. However, it typically offers their disabled passengers some very low-level interfaces for controlling the basic motions of wheelchair, such as a joystick. In this thesis, a novel, user-friendly and low-cost mobility system is developed to significantly extend the usability over the traditional electric wheelchair and provide a high-level of navigation autonomy for the user.

In the platform, a wearable cap device for sensing user's intentional facial muscles activation is developed for the user to control the navigation of smart wheelchair, by measuring the bioelectrical ionic flow of current on user's eyes and jaw muscles with only 3 silver-chloride electrodes attached to the face of user. For navigation tasks that need to be performed frequently, the user can teach the system by demonstrations so that the tasks can be performed autonomously. The human stochastic and dynamic navigational skill is learnt with the cascade neural network and transferred to a robot by showing it how to navigate in different local environments, which are modelled in compact, polar representations by limited on-board range sensors, throughout a demonstrated route. The learned skill model is a reactive sensor-control mapping implicitly stored the relations between different local environmental features and the corresponding demonstrated control commands. For

autonomous navigation, the on-line control command is generated from the learned mapping with the on-line new sensor signals.

To improve the skill learning performance, an extension and realization of active learning for the learning-by-demonstration paradigm is primarily investigated with multi-phase human feedback demonstrations. With this experimental design, the learning performance is experimentally on-line evaluated throughout the learning phases. The approach is useful to identify and collect critical training data, which is hard to achieve for some systems with different dynamic parameters in the demonstration and application stages.

For localization purpose, the sensor-control mapping for navigation is modularized to constitute the sensor-configuration mapping in the form of look-up table, which is learned to localize at demonstrated locations with raw sensor patterns inputs and human-assigned configuration outputs.

The approach is useful as a simple self-contained system for reactive navigation and localization at desired, learned configurations in indoor, static and unstructured environments, such as common household settings. With the developed system, disability not only can extend his/her mobility, but also can significantly improve his/her social life through expanded travel possibilities, closer interaction with other people, and enhanced ability to live independently.

摘要

現今，採用現代電氣和電子技術的電動輪椅已經成爲最爲廣泛使用的行走輔助設備。然而，它通常只能爲殘疾人士提供一些如遥杆的低階介面，以便使用者控制輪椅的基本運動。這項目開發了一個創新的、容易使用且成本低廉的移動系統，它顯著地拓展了傳統的電動輪椅的使用模式，並且爲使用者提供了一個高階自主導航的行走輔助設備。

這項目開發的平台還包括一套頭盔裝置，它能夠通過三個氯化銀電極檢測用戶眼部和頜部肌肉的生物電流，來獲得用戶面部肌肉的運動資訊，進而控制輪椅的運動。對於一些需經常執行的導航任務，使用者可以通過示範學習的方法訓練系統，從而使得導航任務可以被自主執行。基於展示在如何不同的局部環境進行導航，人類隨機的、動態的導航技巧可以通過有限的、機載的感測器以簡潔的極坐標表達方式建模。運用級聯人工神經網路，這些技巧被學習和移植到一個行走輔助系統。此技巧學習模型是一個反應性的感測器控制映射，它隱含著不同局部環境的特徵和相對應的示範控制命令之間的關係。針對自主導航，線上控制命令將由新的線上感測器信號經事先完成學習的映射關係計算得到。

爲了提高模型的學習表現，一個用於示範學習的主動學習的拓展和實現被初步研究，並應用在類比反覆人類回饋範例的導航技巧。通過這項試驗設計，學習的表現在整個學習過程中被試驗性地線上評估。這一方法對於那些難以分辯和收集在示範和應用階段有不同動態參數的系統中獲取的特別訓練資料是很有用的。

爲了確定位置的目的，用於導航的感測器控制映射被模組化以便構造以查看表格形式存在的感測器組態映射。通過學習，根據原始感測器模型的輸入和人類安排組態的輸出，用它來定位於已示範的位置。

這方法適用於簡單獨立的系統在室內、靜態和不規則（例如一般家庭居住的環境）環境中的反應性導航和位置確定。通過這套開發了的系統，殘疾人士不僅可以擴大他/她的活動範圍，而且可以藉拓展出來的行走可能性來顯著地提高他社會生活，拉近與別人的互動關係，同時增強獨立生活的能力。

Acknowledgment

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I am delightful for the joyful experiences with my friends in this department, especially for my colleagues in the Advanced Robotics Laboratory. I never forget our friendships and their concern throughout my study.

Finally, I dedicate this thesis to my parents, brother, Sifu and my girlfriend Rosalie TANG for their unreserved support and love.

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Chapter 1

Introduction

1.1 Motivation

Nowadays, electrically powered wheelchair is the most commonly adopted mobility assistance device utilizing modern electrical and electronic technologies. However, it typically offers their disabled passengers some very low-level interface devices for manual controlling the basic motions of wheelchair, for example a joystick. At present, nowhere do robots promise to enhance the quality of life of humans as much as in the area of rehabilitation. In fact, the latest robotics technologies have the potential to assist physically handicapped and elderly people, especially in the mobility for their day-to-day life [1,2].

Let us look at a typical scenario where a wheelchair-bound individual must navigate through close quarters in his/her home, which, like many homes, was not designed with elderly or handicapped people in mind, by carefully and slowly manipulating the bulky wheelchair through a somewhat rudimentary joystick interface. In order to turn the wheelchair 180 degrees, for example, a laborious sequence of back-and-forth movements might be required. This type of low-level control may not only be frustrating and time-consuming, but may even be impossible for individuals who have only limited control of their arm, such as elderly. On top of that, very similar maneuvering tasks, such as going from the bedroom to the kitchen, may be typically part of the individual's daily routine, which is notoriously difficult to successfully navigate.

Through the smart wheelchair developed, things are made easier and safer for the users. The objective here is to develop a novel, user-friendly and low-cost mobility system to significantly extend the usability over the traditional electric wheelchair and provide a high-level of navigation autonomy for the user. For navigation tasks that need to be performed frequently, the user can teach the system so that they can be performed autonomously. While application, the user can simply select a route from a list of routes that have already been learned by the system, sit on the wheelchair and then being navigated to the destination while avoiding collision from any unexpected obstacles.

With the developed system, disability not only can extend his/her mobility, but also can significantly improve his/her social life through expanded travel possibilities, closer interaction with other people, and enhanced ability to live independently. Furthermore, the development opens up tremendous new mobility interface possibilities, resulting in rich system integration issues, academic research contents and potential product lines in consumer electronics for modern demanding elderly and disabilities health care product developments. With the rapidly shrinking costs of modern computing and sensing, we can expect that the costs of outfitting the mobile platform and interface devices with the required on-board computational hardware and sensors can be kept at a minimum and affordable for the public.

1.2 Organization of the Thesis

In this thesis, a move towards the development of novel, compact and practical robotic wheelchair navigation system is presented for enhancing user mobility in indoor applications, with emphasis on the methodology formulation & design and experimental design & implementation aspects. The thesis is organized as follows.

In Chapter 2, a literature survey is presented, covering the related work for this study such as the learning-by-demonstration paradigm, neural network learning, robot navigation, localization and robotic wheelchair researches.

In Chapter 3, the technical descriptions of the implemented hardware and software platforms, and some basic functionality of the system are presented. The mobile robotic platform I adopted is modified from a commercial robotic wheelchair, TAO-6, manufactured by Applied AI, Inc. For processing higher-level computations, a laptop computer is connected to the wheelchair computer through RS232. A software architecture is designed such that, each computer runs a "receive" program before the counter-part "send" program "transmits" the signal for proper signal communication between the two computers. Besides, two basic functionalities are implemented for navigation and interfacing purposes: collision avoidance and wearable eye-jaw control interface.

In Chapter 4, a minimalistic methodology for developing navigation system with polar representation of the local environmental features is presented. The human stochastic and dynamic navigational skill is learnt with the cascade neural network and transferred to a robot by showing it how to navigate in different local environments, which are modelled in compact polar representations by limited on-board range sensors, throughout a demonstrated route. The learned skill model is a reactive sensor-control mapping implicitly stored the relations between different local environmental features and the corresponding demonstrated control commands. For autonomous navigation, the on-line control command is calculated from the learned mapping with the on-line new sensor signals. Experimental study on the wheelchair platform, which is described in Chapter 3, is conducted for the evaluation of the proposed methodology.

In Chapter 5, in order to improve the learning performance of navigational learning, which is presented in Chapter 4, in terms of the similarities between the demonstrations and autonomous navigation, an extension and realization of active learning for the learning-by-demonstration paradigm by multi-phase human feedback demonstrations is primarily investigated with the application on the human navigational skill modelling. With this experimental design, the learning performance is experimentally on-line evaluated throughout the learning phases. The approach is useful to identify and collect critical training data, which is hard to achieve for some systems with different dynamic parameters in the demonstration and application stages. With this approach, the learning performance of the navigational learning approach is improved.

In Chapter 6, for localization purpose, the sensor-control mapping for navigation presented in Chapter 4 is modularized to constitute the sensor-configuration mapping in the form of look-up table, which is learned to localize at demonstrated locations with raw sensor patterns inputs and human-assigned configuration outputs. The approach is useful as a simple self-contained system for reactive localization at desired, learned configurations in indoor, static and unstructured environments such as common household settings.

In Chapter 7, the key contributions of this study are illustrated. Also, some potential future work is highlighted for some possible extensions of the human navigation skill modelling, multi-phase demonstrations for learning and localization learning presented in Chapters 4, 5 and 6 respectively

Chapter 2

Literature Survey

2.1 Learning-by-Demonstration

In recent years the paradigm of learning-by-demonstration has attracted certain attention. Route programs, which is constituted by step-by-step codes, are the traditional paradigm for instructing a machine. Although this paradigm is explicit and rigorous for human understanding and machine implementation, in some situations it is hard to describe the desired instructions into specific and proper code statements, for example when instructing a robot to follow human actions which are hard to be represented explicitly. Learning-by-demonstration is a good paradigm for tackling this difficulty. With a proper problem formulation and experimental design, the instructing tasks for the robot can be demonstrated by human operator. Then, the demonstrated data can be abstracted and learned for the robot, by constructing computational models with existing machine learning techniques, such as neural network learning. In the past decade, several researchers have proposed various experimental designs and applications [3,4].

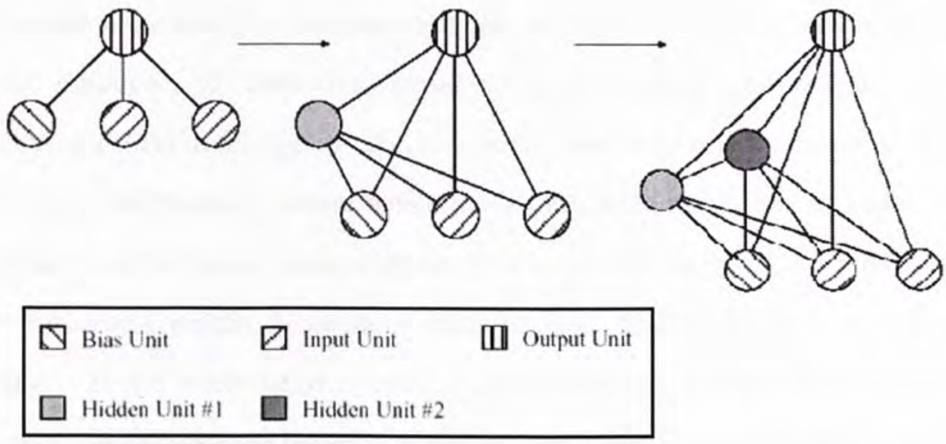

Figure 2.1: The cascade learning architecture adds hidden units one at a time to an initially minimal network.

2.2 Neural Networks

Neural networks are famous for their promising performance as function approximators. They consist of a large number of interconnected processing elements in an architecture inspired by the structure of the cerebral cortex of the human brain. In recent years, neural networks have shown great promise in identifying complex nonlinear mappings from observed data, and have found many applications in nonlinear control [5]. It is commonly believed that neural networks in general are well suited for learning the complex internal mappings from sensory inputs to control action outputs that humans can produce.

In this study, I employed the flexible cascade neural network(CNN) architecture with node-decoupled extended Kalman filter(NDEKF) [4] for modelling the human skill utilized in navigating obstacle course. Though there are many other potential choices of machine learning approaches for the modelling, I adopt the CNN with NDEKF as a starting point with a number of reasons. First, no a-priori model structure is assumed; the neural network automatically adds hidden units to an initially minimal network, as the training requires (Figure 2.1). Theorems by Cybenko [6] and Funahashi [7] hold that, standard layered neural networks are universal function approximators applies also to the cascade architecture. It is because any multi-layer, feed-forward neural network with k hidden units arranged in m layers, fully connected between consecutive layers, is a special case of a CNN with k hidden units with some weight connections equal to zero. Second, hidden unit activation functions are not constrained to be of a particular type. Rather, for each new hidden unit, the incremental learning algorithm can select that functional form, which maximally reduces the residual error over the training data. Typical alternatives to the standard sigmoidal function are sine, cosine or Gaussian functions. Finally, it has been shown that NDEKF, a quadratically convergent alternative to slower gradient descent training algorithms(such as back propagation or quick prop) fits well within the cascade learning framework and converges to good local minima with less computation. The flexible functional from, which cascade learning allows, is ideal for abstracting human navigational skill since we know very little about its underlying nature. By making as few a-priori assumptions as possible in modelling the human skill, we improve the likelihood that the learning algorithm will converge to a good model of the data. For reference, the Appendix A in this thesis contains further descriptions on the CNN with NDEKF.

2.3 Navigation Learning

Essentially, the navigation problem is related to three main questions under a variety of technical scopes and limitations: (1)Where am I? (2)Where is the goal location relative to me? And (3)how do I get to the goal from here [8,9]? In this research area, a research group leaded by Xu at the Robotics Institute, Carnegie Mellon University was investigating outdoor on-road driving systems with learning-by-demonstration paradigm [4]. Human driving strategies have successfully abstracted and transferred to autonomous driving systems.

Moreover, a research group leaded by Inoue at the University of Tokyo was investigating a sequence of images obtained during human-guided movement directed autonomous movement [10]. A model of the mobile robot's route was described in a way that simplified the comparison of stored information and current visual information. Image information about the route was required for representing the environment. As they themselves noted, their approach was more suitable for routes in surroundings such as corridors.

Another research group leaded by Miura at the Osaka University was investigating a method using human involvement whereby an operator guided a mobile robot to a destination by remote control [11]. During a single demonstration, the robot developed a map by observing the surrounding environment in stereovision. It can then localize, compute and follow the shortest path to the pre-determined destination. The objective of the human-guided movement in this case was to build a map with less effort.

In another variation, Kraiss and Kuttelwesch have simulated vehicle navigation through a maze with 5 evenly spaced horizontal bars interspersed with randomly placed cut-outs [12]. The simulated vehicle was taught by emulating a human teacher who drove a point robot.

2.4 Localization

Instead of being the sub-area of navigation problem, the problem "Where am I?" (also known as the localization) can also be an individual study for various research needs.

In the literatures, extensive researches have been done for solving this problem with different practical and theoretical considerations [8,13-15].

Actually, environment modelling and localization can be considered as dual problems; because in order to localize a mobile robot many localization systems require a world model to match observed environment characteristic with the modelled ones, and also because in order to build a world model, most systems require precise localization of the robot [15]. The most common types of environment representations are cell decomposition models, geometrical models and topological models. In this study, a novel environment modelling approach by explicit local range sensing is presented.

On the other hand, there are several directions of location sensing technique, such as scene analysis, triangulation, proximity and dead reckoning. First, scene analysis [16-18], refers to the detection of scene features for inferring the objection location. Second, triangulation is the use of the geometric properties of triangles to compute object location. Third, proximity refers to the detection of an object when it is near to a known location by taking advantage of the limited range of a physical phenomenon. Fourth, dead reckoning refers to incremental positioning methods such as odometry and inertial navigation systems. Among these directions, this study is under the scene analysis framework.

2.5 Robotic Wheelchair

Autonomous robotic wheelchairs represent an important class of autonomous mobile robots and have received increasing attention from researchers. Many robotic wheelchair systems have been developed in a number of research laboratories worldwide during the past decade [19-32]. They aimed to aid disabled people who are unable to drive a standard powered wheelchair.

Madarasz, et al. were the first to design a self-navigating wheelchair for disabled people [19]. The wheelchair was equipped with an on-board computer together with sensors such as ultrasonic range finder, wheel encoders, and a digital camera. The system was designed to navigate autonomously in an office building. To find a path to its destination, it used a symbolic description of significant features of the environment, like hallway intersections or locations of offices.

For commercial applications, Applied AI Systems, Inc. has developed a number of robotic wheelchair prototypes called TAO [20]. A behavior-based approach is used to establish sufficient on-board autonomy at minimal cost, material usage, efficiency, maximum safety, transparency in appearance, and extendibility. The platform adopted in this study is modified from the robotic wheelchair TAO-6 from Applied AI System, Inc.

Although each research group has their own set of requirements for a robotic wheelchair, they all share two basic features [21]. First, a user must be able to navigate a robotic wheelchair safely, and failures must not endanger users. Second, it must interact effectively with the user. Each of the groups has already achieved certain goals in robotic wheelchair development.

Chapter 3

System Implementation

In this chapter, the technical descriptions of the implemented hardware and software platforms, and some basic functionality of the system are presented. The mobile robotic platform I adopted is modified from a commercial robotic wheelchair, TAO-6, manufactured by Applied AI, Inc. For processing higher-level computations, a laptop computer is connected to the wheelchair computer through RS232. A software architecture is designed such that, each computer runs a "receive" program before the counter-part "send" program "transmits" the signal for proper signal communication between the two computers. Besides, two basic functionalities are implemented for navigation and interfacing purposes: collision avoidance and wearable eye-jaw control interface.

3.1 Hardware Platform

The mobile robotic platform I adopted is modified from a commercial robotic wheelchair, TAO-6, manufactured by Applied AI, Inc. TAO-6 has two motors in a mid wheel drive configuration providing good power, acceleration and stability (Figure 3.1). It has two sealed Lead Acid batteries; each of them is 12V, 50 Ah, for a total of 1200W capacity. Most of the electronics are housed in a protective box beneath

Figure 3.1: The wheelchair platform with 7 ultrasonic sensors in the front(Circled).

the seat. The sensors, joystick, and keypad are connected directly to the electronics box. The CPU of the original TAO-6 platform is the Motorola MC68332 32-bit micro-controller. This unit and additional I/O boards handle all the sensor inputs and the user interface. Since the on-board CPU in original TAO-6 can only handle limited calculations. For processing higher-level computations, a laptop computer is connected to the wheelchair computer through RS232. The sensor, keypad and joystick signals are passed to the laptop computer for processing and planning, which can return the control signal to the wheelchair platform.

