A COLLABORATIVE WHEELCHAIR SYSTEM

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Summary

Due to physical or neurological disabilities, many wheelchair users have problems in orienting themselves and maneuvering the wheelchair. They are dependent upon others to push them, so may feel powerless and out of control. The research in this thesis focuses on the development and assessment of a semi-autonomous robotic wheelchair, namely Collaborative Wheelchair Assistant or CWA, which aims at helping these people to regain their mobility.

The CWA distinguishes itself from most other robotic wheelchairs in that it collaborates with the user by making use of his existing sensory-motor skills while assisting in the difficult task of maneuvering with path guidance. It is designed as a passive device, in the sense that it will not move without input from the user. The user controls the speed during the motion, while the system constrains the wheelchair along guide paths, which are pre-defined in software and connect the desired destinations. In case of dangers or obstacles, an intuitive path editor allows the user to deviate the wheelchair from the guide path when needed. Therefore, by using the human sensory and planning systems for obstacle detection and avoidance, complex sensor processing and artificial decision systems are not needed, making the system safe, simple and low-cost.

Three sets of experiments have been conducted to test the CWA. The first set of experiments investigates the efficacy of implementing path guidance on wheelchair control. In this "Investigation on Path Guidance" experiment, the motion efficiency of the CWA and its interaction with the human driver are analyzed and compared with conventional control of a powered wheelchair. It is found that path guidance simplifies the control task for the driver: he can finish the task easily and quickly, while moving efficiently with a conventional wheelchair requires some practice.

The second set of experiments evaluates path design tools developed for the CWA. In this "Collaborative Path Planning" experiment, the provided design tools are evaluated by able-bodied subjects and a collaborative learning approach is proposed, which envisions that the human operator collaborates with the robot using these tools to create and gradually improve a guide path, eventually achieving an ergonomic path. The experimental results show that the subjects can design guide paths with the provided tools, and are satisfied by the proposed approach.

Finally, a set of experiments is conducted with the "real" end users of wheelchair. In this "Evaluation with Patients" experiment, three cerebral palsy (CP) and two traumatic brain injury (TBI) individuals, who could not previously drive a conventional powered wheelchair independently, are trained with the CWA. After a few training sessions, all subjects became able to drive it safely and efficiently in an environment with obstacles and narrow passageways. Eventually, two of the subjects did not need the help of path guidance and were able to drive freely. The results suggest that the CWA can provide driving assistance adapted to various disabilities. It could be used as a safe mobility device for people with large motor control or cognitive deficiencies.

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List of Symbols

Symbol	Description	Units
$B(u)$	B-spline function	
c_c	Curvature	
c_θ	$\cos\theta$	
d	Effective width of the vehicle	m
$\triangle D_k$	Distance traveled by the mid-axis point of the vehicle	m
$\triangle D_{Lk}$	Distance traveled by the left glidewheel	m
$\triangle D_{Rk}$	Distance traveled by the right glidewheel	m
D_S	Distance between the sensory point and mid-axis point	m
g_c	Curvature's derivative with respect to s	
$j_\perp$	Normal input	

Symbol	Description	Units
k_{pl}	Proportional gain	
k_{vl}	Derivative gain	
l	Distance	m
$N_i^p(u)$	B-spline basis function	
$\mathbf{P}_k^-$	*A priori* estimate error covariance	
$\mathbf{P}_k$	*A posteriori* estimate error covariance	
P_i	i-th attraction point	
$\mathbf{Q}$	Driving noise covariance matrix	
$\mathbf{R}$	Measurement noise covariance matrix	
s	Curvilinear coordinate along the path	m
s_θ	$\sin\theta$	
t_θ	$\tan\theta$	
$\mathbf{u}_k$	Input vector	
$\mathbf{v}_k$	Measurement noise	
v	Translational velocity	m/s

Symbol	Description	Units
$\mathbf{w}_k$	Driving noise	
$\mathbf{x}_k$	State vector	
$\hat{\mathbf{x}}_k^-$	*A priori* state estimate at step k	
$\hat{\mathbf{x}}_k$	*A posteriori* state estimate at step k	
$\mathbf{z}_k$	Measurement vector	
$\triangle\theta_k$	Incremental change in orientation	rad
ω	Angular velocity	rad/s
${\sigma_{DL}}^2$	Encoders' measuring variance on left wheel	m^2
${\sigma_{DR}}^2$	Encoders' measuring variance on right wheel	m^2
μ_1	Length of a continuous curve	m
μ_2	Area of the path's deviation from the centerline of the permitted region	m^2
μ_3	Smoothness parameter	
μ_4	Comfort parameter	

Chapter 1

Introduction

1.1 Motivation

The population of wheelchair users has grown immensely during the last three decades of the 20th century. In the United States alone, the population of wheelchair users has quadrupled from 409,000 in 1969 to 1.7 million persons in 1995, and at this rate, there will be 4.3 million users by 2010 [1]. As also stated in [1], this growth is more likely due to changing social and technological factors. Improved design and functions have made the mobility devices more appealing; improved accessibility both at home and in the community may have enabled to be used by more people.

However, of the population of wheelchair users, only a small minority uses powered wheelchair. A recent survey [2], which distinguishes between manual and powered wheelchairs, showed that of the 1.7 million adults who used wheeled mobility devices, merely 155,000 or 9.1% used powered wheelchairs. A similar study in the United Kingdom found that 5.1% of the sample group of wheelchair users were using powered wheelchairs [3]. One major reason preventing the usage of powered wheelchairs is that many potential users lack the necessary steering ability. This is indicated in a clinical survey [4] where 9 to 10% of patients who received powered wheelchair training found it extremely difficult or impossible to use it for activities of daily living (ADL), and 40% of patients found the steering and maneuvering tasks difficult or impossible.

Not all potential wheelchair users possess the fine steering capacities (e.g. obstacle avoidance, doorway passage, and reaching very closely to objects) that are required for their ADL. Driving a powered wheelchair without help of a caregiver could bring them into dangerous situations, such as collisions, falling off ramps, and blocking in the limited spaces. In particular, in a living environment where the maneuvering space is limited, the approach to the furniture and other objects is tightly constrained and the necessity to negotiate doorways requires precise control. In some cases, it takes years to learn to drive a powered wheelchair for daily life. Eventually, this lack of steering ability may result into situations like reluctance/inability to use a powered wheelchair, dependence on caregivers and decrease in the quality of social life.

Assistive robots [5] have the potential to provide these people with effective ways to alleviate the impact of their limitations, by compensating for their specific impairments. In particular, robotic wheelchairs, applying intelligent sensors and navigation techniques from mobile robotics to the control of wheelchairs, can play an important role in these developments [6]. The goal of the research in this thesis is to provide and evaluate a robotic wheelchair, namely the Collaborative Wheelchair Assistant (CWA) (see Fig. 1.1), which aims at improving the mobility and safety of those users who have difficulties in maneuvering a wheelchair for their ADL.

1.2 Approach

This research provides a robotic wheelchair that could help its user in driving more easily and safely. The system is semi-autonomous, allowing the user to be in complete control of the navigation, while helping him or her maneuver the wheelchair to realize the intended movement. The user decides where to go and controls the speed (including start and stop) while the machine assists him or her by guiding the wheelchair along

(a)

(b)

Figure 1.1: The Collaborative Wheelchair Assistant system (CWA) is a robotic wheelchair system based on an effective path guidance strategy, which was tested in experiments with able-bodied (a) and disabled subjects (b).

software-defined paths. An ergonomic path editor allows the user to modify the path on-line to compensate for changes in the environment such as unexpected obstacles or danger on the path. By relying on the inference ability of the user, complex sensor processing and decision systems are not needed, making the system safe, simple, and low-cost.

1.2.1 Target user population

As a mobility aid, the CWA aims at helping people with motor control or cognitive impairments, but with sufficient sensory abilities. Its target patient population consists of people suffering from any of the following deficits:

- bad motor control
- lack of strength or consistent attention
- disorientation
- learning difficulties
- slow reflexes

These deficits can result from diseases such as multiple sclerosis, motor neuron disease, spinal cord injury, cerebral-vascular accident, and cerebral palsy.

To use the system, the user is expected to have the following basic skills:

- be able to see
- be able to activate an interface, e.g. a joystick
- be able to learn using the CWA system
- be able to sense dangers and stop if necessary
- be able to plan his actions

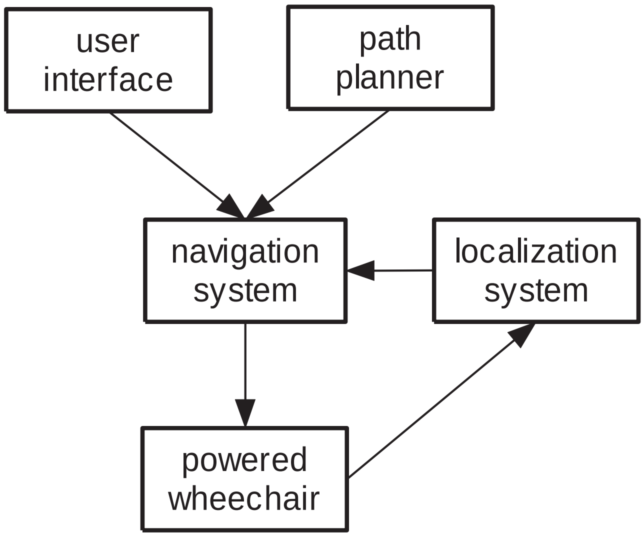


Figure 1.2: Block diagram of the CWA system.

1.3 Thesis Objectives

The first objective of this thesis is to develop an experimental robotic wheelchair. The robotic wheelchair should perform the semi-autonomous navigation in indoor environments, which normally contain confined spaces and require high maneuverability. Figure 1.2 shows a block diagram of the CWA system. The user decides where to go and controls the speed, including start and stop. Her or his commands are passed via the user interface, i.e. a joystick, to the navigation system. In addition to these directional commands, the navigation system needs information about its position in order to travel accurately; this information is gathered from a localization system. Finally, the navigation system guides the wheelchair's motion along a software-defined path generated by the path planner. As the focus of this research is on improving the maneuverability rather than the mechanical designs, the prototype is based on a standard powered wheelchair.

The second objective is to investigate whether and how the path guidance strategy can facilitate the wheelchair driving. The investigation focuses particularly on the aspects of motion efficiency and human machine interaction. Substantial field trials have been conducted with able-bodied subjects. The driving performance of the operator with robotic assistance is analyzed and compared with that obtained with a conventional powered wheelchair. Control effort and intervention levels are important factors in this performance analysis.

The third objective of this research is to explore the path planning in a robotic wheelchair system. The CWA concept is based on guidance along *virtual* paths, which have to be traced by a human operator. A *collaborative learning* strategy is proposed, which aims at providing an intuitive human-machine interface to allow the operator to effectively design and edit guide paths. Field experiments with able-bodied subjects have been conducted to examine the effectiveness of this strategy as well as to establish important ergonomic factors for a guide path.

The fourth objective of this research is to conduct trials with end users of the CWA system. Clinical trials provide a means to assess system performance and to gather user feedback. Three people with cerebral palsy (CP) and two with traumatic brain injury (TBI), who had previously been ruled out as candidates for independent mobility, were recruited. The subjects learned to use the CWA in several sessions spread out over a period of one month, after which their performances of driving the CWA were evaluated.

This work was funded by the National University of Singapore, Grant No. 265-000-141-112, and the experiments were approved by the institutional review board of the National University of Singapore.

1.4 Summary of Contributions

- This research has resulted in an experimental robotic wheelchair, based on an efficient collaboration strategy between the user and the wheelchair.
- A novel localization approach has been developed using the information from odometry and barcodes to provide sufficiently accurate pose estimation for the wheelchair in the specific environment.

- Extensive field evaluations with the CWA were performed with able-bodied subjects, and a thorough investigation of the path guidance at the heart of the CWA concept has been realized.
- A *collaborative learning* approach was proposed for path planning of a robotic wheelchair, tested in experiments, and analyzed using mathematical measures that correlate well with experiencedof ergonomic factors.
- Systematic tests were performed with three CP and two TBI patients, who had been previously ruled out as candidates for independent mobility.

1.5 Outline of this Thesis

The rest of this thesis is organized as follows:

Chapter 2 reviews the existing work and discusses them in relation to the CWA

Chapter 3 introduces the CWA experimental system, including hardware, localization, control algorithms, and path design tools by which the user can easily define guide paths as he wishes.

A systematic study of the efficacy of path guidance is given in Chapter 4. The driving performance of able-bodied subjects with robotic assistance is analyzed and compared with conventional control of a powered wheelchair. Then, the effectiveness of path guidance are discussed.

The path design tools developed and the concept of “Collaborative Learning” are described in Chapter 5. The chapter presents the user evaluation on collaborative path planning, as well as the path design tools. Several important factors for an ergonomic path are also studied.

Chapter 6 reports the end user trials with the CWA system. The usefulness and adaptability of the CWA are discussed. In addition, the driving behaviors of able-bodied and disabled subjects are compared.

Chapter 7 concludes this thesis, and describes possible future research.

Chapter 2

Literature Review

Robotic wheelchairs require the integration of many areas of research, including indoor/outdoor navigation, deliberative/re-active intelligence, sensor fusion, and user interface. In addition, robotic wheelchairs should function reliably and interactively so as to reassure the user and build his/her trust. During the last decade, a great effort was concentrated world-wide towards developing automated wheelchair with some degree of navigational intelligence. This chapter discusses these work (see their descriptions in Appendix A) in relation to the CWA presented in this thesis.

2.1 Acceptability and Autonomy

Robotic wheelchairs are an excellent example of tight coupling between the desires of the operator and the robot. The primary challenge in techniques is to have the chair follow the desires of the operator while maintaining safety in navigation. Also, acceptability, related to the 'willingness' to use a system in a particular context, is critical for the design and development of such a system where robots and humans strictly interact.

Changes in autonomy level came along with these challenges in robotic wheelchairs. Autonomous, supervisory control is used for several projects, including the TAO wheelchair

(Applied Artificial intelligence, Inc., [8]), the *SmartChair* (University of Pennsylvania, [13], the CCPWNS (University of Notre Dame, [17]), the intelligent wheelchair (Osaka University, [18]), and the Autonomous wheelchair (Nagasaki University and Ube Technical College, [19]). Autonomous wheelchairs operate in a manner similar to autonomous robots; the system accepts commands like ‘go to goal’ and then automatically plans and executes a path to the destination, avoiding all obstacles and risks on the way. Smart wheelchairs in this category are most appropriate for users who lack the ability to plan or execute a path to a destination.

Semi-autonomous or shared-control is used for many systems, including the Navchair (University of Michigan, [9]), the OMNI system (University at Hagen, [10]), the smart wheelchair (Call Center at University of Edinburgh, [16]), the Tin Man II (KISS Institute for Practical Robotics, [20]), the Wheelesley (MIT, [21]), the robotic wheelchair (FORTH, [22]), and the Rolland (University of Bremen, [23]). Semi-autonomous wheelchairs leave the majority of planning and navigation duties to the user. These systems, therefore, require more planning and continuous effort and are only appropriate for users who can effectively plan and execute a path to the destination.

A final group of smart wheelchairs offers both autonomous and semiautonomous navigation, including the VAHM wheelchair (University of Metz, [12]), the Senario wheelchair (TIDE, [14]), and the Orpheus wheelchair, (National Technical University of Athens, [24]). In these wheelchair, a hierarchy of operating levels requires varying degrees of control from the wheelchair user.

The CWA system falls into the semi-autonomy category. Rather than taking over the low-level control as other semi-autonomous wheelchairs, the CWA incorporates the user directly into the control loop. In this context, motion control is decomposed into maneuvering, which is difficult for disabled persons and so is attributed to the robotic system using path guidance, and into speed control, which is controlled by the wheelchair user, who can best judge the situation. It is expected that this way of the user involvement can speed up task execution and improve success rate. Perhaps more importantly, the possibility of monitoring and intervening what the robot is doing can reassure the user and enhance his or her trust and acceptance on the system.

2.2 Navigation Principle

The goal of a robotic wheelchair is to transport its user to a desired destination, safely and efficiently. As for conventional mobile robots, the navigation problem can be summarized by three questions [7]: *i*) Where am I? *ii*) Where do I want to go? *iii*) How can I get there? A wheelchair, which has to move a human being, demands different responses to these questions from a conventional mobile robot system: it should consider the particular disabilities, features and wishes of its user. The first question requires knowledge of the robot's location at all times and is commonly referred to as *localization*. The second question can be answered by the user, who decides his or her desired destination. The third question involves route planning and motion execution, i.e. *motion planning*. While the trajectory is usually unimportant for autonomous systems, it is very important for a wheelchair as its motion has to consider safety, comfort, and the individual wishes of its user. Otherwise, the user may be hurt or feel frustrated, and eventually loses trust in the machine.

Several robotic wheelchairs, including the TAO wheelchair (Applied Artificial intelligence, Inc., [8]), the Navchair (University of Michigan, [9]), the OMNI system (University at Hagen, [10]), the Sharioto wheelchair (K.U. Leuven, [11]), the VAHM wheelchair (University of Metz, [12]), the *SmartChair* (University of Pennsylvania, [13]), and the Senario wheelchair (TIDE, [14]), attempt to answer the question of motion planning by using an intelligent sensor-based system. For these systems, control behaviors can be switched in response to different situations during the navigation, such as obstacle avoidance, wall following, doorway passing, etc. (see Fig. 2.1a). While such a system can release the user from the burden of driving, the success of navigation will critically depend on the algorithms and sensor technology, which are often the most computationally expensive and error-prone components, thereby compromising safety. Further, it is difficult to detect and satisfy the user's wishes by artificial intelligence. For example, an

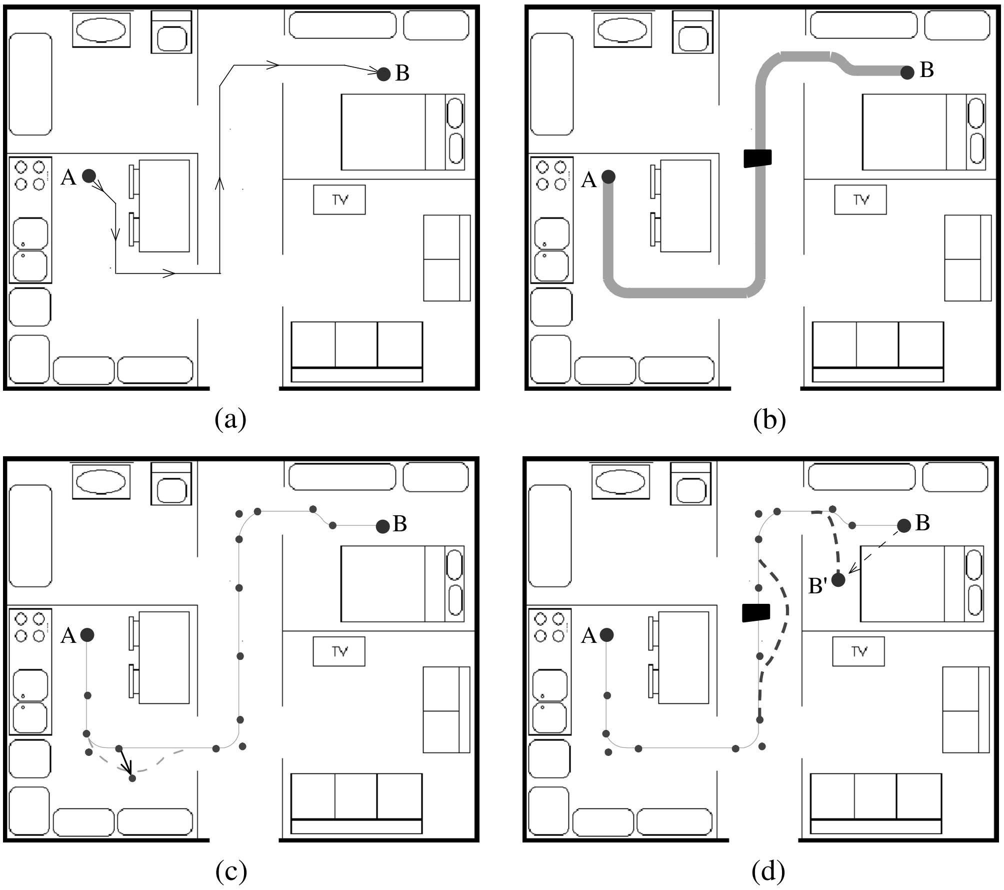


Figure 2.1: Strategies for navigation from "kitchen" to "bedroom" in a household environment. (a) The behaviors during the navigation include avoidance, wall following, doorway passing, etc. An artificial system can switch between different behaviors corresponding to different situations. (b) A physical track directly guides the wheelchair to the destination. However, it is not usable if there are obstacles on it. (c) Using virtual paths enables flexible path managements. The user can modify the coordinates locally based on the floor plan of the environment. (d) During the movement, a flexible path controller enables the user to deviate from the path to reach a desired endpoint or avoid obstacles.

artificial system may choose an awkward direction for the user [12], such as a narrow passageway or one with overhead obstacles, or may prevent movement towards a table or a doorway if the approach is not perpendicular [9]. Some avoidance systems try to maintain a greater distance to the obstacles than necessary, which may be frustrating to a user planning a short cut. Bright lights, foul smell or loud noise may also be obstacles to avoid, but it is not possible to design a sensing system for every such factor.

We believe that the user knows his or her needs best, and that most of the wheelchair users possess some sensing and inference abilities and are generally eager to use them. Therefore, in order to be accepted by potential users, an assistive device should not try to replace these abilities but, in contrast, should complement and use their available skills. Unlike most other wheelchair systems, we assign the task of obstacle detection and avoidance to the user, while providing tools to assist realizing the motions as the user desires. By using the human's sensory and planning abilities, complex sensor processing and artificial decision systems are not needed, making the system safe, simple and low-cost.

Navigating a wheelchair can be realized in a trivial way by moving along physical tracks installed on the floor of the real environment (see Fig. 2.1b) (e.g. the automated wheelchair (NEC Corporation, [15]), the smart wheelchair (Call Center at University of Edinburgh, [16])). This method only requires sensors to detect the track, and the user, controlling the speed and forward/backward directions along the track, is not required to reason the sequence of movements. However, the wheelchair's motion is limited to the tracks, and such system cannot cope with obstacles or user's wishes to deviate from the guide path in order to avoid an obstacle. In addition, these tracks, made of magnetic ferrite markers or reflective tapes, are difficult to install, change, and maintain.

The CWA system studies the advantages of physical tracks but addresses their shortcomings. Instead of physical tracks, we use *virtual* paths saved in software and a path controller to enable the CWA to follow the virtual paths. As with physical tracks, *virtual* paths ensure safe navigation by the fact that the path, created in the real workspace of the wheelchair, is naturally free from fixed obstacles. In addition, the use of virtual paths enables a flexible path management: the user can modify the coordinates locally based on the floor plan of the environment (see Fig. 2.1c), or deviate from the path in real-time in order to reach some place outside the path or reactively avoid obstacles or dangers and re-join the path after clearing the obstacles (see Fig. 2.1d).

Despite these potential advantages, generating paths to guide a wheelchair's motion faces several challenges. Firstly, the path is located in the human living environment, for example the apartment of a user, which is normally unstructured and dynamic. Thus, it is not possible to generate a fixed map and it is difficult to plan paths in such an environment by artificial intelligence. Secondly, as the task of a wheelchair is to carry a human user, the motion along the path should be smooth and comfortable to the user so that the user feels safe and in control. Thirdly, the paths should be adaptable to the user's intentions, which may change over time.

To accommodate these requirements, we propose a *collaborative learning* strategy in which the human operator and the robot collaborate to generate guide paths. Due to differences in strength, age, disability or preference, a good path for one individual may be less so for somebody else. We believe that the paths should be designed by the user, who is best informed about his or her needs, and the system should provide user-friendly and efficient tools for realizing this design. Therefore, we envision that the human operator and the robot, using the provided path design tools, create and gradually improve a guide path, eventually achieving an ergonomic path.

Chapter 3

CWA Experimental System

3.1 Introduction

In this chapter, the CWA experimental system is introduced. The hardware development of the CWA was the work of several students, who spent various amounts of time on this project, under the supervisions of Professors Teo Chee Leong and Etienne Burdet. My main contributions to the CWA system were developments of the control system, the path design tools, and the localization system.

3.2 Hardware

The CWA prototype is built on a Yamaha JW-I powered wheelchair (see Fig.3.1) [26]. A position joystick is used as the interface. In the original wheelchair, the joystick is used to control the wheelchair velocity. The forward/backward angle of the joystick corresponds to the wheelchair's speed in the forward/backward direction, and a right/left angle to the rotational speed in the clockwise/anticlockwise direction. In the CWA, the joystick output is intercepted by the on-board processor and used to compute appropriate signals to control the motors.

