Decomposed Fuzzy Controller for Reactive Mobile Robot Navigation

Munaf S. N. Al-Din

Abstract*— An Autonomous Mobile Robot is an artificially intelligent vehicle that is capable of traveling in unknown, unstructured environments independently. Among the proposed approaches in the literature to handle the navigation problem of a mobile robot is the simple fuzzy reactive approach. This approach, however, occasionally suffers from two problems the combinatorial explosion of the if-then rules in the inference engine, and finally the lack of a unified fuzzy rule-based system procedure. This paper offers an approach to handle the first two problems. In this paper a new approach to the design of simple fuzzy navigation systems is presented. The proposed approach is based on decomposing MIMO fuzzy logic controller into a number of SISO controllers. This approach has the advantage of greatly reducing the number of if-then rules by introducing weighting factors for the sensor inputs, thus inferring the reflexive conclusions from each input to the system rather than putting all the possible states of all the inputs to infer a single conclusion. Simulation and experimental results are presented to prove the efficiency of the proposed approach for mobile robot navigation in unstructured unknown environment.

***Index Terms*— Decomposed fuzzy controller, Mobile robot, Autonomous navigation.**

I. INTRODUCTION

An Autonomous Mobile Robot (AMR) is an artificially intelligent vehicle that is capable of traveling in unknown, unstructured environments independently. AMR uses a sensory system to take readings from its surroundings and make the necessary decisions such as perception and reasoning to control its actuators to perform motions based on the perceived information in order to achieve its prescribed goal(s). With such objectives required to be achieved by AMR's, their utilization in different settings such as, homes, factories, or hazardous environments is increasing steadily.

From the wide spectrum of AMR's objectives, the navigation process is regarded as the key issue in an enormous number of research publications during the past 15 years, e.g., [1-11]. Sensor-based data acquired by the mobile robot provides the necessary information to determine the appropriate control actions to the actuators so that the mobile robot can travel safely in cluttered environments with static and/or moving obstacles. In order to achieve its goal, the AMR is normally required to determine in real-time a safe, smooth, and preferably optimal path from a starting location to an end location (target). Hence, the main issues that need to be addressed in mobile robot navigation are obstacle avoidance, target acquisition, and escaping possible traps [12].

An AMR path planning problem is usually classified into global path planning and local path planning [6,11]. In global path planning, the environment is assumed to be previously known for the navigation system, thus a collision-free path is then generated to pilot the robot to a given target. Several methods that are categorized as global path planning methods have been reported in the literature, e.g., [1, 12-16, 20]. All these methods are search algorithms that have common features such as, the need for complete or partial information concerning the environment, the planning is done off-line, they are time and computationally demanding, and they are prone to a number of problems [6,11]. On the other hand, local path planning methods are basically sense-act (reactive) mapping functions, and are more or less closer to human thinking when driving for the first time in an unknown place. Intelligent decisions are permitted in real-time without any interruption in the mobile robot's motion. Accordingly, these methods are designed such that they require less computational space and time. These methods are classified into model-based methods [17], and artificial intelligence methods that employ fuzzy logic, neural networks, genetic algorithms, or a hybrid of these methods [18-21].

Among all the suggested methods for reactive navigation, fuzzy logic based decision-making has been found to be the most attractive. It is tolerant to noise and error in the information coming from the sensory system, and most importantly it is a factual reflection of the behavior of human expertise. In general, there are two approaches to the application of fuzzy logic in AMR navigation, namely, behavior-based approach and simple fuzzy reactive approach. The first approach involves decomposing the path-planning problem into a set of situation-specific fuzzy behaviors that achieve simple distinct tasks each designed for a particular incentive. The final decision for dealing with complex situations then can be obtained by the combination or coordination of the simple behaviors [8,22-25]. Although, the principles of this approach seem to be simple, the coordination between several decisions obtained from different behaviors is not an easy task. Moreover, this approach suffers from computational complexities when the number of sensors and fuzzy values for the input linguistic variables are increased. This is due to the exponential increase in the number of rules that are required in the fuzzy algorithm for each behavior. In addition, the choice of the weighting factor for each behavior needs extensive training to cover a huge number of situations.

