Development of A Mobile Service Robot

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FINAL REPORT

DEVELOPMENT OF A MOBILE SERVICE ROBOT

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Summary

Service robot is a new emerging technology that will appear in the commercial market in the very near future as expected by major robotic manufacturers. Service robot will be used in every house, workshop, office, shop, restaurant, airport, organization, hospital, gas-station…etc. Its function is to support people in their daily activities and make their lives easier. The ability of the robot to work in harsh and hostile environment makes it ideal for application in Qatar industry and society as well as for all other countries of the world.

This project objective is to develop a mobile service robot capable of moving indoor among work offices and corridors on flat terrain. This includes building up the modules that enable the robot to move safely without collision with either static or dynamic obstacles. The robot control architecture adopts the behavior-based scheme where a number of basic modules are running simultaneously and their outputs are fused to derive motion decisions of the robot.

The robot is equipped with sensors to enable perception of its environment, detection of obstacles and recognition of people and objects of interest. The robot has two video cameras installed onboard to explore the surrounding space. The robot also has four wheels to move easily on flat terrains.

Robot subsystems are controlled by separate microcontrollers. A central master microprocessor is used to establish communication with all other microprocessors. The master control of the robot is controlled by a microprocessor-based control system. A separate computing system is dedicated to the processing of visual information stream coming from the CCD cameras.

Specifically, the main processor receives information from the associated microprocessors, combines the information, and makes the appropriate decisions for the next robot action.

The robot control strategy is based on the behavior based approach that ensures rapid response for immediate actions such as survival and allows for other relatively slower layers to participate at the proper time in guiding robot motion such as searching and approaching a target. In this project we show contributions in the robot control system and in the processing of color images to improve the face detection system.

The robot is capable of avoiding static and dynamic obstacles, move safely in a navigation path according to the task requirements. The robot can detect and track a target based on its color and this target can also be a human face. Detection of human faces is a central issue for service robots because it is intended to serve humans.

1. Introduction

The objective of this project is to develop a service robot capable of moving indoor among work offices and corridors on flat terrain. Mobile service robots are the class of robots that should have the tools to understand the environment at home and office in order to enable its motion and object handling in such spaces.
It is expected that mobile service robots will be a mainstream in the commercial markets in the next ten years for home and office environments [1,2,3,4,5,13]. There is a common belief that the market need for service robots is just about to undergo a radical increase in the next decade. Therefore, research in service robots had received much interest in the development and research communities.
The development of autonomous mobile robots is gaining much interest due to the decreasing prices of sensors and computers, besides the arising need for their application in human friendly environments to improve the quality of life.

The service robot is intended to serve as:

1- An educational tool in the undergraduate courses of control and mechatronics for mechanical engineering students.
2- A platform to conduct research for the faculty and senior undergraduate students to test their measurement and control algorithms.
3- A pilot project/ model to show for the industry in Qatar, the advanced capabilities of the mobile robot for potential customers.

Despite the huge literature of the mobile robot navigation, the development of intelligent robots able to navigate in unknown and dynamic environments is still a challenging task. Therefore, developing techniques for robust navigation of mobile robots is both important and needed for robots to serve humans in such environment.

Fuzzy logic approach, since its inception [18] have long been applied in robotics with many successful applications and regarded as an intelligent computational technique that enables the proper handling of sensor uncertainties [8,12,15]. Fuzzy Logic Control, FLC, enables the system to hedge the uncertainty from affecting the control actions.
The early work in robot control used a functional decomposition following the "Model, Sense, Plan, Act", MSPA serial strategy, which is inherently slow. The strategy will totally fail if one module fails due to its serial nature.
In the literature of mobile robot, we can mark the evolution of behavior based robotics [5,6], as an important event, which resulted in a radical improvement of the performance of real robots in dynamic environments. The new approach was proposed using behavioral decomposition [6] in which the reactive behaviors were designed to run simultaneously in parallel fashion. The behavior-based approach being composed of layers of behaviors, tightly couples perception to actions of the robots, thus giving the fast processing layers the chance to save the robot or people from damages. Furthermore, reactive behaviors allow for incremental improvement and additions of more application-specific behaviors, thus makin the system behavior scalable.

Building several behaviors each concerned with a sole objective, will produce different decisions for the robot control parameters, and they have to be combined in some way to reach a final

motion decision. The fusion of independent behaviors is not an easy task and several approaches were proposed in the literature to solve this fusion problem [5,7,8,10,15]. Coordination of behavior can be classified into two further approaches, a competitive, as was originally proposed by Brooks [7] and cooperative strategies [10].
Depending on the environment, the first competitive approach may fail and become unstable in critical situations demanding higher switching frequencies between behaviors. In the subsumption architecture [7] behaviors are activated once at a time but this may be inadequate for variety of situations requiring several behaviors to be active at the same time.
In the cooperative approach, all behavior contributes to the output, rather than a single behavior dominate after passing an objective criterion. An example of the cooperative approach was proposed by Khatib [11] using artificial potential fields (schemas) to fuse control decisions from several behaviors. The potential field method suffers from being amenable to local minima which causes the control system to stuck and become indecisive. Hybrid technique from competitive and cooperative approaches was proposed by Carreras [10]. However, they used learning to build up the rule set which consumes lot of time and efforts.
The use of fuzzy logic for behavior fusion had been reported by Goodridge [15], where a hierarchy of behaviors was used for mobile robot guidance. Fuzzy rules can be used to design the individual behaviors as well as the way they are integrated to reach a final decision [5,8,12].
In this work, we exploit the potential of fuzzy logic to build a control system having two basic behaviors: obstacle avoidance and target following.

Another issue worked out in this project is the development of robust face detection system as a subsystem for robot-human interface. One potential key to the success of service robots is their ability to interact with humans. The Human Computer Interface, HCI, has been in the focus of several research projects for decades. In this project, the development of a human face detection system intended for use with the service robot is described.
A service robot is required to automatically identify a face and then move toward the face so that the face appears in the image center and the robot stops when the face is near enough for the robot. This behavior is needed for our service robot which will then be used to recognize a certain face out of several faces and follow a path to stand in front of it. Automatic face detection is needed and useful for several computer-human interface applications and we only consider the modality of face detection and its localization in the image for application in mobile service robots. Such system will serve as a module in an integrated system for following a specific human and interacting with him.
The classical approaches for face detection can work with achromatic images, based solely on the features of faces [41]. The performance of such approach is not satisfactory in that it have high positive false rate whenever features similar to the face are present.
The use of color cues can enhance the detection process [62,27,65,66,26], since the human skin color can further constrain the search space. Human skin can be statistically modeled [26,27] and the skin color can be defined within specific bounds which is to be settled prior to the face detection process. Using color cues is problematic in practice due to the dependence on illumination color, the so called color constancy problem. The illumination changes in the scene is known to affect the quality of both human face detection and recognition in the scene images due to variations between the lighting in the face identification process during the construction of face data base and that for which the current image queries are being captured [26, 62, 63]. The geometry of imaging is also known to affect the recognition quality, such as face orientation and

occlusion of face features, but our scope here will be to study the effects due to illumination changes only. Our objective in this work is to develop a system with minimum false positives in the face detection process.
Two different approaches can be found in the literature to solve the illumination changes in face detection and recognition algorithms [94,95,96]. In the first approach, the system learns about different lighting conditions it may encounter by presenting it with exemplars under those conditions. The other would be to preprocess the image by a color constancy algorithm to remove the effects of illumination color and obtain an approximate illumination-independent description of the face color. Since color constancy algorithms claim to solve the illumination problem, they are eligible for use to remove the illumination effects for face finding algorithms. Color constancy algorithms attempt to estimate the illumination color of a scene or obtain an illumination-independent description of the scene colors that describes the physical content of scene surfaces [117, 118]. For the first approach, since all possible illuminants should be known and used to train the system, the system can not adapt to novel illuminants. This drawback is not present in the second approach. However, both approaches were reported to be effective [107].

The work in this report is concerned about two contributions of robot control and robot interface which can be discussed as follows:

- We propose a method to integrate the behavior decisions by using potential field theory [11]. The potential field theory proved to be very efficient especially for fast robots. The theory relies on the physical concept of force vector summation. Forces are virtual and describe the attractions and disattraction in the robot field. The potential field theory had been criticized for being susceptible to local minima and consequently unstable motion. We show that when the vector field is applied to the output from the simple behaviors, which is smooth due to the use of fuzzy logic, it can significantly enhance the performance of the robot navigation system.
  The control system is implemented and used to navigate the service robot so that it can track and follow a target object from its color appearance. Algorithms will be developed for performing simple tasks of the robot namely moving to the target and avoiding obstacles. The robot control architecture adopts the behavior based scheme where two basic behaviors namely, obstacle avoidance and goal seeking, are running simultaneously and their output is fused to derive motion decisions of the robot.

- We show also that the face detection can be significantly improved by pre-processing the input color image by the nose color correction method, developed previously by the author [117,118,119]. We develop a face detection system that uses color features in the detection/recognition stage provided that the image colors are preprocessed by the nose color constancy method. The resulting image is then segmented to extract the human skin regions which reduces the face detection search space considerably and improves the reliability of face detection. We show that the illumination effect should be compensated when color information is used without prior knowledge of the lighting or illumination conditions.

This report is arranged as follows; the next section presents the background of service robots, robot control architectures and casts light on the use of color for object detection and tracking. In Section 3, the models for image acquisition and color spaces used are briefly described. The measurements of target location from the color image are also presented.