7 wide-angle(around 60 degrees of directivity) ultrasonic range sensors, a keypad and a joystick, which are available as parts of the facilities from the original TAO-6 platform, are used in the experiments of this study. The sensors are re-located to

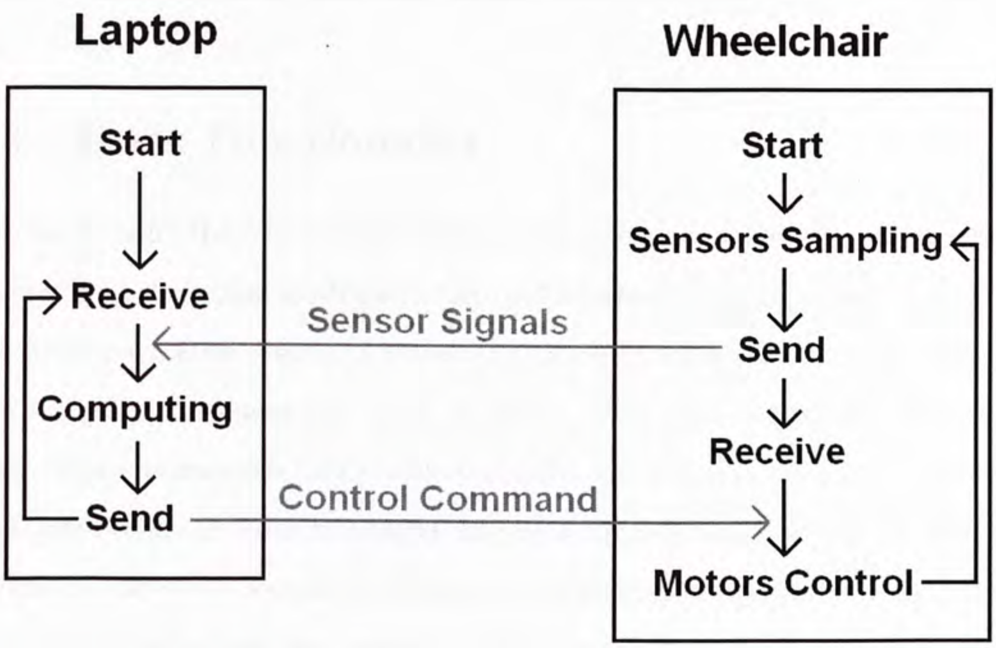

Figure 3.2: Serial communication between wheelchair and laptop computers.

achieve great coverage of the front local environment with respect to the platform. Each sensor returns the "distance to obstacle" value at a resolution of about 35mm per step(discrete value). The sensors have a limited range but can accurately detect obstacles up to around 1.5m. They are operated at different carrier frequencies, sampling simultaneously and repeatedly at a constant frequency about 5 Hz.

3.2 Software Platform

The functioning navigation programs in the wheelchair and laptop computers are written in C programming language. Each program can "transmit" a signal to the counter-part "receive" program despite whether the counter-part can "receive" or not, while the "receive" program "waits" until a signal is received. For proper communication, a communication architecture is designed such that, each computer runs a "receive" program before the counter-part "send" program "transmits" the signal (Figure 3.2).

3.3 Basic Functionality

In order to fulfill the requirements of the wheelchair users with different degrees of disability, I believe that both autonomy and interfacing are important in a smart wheelchair navigation system. A wheelchair user with minor motor impairment may wish to control the wheelchair more effectively. This requires that, the wheelchair offers certain interactions for manual operations. On the other hand, for a user who has limited voluntary body movement, he/she would rely heavily on the autonomous functions. Therefore, besides the developed autonomous navigation to be mentioned in the later chapters with the emphasis on the functionality, two basic functionalities are also implemented for navigation and interfacing purposes with the emphasis on the usability: (1)collision avoidance and (2)wearable eye-jaw control interface.

3.3.1 Collision Avoidance

Collision avoidance is one of the critical factors in the design of robotic wheelchair. Numerous methods for collision avoidance have been proposed and developed extensively [8,9]. The avoidance system has to detect obstacles through its sensors and plan for a suitable action in order to avoid the collision with obstacles. In my system, I utilize ultrasonic range sensors to detect obstacles close to the front of platform.

Ultrasonic range sensor is a good, low-cost obstacle detection solution. The sensor emits a short burst of ultrasound waves when it is "fired". If an object is located in front of the sensor, then some of the ultrasound waves reflect back to the sensor. When the echo from the object is received at the sensor, its associated circuitry sends an signal to the computer which controls the sensor. The computer measures the time that elapsed between firing the sensor and receiving the echo. Since the velocity of ultrasound travelling through air is roughly constant, the computer can calculate the distance between the object and the sensor from the measured time-of-flight. For the simplest case, my smart wheelchair is designated to stop when there is any obstacle under a pre-defined threshold of clearance distance near to the wheelchair.

3.3.2 Wearable Eye-jaw Control Interface

The most typical human control device in a robotic wheelchair is the joystick. However, the joystick requires fine control that some users may have difficulty accomplishing. Alternative advanced controls and interfaces for the robotic wheelchair users are worth exploring, which can meet the requirements for users with different levels of disability. A solution for the problem is to perform the control by eye-gaze and jaw motion [33-38]. In some cases, the users suffer from diseases which damage a majority of the nervous and muscular system in their bodies (such as legs, arms and/or spine cords), but leave the brains and eye movements unimpaired. To this end, an interface is developed which enable a user to control a wheelchair with simple eye-jaw movements. The method presents here is different from the existing work with lesser number of electrodes used.

In my platform, a wearable cap device for sensing user's intentional facial muscles activation is developed for the user to control the navigation of smart wheelchair, by measuring the bioelectrical ionic flow of current on user's eyes and jaw muscle fibre movements (Electro-oculographic(EOG) potential for eye muscles and Electro-myographic(EMG) potential for general muscles), with only 3 silver-chloride electrodes attached to the face of user (Figure 3.3). H2 and H1 detect the horizontal left

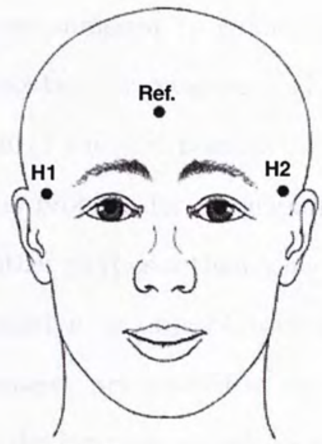

Figure 3.3: The placement of 3 silver-chloride electrodes on the user's face.

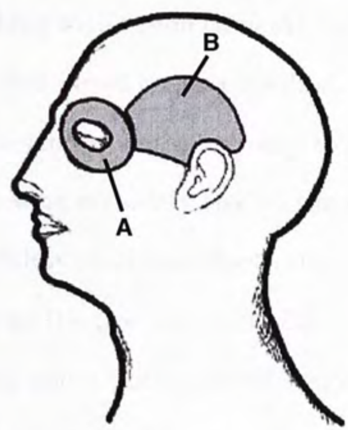

Figure 3.4: The ocular muscle(Region A) and temporal muscle(Region B) on a face.

and right eye movement respectively together with the jaw activation. Ref. serves as the reference point of facial electrical potential. When an electrode is placed at the overlapping areas of facial ocular muscle(Region A) and temporal muscle(Region B), both EOG and EMG signals produced by the eyes and jaw movements are detected (Figure 3.4).

The location of the overlapping area is roughly the location of temple between the eye and ear on each side of the head, and is slightly different from person to person. The 3 electrodes are sufficient to guide a smart wheelchair: one for the ground signal, the remaining two for measuring (1)the eye-gaze at the horizontal direction, and (2)activation of the jaw muscles to trigger the forward/backward command. There is a typical problem for commanding the wheelchair by eye-gaze: user's eyes may move for other purposes than wheelchair navigation control, such as for environmental exploration or object/obstacle tracking. To deal with the this problem, the eye movements are treated as the "switches" to trigger different commands instead of using the interface signals as a direct control.

Comparing with other alternatives for eye-jaw activation detection and measurement (such as eye-balls tracking with vision camera), lower computation and simpler hardware are achieved with this direct contact method. Also, the bio-electric signals are detected with surface electrodes which are easy to apply and can be worn for a long period of time, while posing no safety risk to the user.

For practical implementation, since the bioelectrical signals are weak, an instrumentation amplifier is used as the pre-amplifier. Each signal is a combination of a muscle movement(AC signal) and a potential difference of skin position(DC offset). Two operational amplifiers are used to eliminate the DC offset and amplify the AC signal further. The overall voltage gain is 72dB. In order to separate the signals generated by the eyes and the jaw, three more operational amplifiers are used. The value of the potentiometers are adjusted for the corresponding amplifier in order to match different muscle strengths. Next, two mono-stable multi-vibrators are used to generate a standard TTL signal format. A logic circuit is used to prevent the resultant signals from appearing simultaneously. Two 3-volt 500mAh Lithium coin cells are applied to drive the circuit with the life about 50 hours. Calibration is needed for the electrodes placement and skin conductivity of each individual.

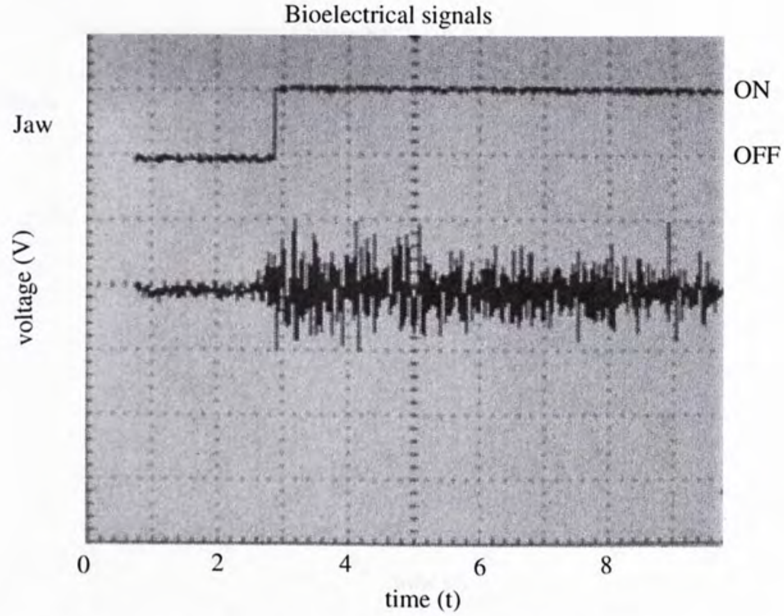

Figure 3.5: Activation of the jaw movement(Top) and the corresponding detected electrical signal(Bottom).

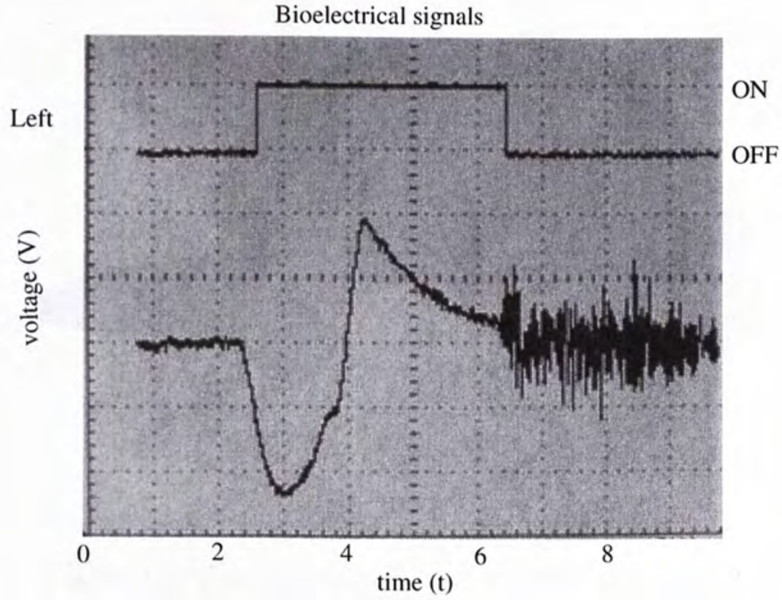

Figure 3.6: Activation of the left-eye movement(Top) and the corresponding detected electrical signal(Bottom).

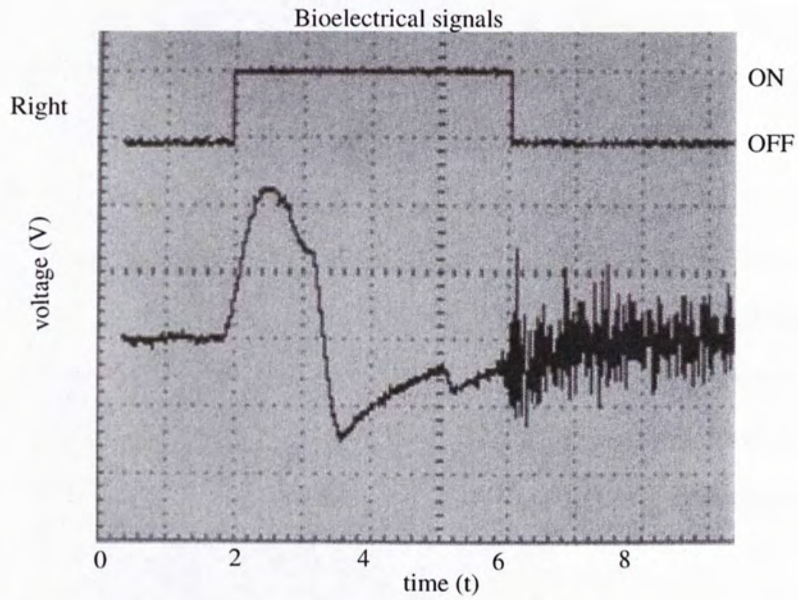

Figure 3.7: Activation of the right-eye movement(Top) and corresponding the detected electrical signal(Bottom).

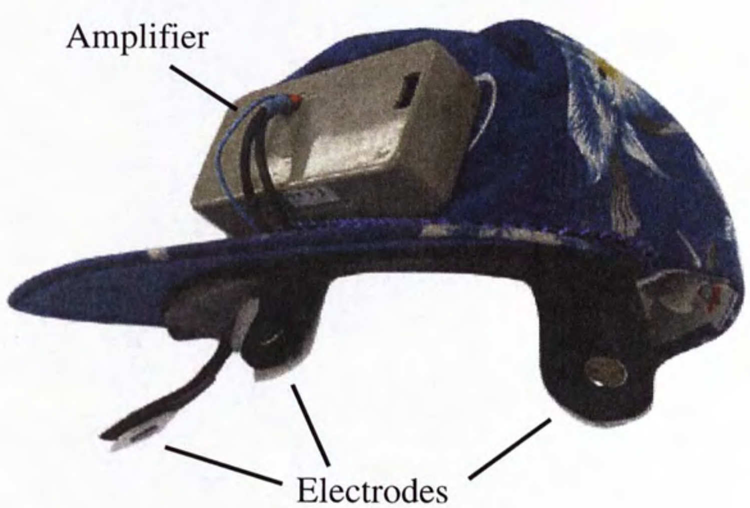

Figure 3.8: The implemented eye-jaw control interface.

When the user issues a jaw motion command, both the electrodes at H1 and H2 detect the electrical activities from the jaw muscle (Figure 3.4), so that the resultant signal oscillates at a very high frequency (Figure 3.5). When the user is looking to the left or right, a large potential difference will be detected at H1 and H2: a negative change indicates the left (Figure 3.6), while a positive change indicates the right (Figure 3.7).

With these results, the interface is verified that it is able to detect 3 types of face motion: (1)looking to the left, (2)looking to the right, and (3)tightening the jaw. Since I have not applied any electrode along the vertical direction of the eye, eyelid movement such as blinking does not interfere with the signals in the H1-H2 electrode pair. The implemented eye-jaw control interface is contained in a cap for wearable convenience (Figure 3.8).

Chapter 4

Learning Human Navigational Skill

In this chapter, a minimalistic methodology for developing navigation system with polar representation of the local environmental features is presented. The human stochastic and dynamic navigational skill is learnt with the cascade neural network and transferred to a robot by showing it how to navigate in different local environments, which are modelled in compact polar representations by limited on-board range sensors, throughout a demonstrated route. The learned skill model is a reactive sensor-control mapping implicitly stored the relations between different local environmental features and the corresponding demonstrated control commands. For autonomous navigation, the on-line control command is calculated from the learned mapping with the on-line new sensor signals. Experimental study on the wheelchair platform, which is described in Chapter 3, is conducted for the evaluation of the proposed methodology.

4.1 Introduction

Essentially, the navigation problem is related to three main questions under a variety of technical scopes and limitations: (1)Where am I? (2)Where is the goal location relative to me? (3)How do I get to goal from here [8,9]? In practice, the environments in which mobile platforms operate are usually modelled in highly complex forms, such as geometric or image representations, and as a result real-time autonomous navigation and localization can be difficult. The difficulty is exacerbated for real platforms with limited on-board computational resources since this paradigm of environmental modelling requires enormous computational power.

Moreover, existing navigation systems for electrically powered wheelchair usually adopt the advanced developments of robotic motion planning research. Since the motion planning researches aim at developing a "versatile" motion planner for tackling the planning task in various operational situations, they have complex algorithms and expensive hardware.

4.2 Problem Formulation

The objective here is to develop a minimalistic methodology for developing navigation system by learning-by-demonstration paradigm with polar representation of the local environmental features. Human stochastic and dynamic navigational skill is learnt and transferred to a mobile robot by showing the robot how to navigate in different local environments throughout a demonstrated, designated route. The aim of this study is to abstract and learn the human navigational task, instead of achieving any optimal motion planning criteria. However, it is a very practical and useful for smart wheelchair to perform route-specific navigation in learned routes.

