IMPLEMENTATION OF TARGET TRACKING IN SMART WHEELCHAIR COMPONENT SYSTEM (SWCS)

by

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ABSTRACT

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Independent mobility is critical to individuals of any age. While the needs of many individuals with disabilities can be satisfied with power wheelchairs, some people with disabilities find it difficult or impossible to operate a standard power wheelchair. This population includes, but is not limited to, individuals with low vision, visual field neglect, spasticity, tremors, or cognitive deficits. To meet the needs of this population, we are developing cost-effective modularly designed Smart Wheelchairs. Our objective is to develop an assistive navigation system which will seamlessly integrate into the lifestyle of an individual with disabilities and provide safe and independent mobility and navigation without imposing an excessive physical or cognitive load.

The Smart Wheelchair Component System (SWCS) can be added to a variety of commercial power wheelchairs with minimal modification to provide navigation assistance. Previous versions of the SWCS used acoustic and infrared rangefinders to identify and avoid obstacles, but these sensors can not support many desirable higher-level behaviors. To achieve these higher level behaviors we integrated a Continuously Adapted Mean Shift (CAMSHIFT) target tracking algorithm into the SWCS, along with the Minimal Vector Field Histogram (MVFH) obstacle avoidance algorithm. The target tracking algorithm provides the basis for two

distinct operating modes: (1) a “follow-the-leader” mode, and (2) a “move to a stationary target” mode.

The ability to track a stationary or moving target will make the SWCS more useful as a mobility aid, and is also expected to be useful for wheeled mobility training and evaluation. In addition to wheelchair users, the caregivers, clinicians, and transporters who provide assistance to wheelchair users will also realize beneficial effects of providing safe and independent mobility to wheelchair users which will reduce the level of assistance needed by wheelchair users.

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PREFACE

Throughout the past two years, many people have contributed to the completion of my graduate studies. I will be forever grateful for the guidance and support that Dr. Richard Simpson, my advisor, provided to me during my past two years of graduate study. I truly admire his dedication and willingness to help, tributes which undoubtedly contributed to the success of my thesis project. I am also very thankful to Dr. Rory Cooper, Director of the HERL, for his willingness to serve on my committee and his many insightful comments and suggestions throughout my thesis studies. He is a world renowned researcher from whom I have learned the art of research and the philosophies of life. I am also very fortunate to have Dr. Edmund F. LoPresti, President of the AT Sciences on my committee, whose expertise in Smart Wheelchair was a great contribution to my understanding and the development of my thesis.

1.0 INTRODUCTION

1.1 MOTIVATION

As the U.S population ages, and as more individuals survive with physically disabling diseases and paralyzing or disabling injuries, the use of assistive technology, and specifically mobility devices, is critical for maintaining independence and function in society. Children without safe and independent self-ambulation are denied critical learning opportunities, which place them at a developmental disadvantage relative to their self-ambulating peers [2]. Adults who lack an independent means of locomotion are less self-sufficient, which can manifest itself in a negative self-image [3]. A lack of independent mobility at any age places additional obstacles in the pursuit of vocational and educational goals. The primary reason for limited mobility of an individual could be sensory, physical, or cognitive.

Assistive technology is likely responsible for improved levels of activity in the elderly[12]. Mobility devices, including wheelchairs, make up a significant portion of the assistive technology in use today. Approximately 6.8 million non-institutionalized Americans utilize mobility assist devices, including wheelchairs, scooters, walkers and canes [10]. The number of wheelchair and walker users has roughly doubled between 1980 and 1990 [11].

While the needs of many individuals with disabilities pertaining to independent mobility can be satisfied with power wheelchairs, some people find it difficult or impossible to operate a standard power wheelchair. This population includes, but is not limited to, individuals with low vision, visual field neglect, spasticity, tremors, or cognitive deficits.

Due to the aging of the industrialized world's population, the needs of the disabled and the elderly are increasingly recognized by politics, industry, and science. Recent developments in research areas such as computer science, robotics, artificial intelligence, and sensor technology allow a significantly broader range of devices that support disabled or elderly people in their daily lives. Rehabilitation and assistive technology practitioners started looking for help from the robotics community in the late 1980's. Subsequently, support was provided by National Science Foundation (NSF), National Institutes of Health (NIH), and the Department of Veteran's Affairs to research organizations in academia and industry. The most common term for the intervention of robotics into wheelchairs is "Smart Wheelchairs" [5].

Investigators at the University of Pittsburgh are developing inexpensive modularly designed Smart Wheelchairs [50][51]. Our objective is to develop an assistive navigation system which will seamlessly integrate into the lifestyle of an individual with disabilities and provide safe and independent mobility and navigation without imposing an excessive physical or cognitive load. Towards this end, we have designed the Smart Wheelchair Component System (SWCS)[50] that can be added to a variety of commercial power wheelchairs with minimal modification. The SWCS is being designed to accommodate all traditional input methods (analog joystick, touch-activated switches, pneumatic “Sip n’ Puff” switches. to be compatible with multiple brands of wheelchairs, and provide collision-free travel in which the user is responsible for planning the actual path of travel to the destination.

The SWCS currently uses acoustic and infrared rangefinders to identify and avoid obstacles, but these sensors do not lend themselves to some desirable higher-level behaviors. To achieve these higher level behaviors a target tracking algorithm was developed and integrated into the SWCS along with the Minimal Vector Field Histogram (MVFH) obstacle avoidance algorithm [28][66]. The target tracking algorithm is integrated with the SWCS as part of two distinct operating modes: (1) a “follow-the-leader” mode, and (2) a “move to target” mode. The ability to track a stationary or moving target will make smart wheelchairs more useful as mobility aids, and is also expected to be useful for wheeled mobility training and evaluation.

1.2 THESIS OUTLINE

An initial prototype has been developed based on an early version of the SWCS. To limit the cost of the system, a Logitech Quickcam Pro-4000 is used for perception and Sonaswitch Sonar, GP2D12 IR and SRF-08 sonar are used as proximity sensors. The computationally efficient Continuously Adaptive Mean Shift Algorithm (CAMSHIFT) is used to track objects using the color probability distribution of the target. The results of testing the system demonstrate that the prototype can track objects efficiently in real time and provide navigation assistance to a wheelchair user. Although these results are promising, the prototype remains several years from commercialization, and further development and testing are needed.

2.0 BACKGROUND AND RELATED RESEARCH

Despite continuing advances in wheelchair and robotics technology, there will always be a population of users whose physical, cognitive and/or perceptual impairments are so severe that they preclude independent mobility. Many of these individuals live in nursing homes or intermediate care facilities, and are transported between locations in manual wheelchairs pushed by caregivers. Our goal is to develop a mobility aid with automated control for individuals who are completely dependent on others for their mobility needs. The device we are developing will reduce the time that people with disabilities spend waiting for someone to move them between locations, and reduce staff time and physical effort required for transportation.

2.1 DISABILITY STAGES

According to Nagi's [16] framework, the dynamic nature of the disability process is represented by movement through four stages: pathology, impairment, functional limitation, and disability. The first stage, pathology, is the presence of a physical or mental condition, such as Alzheimer’s disease, that interrupts the physical, perceptual or mental processes of the human body. Pathology may lead to the second stage, impairment, which is a physiological, anatomical, or mental loss that limits a person's capacity to function; for example, Alzheimer’s disease results in a steady loss of neurons, or nerve cells, that causes progressive dementia, resulting in a steady decline in mental and physical capabilities. Impairment may lead to the third stage, functional limitation, which is limitation in the performance or completion of a fundamental activity. For example, a person with Alzheimer's disease may lose motor skills including the ability to perform activities of daily living (ADLs) such as walking, eating, standing, bathing etc. In the final stage, a functional limitation may lead to a disability, which is a limitation in performing roles and tasks that are socially expected.

2.2 DISABILITY AND MOBILITY DEVICES STATISTICS

There is a significant population of people with disabilities in the U.S. [10] who are unable to perform the ADLs without assistance because of mobility impairment. According to [12], assistive technology is likely responsible for improved levels of activity in these individuals. Mobility devices, mainly wheelchairs and scooters, make up a significant portion of the assistive technology in use today. Table1 shows mobility device usage statistics in the U.S.

Table 1 : Mobility Device Usage in the United States (reported in 1000's) from[10].

Device	All persons	Under 18	18-64	65 & over
All Wheelchairs	1,599	88	614	897
Manual WCs	1,503	79	560	864
Powered WCs	155	18	90	47
Scooters	142	0	78	64

Some of the medical conditions associated with wheelchair or scooter usage are shown in Table-2 below. In the 18-64 age group, multiple sclerosis, paraplegia and cerebrovascular disease are the most prevalent [10]. In the elderly population, age 65 and older, osteoarthritis and cerebrovascular disease are the leading causes of wheelchair or scooter use.

Table 2: Wheelchair & Scooter Use Based Upon Condition (Age 18-64), from [10].

Condition	**Persons in 1000's**
Multiple Sclerosis	58
Paraplegia	48
Cerebrovascular Disease	45
Quadriplegia	44
Osteoarthritis	32
Loss of lower extremity	31
Cerebral Palsy	29
Rheumatoid Arthritis or Polyarthropathies	21
Diabetes	21
Orthopedic impairment of back/neck	21
All Conditions	635

2.3 INTELLIGENT MOBILITY AIDS (IMA)

While the needs of many individuals with disabilities can be satisfied with traditional mobility aids (e.g., manual wheelchairs, power wheelchairs, scooters, etc.) there exists a segment of this community who find it difficult or impossible to use traditional mobility aids independently. These individual don't have the perceptual or motor skills required to effectively and safely maneuver a power wheelchair. Aggressive and unpredictable behavior may cause injuries not only to themselves but also to people around them. This population includes, but is not limited to, individuals with low vision, visual field neglect, spasticity, tremors, or severe cognitive deficits. Individuals in this population often lack independent mobility and are reliant on a caregiver to push them in a manual wheelchair.

To accommodate this population, researchers have used technologies originally developed for mobile robots to create "Smart Wheelchairs"[5]. These devices typically consist of either a traditional mobility aid to which a computer and a collection of sensors have been added or a mobile robot base to which a seat has been attached. The majority of smart wheelchairs that have been developed to date have been tightly integrated with the underlying power wheelchair [21][25][29], requiring significant modifications to function properly. Examples of modifications include adding wheel rotation sensors for dead reckoning and bypassing the wheelchair's motor controller in order to control the wheelchair's motors directly.

The functions provided by these smart wheelchair systems include obstacle avoidance, wall following, door passage, autonomous travel to a destination, track following in a structured environment, and tracking moving or stationary targets. Smart wheelchairs usually have a set of proximity sensors to sense the surrounding objects or obstacles, bump sensors to sense touch and a computer or microprocessor as the controller. The most frequently used sensors are sonar, infrared, and laser scanners, while the most frequently used camera module is the Sony EVI-D31. Another relevant characteristic is that most of these systems require some kind of user input for difficult navigation tasks.

There have also been efforts within the robotics community in designing intelligent mobility systems with the ability to track targets primarily using computer vision [90][92][93]. Vision-based moving-target trackers deal with a real world problem, but they require significant computational power. In addition, the trackers are complicated when distance to a target needs to be computed. Recently there have been efforts in tracking targets using passive sonar mapping [98] and laser guided tracking [99].

2.4 RELEVENT INTELLIGENT MOBILITY AIDS (IMA) RESEARCH

Target tracking intelligent systems uses computer vision, passive sonar mapping [98], laser scanner [99] and Wi-Fi signals [95] for target tracking.

2.4.1 NEPWAK wheelchair

A group from Ryerson University, Canada is using an inexpensive 'Human Tracking and Following' system for the NEPWAK wheelchair platform [95]. Their approach uses a custom-built highly directional, steerable Wi-Fi antenna on the wheelchair that scans the Wi-Fi signal strength of its peer. This is used to track and follow a person carrying a Wi-Fi enabled pocketPC.

Figure 1:NEPWAK wheelchair

Figure 2: ICS-FORTH Wheelchair

2.4.2 ICS-FORTH Wheelchair

Investigators at ICS-FORTH developed navigation methods for robotic wheelchairs[96]. Their work focuses on navigation towards user-selected targets. Computer vision techniques are employed for target tracking; sonar-based reactivity is employed for local, fine control of motion. More specifically, the camera locks on the selected target, while at the same time the sonars are checking for obstacles that may be in the wheelchair's path[97]. The sensory modalities used for the development of the robotic wheelchair are odometry, sonar and panoramic vision. The panoramic camera provides visual data from a 360 degrees field of view and constitutes an important source of sensory information for some of the navigation capabilities.

2.4.3 Wakaumi Wheelchair

Developed a robotic wheelchair that drove along a magnetic ferrite marker lane. A magnetic lane is preferable to a painted line due to its ability to continue to work in the presence of dirt on the line. It uses two IR in front to detect the obstacle. This type of system is useful for a rehabilitation center and nursing home environment to allow people to drive around without the need for being pushed by a caregiver [33].

2.4.4 Intelligent Wheelchair System, Osaka University Japan

This wheelchair has two cameras, one facing toward the user, second facing forward. The user provides input to the system with head gestures, interpreted by the inward-facing camera. The outward-facing camera tracks targets and allows the user to control the wheelchair with gestures when out of the wheelchair. The systems response to user input (facial gestures) adapts based on the wheelchair's surroundings. Dead reckoning and a metric map are first used to drive adaptation, then sonar are used to identify environmental features. When user looks straight ahead for a short time, the outward-facing camera identifies the target and moves toward it. The outward-facing camera is used to (1) identify pedestrians, (2) determine where the user is looking, and (3) move the chair in the opposite direction to avoid collisions. The investigators developed a second prototype that uses IR sensors instead of sonar. The chair automatically switches between modes (wall following, target tracking, obstacle avoidance) based on the environment of the wheelchair.

2.4.5 Mister Ed IBM, US

Mister Ed consisted of a robot base with a chair on top. A subsumption architecture was used for control. Groups of behaviors were activated to achieve specific behaviors (door passage, wall following, target tracking). The user sat in the chair and guided the robot via a hand-held joystick. Below the seat was a bank of toggle switches that allowed the rider to authorize the robot to perform certain tasks autonomously. These activities included steering around obstacles, traversing hallways, turning at doors, and following other moving objects.