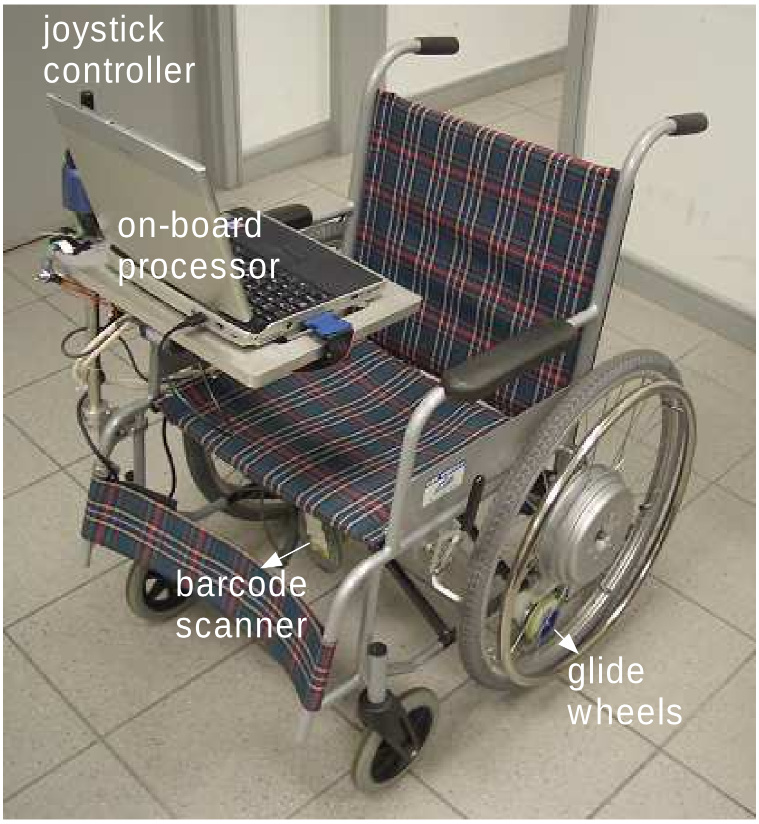


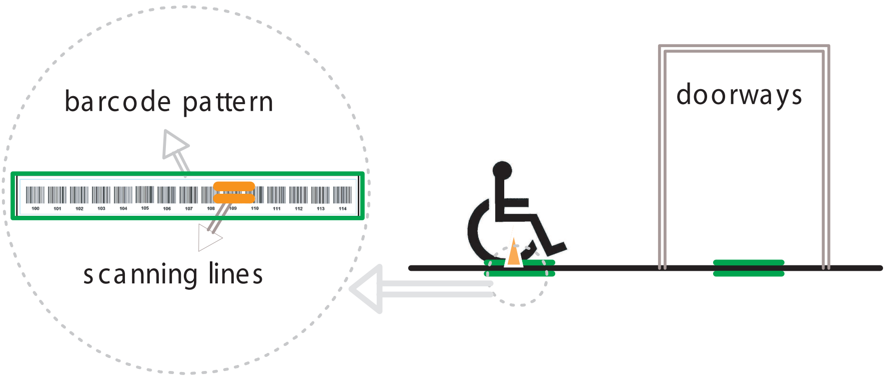
Figure 3.1: CWA prototype. The laptop computer provides programmable motion control and the GUI.

For the prototype, a Toshiba M100 laptop with a Pentium 1.2 GHz processor is used to control the robotic wheelchair and process sensory information. The GUI and integrated controller are written in C, running at the user-level of an Ubuntu Linux 6.06 system with a 2.6.15 kernel patched with Real-Time Application Interface (RTAT) v3.3 for real-time capabilities.

Sensors are limited to two optical rotary encoders attached to glidewheels for odometry and a commercial barcode scanner (Symbol M2004 Cyclone) for global positioning (see Figs. 3.1). For safety, two (Devantech SRF02) proximity sensors are mounted in front of the wheelchair in order to avoid frontal collision: the controller automatically stops the wheelchair if an obstacle is detected within 50*cm*. The implementation of the proximity sensors is done by Brice Rebsamen, and the details can be found in his thesis [27].

3.3 Localization

3.3.1 System description



(a)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Center 107 is placed on position 4,7, orientation 270°
11 (270):      4.000,7.315 4.000,7.270 4.000,7.225
4.000,7.180 4.000,7.135 4.000,7.090 4.000,7.045
4.000,7.000 4.000,6.955 4.000,6.910 4.000,6.865
4.000,6.820 4.000,6.775 4.000,6.730 4.000,6.685
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(b)

Figure 3.2: Absolute positioning using barcodes. (a) Barcode-odometry localization system retrieves absolute positions via a barcode scanner to reduce the estimation error. Barcode patterns, serving as artificial landmarks, are placed at strategic locations, e.g. before narrow passageways or sharp turns, where the positioning has to be accurate. (b) Barcode patterns can be printed on a personal printer and disposed easily. Each set of barcode patterns has a unique code corresponding to global coordinates that have previously been entered into the memory.

The main task of the localization system is to provide accurate pose estimation (i.e. position and orientation) for the wheelchair at a speed up to 0.64*m/s*. Odometry, via encoders on the glidewheels, is installed on the CWA for relative pose estimation. However, as is well known, odometry, integrating position along the path, is not reliable for long distances as the error is also integrated [28]. Therefore, in the CWA, complementary absolute positioning is provided by the observation of barcode patterns from a barcode scanner (see Fig. 3.2). Unique barcode patterns serve as artificial landmarks corresponding to global positions that have been saved into the memory in advance.

The design of the landmarks and positioning of the scanner (see [29] for details) is such that when the wheelchair passes over a landmark, its scanning line could always read one piece of barcode, according to which the controller can retrieve the global positions (see Fig. 3.2). As the odometry can provide accurate estimation for short distances, the landmarks only need to be placed at strategic locations, e.g. before narrow passageways or sharp turns, where more accuracy are needed. Then, the task at hand is to recognize these landmarks (barcodes) reliably and combine this information with odometry in order to estimate the wheelchair's pose.

If we directly calibrate odometric estimates with the external sensory data, the accuracy of the localization is limited by the accuracy of the sensory measurement. Then, we have to assume that the measurements are uncorrupted by any noise. Instead, we use a discrete Extended Kalman Filter (EKF) [30], which realizes a new estimate by weighing the local and global measurements. Thus, a combination of past and current measurement is used to estimate the position and orientation of the vehicle.

The absolute positions can be obtained directly from the coordinates of the barcodes saved in the computer(see Fig. 3.2). However, *no absolute orientation is directly available due to lack of angular sensors.* This means the orientation estimation of the CWA can only rely on odometry without external corrections. In the absence of external information, the uncertainty of the pose estimate from odometry will increase continuously as the robot moves and the accuracy will decrease. To solve this problem, we have developed a numerical approach to estimate the absolute orientation once a barcode landmark is recognized (see Appendix B).

We have evaluated this localization approach through simulation and field experiments in a typical lab environment (see Fig. 4.1), which we will use to test the human-wheelchair interaction provided by the CWA. This simple method was found to provide sufficient accuracy for pose estimations in the environment used in our experiments. In addition, it is cheap and easy to set up: barcode patterns can be printed on a personal printer and dispensed easily.

3.3.2 Discrete Extended Kalman Filter

We describe here how a discrete EKF is used to fuse the relative pose estimation from odometry and global pose estimation from the landmark.

The system model describes how the vehicle's state $\mathbf{x}_k$ changes with time in the presence of the driving noise $\mathbf{w}_k$ resulting from small slippages, error in kinematics and in odometry:

$$\mathbf{x}_{k+1} = \mathbf{f}(\mathbf{x}_k, \mathbf{u}_k, \mathbf{w}_k) \tag{3.1}$$

where $\mathbf{x}_k$ is the state vector, $\mathbf{u}_k$ is the input vector, and the nonlinear function $\mathbf{f}$ relates the state at the previous time step $k-1$ to the current step k. The driving noise $\mathbf{w}_k$ is assumed to be normally distributed with zero mean and covariance matrix $\mathbf{Q}$: $p(\mathbf{w}) \sim N(\mathbf{0}, \mathbf{Q})$. The sensor model can be represented as

$$\mathbf{z}_k = \mathbf{h}(\mathbf{x}_k, \mathbf{v}_k) \tag{3.2}$$

where $\mathbf{x}_k$ and $\mathbf{z}_k$ represent the state and measurement vectors at each time step k, and the nonlinear function $\mathbf{h}$ relates the state $\mathbf{x}_k$ to the measurement $\mathbf{z}_k$. The measurement noise $\mathbf{v}_k$ is assumed to be normally distributed with zero mean and covariance matrix $\mathbf{R}$: $p(\mathbf{v}) \sim N(\mathbf{0}, \mathbf{R})$.

Here, we define $\hat{\mathbf{x}}_k^-$ (note the "super minus") as the *a priori* state estimate at step k given knowledge of the process prior to step k, and $\hat{\mathbf{x}}_k$ as the *a posteriori* state estimate at step k given measurement $\mathbf{z}_k$. We also define $\mathbf{P}_k^-$ as the *a priori* estimate error covariance, and $\mathbf{P}_k$ as the *a posteriori* estimate error covariance. The EKF predicts the next state of the system $\hat{\mathbf{x}}_{k+1}^-$ based on the available system model equation 3.1 and projects ahead the state error covariance matrix $\mathbf{P}_{k+1}^-$ using the time update equations:

$$\begin{aligned} \hat{\mathbf{x}}_{k+1}^- &= \mathbf{f}(\mathbf{x}_k, \mathbf{u}_k) \\ \mathbf{P}_{k+1}{}^- &= \mathbf{A}_k \mathbf{P}_k \mathbf{A}_k^T + \mathbf{B}_k \mathbf{Q}_k \mathbf{B}_k^T \end{aligned} \tag{3.3}$$

The state and error covariance estimates are updated using:

$$\begin{aligned} \mathbf{K}_k &= \mathbf{P}_k^- \mathbf{H}_k^T (\mathbf{H}_k \mathbf{P}_k^- \mathbf{H}_k^T + \mathbf{R}_k)^- \\ \widehat{\mathbf{x}}_k &= \widehat{\mathbf{x}}_k^- + \mathbf{K}_k(\mathbf{z}_k - \mathbf{h}(\widehat{\mathbf{x}}_k^-, 0)) \\ \mathbf{P}_k &= (\mathbf{I} - \mathbf{K}_k \mathbf{H}_k) \mathbf{P}_k^- , \end{aligned} \tag{3.4}$$

where $\mathbf{I}$ is the 3x3 identity matrix, and A, B, H are calculated as the following Jacobians of the system $\mathbf{f}$ and measurement $\mathbf{h}$ functions:

$$\begin{aligned} \mathbf{A}_k &\equiv \left(\frac{\partial f_i}{\partial x_j}\right)(\widehat{\mathbf{x}}_k, \mathbf{u}_k) \\ \mathbf{B}_k &\equiv \left(\frac{\partial f_i}{\partial u_j}\right)(\widehat{\mathbf{x}}_k, \mathbf{u}_k) \\ \mathbf{H}_k &\equiv \left(\frac{\partial h_i}{\partial x_j}\right)(\widehat{\mathbf{x}}_k) \end{aligned}$$

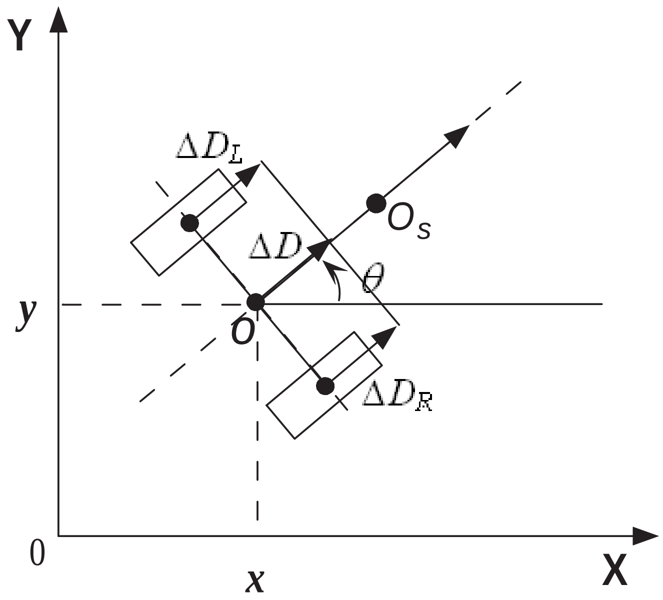


Figure 3.3: The wheelchair is a non-holonomic, uni-cycle type vehicle. O is the mid-axis point between left and right wheels; O_s is the point where the barcode sensor reads barcodes; D_s is the distance between O and O_s. The heading of the sensor aligns with the wheelchair's centerline, i.e. $\theta_S = \theta$. $\triangle D_L$ and $\triangle D_R$ are the displacements measured by the left and right glidewheels. $\triangle D$ is the distance traveled by the mid-axis point of the vehicle.

System modelling

Our vehicle, a non-holonomic, unicycle type (see Fig. 3.3), is modeled by the following kinematic (odometric) equations, which convert the readings at the wheels into data expressing the robot movement.

$$\begin{aligned} x_k &= x_{k-1} + \triangle D_{k-1} \cos\theta_k \\ y_k &= y_{k-1} + \triangle D_{k-1} \sin\theta_k \\ \theta_k &= \theta_{k-1} + \triangle \theta_{k-1} \end{aligned} \tag{3.5}$$

where (x_k, y_k, θ_k) and $(x_{k-1}, y_{k-1}, \theta_{k-1})$ are current and previous poses in global coordinates, $\triangle D_k$ is the distance traveled by the mid-axis point of the vehicle, which can be calculated as

$$\triangle D_k = \frac{\triangle D_{Lk} + \triangle D_{Rk}}{2}, \tag{3.6}$$

where the incremental change in orientation $\triangle\theta_k$ corresponds to the difference of these displacements:

$$\triangle\theta_k = \frac{\triangle D_{Rk} - \triangle D_{Lk}}{d}, \tag{3.7}$$

where d is the effective width of the vehicle.

We can thus write the state vector as $x_k = (x_k, y_k, \theta_k)^T$, the input vector as $u_k = (\triangle D_{Lk}, \triangle D_{Rk})^T$, and the nonlinear function $\mathbf{f}$ as $f(\mathbf{x}) = (f_x, f_y, f_\theta)^T$.

Then we have the linearized system equation:

$$\widehat{\mathbf{x}}_{k+1}^{-} = A_k \widehat{\mathbf{x}}_k + B_k \mathbf{u}_k \tag{3.8}$$

where

$$A_k = \begin{bmatrix} 1 & 0 & -\triangle D_k \sin\theta_k \\ 0 & 1 & \triangle D_k \cos\theta_k \\ 0 & 0 & 1 \end{bmatrix},$$

$$B_k = \begin{bmatrix} \frac{1}{2}\cos\theta_k + \frac{\triangle D_k}{d}\sin\theta_k & \frac{1}{2}\cos\theta_k - \frac{\triangle D_k}{d} sin\theta_k \\ \frac{1}{2}\sin\theta_k - \frac{\triangle D_k}{d}\cos\theta_k & \frac{1}{2}\sin\theta_k + \frac{\triangle D_k}{d}\cos\theta_k \\ -\frac{1}{d} & \frac{1}{d} \end{bmatrix}.$$

Sensor modelling

We can also have the sensory equations:

$$\begin{aligned} x_{S_j} &= x_j + D_S \cos\theta_{S_j} \\ y_{S_j} &= y_j + D_S \sin\theta_{S_j} \\ \theta_{S_j} &= \theta_j \end{aligned} \tag{3.9}$$

where $(x_{S_j}, y_{S_j}, \theta_{S_j})$ and (x_j, y_j, θ_j) are the sensor's and wheelchair's current poses in global coordinates, and D_S is the distance between the sensory point O_s and mid-axis point O (see Fig. 3.3).

Then we have the linearized sensor equation:

$$\mathbf{z}_k = H_k \widehat{\mathbf{x}}_k \tag{3.10}$$

where

$$H_k = \begin{bmatrix} 1 & 0 & -D_S \sin\theta_{S_k} \\ 0 & 1 & D_S \cos\theta_{S_k} \\ 0 & 0 & 1 \end{bmatrix}$$

The absolute positions (x_{S_j}, y_{S_j}) can be directly obtained from the reading of the barcodes. The absolute orientation θ_{S_j} can be estimated by the numerical approach described in Appendix B.

3.3.3 Filter realization

The update of a measurement from the barcode is much slower than the odometry, as it is only available when the robot passes over a barcode pattern. Therefore, before the robot could reach a barcode pattern, its localization has to rely completely on odometry.

When the measurement $\mathbf{z}_k$ is available, the data from odometry and barcodes should be fed into the EKF system. The EKF initial state $\mathbf{x}_0$ is taken to be equal to zero. The initial state error covariance matrix is initialized to the value of the expected system error noise covariance: $\mathbf{P}_0 = \mathbf{Q}$. Then, the EKF predicts the next state of the system and projects ahead the state error covariance matrix using the time update equation 3.3. Then, the Kalman gain matrix K_k is computed and used to incorporate the measurement into the state estimate $\widehat{x}_k$. The state error covariance for the updated state estimate, $\mathbf{P}_k$, is computed using the measurement update equation 3.4.

Driving noise covariance

Here, we compute the driving noise covariance $\mathbf{Q}$. The encoders directly provide displacement information instead of velocities. Therefore, the distances traveled by the left and right glidewheels according to odometry, $\triangle D_{Lk}$ and $\triangle D_{Rk}$, were chosen as variables in the driving function. The covariance matrix of wheel displacement error Q is determined by experimentally establishing the encoders' measuring variances on the two wheels, ${\sigma_{DL}}^2$ and ${\sigma_{DR}}^2$. As the two wheels of the wheelchair are driven by two different motors and their rotations are recorded by encoders installed on two separated glidewheels, we can assume that for a short unit of travel the error incurred on both wheels are uncorrelated.

$$Q_k = \begin{bmatrix} {\sigma_{D_{Lk}}}^2 & 0 \\ 0 & {\sigma_{D_{Rk}}}^2 \end{bmatrix} \tag{3.11}$$

Further, we assume for a short unit of travel, the error is zero mean, white, and uncorrelated with the previous or next unit of travel. The variance of the cumulative error is then the sum of the variance of each statistically independent unit. This leads to an assumption that the variance of each unit of travel is proportional to the distance traveled.

$$\begin{aligned} {\sigma_{D_{Lk}}}^2 &= {k_{DL}}^2 \mid \triangle D_{Lk} \mid, \\ {\sigma_{D_{Rk}}}^2 &= {k_{DR}}^2 \mid \triangle D_{Rk} \mid \end{aligned} \tag{3.12}$$

where k_{DL} and k_{DR} are constants with unit $\sqrt{m}$.

To decide the constants k_{DL} and k_{DR}, the robot was programmed to move along straight lines with distances of $D = 1, 3, 5, 10, 15m$ respectively, starting from the same point. For each distance, the robot executed the run for 10 times. The perceived displacement on each wheel was recorded by the on-board computer. The distance between the start and stop positions was measured externally by tapes as the real displacement. The real and perceived displacements were then compared to obtain the variance of each wheel at a corresponding distance. By least-square fitting for variances with respect to distances, we obtained $k_{DL} = 0.0057\sqrt{m}$ and $k_{DR} = 0.0048\sqrt{m}$. The covariance matrix of wheel displacement error E_{u_k} was set as:

$$\mathbf{Q}_k = \begin{bmatrix} 0.0057^2 \mid \triangle D_{Lk} \mid & 0 \\ 0 & 0.0048^2 \mid \triangle D_{Lk} \mid \end{bmatrix}. \tag{3.13}$$

Measurement noise covariance

Next we computed the measurement noise covariance **R**. One piece of barcode was pasted on the ground, and the barcode scanner at a fixed height approached and read this barcode from all directions. This was repeated 50 times. The positions, retrieved from the barcode, were compared to the real displacements measured by a measuring tape. The standard deviation of measurement error was $\sigma_x = 14.69mm$ and $\sigma_y = 9.86mm$ (the x-y coordinates are with respect to the barcode: their origin is on the center of the barcode, and their directions are as shown in Fig. 3.2). As we have no direct source of the angular measurement, its variance was empirically selected as: $\sigma_\theta = 0.25^o$. Note that in the real run, mean errors in positions have to be subtracted from absolute position estimates as the measurement noise is assumed to be normally distributed with zero mean.

The measurement noise covariance **R** was thus set as

$$\begin{aligned} \mathbf{R} &= \begin{bmatrix} {\sigma_x}^2 & 0 & 0 \\ 0 & {\sigma_y}^2 & 0 \\ 0 & 0 & {\sigma_\theta}^2 \end{bmatrix} \\ &= \begin{bmatrix} 2.158e-4 & 0 & 0 \\ 0 & 9.722e-5 & 0 \\ 0 & 0 & 1.9e-5 \end{bmatrix} \end{aligned} \tag{3.14}$$

3.3.4 Experimental evaluation

Simulations as well as field experiments were performed to evaluate the barcode-odometry localization approach. In all the tests, the robot was commanded to move along a nominal path for 10 times at a constant speed of $0.5m/s$. The nominal path is located in the Control and Mechatronics Laboratory of the National University of Singapore. Here we only use the path AB (see Figure 3.4), which is about $15m$ and accounts for 90% of its total length.

Simulation

In our simulation, the driving noise covariance **Q**, and the measurement noise covariance **R** of equations 3.13 and 3.14 were used to simulate the noise in the real situation. At each sampling period ($t = 0.01 second$), the deviation between the 'real' and 'ideal' positions was calculated, and as was the angular difference between the 'real' and 'ideal' orientations.

The first simulation was conducted by localizing the robot only with odometry (see Figure 3.4). Though the estimated trajectory follows the specified path, the actual position of the robot deviates further from the course as the traveling distance increases. The ellipses, which are two-dimensional sections of the error ellipsoid in the x-y plane, become larger and change shape as the robot moves. It can be seen that the robot cannot safely pass through doorways and narrow passage.

The second simulation was conducted by localizing the robot with the proposed barcode-odometry approach (see Figure 3.5). Six barcode landmarks ($0.75m$ in width) were placed along the path as the landmarks. The first one is close to the starting position to provide a good initial position reading. The second and third are placed in front of the door, because this is the narrowest part of the path ($0.84m$ in width). The fourth one is placed on the other side of the door for some tasks that requires the robot ($0.65m$ in width) to navigate back to the room on the left. Between the fourth and fifth patterns, as there is a large open area, no barcode pattern is placed. Finally, the fifth and sixth are placed in the narrow passage ($1m$ in width). In this case, the robot can safely pass through the door and narrow passage.

We calculated absolute mean of position deviation as well as angular difference (see Table 3.1). Compared with odometry localization, the barcode-odometry localization has improved 72% in position estimation, and its smaller standard deviation indicates a

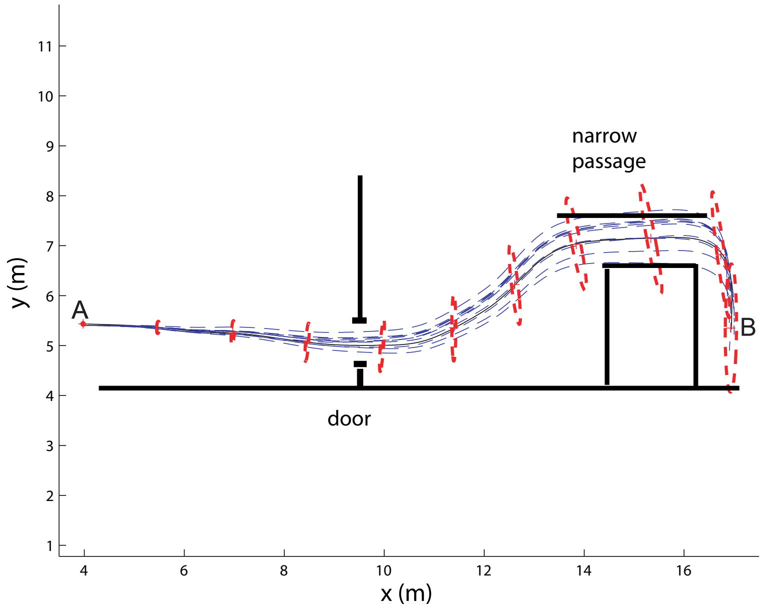


Figure 3.4: Estimation of mobile robot trajectory when using odometry localization. The probability that the robot stays within the ellipses at each estimated position is 95% in these simulations. It can be seen that the robot cannot safely pass through the door and narrow passage.

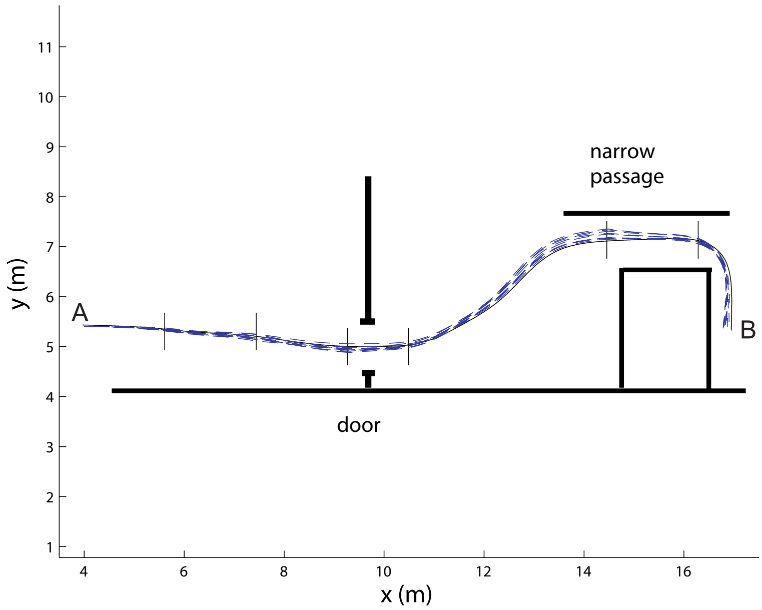


Figure 3.5: Estimation of mobile robot trajectory when using barcode-odometry localization. It can be seen that the robot can safely pass through the door and narrow passage.

Table 3.1: Trajectory estimate comparison between odometry and barcode-odometry localizations. Values are given as absolute mean (standard deviation) over time.

	odometry only	barcode-odometry
position deviation (cm)	16.9(8.8)	4.7(1.5)
angular difference (degree)	3.0(1.0)	2.7(0.6)

more consistent trajectory estimation.

Field experiment

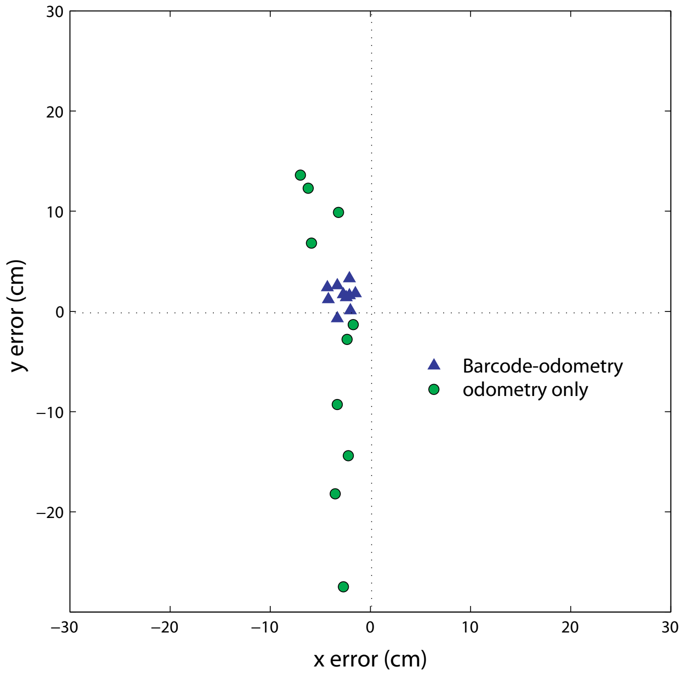


Figure 3.6: Position estimation error at goal point.