4.3 Approach

By using ultrasonic range sensing representation, the autonomous navigation system is capable of extracting the features in different local environments and nav-

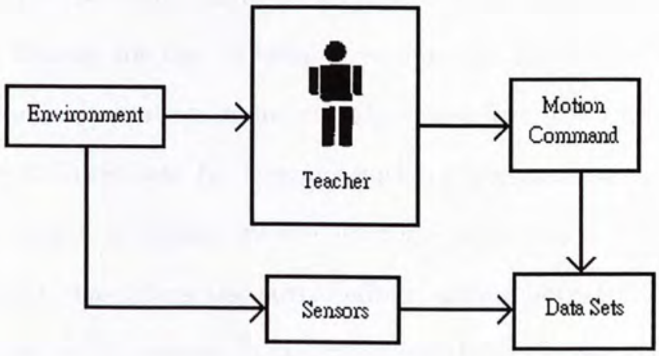

Figure 4.1: The acquisition of demonstrated training data in the experiments.

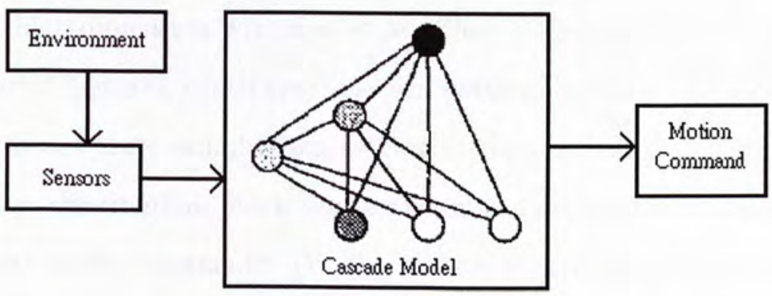

Figure 4.2: The use of learned skill model for reactive autonomous navigation.

igating along the route in real-time by using cascade neural network(CNN) [4]. Node-decoupled extended Kalman filter(NDEKF) is applied to learn and model the demonstrated sensor-motor reactive mapping. The learned network is the reactive sensor-control mapping [39] implicitly stored the relations between different local environmental features and the corresponding demonstrated control commands for autonomous navigation (Figure 4.1). The mapping is used for classification of the distribution of features and the corresponding control commands. On-line control command is calculated(mapped) from the learned mapping with the on-line sampled new sensor signals (Figure 4.2). Since each set of real-time sensor reading is considered as a raw pattern, local surrounding environment is not necessary to be well specular reflectors for the ultrasonic sensing. No noise filtering is undertaken to preserve the all information in the signals. Therefore, the raw sensing data was used directly as training data for learning without any pre-processing.

The sensor vector is chosen as the learning input since it is a compact feature representation describing the surrounding environmental information in term of "polar distance" with respect to the robot/platform during navigation. The ultrasonic range sensor signals are discrete-time, discrete-value with limited sensing range. Therefore, each sensor signal constitutes one dimension in the sensor space, which is in high-dimension with fixed-size. Since different local environments are having different features, which are the sensor patterns in this study, a longer demonstrated route has more sampled sensor vectors(patterns) in the sensor space with more complex distribution. Each sensor vector is associated with a corresponding demonstrated control command. For this reason, unstructured environments, such as a common household setting, are particular suitable for pattern recognition with the developed approach since they have more distinctive local features for recognizing various particular robot/platform configurations in the workspace. In general, each particular route is unique that, its series of local environments(and the corresponding features) are different from that of other routes. Therefore, each specific route is characterized by a specific distribution of all sampled sensor patterns.

Some interpretations can be drawn here for illustrating the characteristics of the approach. First, each pattern of sensor readings(sensor vector) is used for environmental pattern recognition. Second, each associated control command is used for on-line incremental movement. Third, the complete sequence of sensor vectors sampled along the route is actually an acquisition of local environmental(spatial) in-

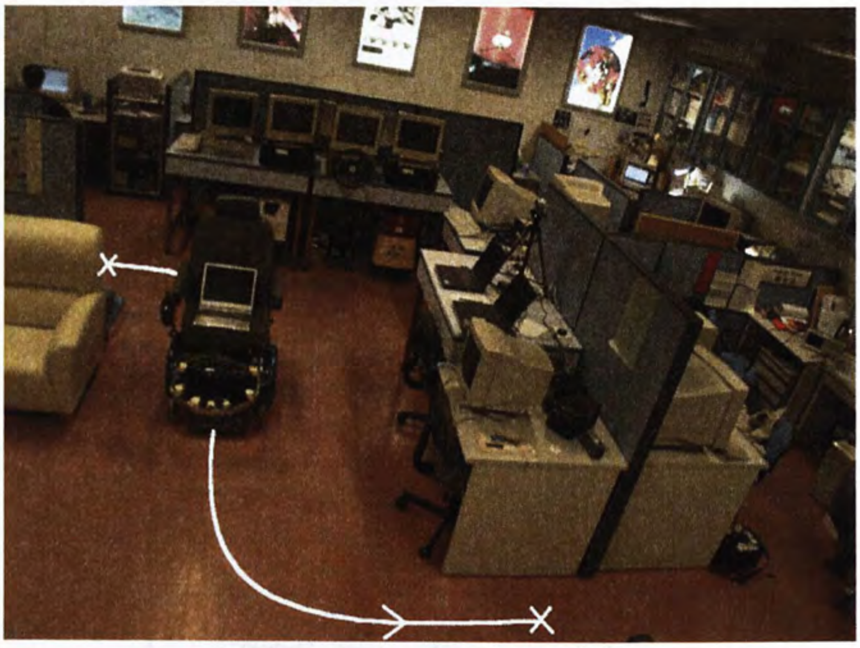

Figure 4.3: A demonstration route in an unstructured indoor environment.

formation, which is the complete global environmental model. Fourth, the complete sequence of control commands(trajectory) applied along the route is actually an acquisition of "sub-goal" information, which gives the complete, sufficient destination information. With the presented methodology, the navigation problem and its associated environmental modelling issues are tackled for the specific mobility-assisting rehabilitation applications.

4.4 Experimental Study

4.4.1 Settings

By human operation, the wheelchair platform is controlled via the use of keypad(3 discrete control states: move straight, turn left or right) to navigate a designated route 10 times in a static indoor unstructured environment, intending to obtain the similar position/velocity profile. In each operation, the platform moves at speed

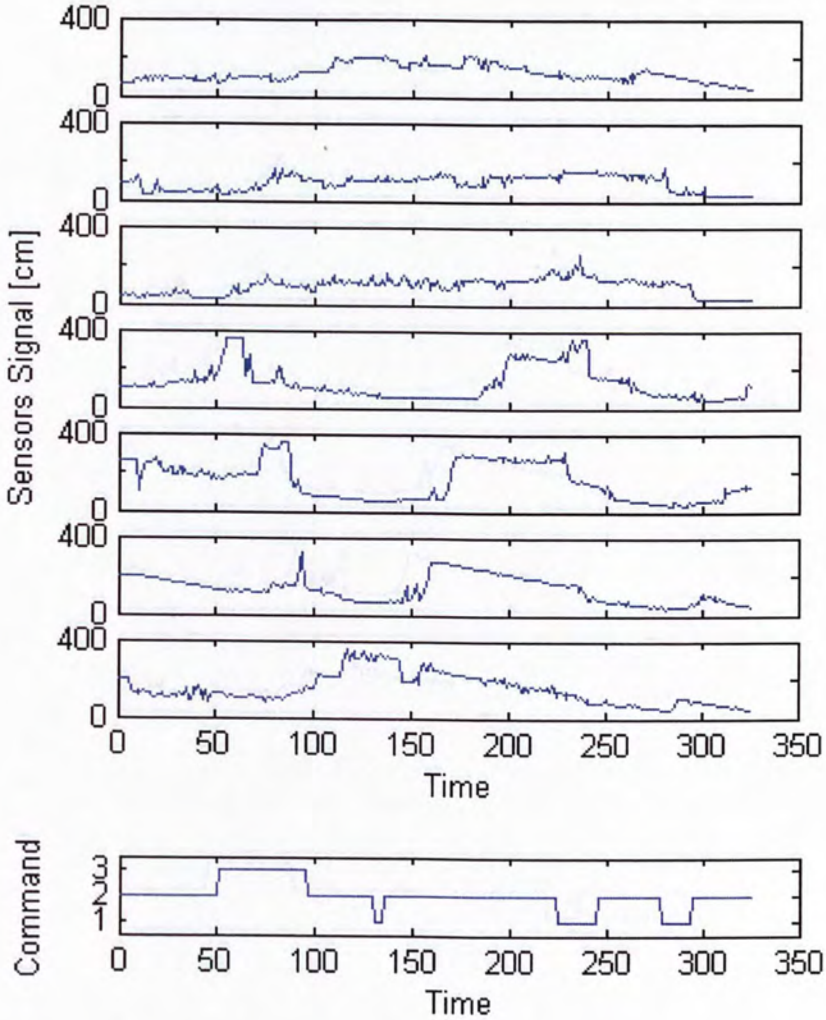

Figure 4.4: The sensor trajectory and corresponding demonstrated control command in the first demonstration.

about 0.8m/s for sensors sampling along the demonstrated route (Figure 4.3).

Throughout each operation, signals from the 7 sensors are sampled constantly as the CNN learning inputs. At the time of each sampling, the control command, determined by the demonstrator, corresponding to the sampled sensor pattern is also recorded to form a set of training data. Throughout each operations, about 320

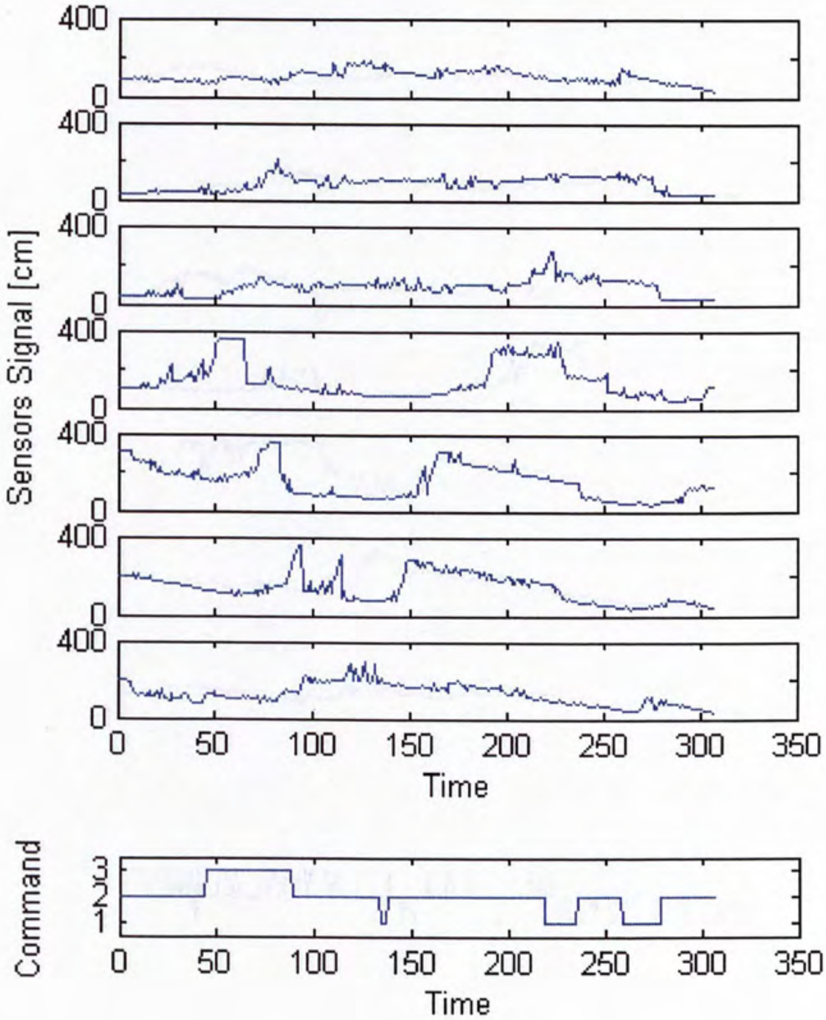

Figure 4.5: The sensor trajectory and corresponding demonstrated control command in the second demonstration.

pairs of CNN inputs and output are sampled. For the off-line supervised learning, totally about 3200 sensor-control training sets are recorded in 10 demonstrations (Figures 4.4,4.5, B.1-B.8). In the figures, the commands 1, 2 and 3 refer to the discrete control commands turn left, move straight and turn right respectively. The data is firstly shuffled randomly and then used for training and cross validation. To

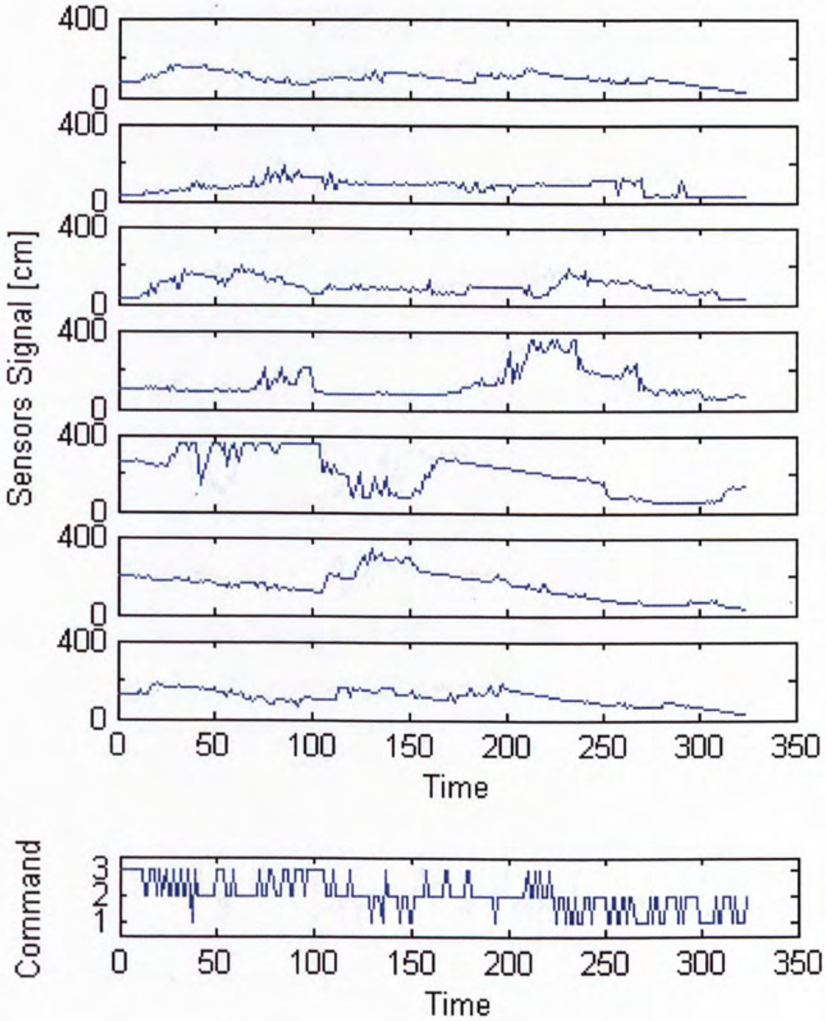

Figure 4.6: The sensor trajectory and corresponding control command resulted from the first learned skill model in the first testing of autonomous navigation.

remain the simple input-output relationship, no previous input or output state is adopted.

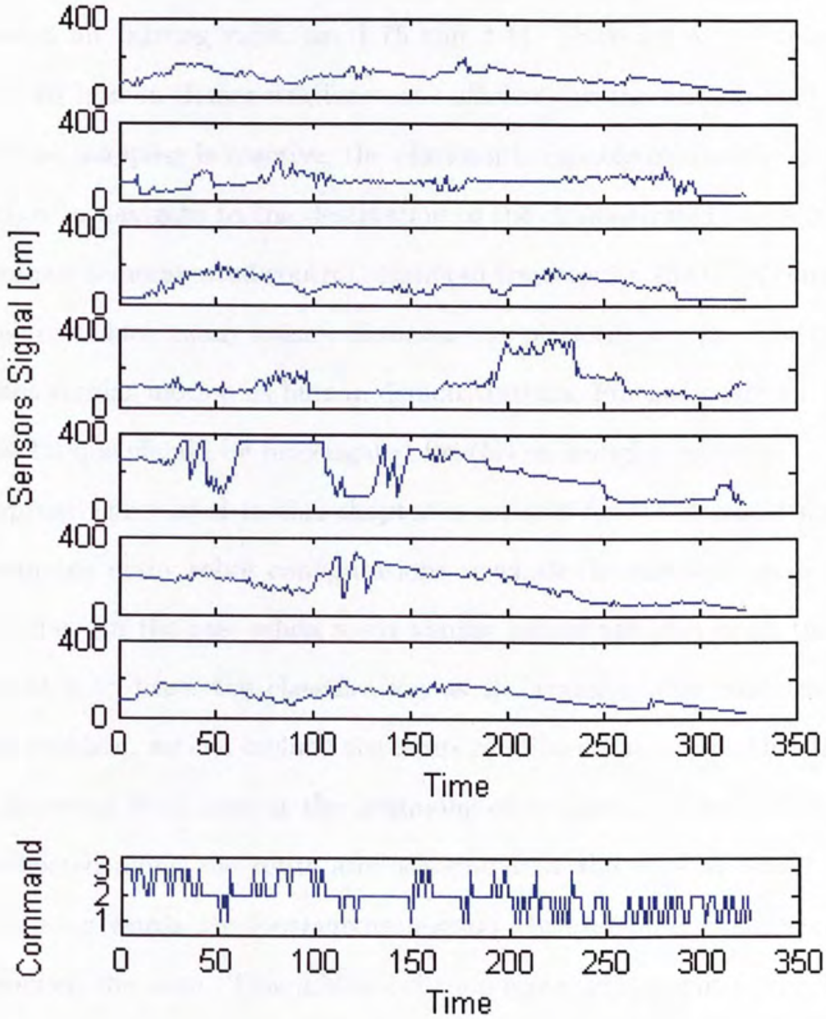

Figure 4.7: The sensor trajectory and corresponding control command resulted from the first learned skill model in the second testing of autonomous navigation.

4.4.2 Results

After off-line learning, a trained CNN with 15 hidden nodes had the capacity to complete the learning navigation with the platform moving at the speed 0.8m/s. Two testings of autonomous navigation are undertaken (Figures 4.6,4.7). The thresholds for determining the discrete control command, 1 for turning left, 2 for moving straight and 3 for turning right, are 1.75 and 2.44. From my experimental experience, 6 to 10 human demonstrations are sufficient for the navigational learning task. Since the mapping is reactive, the platform is capable of starting at mid-way and continues to navigate to the destination of the demonstrated route. Compare with the human demonstrated control command trajectories, the CNN control command trajectories have many noises. However, the platform acts as a low-pass filter and performs similar motion as human demonstrations. Further study for a "smart filtering" technique should be investigated for this meaningful problem.