In section 4, we present the design of fuzzy logic controller responsible for target tracking behavior, obstacle avoidance behavior and combining both behaviors. The principles of face detection algorithm are also summarized in this section. Section 5 describes the configuration of the robot structure, software and systems integration. The service robot control system architecture for detecting and following humans surrounding the robot is also presented.

The results of robot control experiments in following the target are presented in Section 6 together with the results of face detection experiments. Conclusions are finally summarized in Section 7.

2. Background

2.1. History and State of the Art Service Robots

The development of service robots had been conducted for the last twenty years for several purposes, including educational and real market applications. The challenges, engineering student have to integrate advanced control theory, machine vision, vehicular electronics, and mobile platform fundamentals to design and build an unmanned system make it a very attractive project for technical colleges and schools [1,2,3,4,5,13].

The big car manufactureres also started to build up service robots as a potential trend in the technology markets. The mobile robot is an intelligent, autonomous ground vehicle that provides a test bed system for conducting research on mobile vehicles, sensor systems and intelligent control.

Most of the development had been made in Japan, USA and Europe. The robot industry in Japan, in particular, is probably the largest in the world. Some landmark innovation will be summarized in this section and it is relevant to our robot development.

2.1.1. Fujitsu Service Robot

This robot is shown in Fig.1 and it has two hands to handle objects. The key Specifications are as follows:

- Dimensions: 644 mm (width) x 566mm (depth) x 1300 mm (height)
- Weight: 63 kg
- Mobility of operable parts: Head: 2 degrees of freedom, Arms: 4 degrees of freedom, Hands: 1 degree of freedom, Wheels: 2 degrees of freedom
- Speed: 3 km/hr
- Sensors: 8 CMOS cameras, 2 ultrasonic sensors, 2 proximity sensors
- User interface: 10.5" TFT touch panel monitor, 3 microphones, 1 speaker
- Expansion interfaces: Wireless LAN (802.11b equipped)
- OS: Main CPU- WindowsXP ® embedded, DSP: DSP/BIOS
- Battery type: Nickel-Metal Hydride (NiMH, in main unit)
- Charging method: Non-contact self-charging (enables 24-hour continuous operation)

Fig.1. Fujitsu Service Robot with two hands at work.

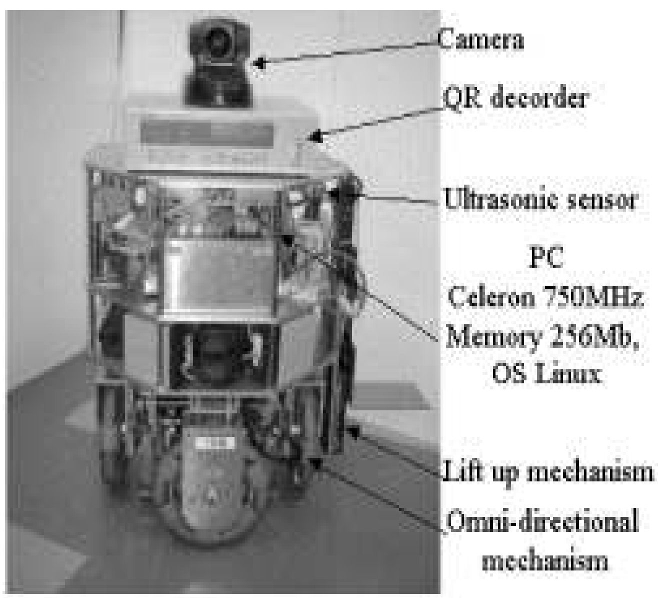

Fig.2. View of Japanese Service Robot named "ZEN"

Fig.3. Open Robot Project.

Fig.4. Robo Waiter serving Guests

Fig.5. Nice shot of AIBO entertainment dog while sitting on the charging station, Product of Sony Corporation.

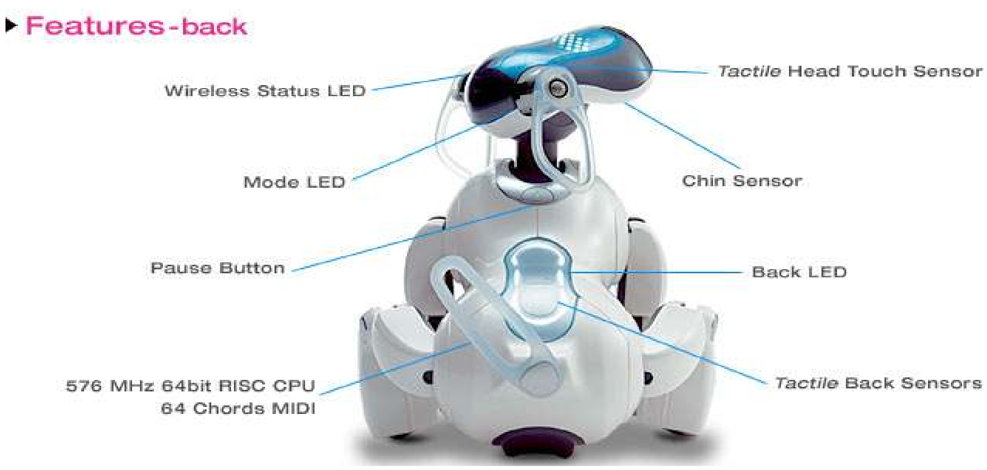

Fig.6. The features of AIBO robot.

Fig.7. AIBO User Interface Here's a shot of the PC-based control system for AIBO – includes a representation of the robot's position, coupled with an image from its cameras.

Fig. 8. The Dragon Robot.

2.1.2 Japanese object handler "ZEN"

Uses a lift mechanism to carry objects and change their location as shown in Fig. 2.

2.1.3. The Open Robot Project

It is shown in Figure 3, which consists of cheap components such as

- Cheap mobile robot chassis.
- Internet camera,
- Cheap plastic body.

2.1.4. Robowaiter project

It is implemented by Zagros Company in the USA and can be seen at work serving guest of party with drinks in Figure 4.

2.1.5. Sony AIBO "The companion"

It is perhaps the first mobile robot for real entertainment with huge amount of sales world wide. It impressed the Japanese people who adore the dog as a house bet. The dog can learn from the people at house and behaves friendly with them. Figure 5, shows AIBO sitting on the charging station. Figure 6 shows the main features of AIBO, and Figure 7 shows the user interface of AIBO showing his model and his camera view of the surroundings.

2.1.6. The Dragon Robot

Produced as a joint project of TMUSK and Sanyo, the Banryu "guard dragon" is a consumer robot that can walk and climb stairs as shown in Fig.8. It features remote control via computer wireless LAN, PDA, or 3G handset. It also has voice recognition and speech synthesis, giving it a second role as a guide/introducer in corporate tradeshows.

2.2. Robot Control Techniques

Since, data available from sensory information contains a considerable amounts of uncertainty due to the sensor itself or the techniques used to extract data from the sensors, fuzzy logic-based techniques lends itself as a plausible tool for addressing this problem of interpreting data with significant uncertainties. Fuzzy logic techniques had been used for navigation research since the early appearance of the technique, and still an active research domain, [15,16,17,18,19,20,21,22]. Fuzzy logic approaches have long been applied to robotics with many important solutions and successful applications and regarded as intelligent computational technique that enable the proper handling of sensor uncertainties. The literature of the mobile robot navigation is quite large, see good overview in [8].

The robot control strategy can be classified into three major trends:

1. Model Based Navigation.
2. Behavior Based Navigation.
3. Probabilistic Inference.

It was realized in the literature, during the mid eighties of the previous century, that the complex behavior of a mobile robot can be built using a set of primitives or simple behaviors and combining their outputs in a way to reach final motion commands, [8,9]. This approach was proposed in opposition to the early, Model, Sense, Plan, Act, MSPA, strategy in which the inherent computational complexities would have slow down the speed of robot reactions. One simple behavior is the tracking a moving target, which is gaining much interest for mobile robot navigation,[6,12,21].

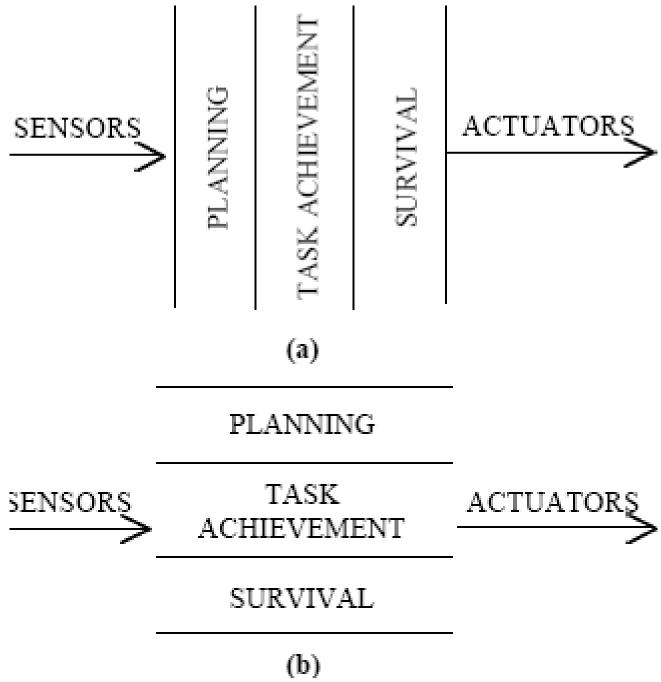

Fig. 9 Schematic comparison between a) Model Based Navigation and b) Behavior based navigation.