2.5 ANALYSIS AND MOTIVATION

Many smart wheelchairs (e.g. CPWNS, Rolland, Maid, SENARIO) provide safe navigation between predetermined points on an internal map is stored in memory. CPWNS, Rolland, Maid, SENARIO, VAHM etc, provide navigation assistance among internally mapped points. Other wheelchairs, such as the Luoson III, Smart Wheelchair (NEC Corp.), and Wakaumi follow tracks laid on the ground. Other wheelchairs such as SWCS, NavChair, Hephaestus and the CALL center chairs provide basic obstacle avoidance and place responsibility for path planning on the operator.

While the NEPWAK wheelchair[95] and ICS-FORTH[96][97] provide target tracking, the NEPWAK wheelchairs tracking capabilities are limited towards the direction of Wi-Fi signal strength so it is always fixed. ICS-FORTH has the capability of tracking just one color (orange). Furthermore the estimation of target distance is done using sonar sensors which limits its ability to track distant objects.

The ability to track a stationary or moving target will make smart wheelchairs more useful as a mobility aid, and it is also expected to be useful for wheeled mobility training and evaluation, as well. Caregivers, clinicians, and transporters who provide assistance to wheelchair users will also benefit from a reduction in the level of assistance needed by wheelchair users.

3.0 HARDWARE

3.1 WHEELCHAIR

The present version of the SWCS is a midwheel drive Jet-10 manufactured by Pride Mobility, USA (See Figure 3). The primary reason for choosing a midwheel drive wheelchair is greater maneuverability and clearance over drop-offs, and because it is easy to mount drop-off detector sensors and bump sensors without extra structural addition [48]. Both wheels are differentially driven and there are two passive castors in back of the driving wheels and two in front of the driving wheels. It is powered by two 12V batteries (60AH) and reaches a maximum speed of 6 miles/hour.

Figure 3: Jet Midwheel drive chair

3.1.1 Joystick

The Jet-10 is steered by a standard proportional joystick. There is a four voltage axis in the joystick to control the movement of wheelchair. These axes are Forward, Reverse, Right and Left and are referred to as Joystick Parameters. The voltage range along any axis for this joystick varies from 0.90-4.95 volts. Voltage dependence of joystick parameters are as follows:

Reverse ≈ 4.95 - Forward ;
Left ≈ 4.95 – Right ;

Here we consider the two joystick axes as independent (Forward and Right) and the remaining two dependent. The joystick forward voltage and forward velocity relation follows the curve shown in Figure 4. While plotting this curve we are keeping the other joystick parameters set as follows:

Reverse ≈ 4.95 – Forward
Left ≈ Right ≈ 2.49
Velocity=-35.4062*Voltage + 88.2676 , where velocity is measured in inches/sec.

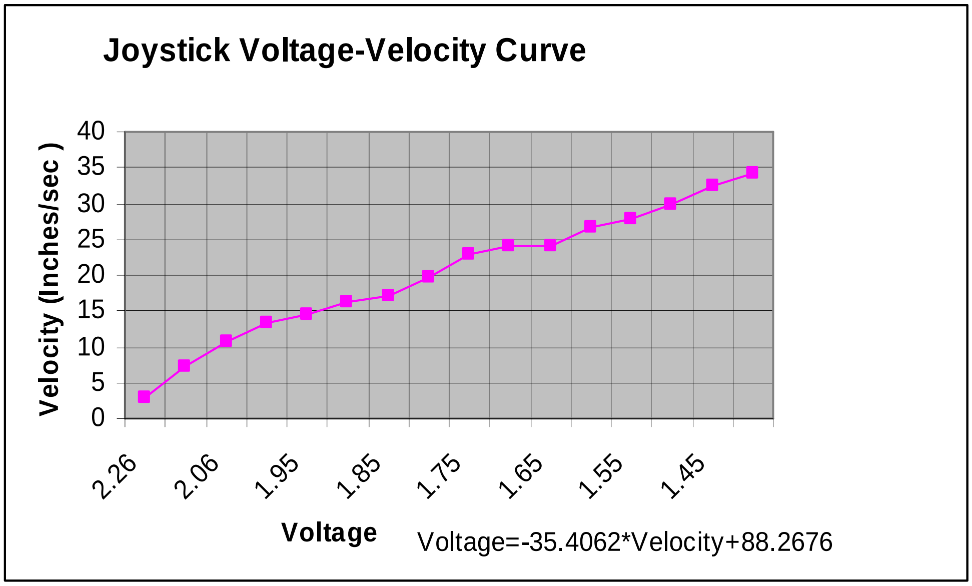


Figure 4: Voltage Velocity Curve

When the wheelchair is not moving and the joystick power is switched on, the mean, median and standard deviation for our proportional joystick axis is shown in Table 3.

Table 3: Wheelchair Idle condition Joystick Parameters

	Forward	Reverse	Right	Left
Mean	2.50	2.47	2.49	2.47
Median	2.50	2.47	2.49	2.47
Std	0.001	0.001	0.001	0.001

3.1.2 Turning radius of the wheelchair:

The relationship between turning radius of the wheelchair and joystick parameters is shown in Equation 1. If rotational speed (measured in rotations/sec) of the two wheels are N1(right wheel) and N2 (left wheel) for a given joystick position, and if the wheelchair is turning right as shown in Figure 5, the rotational speed of left wheel should be greater then rotational speed of right wheel in this case the turning radius **R** of the wheelchair is given by the relation

$$R \approx \frac{27.5 \times N_2}{\Delta N} \approx \frac{27.5 \times N_2}{57.334 \times \Delta V} \qquad \text{---(1)}$$

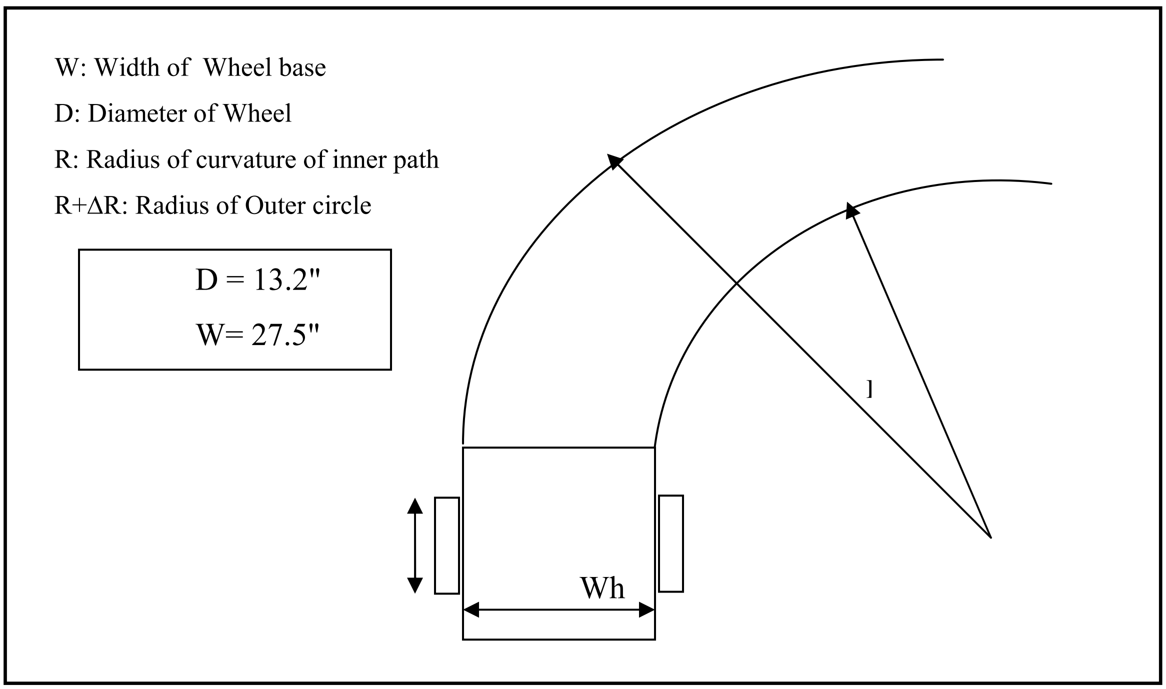


Figure 5: Wheelchair Turning Radius

3.2 SENSORS:

Available choices for proximity sensors include sonar, IR, radar, laser scanners and laser line stripers. A laser scanner is the most accurate sensor, but it's price ($5000 per unit) and resource consumption are too high for our purposes. The laser line striper is a high resolution short range sensor but it's performance under sunlight, cost ($US 1000), availability and safety (class III laser) issues limit its use for our purposes[109].

Even though sonar and IR have limitations they serve as a complementary sensor pair, so the surfaces which can not be detected by one sensor can be detected by the other sensor. Hence, using sonar and IR together can fulfill most of the requirement for a smart wheelchair to be a dependable platform. In keeping with our goal of producing a system that was both modular and configurable, one sonar and one infrared sensor were housed together, which we refer to as a "sensor module."

Fourteen sensor modules were mounted on the wheelchair lap tray with the use of Velcro and duct tape, and five sensor modules are mounted on the wheelchair body on the circular frames. For maximum coverage area, nineteen Sonaswitch sonar and two GP2D12- IR were used. Sensor placement around the wheelchair is shown in Figure 6

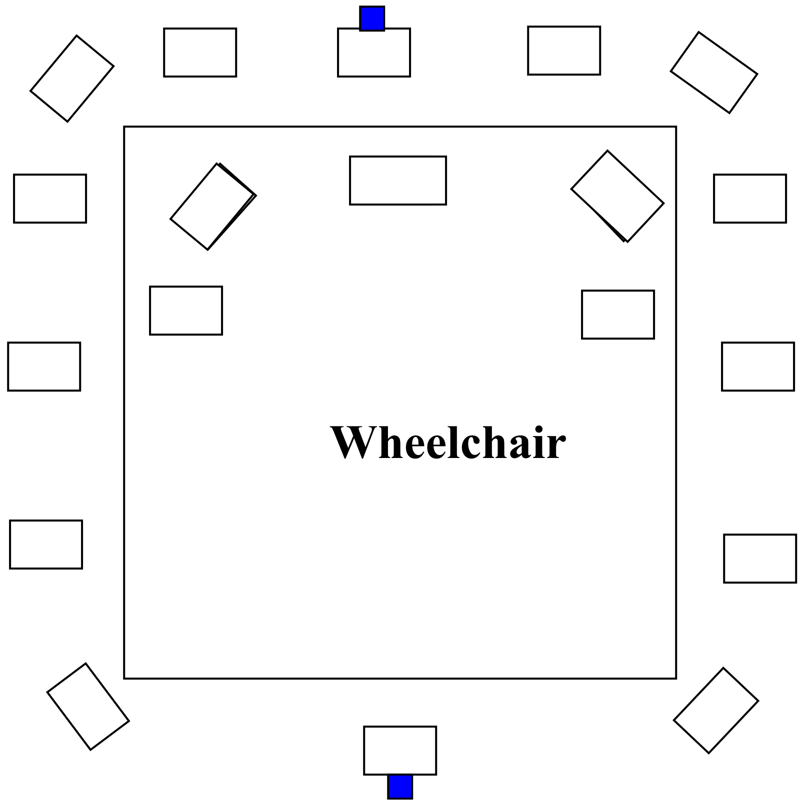
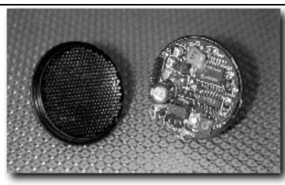


Figure 6: Sensor Schematic in SWCS

3.2.1 Sonar Sensor

The SWCS primarily uses Sonaswitch MiniA sonar sensors (See Figure 7). The selection criterion for this sensor was based on an evaluation of low cost range finders [52].The Sonaswitch Mini-A works better then it's counterpart Poloroid[58] sensors on angular and smooth surfaces. The range of this sensor is adjustable from 10 cms to 2.5 meters[57].

The MiniA is an analog sensor, and it's voltage reading varies based on detection distance. The relationship between voltage and detection distance is linear, and voltage varies from 0-5 volts. For our application the gains and range of the sensors were calibrated to detect obstacles at a minimum distance of 10 cms and a maximum of 2.20 meters.

 **Figure 7: SonaSwitch**	 **Figure 8: GP2D12 IR**	 **Figure 9: Deventech SRF08**

3.2.2 IR

The SWCS uses Sharp-GP2D12 IR range finders (see Figure 8). This sensor takes a continuous distance reading and reports the distance as an analog voltage with a distance range of 10cm (~4") to 80cm (~30"). This sensor is a short range sensor and works well on surfaces with low reflectivity and can reliably detect inclined surfaces with a maximum detection angle of 43^0. The IR Sampling rate for the SWCS is 10Hz.

Currently the SWCS uses two GP2D12 sensors, placed as shown in Figure 6. Interfacing these sensors to the computer is done through NI Daq-1200 and Daq-6024E cards.

3.2.3 SRF08

This sonar sensor from Devantech can detect objects within a range of 3cm to 6m. The SRF08 is connected to the SWCS using an IIC bus [88]. 16 SRF08 modules can be connected on a single digital data communication line, which reduces hardware cost for extra sensors. Interfacing the SRF08 sensors to the SWCS controller is done through a BasicStamp-2p (40-pin) and the digital input lines of two DAQ cards (see Figure 11).

3.3 CAMERA

The Logitech Quickcam Pro-4000 is a USB based camera with a field of view of 45 degrees. The camera was calibrated using a standard perspective camera model [89] using Intel OpenCV. The intrinsic and extrinsic parameters (given by the matrix in Figure 10) are required to find the correspondence between an image and world coordinates.