On the other hand, the simple fuzzy reactive approach, which is basically a classical implementation of a fuzzy rule-based system, is less sensitive to the problems associated with the behavior-based approach. Depending on the number and the nature of the input variables a rule base, or fuzzy algorithm, can be designed to suite a semi-general situation [5-8,26-27]. The design of the fuzzy algorithm is basically creating rules that reflect the basic reflexive behaviors of human beings in driving a car in unfamiliar environments.

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These rules are stimulated by locally available information about the environment in order to avoid obstacles and reach a desired goal without any usage of memory for the previously encountered situations. Although, the design and implementation of such systems seems to be a simple task, they suffer from three major shortcomings. The first problem is the suffering from local minima or trap situation. However, a number of trap escape algorithms have been suggested in the literature [11,28-30]. The other two problems, which are not mentioned in the literature, are the lack of a unified fuzzy rule-based system similar to that adopted in the solution of classical control problems, and the huge expansion in the fuzzy rule-based system when better precision is needed. The first of these two problems is due to differences in strategies adopted by different researchers in the field. The second problem arises when the number of input variables and their fuzzy values are increased, e.g., when using four input variables each mapped by seven fuzzy values then 2401 if–then rules are required to completely define the rule-base of the inference system.

In this paper a new approach to the design of a simple fuzzy navigation system is described. The suggested system has the advantage of greatly reducing the number of if-then rules by inferring the reflexive conclusions from each input to the system, rather than putting all the possible states of all the inputs to infer a single conclusion.

II. NAVIGATION SYSTEM STRUCTURE AND METHODOLOGY

The navigation methodology proposed in this paper utilizes human experience to generate the reaction of the mobile robot towards the surrounding through fuzzy reasoning. The main objective of the proposed method is to reduce the size of the fuzzy inference system without affecting the efficiency and performance of the navigation system when compared to other classical implementations of reactive fuzzy navigators [5-8, 26-27].

Before introducing the structure of the proposed fuzzy system, a brief clarification to the understanding of the authors to the navigation problem is given. Autonomous mobile robots at least need to achieve a simple goal of traveling safely and purposefully from one location to another in an environment that is unstructured and subjected to unpredictable changes. Like human beings, AMR should be self-reactive in the real world through decisions produced by a real-time navigation system. The reactions to the perceived surrounding can be inferred from either reflexive behavior or logical behavior. Reflexive behavior is activated only when a sudden and unpredictable change in the surrounding occurs, such as an unpredictable movement of a non-static object or the unexpected appearance of a static obstacle. It is hard to state that decisions taken under reflexive behavior are to be taken without any conscious analysis of the environmental situation [11], but it can be argued that decisions under severe conditions could result in unwise reactions because of the lack of capability in producing adequate solution.

The other type of behavior associated with intelligent systems is the logical behavior. When fully conscious attention is paid to the environment, this behavior is responsible for generating decisions that result in robust real-time reactions towards the foreseen surrounding. It should be noted that although the decisions and their associated actions are near optimal, at the time scale of the environment, but they are in the general case obtained from partial and rough awareness of the environment. Therefore, it is more reliable to incorporate fuzzy logic to model or describe the foreseen surrounding in order to obtain instinctive decisions.

Various algorithms have been proposed to attack the problem of generating collision free trajectories for a mobile robot by utilizing the theory of fuzzy sets. Researchers in the field agree that the robot navigation problem is decomposed mainly into goal reaching and/or obstacle avoidance problems. For each problem there are a number of possible situations that can be faced and must be solved to obtain a non-strict optimal trajectory for the robot.