To the human engineer, the problems faced by a mobile robot may seem as logical as those faced by a computer that plays strategy games or plans shipping routes. Given an objective, the robot must formulate a solution based upon available paths. Top-down design methodology suggests that the strategic decisions made by the robot will require the execution of individual path, which in turn will require the control of motors. The operation of such a system could be described as a cycle of world model construction, path generation, actuator output, sensor readings. The control flow for this scheme is illustrated in Fig.9.

For industrial manufacturing robots, traditional sense-model-plan-act schemes usually work well. Parts arrive on an assembly line controlled by a computer and are positioned precisely in front of the robot. The required set of assembly tasks are read from memory and the robot performs the inverse kinematic transforms required to determine the proper trajectories for its joint motors. Encoders provide the computer position feedback as it swings the arm through its required motions.

The success of most established robotics and artificial intelligence techniques may be owed to the finite, knowledge-based nature of the applications to which they have been applied. Take a computer chess game as an example: At any given turn, the computer knows the position of every piece on the board. It has also been provided with the rules regarding every possible move. This allows the computer to generate a search of every possible board configuration within some arbitrary distance from the present state, and calculate which option would most likely yield strategic gain. The world model is complete enough for the computer to effectively consider its relevant options and the consequences of its decisions.

Parallel organization can improve the speed, reliability, and scalability of autonomous machines and other AI applications. Brooks [7] introduced the paradigm of layered control to the robotics community. Rather than decomposing the autonomous control problem into separate layers in a sense/model/plan/act scheme, Brooks advocates an architecture where each layer tightly couples sensing to actuators. Multiple task-achieving behaviors are stacked in parallel, as illustrated in Fig. 9.b, realizing an emergent functionality. This scheme allows rapid and robust interaction with the environment, and offers incremental development of capabilities. Brooks' subsumption architecture, used to define behaviors and the interactions between them, is implemented on a wide variety of mobile robots at MIT. In the subsumption architecture, high-priority behaviors such as collision avoidance subsume other behaviors, such as goal seeking. The arbitration scheme is based on hierarchical switching. Connell used the subsumption architecture to control a mobile robot designed to search for and collect empty soda cans. This robot, named Herbert, employed a collection of processors for the tasks of vision processing, navigation, and manipulation. This robot illustrated the complexity of tasks that could be performed without a centralized world model. A variety of behavior-based control schemes have been inspired by the success of Brooks work and the growing cooperation between the scientific communities of biology and robotics. Arkin [2] describes the use of reactive behaviors called schemas. Potential field techniques define the output of each schema, which are then combined by weighted summation.

Several robots in the literature have used fuzzy logic in some form. Sugeno [134] developed a fuzzy control system for a model car capable of driving inside a fenced-in track. Ultrasonic sensors mounted on a pivoting frame measured the car's orientation and distance to the fences. Sonar is used by Flakey to construct a cellular map of its environment. A high-level supervisory process then extracts the locations of landmarks and features such as walls. These values are passed to selected fuzzy control behaviors to generate the proper wheel velocities. Computer simulations by Ishikawa [136] feature a mobile robot that navigates using a planned path and fuzzy logic. Fuzzy logic is used to keep the robot on the path, except when the danger of collision arises. In this case, a fuzzy controller for obstacle avoidance takes over. Song and Tai [137] present a scheme for independent control of two drive wheels on their simulated robot. When an obstacle is detected (in simulation) by one of the robot's proximity sensors, the fuzzy controller increases the speed of the wheel on that side to turn away from it.

Pin, et al. [138] use custom designed VLSI fuzzy inferencing chips for navigation of a mobile robot in a-priori unknown environments. Their scheme uses ultrasonic range data from the front, left and right sides of the robot, as well as the azimuth and range to the goal location. Multiple behaviors are combined directly by superposition. The system is more impressive than the previous examples because it does not require a supervisor or world model; yet it allows the robot to effectively seek a goal, avoid obstacles, and avoid getting stuck in dead alleys. The VLSI chips also do fuzzy inferencing very quickly, completing a full rule base evaluation in 30 sec. However, the resolution of the inputs to the system is limited to six bits, and the membership value resolution is only four bits. This limits the "fuzziness" of the variables to discrete values that may be too crude to properly represent data for some applications.

The fuzzy controllers for the mobile robots described above are very simple, using only a few inputs in each case. The schemes used by Sugeno's car and Flakey involve the extraction of specific state variables from sensor data (i.e. the orientation of walls) before the fuzzy control stage. Thus the sensor data has been matched to a world model. The resulting effect is to reduce the size of the input space to the rule set. The robot described by Pin, et al. features 15 ultrasonic rangefinders, without matching data to a world model. However, the sonar data is bunched together into three inputs, each being the minimum of a neighborhood of five, before being sent to the controller. Another disadvantage of their system is the need for special computer hardware for real-time operation.

Most fuzzy control applications, such as servo controllers, feature only two or three inputs to the rule base. This makes the control surface simple enough for the programmer to define explicitly with fuzzy rules. The above robot examples exploit this principle, in order to explore the feasibility of using fuzzy control for their tasks. But these robots are novelties, in that their purpose is limited to testing simple fuzzy control rules in simple environments.

- The subsumption architecture proposes that complex behaviors are build up of the interaction of simple primitive behaviors.
- The fusion is responsible for competition among different primitive behaviors.
- Behaviors are less brittle than controllers.

The Model based approach is too slow to use. The probabilistic approach is a new one and lies midway between the model based and the behavior based approaches. We will consider the probabilistic approach later for doing other tasks of localization and mapping and will not use now due to its excessive complexity and computational load on the robot computing system. We will employ the behavior based approach in this project.

2.3. Use of Color in Face detection

Color analysis is an important general research area of computer vision. Color information is much more appropriate than gray level information for detecting and classifying objects and surfaces.

Fig.10. The detection of human face by using skin color statistics.

Research groups focused its research on development of approaches to illumination invariant color machine vision in order to improve the performance of current color measurement and recognition techniques and to increase their domain of applications. Face databases, which contains color images of faces under different illuminants and camera calibration conditions as well as skin spectral reflectance measurements of each person, had been collected by several research groups. Using such databases, methods for color correction of face images under different illuminants can be tested and compared, see example in Fig. 10 of a face database.

The lighting problem cab be solved by either two ways, the first is by using a learning algorithm such as a neural network or other learning technique and take picture of a face under different lighting as training cases for the algorithm. The other approach considers preprocessing by a color constancy method. One other problem is the high rate of false detections. The second approach will be used in this project.

3. Basic Models

3.1. Image Acquisition Model

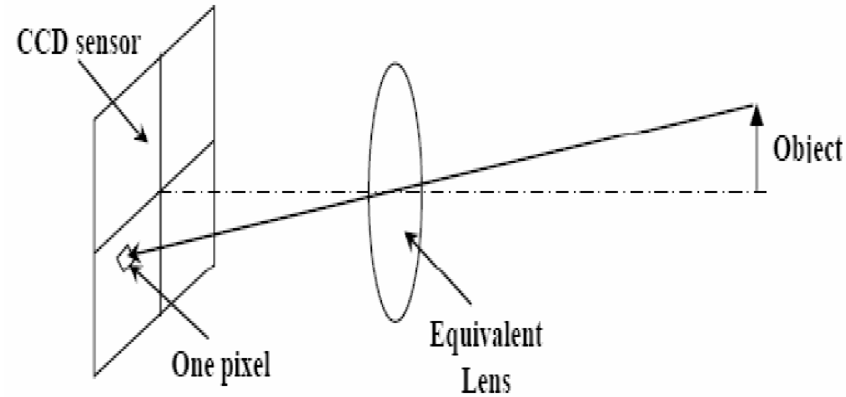

Fig. 11. Model of the Imaging Process.

Scene surfaces reflect light toward the camera lens when it receives sufficient illumination from the environment. The lens then collects the reflected light and form an image at the sensor plane, as shown in Fig.11. The incident radiation is then integrated both spatially and spectrally through the elements of the CCD sensor elements (the camera used is made by CCD technology), and hence the color responses at a pixel can be described by

$$K\left(x,y,c\right) = \iiint E\left(X,Y,\lambda\right)\ F_c(\lambda)\ dX.dY.d\lambda \qquad (1)$$

Where: $K(x, y, c)$ is the intensity of the image observation corresponding to (x, y) location in the image. $c \equiv (r, g, b)$ is the conventional vector representation of color attributes corresponding to (Red, Green, Blue). and $E\ (X,\ Y,\ \lambda)$ is the scene incident radiation. (x, y), are the image coordinates measured in pixels and (X,Y) are the world coordinates
λ is the wave length of light and $F_C\,(\lambda)$ is the spectral response function of the camera optics and sampling filters giving the color $c \equiv (r, g, b)$.
Equation 1, is the imaging model and shows that every pixel in the image provide a color vector of three entities, that is RGB, in response to the scene incident reflection over the visible spectrum. The video digitizer captures the input video signal through 8 bit resolution for each color channel.
The camera is calibrated to remove the fixed pattern offset noise and to produce almost linear response to the incident radiation.