The approach presented in this chapter is suitable for the demonstrated route without involving many robot configurations at which the sampled sensor patterns are very similar. In the case when many similar sensor patterns exist, the trained model is unable to learn the classification as the training data contradicts. For solving this problem, we can include the temporal dimension as an additional learning input, counting from zero at the beginning of navigation. The sampled sensor patterns collected along the route are "separated"by the time at which they are sampled. In other words, the local environmental features are now described by one more dimension, the time. This additional time input adjustment is also tested in the experiments, yet the learned model is still able to finish the autonomous navigation task without much difference in performance. However, some demonstrated routes could be problematic and will be discussed in Chapter 6.

4.5 Discussions

The experimental study on a smart wheelchair shows the feasibility of this practical autonomous navigation approach for indoor route-specific application. As the learned model is able to lead the smart wheelchair to accomplish the demonstrated route, the model is defined being capable of effectively abstracting human navigational skill with limited environmental information sufficient for the navigational task. With this autonomous navigation ability, the platform can free the user from much of the low-level control now required in electrically powered wheelchairs.

Depending on the complexity of the skill model, the overall human skill model can typically be composed of a number of simpler sub-models that each of which specializes a specific segment of the learned route. The transition between consecutive skill models is according to recognition of the ending patterns of former model. An certain overlapping route segment for the skill models is needed for the transition.

Chapter 5

Learning from Multi-phase Demonstrations

In this chapter, an extension and realization of active learning for the learning-by-demonstration paradigm by multi-phase human feedback demonstrations is primarily investigated with the application on the human indoor navigational skill modelling presented in Chapter 4. With this experimental design, the learning performance is experimentally on-line evaluated and improved over the learning phases in terms of the similarities between demonstrations and autonomous navigation. The approach is useful to identify and collect critical training data, which is hard to achieve for some systems with different dynamic parameters in the demonstration and application stages. With this approach, the learning performance of the navigational learning approach is improved, as shown in the experimental results.

5.1 Introduction

Conventional learning-by-demonstration paradigm utilizes off-line learning to capture the features exhibited during demonstrations. However, the dynamics parameters of the system are in general different in the demonstrations and application stages. For instance, when the control profiles of a human demonstrator and a computational skill model(for automation) are different, their corresponding dynamics of the platform are in general different, such as frictional and slipping effects. As a result, significant errors can exist in the application stage.

One of the leading, emerging topics in current machine learning research is active learning [40-42], which provides automated means of determining which potential new data points would be most useful to label. It could suggest new data that would allow machine learning classifier to best correct the predictions coming from the realistic model, towards much more accurate overall classifications. Thus active learning methods directly address the issue of automating the process of determining what predictions to make and what data to gather to test them. However, since active learning is aimed at automatically determining new critical training data, this concept is not directly applicable for the learning-by-demonstration applications, in which the training data is provided during human demonstration.

In order to achieve a reliable and systematic learning process for the learning-by-demonstration paradigm, I extend and realize the concept of active learning by performing multi-phase on-line human feedback demonstrations. The approach is useful to identify and collect critical training data, which is hard to achieve for some systems in a single-phase demonstration for learning. Moreover, the learning performance can be observed in the learning process in an experimental way.

5.2 Problem Formulation

The learning procedure takes several phases. At the first phase, the off-line learning is adopted. After the testing of the learned training model, human demonstrator investigates the learning performance and performs corrections(demonstrations) whenever faults occur in critical segments of the trajectory. At the same time, the critical training data is found actively and manually for learning in order to achieve better learning performance in next learning phase. Hence, the approach is an extension of active learning for the learning-by-demonstration paradigm. The new training data obtained in a new demonstration is added to the previous training data for new model training. Several phases go on until the learning performance is satisfied by the demonstrator.

5.3 Approach

In order to illustrate the developed experimental design, I apply this approach to abstract and learn human navigational skill with the cascade neural network. At the first demonstration phase, a trained skill model is obtained from the training of the demonstrated data. Then, in the first autonomous navigation, whenever human discovers any improper motion control determined from the skill model, a correction is made by adjusting the control command to a correct one. The new corrected control commands and their corresponding sampled sensor patterns are added to the training data obtained in previous training step(s) for new model training. The procedure goes on in the next a few autonomous navigation in order to find critical training data for improvement of learning performance (Figure 5.1).

5.4 Experimental Study

5.4.1 Settings

In the whole learning and demonstration process, there are a total of 3 demonstrations and 3 autonomous navigation. In all autonomous navigation, the wheelchair completed the learning tasks without collision with the surrounding obstacles. During each phase of autonomous navigation, around 20 control commands are corrected

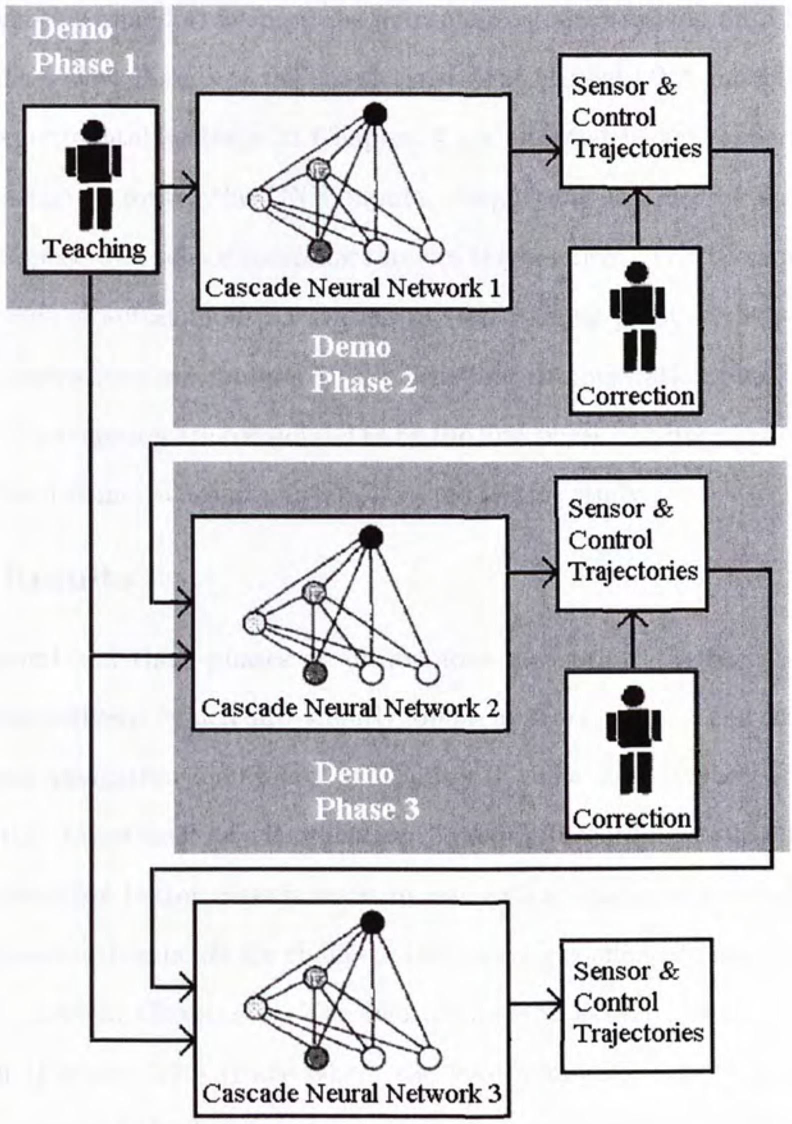

Figure 5.1: A 3-phase demonstration process in learning human skill for the autonomous robot navigation.

(demonstrated) and added with their corresponding sampled sensor patterns to the training data obtained in previous demonstration phase(s). The corrections are based on the human control strategy adopted in the first phase of demonstration(10 times). The reason that, small amounts of data are corrected in each later demonstration phase is aimed at keeping the percentage of new training data low. This is likely to allow slow change of the characteristics of learned CNN model.

The experimental settings in Chapter 4 are adopted in this experiment that, the demonstrated route, the CNN inputs, output and number of hidden nodes, navigation speed and sensor sampling rate are the identical. The 10 demonstrations and 2 testings of autonomous navigation are the starting point of this study. Here, these demonstrations are considered to be the first demonstration phase. Also, that 2 testings of navigation are considered to be the first phase of autonomous navigation for the second demonstration phase conducted in this study.

5.4.2 Results

At the second and third phases of autonomous navigation, the thresholds are 1.7 and 2.4 respectively, which are slightly different from that of the first phase of autonomous navigation mentioned in Chapter 4. The shift in the two thresholds refers to the adjustment of classification boundary(according to the new critical training data) for better classification in navigation control commands. Though the classification thresholds are changed, the training coefficients remain unchanged with those used in Chapter 4. The two testings of second phase of autonomous navigation (Figures 5.2,5.3) are where the final demonstration phase took place. The two testings of third phase of autonomous navigation (Figures 5.4,5.5) are the final testings.

5.5 Evaluation of Learning Performance

The feasibility of this approach is defined as the achievement of the 2 learning objectives: (1)The completion of all autonomous navigation along the demonstrated route without any collision, and (2)An increase in similarities between the demon-

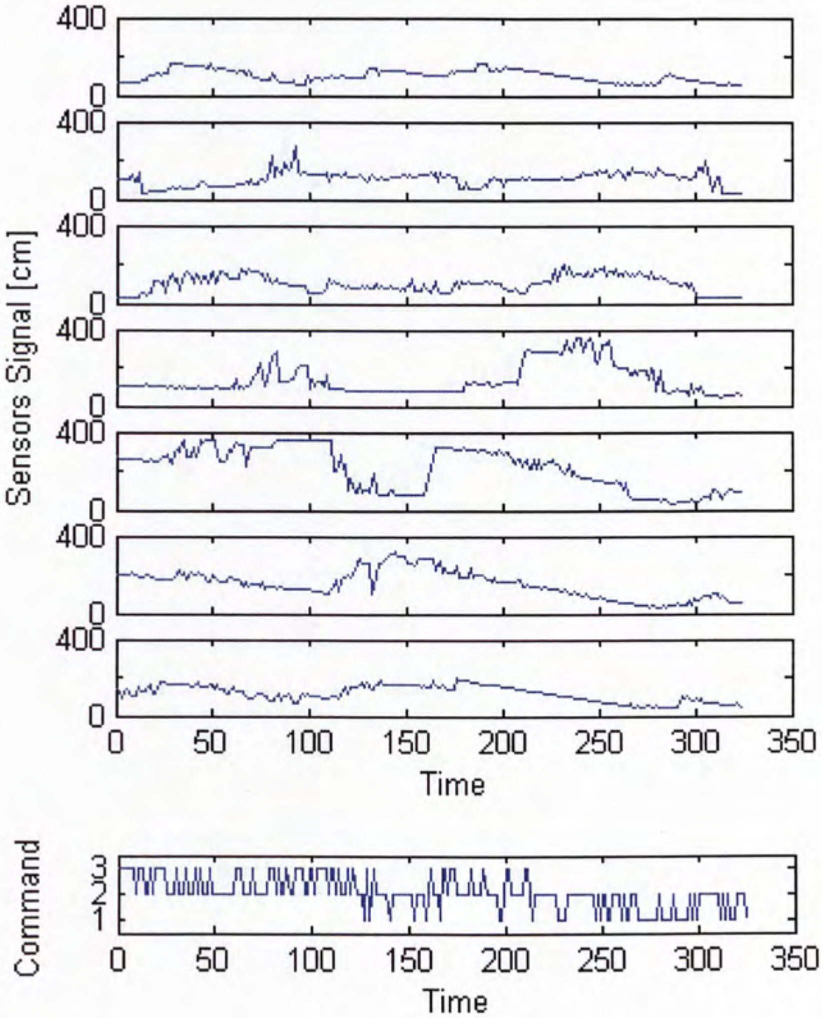

Figure 5.2: The sensor trajectory and corresponding control command resulted from the second learned skill model in the first testing of autonomous navigation.

strations and autonomous navigation over the learning phases.The first requirement has been satisfied in the experimental study. Therefore, an analysis is needed for evaluating the fulfillment of the second requirement in the study.

During each navigation in the experiments, a sensor trajectory is sampled which is a unique series of the local environmental features (with orientation) along the

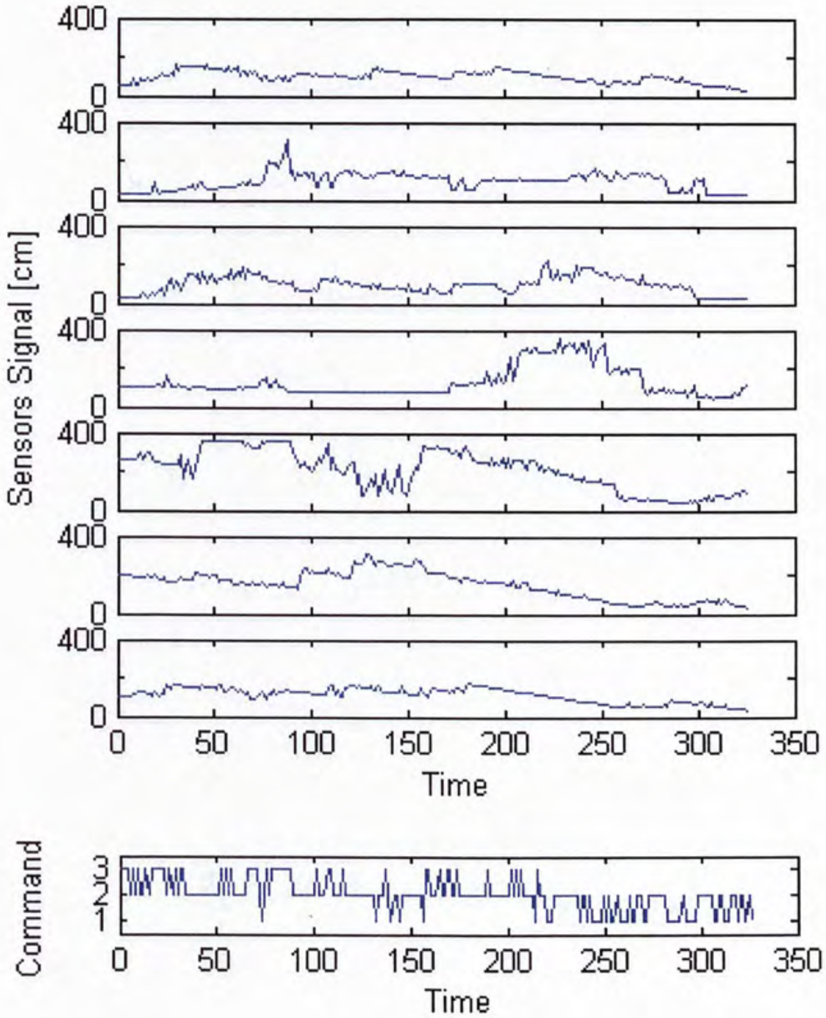

Figure 5.3: The sensor trajectory and corresponding control command resulted from the second learned skill model in the second testing of autonomous navigation.

specific navigation route with respect to the moving wheelchair. Since all the human demonstrations and autonomous navigation have certain stochastic variations in motion, the sampled sensor trajectories also possess this kind of statistical property. In other words, all sensor trajectories are slightly different. To evaluate the similarity between human demonstrations and autonomous navigation in terms of this

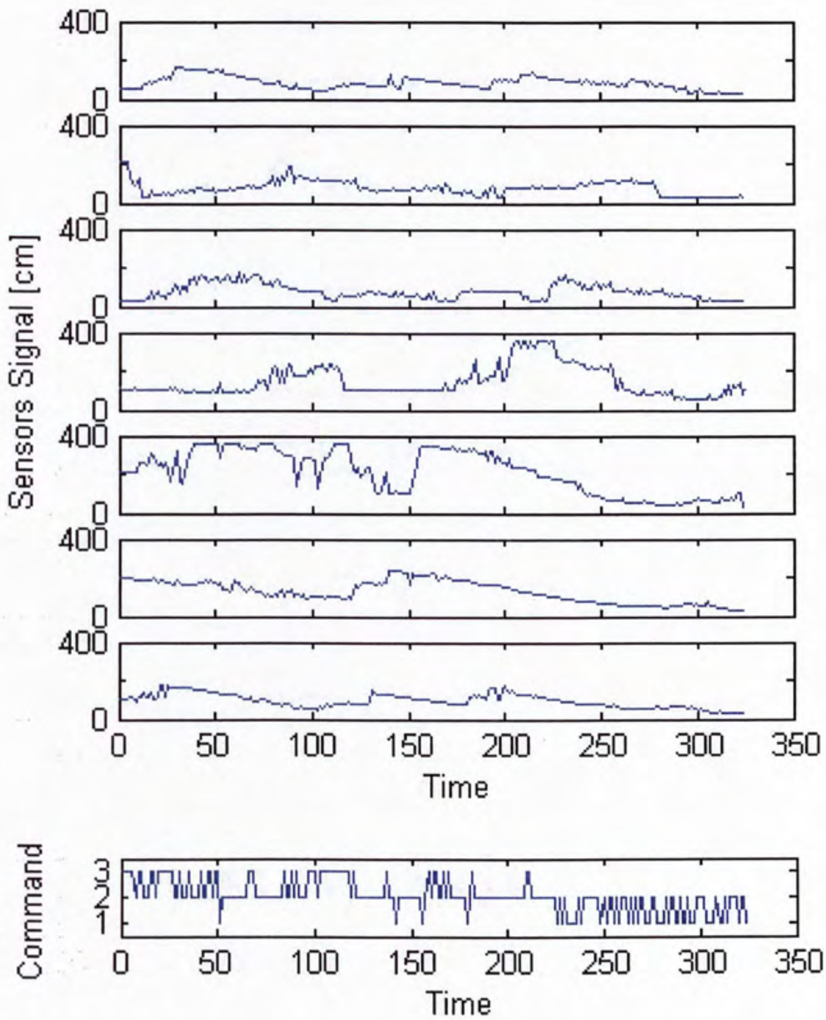

Figure 5.4: The sensor trajectory and corresponding control command resulted from the third learned skill model in the first testing of autonomous navigation.

characteristic, I adopt Hidden Markov Model(HMM) to account for the similarity measure.