In the proposed approach, the robot is required to behave in a similar manner to that of an expert human driving his/her car. In general, humans don't construct in their minds a full fuzzy model that contains all the possibilities of the If-Then rules, but instead, they give weighting factors to separate decisions made based on information from the different senses. With this point of view in mind, it is believed that a simpler fuzzy system can be made by considering the navigation system to be made up from simple fuzzy systems, each responsible for an independent decision corresponding to a single sensor. These decisions are then combined, with the same level of simplicity, to obtain a final conclusion. Accordingly, the structure of the proposed system is shown in Figure 1. As it can be seen in figure 1, the multi-input system is decomposed into four input variables, which are required to provide the necessary information for the navigation system to safely drive the mobile robot through an unknown and unstructured environment to reach the desired target. These inputs are: distances d_f, d_r, and d_l, measured by three ultrasonic sensors. These distances are the distances between the robot and any possible obstacle with respect to the local front, right, and left directions of the robot, respectively. The forth input is the distance directed towards a virtual direction between the robot and the target, d_t. The idea of using a virtual target orientation instead of the real orientation comes from a realistic representation to the behavior of expert driver, where it is impossible for a driver to abandon his attention to the frontal sight when leaving a one-sided blocked target behind him and concentrates on the real target orientation. Under this situation the driver put some concentration towards a virtual orientation at the same side of the target, which should not exceed a certain limit in the range of the frontal sight. The outputs of the system are the steering angle (θ) and the speed of the robot (υ_f). The structure of the five fuzzy system blocks that are connected to the inputs are SISO systems. The main function of these subsystems is to generate weighting factors (ω_i) that represent the degree of obstacle avoidance at the corresponding side of the robot. Only five if-then rules are needed to define the fuzzy algorithm of the inference engine for each subsystem (see Table 1). The Center of Area method is then used to obtain the crisp value for each weighting factor. The four input variables are represented by five fuzzy values with the corresponding membership functions shown in Figure 3.

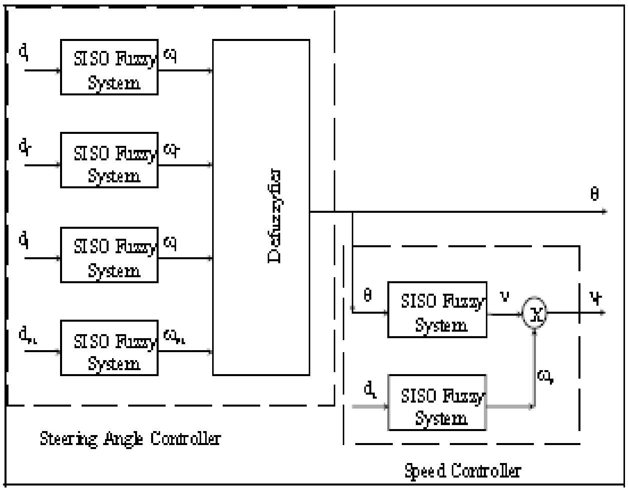


Fig- 1: Structure of the Proposed Controller

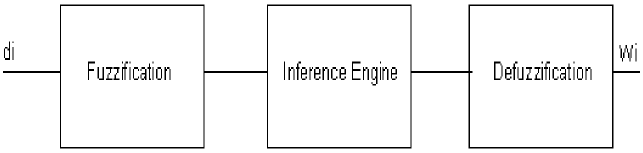


Fig-2: Simple SISO Fuzzy System

Table 1: Distance-Weighting Factors Inference Rule-Base

If d_i is VL Then ω_i is 1.0
If d_i is L Then ω_i is 0.75
If d_i is M Then ω_i is 0.50
If d_i is S Then ω_i is 0.25
If d_i is VS Then ω_i is 0.00

The second stage of the fuzzy steering angle controller is a simple defuzzifier, which receives the four weighting factors coming from the previous fuzzy subsystems, and treats these factors as the degree of fulfillment for the corresponding fuzzy values of the steering angle of the robot. The Center of Area method is also used in this block to obtain the final crisp value for the steering angle of the robot. The membership functions for the fuzzy values of the output variable θ are shown in Figure 5. Only three of the fuzzy values are shown in Figure 5 that represent the turning angle to the left, center, and right respectively. The fuzzy set that represent steering angle towards virtual target orientation is similar to the fixed sets, and it is not shown here because it is designed to be floating one and its center moves in the range [-30°, 30°].

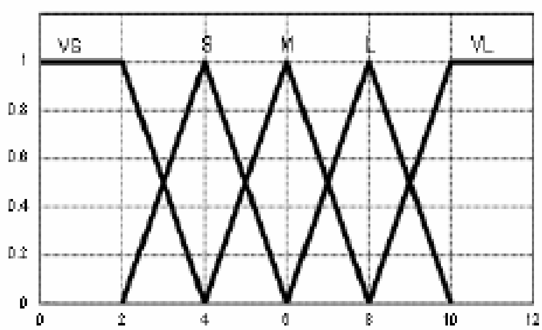


Fig-3: Fuzzy Set Definition for the Input Distance Variables.