3.2. Object Detection Using 2D Chromaticity Color Space

In this work, we define the face (skin) color using the normalized rgb space defined as follows

$$q_1\left(x,y\right) = \frac{k_c\left(x,y,r\right)}{\sum_{c=r}^{c=b} k_c\left(x,y,c\right)} \qquad (2)$$

$$q_2(x,y) = \frac{k_c(x,y,g)}{\sum_{c=r}^{c=b} k_c(x,y,c)} \tag{3}$$

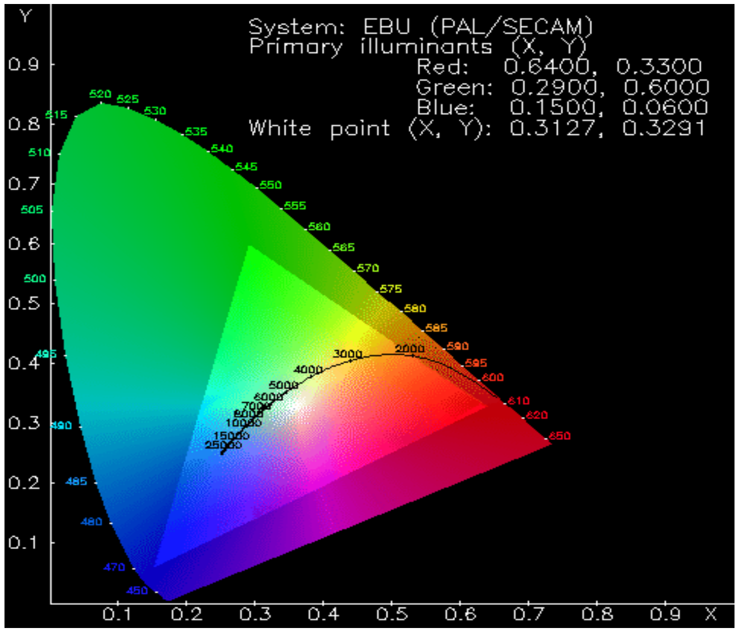

Fig.12. The two dimensional chromaticity diagrams.

The chromaticity space converts the three dimensional color representation (r,g,b) into a two dimensional space described by (q1,q2). Description of color becomes therefore unique by using only two descriptors, namely the red and green chromaticities, as can be seen from Fig.12. The object color is defined within ranges of red and green chromaticities. The limits of chromaticity zone for face color are described by the following constraints:

$$q_1 \in \left(q_1^l \approx q_1^h\right), \quad q_2 \in \left(q_2^l \approx q_2^h\right) \tag{4}$$

The segmentation process is then based on the color chromaticity as follows

$$m(x,y) \left\langle \begin{array}{l} = 255 \quad if \quad Eq(4)\, is\, satisfiea \\ \qquad = 0 \quad [else] \end{array} \right. \tag{5}$$

The matrix $m(x,y)$ is written to a monochromatic image, in which the skin pixel color is written as it is while the background is written as dark pixels. We implemented a color segmentation algorithm based on this criterion. The output image is then forwarded to the face detection/ recognition algorithm.

3.3. Perceptually Uniform Color Space

The Hue, Saturation and Intensity, HSI color space is used since it is perceptually uniform and found previously [119], to give better results regarding the detection of object from color appearance in the image, see Fig.13. Perceptually Uniform, PU, color spaces are more suitable for color recognition than the RGB space, since the quality of recognition will always be judged by a human observer [40,41,42,43,44,45].

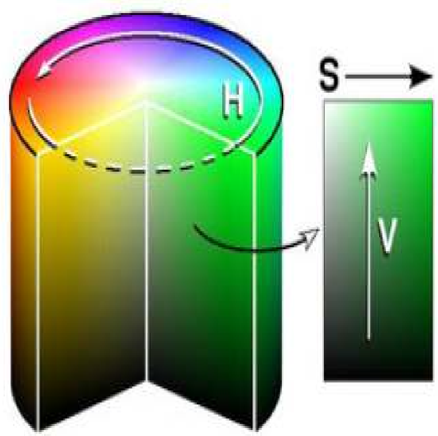

Fig.13. HSV color space represented in cylindrical shape, Hue is the angle, Saturation is the radius, and height is the value.

The PU color space of HSI has the advantage that the object color is encoded mainly in the angle of the hue. This angle representation of color is easier in target color definition and less sensitive to changes of illumination intensity, but certainly changes when the illumination color is changed if the color is not balanced. Therefore we compute the Hue, H and Saturation S using the following formulae:

$$H = \arctan\left(\frac{\sqrt{3}(G-B)}{(2R-G-B)}\right) \tag{6}$$

$$S = 1-\left(\frac{\min(R,G,B)}{I}\right) \tag{7}$$

$$I = (R+G+B)/3 \tag{8}$$

The target object color is defined in terms of limiting hue angles and limiting saturation values describing the boundaries of a color zone in the H_S diagram that can be described by the following constraints:

$$h \in \left(h^l \approx h^h\right), \quad s \in \left(s^l \approx s^h\right) \tag{9}$$

4. The System Design

The major systems are classified as mechanical, electrical and computer systems. A laptop provides a modern operating system for ease of software development. The electrical systems of the robot include the motion controller, the cameras.

Steering is achieved by applying differential speeds at the right and left wheels. The obstacle avoidance system sends data to the computer which is also used to determine the change in performance of the motors. The motion control of the Bearcat Cub has the ability to turn about its drive axis which is called Zero Turning Radius (ZTR).

4.1. The Robot Control Architecture

The robot control architecture adopts the behavior based scheme where three behaviors are running simultaneously and their output is fused to derive final motion decision of the robot as shown in Fig.14.

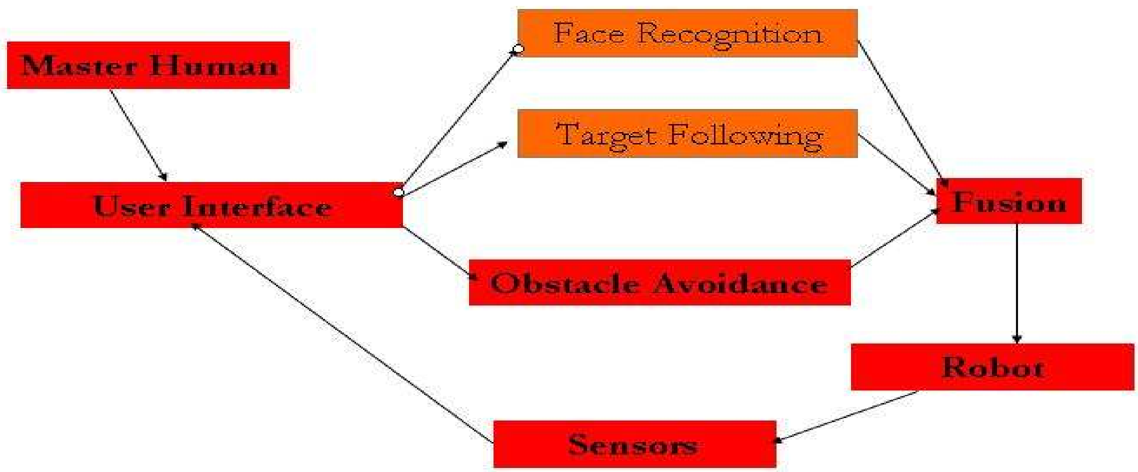

Fig.14 The robot control architecture.

Severalprocessors are running in parallel to implement the primitive behaviors.
A master host PC mounted onboard of the Mobile Robot is used to synchronize the output of the microcontrollers/microprocessors and send a final decision to the Robot wheels.

4.2. Design of Fuzzy Logic Controller

The goal of the fuzzy logic controller is to enable the mobile robot to satisfy two objectives namely; target following and obstacle avoidance. In this section, we describe the design of each behavior and then show how to combine their results.

4.2.1. Design of Target Following Behavior

The output of this behavior will decide the steering angle of the robot needed to make the target image appears continually in the middle of the image.

The sensory information available for the steering command is the average horizontal target position in the image, shown in Fig.15. The horizontal component of motion is only selected since the robot and target are both assumed to move on a flat terrain and the camera orientation relative to the floor is fixed. The steering changes the target image position and hence, the motion attributes chosen as the input fuzzy linguistic inference layers for the FLC are selected to be:

1. Target image horizontal displacement
2. Target image horizontal velocity.

The membership functions for these two layers are shown in Fig.16. The fuzzy logic controller used to control the mobile robot uses triangular membership functions to fuzzify the data measured by the vision system. The input fuzzy variables are divided into three overlapping fuzzy set functions. In our implementation, the linguistic descriptors for the image horizontal displacement in the fuzzification step are defined as : 1) Left (L) , 2) Middle (M), and 3) Right (R), as shown in Fig.16. a.

The target image horizontal velocity is described by three fuzzy variables defined as : 1) Getting Left (GL) , 2) Getting Middle (GM), and 3) Getting Right (GR), as shown in Fig.16.b. The shape and relative overlap of the fuzzy variables (that is tuning), are determined based on our experience gained from early experiments with the robot. The two fuzzy variables are then used to derive the output steering state. Three output states are used for steering namely, 1) Turn right, SR, 2) Go straight, STR and 3) Turn Left, SL, as shown in Fig.16.c. For each fuzzy linguistic interference process we define a 3*3 fuzzy rule matrix as shown in Table 1.

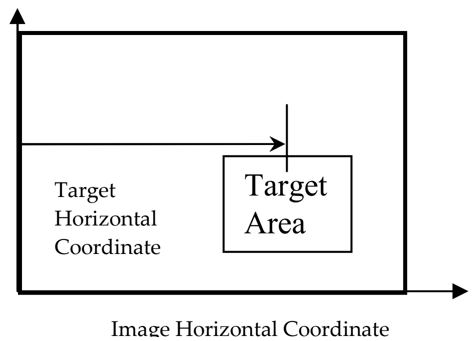

Fig.15. Schematic representation of target measurement in the image showing extracted target region.