An HMM is a Markov chain (doubly stochastic trainable model) whose states cannot be observed directly, and was developed for solving real-life problems [43]. For example, HMMs have found their widest application in speech recognition

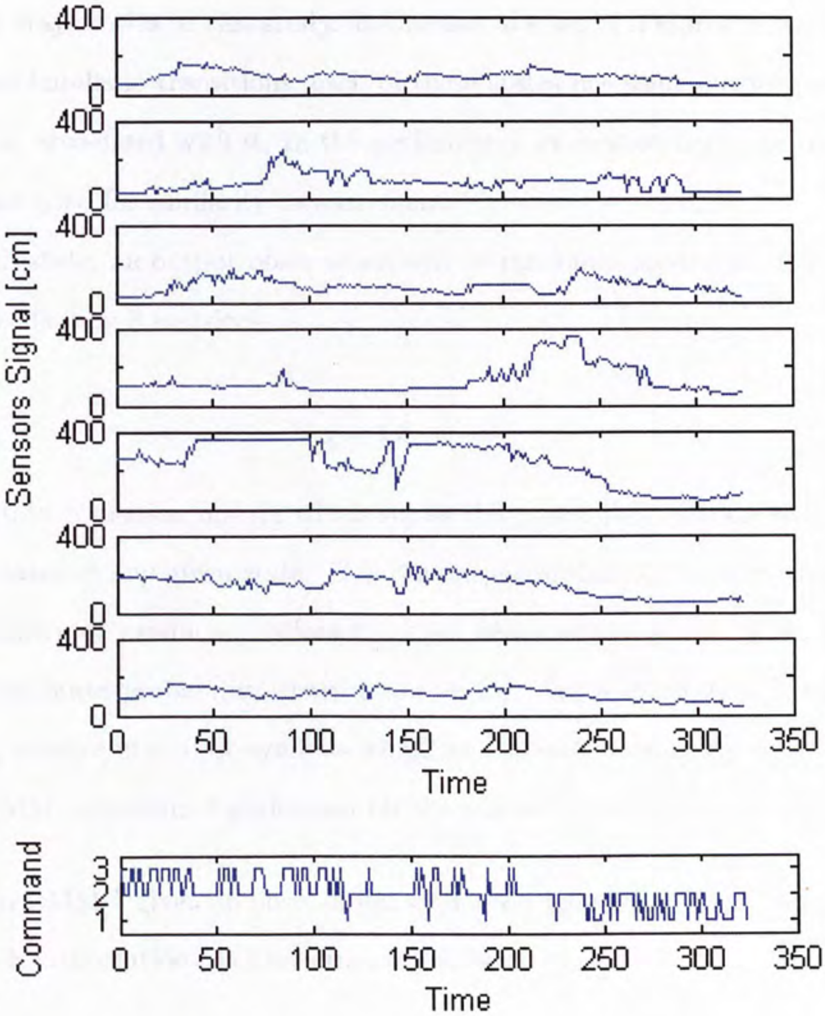

Figure 5.5: The sensor trajectory and corresponding control command resulted from the third learned skill model in the second testing of autonomous navigation.

[44], where human auditory signals are analyzed as speech patterns by a variety of stochastic signal processing. This technique provides an efficient and effective method to induce invariants during modelling. Also, trajectories with high degree of sequential structure and in different lengths can be encoded with this statistical modelling technique without any priori assumption about its statistical distribu-

tion. With these properties, HMM is a suitable tool for modelling and analysis of the sensor trajectories in this study. It consists of a set of n states, interconnected through probabilistic transitions; each of these states has some output probability distribution associated with it. In the performance evaluation here, the continuous HMM is adopted for similarity measurement.

At each state, an output observation will be randomly produced. The HMM λ can be specified by 3 matrices.

$$\lambda = \{A, B, \pi\} \tag{5.1}$$

A is the state transition matrix which shows the probability of transition between different states at any given state. B is the output probability matrix which shows the probability of producing different output observations at any given state. π is the initial state probability distribution vector. For a given λ, it is capable of producing a series of output symbols which we call observation sequence O. There are two HMM operations I performed for the sensor trajectories similarity study.

- Train HMM λ given an observation sequence : maximize $P(\lambda|O)$ using Baum-Welch Expectation Maximization algorithm.

- Calculate the probability that a given observation sequence O is generated from a HMM model λ : calculate $P(O|\lambda)$ using Forward-Backward Algorithm. After calculating $P(O|\lambda)$, it is normalized by the length of the sequence T, then being applied log to prevent the data underflow problem. This probability is called log-likelihood.

To show the stochastic similarities between sensor trajectories obtained from human demonstrations and autonomous navigation, a left-right Gaussian HMM is

Table 5.1: The log-likelihoods of sensor trajectories in autonomous navigation with 2 trained HMMs.

	HMM with 7 Hidden Nodes	HMM with 8 Hidden Nodes
Navigation 1: Test 1	-9587.7	-9587.5
Navigation 1: Test 2	-9657.1	-9585.6
Navigation 2: Test 1	-9332.0	-9147.2
Navigation 2: Test 2	-9080.9	-9179.6
Navigation 3: Test 1	-8972.1	-8995.1
Navigation 3: Test 2	-8657.1	-8774.2

trained with the first 10 demonstrated sensor trajectories. Then the sensor trajectories sampled during different phases of autonomous navigation are used to calculate the log-likelihood values with the trained HMM of demonstrations (Table 5.1). From the results, the increase in the log-likelihood values in the later autonomous navigation reflects the higher similarity between the later autonomous navigation and the initial 10-time human demonstrations.

5.6 Discussions

The preliminary results are positive to show that the multi-phase demonstration process yields positive result for the learning performance. However, there are two possible sources of factor accounting for this improvement: (1)The developed multi-phase learning is a feasible experimental design for increasing the learning performance, and (2)The increase in training data yields a better learning performance. The argument of the source of improvement factor here is a future work for this study. Nonetheless, the developed multi-phase approach is shown as a systemic learning process for identifying and collecting critical learning data for the learning-by-demonstration paradigm.

Chapter 6

Localization Learning

In this chapter, for localization purpose, the sensor-control mapping for navigation presented in Chapter 4 is modularized to constitute the sensor-configuration mapping in the form of look-up table, which is learned to localize at demonstrated locations with raw sensor patterns inputs and human-assigned configuration outputs. The approach is useful as a simple self-contained system for reactive localization at desired, learned configurations in indoor, static and unstructured environments such as common household settings.

6.1 Introduction

This study is inspired by the previous study on developing a navigation approach with local environment modelling in unstructured environments, presented in Chapter 4. As an extension of this navigation approach, there is a possibility to modularize the sensor-control mapping into the sensor-configuration and configuration-control mappings. The sensor-configuration mapping is actually the localization problem, which is essential for achieving the context-awareness (such as locate the user) in a pervasive computing/robotic system, and is the concern in this study. With this motivation, I developed a localization system for practical applications with similar formulation and settings of the presented human navigation skill modelling. The difference and difficulty here are to achieve precise mapping for the accurate mapping output(configuration).

6.2 Problem Formulation

The objective of this study is to utilize on-board range sensing information to concisely model local unstructured environment(with respect to the robot/platform) for localization in the learned configurations in order to achieve acceptable accuracy with low on-line computational demand and low-cost hardware requirements. With this objective, I formulate the localization problem into 2 consecutive sub-tasks: (1)model the local environment in a polar coordinate representation with on-board range sensing, and (2)construct a mapping between range sensing patterns(polar input) and absolute robot/platform configuration(Cartesian output) for real-time sensor pattern recognition and configuration estimation. The feasibility of this study depends on the practical localization accuracy, which is off-line investigated.

6.3 Approach

The developed localization approach has five steps: (1)use sensor patterns, which are sampled from several ultrasonic range sensors at various robot/platform configuration, to model local environments, (2)manually estimate and assign the corresponding configuration to each sampled sensor pattern, (3)form a look-up table for the sensor-configuration mapping, (4)on-line search the closest sensor pattern in the constructed look-up table for the real-time sampled sensor pattern, and (5)adopt the corresponding configuration output of the closest sensor pattern in the table as the real-time configuration.

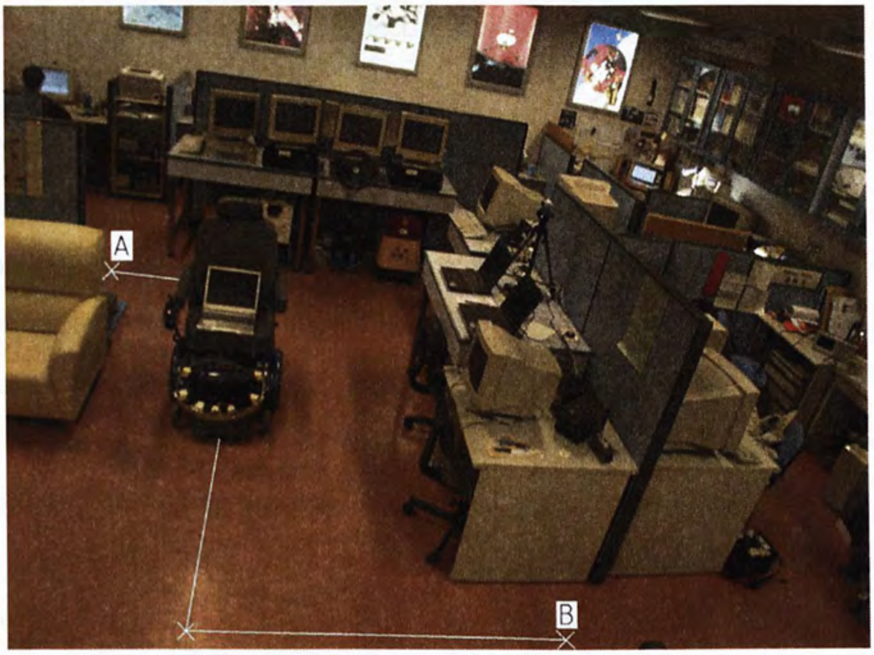

Figure 6.1: A demonstrated route(A to B to A) in an unstructured environment.

Instead of achieving function approximation with machine or statistical learning techniques [40], such as neural network and support vector machine, the constructed mapping is explicitly listed out in a look-up table for real-time sensor input searching while avoiding approximation and simplification of the actual complex mapping relationship.

6.4 Experimental Study

6.4.1 Settings

7 ultrasonic range sensors and a joystick are used in this experiment. By human operation, the wheelchair platform is controlled via the use of joystick to navigate a designated route 5 times in a static, unstructured environment (Figure 6.1), intending to obtain the similar position/velocity profiles. In each operation, the platform

moves at speed about 0.8m/s for collecting raw local range patterns(about 260 samples) along the route.

Since the platform is operated at roughly constant speed along the designated route, the platform configuration(planar position and orientation) is off-line assigned by human estimation to the corresponding sensor pattern. A look-up table is constructed with all raw sensor patterns(input) sampled along the route and its labelled configuration(output). One (Figures 6.2,6.3) and three (Figures 6.2-6.7) navigational operations are used to construct two independent localization look-up tables from 259 and 796 sensor patterns respectively. Another two operations are used to off-line evaluate the localization performance of the two constructed look-up tables (Figures 6.8-6.11). The accuracy of the assigned robot configuration x, y and orientation, due to human labelling errors, is an issue to be investigated in the later part of this chapter.

6.4.2 Result 1: Localization Performance

Each constructed localization look-up tables are evaluated with two new navigational operation data (Figures 6.8-6.11). Each untrained sensor pattern is matched with the closest sensor pattern stored in each look-up table with minimum Euclidean distance in the 7-D sensor space as criteria. The corresponding configuration output for the matched sensor pattern in the table is considered to be corresponding configuration of the matching sensor pattern. From the results, the errors in configuration output x, y and orientation are bounded around +/- 25 cm/degree between the actual values in most times, except for a few significant errors (Figures 6.12-6.15). Therefore, the developed approach has acceptable accuracy, even with the involvement of human assignment errors.

Also, it is clear that the two look-up tables constructed from one and three op-

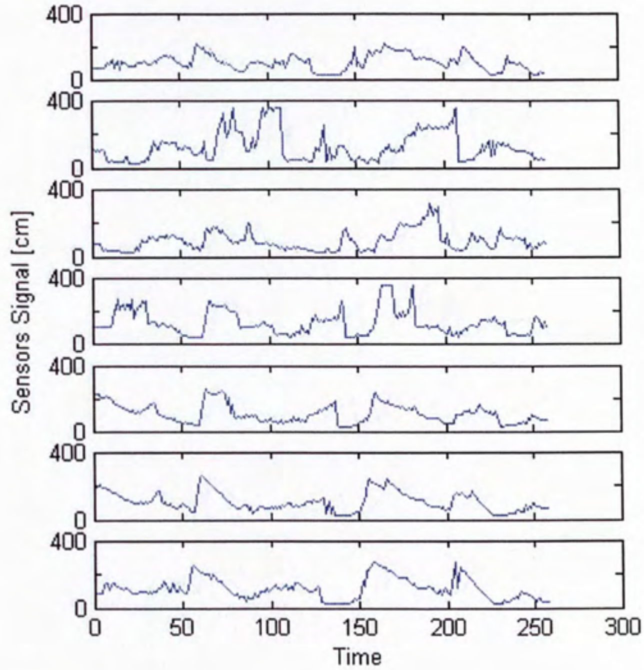

Figure 6.2: The sensor trajectory of first training route.

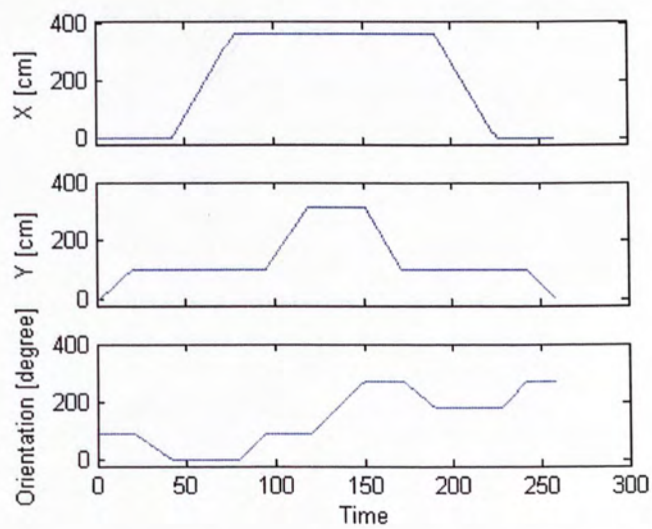

Figure 6.3: The human-assigned control command trajectory of first training route.

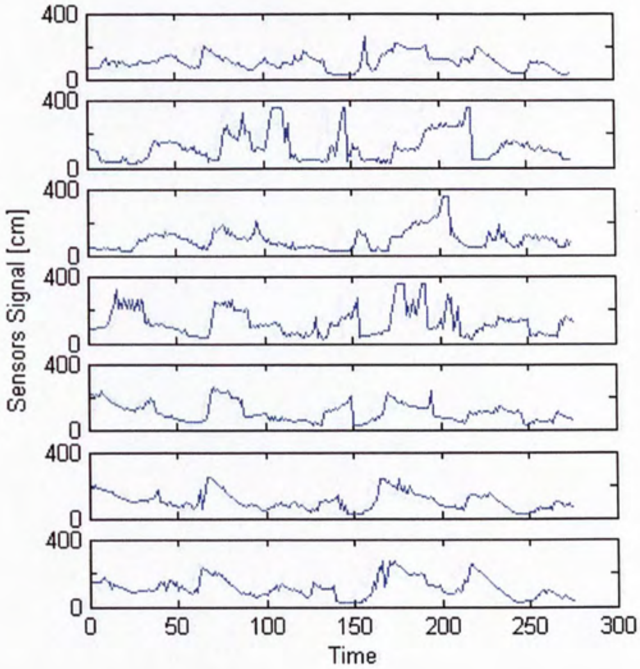

Figure 6.4: The sensor trajectory of second training route.

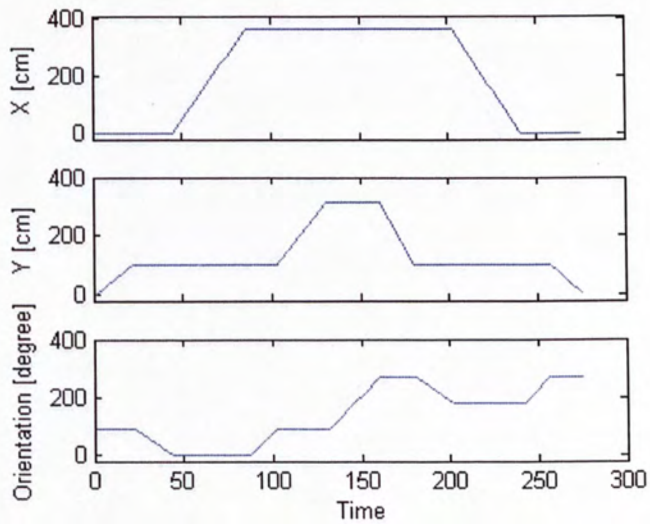

Figure 6.5: The human-assigned control command trajectory of second training route.

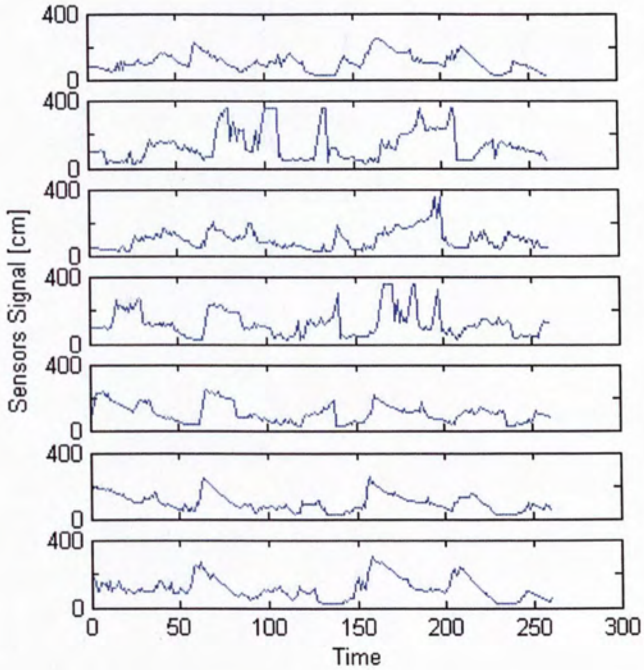

Figure 6.6: The sensor trajectory of third training route.