In the field experiment, the CWA is programmed to automatically carry a human subject to traverse the nominal path. The on-board computer logs both the combined position information by barcode-odometry localization and raw odometry data. The estimation error at the goal position is accounted for comparison.

The experimental results are shown in Figure 3.6. The circles in the figure show the position estimation error with only the odometry (Mean (-0.2, 0.7), SD (0.8, 16.2)*cm*), while the triangles indicate the error with the barcode-odometry localization (Mean (0.7, -1), SD (1.4, 1.5)*cm*). It can be seen that the deviation in y-axis is clearly smaller in the case with the barcode-odometry localization.

3.4 Flexible Path Guidance

3.4.1 Path controller

A path following controller constrains a robot along a guide path, but does not restrict the speed. If the position sensors detect that the robot is off the path, the controller steers it back onto the guide path. Here we extend the functionality of the path controller in [31] by introducing an *elastic path controller* (EPC). If the user sees an obstacle on the path, the system should allow him to avoid it. The EPC enables the user to curve the path reactively in order to avoid dangers without violating constraints imposed by the task. We first follow the exposition of [31] for the kinematics and path following controller, from which we then extend to an elastic path controller. This controller is developed by Long Bo, in his works [32, 33].

Kinematics

The wheelchair has two actuated wheels on a common axis. Using a reference point taken midway between these two wheels (see Fig. 3.7), the kinematic equations are as follows:

$$\begin{aligned} \dot{x} &= v\cos\theta \\ \dot{y} &= v\sin\theta \\ \dot{\theta}_m &= \omega \end{aligned} \tag{3.15}$$

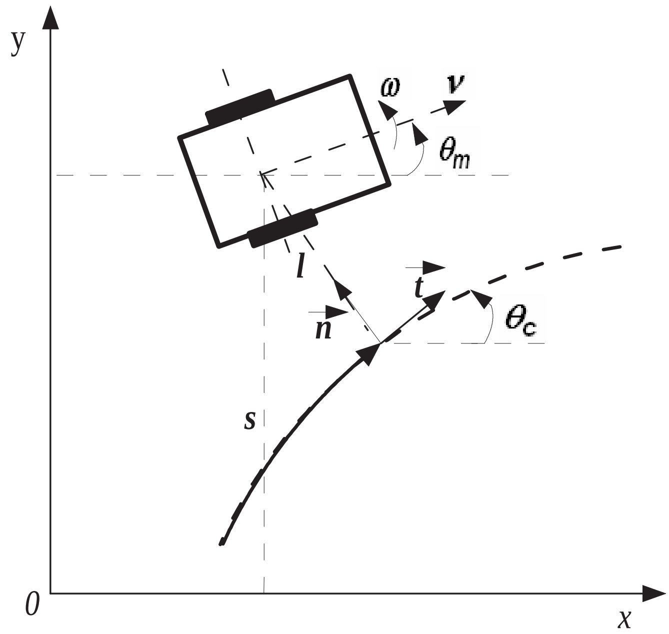


Figure 3.7: Wheelchair's kinematics.

where v and ω are the translational and angular velocities respectively, and θ_m is the wheelchair's orientation with respect to the fixed frame.

Path following controller

To develop a time-independent path following controller, we first describe the kinematics relative to a frame consisting of a curvilinear coordinate s along the guide path. Let l be the distance of the reference point of the wheelchair to the guide path along the normal, and let θ_m be the wheelchair's angle relative to a reference Cartesian frame (x,y). The kinematics of equation 3.15 can then be rewritten as

$$\begin{aligned} \dot{s} &= \frac{v c_\theta}{1 - c_c\, l}, \quad c_\theta \equiv \cos\theta \\ \dot{l} &= v s_\theta, \quad s_\theta \equiv \sin\theta \\ \dot{\theta}_m &= \omega. \end{aligned} \tag{3.16}$$

Here, $\theta = \theta_m - \theta_c$ is the error between the vehicle orientation θ_m and the tangent to the guide path θ_c in the (x,y)-frame, $v = \sqrt{\dot{x}^2 + \dot{y}^2}$ is the translational speed and c_c is the guide path's curvature.

Equation 3.16 depends on time, thus we reparameterize it with the distance travelled by the vehicle along the path, $\eta \equiv \int_0^t |\dot{s}|$:

$$\begin{aligned} s' &= \text{sign}\left(v\frac{c_\theta}{1-c_c\,l}\right) \\ l' &= t_\theta\,(1-c_c\,l)\,\text{sign}\left(v\frac{c_\theta}{1-c_c\,l}\right), \quad t_\theta \equiv \tan\theta \\ \theta' &= \frac{\omega\,|1-c_c\,l|}{|v\,c_\theta|} - c_c\,\text{sign}\left(v\frac{c_\theta}{1-c_c\,l}\right) \end{aligned} \tag{3.17}$$

where $()' \equiv \frac{d}{d\eta}$. The control objective is to stabilize the output l to zero. A second derivative of l is needed as the control variable ω does not explicitly appear in the expression of l':

$$l'' = \frac{\omega}{v c_\theta^3}(1-c_c\,l)^2 - c_c(1-c_c\,l)\frac{1+s_\theta^2}{c_\theta^2} - g_c\,l\,t_\theta \tag{3.18}$$

This equation is linearized to

$$l'' = u \tag{3.19}$$

by setting

$$\omega \equiv v\,\frac{c_\theta}{1-c_c\,l}\left(u\,\frac{c_\theta^2}{1-c_c\,l} + c_c(1+s_\theta^2) + g_c\,l\,\frac{\sin 2\theta}{2(1-c_c\,l)}\right). \tag{3.20}$$

Using the auxiliary control

$$u \equiv -k_{pl}\,l - k_{vl}\,l' \text{ with } k_{pl} > 0, k_{vl} > 0\,, \tag{3.21}$$

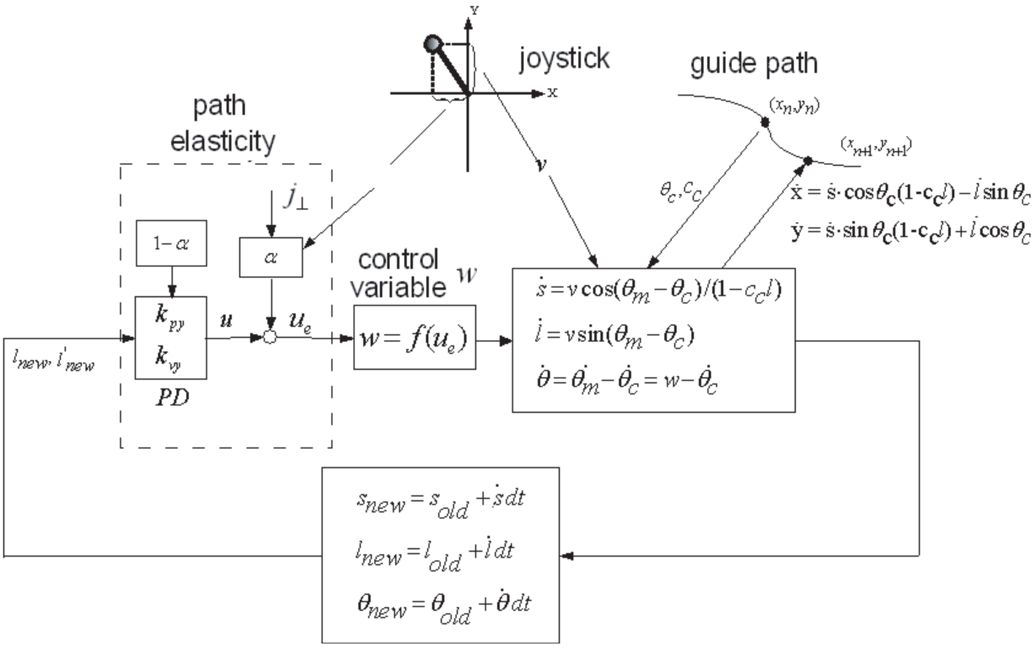


Figure 3.8: Block diagram of the elastic path controller.

it is shown in [31] that, provided appropriate initial conditions are fulfilled, equation 3.16 has a solution and l converges to 0.

With this controller, the user only needs to input the translational velocity v, and the angular velocity ω is calculated using equation 3.20. With these two inputs, the wheelchair can move along the path and stop at user's will.

Elastic Path Controller

The idea of the *elastic path controller* (EPC) is to allow the user to deviate from the guide path when needed. For this purpose, the controller in equation 3.21 is modified as follows:

$$u = -(1-\alpha)(\underbrace{k_{pl}\,l + k_{vl}\,l'}_{restoring\ force}) - \underbrace{\alpha j_\perp}_{deviation\ input} \tag{3.22}$$

where $k_{pl} > 0, k_{vl} > 0$, $j_\perp$ is the *normal input*, and the *elasticity parameter* α (value between 0.1 to 0.9) is used to balance the influence of the deviation input applied by the user and the attraction from the guide path.

Using equation 3.22, the closed-loop system of the controller with elasticity can be described by:

$$\begin{aligned}
\dot{s} &= \frac{v\,c_\theta}{1-c_c\,l}\,, \quad c_\theta \equiv \cos\theta \\
\dot{l} &= v\,s_\theta\,, \quad s_\theta \equiv \sin\theta \\
\dot{\theta} &= v\frac{c_\theta}{1-c_c\,l}\left[l\frac{c_\theta}{1-c_c\,l}\left(g_c s_\theta - (1-\alpha)\,k_{pl}\,c_\theta\right) + \right. \\
&+ s_\theta\left(c_c\,s_\theta - (1-\alpha)\,k_{vl}\,c_\theta\,\mathrm{sign}\left(\frac{vc_\theta}{1-c_c\,l}\right)\right) + \\
&- \left.\alpha\,j_\perp\frac{c_\theta^2}{1-c_c\,l}\right]\,.
\end{aligned} \tag{3.23}$$

Fig. 3.8 gives the block diagram of the elastic path controller. The joystick input to the EPC is designed as follows: the parallel angle of the joystick (relative to a local frame fixed to the vehicle) corresponds to the translatory velocity, while the normal angle corresponds to the desired deviation from the guide path, and is computed by projecting the normal input, relative to the current wheelchair direction, onto the normal to the guide path. This projection prevents a too large change of orientation relative to the guide path and limits it to 90^o.

3.4.2 Operation modes

The EPC enables the CWA to follow a guide path with the speed specified by the human user. The strength of this interaction can be tuned with the elasticity parameter α:

- $\alpha = 1$ corresponds to *free mode* (FM), in which the user drives the CWA like a standard motorized wheelchair.

- $\alpha = 0$ corresponds to *guided mode* (GM), in which the CWA provides path guidance and guides the user to move freely along the guide path. If the CWA detects that the wheelchair is off the path, the controller steers it back onto the guide path.

- α between 0.1 to 0.9 corresponds to *elastic mode* (EM), in which the user can deviate the wheelchair away from the guide path by applying a normal input while still feeling the path attraction.

3.5 Flexible Path Design

3.5.1 GUI and guide paths

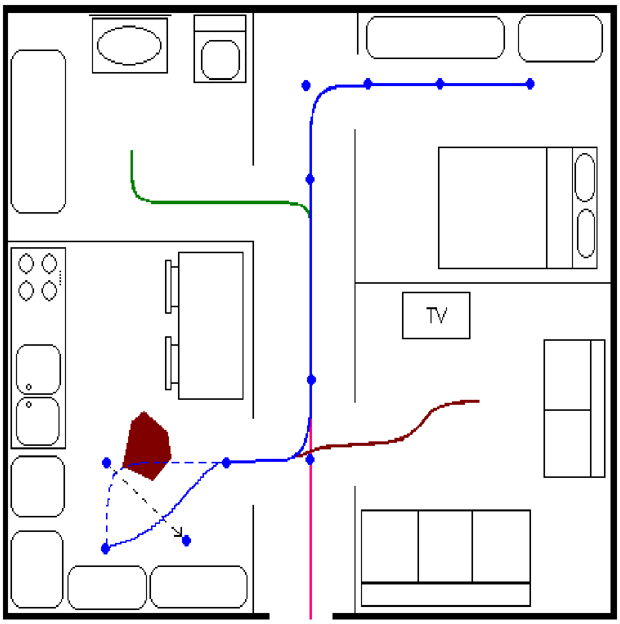


Figure 3.9: Example of a map with wheelchair paths in a home environment. The paths are defined by a small number of control points which have an intuitive geometric meaning as attraction points of B-spline curves, and can be used to modify the path. For example the figure shows how the path in the kitchen is modified to avoid a large object representing an obstacle. The furniture and signs are for illustration purpose only.

The user issues commands to the controller via the Graphical User Interface (GUI), which provides a list of possible destinations and a map view displaying the guide path and the wheelchair's navigation as geographical locations. Fig. 3.9 shows such a map for a typical home environment. The GUI is *context dependent* and will prompt the user only with the possible destinations connected to the current location. This reduces the selection to a few possibilities and simplifies the selection process. Upon selection of a destination such as "go to the kitchen", the robotic wheelchair guides the wheelchair along the pre-defined path to its destination. To run the system, a user needs to first choose the destinations and the operation mode, before activating the motion via a joystick. For users unable to use a joystick for input selection, switches are added to the wheelchair.

B-spline curves [34, 35] were chosen to code the guide paths, as their computation is fast and stable, and the shape of the resulting curve is smooth and can be easily controlled. A B-spline function $B(u)$ is a piecewise polynomial function of the form

$$B(u) = \sum_{i=0}^{n} N_i^p(u) P_i \tag{3.24}$$

where $P_0, P_1, \ldots, P_n$ are the $n+1$ unknown attraction points, and $N_i^p(u)$ are B-spline basis functions of degree p and a knot vector $u = (u_0, u_1, \ldots, u_m)$, and u_i are real numbers called knots that act as points between every two consecutive attraction points. We used cubic uniform B-splines, which are sufficiently smooth for our path controller as they are continuous up to the third derivative, i.e. the derivative of curvature. Consequently, the $m+1$ knots are equally spaced, i.e., $u_{i+1} - u_i$ is a constant for $0 \leqslant i \leqslant m-1$.

We note that existing maps of the environment such as those available from architect drawings can also be incorporated into a library of guide paths. Thereafter, the tools presented in the next section can be used to optimize paths obtained from any source or paths inherited from other users. It is also straightforward to extend the map by adding new paths and nodes, or connecting two maps together, for instance at a lift. Eventually, the collection of many paths from the environment would result in a topological map (e.g. Fig. 3.9 without the furnitures) after entering the relevant location names, as well as attributes relating to these branches.

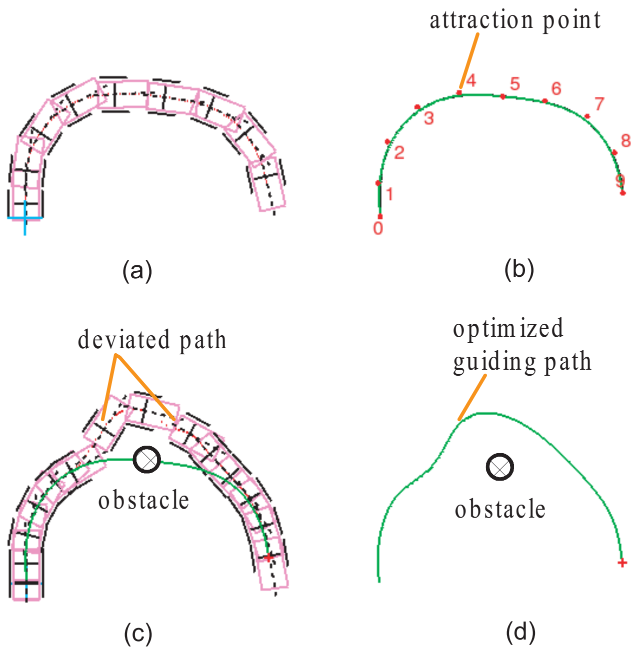


Figure 3.10: Defining a wheelchair path by WTP (a,b) and using the EPC (c,d). The path traced in a) is recorded into the memory. b) A B-spline fit of the recorded path can be used as wheelchair path. The user can bend the path on-line using the EPC c), which can be used as a new wheelchair path for subsequent movements d).

3.5.2 Path design tools

A *walk through programming* (WTP) approach can be used to create guide paths. In the WTP approach, the wheelchair user or a helper can push or drive the wheelchair freely in the working environment, during which the coordinate values are recorded (Fig. 3.10a). These values are least-square fitted with B-spline (Fig. 3.10b), and then compressed, yielding a smooth path for subsequent movements. The path can be retraced with the WTP until the user is satisfied.

Alternatively, EPC and GUI can be used to help design or modify the path. The EPC allows the user to deviate from the path in real-time in order to reach some place outside the path or reactively avoid obstacles or dangers (see Fig. 3.10c) and re-join the path after clearing the obstacles. After the modifications, the wheelchair user has the possibility to store these path modifications for subsequent movements (see Fig. 3.10d). Also, the few B-spline attraction points determining the path have a clear geometric meaning and can be shifted on the GUI in order to modify the path.

3.6 Summary of the Chapter

In this chapter, the CWA prototype was described. It was shown that the CWA concept does not require complex sensor processing nor a decision system, and is relatively low-cost. The navigation was realized by using an elastic path controller (EPC). This dedicated controller can guide the wheelchair moving along a guide path, and even allows the user to curve the path reactively in order to avoid dangers on the way. By tuning with the elasticity parameter , the system has three operation modes: free mode (FM), guided mode (GM), and elastic mode (EM).

Several design tools were developed for the CWA to create or modify guide paths. Walk through programming (WTP) enables the user to teach a guide path by moving the wheelchair freely in its working environment. The path can be retraced with the WTP until the user is satisfied. Alternatively, the path can be modified by using EPC or using a graphical user interface (GUI) on which it can be manipulated from a few attraction points.

To ensure reliable navigation, the system always needs to know its location precisely. A barcode-odometry localization combining information from odometry and unique barcode patterns was developed, and tested in simulations and field experiments. The testing results showed that this simple approach could provide sufficient accuracy for pose estimations in the desired environment.

Chapter 4

Investigation on Path Guidance

4.1 Introduction

The concept at the heart of the CWA is to rely on the users motion planning skills and to assist the difficult maneuvering task with path guidance. The user decides where to go and controls the speed (including start/stop, forward/backward), while the system guides the wheelchair along a software-defined path that connects the desired destinations.

This chapter presents an experimental investigation of the CWA system performed with able-bodied subjects. We study in particular the motion efficiency and human-machine interaction of the CWA system. The driving performance of the operators with robotic assistance is analyzed and compared with the conventional control of a powered wheelchair. This enables us to examine the effectiveness of path guidance, i.e. to address whether and how it could assist the user in driving a wheelchair.

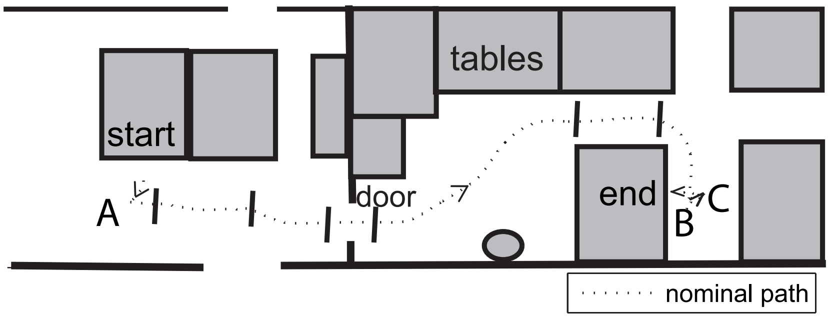


Figure 4.1: The experimental environment. The nominal path, which is not marked on the floor but pre-defined in software, is from *start* table to *end* table, placed in two different rooms separated by one (narrow) door.

4.2 Methods

4.2.1 Subjects

Five able-bodied (male) subjects with ages between 25 and 36 were informed about the experiments, and gave their consent prior to participation. None of these subjects had driven a wheelchair before.

4.2.2 Experimental environment

The experimental environment depicted in Fig. 4.1 was designed in the Control and Mechatronics Laboratory of the National University of Singapore. It contained tables which served as the start and end points for the wheelchair and various fixed obstacles such as chairs, fire extinguisher, narrow doorways etc. Note that the obstacles shown in Fig. 4.1 were not displayed on the GUI. Six barcode landmarks were placed in this environment for global positioning.

The nominal guide path, not drawn on the floor, was taught to the CWA in software through WTP. As illustrated in Fig. 4.1, the wheelchair is first at the *start* table. It backs away and stops at position *A* to adjust its heading, crosses the narrow doorway towards position *B*, from which it backs into position *C*, and then approaches and stops in front of the *end* table. The controller is programmed to automatically load the next path segment when the wheelchair reaches the end of a segment.

4.2.3 Protocol

The subject was first seated on the wheelchair with motors turned off, while safety measures such as the power button were explained to him. Then the two driving modes, free mode (FM) and guided mode (GM), were described. The joystick interface was shown and explained to him, and he then practiced with it. Once the subject was comfortable with the interface, he tried the guided motion and free motion until he expressed an understanding on each of them. The subjects usually spent about 10 minutes on both modes of operation.

After training, the subject was tested in the experimental environment shown in Fig. 4.1. He was told that the task is to drive the wheelchair safely from the *start* table to the *end* table. The wheelchair (0.65*m* in width) has to pass through the doorway (0.84*m* in width) without scratching the doorframe and stop right in front of the *end* table, such that he could type on the keyboard placed on it. As mentioned in the previous section, the nominal path is used only in GM and not marked on the floor. In FM, the subject has to complete the task by relying on his own driving skills.

The subjects had to repeat this movement 10 times alternating the control mode between FM and GM, in the order FM, GM, FM, etc., i.e., without and with robotic assistance, respectively. They were instructed to try to minimize the movements of the joystick.

4.2.4 Data analysis

Two aspects of performance were investigated to infer how the subjects used the CWA: speed and user interaction. The *mean speed* was estimated as the traveling distance di-

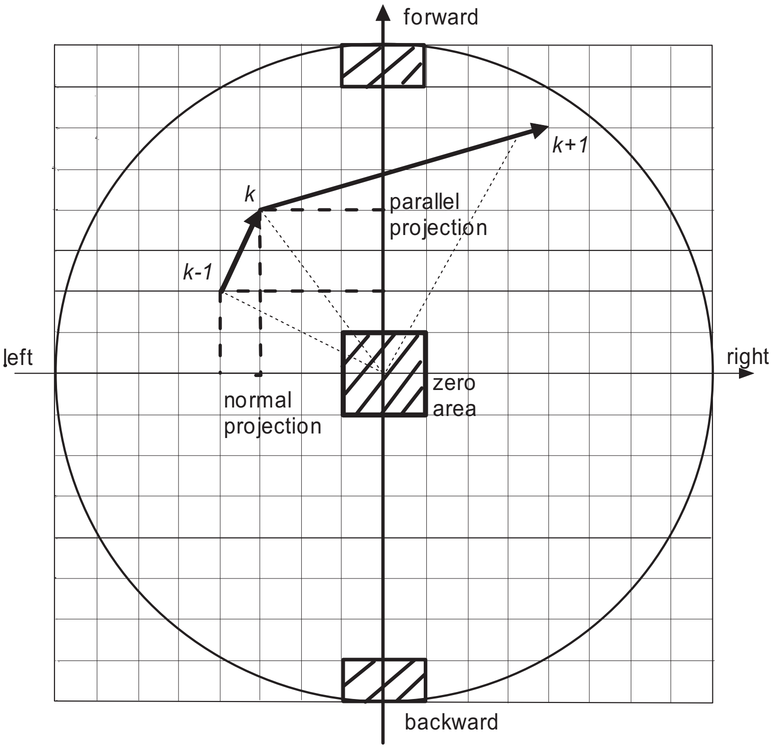


Figure 4.2: Joystick configuration and joystick move. The joystick range is divided into a 16x16 checkerboard. Joystick move at instant *k* is defined as the vector between lever positions in two consecutive positions at *k-1* and *k*. Then the total *joystick move* is defined as the sum of the norm of these differences during the whole movement. *Parallel move* and *normal move* are defined similarly from projections onto the corresponding axes. The extreme area is the shadow area, which corresponds to either maximum or zero speed. The zero area is treated as zero move.

vided by the time spent to complete the task. While it is not required that the user drives at high speed, a low speed indicates maneuvering difficulties. *User interaction* was evaluated by analyzing the user's maneuvering on the joystick control interface (recorded at 50*Hz*). Two important aspects of user interaction were studied: *joystick move*, which measures the variation of joystick position, and the *intervention level*, which quantifies how often the wheelchair drivers needs to modify their inputs. The hypothesis is that continuous motion control will require constant attention and thus a significant effort. Conversely, little intervention means that the driver can relax during most of the path and concentrate on other aspects such as obstacles avoidance.

As illustrated in Fig. 4.2, the range of the position joystick is first divided into a 16x16 checkerboard. The joystick position is taken with respect to the checkerboard, and only positions maintained longer than 100*ms* are considered (such that fast oscillations are not accounted for). *Joystick move* at instant *k*, is defined as the norm of the vector difference between lever positions in two consecutive positions at *k-1* and *k* [20]. Then, the total joystick move is defined as the sum of joystick moves during the whole movement. *Parallel move* and *normal move* at instant *k* are defined similarly from projections of joystick move at instant *k* onto the corresponding axes. The joystick move within the zero area is treated as zero move.