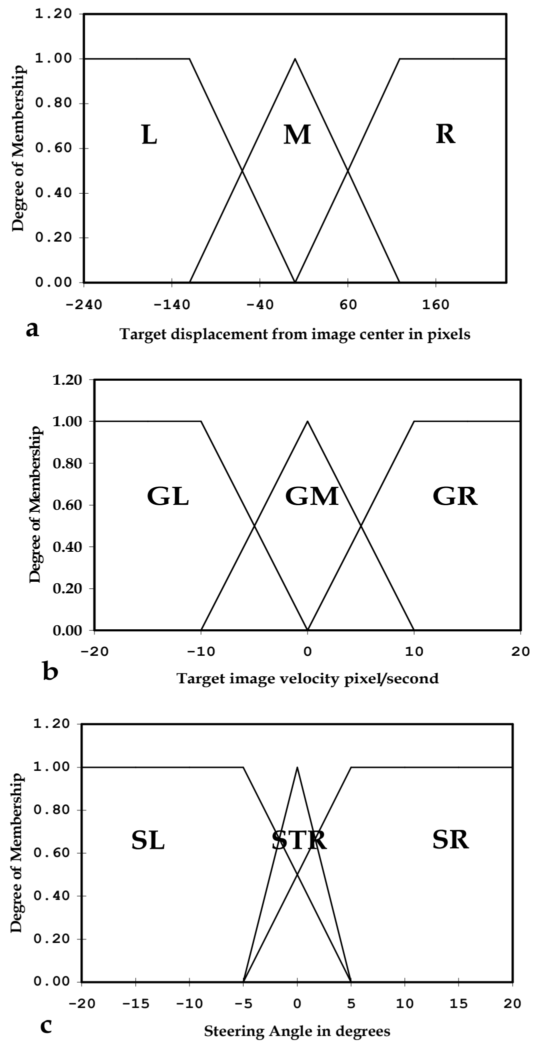

Fig. 16. Membership functions for the input variables of the steering FLC.

Table. 1 The Fuzzy Rule Matrix for the Target following FLC. (The columns show states for the target horizontal velocity, while the rows show states of target horizontal displacement)

	GL	GM	GR
L	SL_1	SL_2	STR_1
M	SL_3	STR_2	SR_1
R	STR_3	SR_2	SR_3

The motion decision for the tracking behavior is calculated through the fusion of the image displacement and image velocity in the fuzzy logic inference matrix.
The values of matrix entry is calculated by finding the minimum of the two input variables, for example

$$SL_1 = \text{minimum (G,L)} \tag{10}$$

The three output variables are then computed using the root of sum squared of contributing variables as described by the following equations

$$SL = \sqrt{SL_1^2 + SL_2^2 + SL_3^2} \tag{11}$$

$$STR = \sqrt{STR_1^2 + STR_2^2 + STR_3^2} \tag{12}$$

$$SR = \sqrt{SR_1^2 + SR_2^2 + SR_3^2} \tag{13}$$

Finally, the normalized control command are calculated by the defuzzification computations that are based on the center of gravity (or centroid) method and can be described by the following equation

$$SCmd = \frac{(SL \times -1 + STR \times 0 + SR \times 1)}{(SL + STR + SR)} \tag{14}$$

Where -1 is the center value for left steering, 0 is center for the straight steering and +1 is the center for right steering. The steering command, *SCmd,* is evaluated from Equation 13 and then directly sent to the steering motor subject to a no change zone in the range (-0.2 : +0.2), and steer left if the value is negative and outside the no change zone, and steer right if the value is positive. The final control algorithm is implemented in C-code and the flow chart for the whole control system is shown in Figure 18. The block diagram is shown in Fig.17.

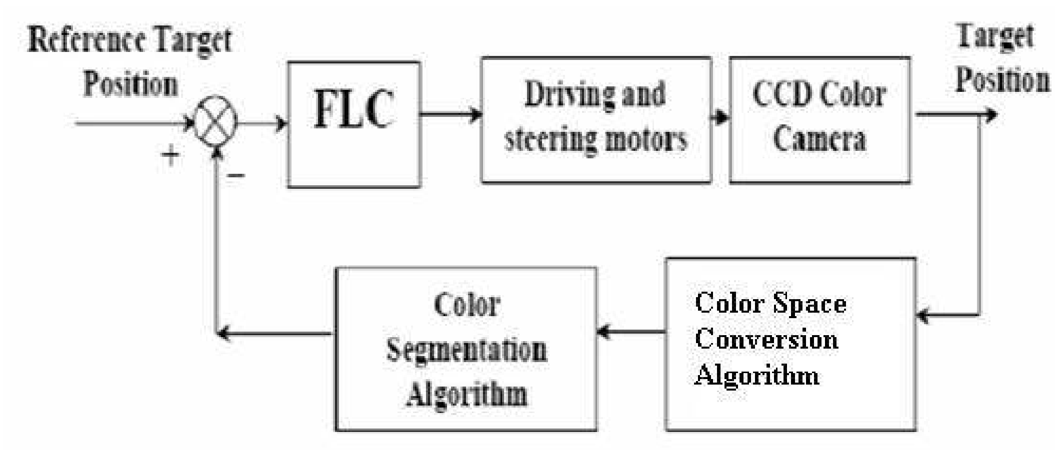

Fig.17. Block diagram of the robot control system, for the target following behavior.

4.2.2. Design of Obstacle avoidance behavior

In the obstacle avoidance behavior, the two front sensors are input variables for the FLC responsible for obstacle avoidance, while the output variable is the steering angle. If the right sensor only indicates an obstacle, the robot will execute local maneuvering to escape from the right region obstacle and find its way through the left region. This behavior enables the robot to find passable areas around it without having a prior model of the required route.

The steering angle has three membership functions, Steer Left, SL, Steer Right, SR and STRaight, STR. It should be noted that based on the limit of the obstacle distance corresponding to the "N" linguistic variable, the robot may escape the obstacle by steering or may have to stop, in case the distance is very small to enable maneuvering without crash. If the distance is small, then after stopping the robot, a supplementary maneuvering behavior is activated to move the robot slightly backwards before moving ahead again, which is also experienced by human drivers facing same situation. The output vector has a decreasing magnitude when the average distance from the obstacle is increased.

4.2.3. Fusion of behaviors

We have two decisions for the steering angle computed from the two behavior implementations. The decision is fused through using the potential field method by vector summation of the two vectors resulting from each behavior. The velocity vector from goal seeking behavior has a velocity amplitude maximun when steering is straight and decreases according to a linear model when the steering is off-axis. Then using vector mechanics, the combined Euclidean magnitude and direction are computed and used to steer the vehicle. This method differ from the main potential field theory in the way the input vectors are generated, in our case it is generated through the fuzzy logic in each separate behavior in contrary to the direct construction of such vector in the main theory.

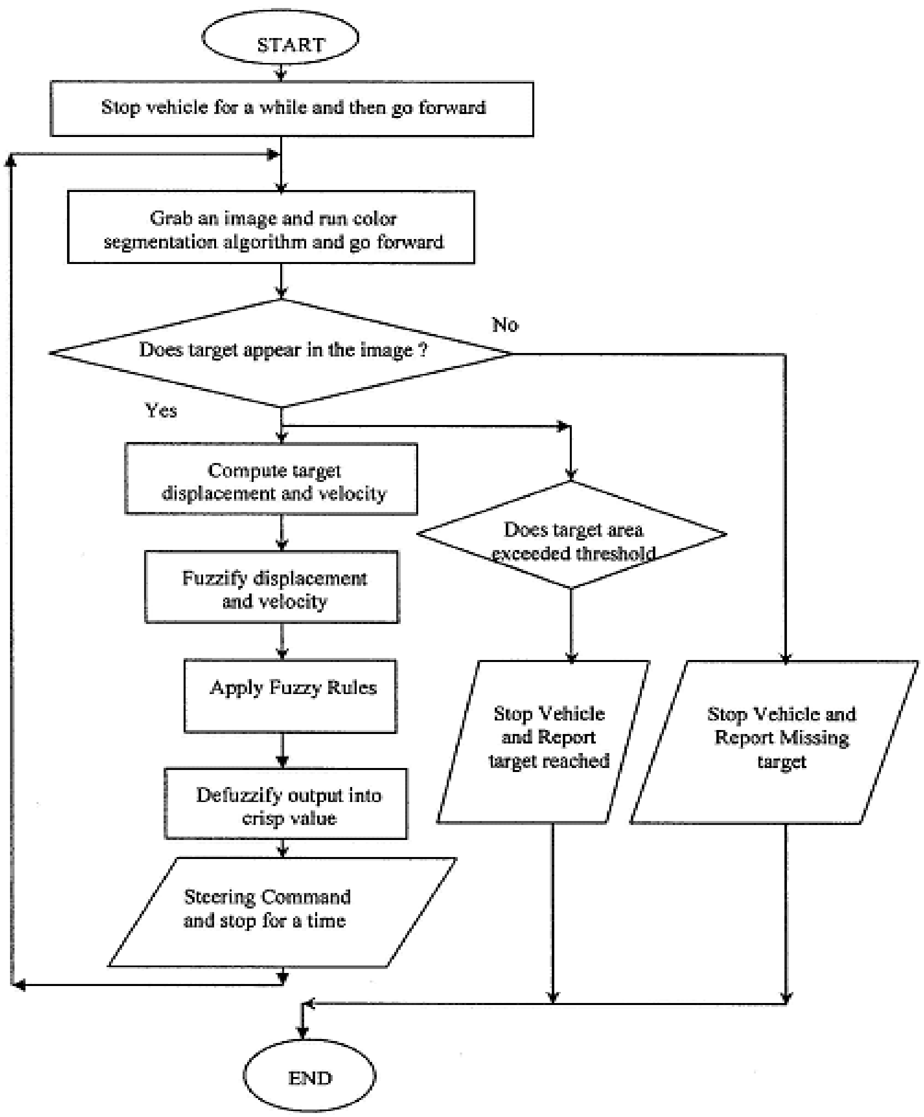

Fig.18. The robot control algorithm.