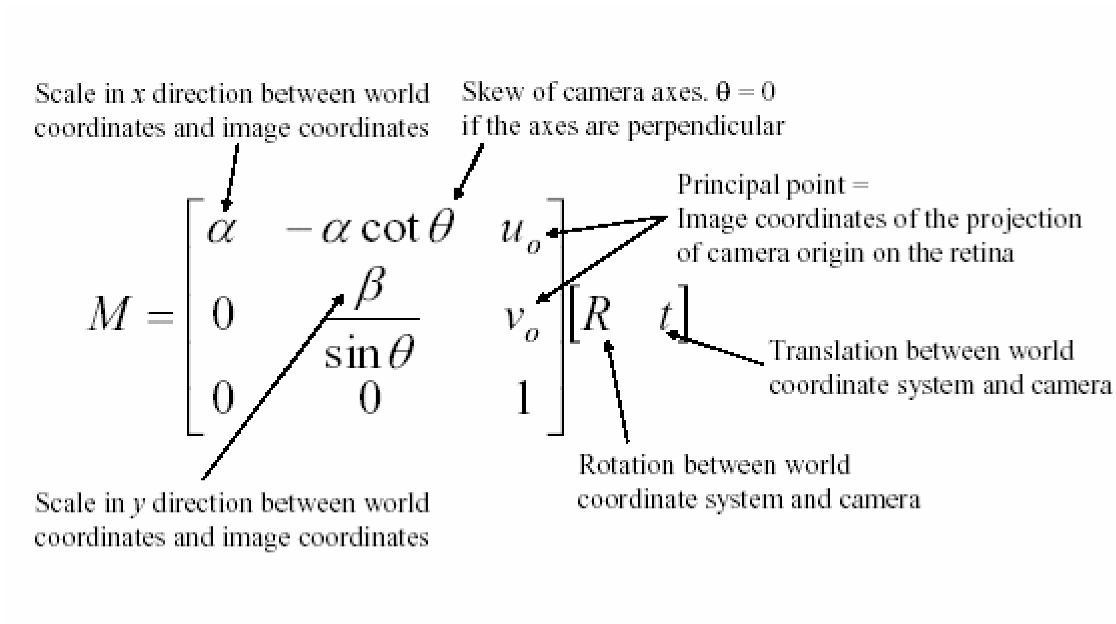


Figure 10: Standard Perspective model from [83]

Camera calibration and interfacing is done using OpenCV Beta 4.0.This is a collection of C functions and C++ classes which make image processing and computer vision algorithms easy to implement. OpenCV provides standard functions required for camera calibration. The obtained camera calibration parameters are listed in Table 4 and Table 5.

Table 4: Camera Matrix

[626.317	0	295.359]
[0	629.92	234.565]
[0	0	1]

Table 5: Distortion Matrix

[-0.124954	0.0948584]
[0.00378635	-0.00846655]

3.4 DATA ACQUISITION DEVICES

The SWCS uses NI DAQ-1200 and NI DAQ-6024E PCMCIA cards. Both DAQ cards have digital and analog input lines and output lines. All analog and digital inputs from Sonaswitch Mini-A, GP2D12, Joystick and SRF08 connect to these cards (as shown in Figure 11). The SWCS controller software uses NI-DAQ libraries written in Microsoft Visual C++ to communicate with the DAQ cards.

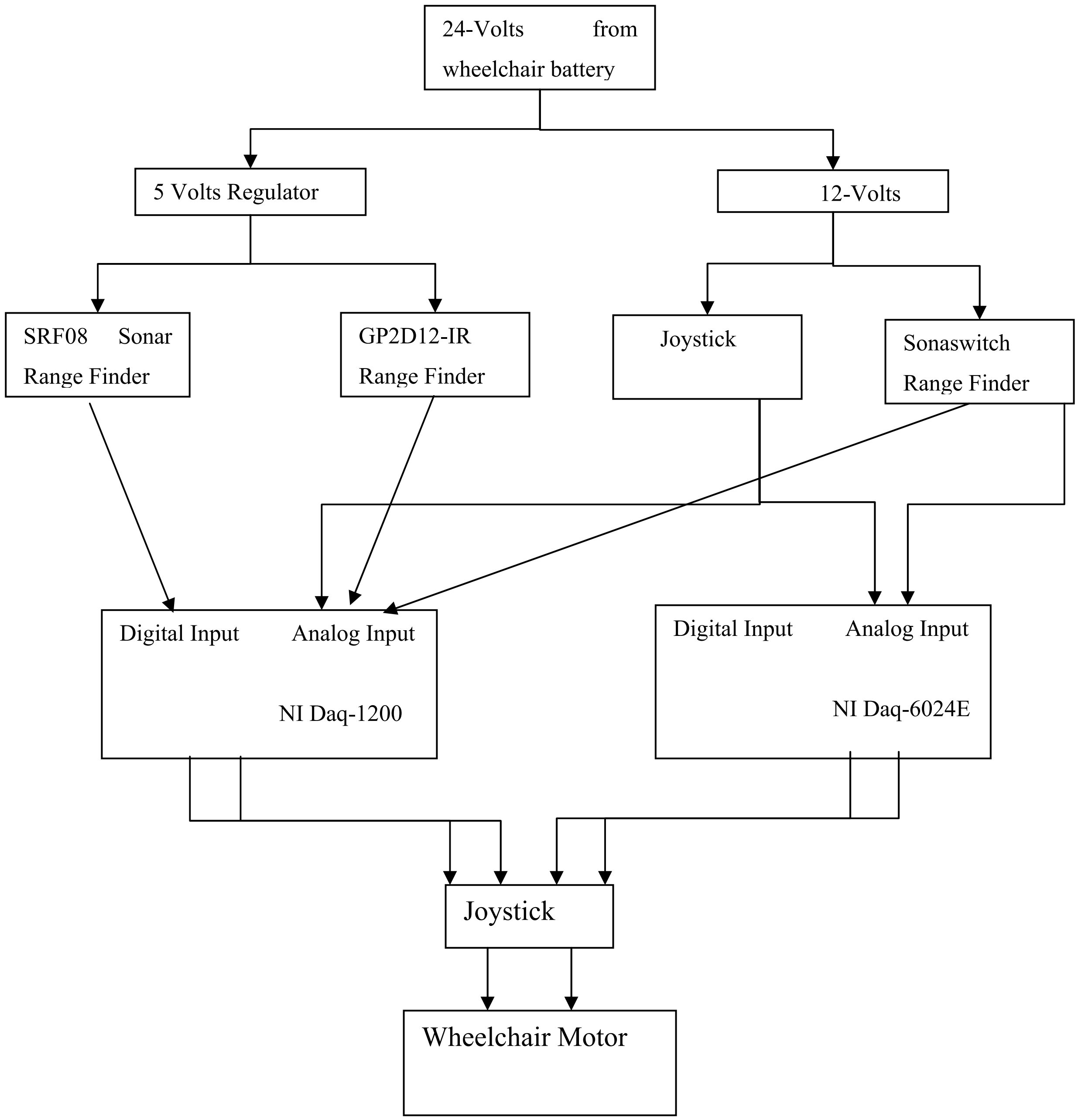


Figure 11: Hardware integration schematic

After integrating all the hardware in midwheel drive chair the complete system picture is shown in Figure 12.

Figure 12: SWCS Finished view after hardware Integration

4.0 CONTROLLER

4.1 CONTROLLER TYPES

The control software was written in Microsoft Visual C++ 6.0 and implemented on a Pentium III, 933Mhz, 528MB RAM Toshiba Laptop. The controller for the SWCS provides both Semi-autonomous and Autonomous modes of operation. In this thesis, we evaluated the performance of the wheelchair in autonomous mode only because there is not enough space in the present wheelchair for any user to sit and drive the chair towards the targets being tracked.

4.1.1 Semi-Autonomous Controller

In semi-autonomous mode the controller takes input from the user and modifies it to achieve the desired task of tracking (see Figure 13). The driver has primary control of the wheelchair's motion while the controller provides collision avoidance the user has the ability to override the signals generated by the controller at any time.

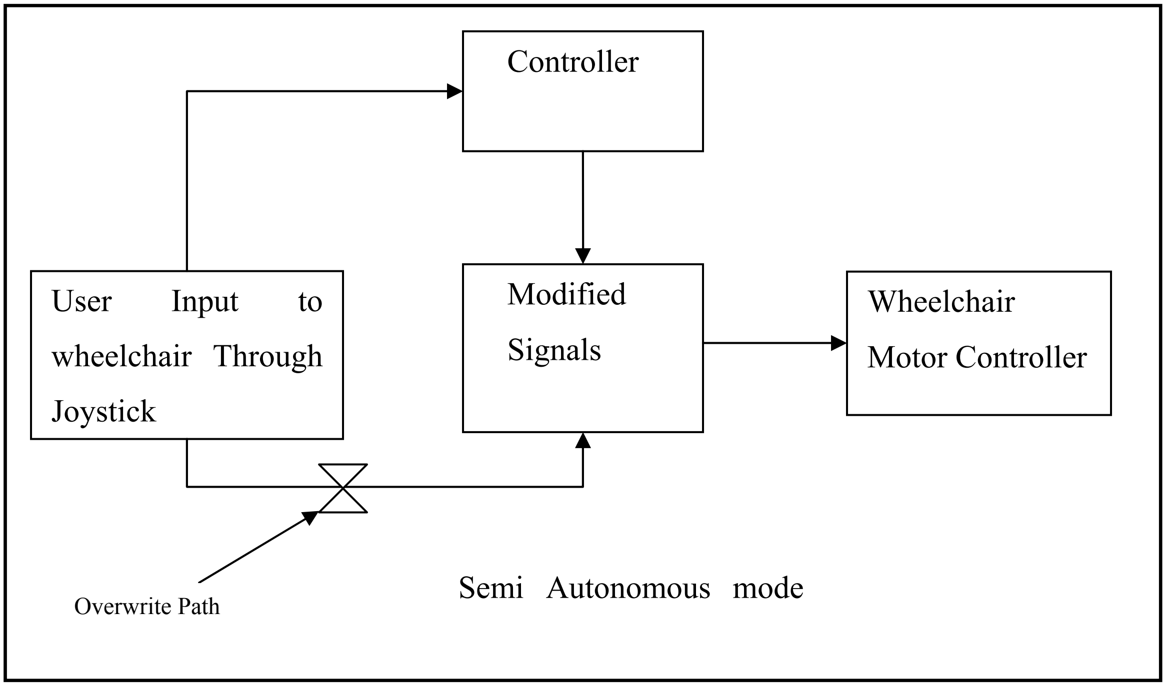


Figure 13: Semi Autonomous mode control schematic

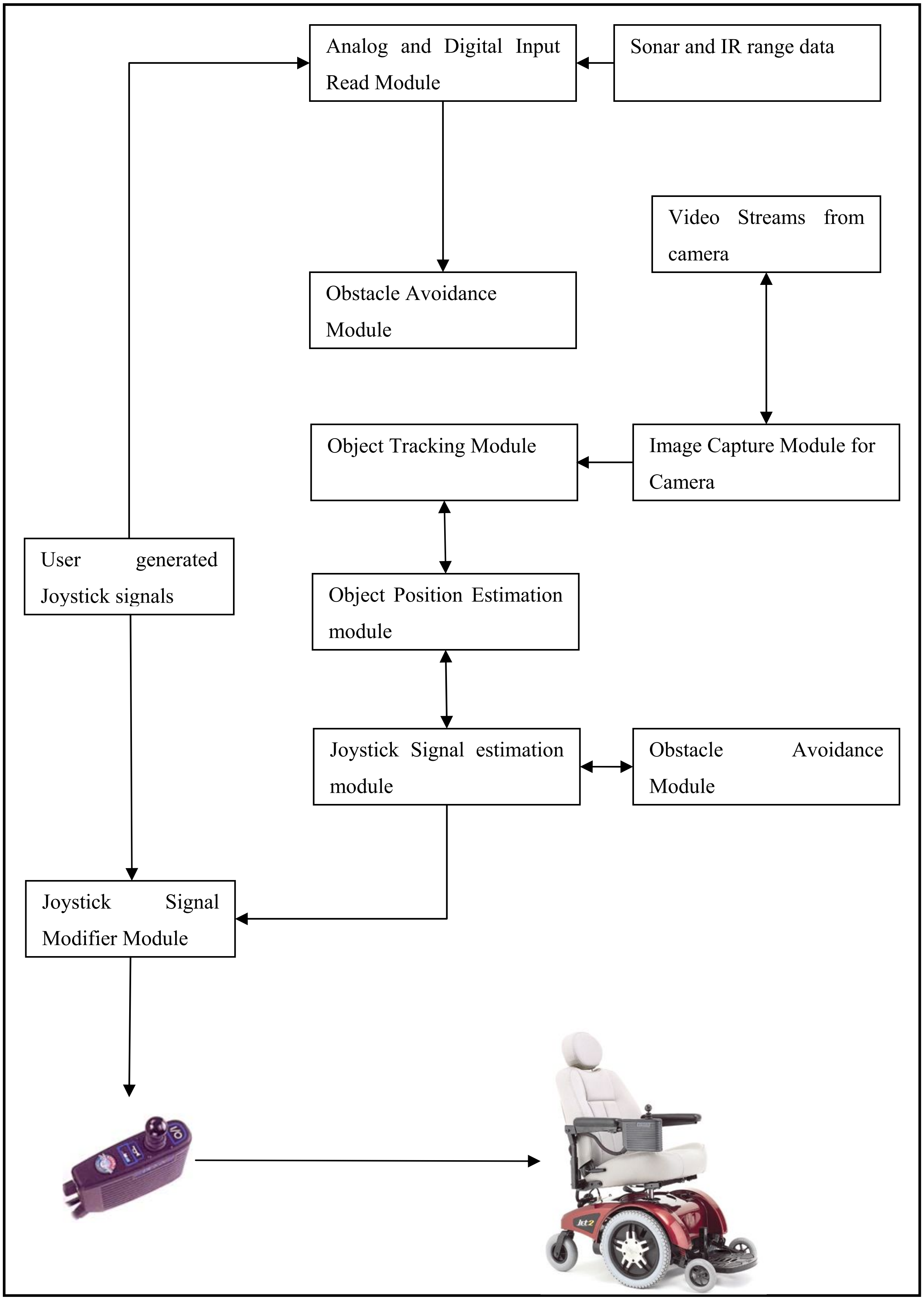


Figure 14: Semi Autonomous Modular Controller Design Schematic

4.1.2 Autonomous Controller

In autonomous mode the user selects a moving or stationary target to track or follow. Once the target is selected the controller will generate the appropriate signals required for the SWCS to follow the moving object or reach the stationary object.