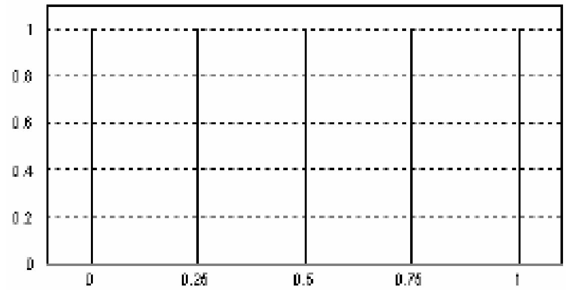


Fig. 4: Output Fuzzy Singletons for the Weighting Factors

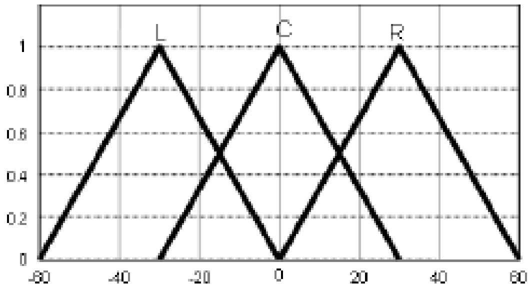


Fig. 5: Fuzzy Set Definition for the Output Variable θ

Once the final value for the steering angle θ is obtained, the calculation of the speed can be computed by the second stage of the system, the right block in Figure 1. This fuzzy controller is also decomposed into simple SISO fuzzy controller of a similar structure as shown in Figure 2. The input to the first fuzzy subsystem of this stage is the absolute value of the steering angle |θ|, where the membership functions that represent this input variable are shown in Figure 6. It should be clarified that variable θ is at the same time an output variable obtained from the previous stage and it is an input to the final stage. The fuzzy sets for the output variable the translation velocity ν are shown in Figure 7, where its represented in normalized values between [0, 1], so that any scaling value to this value may be used to suit any prototype, without changing the definition of the fuzzy sets. The if-then rules used to define fuzzy algorithm of the inference engine of this stage are listed in Table 2.

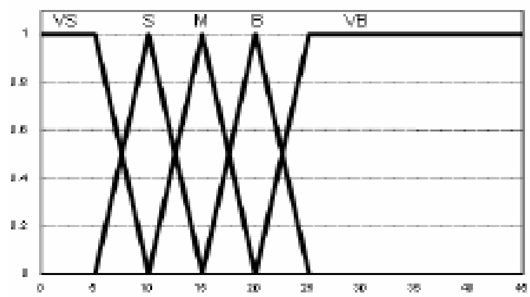


Fig-6: Fuzzy Set Definition for the Second Stage Input Variable |θ|

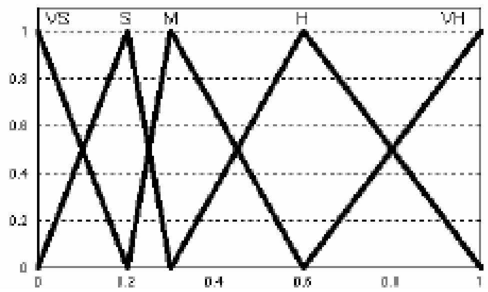


Fig-7: Fuzzy Sets Definition for the Second Stage Output Variable □

Table 2: □□|-□□ Inference Rule-Base

If $|\theta|$ is VB Then ν is VS
If $|\theta|$ is B Then ν is S
If $|\theta|$ is M Then ν is M
If $|\theta|$ is S Then ν is H
If $|\theta|$ is VS Then ν is VH

The second element of the speed controller receives the actual distance between the robot and the target, which is represented by a single fuzzy set as shown in Figure 8. The function of this subsystem is to generate a weighting factor that controls the translation speed of the robot when reaching the target, where the behavior of this element is also based on the fuzzy set theory and it can be stated that is similar to Larson product implication operator.