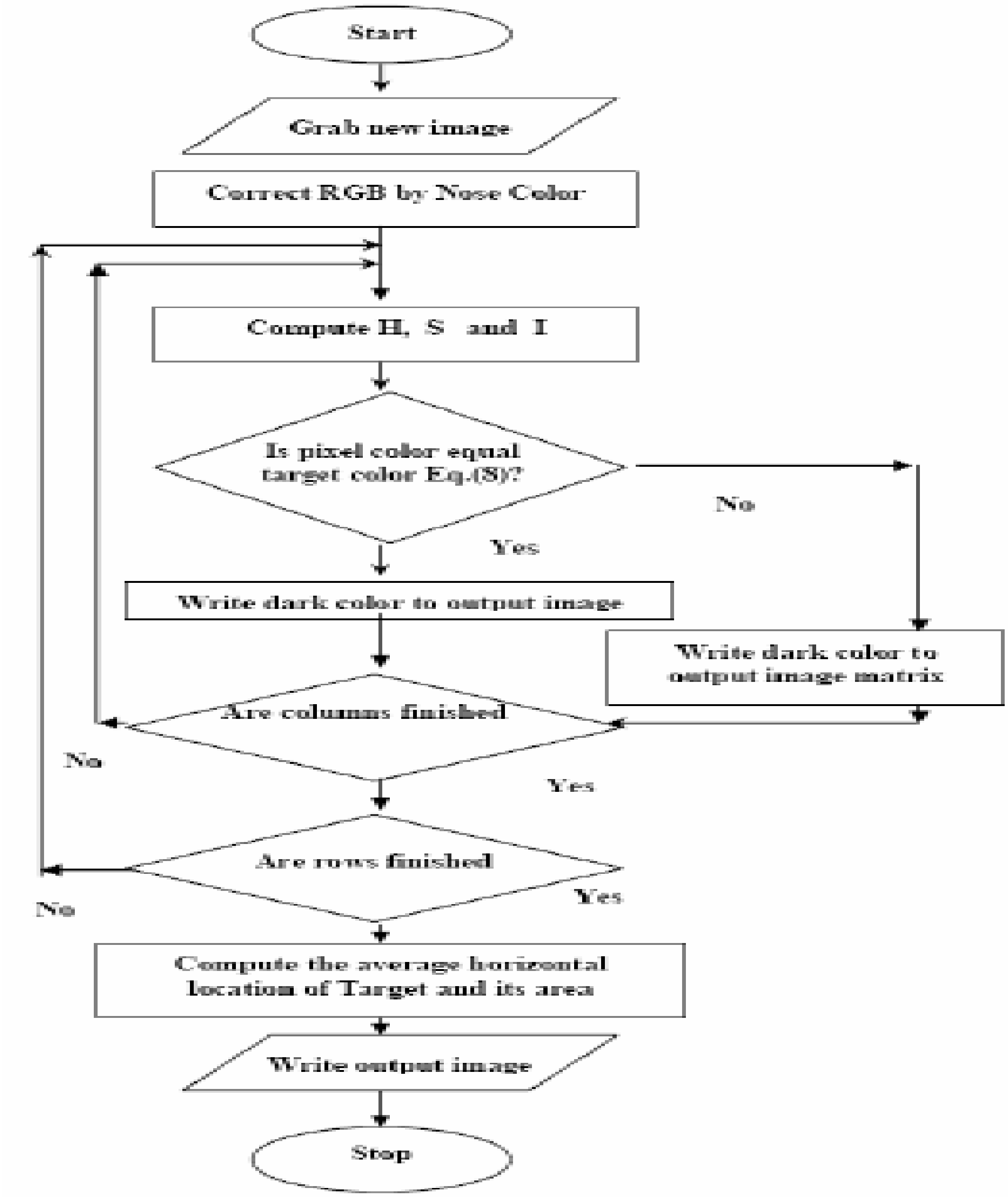

Fig. 19. Flow Chart of the color segmentation algorithm.

The target is detected in the image by a selection criterion based on whether the pixel color lies within the boundaries of the H-S zone, known *apriori* for the target. The segmented image is written into another color image. The average horizontal coordinate of the target region is computed and forwarded as input to the controller.

4.3. Face Detection Algorithm

The algorithm proposed by Viola and modified by Leinhart [29,30] is used for face detection using the cascaded trained classifier implemented in the OpenCV library [14]. The algorithm works by scanning the image with a variable size classifier namely a cascade of boosted classifiers working with Haar-like features. The training positive examples that are scaled to the same size and negative examples that is arbitrary images of the same size.
The classifier outputs a "1" if the region is likely to show the face else it shows "0". The classifier is resizable in order to be able to find the objects of interest at different sizes. The scan procedure should be done several times at different scales in the image to detect faces of unknown size in the image.

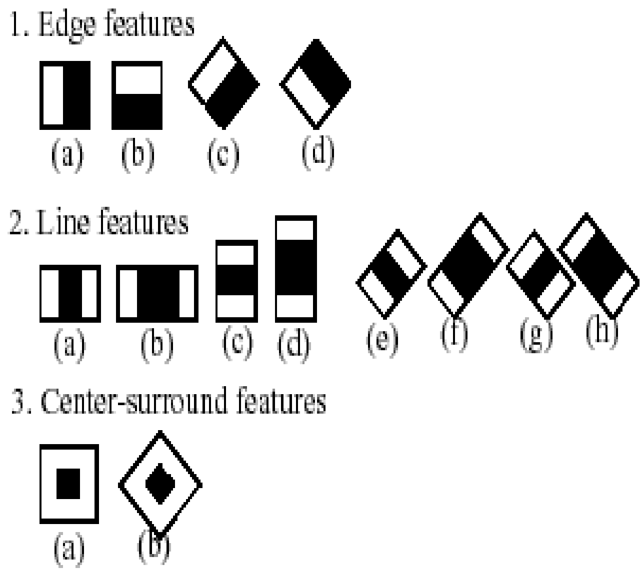

Fig. 20. The Haar classifier training patterns.

The word "cascade" in the classifier name means that the resultant classifier consists of a set of other classifiers that are applied in sequence to a particular image area until the candidate is rejected or passed at some stage. The boosting technique used is the weighted voting method. The basic classifiers are decision-tree classifiers with at least 2 leaves. Haar-like features are the input to the basic classifiers. The following Haar-like features are employed in this algorithm:
1. Edge features, 2. Line features, and 3. Centre –surround features.
The classifier is trained over few hundreds of human faces.
The algorithm is suitable for fast face detection, but we observed that the false positive detection rate is high and areas in the image which is not face and not having the human skin color may be mis-registered as a human face. Therefore, we propose to constrain the search space by incorporating the skin color constraint.
In the implementation of the openCV [14], there is one pruning method to accelerate the face detection algorithm, if it is selected, the function uses Canny edge detector [55] to reject some image regions that contain too few or too much edges and thus may not contain any human face.
Since the input image is segmented by its color chromaticity to include only the human skin regions, the search space is significantly reduced, and hence no further pruning is needed.

The basic sequence of the software is described in Fig. 21. The input color image is at first pre-processed for color correction by the nose color correction algorithm [117] to remove effect of light color and intensity.

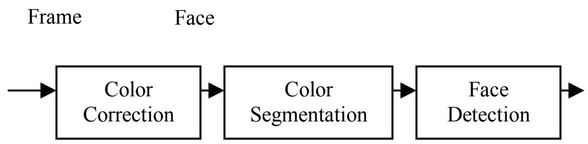

Fig. 21. Face Detection Algorithm Scheme.

The output image is then segmented according to the criterion described in equation (6) and the areas corresponding to human skin color is only visible in the output image from that algorithm. The face detection algorithm scans the image containing skin color to detect the face candidates. It is assumed, in our current application, that only one human face exist inside the image, although this assumption will be relaxed when the detection process is replaced or becomes coordinated with a face recognition algorithm to select the person of interest.

The area of the detected face inside the image is computed and used to control the motion of the mobile robot. Since the focal length of the camera lens is fixed, the image area is related to the robot distance from the face. The robot stops after the area of face exceeds a threshold corresponding to a distance of one meter, or other appropriate distance.

The average horizontal displacement of the face area pixels and the horizontal component of velocity (computed in the image plane) of the center of the face are also computed from the image sequence being processed. The three attributes of the face, namely area, average displacement and average velocity in the image plane are then fed to the control algorithm. The area is used by the controller to stop the vehicle after reaching specific distance from the human face. The displacement and velocity of the face area are fed to a fuzzy logic controller, FLC, to control the steering of the vehicle based on inference rules.