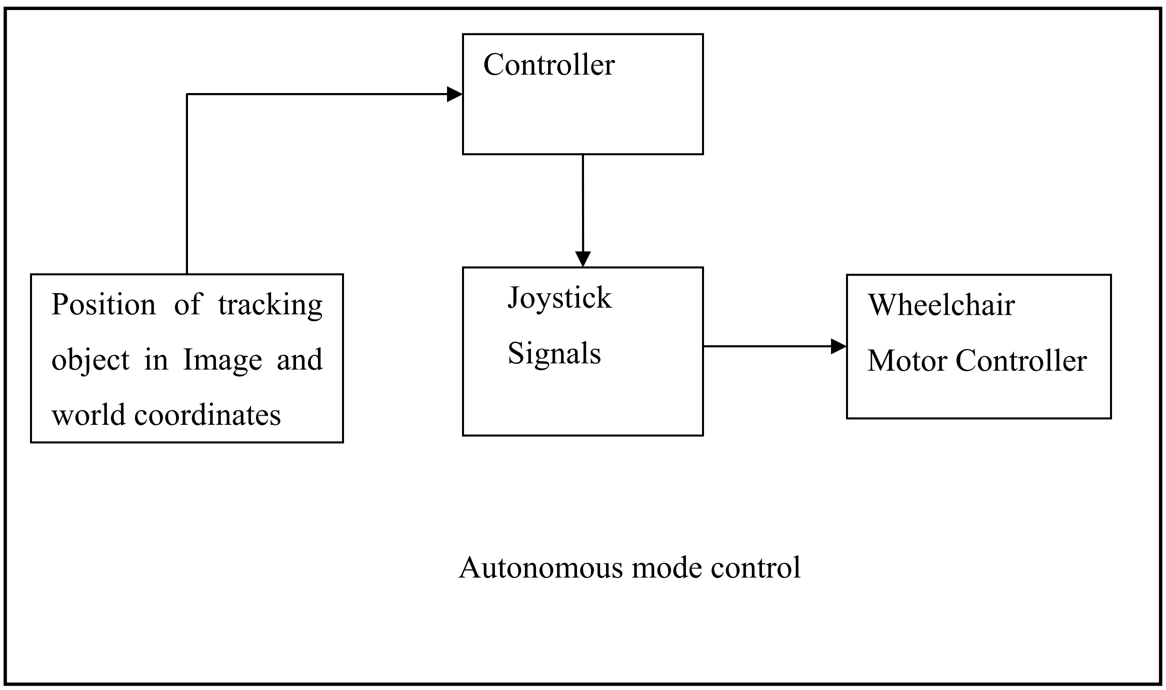


Figure 15: Autonomous Mode Control Schematic

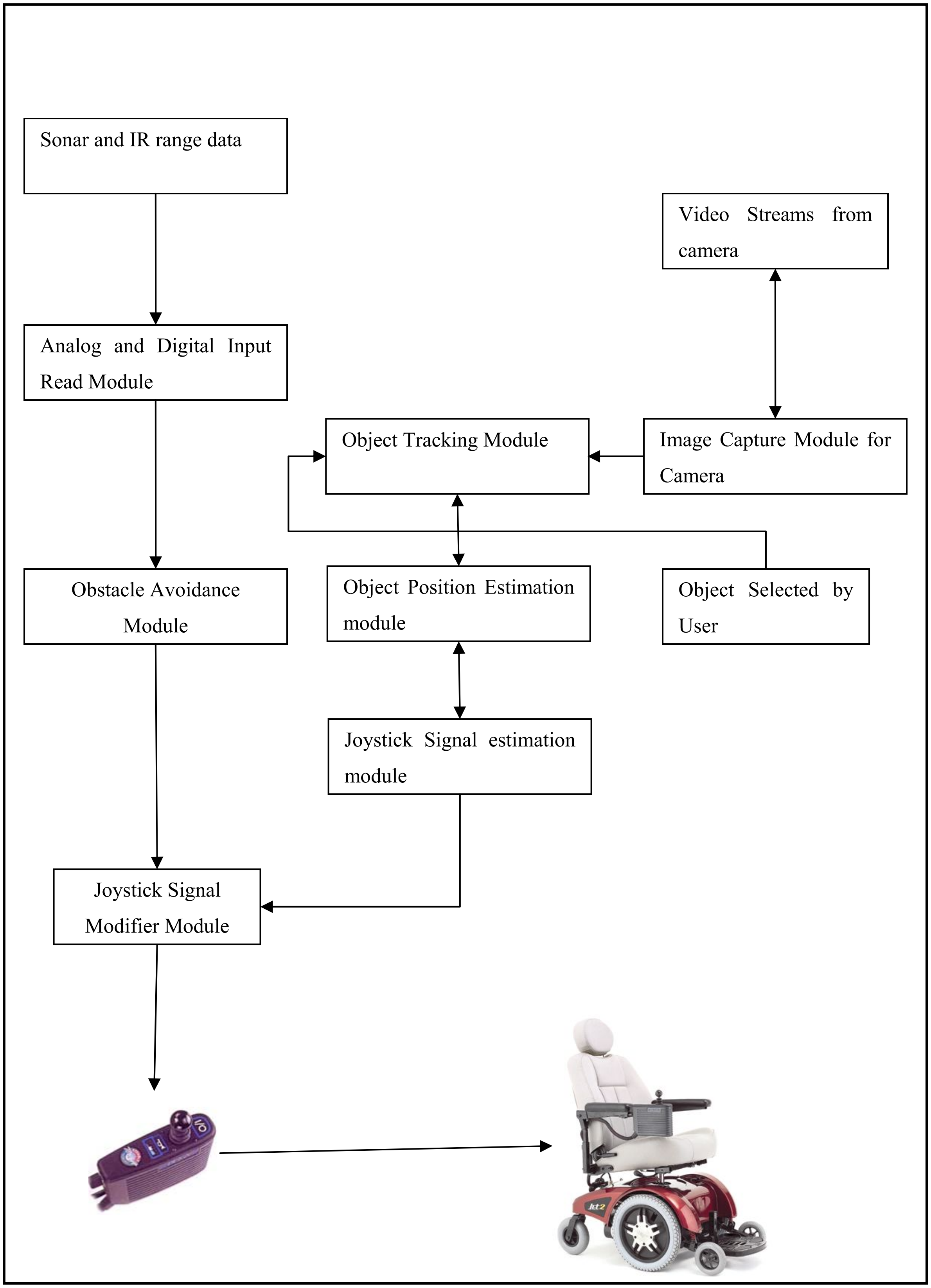


Figure 16: Modular Components in Autonomous Mode Control Architecture.

4.2 CONTROLLER MODULES

Controller modules include: sensors and joystick signal reading module, obstacle avoidance module, image capture module, target tracking module, target position estimation in world coordinate module, joystick signal estimation and wheelchair motion parameter generation module. All these modules are explained in the following sections below.

4.2.1 Analog and Digital input reading module

All analog and digital inputs are read through a NI Daq-1200, and a NI Daq-6024E PCMCIA card. Software routines for this module are implemented in Microsoft Visual C++ using National Instrument DAQ Libraries. Sensors read in this module include the SonaSwitch and GP2D12-IR to determine the proximity of obstacles around the wheelchair, and joystick signals to determine the wheelchair motion parameters such as speed, direction and radius of curvature.

4.2.2 Obstacle avoidance Module

The obstacle avoidance module chooses the path of travel for the SWCS to avoid obstacles on the path generated by the computer (autonomous mode controller) or wheelchair user(semi-autonomous mode) while tracking a target. The SWCS uses the Minimal Vector

Field Histogram (MVFH) algorithm [30] for avoiding obstacles without compromising speed, comfort and safety of the wheelchair user [31]. The MVFH method (developed by Bell [69]) is based on the Vector Field Histogram (VFH) algorithm by developed by Borenstein and Koren[66][67] which was originally designed for autonomous robots[68]. The MVFH code for the SWCS was developed by Dr. Richard Simpson.

MVFH is a good choice for human-machine systems in which the machine must share control with the user [28][32]. MVFH obstacle avoidance modifies the user's input command to achieve safe travel. This approach allows the user effective control while overriding unsafe maneuvers. MVFH accounts for the sensors' shortcomings, such as inaccuracies, crosstalk, and spurious readings by using a histogram that is updated by rapidly firing 19 sensors around the robot during motion.

A virtual window 3000x3000mm is created overlaying the wheelchair and centered at the wheelchair's geometric center. This virtual window is called the certainty grid (see Figure 17). This window is further divided into square cells of 100x100 mm. For safety purposes a rectangular area around the wheelchair is defined such that the center of the rectangular area coincides with the center of wheelchair, In Figure 17 shaded grid cells show this area. If anything is detected in this region SWCS will simply stop. For efficient detection of the obstacles in the safety zone we are using IR sensors which are short range[10– 60cm] sensors.

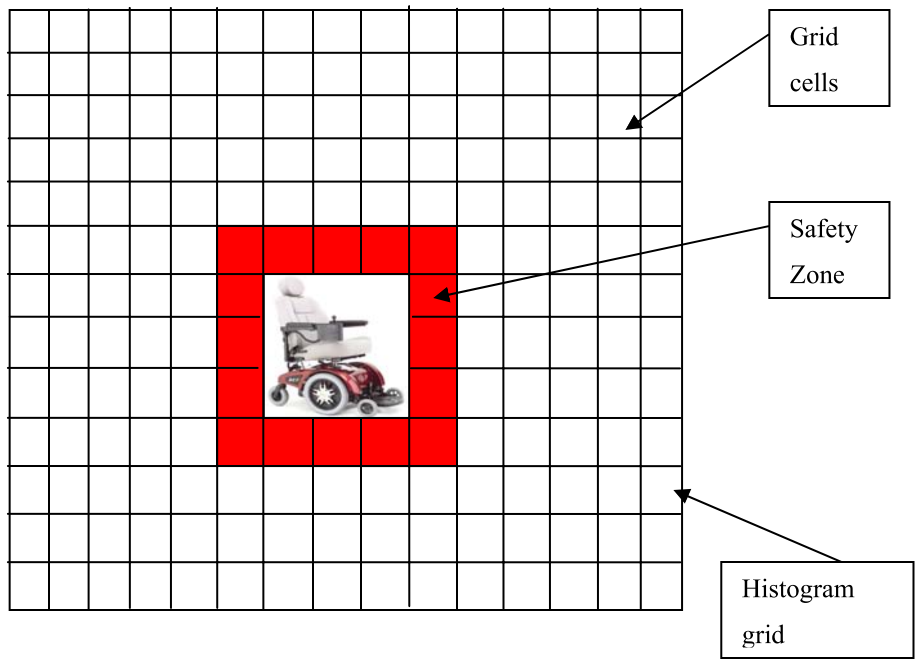


Figure 17: Virtual Satey Grid Around SWCS

Each cell is assigned a certainty value, which represents the possibility of an obstacle occupying a given cell. Higher certainty values correspond to a greater probability of an obstacle being present in the specified cell. The certainty values in the certainty grid are calculated based on sensor readings in the grid world coordinate system (see Figure 18).

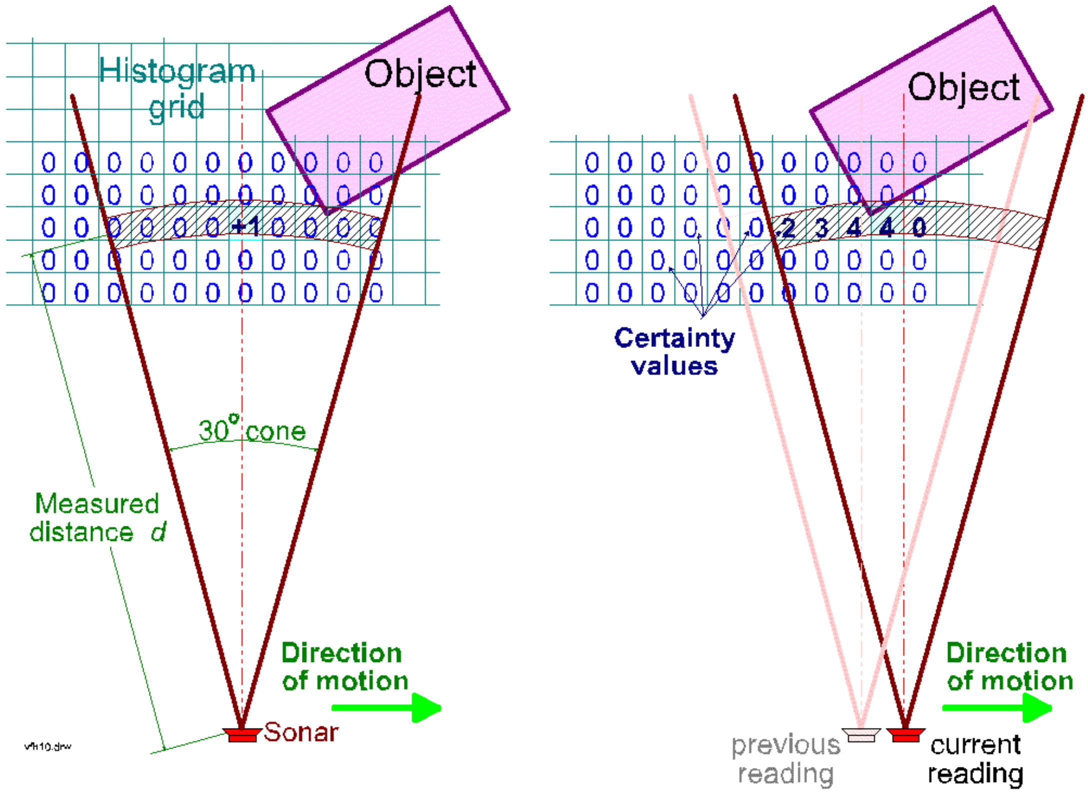


Figure 18: Updated Grid Cells in Sonaswitch field of view (figure taken from [66]) .

The certainty grid can be divided into 72 angular sectors each 5 degrees. These 72 angular sectors represent possible joystick inputs. There is a linear correspondence between these sectors and the corresponding wheelchair turning radius. MVFH uses an intermediate data structure, called the polar histogram (H). H is an array of 72 (5-deg wide) angular sectors.