Intervention level is inferred from the intervention time and the use of extreme joystick configuration corresponding to maximum speed. *Intervention time*, the control effort that is intended to alter the current course or prevent collision, is defined as the sum of time periods during which the joystick position is modified (w.r.t the checkerboard), divided by the total wheelchair moving duration. In addition, to analyse if the subject mostly drives with the maximum or zero speed, we examine how often the joystick is at extreme positions corresponding to these speeds (see Fig. 4.2).

Directional *t*-tests were used to compare data in GM versus in FM. The null hypothesis is that "the means of the given groups of samples are equal". A p-value of less than 5% means that the hypothesis is rejected, corresponding to a significant difference.

4.3 Results

In all trials, the subjects could reach the destination without colliding with any obstacle. This shows that the allocated training allowed the subjects to be comfortable operating the wheelchair. The effectiveness of the path guidance was evaluated by examining the statistical significance of the following characteristic variables.

4.3.1 Speed

The traveling distance in FM was significantly less than that in GM ($p<0.0001$). However, the required time to perform a movement was significantly larger in FM than in GM ($p<0.002$). Correspondingly, speed in GM was significantly higher than that in FM ($p<0.001$). Further, while the movement time decreased significantly between the first and fifth trials in GM ($p<0.021$), it did not change between consecutive trials in FM ($p>0.213$).

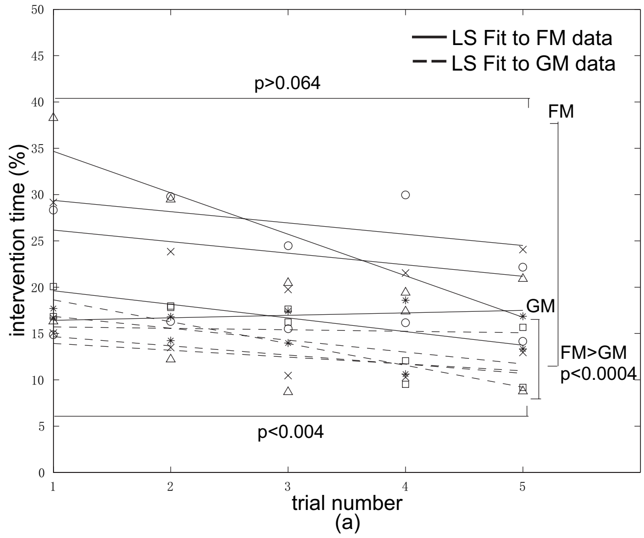
4.3.2 User interaction

Intervention Level

As shown in Fig. 4.3a, intervention time was significantly larger in FM than in GM over trials ($p<0.0004$). The intervention time was reduced significantly between the first and fifth trials in GM ($p<0.004$), but not in FM ($p>0.064$). In addition, the number of non-extreme positions visited during movement in GM was significantly less than that in FM ($p<0.0001$). Also, the subjects spent significantly less time outside the extreme positions in GM than in FM ($p<0.0001$).

Joystick Move

As shown in Fig. 4.3b, the total joystick move in GM was significantly smaller than that in FM ($p<0.0001$). For every subject, even the maximum value in GM was clearly smaller than the minimum value in FM. In FM the joystick move decreased in roughly the first three trials and then converged to a stable value. It appears that the joystick move was reduced significantly in FM but not in GM: the total joystick move in the fifth trial was significantly less than that in the first trial in FM ($p<0.046$), but not in GM ($p>0.083$).



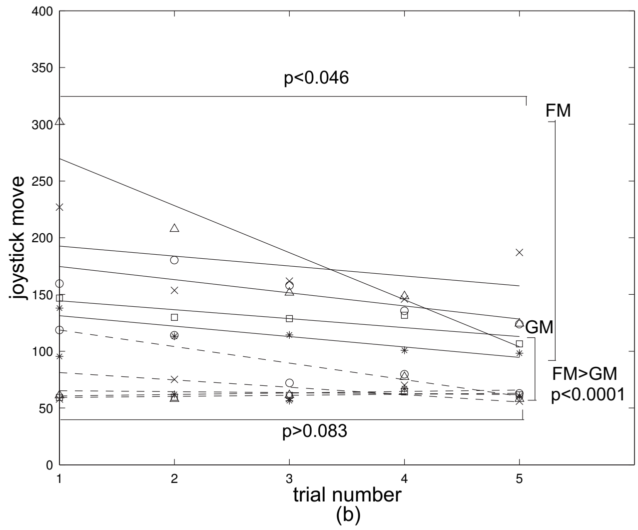


Figure 4.3: The effort to maneuver the wheelchair can be inferred from the intervention level (a) and joystick move (b) for subjects A to E. Both are smaller in guided mode (GM) as in free mode (FM).

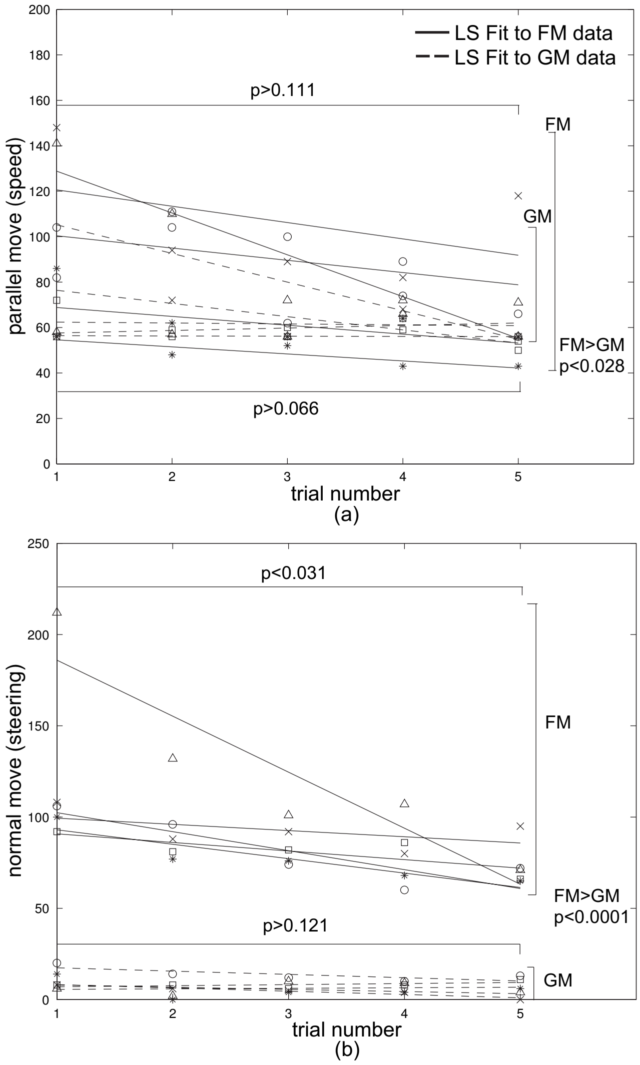


Figure 4.4: Parallel joystick move (a) corresponding to speed during movement and normal move (b) corresponding to steering for subjects A to E. The normal move is much reduced in GM.

No significant change of parallel move was observed in FM ($p>0.111$) or in GM ($p>0.066$) between the first and fifth trials. Parallel move was significantly larger in FM as in GM ($p<0.028$) (Fig. 4.4a).

Significant changes of normal move between the first and fifth trials were observed in FM ($p<0.031$) but not in GM ($p>0.121$). It can be seen in Fig. 4.4b that the normal move in FM was still significantly larger than that in GM ($p<0.0001$).

Driving Behavior

Fig. 4.5a shows the joystick input of a typical subject during the movement. We observe distinct behaviors in FM and GM. In FM, the subject continuously moves the joystick both in parallel and normal directions, while in GM he keeps the joystick at maximum during large portions of the movement, and practically does not need normal input. This is particularly clear in Fig. 4.5b.

4.4 Discussion

This section analyzes the results of the last section and examines how and whether path guidance could assist the user in driving a wheelchair.

Does path guidance facilitate the driving?

We examined the joystick move, which reflects the user's driving effort. As shown in Section 4.3.2, the joystick move in FM decreases over trials, suggesting that the subjects *learned* to drive the wheelchair in the experimental environment in a few trials. On the other hand, joystick move in GM did not change significantly with repeated trials. Further the maximum value in GM was much smaller than the minimum value in FM. These facts show that with path guidance, the wheelchair user can drive efficiently

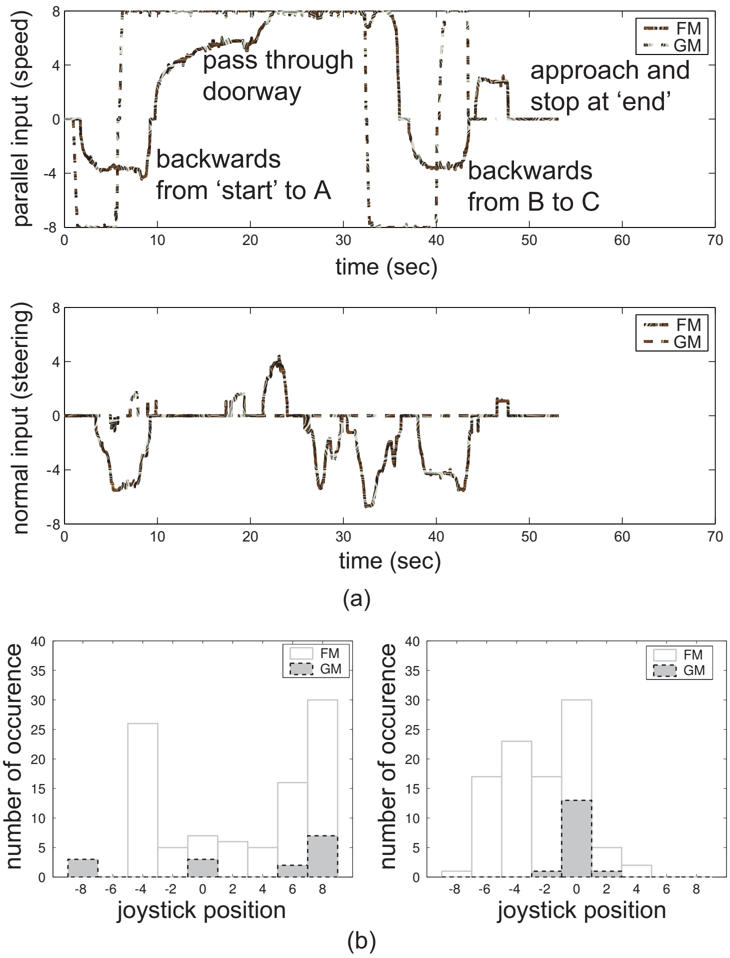


Figure 4.5: Joystick move in GM versus FM after adaptation. (a) shows the parallel and normal moves of subject B during the fifth trial. (b) is the histogram of positions visited during this movement. Left shows the parallel input and right the normal input. In GM the joystick was kept at maximum during large portion of the movement and almost no normal input was required.

from the initial trial onwards, while moving efficiently with a conventional wheelchair requires adaptation

How does path guidance facilitate the driving?

To answer this question, we decomposed joystick move into its parallel component (speed) and normal component (steering). Path guidance required less effort in controlling the speed, as the parallel component is much smaller in guided compared to free mode (see Section 4.3.2). However, as shown in Section 4.3.1, speed was not compromised by path guidance: able-bodied subjects attempt to take shortcut when they were not constrained by the path, but they did not gain time to complete the task as they could not run the wheelchair at maximum speed and had to slow down when navigating round corners or narrow passageways (see Fig. 4.5a).

Normal input, corresponding to the steering necessary to orientate the wheelchair, is the most difficult feature to control in a power wheelchair. The evolution of normal move in FM showed the difficulty in maneuvering a wheelchair, as several trials were required before the subjects could perform well and minimize normal move and intervention level (see Section 4.3.2). In contrast, path guidance takes over the steering task such that little normal input was needed in GM.

How do operators use path guidance?

The intervention level was used in order to study how the users make use of path guidance. During the wheelchair movement, the joystick position did not always need to be modified. If the user felt that the motion was safe and comfortable, he could just hold the joystick at the same position. Otherwise, he had to modify its orientation in order to alter the current course or react to obstacles. As shown in Section 4.3.2, using path guidance greatly reduced the intervention level. Consequently, the driver could relax as he/she did not need to continuously modify the joystick position but could, in contrast, leave it at the extreme position most of the time. This was shown to happen in Section 4.3.2.

4.5 Conclusion

In this chapter, user tests were conducted to investigate the efficacy of path guidance in assisting the control of a powered wheelchair. Five able-bodied subjects performed a navigation task with and without path guidance assistance. Their performances were studied particularly in the aspect of motion efficiency and human machine interaction. The comparison results showed that in the tests with path guidance assistance,

- the navigation is safe: no obstacle collisions occurred in any of the test, i.e. no danger was encountered.
- the speed is not compromised, and is more uniform than with free motion.
- the user control is drastically simplified by the exemption from the steering task, and does not require learning
- the driver does not need to modify the control input very often.

These points demonstrate the advantages of using path guidance, and show the effectiveness of the shared control strategy between the user and the wheelchair.

Chapter 5

Collaborative Path Planning

5.1 Introduction

One of the main challenges in robotic wheelchairs is to plan paths for (semi)autonomous navigation. As these robots are to be deployed in varied environments, which may further change over time, it is difficult or impossible to have professional experts spend much time to set up each individual robot and adjusting it to the characteristics of its particular environment [36].

One possible solution is to let the robot autonomously generate a collision-free path between two known destinations, e.g. the VHAM wheelchair (Universite de Metz, [12]), the *SmartChair* (University of Pennsylvania, [13]), and the smart wheelchair TGR Explorer (Marche Polytechnic University, [37]). Although it would be desirable to have a robot with such properties, it is not possible to generate a fixed map for an unstructured and dynamic human living environment, and it is difficult to plan paths in it by artificial intelligence. Such an approach is moreover limited by the complexity and high cost of sensor processing, as well as by the accuracy of the sensors.

Another solution is to let a human operator teach the path to the robot in advance, e.g. the SENARIO autonomous wheelchair [14], the SIRIUS system (Universidad de Sevilla,

[38]), and the CCPWNS autonomous wheelchair (University of Notre Dame, [17]). In this approach, the robot explores an environment together with a human teacher. The geometric information is provided by the robot's positioning system. Compared with the first solution, this approach reduces the requirements on the machine by sharing tasks with humans. It is preferable, as personal and service robotics usually need to be low cost devices.

However, one major problem with this approach is that it is not easy to make changes on pre-taught paths, which are usually saved as coordinates in memory. The operator has to work directly with these coordinates without being able to refer to the real environment. This would require experience and several trials. Alternatively, a new path can be traced. However, this is troublesome and undesirable [39], in particular for a long path. The human user is usually not a robotic expert and often not interested in technical matters. To cope with these issues, we propose a *collaborative learning* strategy, in which the human operator and the robot, using suitable design tools, interact to create and gradually improve a guide path, eventually achieving an ergonomic path.

This chapter reports experiments performed to examine this strategy. For this purpose, able-bodied subjects were asked to use the path design tools to adapt a given guide path to the changing environment. We analyzed features of their designs as well as user evaluation under representative conditions. This was complemented by a questionnaire filled out by the subjects after the experiments. The results demonstrated the effectiveness of collaborative learning and showed the utility and complementarity of the provided path design tools. They also gave some insight into the ergonomic factors that need to be taken into account when designing guide paths for wheelchairs.

5.2 Methods

The design tools described in Section 3.5.2 of Chapter 3 were evaluated in experiments examining how humans use these tools to adapt a wheelchair path to the task and to their wishes.

5.2.1 Subjects

Fifteen (13 male and 2 female) subjects aged 23 to 32, without known motor disability, were informed about the experiments, and gave their consent prior to participation. None was a regular wheelchair user.

5.2.2 Training

On the first day, the subjects were trained to use the CWA system and the path design tools.

Learning the driving modes of the CWA

The subject has first to sit in the wheelchair with the motors turned off while safety measures such as the power button are explained to her or him. The joystick interface is explained to the subject who then practices with it. Once the subject is comfortable with the interface, the two driving modes, free mode (FM) and guided mode (GM), are described to her or him. A nominal path (see Fig. 5.1a) is used to train operating in GM, and the subject has to experience motion guidance along this path for at least two trials (including forward and backward) until (s)he claims understanding of how to operate the system in GM. The subject is then instructed to move in FM along the same nominal path and required to successfully perform this task in three trials. A trial is considered as failed if the wheelchair deviates from the nominal path by more than 15*cm*. On average, the subjects practised 2.30 ($\pm$0.7 standard deviation) trials in GM and 5.4($\pm$1.7) trials in FM.

Then, the subject is asked to navigate through a narrow passageway (see Fig. 5.1b). The width of the passage is 80*cm*, while the wheelchair width is 65*cm*. Learning is consid-

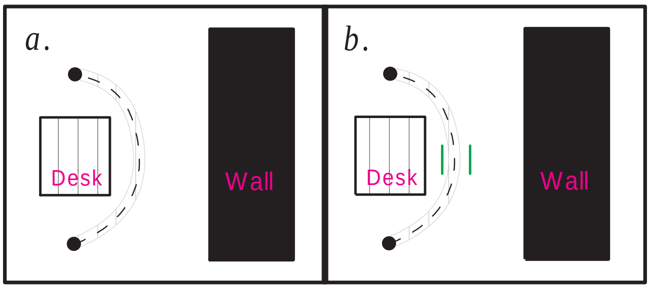


Figure 5.1: Training environment for learning driving free mode (FM) and guided mode (GM) with the CWA. The nominal path (dashed line) is saved in the computer memory for guided motion, and is also marked on the floor for the wheelchair to follow in free motion. A trial consists of one round-trip movement along the nominal path. The trial is considered as successful if the center of the wheelchair remains in the shadow zone, i.e. deviates less than 15*cm* from the nominal path.

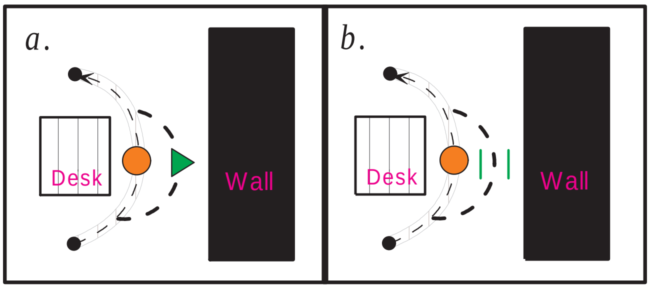


Figure 5.2: Training environment for learning path design tools. a) A cylinder-like dustbin is placed on the path, and the subject has to navigate the wheelchair, avoid it and pass through the triangular area. b). A narrow passage is placed in the environment. The subject has to adapt the nominal path to this change using the path design tools.

ered complete when the subject can successfully control the wheelchair to follow the nominal path and go through this passage without hitting any obstacles in three consecutive trials. On average, the subject practised $4.8(\pm 2.2)$ trials, including $1.8(\pm 2.2)$ failed trials. The total time spent in this phase was less than 30 minutes.

Learning path design tools

Once the subject is familiar with maneuvering, path design tools for *collaborative learning* are explained to her or him. The subject starts to practice using EPC in the environment (see Fig. 5.2a) to avoid the obstacle placed on the path and pass through the

Table 5.1: Test procedure of adapting a path to changes in the environment.

steps	group A	group B	group C
1	design with EPC	design with GUI	design with EPC&GUI
2	design with GUI	design with EPC	
3	design with EPC&GUI		
4	grade paths from steps 1 to 3		
5	questionnaire		

triangle area marked on the floor. (S)he is instructed to practice until (s)he can successfully accomplish the task in three consecutive trials.

Then, a narrow passageway is placed in the environment (see Fig. 5.2b), and the subject is asked to modify the nominal path of Fig. 5.2a to pass through this passageway. The subject completes this task using the EPC, and then repeats the same task with the GUI. In each case, the subject is instructed to experience the resulted guidance before modifying the nominal path, and to repeat a movement until (s)he was satisfied.

The total time spent in this phase is less than 20 minutes. On average, the subject practised EPC for $3.7(\pm 1.1)$ trials. For the path modification task, the subjects, using the EPC, needed an average of $2.6(\pm 2.2)$ trials, including $1.5(\pm 2.2)$ failed trials; using the GUI, they needed $3.6(\pm 1.4)$ trials, including $2.6(\pm 1.4)$ failed trials.

5.2.3 Adapting a path to changes in the environment

Performance after learning is tested the next day in the environment of Fig. 5.3a, which includes walls, pillars, and a movable box which acts as the obstacle. The subject is first shown a guide path, which is generated by the experimenter (solid line in Fig. 5.3a), and is instructed to experience guided motion twice.

Then the box is shifted to a new position (see Fig. 5.3b). The design task is to adapt the path to the environment modification until the subject is satisfied with the new wheelchair path, called *optimal path*. Note that the box can always be seen by the subject from the start position, both before and after it is shifted.

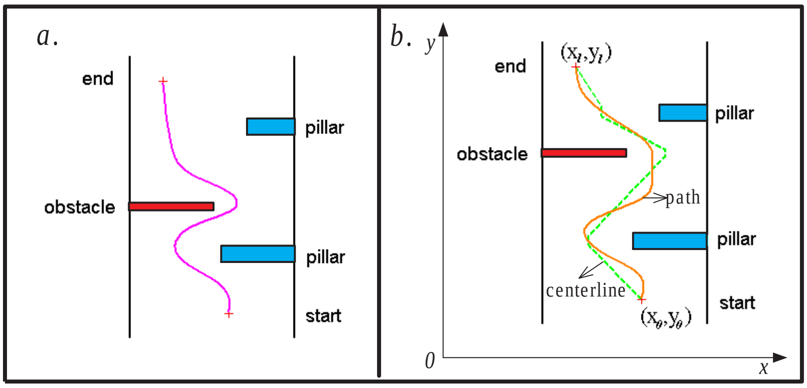


Figure 5.3: The environment in which path design tools are tested. a) A (red) box is placed as obstacle. The nominal path is designed by the experimenter. The subject experiences this path twice in guided motion. b) The box is then shifted, and the subject is instructed to design a new path adapted to this change. Safety margin is calculated from the deviation area of the path (solid) relative to the centerline (dashed) of the permitted region for the wheelchair.

The subjects are arranged into three groups of five and they perform tests as illustrated in Table 5.1, so that the effect of EPC, GUI and EPC&GUI can be investigated independently:

- Group A starts designing paths with EPC, and Group B with GUI. Group C designs paths with EPC&GUI.
- Group A repeats the same task with GUI, and group B with EPC.
- Both groups A and B repeat the task with EPC&GUI.
- Each subject in groups A and B creates 3 paths in the above three steps. These 3 paths are shown in random order to him, who, sitted in the wheelchair, would experience a path with the system moving autonomously at a constant speed. The subject was then required to grade these paths according to their satisfaction from 1 to 5 (‘1’ worst, ‘5’ best).
- At the end of the test, the subjects of groups A and B have to complete a questionnaire analyzing which features they consider important for the design tools, and how they like the different design methods.

5.2.4 Data analysis

We evaluate the path's features using measures of safety, smoothness, comfort, and length. Optimal paths may minimize these measures.

We assume that the trajectory is a continuous curve such that we can compute the length

$$l \equiv \mu_1 = \int_{(x_0,y_0)}^{(x_l,y_l)} \left((\frac{dx}{dt})^2 + (\frac{dy}{dt})^2 \right)^{\frac{1}{2}} dt \quad [m] \,. \tag{5.1}$$

A *safety* measure is then defined as the area of the path's deviation from the centerline of the permitted region for the wheelchair (see Fig. 5.3b):

$$\mu_2 = \frac{1}{l} \int_{y_0}^{y_l} |x_p - x_c| \, dy \quad [m^2] \,, \tag{5.2}$$

where the coordinates are defined in Fig.5.3, the subscript p denotes the path and c the centerline. The path has a larger safety margin when the deviation area is smaller, indicating that the path is 'safer'.

A path can be characterized by the path length s and the curvature along the path $c(s)$. We define *smoothness* as

$$\mu_3 = \frac{1}{l} \int_0^l (c(s))^2 \, ds \,, \tag{5.3}$$

and *comfort* as:

$$\mu_4 = \frac{1}{l} \int_0^l \left(\frac{dc(s)}{ds} \right)^2 ds \,. \tag{5.4}$$

These cost functions can be interpreted from the viewpoint of dynamics [40]. For a plane curve, the curvature at a given point has a magnitude equal to the reciprocal of the radius of an osculating circle (a circle that "kisses" or closely touches the curve at the given point). The centrifugal acceleration in a curve of radius R negotiated at speed v

Table 5.2: Significance level (p-value) for the difference of path features between EPC in groups A and B (1st column) and between GUI in groups A and B (2nd column).

feature	EPC Paths in A and B	GUI Paths in A and B
length	0.505	0.134
safety	0.690	0.204
smoothness	0.538	0.553
comfort	0.503	0.803
no. of trials	0.333	0.810
no. of failure trials	1	0.762

is $a = \frac{v^2}{R}$. When a vehicle moves along the path at constant velocity, the instantaneous centripetal acceleration of the vehicle is proportional to its curvature. The smoothness measure is the integral of (square of) acceleration. In addition, the integral of square of the variation of acceleration or jerk is taken as a measure of comfort, since jerk should be minimized for comfortable vehicle control.

Directional t-tests were used to compare the features of paths. For answers to the questionnaire, Wilcoxon rank-sum tests were used. The null hypothesis is the means of the given groups of samples are equal. The hypothesis is rejected if the p-value is less than 0.05, i.e. there a significant difference with 95% confidence level.

5.3 Results

The first result is that all fifteen subjects could design suitable wheelchair paths using only very few trials. Further, no significant difference was found on length, safety, smoothness, comfort, number of trials or number of failed trials in either EPC or GUI between the subjects in group A and B (see Table 5.2). Therefore, the order in which the tools were used does not influence the results. In particular, for group A, the design experience with EPC in step 1 does not help the design with GUI in step 2. Similarly, for group B, the design experience with GUI in step 1 does not help the design with EPC in step 2.