5. Experiments and Results

5.1. System Configuration

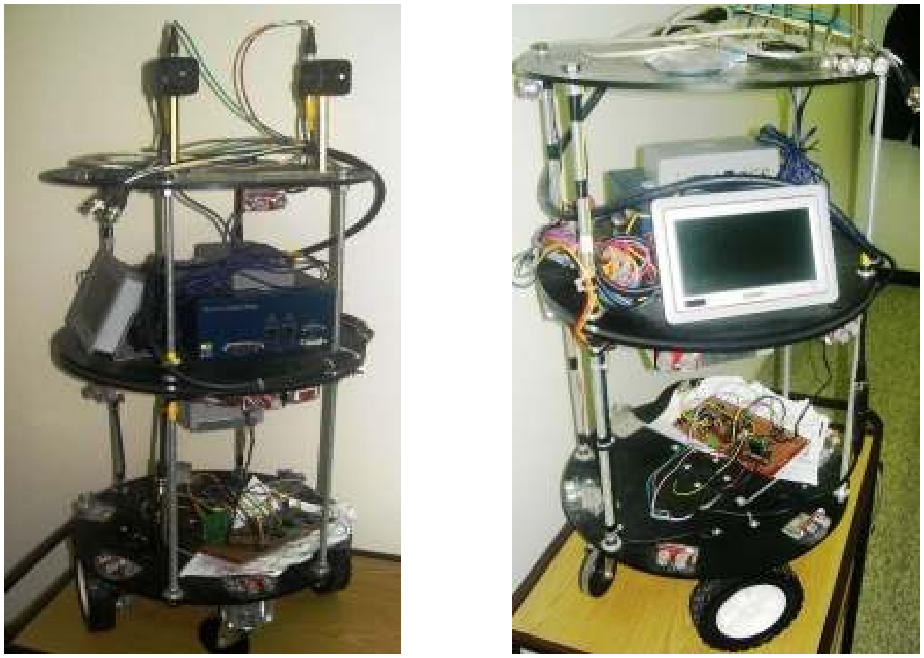

Fig.22. Photograph of the service robot.

The robot has four wheels to move easily on flat terrain as shown in Fig.22. The two side wheels are driven by two independent servo motors, while the front and rear wheels are castor wheels and provided only to improve the mechanical stability of the robot. This configuration allows the robot to be used for moving on flat terrain. The robot consists of three layers of strong acrylic sheets supported by four long pillars. The lower level contains microcontroller circuit for controlling low level motor motion and reading of ultrasonic sensors and encoder readings. The second level carries the foursight vision processor and creen for displaying camera image, while the third carries the two cameras and the main microprocessor.
The robot is equipped with 16-ultrasonic sensors to enable perception of its environment, detection of obstacles. The robot has two color video cameras installed onboard to explore the surrounding space and to recognize people and objects of interest. The cameras provide the image that is used by the target following and obstacle avoidance systems.
The main microprocessor is the central driving force of the mobile robot. It processes data from the the motion control system and the vision module. As weight is one of the major considerations in the robot design, a laptop is used as the main microprocessor for the robot. The movement of the vehicle is determined by the software with inputs from different components. The programs are written in C code. Inputs from both the cameras are fed into the Matrox foursight module to process the image as a special vision microprocessor.

Input to the avoidance microcontroller is two bits containing higher goal decisions and it encode the commands of moving forward, backward or stopping. The decision sent to the vehicle is the speed and directions to the two servomotors.

The images received from the cameras are digitized via a Meteor II frame grabber and stored in the memory of the foursight computer for online processing by specially designed software written in C code. We implemented algorithms that grab, calibrate the color image to eliminate the camera offset. The target color is identified to the system through measurement of it Hue-Saturation zone. The color attributes of the target are stored in the program for later comparison. Then the motion attributes of the target extracted area are computed and passed to main microprocessor where the data is used by the FLC module. All programs are implemented in C++ code and several video and data processing libraries are used, including MIL and OpenCV. A summary of robot main specifications is listed in Table 2.

Table 2. Specification of the mobile robot

Item	Description
Size	40 cm diameter base, 90 cm Height.
Weight	20 kg
Power	12 V battery.
No. of Wheels	4
Steer & Drive mode	Differential wheels with zero turn radius.
Camera	Two Color CCD camera
Frame rate	30 frames per second
Image standard	NTSC
Image size	640×480 pixel × pixel
robot speed	Maximum 50 cm/s

An experimental program was conducted to:

- Explore the effectiveness of the control system in safely guiding the robot to detect the target by its color. Experiments were conducted for separate independent behaviors and then for combined behaviors.
- Test the performance of the face detection system.

5.2. Target/ Face detection and tracking experiments

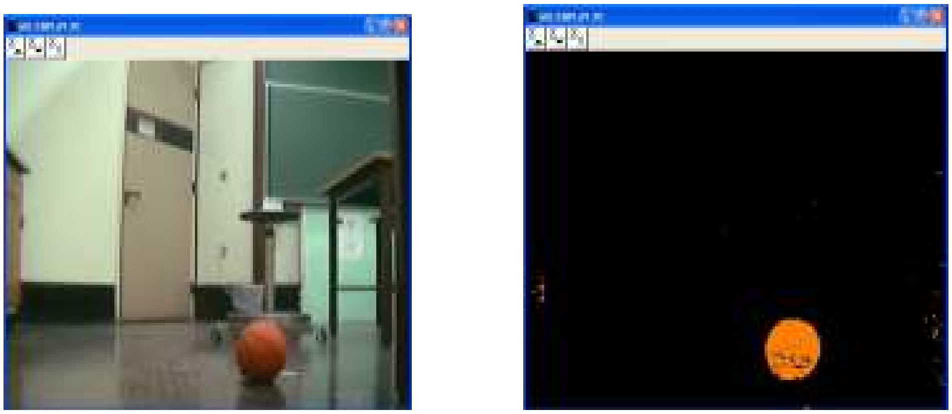

Fig. 23. The separation of the target from image background using color.

Fig.24. The segmented image showing the detected target area.

The extraction of target area is shown in Fig.23 and Fig 24, where the left image shows original captured image and the left one shows the extracted target area. In Fig 25, we show the Hue Saturation histogram for the target, which is red object in our case. The hue range is from 0 to 360 degrees and the saturation ranges from 0 to 255. It is worth noting that the hue angle is repeated and hence 0 degree is same as 360 degree, therefore the region shown can be described in limited bounds. The dark regions in the graph correspond to a high number of pixels in the target area having the same H-S point. This defines the color zone mentioned early in this paper and the bounds are extracted from this figure.

Figure 26 shows a sample experiment of detecting human faces from an image of the video stream. The human face image is visible in the main image, while the nose image appears in the fixed location of lower left corner and its reflection color represents the spatially uniform illumination color in the scene. The illumination color is measured from the nose image and then globally discounted from the whole image colors. The skin color is detected based on corrected pixel colors and then an image containing the skin only is presented to the facial face feature finding algorithm. The image shown in Fig.26 shows the detected human face and a red box defining its area in the image.

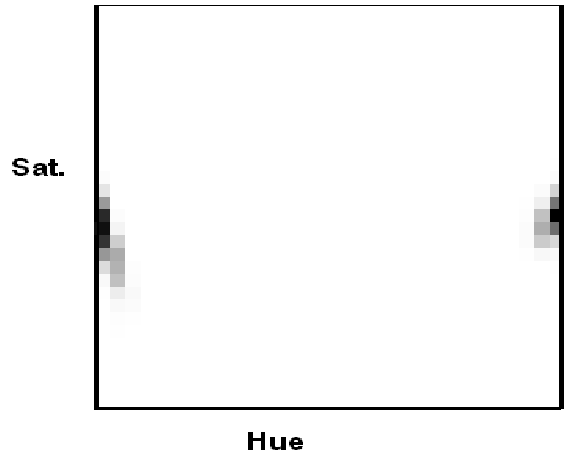

Fig.25. The Hue Saturation diagram showing regions of darker intensity as those corresponding to higher voting of the target object pixels (corresponding to red color in this case). The range of hue is from 0 to 360 degree, and for saturation from 0 till 255.

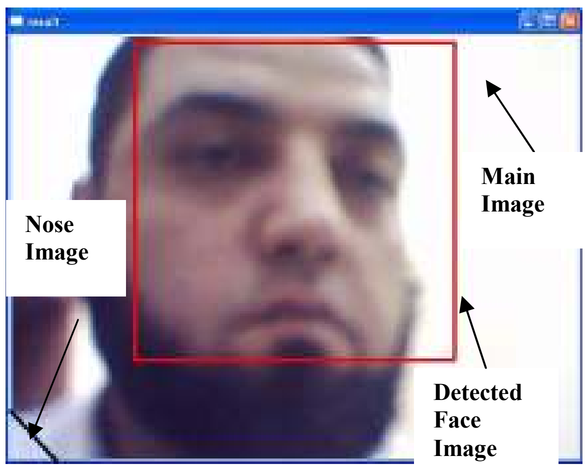

Fig. 26. The human face detection in the main image and the nose image used for color balance.

Fig. 27. Human face detection sample. a) The face detected with another false positive candidate, when skin color is not used for detection. b) The face is only detected when color is used for face detection.