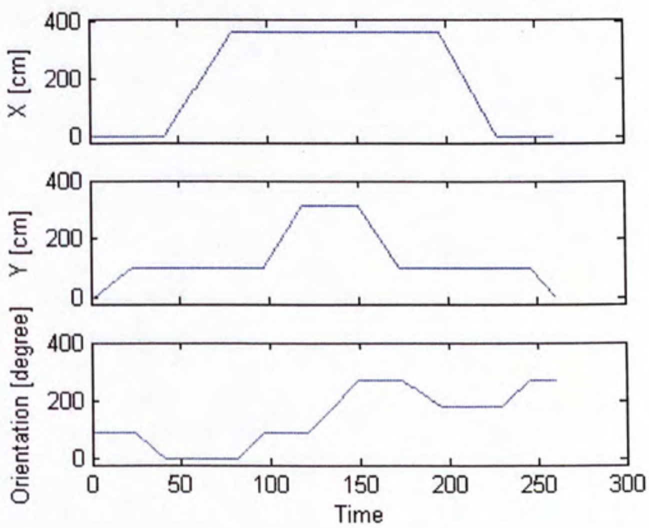

Figure 6.7: The human-assigned control command trajectory of third training route.

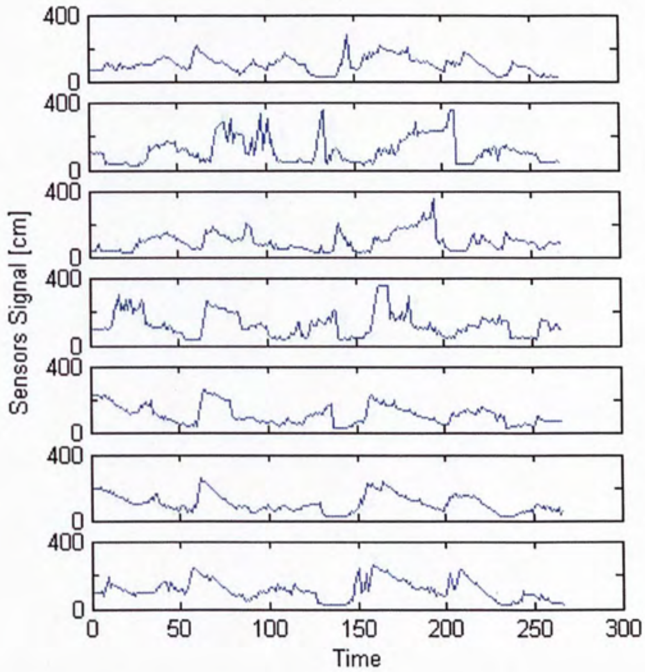

Figure 6.8: The sensor trajectory of the first untrained route.

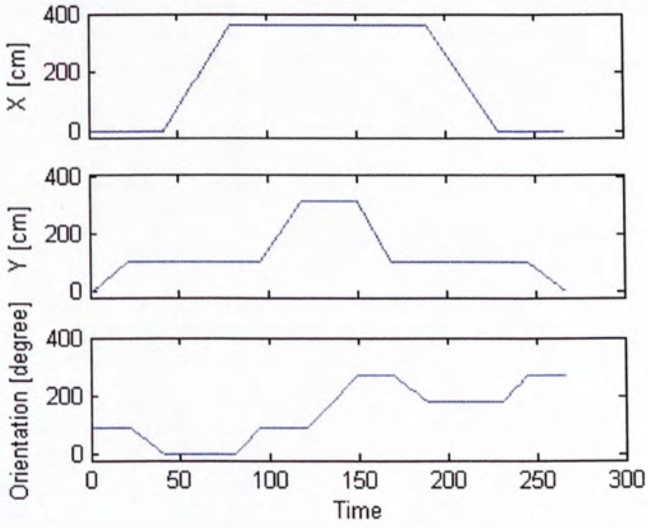

Figure 6.9: The human-assigned control command trajectory of the first untrained route.

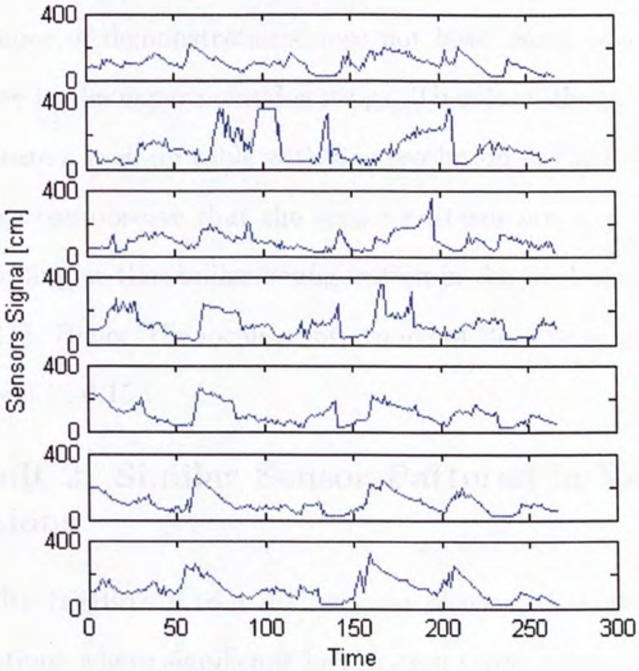

Figure 6.10: The sensor trajectory of the second untrained route.

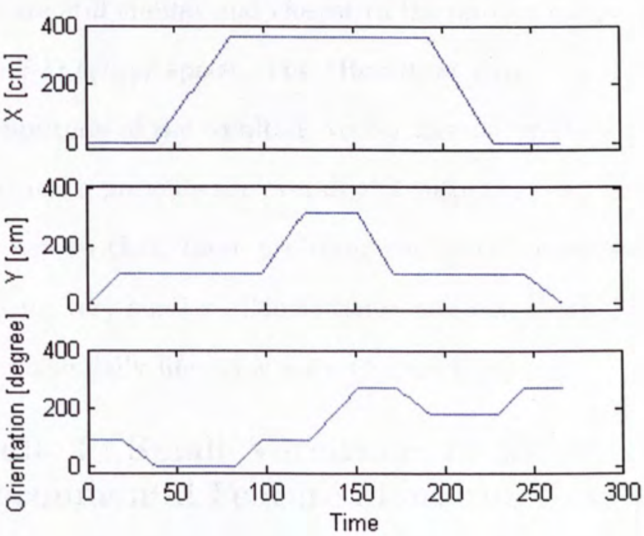

Figure 6.11: The human-assigned control command trajectory of the second untrained route.

erations obtain similar localization results for the two new operation data. In other words, the number of demonstrations does not have much effect on the localization performance in the experimental settings. Therefore, the sampling rate is high enough to generate a look-up table with fine resolution in the settings.

Moreover, we can observe that the sensor patterns are very similar(high precision) when sampling at the similar configuration in the workspace in all operations (Figures 6.2-6.11). Hence, the localization results of the 2 untrained routes are very similar (Figures 6.12-6.15).

6.4.3 Result 2: Similar Sensor Patterns in Various Configurations

From the results (Figures 6.16-6.19), we can observe that at each of the locations/configurations where significant localization errors exist, the on-line sampled sensor pattern is matched to a "far-away" and mismatched location at which the sensor patterns are still similar and closest to the on-line sampled one in Euclidean distance on the 7-D sensor space. The "Resultant Error" in the Figures 6.16-6.19 refers to the magnitude of the resultant vector formed by the 3 scalar errors in x, y and orientation, and represents the overall of 3 output errors. The physical meaning of this result refers to that, there are some configurations at which their sampled sensor patterns are very similar. Conceptually and empirically, this phenomenon is often to occur in the daily life experience (Figure 6.20).

6.4.4 Result 3: Small Variations in Major Dimensions of Environmental Feature along the Route

From the experimental results, we can observe that the variations in each sensor signal are little at most of the time along the route (Figures 6.21,6.22). Also, for each sensor, at the times when significant variations exist, the variations in the

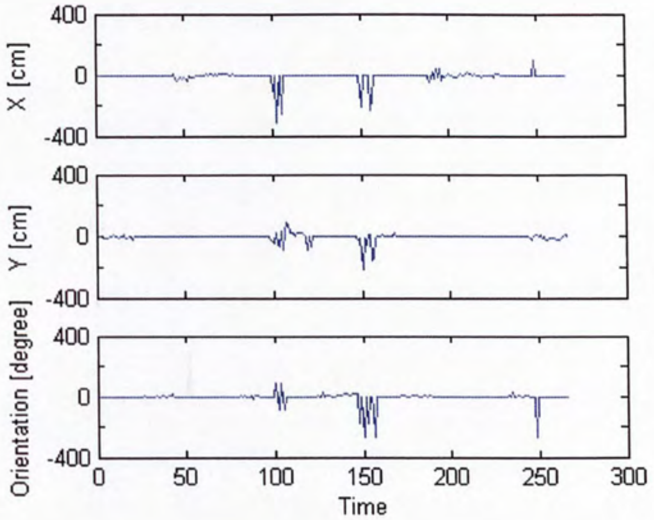

Figure 6.12: The errors(x, y & orientation) in the look-up table with 1 training route for the first untrained route.

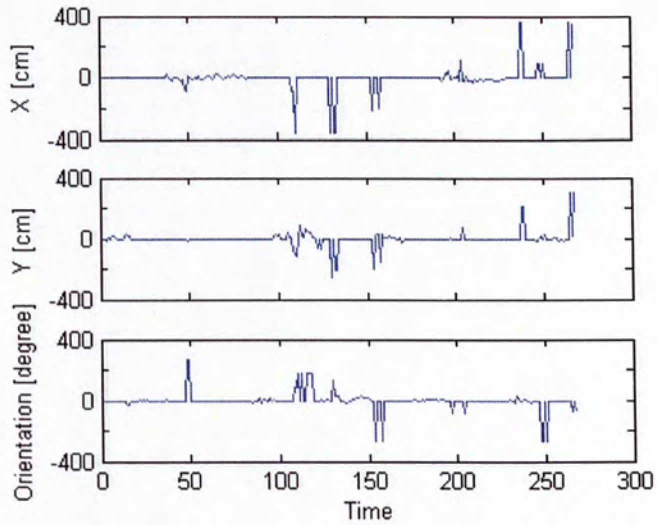

Figure 6.13: The errors(x, y & orientation) in the look-up table with 1 training route for the second untrained route.

other sensor signals are relatively little. In other words, significant variations do not happen simultaneously in the majority of sensors. Moreover, the average of variations in all sensor signals alone the route is roughly bound around +/- 15 cm

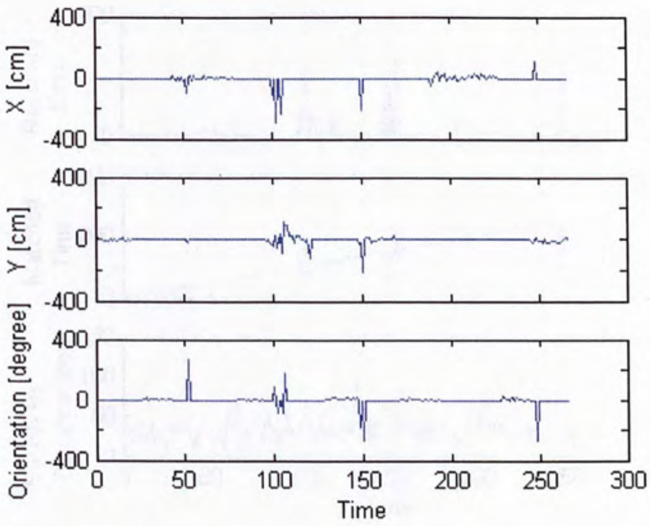

Figure 6.14: The errors(x, y & orientation) in the look-up table with 3 training routes for the first untrained route.

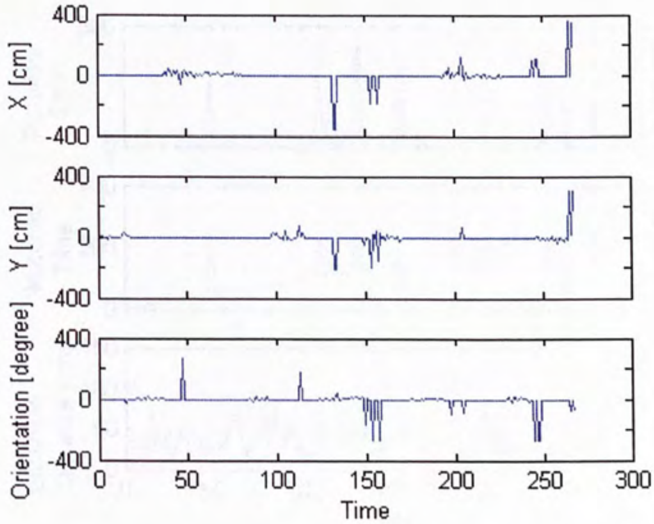

Figure 6.15: The errors(x, y & orientation) in the look-up table with 3 training routes for the second untrained route.

(Figure 6.23). The physical meaning of this result is that, nearby configurations have similar sensor patterns which describing the similar local environmental features.

Empirically, this explanation matches with the daily life experience that, similar

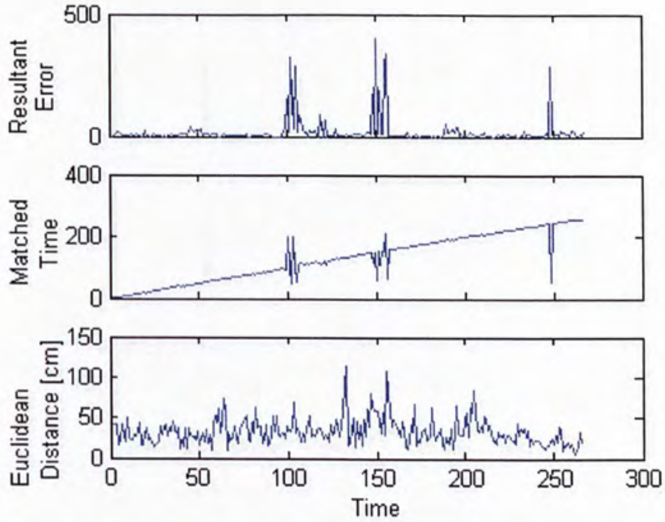

Figure 6.16: In the look-up table with 1 training route for the first untrained route, significant errors appear when similar sensor patterns occur in various configurations.

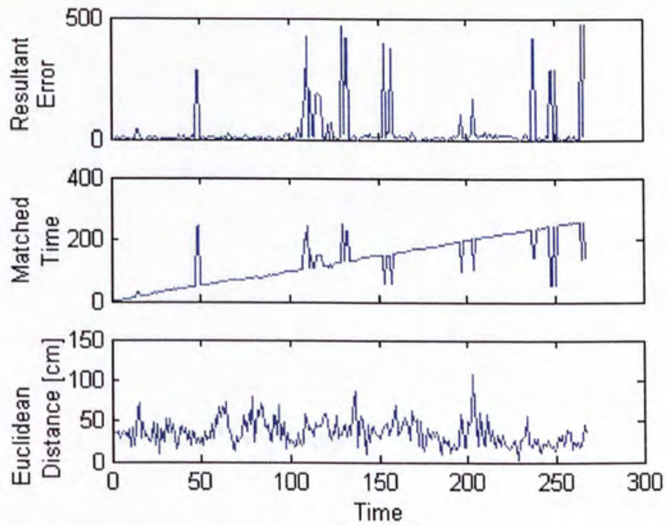

Figure 6.17: In the look-up table with 1 training route for the second untrained route, significant errors appear when similar sensor patterns occur in various configurations.

visual images are perceived when human senses in nearby locations and/or orientations. Moreover, the less difference in sensing positions and/or orientations yields the higher similarity in the perception. On the other hand, it is reasonable to state

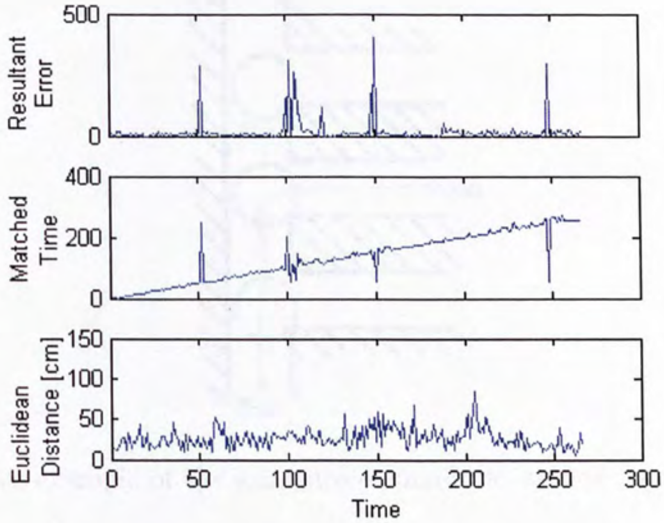

Figure 6.18: In the look-up table with 3 training routes for the first untrained route, significant errors appear when similar sensor patterns occur in various configurations.

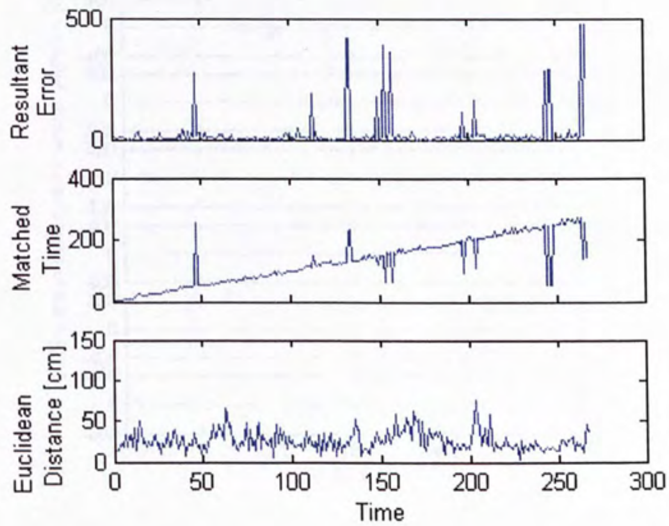

Figure 6.19: In the look-up table with 3 training routes for the second untrained route, significant errors appear when similar sensor patterns occur in various configurations.

that, the less "percentage" or "weight" of the environmental change yields higher similarity between the original environment and changed environment at the same

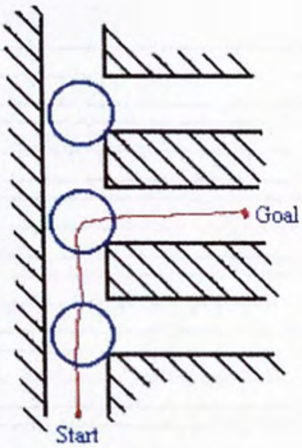

Figure 6.20: An example of the existence of similar local environments(Circled).