To make things computationally efficient, only the cells in the area which affect the motion of the wheelchair at any given instant are considered active cells. The contents of each cell in the active window is mapped into the corresponding sector of the polar histogram (see Figure 19), resulting in each sector S holding a value h_S. Thus, h_S is higher if there are many cells with high confidence values (CV) in one sector. Intuitively, this value can be interpreted as the polar obstacle density in the direction of sector S.

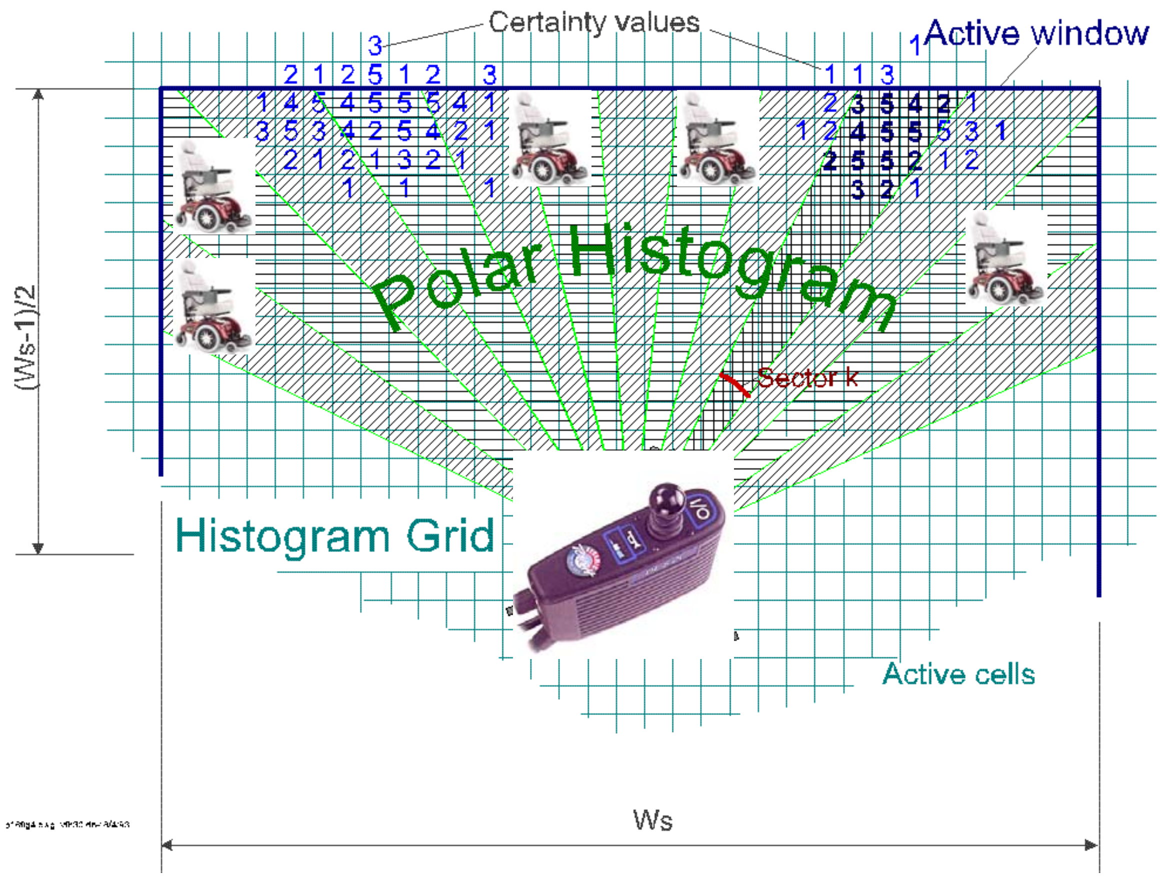


Figure 19: Mapping of wheelchair motion sectors in the Grid (from [66])

For safe motion of the wheelchair we define a polar obstacle density threshold. This threshold depends on the safe region around the wheelchair. Usually at a given time there could be more than one sector with an obstacle density less than the threshold. The VFH algorithm selects the one that most closely matches the direction to the target. In MVFH, instead of searching for a direction of travel near to the desired direction of travel, a parabolic weighting function (curve "w" in Figure 21) is added to the polar histogram (curve "h"), and the direction of travel with the resulting minimal weighted obstacle density (Θ_s) is chosen. As seen in Figure 21, the weighting function is a parabola with its minimum at the direction of travel indicated by the wheelchair's joystick position. So the direction indicated by the user's input from the joystick receives the least amount of additional weight (obstacle density) and those directions furthest from the user's goal receive the most weighting, which predisposes the chair to pursue a direction close to the user's goal.

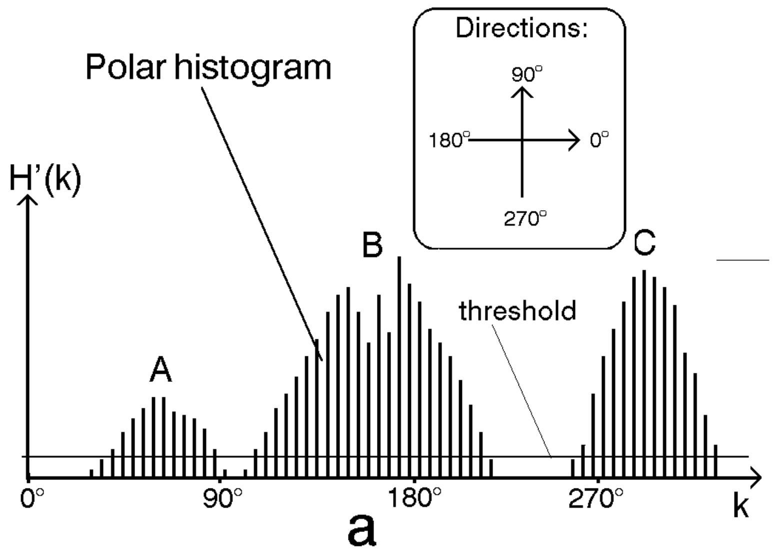


Figure 20: Obstacle density histogram (Taken from [108])

Next, the wheelchair's speed is determined based on the proximity of obstacles to the projected path of the chair. This step models the shape of the wheelchair exactly, which allows The chair to approach objects more closely than VFH while still maintaining the safety of the vehicle.

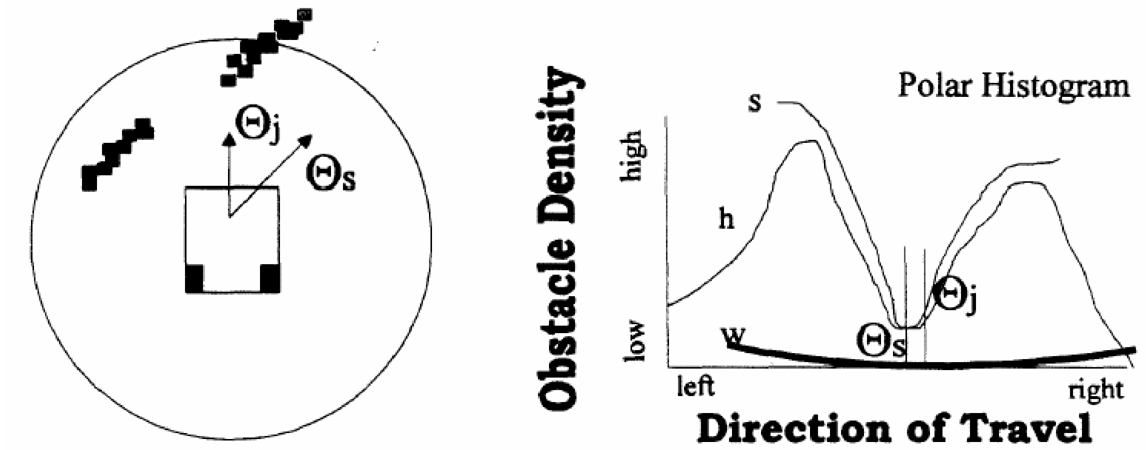


Figure 21: Applying Parabolic Weighting Function to Obstacle Density Histogram (Figure Taken from [108])

There were many implementation issues in the application of the MVFH method to a power wheelchair system. First, the power base is significantly different than typical mobile robots. For example, the pneumatic tires, wheel slippage, and loose drive train make turning radius and motion path estimation less accurate. The geometry and kinematics of the wheelchair are significantly more complicated than those of most mobile robots. In addition, the user must feel safe and in control of the wheelchair; the system's reaction to input must be intuitive enough to inspire confidence and allow understanding; and the wheelchair's motion must be smooth and comfortable [108].

4.2.3 Computer Vision Module

Computer vision was implemented using the Intel OpenCV [80] libraries. OpenCV implements a wide variety of tools for image interpretation. It is compatible with the Intel® Image Processing Library (IPL) that implements low-level operations on digital images. OpenCV is primarily a high-level library implementing algorithms for calibration techniques (Camera Calibration), feature detection (Feature) and tracking (Optical Flow), shape analysis (Geometry, Contour Processing), motion analysis (Motion Templates, Estimators), 3D reconstruction (View Morphing) and object segmentation and recognition (Histogram, Embedded Hidden Markov Models, Eigen Objects).

4.2.4 Image capture module

We are using the CvCam library in OpenCV to capture images from the camera. CvCam is a universal cross-platform module for processing video streams from digital video cameras. It is implemented as a dynamic link library (DLL) for Windows. CvCam provides a simple and convenient Application Programming Interface (API) for reading and controlling a video stream, processing its frames and rendering the results. CvCam is distributed as a part of Intel's OpenCV project under the same license and uses some functionality of the Open Source Computer Vision Library[80].

4.2.5 Target Tracking Module

4.2.5.1 Design Criteria for the SWCS Target Tracking Algorithm

The target tracking algorithm for the SWCS must be robust and efficient so that objects can be tracked in real time (30 frames per second) while consuming as few system resources as possible. The algorithm should be able to serve as part of the SWCS obstacle avoidance algorithm (VFH and MVFH). The tracker should work on inexpensive consumer cameras (Logitech Quickcam pro-4000) and should not require calibrated lenses.

4.2.5.2 Background: Target Tracking Algorithm

Tracking is an active field in computer vision with applications in diverse fields such as security, robotics, biology and gaming. Most tracking algorithms developed use methods such as tracking contours with snakes [60][61][62], using Eigenspace matching techniques [63], maintaining large sets of statistical hypotheses [64], convolving images with feature detectors [65], point distribution models, active appearance models [105][106][107] or blob tracking[111]. All these approaches are computationally expensive and are not robust in noisy or cluttered environments.

The robotics community typically uses color-based target tracking algorithms [71][72][73][74][75], yet even these simpler algorithms are too computationally complex due to their use of color correlation, blob and region growing, Kalman filter smoothing and prediction, and contour considerations. The complexity of these algorithms derives from their attempts to deal with irregular object motion due to perspective (objects near the camera seem to move faster than distant objects); image noise; distracters, such as other similar color distribution in the scene; and lighting variations.

4.2.6 Continuously Adaptive Mean Shift Algorithm(CAMSHIFT)

The algorithm best suited to the needs of the SWCS is the Continuously Adaptive Mean Shift Algorithm (CAMSHIFT)[78], which was first introduced for tracking human faces for providing perceptual user interfaces in games[79]. CAMSHIFT is based on robust statistics and probability distributions. Robust statistics are those that tend to ignore outliers in the data (points far away from the region of interest). Thus, robust algorithms help compensate for noise and distracters in the image data. CAMSHIFT is also based on a robust nonparametric technique for climbing density gradients to find the mode of probability distributions called the adaptive mean shift algorithm [74][75][76][77].

The whole CAMSHIFT algorithm is summarized in Figure 22. In the CAMSHIFT algorithm each video frame is converted to a color probability distribution image (Figure 28) [81] via a color histogram model of the target selected by the user (e.g., the color probability distribution of the clothes of the person the SWCS instructed to follow). The center and size of the target are found via the CAMSHIFT algorithm operating on the color probability image. The current size and location of the tracked object are reported and used to set the size and location of the search window in the next video image. The process is then repeated for continuous tracking. The algorithm is a generalization of the Mean Shift algorithm as mean shift is used to set the iteration policy for the search window size and center for every frame. The shaded region in Figure 22 represents the Mean Shift Algorithm.