5.3.1 Comparison between EPC and GUI

Then, we compared the optimal paths designed by EPC (group A) and GUI (group B) in step 1, and we observe that:

- The paths designed by EPC are significantly longer than those by GUI ($p<0.0027$). However, the relative differences are minimal, i.e. the standard deviation is less than 1% of the mean path length.
- The path tends to be significantly safer when designed by EPC than by GUI ($p<0.0608$).
- The paths designed by EPC and by GUI are not significantly different in smoothness ($p>0.3483$) or comfort ($p>0.6903$).
- It takes less trials to design a path with EPC. On average, it takes 2.0 (±0.7) trials, including 0.4 (±0.6) failed trials, to design a path with EPC, while it takes 3.2 (±2.1) trials, including 1.6 (±1.5) failed trials, to design a path with GUI.

5.3.2 Complementarity of EPC and GUI

We compared also the paths designed by EPC&GUI (group C) with those designed by EPC (group A) and GUI (group B) in step 1, and observed that:

- The paths designed by EPC&GUI are significantly shorter than those by EPC ($p<0.0151$), but longer than those by GUI ($p<0.0027$).
- There are no significant differences in safety between the paths designed by EPC&GUI and by EPC ($p>0.6317$), and between EPC&GUI and GUI ($p>0.4694$).
- The paths designed by EPC&GUI are significantly smoother than those designed by EPC ($p<0.0212$), and by GUI ($p<0.0099$).

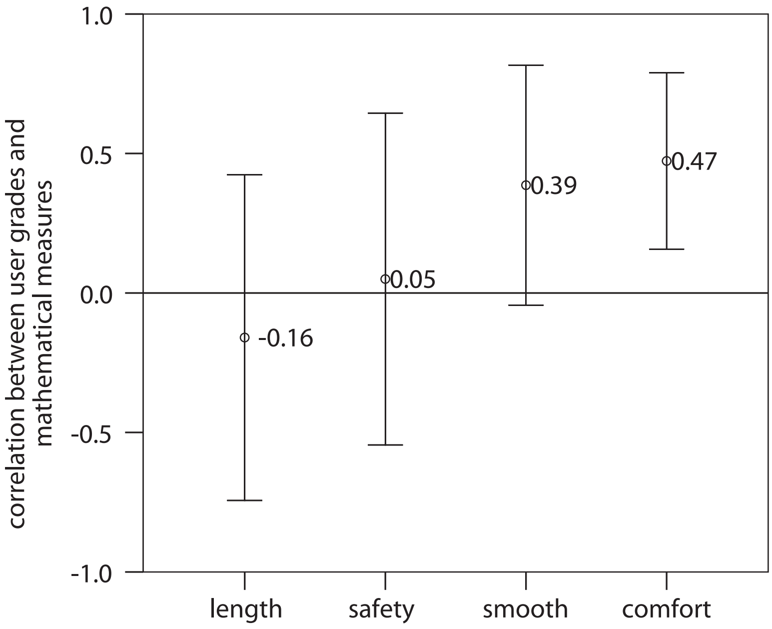


Figure 5.4: The correlationship between the user grades and four mathematical measures. Error bars show 95% confidence interval of mean. Numbers beside error bars indicates means.

- The paths designed by EPC&GUI tend to be significantly more comfortable than those designed by either EPC (p=0.0592) or GUI (p=0.0576).

5.3.3 Relationship between user grades and path features

What does the user consider to be the most significant path feature when evaluating the path ergonomics? To examine this question we computed, for each subject, the mathematical measures of length, safety, smoothness, and comfort for the 3 paths created in the steps 1-3 of Table 5.1, and calculated the correlation coefficients between these measures and the user grades in step 4 using Spearman's Rank Correlation.

The results are shown in Fig. 5.4. Both smoothness and comfort are positively correlated with subjective grades, while safety and path length are not. We note that as the path lengths variations between different trials are small (14.86($\pm$0.20)m), they may not have been perceived by the subjects.

5.3.4 Questionnaire on path design tools

Table 5.3: List of important features for an ergonomic path as ranked by the subjects

ranking	User rank
1	safety
2	comfort
3	smoothness
4	short path
5	little maneuvering effort

The questionnaire filled by subjects at the end of the tests complements the quantitative results on an ergonomic path. The subjects first listed the features for ergonomic paths in the order of importance as shown in Table 5.3. They then had to answer four questions as shown in Fig. 5.5. The results reveal that:

- The subjects found it “easy” to learn using EPC. They rated similarly for GUI and EPC&GUI ($p>0.8695$), which are “average” to “easy”. The differences are not significant between EPC and GUI ($p>0.3198$), nor between EPC and EPC&GUI ($p>0.2874$).
- They found it “average” to “easy” to design wheelchair paths with EPC and EPC&GUI (these are rated similarly as $p>0.7115$), and “average” for GUI. The difference between EPC and GUI is significant ($p<0.0135$), as well as between EPC&GUI and GUI ($p<0.0370$).
- They found EPC&GUI is a “good” to “excellent” method to design wheelchair paths, EPC is an “average” to “good” method, and GUI is an “average” method. The difference between EPC&GUI and GUI is significant ($p<0.0095$),
- The subjects chose “maybe” to “yes” to use EPC and EPC&GUI to design wheelchair paths, but “no” to “maybe” to use GUI. They prefer EPC to GUI, i.e. the difference is significant ($p<0.0234$), and they strongly prefer EPC&GUI to GUI, with a highly significant difference ($p<0.001$).

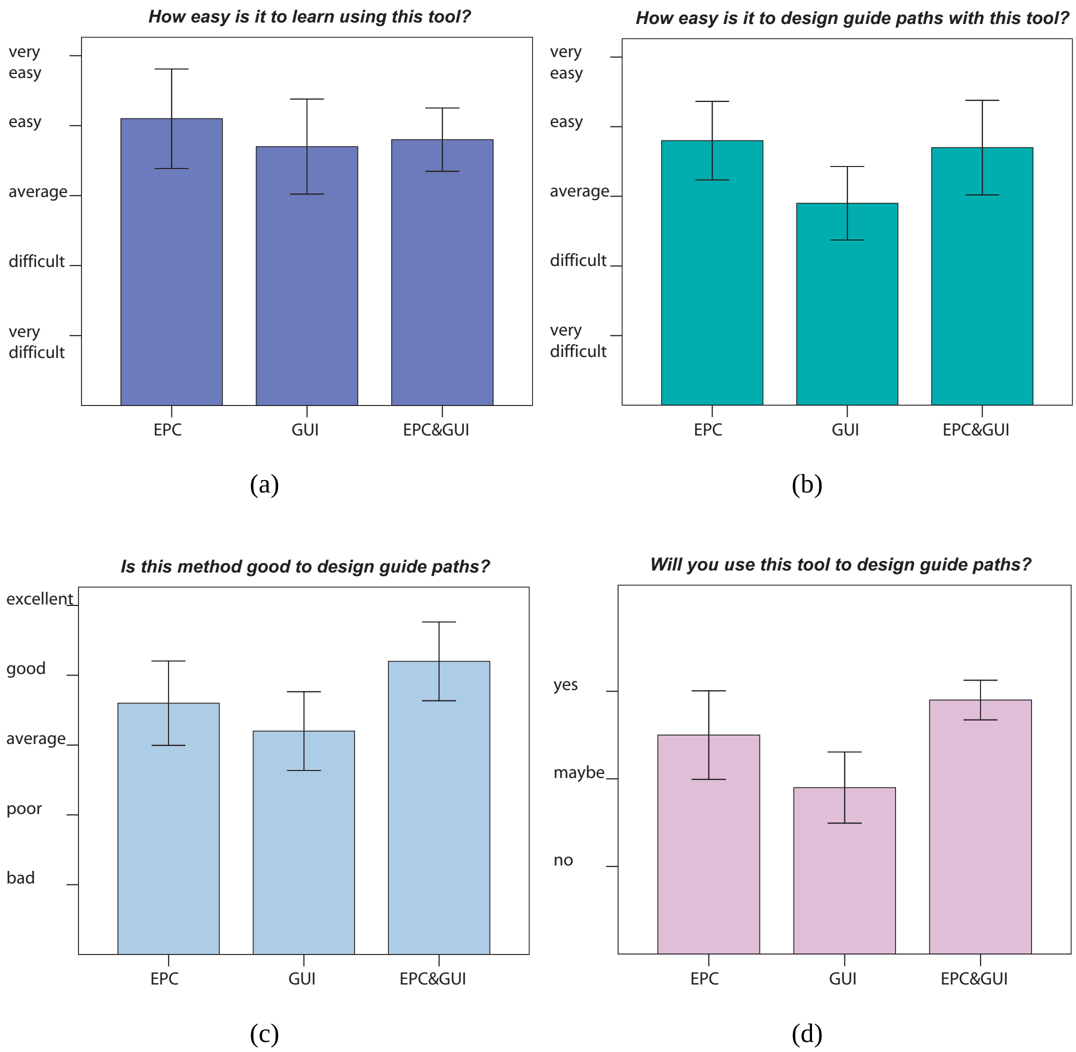


Figure 5.5: Questionnaire results on path design tools. Error bars show 95% confidence interval of mean.

5.4 Discussion

This section examines the efficiency of the design tools in adapting guide paths to changes in the environment and analyzes how the subjects use them. In addition, it gives some insight into ergonomic factors for guide paths.

Necessity and complementarity of EPC and GUI

In an unstructured environment, it is difficult to provide a precise and reliable map, especially for environments filled with (moving) humans. The EPC is very useful in this case, as it enables users to modify the path or to avoid the obstacles *online*. In contrast, if a subject uses the GUI to modify a path, the modification relies on the subject's spatial representation capabilities and may not be very accurate unless a precise map is available. This explains why paths designed by EPC are safer than that by GUI, and fewer trials and fewer failed trials are necessary to design satisfactory guide paths with EPC than with GUI, as was found in Section 5.3.1. In addition, the experimental results also show that the design experience in GUI does not help the design in EPC.

In view of these potential disadvantages, is the GUI unsuitable as a path design tool? As shown in Section 5.3.2, the paths designed by EPC&GUI are superior to those designed by EPC (and GUI) alone in terms of smoothness and comfort. In addition, relative to those designed by EPC, the paths designed by EPC&GUI are shorter, and do not compromise the safety margin relative to the paths designed by EPC. Therefore the GUI should not be discarded, but used together with the EPC.

Correspondingly, in the questionnaire, the subjects were satisfied most by EPC&GUI. The user feedback in Section 5.3.4 shows that none of the subjects found it difficult to learn and use the tools, and they found that EPC&GUI is a good method and would use it to design guide paths, while GUI was graded last in all aspects.

Collaborative learning

We observe that when they can use both EPC&GUI, the subjects all chose to start with EPC in order to trace a guide path, which they could then modify using GUI. The previous analysis suggests that the subjects used GUI to improve the path ergonomics and shorten the path. Therefore, we propose the following *collaborative learning strategy* to design paths for unstructured and dynamic environments:

(1) An initial path can be created using the WTP, i.e. the wheelchair user or a helper moves the wheelchair and so teaches the guide path to the system.

(2) The EPC can be used to deal with changes in the environment affecting a guide path, and to improve a guide path.

(3) The GUI can be used to improve the ergonomics of an existing path, in particular to reduce the jerkiness of a path.

(4) If a path requires many changes in practice, the designer should go back to step 1) and trace a new path.

Ergonomic path

What are the characteristics of *ergonomic paths*, i.e. paths providing the best path guidance assistance for wheelchair users? We analyzed the correlationship between the user grades and the quantified path features in length, safety, smoothness, and comfort. Length was the least important factor, in particular as the differences in length were small.

Despite the fact that safety was ranked the highest by the subjects in the questionnaire, their grades are positively correlated with smoothness and comfort but not with safety. In fact, the collected paths were all safe paths, as they can carry the user safely in the environment. Therefore, our interpretation is that the users put more weight on smoothness and comfort once they are ensured the path has sufficient safety margin to maneuver. In view of these results, we propose that ergonomic paths for a wheelchair are safe paths, which are considered to be smooth and comfortable by the human user.

5.5 Conclusion

This chapter explored the issue of path planning for a wheelchair. We proposed a collaborative learning strategy, which envisions that the human operator and the robot interact to create and gradually improve a guide path using the provided design tools: a graphical user interface (GUI) on which a path can be manipulated *offline* using a few attraction points, and an elastic path controller (EPC), which enables the *online* path modification. Fifteen able-bodied subjects adapted a given guide path to the modified environmental condition. We used mathematical measures to analyze these paths in terms of the identified ergonomic factors of a guide path, including length, safety, smoothness, and comfort. This was then complemented by a questionnaire filled out by the subjects after the experiments. The results from these experiments and user evaluation showed the utility and complementarity of these design tools. The subjects, with little learning, were able to use them to design guide paths, and were satisfied. Further, the analysis on ergonomic paths, i.e. paths providing the best guidance, showed that the users put more weight on smoothness and comfort once they are ensured that the path has sufficient safety margin to maneuver, while length was the least important factor, in particular as the differences in length were small.

Chapter 6

Evaluation with Patients

6.1 Introduction

While considerable effort has been devoted to developing robotic wheelchairs, relatively little attention has been paid to evaluating their performances [43], and very few papers report results with disabled subjects, the real end users. In addition, conducting user trials with robotic wheelchairs is difficult for several reasons. Some wheelchair users do not show any immediate improvement in their navigation skills. This could be because the user is already so proficient that little improvement is possible, or conversely that the cognitive or physical impairment can be so severe that improvements are limited within a short time span. Users who have the potential to show large performance improvements often have little or no experience with independent mobility, and may need a significant amount of training before they could reach acceptable performance.

One of the few systems with reported evaluations by able-bodied and disabled subjects is the Hephaestus Smart Wheelchair System [44], which assists the user to avoid obstacles. It was found that able-bodied subjects performed better without this assistance and in fact, preferred not to use it as they felt that the attempts to modify their input were more intrusive than helpful. The cerebral palsy and post-polio subjects testing this system indicated that they liked the sense of security it provided, despite the fact that tests showed that the system generally did not lead to any immediate improvements in performance.

Another wheelchair system which was tested with disabled subjects is the UK CALL Center Smart Wheelchair [16]. It is equipped with selectable tools such as line following, collision detection, communication aids, etc., and was used by children to learn how to drive a wheelchair . The study with children with different disabilities indicates that the increase in mobility has wide ranging and powerful effects on learning, communication, motivation and social interaction.

This chapter reports the clinical evaluation of the CWA system. Three cerebral palsy (CP) and two traumatic brain injury (TBI) individuals performed experiments to evaluate the CWA (Fig. 1.1b). All subjects had previously been ruled out as candidates for independent mobility by conservative prescription criteria. Through this research, we explore whether and how path guidance can help in wheelchair control, and how the use of the CWA system can be adapted to particular disabilities.

6.2 Methods

6.2.1 Experiments

Subjects

Five (4 male, 1 female) subjects, aged between 16 and 48, were informed about the experiments and they or their guardians gave their consent before performing the experiments. These CP and TBI subjects were selected from amongst clients of the Singapore Society for the Physical Disabled (SPD). All subjects were initially not able to use a conventional powered wheelchair.

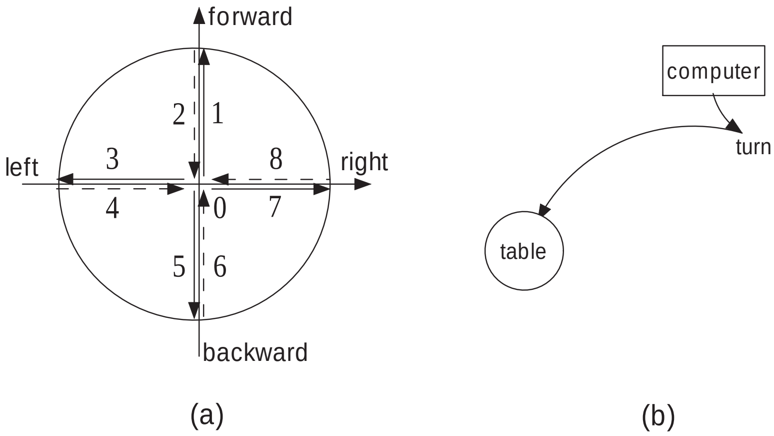


Figure 6.1: Evaluation of motor condition on disabled subjects. (a) Joystick movements are performed in the forward, left, backward, and right directions, repeatedly. (b) Controlling the wheelchair from a computer to a table with and without path guidance assistance.

Pre-training

The operation of the joystick was first explained to the subjects. They were then instructed to repeatedly move the joystick in the forward, left, backward, and right directions (Fig. 6.1a), with the motors switched off. They were required to reach the maximum in a direction, and then back to the zero position, before moving in the next direction.

The subjects were then told how to use the free and guided modes. Then a simple driving test was performed in two modes, consisting of driving the wheelchair from a computer to a table in an obstacle-free environment shown in Fig. 6.1b.

Training

The subjects received training in the use of the CWA system. Basic driving skills were first trained, such as moving forward, backward and turning using path guidance assistance, i.e., driving in GM. Advanced driving skills were trained, such as driving the wheelchair along different paths while tuning the speed, and using the elastic mode

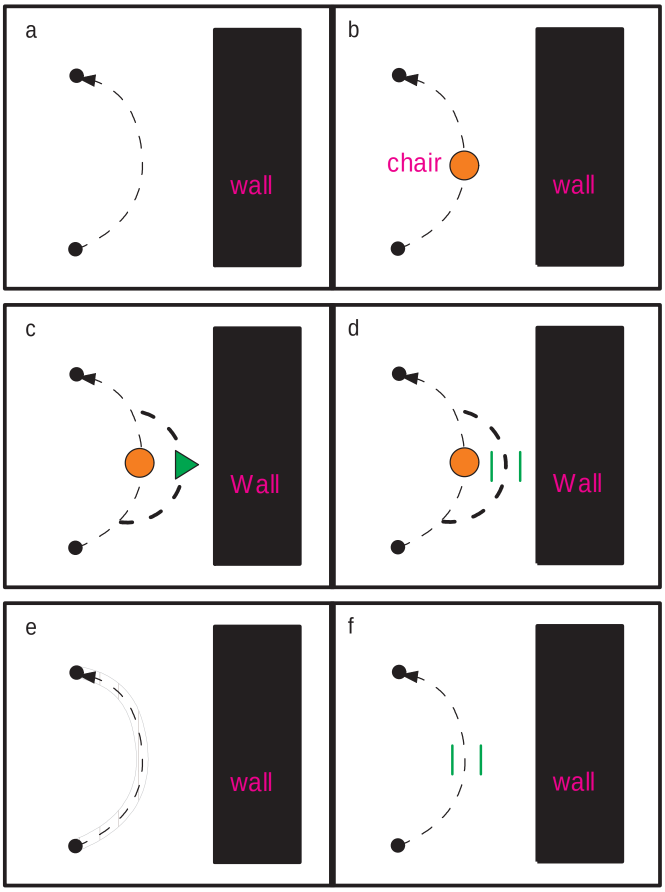


Figure 6.2: Training for the disabled subjects to drive with the CWA. The top panels show the environments used to train driving in GM (a) and in EM (b). The middle panels illustrate the tests for driving with path guidance. The first test consists of successfully passing through the marked area for three trials (c), the second to successfully pass through the (84*cm* wide) doorway once (d). The bottom panels illustrate the evaluation of driving without path guidance. A first test consists of following a path drawn on the floor for three trials (e). The wheelchair can maximally deviate 15*cm* from the nominal path during the movement. The second test is to pass through the 84*cm* wide doorway for three trials without bumping into it (f).

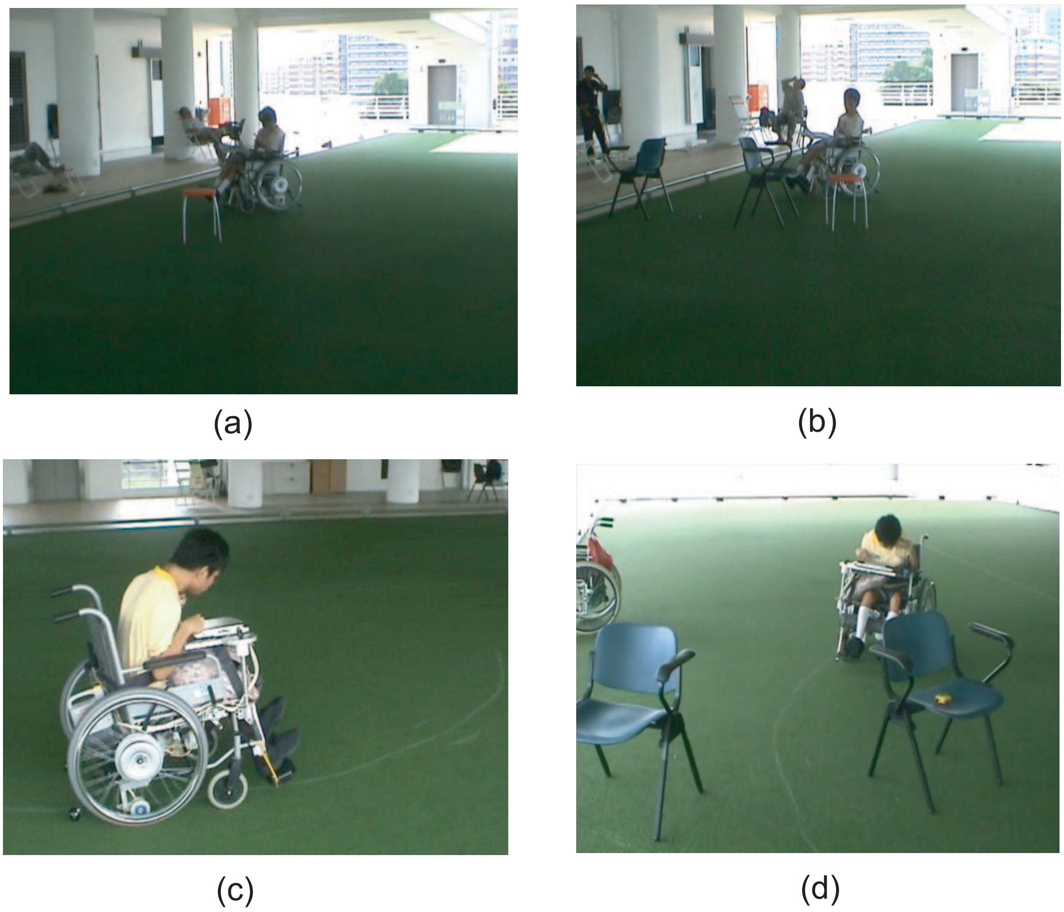


Figure 6.3: Photos of training environments. (a)(b)(c)(d) correspond to Fig.6.2(c)(d)(e)(f).

(EM) to deviate from the reference path in order to avoid obstacles. They had to meet the requirements of a given step before progressing to the next one.

Driving with path guidance The operation in GM was explained to the subject, who then experienced this motion mode by moving along a straight line. The subject had to experience motion guidance along the nominal path of Fig.6.2a for at least two trials in the forward and backward direction until (s)he claimed to understand how to operate the system in GM.

The Elastic Mode tool was explained to the subject and experienced by letting him or her avoid a chair placed on a 8*m* long straight path (twice on each side). Then a chair was placed on the previous nominal path, as shown in Fig. 6.2b. The task in this session was to move along the nominal path and use EM to avoid the chair. Two evaluations were performed as shown in Fig. 6.2c,d. A test was considered as failed if the subject could not complete the task in 10 trials. The subject had to complete the first test before starting with the second.

Driving without path guidance The final training session was for the subject to learn driving skills such as forward, backward, turning, and driving to different destinations in free mode, i.e. without path guidance. To evaluate if a subject was able to drive in FM, two evaluations were conducted as shown in Fig. 6.2e,f. The subject had to complete the first test before starting with the second. Either of these tests was considered as failed if it was not successfully completed within 10 trials.

Navigation test

After the training was completed, the subject was tested on a navigation task. This task had been previously tested with able-bodied subjects in Section 4.2.2 of Chapter 4 and so their performances could be compared.

Each subject had to perform a series of 10 trials alternating between the two control modes: free mode (FM) and guided mode (GM), i.e. without and with robotic assistance, in the order of FM, GM, FM, etc. The subject was instructed to minimize the movements of the joystick.

6.2.2 Data analysis

Aspects of human-machine interaction such as driving behavior, required effort, safety, were analyzed.

The *time to complete the task* and a *safety measure* consisting of the total number of collisions that occurred in a trial were computed.

User interaction was evaluated by analyzing the user's maneuvering on the joystick control interface (recorded at 50*Hz*). Two important features: *joystick move* and *intervention level* as defined in Section 4.2.4 of Chapter 4.

The frequency content of the (parallel or normal) joystick input was computed using Fast Fourier Transform (FFT). Since the joystick input was recorded at 50*Hz*, the spectrum was analyzed in [0, 25]*Hz* (for instance, see Figure 6.4). The tremor, typically in [3,12]*Hz*, is contained in this interval (see the details in [45]). Therefore, the total frequency content and tremor frequency content are defined using the amplitude integrals of FFT over these intervals.

Directional *t*-tests were used to compare data in GM versus FM, after Lilliefors tests checked that these data were normally distributed. The null hypothesis is that the means of the given groups of samples are equal. A p-value of less than 5% means that the hypothesis is rejected, corresponding to a significant difference.