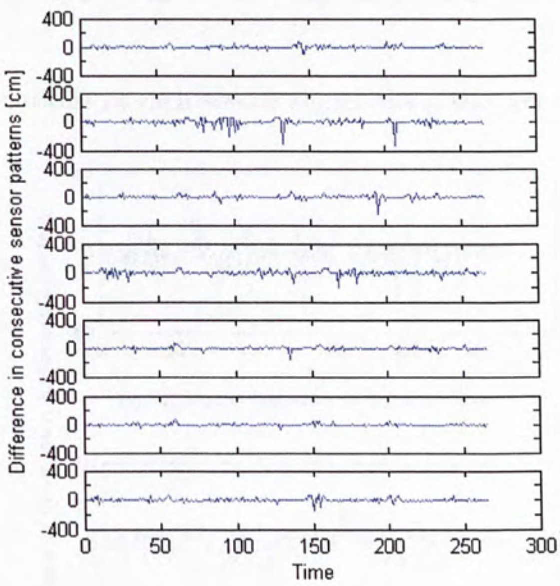

Figure 6.21: Variations in each sensor signal along the first untrained route.

sensing configuration in term of the environmental representation. Therefore, the robustness of the environmental model for localization is proportional to the "percentage" and "weighting" of the environmental change.

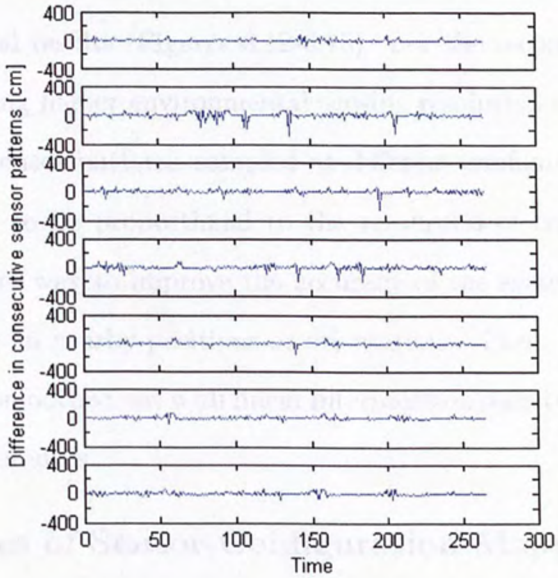

Figure 6.22: Variations in each sensor signal along the second untrained route.

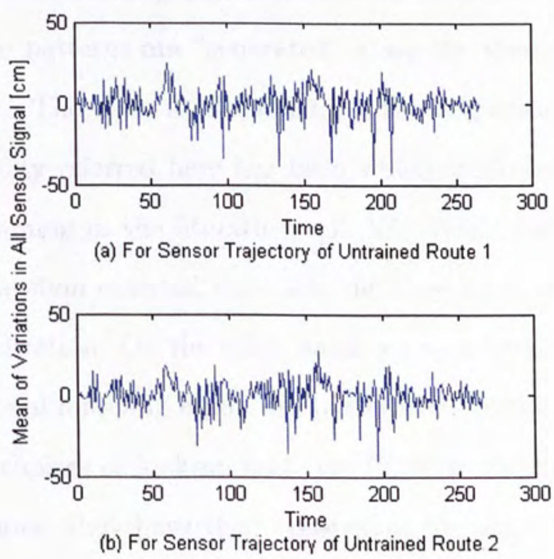

Figure 6.23: Mean of variations in all sensor signals along the route.

6.5 Discussions

6.5.1 Accuracy

There are two possible sources of errors: (1)assigned mapping output(configuration), and (2)similar sensor patterns in different configurations. For the first error source, the acceptable error bound does exist for the assigned mapping output, as shown in the experimental results (Figures 6.12-6.15). For the second error source, more sensors for achieving higher environmental sensing resolution is likely to reduce the similarity of the sensor patterns sampled at different configurations. The number of sensor is likely to be proportional to the resolution of environmental features modelling. Another way to improve the accuracy of the system is to perform consecutive samplings in nearby positions or orientations. Then, the resultant look-up table outputs are smoothed out with linear interpolation based on the actual position or orientation differences.

6.5.2 Choices of Sensor-Configuration Mappings

Instead of having purely reactive planning, we may also try to include the temporal dimension for better configuration pattern recognition. With this additional dimension, all sensor patterns are "separated" along the time they sampled in the demonstrated route. The time is counted from the beginning of the route. The curse of dimensionality referred here has been widely addressed in the framework of dynamic programming in the literatures [45,46]. While real-time sensing information acts as the system external feedback, the time input serves as the internal information for localization. On the other hand, we may adopt the previous sensor states as the additional mapping inputs for pattern recognition.

Although these choices of look-up table are likely to reduce similar patterns in different configurations, they have their constraints for practical applications. For the time input case, the robot/platform is required to perform the same navigation as that of demonstration in order to have same temporal dimension or trajectory profile. For the previous sensor states case, the robot/platform is required to have part of navigation same as that of demonstration in order to have same previous states. Both the time input case and previous sensor states case have velocity and position/orientation constraints based on the demonstration.

Chapter 7

Conclusion

In this chapter, the key contributions of this study are illustrated. Also, some potential future work is highlighted for possible extensions of the human navigation skill modelling, multi-phase demonstrations for learning and localization learning presented in Chapters 4, 5 and 6 respectively.

7.1 Contributions

In this thesis, a move towards the development of novel, compact and practical robotic wheelchair navigation system is presented for enhancing user mobility in indoor applications. Human skill abstraction, environmental modelling, and navigation & localization learning are the core theoretic foci of the investigations and evaluations done in this study, with emphasis on the methodology formulation & design, and experimental design & implementation aspects. Several significant contributions have been established in the study presented in this thesis, as stated in the following.

In Chapter 3, a novel wearable eye-jaw control cap interface is developed and tested. It is a simple, low-cost and effective solution for manual control on an electrically powered wheelchair for users even with limited dexterity on their legs, arms and/or spine cords.

In Chapter 4, a navigation learning approach is presented. Cascade neural network is adopted for abstracting the human skill in form of reactive mapping between raw sensor pattern inputs and human-assigned control command outputs, sampled in the demonstrations. Local Environments are represented in form of range sensor vector for pattern recognition during autonomous navigation. With this approach, high-level navigation autonomy is achieved for applications in robotic wheelchairs. Also, the approach possesses several advantages for practical applications. First, environment is represented in an efficient and compact computational model, instead of the existing complex representations such as cell decomposition, geometric, topological or vision models. All of these benefits are good for real-time robot planning. As a result, relative less on-line computational demand, lower data storage memory and cheaper hardware equipments are required. Second, since the trajectory planning is reactive and in real-time, the planning has certain fault-tolerant capability that, momentary control errors, ambiguous sensory data and little errors in the trained model are by-passed. Third, with this learning-by-demonstration method, user who does not have technical backgrounds is still able to easily teach his/her platform personally in a simple and direct way. Fourth, limited local environmental information is sensed and processed with the on-board computing in a self-contained platform for navigation, without any additional positioning device. Fifth, instead of simulating physical phenomenon, this reactive mapping is obtained from human demonstrations. Hence, arbitrary desired path shape can be achieved as needed. Sixth, the platform's physical shape and size are abstracted in the skill model during the learning process. Therefore, the approach is suitable for mobile platform with any shape and size. With the approach presented in Chapter 4, the user can teach the system so that they can be performed autonomously for the navigation tasks, that need to be performed frequently. While application, the user can simply select a route from a list of learned routes, sit on the wheelchair and then being transported to the destination.

In Chapter 5, an extension and realization of active learning for the learning-by-demonstration paradigm is primarily investigated, achieving good learning performance in terms of the similarities between demonstrations and autonomous navigation. The approach is presented and illustrated with an example of human indoor navigational skill modelling by multi-phase human demonstrations. With this approach, demonstrations are learned in several phases with on-line human feedback assistance. The learning performance is directly, experimentally observed and evaluated by on-line testing throughout the learning phases. The approach is useful to strategically identify and collect critical training data, which is hard to achieve for some systems with different dynamic parameters in the demonstration and application stages. Moreover, the concept is generic and hence can be adopted on many learning-by-demonstration applications.

In Chapter 6, a localization learning approach is presented. A explicit look-up table is used for localization at demonstrated locations with raw sensor patterns inputs and human assigned position/orientation outputs. This approach is useful, easy to implement, and suitable as a simple, low-cost and self-contained system for reactive localization at desired, learned configurations in indoor, static and unstructured environments such as common household settings with acceptable accuracy. As an alternative, the approach can be used with existing simple positioning systems, such as wheel encoder, to achieve low-cost error-compensation for increasing the overall localization accuracy of those existing positioning systems.

The impacts of this study are: (1)The extension of the usability and functionality over the traditional electric wheelchair, which significantly assists the user's mobility in his/her day-to-day life. (2)The remarkable improvement of a wheelchair-bound user's social life, through closer and more interactions with his/her family and friends, and more participation in variety of public activities. (3)Tremendous new mobility interface possibilities could be open up and investigated as a result of the findings, resulting in rich system integration issues, academic research contents and potential product lines in consumer electronics for modern demanding rehabilitation and health-care product developments.

7.2 Future Work

Besides the above contributions, the study can be generalized in certain aspects. For the navigation study, there are certain issues we may explore. First, how does the number and location of sensors on the platform affect the navigation learning? Also, are there cases where the limited number of sensors becomes problematic? Second, is it possible to replace the implicit CNN skill model by an explicit look-up table? Is it possible to make some comparisons between the 2 methods? Third, what kinds of dynamic obstacles, and how much changes in the learned environment can the trained model tolerate? Since static obstacles cannot be identified from its surrounding environment in the approach, all static objects in the environment are considered as static obstacles for the navigation of platform. Therefore, the existence of new static obstacles can be considered as the change in the learned environment.

For the multi-phase demonstrations study, we may extend the work to rigorously show that, the better learning performance over the learning phases is caused by adding the strategically collected critical data in the neural network training data sets, rather than caused by adding merely more data. Moreover, the x-y Cartesian trajectory exhibited in navigation is also a suitable measure for performance evaluation.

For the localization study, we may explore some investigations in certain prospective. First, two types of sensing information could be adopted: color sensors(for example a camera) and range sensors(for example an ultrasonic or laser range finder). Each of them can be used individually for localization, while they also can form a hybrid/integration system for error-compensation purpose. Instead of comparing the localization performances between vision and range sensing [47], we aim at the synthesis of vision and range sensing from the view point of their physical meanings. Second, two types of sensing coverage could be considered: planar and spherical. Third, three types of Cartesian mapping outputs could be learned by demonstration: route(1-D), area(2-D) and space(3-D) of configurations. Therefore, this study is a localization work focusing on one of these scope combinations.

Appendix A

Cascade Neural Network

Since most neural networks used today rely on rigid, fixed architecture networks and/or with slow gradient descent-based training algorithms, they may not be a suitable method to model complex, dynamic and nonlinear sensor-control mapping. To avoid these problems, a neural network learning methodology is adopted, which can efficiently model human control skill [4]. This methodology consists (1)flexible cascade neural networks(CNN), which dynamically adjust the size of the neural network as part of the learning process, and (2)node-decoupled extended Kalman filter(NDEKF), a faster converging alternative to backpropagation.

Denote ω_k^i as the input-side weight vector of length n_w^i at iteration k, for $i \in \{0, 1, \ldots, n_o\}$, and,

$$n_w^i = \begin{cases} n_{in} + n_h - 1 & i = 0 \\ n_{in} + n_h & i \in \{1, \ldots, n_o\} \end{cases} \tag{A.1}$$

The NDEKF weight-update recursion is given by, staring from Eqs. (A.3) to (A.6), {}'s, ()'s and []'s evaluate to scalars, vectors and matrices respectively

$$\omega_{k+1}^i = \omega_k^i + \{(\psi_k^i)^T (A_k \xi_k)\} \phi_k^i \tag{A.2}$$

where ξ_k is the n_o-dimensional error vector for the current training pattern, ψ_k^i is the n_o-dimensional vector of partial derivatives of the network's output unit signals with respect to the ith unit's net input, and,

$$\phi_k^i = P_k^i \zeta_k^i \tag{A.3}$$

$$A_k = \left[I + \sum_{i=0}^{n_o} \{(\zeta_k^i)^T \phi_k^i\}[\psi_k^i (\psi_k^i)^T] \right]^{-1} \tag{A.4}$$

$$P_{k+1}^i = P_k^i - \{(\psi_k^i)^T (A_k \psi_k^i)\}[\phi_k^i (\phi_k^i)^T] + \eta_Q I \tag{A.5}$$

$$P_0^i = (1/\eta_P) I \tag{A.6}$$

where ζ_k^i is the n_w^i-dimensional input vector for the ith unit, and P_k^i is the $n_w^i \times n_w^i$ approximate conditional error covariance matrix for the ith unit. The parameter η_Q is introduced in Eq. (A.6) to avoid the singularity problems for error covariance matrices. Throughout the training, we use $\eta_Q = 0.0001$ and $\eta_P = 0.01$.

The vector ψ_k^i can be computed in this way: let O_i be the value of the ith output node, Γ_O be its corresponding activation function, net_{Oi} be its net activation, Γ_H be the activation function for the current hidden unit being trained, and net_H be its net activation. We have,

$$\frac{\partial O_i}{\partial net_{Oj}} = 0, \forall i \neq j \tag{A.7}$$

$$\frac{\partial O_i}{\partial net_{Oi}} = \Gamma'_O(net_{Oi}), i \in \{1, \ldots, n_o\} \tag{A.8}$$

$$\frac{\partial O_i}{\partial net_H} = w_{Hi} \cdot \Gamma'_O(net_{Oi}) \cdot \Gamma'_H(net_H) \tag{A.9}$$

where w_{Hi} is the weight connecting the current hidden node to the ith output node.

Appendix B

Trajectories for the Navigation Learning in Chapter 4

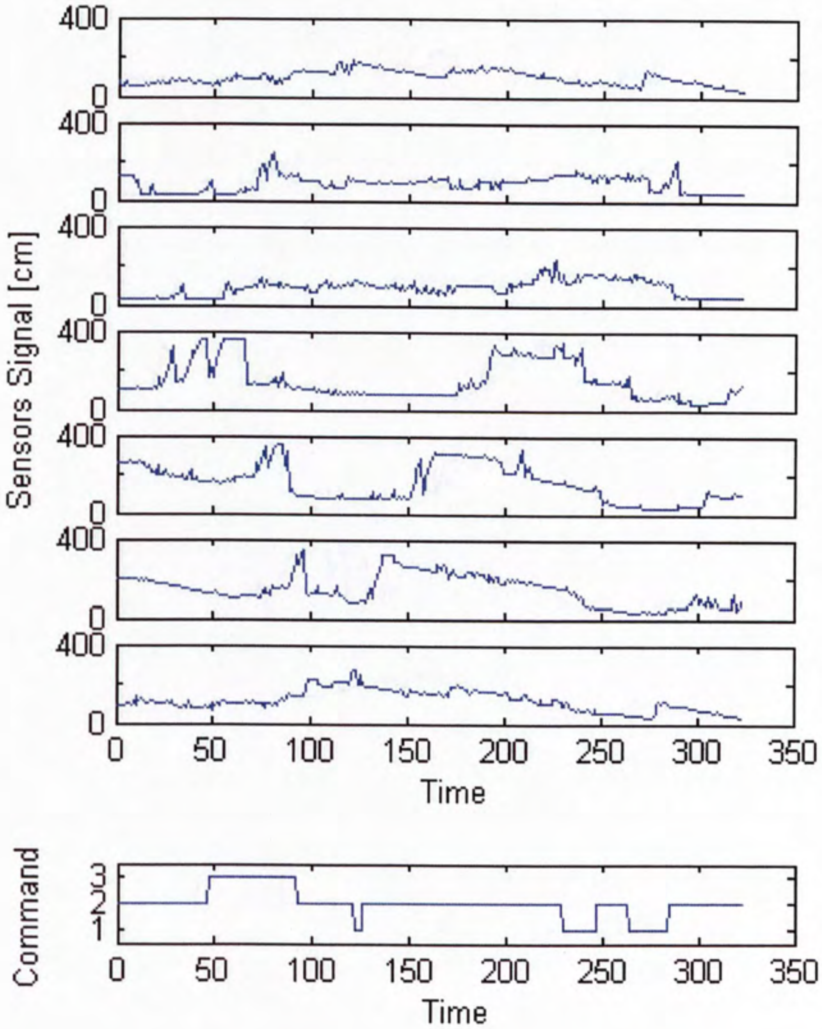

Figure B.1: The sensor trajectory and corresponding demonstrated control command in the third demonstration.

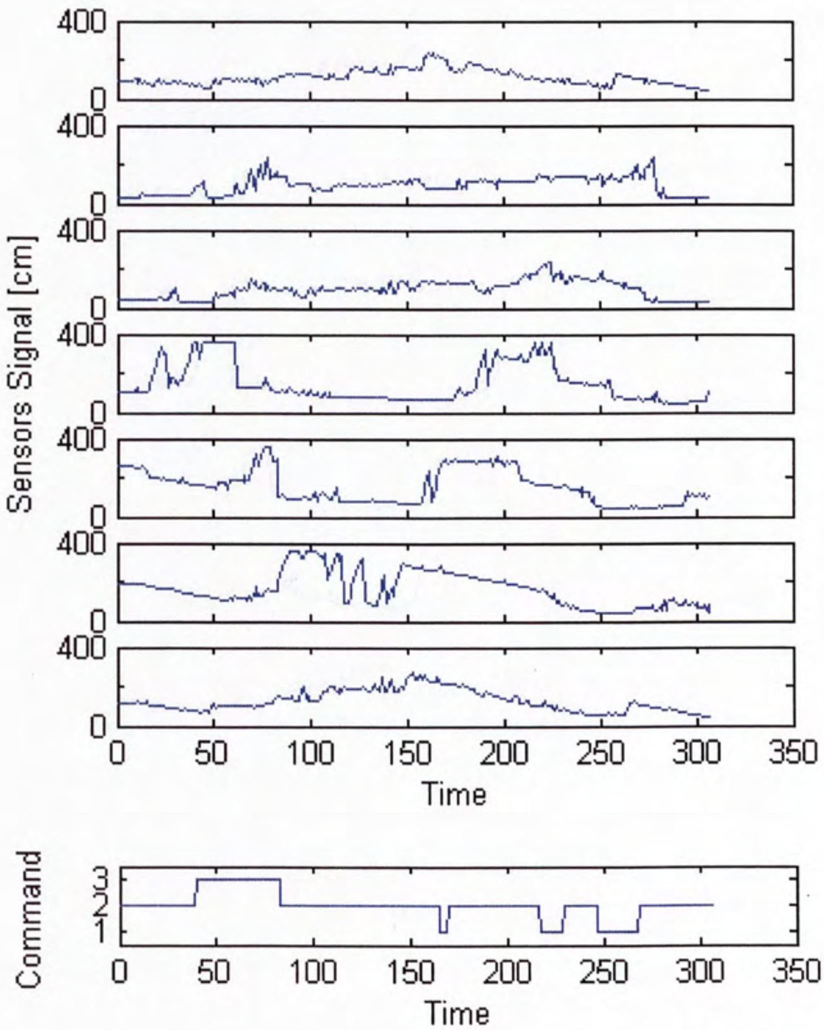

Figure B.2: The sensor trajectory and corresponding demonstrated control command in the fourth demonstration.