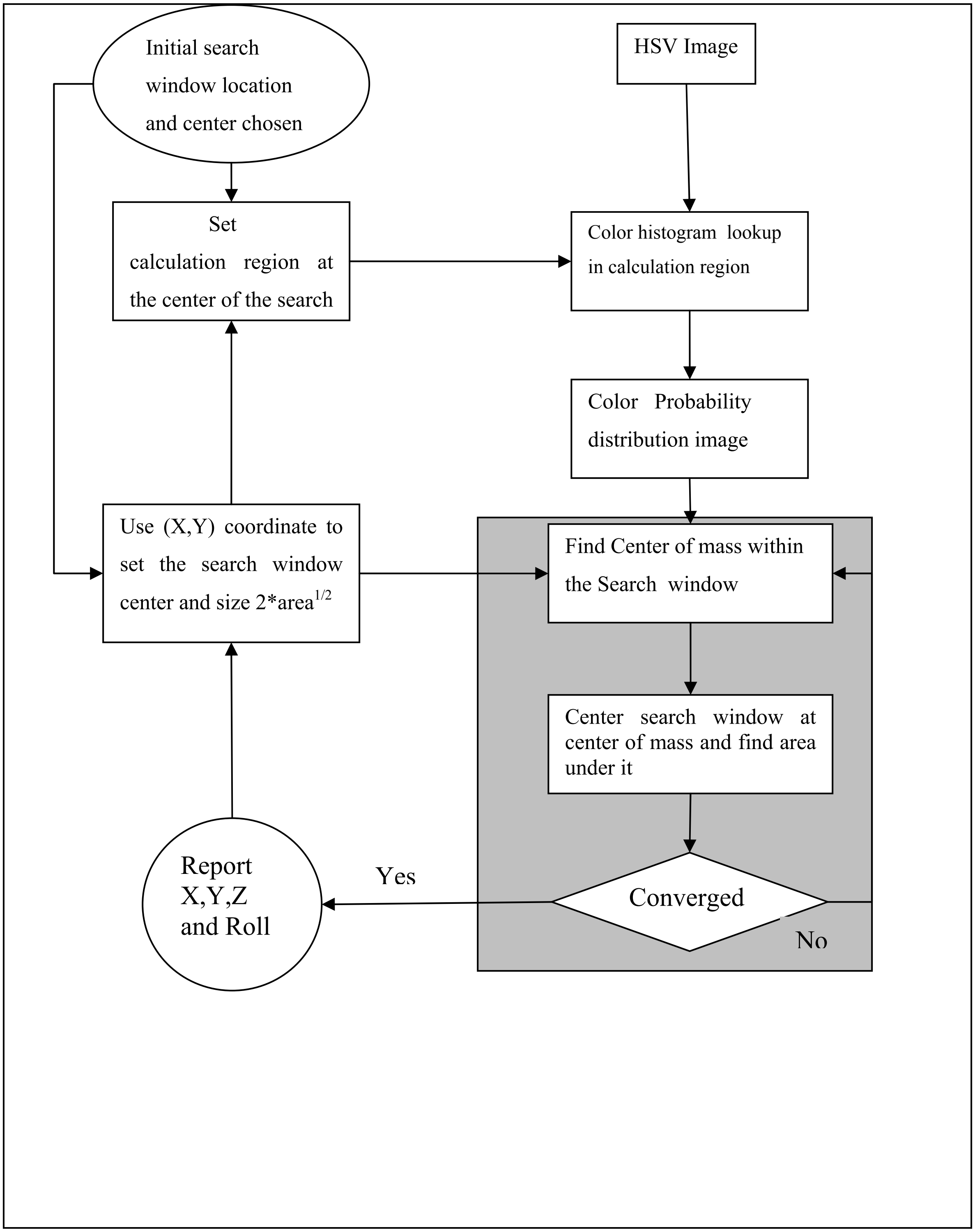


Figure 22: Continuously Adaptive Mean Shift Algorithm (CAMSHIFT)

4.2.6.1 Conversion of color space from RGB to HSV

Color is intuitively an important cue for understanding images. In particular, objects that look similar in black and white images can be discriminated more easily in color images. Colored light is described by its power distribution spectrum $E(\lambda)$, the power emitted for every wavelength λ. For computer vision, we consider the visible wavelength between 400nm and 760nm. The power distribution contains two types of information:

1. The overall intensity or brightness of the light which is the integral of the power spectrum over all the wavelengths (i.e., the total power transmitted).

2. The relative values of the $E(\lambda)$'s, which carries information about color. For example, an almost flat spectrum corresponds to white light (little color), a spectrum with a single peak corresponds to a pure saturated color.

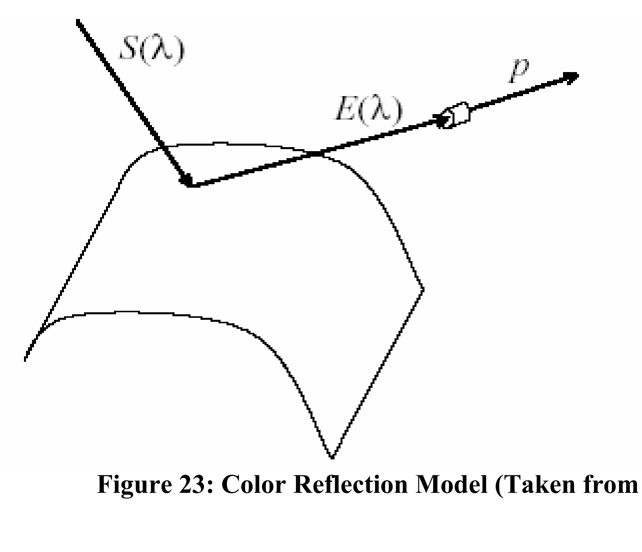


Figure 23: Color Reflection Model (Taken from [83])

$$P = \int \sigma(\lambda) * \rho(\lambda) * S(\lambda) d\lambda \qquad ----2$$

$\sigma(\lambda)$: Photoreceptor Sensitivity

$\rho(\lambda)$: Spectral Albedo

$S(\lambda)$: Spectral Power Distribution of Source Light

P: The color observed in an image

The color of an object in an image depends on the lighting conditions S(λ). This could create problems if there are variations in the lighting conditions where the object is moving. The primary color space RGB(Red, Green, Blue) depends on lighting conditions [84], so using RGB space in our algorithm would give erroneous results, which is why we are using Hue, Saturation, Value (HSV) space. The HSV model was created by A. R. Smith in 1978. Hue, Saturation and Value can be defined as follows.

1. The blend of the three components(RGB) is defined by a single parameter called "Hue"
2. The "Saturation" parameter determines how grey or pure the color will be.
3. The "Value" parameter defines the brightness of the color.

If we represent the RGB color space as a 3-D cube (see Figure 24) the HSV space will be the locus of planes where R+G+B=C. This locus can be represented by a cone (see Figure 25). The HSV coordinate system is cylindrical, and the colors are defined inside a hexcone or cone. The hue value H runs from 0 to 360º. The saturation S is the degree of strength or purity and is from 0 to 1. Purity is how much white is added to the color, so S=1 produces the purest color (no white). Brightness (V) also ranges from 0 to 1, where 0 is the black. It is easy to remove the lighting effects from the HSV space by considering just the Hue channel.

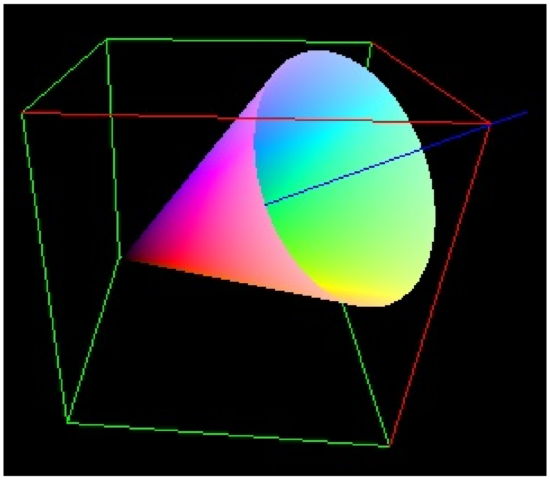


Figure 24: Mapping of HSV color space in RGB Space

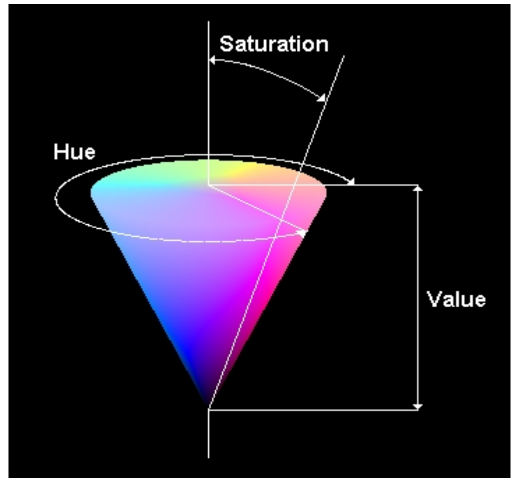


Figure 25: HSV color space description

Once the image is converted into HSV space, only the hue channel is used for further calculation. The primary reason for selecting hue channel is that this channel does not get affected by the lighting conditions. Secondly, using a single channel makes the algorithm computationally efficient.

When using real cameras with discrete pixel values, a problem can occur when using HSV space (see in Figure 25). When brightness is low (V near 0), saturation is also low (S near 0). Hue then becomes quite noisy, since in such a small cone, the small number of discrete hue pixels cannot adequately represent slight changes in RGB. This leads to wild swings in hue values. To overcome this problem, we simply ignore hue pixels that have very low corresponding brightness values. This means that for very dim scenes it simply cannot track. When light is very bright the white color can be predominant on the object color, so we will have to give some upper threshold to brightness values. Selecting the object surface and color carefully can eliminate this problem.

4.2.6.2 Color Look-up histogram creation

Once the HSV color space is obtained, a color histogram of the target window selected by the user is created. The histogram is created using hue (8 bits per pixel), which varies from 0-255 (see Figure 26). Histogram bin size in Figure 26 shows the number of pixels in the selected window which have that corresponding pixel value. This histogram is used as the template to convert an incoming image to a corresponding probability density image (see Figure 27).

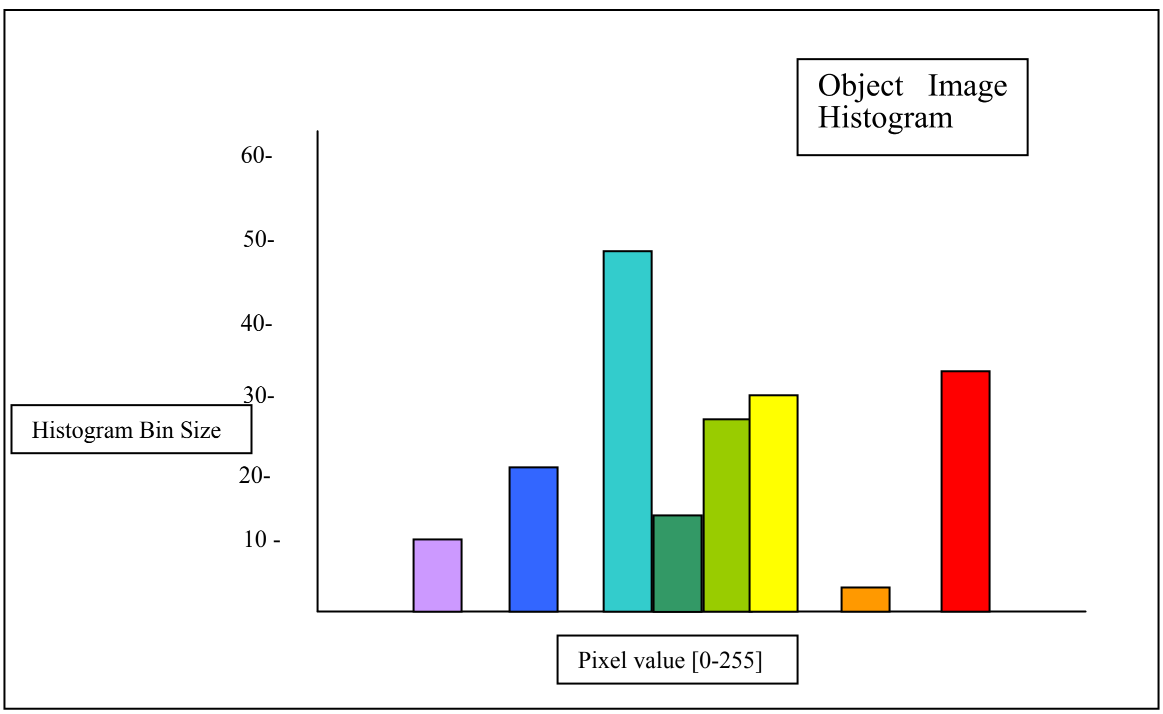


Figure 26: Hue Histogram of a Color Image

4.2.6.3 Creating Color Probability Density Image

The color probability density image is a grey scale image which shows the probability of each pixel in a given image being part of the target region. This is achieved by first normalizing the hue histogram. The image histogram (shown in Figure 29) can then be converted to the corresponding color probability distribution histogram in which each bin represents the probability of the corresponding pixel intensity in the target region. Secondly, as we have this template in the form of a pixel probability distribution, we can convert an incoming video stream into a probability density image which is a grey scale image that shows the probability of each pixel in a given image being part of the target region (see Figure 28). This calculation is done by comparing each pixel of the video stream with the pixel probability distribution template.

The calculation of the probability density image is a computationally intensive process which restricts the size of the image that can be captured from the camera. In our case, we are capturing frames of size 320x240 pixels. The probability density image is an 8-bit Grey level image in which probabilities range in discrete steps from zero (probability 0.0) to the maximum probability pixel value (probability 1.0). The greater the brightness of a pixel in the probability image, the higher the probability that the pixel is a part of the target being tracked.

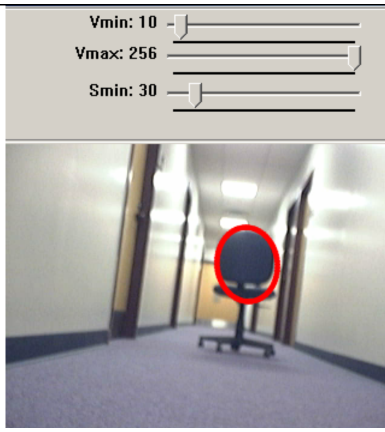


Figure 27: Target Image shown by tracking ellips

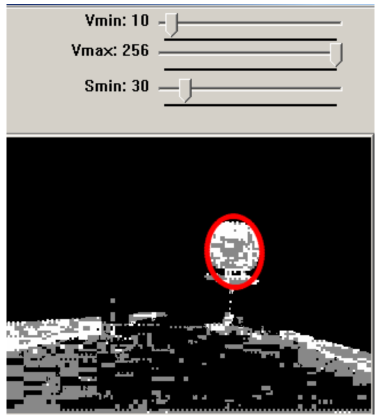


Figure 28: Probability density image showing target

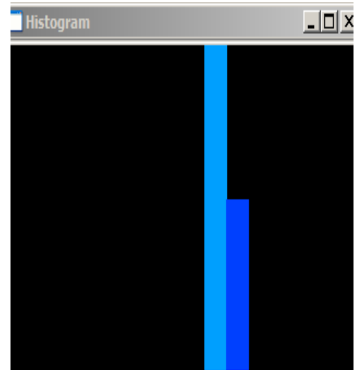


Figure 29: Hue histogram showing the tracking template

4.2.6.4 Searching For a Target in the Probability Density Image

The two key components in the search are (1) the search window center and size at the beginning of the search and (2) the algorithm which guides the convergence of the search window on the target. Both of these parameters effect the amount of computation and robustness of the algorithm.