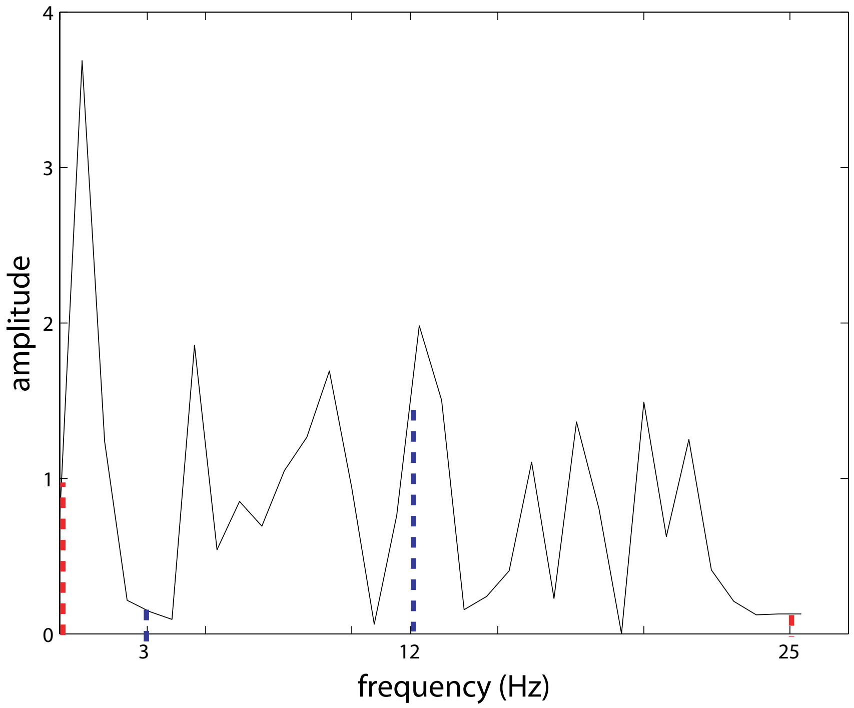


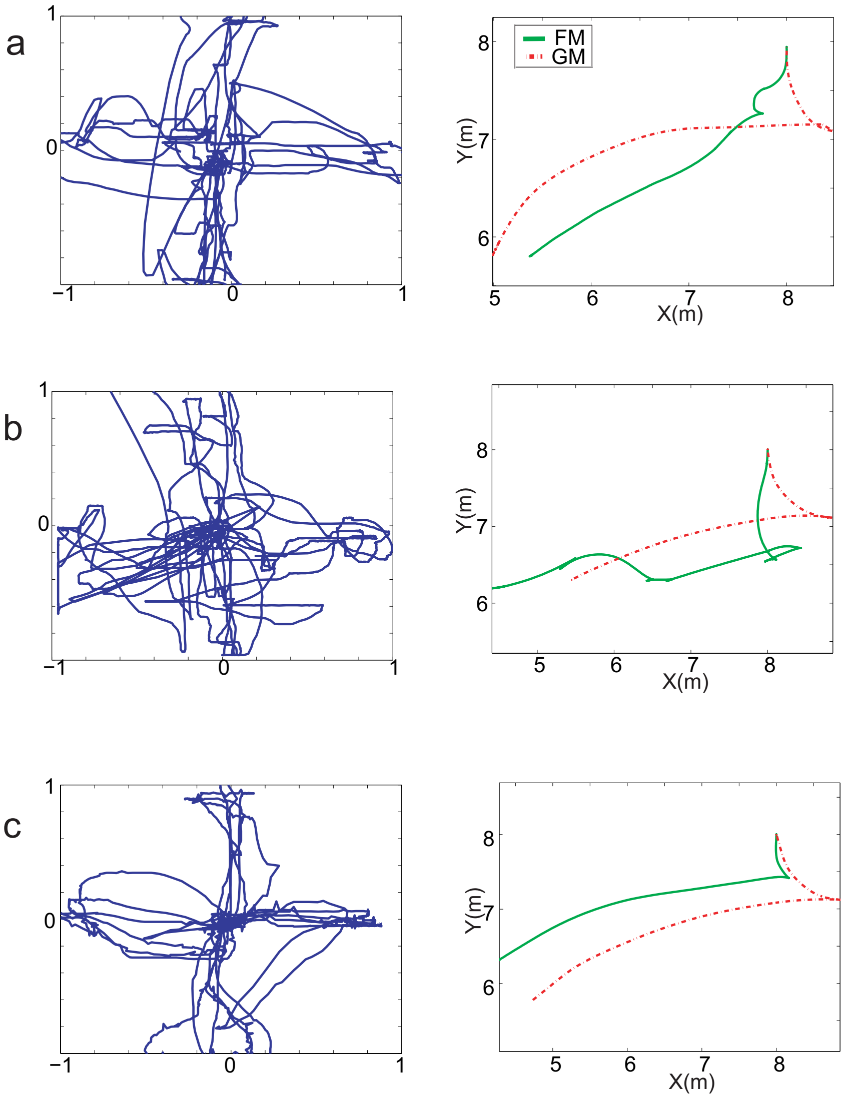
Figure 6.4: Typical frequency spectrum of the joystick input. The total frequency content is the area within [0,25]*Hz*, and tremor frequency content is the area within [3,12]*Hz*.

6.3 Initial Motor Control Assessment

The selected subjects have distinct affects, and so differ widely in motor control performance. Therefore, we start by presenting them one by one before examining the overall behavior and comparing with the behavior of able-bodied subjects.

6.3.1 Subject A

Subject A is a 26 years old (at the time of the experiments) male with CP. Because he suffers from large involuntary motion of his arms, he is unable to control a powered wheelchair by fine movement. He has good understanding but cannot talk clearly, and so comes to SPD for learning how to use communication devices and computers, on which he types with a stick holding with his left hand. Subject A needs assistance to


a
b
c
FM
GM
X(m)
Y(m)

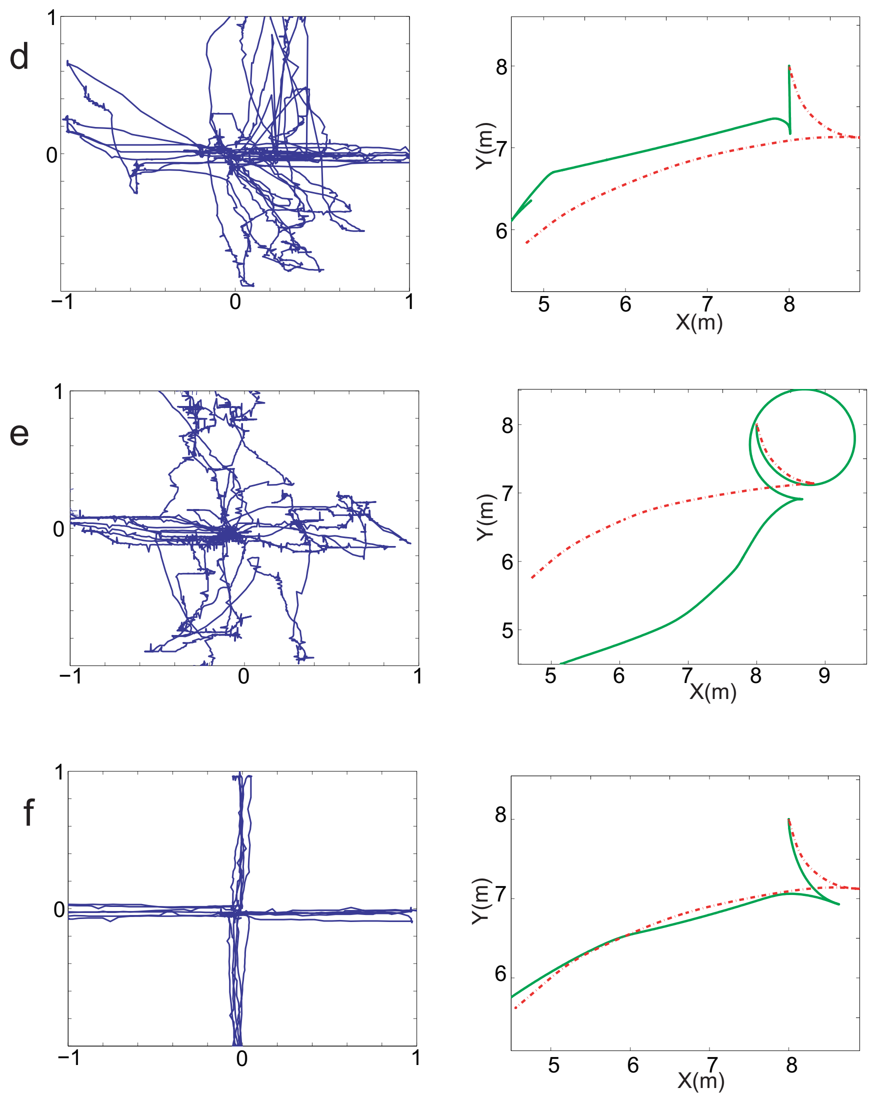


Figure 6.5: Initial assessment of subjects A to E and comparison with a typical able bodied behavior (F). Left column: The last three trials of reaching movements in 4 directions in the order of forward, left, backward, and right. Right column: Driving the wheelchair in guided mode (dashed) and free mode (solid line).

be brought from one place to the other, and as a consequence has to stay at home most of the time. At home he uses a manual wheelchair which he pushes backwards with his feet.

To let subject A control the wheelchair, the joystick was first moved close to him so that he could reach it easily. When holding his right hand, we felt very large involuntary force in the left and right directions relative to his upper body. This prevents him from using a normal powered wheelchair.

The initial assessment showed that the patient could move the joystick in forward and backward directions. However, even after practice he still had problems in accurately moving it to the left and right directions. Fig.6.5A(left) shows the last three trials, i.e. trials 13 to 15.

Successful trajectories of driving from computer to table in FM and GM are shown in Figure6.5A(right). The movement without assistance is jerky. It is observed that the patient could not control his hand very well when moving forward. Furthermore, the patient is unable to maneuver the wheelchair backwards, as he always turned it to the wrong way. Both parallel and normal inputs had much smaller frequency contents in GM than in FM (see Figure 6.6). The tremor was greatly reduced in GM, suggesting that path guidance indeed simplified the control for this subject.

6.3.2 Subject B

Subject B is a 23 years old male with CP who receives day care at SPD. He has no problem in speaking or understanding, but is very sensitive and gets irritated easily. He has a manual wheelchair but has to rely on a caregiver to push it. He has no prior experience with a powered wheelchair.

Subject B first tried to control the joystick with his left hand. However the result was not very good. As his elbow seemed to be very tight, we placed his arm on the arm rest for a larger reaching range. He had learned to use Pathfinder (a communication device, see http://www.prentrom.com) with his little finger, and so we let him grip and move the lever with his ring and little finger in all directions. In this way, he was more relaxed and could successfully activate the joystick. After successfully running the system on the guide path in GM, he was happy to control the joystick by himself and, given the new-found mobility, was eager to continue the training. When he holds the lever, his body tends to shrink, and thus cushions are used to support his body and strains are added to prevent him from slipping off.

Fig. 6.5B(left) shows the last three trials (i.e. trials 18 to 20) performed by subject B for moving the joystick in four directions. He could push the lever forward and left easily, but had problems in moving it backwards and could hardly move it to his right.

Paths from computer to table performed in FM and GM are shown in Figure 6.5B(right). In GM, he could use the system easily. When he moved in FM, the performance was very poor, perhaps due to a lack of driving experience and inability to control the joystick properly. While driving, he tends to look down at his left hand instead of ahead. It seemed very difficult for him to extend his arm in order to hold the joystick. His whole body shrank when he tried to control the joystick, and he often had to stop due to spasticity. Both parallel and normal inputs had much smaller frequency contents in GM than in FM (see Figure 6.6). The tremor was greatly reduced in GM, suggesting that path guidance did simplify motion control for this subject.

6.3.3 Subject C

Subject C is a 48 years old male with CP who receives day care at SPD. He cannot talk clearly and so uses a Lightwriter (a communication device, see http://www.prentrom.com). He has used a powered wheelchair within SPD about 7 years ago, but as he ran into people frequently, he is now using a manual wheelchair, which he pushes slowly by using his right hand.

When he used the index finger of the left hand to type on a speech generating device, we

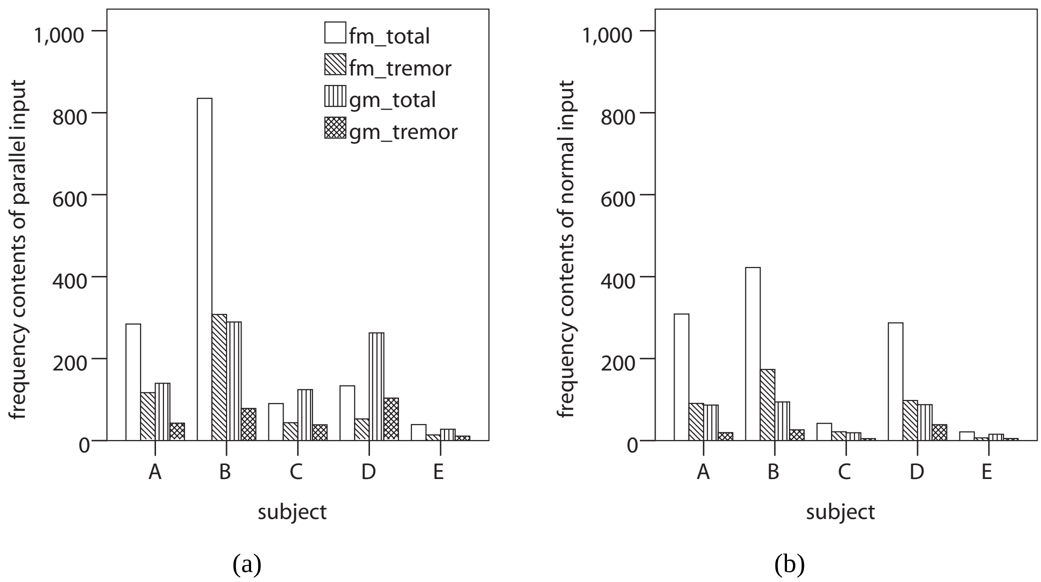


Figure 6.6: Total frequency spectrum and tremor area of parallel input (a) and normal input (b) in free and guided motions during initial assessment (right column of Figure 6.5).

noticed a lot of involuntary movement which rendered his typing inaccurate. However, when he controlled the joystick with the left hand holding the lever, the movement was much more stable, and so we adopted this method for him to control the wheelchair. Cushions were added to support his body, as well as seat belts to prevent him from slipping off.

Figure 6.5C(left) shows the three last trials (i.e. trials 18 to 20) performed by subject C for moving the joystick in four directions. He could control the joystick well compared to the other subjects, but had some involuntary movements and some deficit moving in the right and backward directions. The path from the computer to the table demonstrated his good driving ability. However, he was easily distracted by other people or sound encountered during driving. The normal input had a much smaller frequency content in GM than in FM, but parallel input did not (see Figure 6.6).

6.3.4 Subject D

Subject D is a 28 years old female with TBI due to a car accident which occurred when she was 22 years old. She comes to SPD to learn to talk using a speech device. She has a manual wheelchair which is pushed by the caregiver. Her mother thinks that her condition has improved significantly in the last five years, and she wants to see if her daughter can use a powered wheelchair in the future. The subject cannot control her left arm and right leg. She also gets tired easily and can normally concentrate for only about 10 minutes before she has to rest.

Subject D could catch the joystick with the right hand easily. When she drove the wheelchair straight, she could not control her strength and always moved the lever instantly to the maximum. She did not know to stop before running into people and obstacles. She was very curious about the surrounding and easily forgot that she was driving.

We observe in the last three trails (i.e. trials 18 to 20) in the four directions (see Figure6.5D(left)) that she did not have much tremor, but that her control was inaccurate. The forward and backward movements were fine, but as she could not control her strength well, she bent the lever too much. Left and right movements were also not accurate. She was unable to move left even after several rounds of trials. The trajectories of moving from computer to table with and without path guidance (see Figure 6.5D(right)) were not bad, but exhibited sudden changes. The normal move was greatly reduced in GM, but the parallel input was not (see Figure 6.6).

6.3.5 Subject E

Subject E is a 16 years old male with TBI due to a car accident, which happened when he was 6 years old. He comes to SPD to use the augmentative speech device. He can spell word by word to communicate with people. However, his actions are very slow and he is often using the index finger of his right hand to point at things. Once he gets tired, the test cannot continue on the same day. He also has very poor concentration and he would often latch on to an idea or activity and persist with it. He uses a manual wheelchair and relies on the caregiver to push it. His parents have just bought him a powered wheelchair to use at home, with which he ran into people several times due to lack of attention.

We noted that he has very little power in his wrist, which felt limp. Hence, when he used his arm to push the joystick, his hand will bent over. When holding his wrist, we could feel that his arm was quite strong but the wrist joint did not function. We hoped that a wrist restraint could keep it straight, but he refused to wear the restraint, which he felt was too tight. Hence, we lowered down the joystick position so that his arm could extend more. Then his hand tried to hold the lever in different ways to move the wheelchair straight. It took a while for him to realize that holding the lever in his palm was more effective than pushing it with one or two fingers. Using his palm, he tried path guidance from the computer to the desk and he was very happy when he could complete the move. However, he tended to lose his concentration and would revert to activating the lever with his finger.

Subject E performed the joystick movement assessment in the four directions for 10 times. The paths of the last three trials are shown in Figure6.5E(left). This subject had little tremors in his hand. Through practice, the tremor was reduced significantly in the lateral left and right directions. However, the movement was still not as good as in the forward and backward directions. The range of his hand movement was also very limited.

The paths used in FM and GM when moving from computer to table (see Figure6.5E(right)) illustrate that this subject could drive in GM but not in FM, as he was insufficiently aware of his environment. Once he held the joystick in some 'comfortable' position, he would like to keep it there without noticing his surrounding, in particular when moving the wheelchair backward. Therefore, even though his motor control was not very bad, we felt that he should not drive a powered wheelchair independently if not in a controlled and safe environment. Both parallel and normal inputs had much smaller frequency

Table 6.1: Number of trials taken by disabled subjects to complete training tests.

subject	A	B	C	D	E
EM test of Fig.6.2c (min=3)	3	6	3	5	fail
EM test of Fig.6.2d (min=1)	1	4	2	5	n.a.
FM test of Fig.6.2e (min=3)	3	8	3	6	fail
FM test of Fig.6.2f (min=3)	4	6	3	5	n.a.

contents in GM than in FM (see Figure 6.6).

6.4 Performance with the CWA

6.4.1 Training

All the subjects were able to drive in guided mode. The results for tests in Fig. 6.2c,d,e,f are given in Table. 6.1. After training, all, but subject E, were able to drive in elastic mode. While the same four subjects passed the free mode test, subjects B and D required more trials to succeed. Typical trajectories during the tests are shown in Figs. 6.7 and 6.8.

6.4.2 Navigation test

Subjects A,B,C,D could complete the five trials of the navigation test (Fig. 4.1) in both FM and GM. Subject E could drive in GM only. So while his data are shown in Figs.6.10,6.11, the comparison between FM and GM is performed with the data of subjects A,B,C,D only.

The mean time spent to complete the navigation task and mean number of collisions over five trials are given in Table 6.2, and the mean and standard deviation are given in Table 6.3. Collisions happened in FM for every subject, but no collision happened in GM. The time to complete the task was not significantly changed between the first and fifth trials in FM ($p>0.790$) and GM ($p>0.405$), suggesting that the training was

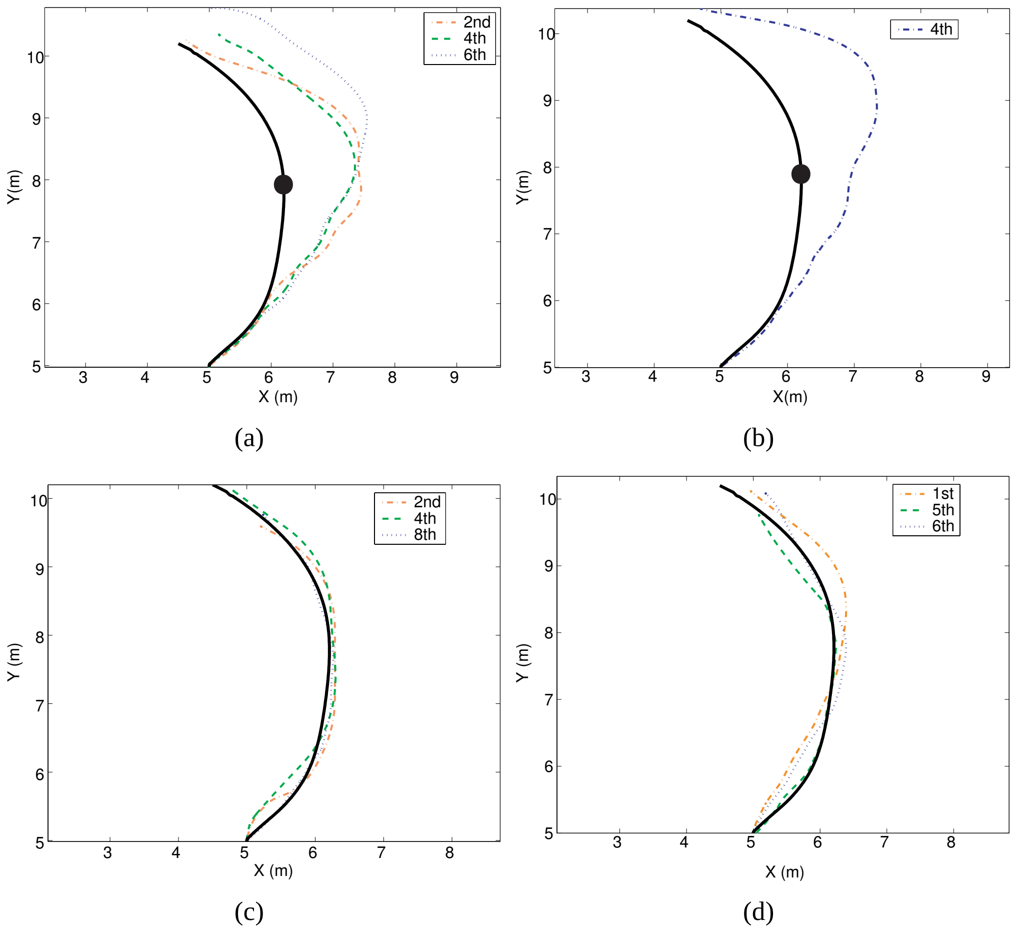


Figure 6.7: Paths of subject B for successful trials in the tests of Figure 6.2c,d,e,f for driving with path guidance (A,B) and without path guidance (C,D). The solid line represents the nominal path and the circle represents the chair used as an obstacle.

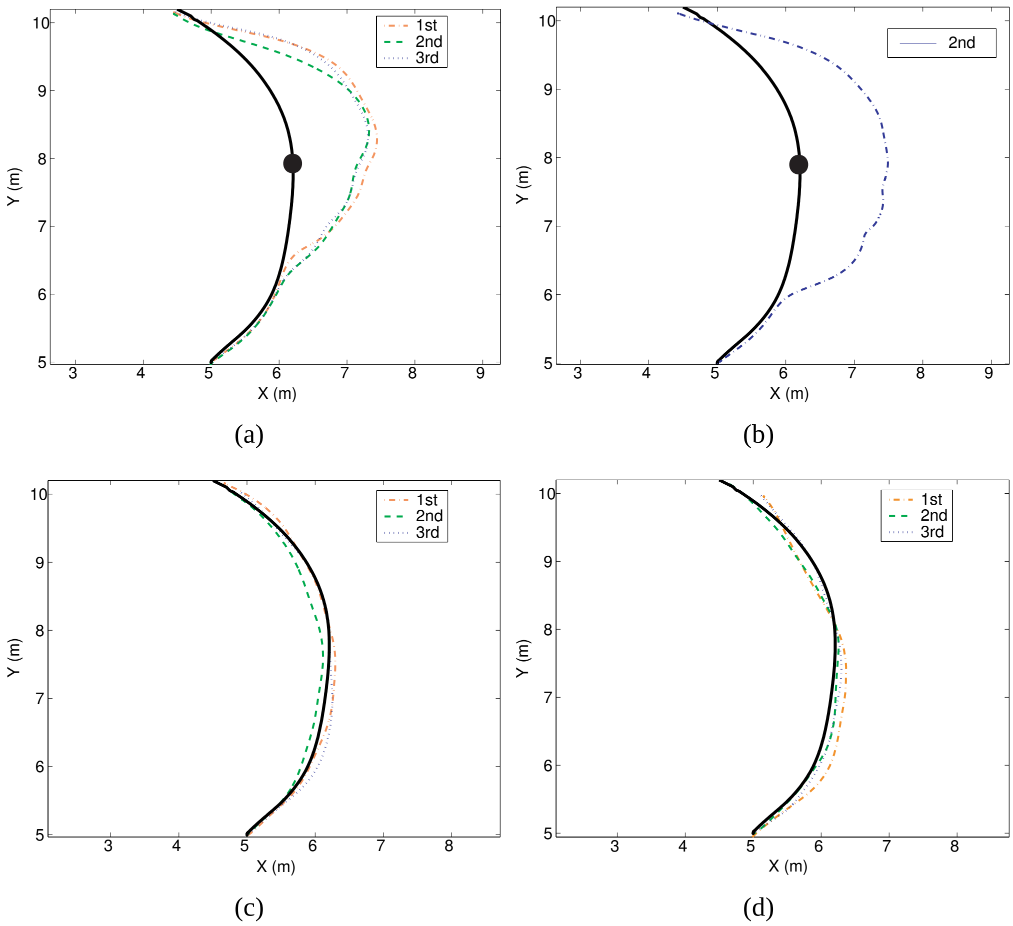


Figure 6.8: Paths of subject C for successful trials in the tests of Figure 6.2c,d,e,f for driving with path guidance (A,B) and without path guidance (C,D). The solid line represents the nominal path and the circle represents the chair used as an obstacle.

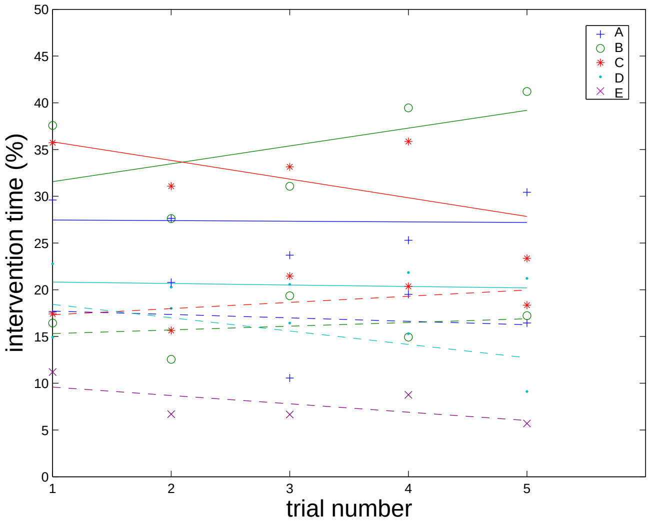
Table 6.2: Time to complete the navigation task and number of collisions over five trials.