The merit of using color is clear from the sample experiment presented in Fig.27. The use of face detection algorithm without color information delivers the image on the left, Fig.27.a where the child face is detected but also one false positive candidate exist in the chair texture. When the color information is used, the image on the right, Fig.27.b, is delivered which shows only the child face with no false candidates. Fig. 28 shows the human skin color separated for the same picture of Fig. 27, which helped to remove the false detection on the left since its color is not that of human skin.
Fig. 29 shows the caption of real time correction and face detection software obtained from the system where the human face is detected after preprocessing to identify the human skin color and to remove the effect of illumination changes by using the nose method.
The system was tested to follow a human face visible at a distance of 3 meters and the vehicle detected the face and approached the face and stopped at a distance of 1 meter. Several test runs, showed that the robot system is effective in detecting human faces and navigating in the environment using such information to become near the detected human.
The face detection was tested when the illumination was changed from halogen to tungsten lamp. The skin color was significantly changed and the faces can not be detected when the color information is used directly due to the severe color changes. When the nose preprocessing was used, the corrected skin color showed less variance under varying illumination, and the faces were consequently detected. However, severe changes of illumination color may cause intolerable color changes that may not be recovered by the nose preprocessing.

It must be noted that the implemented behavior is not capable of following the person of interest but rather to identify him. If the robot is needed to follow that person, then the face shall be memorized with other associative features such as the human cloth color, human body features.
The feature association enables the robot to follow the person without being able to continually visualize his face. This intuition is in compliance with what we, humans, do in similar circumstances.

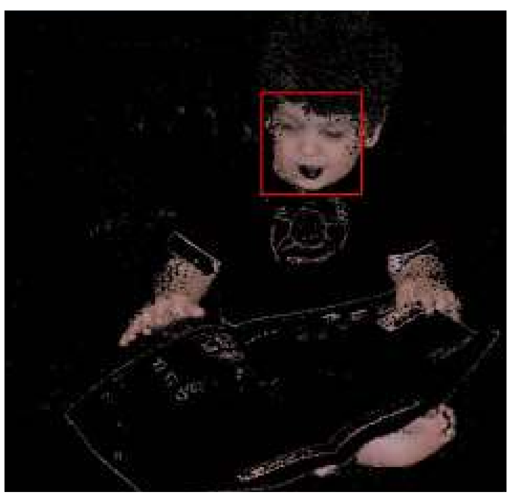

Fig 28. The separation of human color skin result for image of Figure 27.

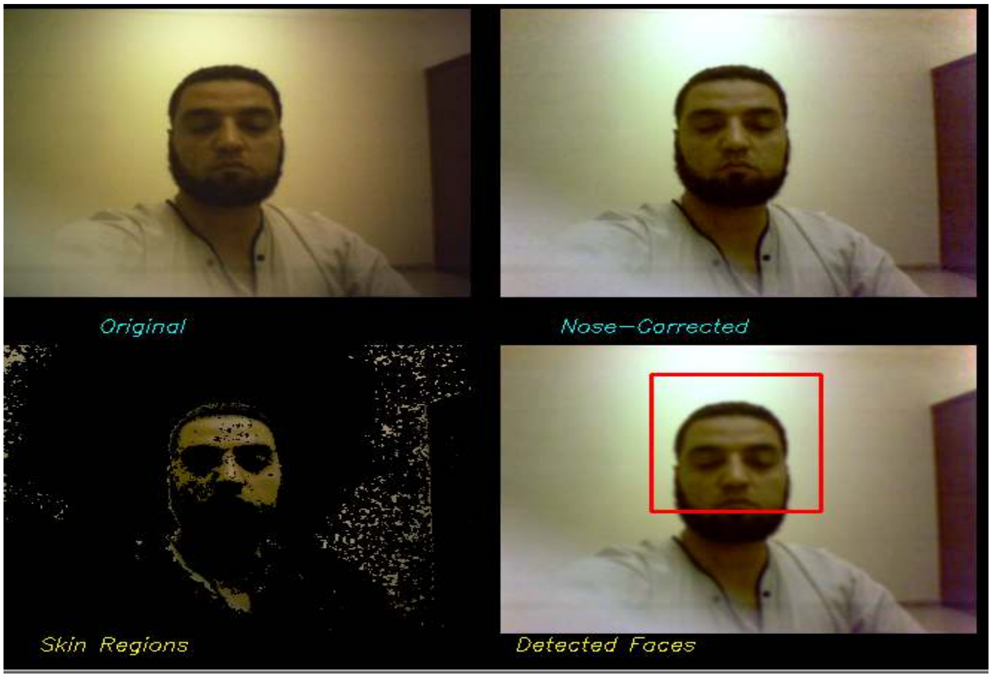

Fig. 29. A sample showing the original, nose corrected image, skin color segmented from image colors, and the detected face overlayed on the corrected image.

5.3. Experiments for control system.

The control system, shown in Fig.14 had been implemented for navigating the mobile robot which captures two color image, and process them via the vision processing computer. The nose image color is measured and then the whole image colors are processed to obtain the Nose-Corrected image colors. The illumination color effects are removed in the corrected images and colors appear as if imaged under the illumination of a white color.

We developed an algorithm to extract the face area and its location in the image based on the human skin color model to improve the face detection accuracy and reduce false detection rate. Then, the motion attributes of the face image are computed and passed to the control module. A Fuzzy Logic Controller is designed and used to control the vehicle steering based on the image measurements. The objective is to move the robot in front of the person of interest and keep him in the middle of the camera view at a certain distance.

The target following experiments showed that, when the FLC parameters were tuned properly, it followed the target whether the target is fixed or moving with speeds comparable to robot speed.

The robot starts to move as shown in the robot track, Fig.30 and keeps moving forward. During the robot motion, the target continuously approaches the image center and consequently the target area increases in the segmented image. It followed the target even when it is moving in curved routes, as long as the target is visible.

An experiment to test the obstacle avoidance behavior is shown in Fig.31. The dotted line shows the robot path when working with obstacle avoidance only. The robot evades the obstacles and move towards free areas based on the sequence of obstacles faced.

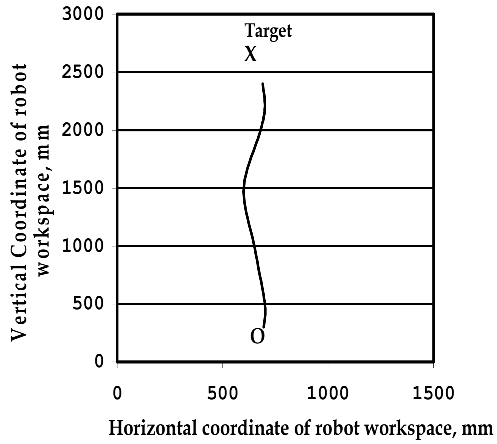

Fig. 30. The real track of the robot while following the colored target.

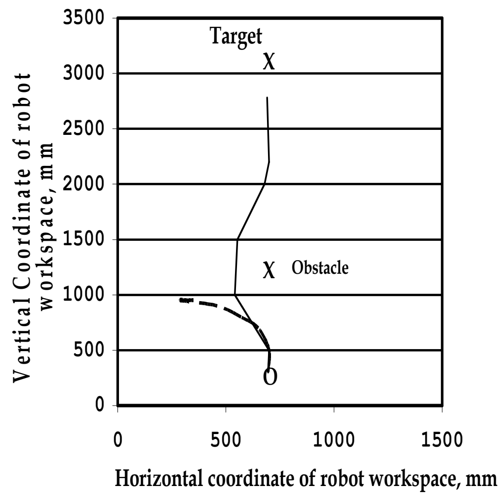

Fig. 31 The real track of the robot while following the colored target.

The robot stops when the landmark area in the image exceeds a certain empirical threshold so that the robot stops at about 25 cm in front of the target, or the sensors detect an obstacle less than 30 cm close to it.

The target following behavior is then integrated with the output from obstacle avoidance behavior using vector summation principle. The heading angle is then executed by the differential wheels. An experiment showing the combined effect of both behaviors is shown also in Fig.31. The solid line shows the robot track when both behaviors are combined, the robot evades the right target but soon recovers and steer right toward the target.

In the future, the robot needs a SLAM algorithm to hold a map of the environment and plan its path according to the map and perception of its location inside the map. This will be left for future research.

6. Conclusions

A mobile service robot had been developed that can move on a flat terrain. The robot structure had been designed in a modular fashion and the modules are then integrated. The robot can perceive its environment through several sensors including ultrasonice range sensors and CCD color cameras. The following have been achieved:

1. A vision-based control system was implemented that enables the mobile robot to track and follow a moving target.
2. The algorithms for color object detection, extraction and measurement of target features had been developed.
3. Fuzzy logic controllers had been designed to produce two concurrent behaviors of target following and obstacle avoidance. The decision from the two behaviors is combined using the potential field theory, which produces a final decision vector for robot motion.
4. A system for automatic face detection using color information as well as face features. The system delivers less false face candidates and is reliable against the changes of scene illumination.

The system was used to detect a single human face and control the motion of the mobile robot to become near to the detected face. The measurement of the face spatial location and area of the detected face surrounding window are used to steer and drive the robot.

The human skin color is then reliably identified and extracted from the image. The skin regions are then used only to find faces among them. The experimental results showed that using the skin color constraint reduces significantly the rate of false face detection and only the true human faces are delivered. The system is reliable and useful for human-robot interaction applications.

The control system succeeded also in guiding the robot reliably in both tracking of the target and following it keeping a reasonable distance between them. Fuzzy control provided smooth and reliable navigation that circumvents the inherent uncertainities and noise in the sensing process. Furthermore, the fusion of behavior commands was successful using the potential field theory due to the smooth decisions from the individual behaviors.

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