4.2.6.5 Target Search Window Center and Size Estimation

Estimation of the search window center and size depends on the previous image. The search window for a given frame (at time t) is centered at the centroid of the tracked target in the probability density image at time t-1. If $I(x,y)$ is the pixel (probability) value at position (x,y) in the image, and x and y range over the search window then:

The zeroth moment of the image is given by equation

$$M_{00} = \sum_x \sum_y I(x,y) \qquad \text{------------------- (3)}$$

The first moment is given by

$$M_{10} = \sum_x \sum_y x.I(x,y)\ ,\ M_{01} = \sum_x \sum_y y.I(x,y) \qquad \text{-----------(4)}$$

$$M_{11} = \sum_x \sum_y x.y.I(x,y) \qquad \text{----------------------------------(5)}$$

The second moment is given by

$$M_{20} = \sum_x \sum_y x^2.I(x,y),\ M_{02} = \sum_x \sum_y y^2.I(x,y) \text{----------(6)}$$

The initial search location or window centroid is given by

$$Xc = \frac{M_{10}}{M_{00}}\ ,\quad Yc = \frac{M_{01}}{M_{00}} \qquad \text{------------------(7)}$$

The size of the calculation window is a function of the zeroth moment of the window. The SWCS uses an elliptical window for the search. The minor and major axis of this elliptical window represents the width and length of the target in the image (Equation. 11). The orientation of the major axes of the elliptical window is given by Equation 12.

$$A = \frac{M_{20}}{M_{00}} - X_c^{\,2} \qquad \text{-------- (8)}$$

$$B = 2*\left(\frac{M_{11}}{M_{00}} - X_c{}^*Y_c\right) \qquad \text{--------(9)}$$

$$C = \frac{M_{02}}{M_{00}} - Y_c^{\,2} \qquad \text{--------(10)}$$

The length(L) and width(D) are the two eigen values of the tracked probability image distribution which are given by :

$$L=\frac{\sqrt{(A+C)+\sqrt{B^2+(A-C)^2}}}{\sqrt{2}}\ ,\quad D=\frac{\sqrt{(A+C)-\sqrt{B^2+(A-C)^2}}}{\sqrt{2}} \quad \text{-------}(11)$$

The angle of the Major axis (higher Eigen value) is given by θ from vertical

$$\theta=\frac{\tan^{-1}\left(\frac{2*B}{A-C}\right)}{2} \quad \text{-------}(12)$$

The initial size of the search window is always a function of the zeroth moment (M_{00}). The units of the function M_{00} must be converted in order to implement the search window size in the CAMSHIFT algorithm. In a given probability distribution image (at time "t-1"), if maximum pixel intensity is I_{max}, then we can set the width of the search window as:

$$W=1.2*2*\sqrt{\frac{M_{00}}{I_{\max}}} \quad \text{-------------}(13)$$

$$L=3.4*\sqrt{\frac{M_{00}}{I_{\max}}} \quad \text{-------------}(14)$$

The SWCS sets the length of the search window to 1.4W for our application. Implementation of window location and size is done as per [79]. Since CAMSHIFT is an algorithm that climbs the gradient of a distribution, the minimum search window size must be greater than one in order to detect a gradient. Also, in order to center the window, it should be of odd size. Thus for discrete distributions, the minimum window size is set at three pixels.

4.2.6.6 Iteration & Convergence of the Search Window

Iteration of the search window to track the target is done using the Adaptive Mean Shift Algorithm [78]. The Mean Shift algorithm is a non-parametric technique that climbs the gradient of a probability distribution to find the nearest dominant mode (peak)[82]. At this peak the search window converges with the probability distribution image of the target in a small number of iterations. The mean shift algorithm can be summarized by following five steps:

1. Choose a search window size (W and L).
2. Choose the initial location of the search window(Xc,Yc).
3. Compute the mean location of the target in the search window.
4. Center the search window at the mean location computed in Step 3.
5. Repeat steps 3 and 4 until convergence (or until the mean location moves less than a preset threshold).

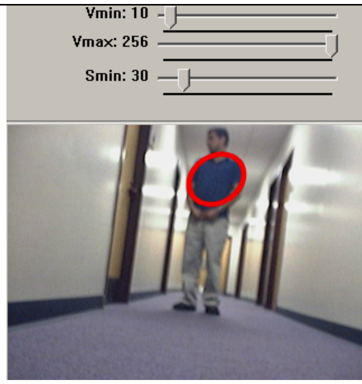


Figure 30: Tracking a Person

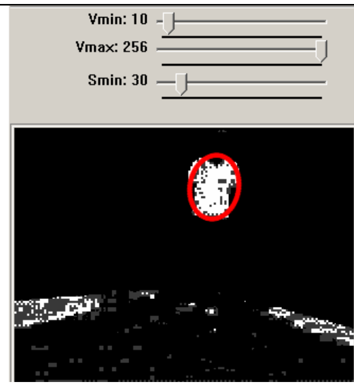


Figure 31: Probability density image of target showing the convergence of algorithm in presence of noise

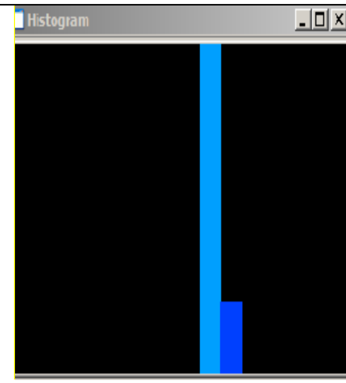


Figure 32: Hue Histogram of Target

4.2.7 Target Position Estimation in the World Coordinate system

The CAMSHIFT algorithm can report information about four degrees of freedom (DOF): (1) Xc, (2) Yc, (3) area of the object which is directly related to the distance of the object form the camera(Z), (4) rotation (θ) of the major Eigen value of the target distribution. Conversion from image coordinates to world coordinates requires the camera calibration or transformation matrix. As the relative distance between the target and the camera is not fixed and target size and shape varies constantly, it is difficult to estimate the exact position of the target in the world coordinate system.

4.2.8 Wheelchair motion strategy

Each time a new frame is captured, the validity of the target captured in the image is decided based on the previously measured target center, area, width and height. If the current calculated (X,Y,A,L,W) values are within the expected ranges, the target is considered valid target. Otherwise it is classified as a false positive case. False positive cases can occur because of noise, occlusion or too much variation in the lighting conditions. If the target is invalid then the wheelchair stops, waits and searches the image until a valid target is identified. The search policy for a valid target involves the starting location of the search window, which is calculated based on the Gaussian estimator from the database.

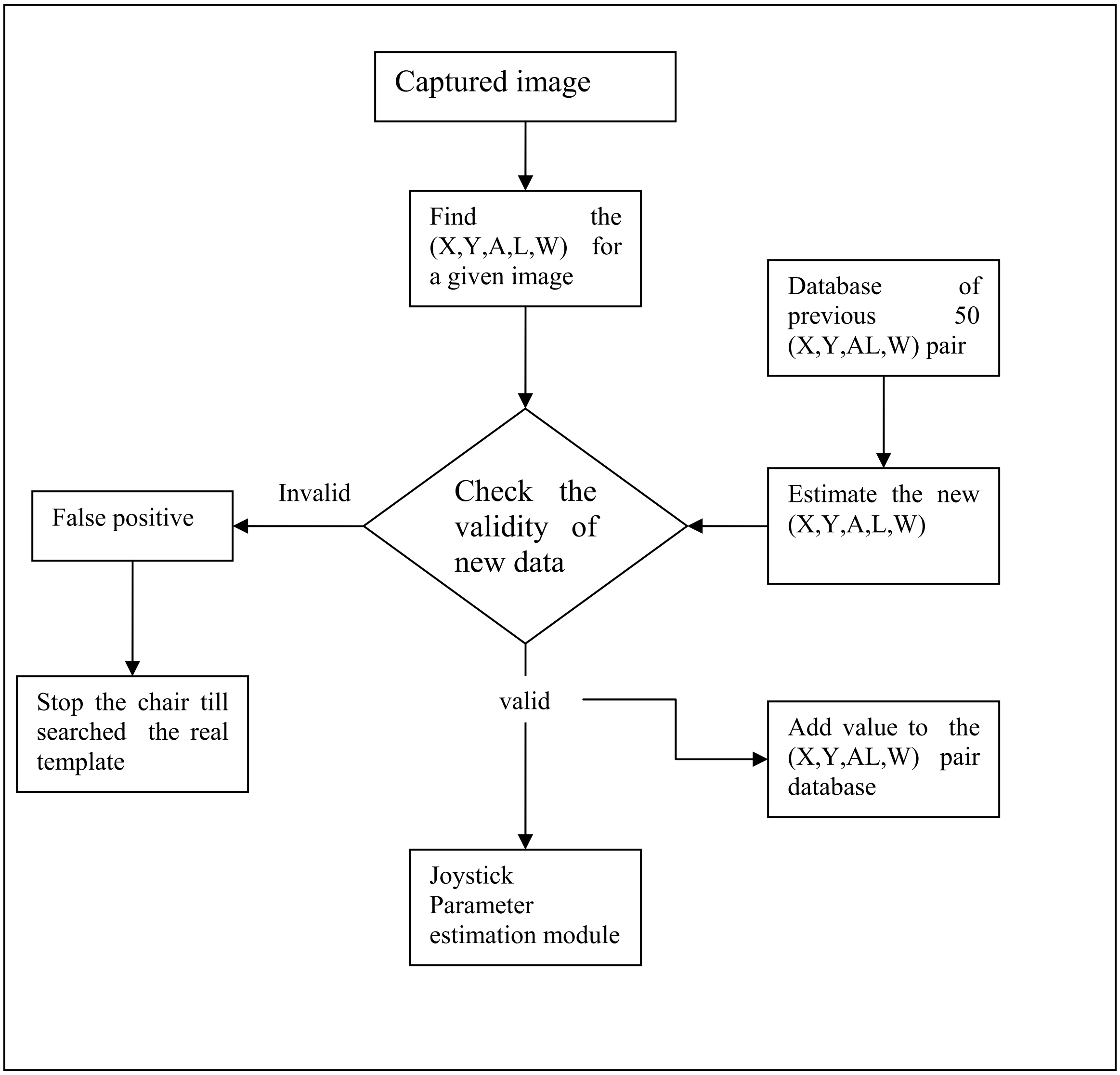


Figure 33: Controller decision making strategy

While the target in the captured frame is valid, the correct parameters (X,Y,A,L,W) are sent to the joystick parameter estimation module to create the desired wheelchair motion.

4.2.9 Joystick Parameter Estimation Module:

The joystick parameter estimation strategy is defined for tracking moving and stationary targets. Joystick parameters are estimated through a deterministic system designed and trained on different target sizes. The wheelchair's speed is controlled by the area of the object while The wheelchair's turning radius is controlled by the center of the target within the image. The smaller the area of the target, the greater the speed of the wheelchair and the further the lateral shifting of the target from the center of the image, the smaller the turning radius will be. Joystick forward and reverse voltages are varied from 2.46 to 1.50 volts while joystick left and right axis voltages vary from 2.46 to 2.25 volts. Limiting the joystick left and right signals helps to better control the wheelchair but also limits the turning radius of the wheelchair. The joystick parameter estimation strategy for tracking moving and stationary targets is described below.

4.2.9.1 Moving Targets:

If the initial position of the tracking region is (Xc,Yc,A) then the SWCS objective is to:

1. Minimize [$Xc-X_{image}$, $Yc-Y_{image}$]
2. Minimize[$A-A_{image}$]
3. Minimize[F(joystick signals at time t-joystick signals at time t-1)] .
4. Avoid obstacles.

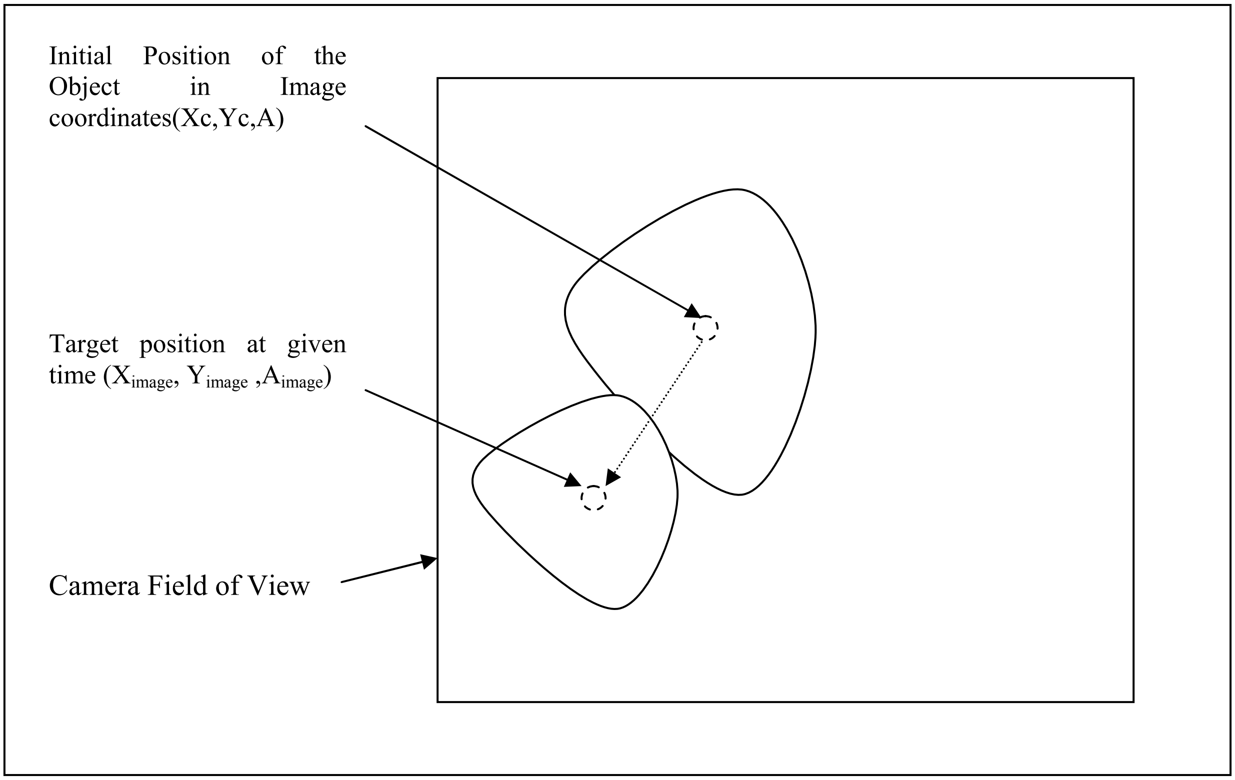


Figure 34: Movement of target in field of view of camera

4.2.9.2 Stationary Targets:

If the initial position of the tracking region is (Xc,Yc,A) then the SWCS objective is to:

1. Minimize [Ximage-160, Yimage-120]

2. Maximize[A_{image}]

3. Minimize[F(joystick Signals at time t-joystick signals at time t-1)] .

4. Avoid obstacles.

5.0 TESTING, RESULTS AND DISCUSSION

5.1 TRACKING MOVING TARGETS

The SWCS was tested for its ability to track both moving and stationary targets in real world settings. The ability of the SWCS to follow a moving target was evaluated using target objects of different sizes, color patterns, following distances and motion patterns. Testing was done in both indoor and outdoor environments in the presence of obstacles. Performance measures of interest included:

- Percent of time the target was visible within the camera's field of view and identified by the vision algorithms;
- Average, maximum, minimum and standard deviation of the distance between the wheelchair and the target;
- Number of collisions with obstacles;
- Average and minimum distance between the wheelchair and obstacles;
- Minimum turning radius;

5.1.1 Outdoor Test

The SWCS was tested on the Cathedral of Learning lawn at University of Pittsburgh, on a day in which weather was cloudy and humid. To test the robustness of the tracking algorithm, the color distribution pattern of the target (a green shirt) was very close to the background, which included green trees and a grass field (see Figure 35). Possible occlusion and obstacles by people, trees and buildings, and noise created by the background tested the robustness of the tracking and obstacle avoidance algorithm, while the field was rough enough to check the reliability and robustness of hardware integration. The size of the Cathedral of Learning premise was suitable for checking the maximum detection and following distance too (see Figure 36).