Subject A			Subject D		
Condition	Time (sec)	Collision	Condition	Time (sec)	Collision
fm1	71.7	0	fm1	86.5	1
fm2	58.84	1	fm2	109.26	5
fm3	63.04	0	fm3	80.94	1
fm4	66.82	0	fm4	73.44	0
fm5	67.82	0	fm5	94.96	3
gm1	56.04	0	gm1	62.52	0
gm2	63.96	0	gm2	67.76	0
gm3	64.04	0	gm3	68.52	0
gm4	65.48	0	gm4	67.86	0
gm5	58.96	0	gm5	66.9	0
Subject B			Subject E		
Condition	Time (sec)	Collision	Condition	Time (sec)	Collision
fm1	81.18	1	fm1		
fm2	113.94	1	fm2		
fm3	95.66	2	fm3		
fm4	101.14	3	fm4		
fm5	120.58	2	fm5		
gm1	112.32	0	gm1	216.26	0
gm2	160.82	0	gm2	225.48	0
gm3	67.38	0	gm3	217.48	0
gm4	103.66	0	gm4	309.92	0
gm5	93.22	0	gm5	237.16	0
Subject C					
Condition	Time (sec)	Collision			
fm1	65.6	1			
fm2	55.6	0			
fm3	56.48	1			
fm4	53.88	0			
fm5	68.32	1			
gm1	63.98	0			
gm2	62.4	0			
gm3	62.44	0			
gm4	63.94	0			
gm5	60.58	0			

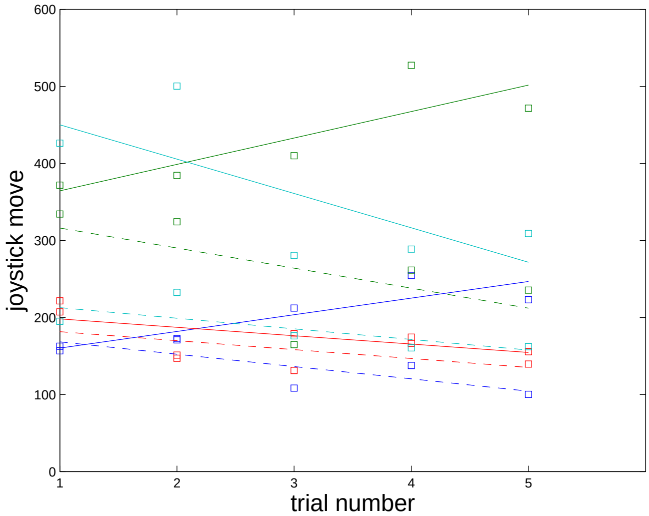
Table 6.3: Mean (standard error) of time to complete the navigation task and number of collisions happened over five trials.

	time (seconds)		no. of collisions	
subject	FM	GM	FM	GM
A	65.64(2.19)	61.70(1.79)	0.2(0.20)	0(0)
B	102.50(6.93)	107.48(15.32)	1.8(0.38)	0(0)
C	59.98(2.91)	62.67(0.63)	0.6(0.25)	0(0)
D	89.02(6.16)	66.71(1.07)	2.0(0.89)	0(0)
E	n.a.	241.26(17.57)	n.a.	0(0)

sufficient. The task completion time was not significantly different in FM and GM ($p>0.183$) and equal to about twice the mean time taken by the able-bodied subjects of Chapter 4.



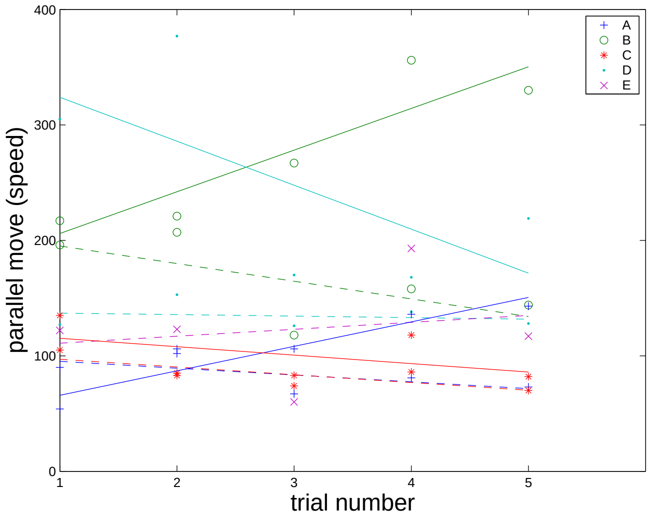
(a)



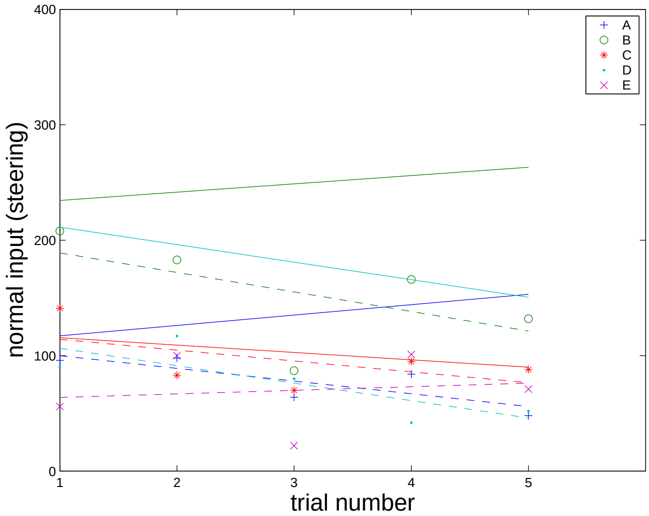
(b)

Figure 6.9: Intervention time (a) and joystick move (b) in all the trials

As shown in Fig. 6.9a, the intervention time was significantly larger in FM than in GM ($p<0.0001$) over the five subjects. No significant decrease was observed between the first and fifth trials in FM ($p>0.343$) or GM ($p>0.285$). In addition, the number of non-extreme positions visited during movement was significantly smaller in GM than in FM ($p<0.01$). The time spent outside the extreme positions tended to be significantly less



(a)



(b)

Figure 6.10: Parallel move (a) and normal move (b) in all the trials.

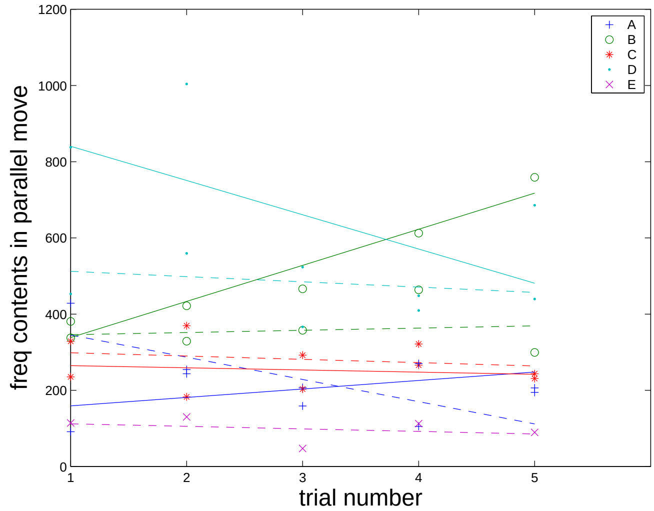
in GM than in FM ($p<0.052$).

As shown in Fig. 6.9b, the *total joystick move* was significantly smaller in GM than in FM ($p<0.002$). For every subject, even the maximum value in GM was clearly smaller than the minimum value in FM. The slope of the least-square (LS) straight line was not significantly negative in FM ($p>0.502$), but was negative in GM ($p<0.007$, mean slope $\bar{s} = -16.84$), indicating a decrease of total joystick movement in GM. *Parallel move* was significantly larger in FM as in GM ($p<0.002$, Fig.6.10a). The LS straight fit had a significantly negative slope in GM ($p<0.044$, $\bar{s} = -7.3$) but not in FM ($p>0.566$), indicating a decrease of joystick move in GM. *Normal move* in FM was also significantly larger than that in GM ($p<0.0004$, Fig.6.10b). Negative slope of the LS fit of the straight line in GM ($p<0.003$, $\bar{s} = -13.10$) indicated a decrease of normal move, while this slope was not negative in FM ($p>0.414$).

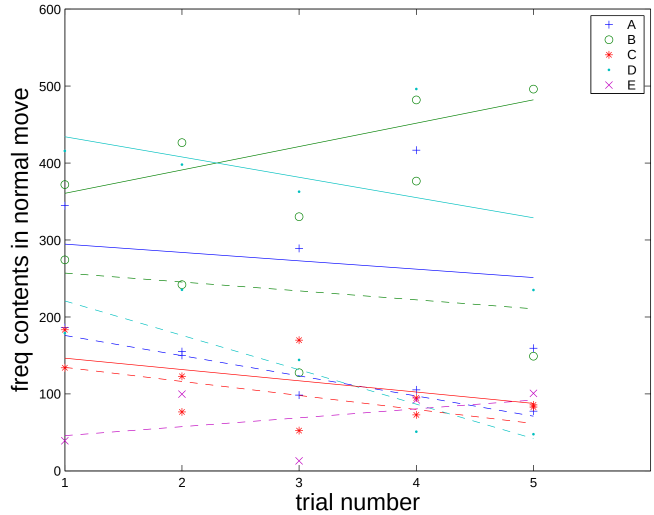
The *frequency content* of parallel input was significantly smaller in GM than that in FM ($p<0.0252$) (Fig. 6.11) and no significantly negative slope of the LS fit was observed in FM ($p>0.551$) or in GM ($p>0.133$). The *tremor content* of parallel input was not significantly different in FM or GM ($p>0.067$) (Fig. 6.12), and no significantly negative slope was observed in the LS fit in FM ($p>0.233$) or in GM ($p>0.369$).

The *frequency content of normal input* was significantly smaller in GM than that in FM ($p<0.0005$), (Fig. 6.11) and significantly negative slope was observed in the LS fit of normal input in GM ($p<0.020$) but not in FM ($p>0.346$). The tremor content in GM tends to significantly smaller than in FM ($p<0.0005$) (Fig. 6.12) and significantly negative slope of LS fit was observed in GM ($p<0.022$, $\bar{s} = -10.86$) but not in FM ($p>0.066$).

The relationship between the total frequency contents of parallel and normal inputs are shown in Figure6.13. As expected, parallel and normal inputs are positively correlated in FM, both for disabled subjects (c=0.5) and able-bodied subjects (c=0.7). In GM, they are weakly correlated for disabled subjects (c=0.3) and somehow anticorrelated for able-bodied subjects (c=-0.2), though this latter result may be unreliable as normal

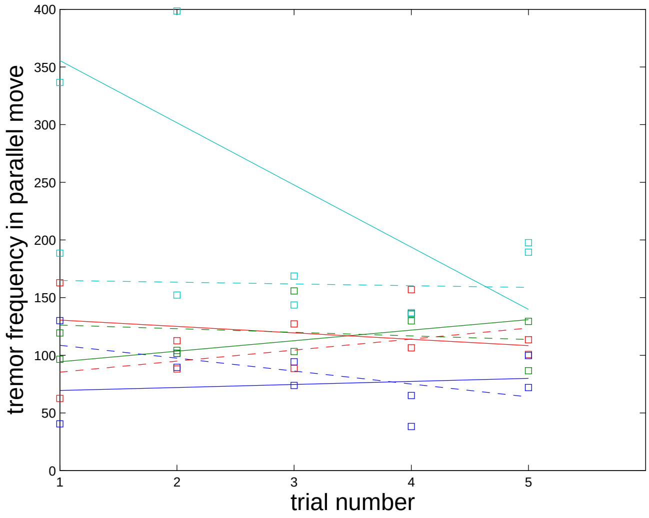


(a)

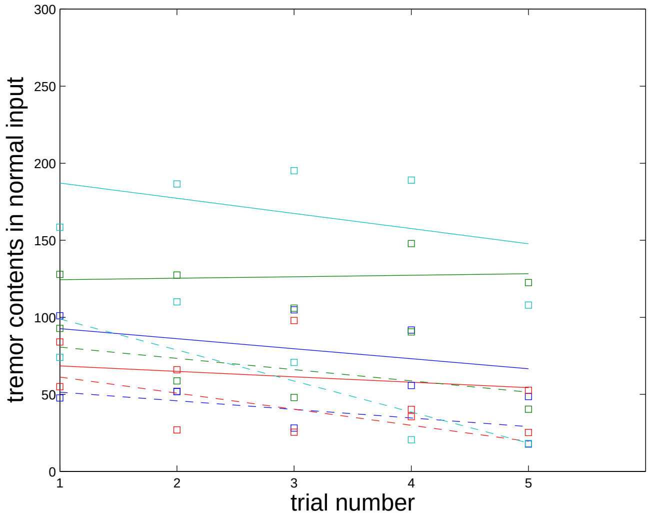


(b)

Figure 6.11: Total frequency contents. (a) and (b) show the total parallel and normal inputs in all the trials.



(a)



(b)

Figure 6.12: Tremor frequency contents. (a) and (b) show the total parallel and normal inputs in all the trials.

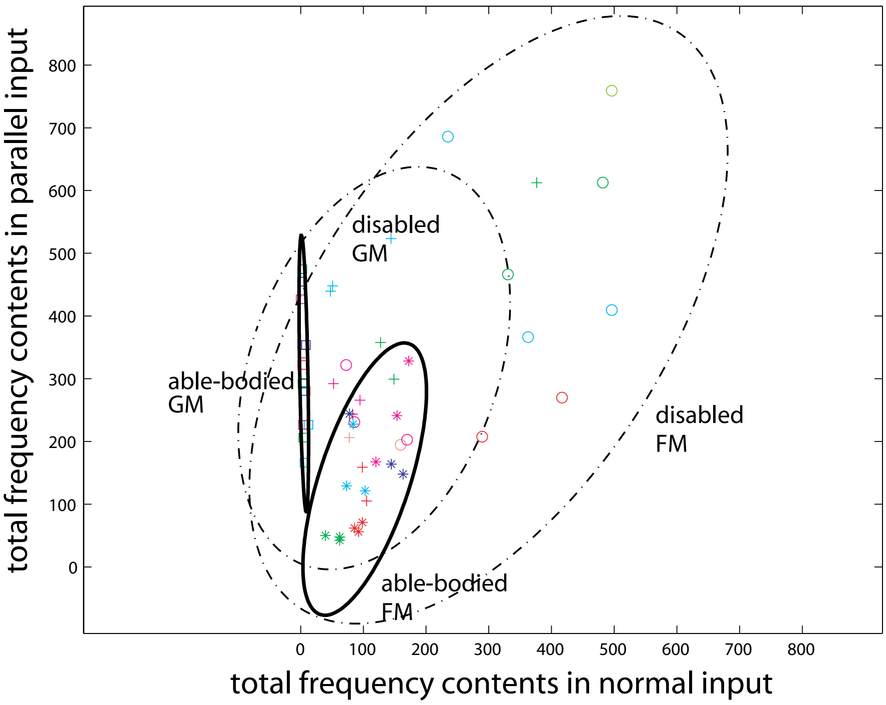


Figure 6.13: How parallel and normal inputs are used (in the last 3 trials) by disabled and able-bodied subjects. Error ellipses of the actual data are overlayed on the plots at the confidence level of 95%. Solid ellipses are for the data of able-bodied subjects (The ‘star’ represents for FM, ‘square’ for GM) and dashed ellipses for disabled subjects (‘cicle’ for FM, ‘cross’ for GM). Note that the large axes of the ellipses go almost through (0,0).

input is negligible in able-bodied subjects.

6.5 Discussion

The purpose of this study was to investigate whether path guidance can help in wheelchair control and how the collaborative wheelchair assistant (CWA) system is adapted to particular disabilities. A first point to note is the very large variability in control characteristics and performances between disabled subjects, as documented in the initial assessment. This emphasizes the importance of interfaces adapted to each specific subject, and suggests the utility of developing adaptable interfaces. The results of Section 6.4 enable us to address major questions about the use of the CWA as will be described in this section.

Does path guidance facilitate the driving?

Although no subject was able to move independently with the powered wheelchair prior to using the CWA, all subjects learned and became eventually able to drive using path guidance. So path guidance helped the disabled subjects to gain mobility. In addition, no collision was observed in GM, while some collisions happened to all subjects when they were driving in FM, due to either bad motor skill or lack of concentration.

We examined the joystick move, which reflects the user's driving effort. As shown in Section 6.4.2, the joystick move decreased significantly in GM, both in its parallel and normal components, suggesting that the subjects learned to drive the wheelchair in the experimental environment after a few trials. On the other hand, the subjects were not able to perform better in FM even after repeated trials, which indicates the difficulty the subjects had to control the wheelchair. Further, the joystick move is much less in GM showing that path guidance greatly reduced the driving effort.

Table 6.4: Comparison of motion features in FM and GM for disabled and able-bodied subjects. Values are given as mean (standard error).

	disabled subjects		able-bodied subjects	
	FM	GM	FM	GM
time (seconds)	79.29(17.73)	74.64(5.63)	45.20(1.30)	38.44(1.10)
intervention time (%)	28.76(1.55)	16.83(0.74)	21.99(1.21)	13.75(0.60)
joystick move	293.5(27.8)	186.1(14.3)	151.0(8.9)	69.1(3.4)
parallel move	183.7(22.0)	116.5(9.1)	79.4(5.8)	64.5(2.8)
normal move	167.0(13.7)	101.2(10.0)	91.5(6.0)	7.7(0.9)
parallel frequency content	411.4(55.1)	338.0(27.4)	152.5(21.8)	298.7(18.3)
normal frequency content	298.2(32.2)	146.7(19.1)	128.3(17.0)	5.5(0.7)
parallel tremor content	138.6(19.6)	118.1(8.6)	44.2(6.1)	106.4(8.2)
normal tremor content	108.7(10.9)	51.3(6.2)	49.3(4.6)	1.84(0.3)

How does path guidance facilitate the driving?

To answer this question, joystick move was decomposed into its parallel component, i.e. speed, and its normal component, i.e. steering. Path guidance required less effort in controlling the speed, as the parallel component is much smaller in guided compared to free mode (Table 6.4). However time spent was not compromised by path guidance. The frequency content in parallel input was much less in GM, showing that the subjects can control the speed more consistently.

Normal input, corresponding to the steering necessary to orient the wheelchair, is the most difficult feature to control in a powered wheelchair. Normal input was much less in GM than in FM. Further, the normal input in FM was not reduced over the trials. In contrast, it decreased across trials in GM. This shows that the subjects learned to let path guidance take over the steering task, resulting in a reduced amount of normal input in GM.

How do operators use path guidance?

The intervention level was computed to examine how users make use of path guidance. During wheelchair movement, the joystick position does not need to be modified continuously. If the user feels that the motion is safe and comfortable, (s)he can just keep the joystick at the same angle, and only has to modify its orientation in order to alter the current course or avoid obstacles.

As shown in Section 6.4.2, using path guidance greatly reduced the intervention level. This suggests that the drivers relaxed as they did not need to continuously modify the joystick position and felt sufficiently safe.

Comparison with able-bodied subjects

The results of motion features in FM and GM for able-bodied (analyzed in Chapter 4) and disabled subjects are given in Table 6.4. For able-bodied and disabled subjects, the intervention level and joystick move were significantly less in GM than in FM. All subjects left the joystick at extreme positions more often in GM than in FM. This indicates that path guidance simplifies the control drastically from the initial trial in comparison to a conventional powered wheelchair. Furthermore, all of the subjects gave positive feedback about their use of path guidance and of the CWA.

Although able-bodied subjects do not need path guidance, their performance were not worse in GM compared to FM, i.e. path guidance did not deteriorate performance. This may be due to the fact that rather than intrusively modifying the user's input as other robotic wheelchairs (e.g. [44]), path guidance takes over the steering task such that little normal input needs to be used.

The disabled subjects spent a much longer time to perform the navigation task compared to able-bodied subjects. For the able-bodied subjects, driving is easy and so they try to finish it quickly. For the disabled subjects, time is not so important as long as they can complete the task.

In FM, able-bodied subjects showed adaptation in normal joystick move, while disabled subjects did not. This illustrates the difficulty of driving a wheelchair, as even able-bodied subjects need practice to improve the driving, while disabled subjects cannot drive properly. In GM, disabled subjects showed adaptation in parallel and normal joystick moves, while the able-bodied subjects did not. This is probably because able-bodied subjects can adapt their skills quickly, thus they can drive efficiently from the initial trial onwards. Disabled subjects, on the contrary, despite knowing how to operate in GM, need a few trials to reduce the effort.

Fig. 6.13 illustrates the specific strategies used by disabled and able-bodied subjects with and without path guidance. Path guidance enables able-bodied subjects to use only negligible normal input, and help disabled subjects to reduce it. For able-bodied subjects, the variability between trials is smaller in GM than in FM, illustrating the control simplification brought by path guidance. This also holds for disabled subjects, though they have more variability than able-bodied subjects and are unable to reduce the normal input to zero.

Subject-specific system adaptation

The training results in Section 6.4.1 showed that the subjects exhibited different abilities in wheelchair control. Can the system be customized to particular disabilities and, if yes, how should it be adapted?

Subjects A and C passed all the tests in a nearly minimum number of trials. This shows that training with the CWA can provide these subjects with the ability to drive freely, such that they may not require path guidance assistance after a while. Therefore, for such subjects, the CWA can be used as a tool to gradually learn to drive the wheelchair safely. However, Subject C had several collisions when driving in FM, due to a loss of attention. Therefore, bumpers and simple obstacle detection sensors should be installed to let such subjects drive a powered wheelchair freely.

Subjects B and D passed all the tests, but needed many more trials than subjects A or C. These subjects became able to use path guidance and to avoid obstacles by using EPC to deviate from the path when needed. However, they had insufficient motor control and thus were not proficient enough to drive freely by the end of our training. Such subjects should drive with path guidance and use EPC to enjoy more freedom, but probably should not use a conventional wheelchair.

Subject E did not pass any test in FM or EM. He had very poor concentration and got tired easily. Therefore, to make him improve his skills may require a long process. He should (at least for the moment) remain constrained on the guide path, while he can already enjoy the possibility to control speed (including stops) as he wishes.

6.6 Conclusion

Clinical evaluation of the CWA was conducted with three cerebral palsy (CP) and two traumatic brain injury (TBI) subjects, who initially could not use a conventional powered wheelchair. Initial assessments were performed to understand their motor control. These subjects were then trained to use the CWA with and without path guidance assistance before completing a navigation task. After a few training sessions, all subjects became able to drive safely and efficiently in an environment with obstacles and narrow passageways. Eventually, two of the subjects did not need the help of path guidance and could drive freely. The results suggest that the CWA can provide driving assistance adapted to various disabilities. It might hence provide a way to increase the mobility of some subjects, who are currently not allowed to drive a powered wheelchair due to motor control or cognitive deficiencies. It can potentially also be used as a safe training device for some subjects who eventually learn to control a normal powered wheelchair.

To compare driving behaviors with able-bodied subjects, the patients also performed the same navigation task as what was performed in Chapter 4. The results illustrate the difficulty of driving a conventional wheelchair, as even able-bodied subjects need practice to improve their driving, while disabled subjects cannot drive safely at all. When assisted by path guidance, able-bodied subjects can adapt their skills quickly, and disabled subjects show obvious improvement with practice. All subjects gave positive feedback about their use of path guidance and the CWA.

Chapter 7

Conclusion and Future Work

The goal of this research thesis was to design and evaluate a robotic wheelchair, CWA for those users who have difficulties in maneuvering a conventional powered wheelchair. This chapter draws overall conclusions, in which we make some conclusive remarks on the work accomplished to fulfill the objectives of this research thesis. In addition, during the research for this thesis, we came across some issues that could further enhance the applicability of our work, which we would like to mention here as topics for future research.

7.1 Conclusions

Due to fatigue, or physical or cognitive limitations, many disabled people encounter difficulties in maneuvering their wheelchairs, in particular during the early stage of use. Most of them have sufficient sensory and inference capabilities to analyze the environment that they are moving in and are eager to use these abilities. In contrast, mobile robotics allows for precise control over the wheelchair's motion but still struggles to create artificial systems with enough sensory and inference capabilities to enable the fully automated navigation. The differences in cognition and motor control between disabled humans and mobile robots has led us to rely on the wheelchair users rather than on complex artificial sensory and inference systems to design the CWA.

The concept at the heart of the CWA is to rely on the user's motion planning skills while assisting the maneuvering with flexible path guidance. The user decides where to go and controls the speed, including start and stop, while the system guides the wheelchair moving along a software-defined path that connects the desired destinations. In this context, motion control is decomposed into *maneuvering*, which is difficult for disabled persons and so is attributed to the robotic system guiding motion along paths predefined in software, and into *speed control*, which is performed by the wheelchair user, who can best judge the situation.

Collaborative wheelchair system

The CWA prototype presented in this thesis demonstrates that the CWA concept does not require complex sensor processing nor advanced decision system, and can therefore be realized at a relatively low-cost.

In order to realize proper navigation, an elastic path controller (EPC) was developed. It can control the wheelchair moving along a guide path, and even allows the user to curve the path reactively in order to avoid dangers on the way. By tuning the elasticity parameter, the system can operate in three modes: free mode (FM), guided mode (GM), and elastic mode (EM).

Several design tools were developed to create/modify guide paths. Walk through programming (WTP) enables the user to teach a guide path by moving the wheelchair freely in its working environment. The path can be retraced with the WTP until the user is satisfied. Alternatively, the path can be modified by using EPC or using a graphical user interface (GUI) on which a path can be manipulated by moving attraction points.

A simple barcode-odometry localization subsystem includes two optical rotary encoders attached to glidewheels for odometry and a commercial barcode scanner for global positioning. A discrete Extended Kalman Filter (EKF) is used to combine the information of odometry with that of barcode patterns. The results from simulations and field experiments showed that this simple approach could provide sufficient accuracy for pose estimations in the desired environment.