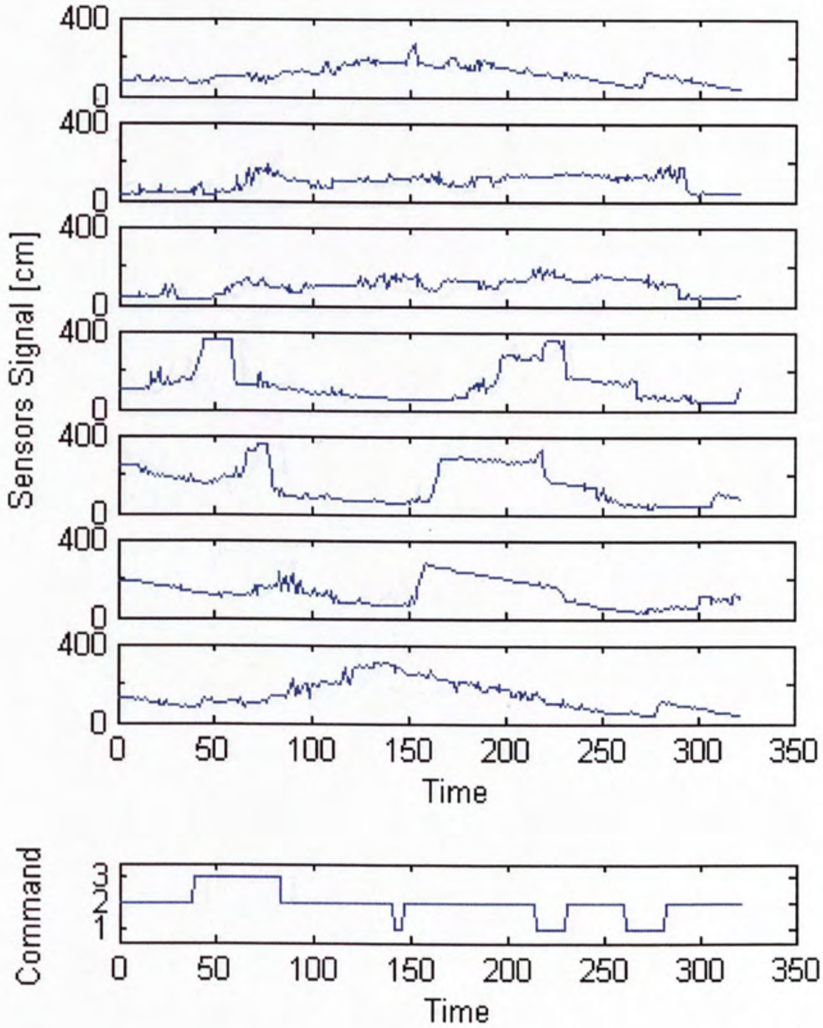

Figure B.3: The sensor trajectory and corresponding demonstrated control command in the fifth demonstration.

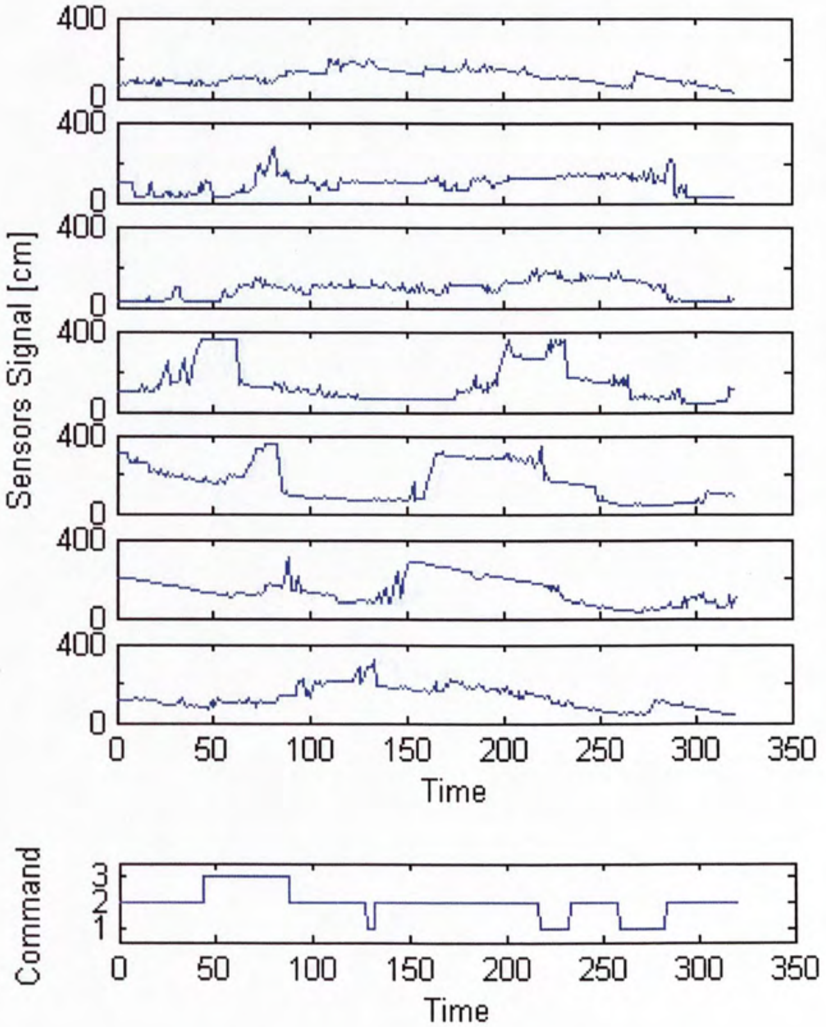

Figure B.4: The sensor trajectory and corresponding demonstrated control command in the sixth demonstration.

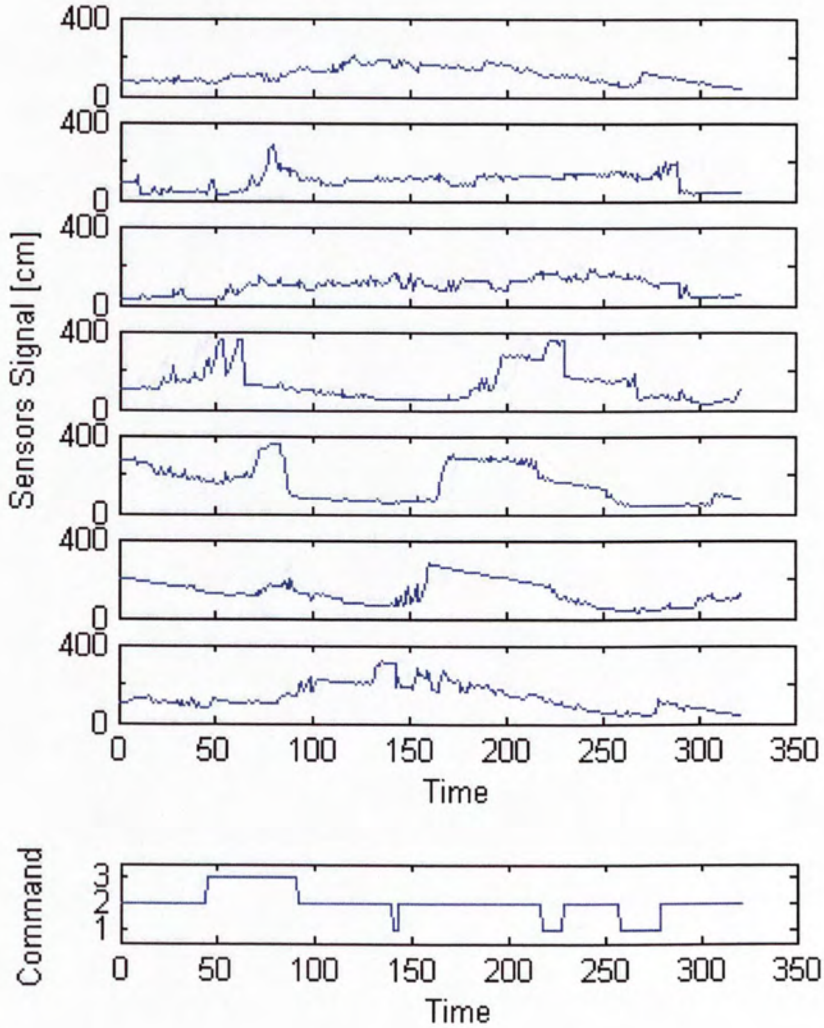

Figure B.5: The sensor trajectory and corresponding demonstrated control command in the seventh demonstration.

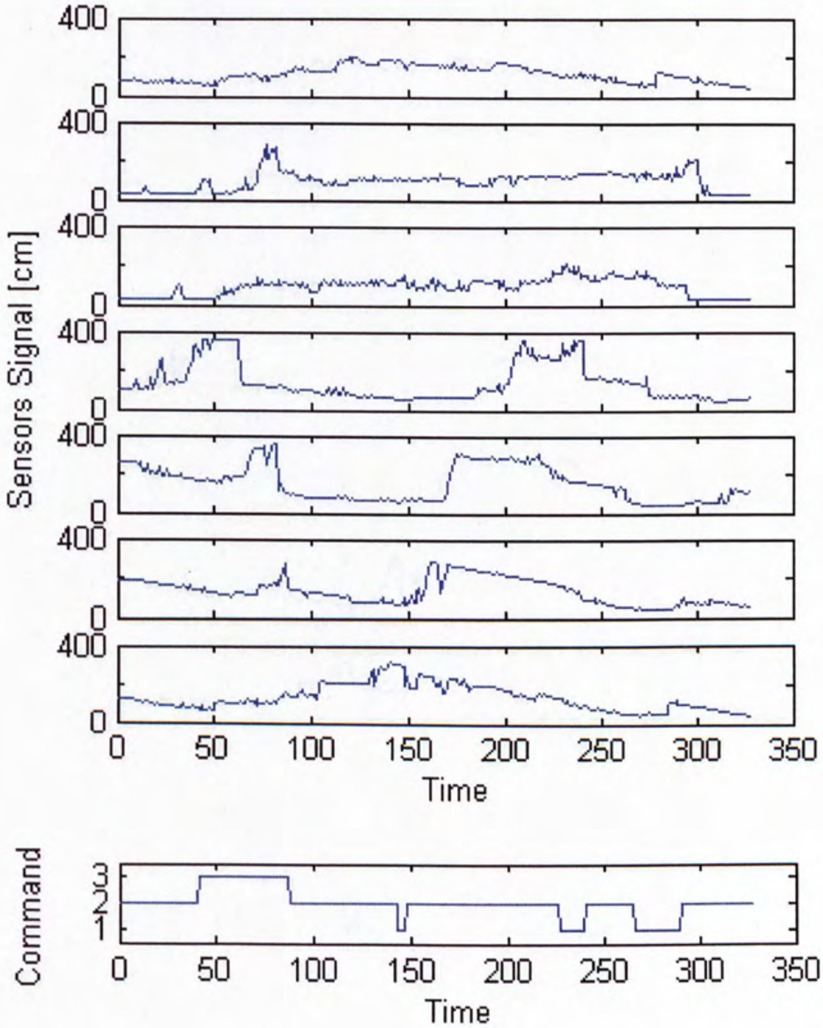

Figure B.6: The sensor trajectory and corresponding demonstrated control command in the eighth demonstration.

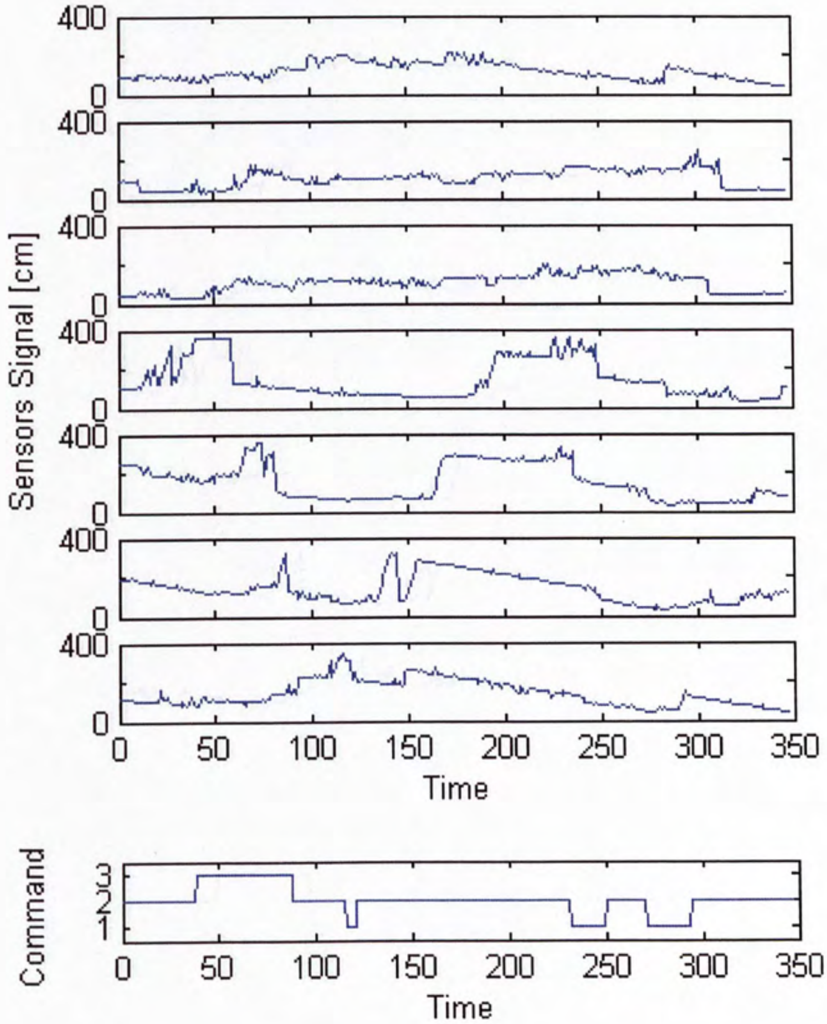

Figure B.7: The sensor trajectory and corresponding demonstrated control command in the ninth demonstration.

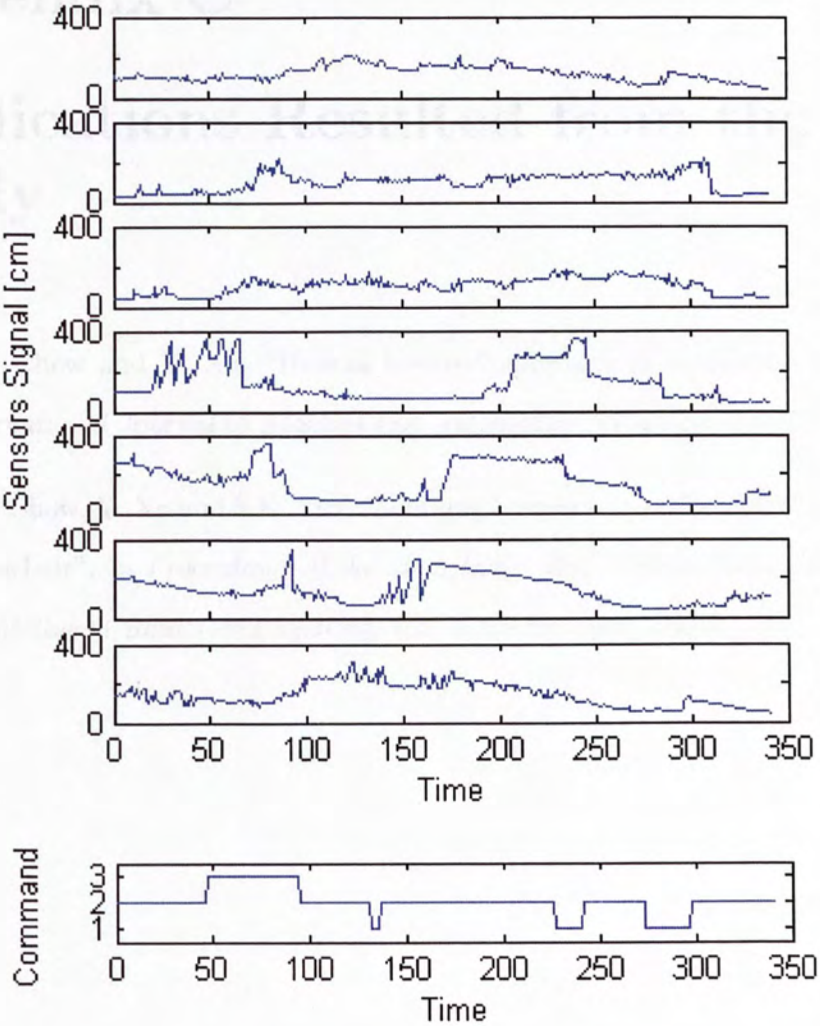

Figure B.8: The sensor trajectory and corresponding demonstrated control command in the tenth demonstration.

Appendix C

Publications Resulted from the Study

1. H.N. Chow and Y. Xu, "Human inspired approach to navigation control", *International Journal of Robotics and Automation*, 17(4), pp.171-177, 2002.

2. H.N. Chow, Y. Xu and S.K. Tso, "Learning human navigational skill for smart wheelchair", *in Proceedings of the 2002 IEEE/RSJ International Conference on Intelligent Robots and Systems*, vol. 1, pp.996-1001, 2002.

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