Figure 35: Wheelchair following target in cathedral of learning field

Figure 36: Maximum detection distance of SWCS in presence of noise

Table 6: Results of testing SWCS tracking moving target outside environment

S.No.	Radius of the ground traveled	System Failure	Maximim Detection Distance(meter)	Average speed Met/sec	No. occlusion	No. of collision
1	≈25	None	≈ 20	0.15	6	0
2	≈20	None	≈20	0.25	3	0

While traveling in the Cathedral field the speed of wheelchair was reduced, while the speed of the target was normal walking speed. This was done to make the wheelchair motion less bumpy while maintaining the security of the laptop that was sitting on the lap tray. The circular motion of the object was chosen to test the tracking capabilities while object was in extreme position in the lateral field of view. In both the tests there were no collisions or system failures (see Table 6). The wheelchair motion was neither jerky nor jumpy even on the extreme surface condition of field with mud and bumps etc. Wheelchair was able to follow the target even when it was 20 meters away and lighting conditions were dim (see Figure 36).

5.1.2 Indoor Testing

Indoor testing of the SWCS was done inside AT Sciences[112] within an area of 30'x12'. Tests were performed to check the wheelchair's ability to track the moving target in office spaces while obstacles are in close proximity. During this testing we increased the speed of the wheelchair to test the performance at high speed in office spaces.

Table 7: Tracking moving target in office spaces.

S.N0.	**Speed(meter/sec)**	**Distance Maintained**	**System Failures**
1	0.20	≈ 2.5 meters	None
2	0.30	≈ 1.8 meters	None
3	0.35	≈ 1.5 meters	None

The wheelchair was able to track the moving target while remaining in close proximity to the target. When tracking targets in indoor environments the wheelchair needs to maintain close proximity to the objects so the joystick parameters were set to achieve this. The best speed achieved for indoor tracking was 0.40 meter/sec.

It was also determined that it is not appropriate to use obstacle avoidance while using the wheelchair in indoor environments because of the close proximity to the target. Further, the presence of obstacles might steer the wheelchair such that the target goes out of the field of view. So, in indoor conditions, the wheelchair stops if it sees an obstacle and once the obstacle is removed from the way it starts tracking again. While the wheelchair was following the target in a corridor width of approximately 6 feet wide the threshold of some of the side sensors were adjusted to avoid possible halting of the wheelchair.

5.2 STATIONARY TARGET

The ability of the wheelchair to move towards stationary objects was evaluated using a 12”x18” target at an initial distance of 30 feet. Performance measures of interest include:

- Percent of time the target is visible within the camera’s field of view and identified by the vision algorithms
- Time to reach target
- Average, maximum and minimum distance between wheelchair and target at end of trial
- Average, maximum, minimum and standard deviation of the wheelchair’s speed

Table 8: Performance results following stationary targets

Distance (feet)	Percent success	Maximum Time (Sec)	Minimum Time (Sec)	Maximum Distance(feet)	Minimum Distance
30	≈ 60%	76	44	3.5	1

Tracking a stationary target failed 40% of time. The failures were primarily caused by the initial response of the wheelchair to the joystick parameters generated by the target tracking algorithm. This initial response was caused by the position of the rear castors at the starting of the trial. Secondly, incorrect estimation of target distance and position caused some errors in the estimation of joystick parameters. In tracking a moving target, the position of the target is always measured relative to previous target positions, whereas tracking a stationary target requires position to be measured on an absolute scale. At every step, the wheelchair motion strategy is to maximize the area of the target while moving close to the stationary target and maintaining the center of the target close to the center of field of view.

5.3 MINIMUM TURNING RADIUS TEST:

The minimum turning radius is an important aspect of performance in indoor environments. Turning radius determines the ability of the wheelchair to perform the sharp turns in corridors. Since the tracking algorithm is dependent on the area and center of the target, and target area is dependent on the distance between the target and the camera, it is necessary to consider the average distance between the target and the wheelchair while calculating the minimum turning radius of the chair (see Figure 37).

Figure 37: Testing Minimum Turning Radius of SWCS

Table 9: Minimum Turning radius of the SWCS while tracking moving targets

S. No.	Minimum Turning Radius (meters)	Average distance between target and wheelchair (meters)	System Failures
1	≈ 5	3.5	None
2	≈ 3.5	6	None
3	≈ 3	7.5	None

As the distance between the target and the camera increases, the turning radius decreases. Objects near the camera look larger than those far away from the camera, and objects near the camera moves faster than those far away from the camera. The main tracking parameters being used are the center and the area of the target, and target close to camera occupy more area and the geometric center of the object is always close to the center of the field of view (see Figure 38) which limits the joystick parameters and the turning radius.

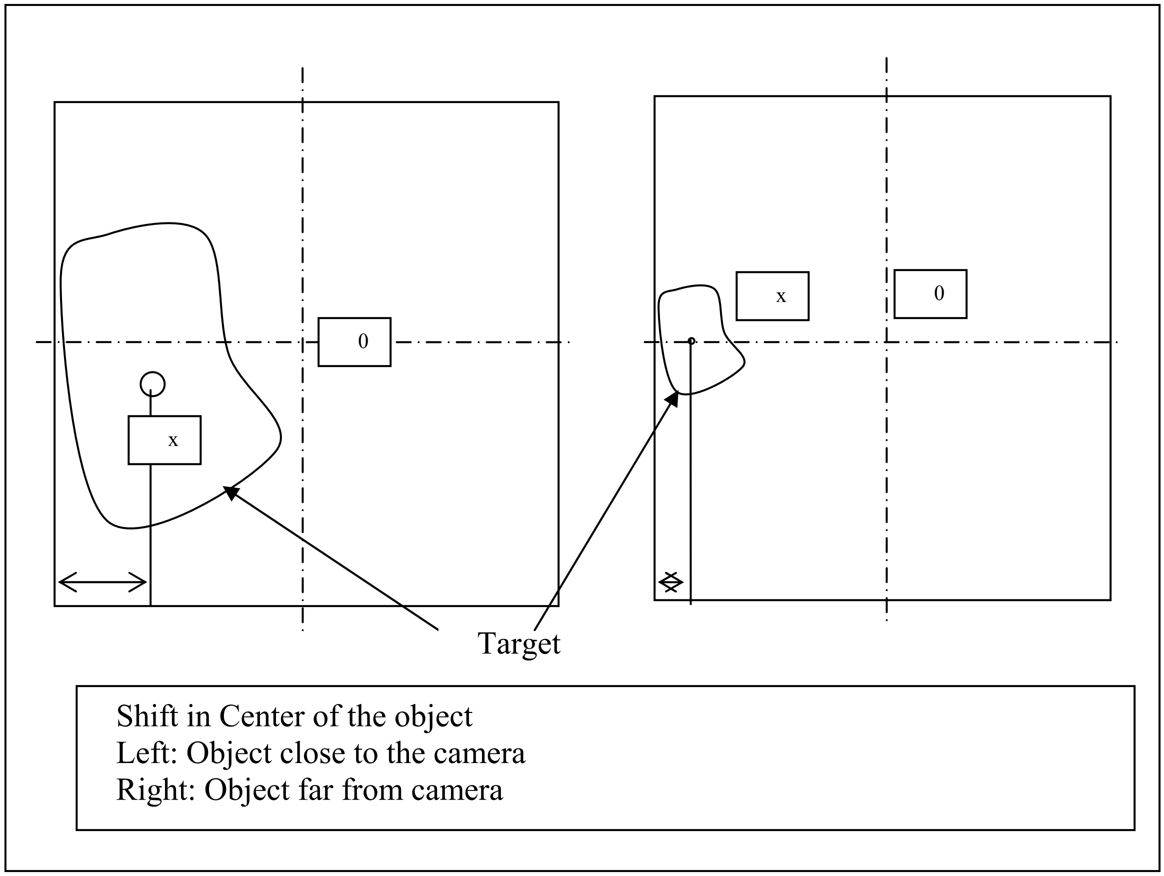


Figure 38: Shift in the target center with respect to distance from camera

5.4 MINIMUM DOOR WIDTH TRAVEL

The ability to pass through door ways is an important criterion of performance for the SWCS in indoor environments [102]. The ability of the SWCS to cross doorways of different widths while following a moving target was tested. Doorways were simulated using cardboard boxes and wooden boards. The wheelchair was able to pass through doorways as narrow as 32" wide. To make wheelchair pass through, the threshold of some of the side sonar sensors was changed so that it did not stop in the middle of the doorway.

Table 10: Performance of SWCS while crossing doors.

Door Width	Speed of the chair(meters/sec)	Pass or failed	Sensor Adjustment
36"	0.35	Pass	No
35"	0.35	Pass	No
34"	0.35	Pass	Yes
33"	0.30	Pass	Yes
32"	0.30	Pass	Yes

6.0 CONCLUSION & FUTURE DIRECTIONS

In this thesis, we have shown an implementation within the SWCS of a computationally efficient and robust target tracking algorithm (CAMSHIFT) based on computer vision. The SWCS is an assistive robotic wheelchair system that can potentially be integrated into the everyday life of people with disabilities who are currently unable to drive a standard powered wheelchair or need caregivers to move around. The ability to track a stationary or moving target will make the SWCS more useful as a mobility aid, and is also expected to be useful for wheeled mobility training and evaluation, as well. In addition to the wheelchair user, caregivers, clinicians, and transporters who provide assistance to wheelchair users will also receive benefits from providing safe and independent mobility to wheelchair users, by reducing the level of assistance needed by wheelchair users.

Even though the CAMSHIFT is independent of the lighting condition, we chose the maximum and minimum values of saturation and value in HSV space to make the algorithm robust for outliers. In future work, the light sensor of the SRF08 sonar sensor will be used to adjust the saturation and value parameters to make the algorithm robust in lower light conditions.

Using CAMSHIFT as the target tracking algorithm allows the SWCS to track moving targets efficiently. The primary limitations in target tracking is the limited field of view of the camera($\approx$ 45°), zero degrees of freedom of the camera mounting (no pan or tilt), and the low quality of the image generated (8 bit per pixel) . Secondly, to make the wheelchair follow the target efficiently we need some mode of feedback, which can be provided by incorporating wheel encoders into the wheelchair. Encoders will make the state and response of the system easy to understand and will further help in designing a better control system.

Performance of the SWCS in tracking stationary targets is less accurate, mainly because of the initial response of the wheelchair to the joystick parameters and error in estimating the position of the target. Furthermore, there is no feedback from the wheelchair to the controller. In the future we will be using a wheelchair with steadier performance for given joystick parameters and a sturdy structure. We also plan to use wheel encoders to provide feedback about the response of the system for given joystick parameters.

Performance of the SWCS depends on the estimation of joystick parameters based on the estimated position of the target within the camera field of view. It is difficult to estimate the position of the target accurately because of non-linearity and variations in the size of the targets, so it is difficult to find a classical control approach that will work well for our purposes. Since the target position and selection of corresponding joystick parameters form a Markov Decision Process (MDP) [100],we can apply a reinforcement learning algorithm to determine the correct joystick parameters for a given target position. Reinforcement learning algorithm map situations to actions to maximize a numerical reward signal [101] while following a defined policy. While designing the reinforcement learning algorithm for SWCS we need to define a policy for joystick parameter selection so system which minimizes jerk and maximizes user comfort.

Presently the SWCS is not ready to test on human subjects because the seat is occupied by an extra pair of batteries. Hardware changes are necessary, especially in the power distribution line, by using DC-DC converters instead of normal voltage regulators and some more filtering circuits to reduce high frequency noise caused by the sonar and IR sensors. Secondly, we will be adding a new lap-tray design specifically for the SWCS which will have a provision for sensor mounting, a place to fix the joystick and will give enough space for the user to sit comfortably on the wheelchair. Drop-off detection and bump sensors will be used in the near future to make the system more reliable and dependable. We are also planning to put an additional module on the SWCS for localization during indoor use. This will help the SWCS to take the user between specified locations.

This research resulted in many steps towards the goal of a deliverable system.

- The SWCS provides assistive navigation in novel indoor and outdoor environments by following a moving or stationary target and avoiding obstacles.

- Modular control software was developed which allows for future integration of other modules such as localization and line tracking.

- The system can be added to other wheelchairs without significant changes in hardware

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