Path guidance investigation

Experiments with able-bodied subjects were performed to evaluate path guidance for assisting the control of a powered wheelchair. The results of these experiments showed that with path guidance assistance,

- the navigation is safe: no obstacle collisions occurred in any of the test, i.e. no danger was encountered.
- the speed is not compromised, and is more uniform than with free motion.
- the user control is drastically simplified by the exemption from the steering task, and does not require learning
- the driver does not need to modify the control input very often.

This investigation demonstrates the advantages of using path guidance, and shows the effectiveness of the shared control strategy between the user and the wheelchair.

Collaborative path planning

A *collaborative learning* approach was explored for path planning of the wheelchair. Similar to the collaborative control strategies developed for teleoperated mobile platforms [41], the human operator and the robot “dialog” to succeed in the task using the best of their respective abilities, through context dependent menus. In our case, we use a more direct dialog based on physical interaction and vision rather than on language.

We proposed that the human operator and the robot, using suitable design tools, interact to create and gradually improve a guide path. Guide paths could be created and adapted to modified environmental conditions using three tools: a GUI on which a path can be manipulated *offline* using a few attraction points, WTP, and EPC for *online* path modifications.

While this strategy was sketched in the context of an industrial assistive device [42], it has been tested here for the first time in experiments with human subjects. Experiments with able-bodied subjects have tested the efficacy of the design tools to adapt guide paths to changes in the environment and analyzed how the subjects use them. In our analysis, relevant ergonomic factors of a guide path were identified and described using mathematical measures. The results from these experiments and user evaluation demonstrated the effectiveness of our approach and show the utility and complementarity of the path design tools. The subjects, with little learning, were able to use these tools to design guide paths, and were satisfied by this approach. Furthermore, the analysis on ergonomic paths, i.e. paths providing the best guidance, showed that the users put more weight on smoothness and comfort once they are ensured that the path offers sufficient safety margin to maneuver, while length was the least important factor, in particular as the differences in length were small.

Evaluation with patients

Clinical evaluation of the CWA was conducted with three cerebral palsy (CP) and two traumatic brain injury (TBI) patients, who initially could not use a conventional powered wheelchair. Initial assessments were performed to understand their motor control. These subjects were then trained to use the CWA with and without path guidance before completing a navigation task. After a few training sessions, all of the subjects became able to drive the wheelchair with path guidance safely and efficiently in an environment with obstacles and narrow passageways. The CWA enabled the subjects to drastically reduce their control effort and intervention without compromising performance. Eventually, two of the subjects did not need the help of path guidance and could drive freely. The results suggest that the CWA can provide driving assistance adapted to various disabilities. It might hence provide a way to increase the mobility of some subjects, who are currently not allowed to drive a powered wheelchair due to motor control or cognitive deficiencies. It can potentially also be used as a safe training device for some subjects who eventually learn to control a normal powered wheelchair.

In order to compare driving behaviors with able-bodied subjects, the patients also performed the same navigation task as what was performed in the path guidance investigation. The results illustrate the difficulty of driving a wheelchair without robotic assistance, as even able-bodied subjects need practice to improve their driving, while disabled subjects cannot drive safely at all. With path guidance, able-bodied subjects can adapt their skills quickly, and disabled subjects show obvious improvement with practice. All subjects gave positive feedback about their use of path guidance and the CWA. This may be due to the fact that, in contrast to other robotic wheelchairs as for instance the Hephaestus smart wheelchair [44], rather than intrusively modifying the user's input, path guidance takes over the steering task. Since operating the wheelchair is greatly simplified, the user need not worry about maneuvering, and can concentrate on other tasks, thereby reducing the mental load of driving.

7.2 Future Work

A more sophisticated localization system may be desired. As the focus of this research thesis was to study the human-wheelchair interaction, the simple barcode-odometry system developed was sufficient for the representative environment used in the experiments. Further studies on the localization using barcodes could be explored to see how the system can be deployed for other indoor environments as it is simple, low-cost, relatively accurate and needs minimal infrastructure modification. In addition, the addition of an angular sensor to measure orientation would allow the CWA to navigate more efficiently in less controlled environments.

Several issues on path management can be further explored. Firstly, with a growth in the number of destinations, the number of paths would increase rapidly (no. of paths $=\frac{n(n-1)}{2}$, n is the number of destinations). For instance, 40 paths are required to connect 10 destinations, and 190 for 20 destinations! Thus, when the number of destinations is large, it is necessary to examine how to efficiently manage these paths in memory. Secondly, a path could be realized by connecting multiple existing paths between two destinations. This method can possibly reduce the number of paths, and can offer the user more choices for his navigation. Thirdly, changing paths during navigation should be allowed. For instance, when a user is driving along a path towards the kitchen, the door bell rings and he should be able to turn to the door. In the CWA prototype, the user can either use EPC to deviate from the original path or has to finish the current path (i.e. arriving at the kitchen) before loading a new path (from the kitchen to the door). Using the EPC for long distances is not efficient while the user can be expected to reject a solution in which he has to complete a meaningless first movement before he can embark on a meaningful second one. A better solution would be that when a destination is changed, the system should immediately react to provide an alternative path connecting the current wheelchair position and the new destination. This issue may be considered together with that of using multiple paths.

Further evaluations with more groups of patients are worthy of study. The evaluation of the CWA with the five CP and TBI patients has successfully demonstrated the usefulness of the CWA system. For users with poor motor control or driving skills, the CWA enables them to become a powered user by cancelling their involuntary hand input that is not compliant with their intention, as what we have tested with CP and TBI patients. For users with mental disabilities, they may have orientation or navigational problem or may be unable to remember the initial intention or simple routes. Using pre-defined paths, the CWA brings such users to their intended destination without requiring them to know the way. The CWA could help users lacking consistent attention or strength, by reducing their driving effort, such that they can use their remaining strength to perform other tasks in addition to controlling their wheelchair.

In the course of the experiments, several potential subjects could not participate in the experiments as they need wheelchairs customized for their purposes such as special supports etc. Hence a useful extension to the project would be the development of a universal mobility base to support the subject's specific wheelchair. This platform, which would be equipped with sensors and flexible input devices, could implement the CWA. Thus it would avoid the need to have to redesign a CWA wheelchair for each user. Such a universal platform would be useful in many public places such as airports or hospitals.

The CWA can be developed as a learning tool. We have seen during the experiments with disabled persons that the CWA enables safe training in an environment limited by guide paths. One possible extension is that, when the wheelchair automatically moves along a guide path, a feeling of correct driving behavior could be provided to the wheelchair user in the form of force feedback, using a dedicated joystick. In this way the user may be able to better link the joystick input with the resulting wheelchair motion, and thus develop his driving capabilities more efficiently.

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List of Publications

Journal papers

- Q. Zeng, E. Burdet, B. Rebsamen, and C.L. Teo, “Collaborative path planning for a robotic wheelchair,” *Disability and Rehabilitation: Assistive Technology*, 3(6): 315-24, 2008.
- Q. Zeng, C.L. Teo, B. Rebsamen, and E. Burdet, “A collaborative wheelchair system,” *IEEE Transactions on Neural Systems and Rehabilitation*, vol. 16, no. 2, April. 2008.
- Q. Zeng, E. Burdet, and C.L. Teo, “Evaluation of a collaborative wheelchair system in cerebral palsy and traumatic brain injury users,” *Neurorehabilitation and Neural Repair*, 2008.

Conference papers

- Q. Zeng, E. Burdet, B. Rebsamen, and C.L. Teo, “Design of a collaborative wheelchair with path guidance assistance,” in *IEEE International Conference on Robotics and Automation* (ICRA), pp. 877–882, 2006.
- Q. Zeng, C.L. Teo, B. Rebsamen, and E. Burdet, “Evaluation of the collaborative wheelchair assistant system,” in *IEEE International Conference on Rehabilitation Robotics* (ICORR), pp. 601–608, 2007.

- Q. Zeng, E. Burdet, B. Rebsamen, and C.L. Teo, "Experiments on collaborative learning with a robotic wheelchair," in *International Convention for Rehabilitation Engineering & Assistive Technology* (i-CREATe), pp. 57–62, 2007.
- Q. Zeng, E. Burdet, and C.L. Teo, "User evaluation of a collaborative wheelchair system," in *30th Annual International Conference of the IEEE Engineering in Medicine and Biology Society* (EMBC'08), pp. 1956–1960, 2008.
- Q. Zeng, C.L. Teo, and E. Burdet, "Is the collaborative wheelchair adapted to cerebral palsy and traumatic brain injury subjects?," in *30th Annual International Conference of the IEEE Engineering in Medicine and Biology Society* (EMBC'08), pp. 1965–1968, 2008.

In addition, collaborative work with Brice Rebsamen in the context of his PhD thesis [27] resulted in one journal paper [47] and three conference papers [48, 49, 50].

Appendix A. List of Existing Robotic Wheelchairs

During the last decade, a great effort was concentrated world-widely towards developing automated wheelchair with some degree of navigational intelligence. This section gives a brief review of other research on robotic wheelchairs, identified by a search of the literature.

(1) TAO Project (Applied Artificial intelligence, Inc., Canada)

Tao project [8] developed an add-on intelligent system that can be installed on any standard powered wheelchair with minimum modifications. The TAO wheelchair performs landmark-based navigation in autonomous mode. The system uses two processor boxes: one for vision and one for non-vision behavior generations. Two CCD color cameras are used for vision system. Several bump sensors and 12 infrared sensors are equipped for detecting obstacles close to the chair. A subsumption approach has been implemented, under which several behaviors emerge, including collision avoidance, door passage and wall following. A keypad and miniature television set are installed temporally to enter instructions and for monitoring. The user can override the control in autonomy mode with a joystick.

(2) Navchair (University of Michigan, U.S.)

The Navchair [9] navigates indoor environments with three operating modes: general obstacle avoidance, door passage and automatic wall following. Sonar sensors have been used to create a map of the chair's surroundings. The system provides shared-control where a human is responsible for path planning and most of the navigational responsibilities while the NavChair could automatically adapt the correct operating mode based on user behavior and environmental status. The user can use either a joystick or voice commands as the access method.

(3) Omni (University at Hagen, Germany)

The OMNI project [10] aimed at developing an advanced wheelchair with high maneuverability and navigational intelligent, thus well suited for vocational rehabilitation. The chair can move in any direction, with the linear motion being combined with a rotation around its center. The system assists control through obstacle avoidance, walling following, door passage and limited back tracing of the most recent manoeuvres. The drive of this system is based on a custom-designed omni-directional wheelchair. Ultrasonic and infrared sensors have been used for environmental analysis. A modular human-machine-interface is able to connect different input devices, subject to different users' abilities.

(4) Sharioto (K.U. Leuven, Belgium)

Sharioto [11] is a semi-autonomous wheelchair. Different types of distance sensors are used to detect features in the environment (ultrasonic sensors, infrared sensors, and a 'Lidar' infrared scanner) and a gyroscope for heading correction. The system provides behaviors including collision avoidance, obstacle avoidance, wall following, docking at a table. Moreover, the system implicit helps its user by estimation of the user intentions on these behaviors. The behavior changes are triggered by user signal and sensor information. Work continues on designing good activation function for each behavior.

(5) VAHM (University of Metz, France)

VAHM [12] operates in a semiautonomous or autonomous mode. Mode decisions are made manually. VAHM uses multiple representations of environment (topological, metric) and infrared beacons for path planning. In semiautonomous mode, the system provides wall following and obstacle avoidance. In autonomous mode, the system performs global path planning w free from non-modeled objects. Ultrasonic transducers and contact sensors are installed for accurate position and local primitives. The human-machine-interaction is carried out through a LCD screen. The robot's reachable environment may be represented geometrically seen from above. The user can point the navigation target with a proportional sensor or through a screen scanning stopped by a switch.

(6) SmartChair (University of Pennsylvania, U.S.)
The SmartChair [13] navigates autonomously with a map of the environment. The system consists of a vision-based virtual interface and a suite of sensors (laser range finder and shaft encoders). An omni-directional camera, mounted over the user's head, allows the user to view 360 degrees around the chair. A projector system displays the map image on the laptray and enables the user to intervene the system in real time by clicking on a point on the map image during the execution of an autonomous task.

(7) Senario (TIDE, Finland)
The Senario wheelchair [14] navigates indoor environment in a semi-autonomous or fully autonomous mode. In semi-autonomous mode, the system accepts incremental commands from the user, and in fully autonomous mode, the system accepts commands like 'go to goal' and then automatically plans and executes a path to the destination, avoiding all obstacles and risks on the way. There are 13 ultrasonic sensors, two infrared range finders and two encoders. The user interface is either a joystick or voice control.

(8) Automated wheelchair (NEC Corporation, Japan)
Automated wheelchair system [15] can navigate both indoors and outdoors, guided by a magnetic ferrite marker lane, which is minimally influenced by dirt or other nonmagnetic materials. A guide sensor is used to detect the lane and two infrared sensors are installed in the front for obstacle detection. The operation of the wheelchair is involved by pushing a button.

(9) Smart wheelchair (Call Center at University of Edinburgh, UK)
The CALL Center's smart wheelchair [16] was originally developed as an edu-

cational and therapeutic resource for severely disabled children. Bumpers detect collisions; several behaviors can be selected to correct the bump for the user. A line following behavior can follow reflective tape on the floor. An explicit subsystem responds and reports what the system is doing to the user via a speech synthesizer or input device. The chair can be driven by a number of methods such as switches, joysticks, laptop computers, and voice-output.

(10) CCPWNS (University of Notre Dame, U.S.)

An autonomous wheelchair [17] allows the user to retain supervisory control of the wheelchair at all times. The user can select the nominal speed of the chair, stop and select a new destination or stop and take over control. Visual cues from two CCD cameras are used to correct the pose estimation errors from the odometry. The automatic guidance of the wheelchair is carried out through a *teach-repeat* procedure: the chair needs to be manually led along those interest paths, which are simultaneously 'taught' to the system, as from location to location, and stored for future playbacks. The system provides obstacle detection only. When obstacles happen on the wheelchair's path, the user needs to take over control to maneuver around and can then pass control back to the system.

(11) Intelligent wheelchair system (Osaka University, Japan)

The intelligent wheelchair [18] integrates autonomous capabilities and interface by face direction. The system is equipped with 16 ultrasonic sensors and two video cameras. One camera is installed to observe the user's facial gesture. Another camera is set up to track targets, avoid collision and allow user to control wheelchair with gestures when out of wheelchair. The chair automatically switches between modes (wall following, target tracking, obstacle avoidance) based on wheelchair surroundings.

(12) Autonomous wheelchair (Nagasaki University and Ube Technical College)

An autonomous wheelchair [19] has been developed, with the capability of self-localization. The ceiling lights are chosen as landmarks to realize the self-localization and auto-navigation of the wheelchair, requiring no environmental modification.

However, the system requires a map in advance including these landmarks. An azimuth sensor is used to give the angle between a fixed point and a particular object. Two CCD cameras are used; one for detecting the ceiling light landmarks and the other is used in conjunction with a laser range finder for obstacle detection.

(13) Tin Man II (KISS Institute for Practical Robotics, U.S.)

The Tin Man II wheelchair [20] is a semi-autonomous wheelchair, which requires less frequent user controls than conventional powered wheelchairs. There are 12 infrared proximity sensors, 7 sonar sensors, a front contact bumper and wheel encoders. In semi-autonomous mode, the user can drive the chair with a joystick with obstacle avoidance assistance. In addition, the user can push one button to turn while avoiding obstacles or push another button to move forward while avoiding obstacles. Tin Man systems have been purchased by several research groups, resulting in increased research in the field of robotic wheelchairs with a fairly standardized platform.

(14) Wheelesley (MIT, U.S.)

The Wheelesley wheelchair [21] performs semi-autonomous navigation in both indoor and outdoor environments. There are 12 proximity sensors, 6 ultrasonic range sensors, 2 shaft encoders and a front bumper with sensors. The system uses computer vision for obstacle detection and could switch automatically between indoor and outdoor navigation modes. The user interface of the chair has been customization into two different access methods: eye tracking and single switch scanning. Work is continuing on automatic mode selection and the vision system for outdoor navigation.

(15) Robotic wheelchair (FORTH, Greece)

A semi-autonomous wheelchair [22] provides behaviors including obstacle avoidance motion in the middle of the free space, target tracking and person following. The sensory modalities used are odometry, sonars and panoramic vision. The panoramic camera provides visual data from a 360^o field of view and sensory information for some of navigation capabilities. Some of the tasks are carried out in cooperation with the user; the user gives high-level commands by selecting the person to follow by pointing on a touch screen or selecting the motion direction by voice commands.

(16) Rolland (University of Bremen, Germany)

Rolland [23] has three operating modes: turn-in-place, wall following, and trajectory playback. Sensory information from sonar and dead reckoning are fused to self-localize and trigger mode changes. User teaches trajectory using turn-in-place and wall following behaviors, and the trajectory can be repeated in the future. The chair could autonomously navigate between positions on map. The operating modes can switch automatically, triggered by obstacle density. When approaching an obstacle, the system would slow down and adapts the speed ordered by the user via the joystick for obstacle avoidance. Work is continuing on commanding the chair with a speech input control interface.

(17) Orpheus (National Technical University of Athens, Greece)

Orpheus [24] navigates in a semi-autonomous or fully autonomous mode. The navigation of the robot is based on qualitative map (Qmap) of the environment. The Qmap describes variations in sensor behavior between adjacent regions in space. The system uses these representations to localized, guide planning and reaction. In semi-autonomous mode, the user would guide the chair manually. The robot performs obstacle avoidance. In fully autonomous mode, the robot was instructed to navigate automatically to a specific target on the Qmap. 8 proximity (ultrasonic) sensors are mounted in a ring around the robot. Encoders are used to compute the orientation.

(18) RHOMBUS (MIT, U.S.)

RHOMBUS [25] is a hybrid wheelchair/bed system consisting of an omnidirectional vehicle and a reconfigurable chair. In the bed mode, it can shift a patient between the bed and wheelchair without changing seating. In the wheelchair mode, it performs omnidirectional navigation within the home environment. The chair can be driven manually using either a joystick or pressure sensitive footpads, or driven automatically by having the computer execute a preplanned route. A teleconferencing/control panel allows the patient to communicate with a remote caregiver and control the chair through a GUI.

(19) Sirius (University of Seville, Spain)

Sirius [38] has been developed to improve the maneuverability of powered wheelchairs. The system is semi-autonomous, providing obstacle detection and avoidance using 4 ultrasonic sensors: two frontal (at left and right sides) and two lateral. In addition, the system always memorizes the last trajectory and this allows the user to quickly and easily return to the previous location by pushing a button. This feature may be useful in difficulty small areas (e.g. bedrooms) where a chair must navigate.

(20) Hephaestus (TRACLabs, Houston)

The Hephaestus smart wheelchair [44] providing obstacle avoidance is intended to be used either as as a mobility aid or and as a training tool. The system can be compatible with multiple brands of wheelchairs and does not require any modifications to underlying power wheelchair. The prototype system, makes use of 16 sonar sensors to detect obstacles around the wheelchair. Up to 24 switches can be placed anywhere on the wheelchair as bump sensors.

(21) Luoson III (National Chung Cheng University, Taiwan)

Luoson III [46] provides shared navigation assistance for the blind. There are 2 electric compasses, a ring of 16 ultrasonic range sensors, and a vision system, which consists of a 4-channel image grabber, a color camera and a mono camera. The system could detect the distance between objects by ultrasonic sensors and provide force reflective information to user hand through a force-feedback joystick. Hence, even if the user is blind, he can still sense the environment through the joystick.

Appendix B. Orientation Estimation

The absolute position (x_{S_j}, y_{S_j}) can be obtained directly from the coordinates of the barcodes saved in the computer. However, *no absolute orientation is directly available due to lack of angular sensors.* To solve this problem, we have developed a numerical approach to estimate the absolute orientation θ_{S_j}.

We consider that the estimate error in position prior to a barcode update is caused by the angular error, α, which is not completely corrected at the previous barcode update (see Figure 1). As the odometry is accurate within short distances, we assume that this angular error does not change between two landmarks.

By laws of cosines, we have

$$| BC |^2 \quad = \quad | AB |^2 + | AC |^2 - 2 \mid BC \mid\mid BC \mid cos(\alpha) \tag{1}$$

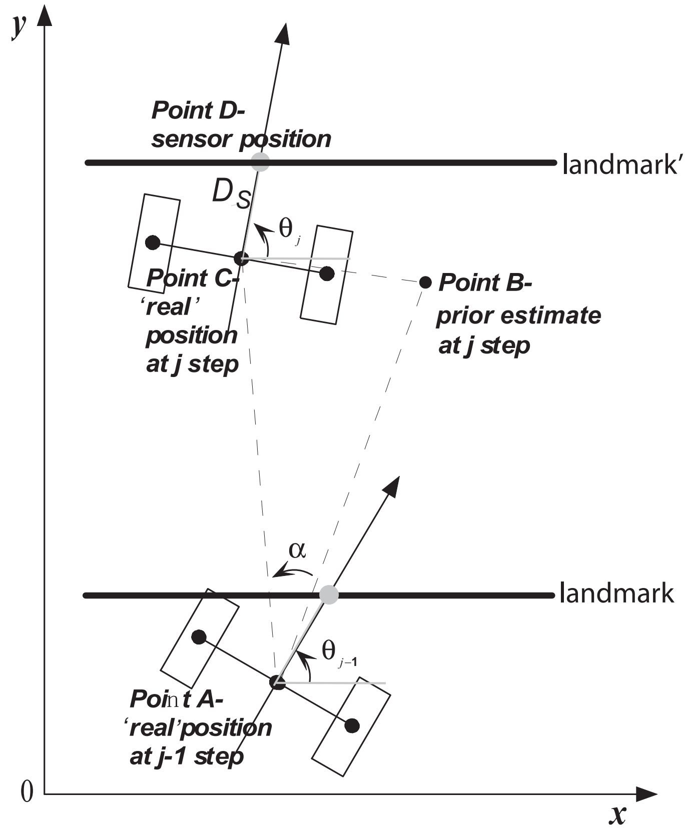

Figure 1: Orientation estimation using position information. Before the sensor reads the barcode landmark at Point D on state j, the angular error α, which is not fully corrected at the barcode update state $j-1$ at Point A, causes the system to think its real position at Point C as point B.

where

$$
\begin{aligned}
AB &= (x_{j-1} - x_j^-)i + (y_{j-1} - y_j^-)j \\
AC &= (x_{j-1} - x_j^-)i + (y_{j-1} - y_j^-)j \\
BC &= (x_j - x_j^-)i + (y_j - y_j^-)j \\
x_j &= x_{S_j} - D_S \cos\theta_j \\
y_j &= y_{S_j} - D_S \sin\theta_j \\
\theta_j &= \theta_{S_j} = \alpha + \theta_j^-
\end{aligned}
$$

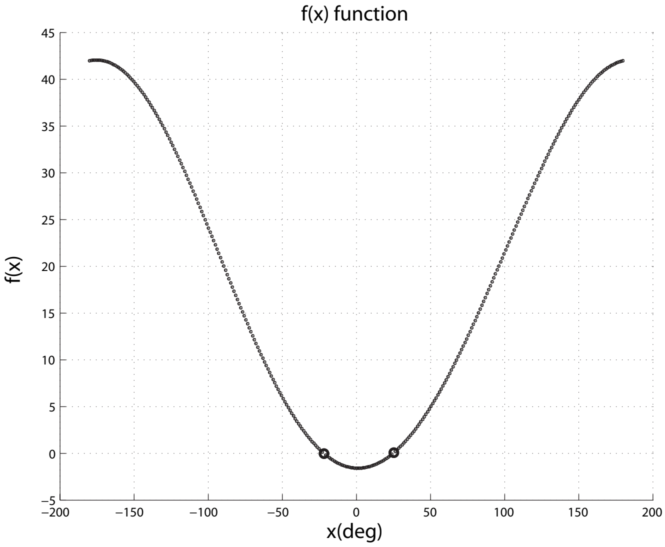

Figure 2: A typical representation of function $f(\alpha)$ with α in $[-\pi,\pi]$. Here we assume $(x_{s_j},y_{s_j}) = (3,7), (x_j^-,y_j^-,\theta_j^-) = (1,6,\pi/4), (x_{j-1},y_{j-1}) = (2,2)$ and $D_S = 0.35m$. The two circles are two roots, which satisfy $f(\alpha) = 0$.

$(x_j,y_j,\theta_j)^T$ is the real pose at the barcode update state j, $(x_{S_j},y_{S_j})^T$ is the sensory reading from the barcode. The "super minus" denotes the prior state estimate. Thus, $(x_j^-,y_j^-,\theta_j^-)^T$ is the prior estimate at the state j.

To find the value of α satisfying equation 1, we first build a function $f(\alpha)$:

$$f(\alpha) \;=\; |BC|^2 - |AB|^2 - |AC|^2 + 2\,|BC|\,|BC|\cos(\alpha) \tag{2}$$

Brent's method [51] is used to find the root, α, such that $f(\alpha) = 0$. This numerical method requires initial estimates, which bracket a root, and the function evaluated at the two initial estimates should have opposite signs. It can be seen that $f(\alpha)$ has the characteristic of a cosine function (see Figure 7.2), and it can be proved that $f(0) \leqslant 0$. There is a special case that when $f(0) = 0$, the function has only one root, i.e. $\alpha = 0$. Other than that, we always have $f(0) < 0$. Therefore, $f(0)$ is chosen the negative initial estimate for finding the root. Since α is the angular error, it is realistic to limit it within

$[-\pi/2, \pi/2]$. By searching between $[-\pi/2, 0]$ and $[0, \pi/2]$, two roots, α_1 and α_2, can be derived with the same value but the opposite sign.

By using the condition that the sensor direction should align with that of the wheelchair, we can set up equation 3. In the ideal case, it should equal to '0'. Thus, one of the two roots, α_1 and α_2, which results into a smaller equation value, should be the angular error α. Finally, we can obtain the absolute orientation as $\alpha + \theta_j^-$.

$$\left| \arctan\left(\frac{y_{S_j} - D_S \sin(\alpha + \theta_j^-)}{x_{S_j} - D_S \cos(\alpha + \theta_j^-)}\right) - (\alpha + \theta_j^-) \right| \tag{3}$$