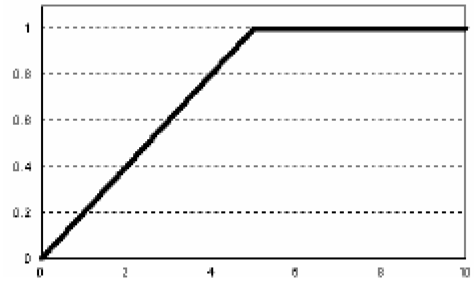


Fig. 8: Fuzzy Set Definition for the Target Distance Variable

III. SIMULATION RESULTS

In order to confirm the efficiency of the proposed method, a simulation program with a graphical user interface has been developed. The robot is depicted in the simulation as a circle to resemble a prototype mobile robot that the authors have designed and constructed for experimental purposes. It is noted here, that errors due to wheel slippage and other motion errors were not considered in the simulation. For distance measurements four ultrasonic sensors were used with the real robot, each modeled by a number of rays within a sector region of a wide beam-angle. The distance measured by each sensor is considered to be equal to the minimum distance obtained within the sector of each sensor while taking into consideration the minimum reliable distance that can be measured by actual ultrasonic sensors. A total of ten different simulation cases are presented in this section to analyze the reaction behaviors of a mobile robot in avoiding a variety of unknown static obstacles placed randomly in a portion of an unknown environment. In all these cases the robot is assumed to be initially moving with full speed and its relative steering angle is assumed to be zero. The analysis of the reaction behaviors of the robot is based on observing the instantaneous variation of the four weighting factors and their influence on both the steering angle and speed.

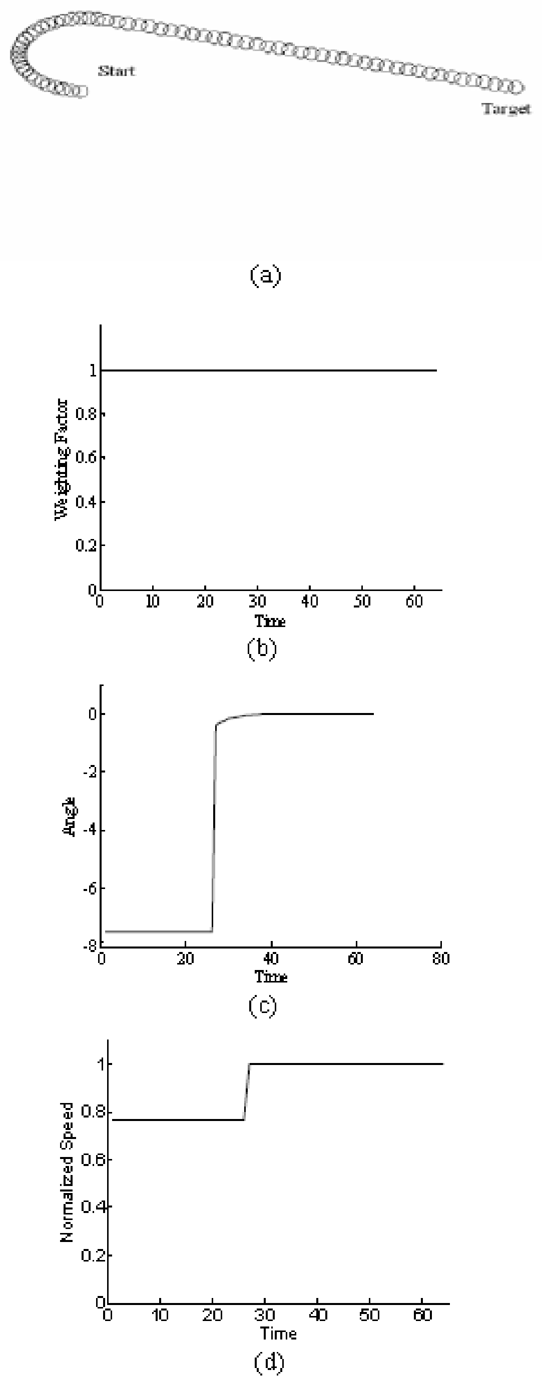
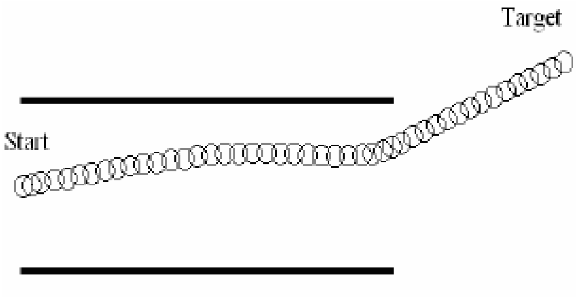


Fig-9: a): Robot Trajectory; b) Variation of weighting factors; c) Variation of steering angle; d) Variation of speed with time for case 1.

In the first case, Figure 9, the robot is initially oriented in an opposite direction to the target. In this case no obstacle is sensed by any of the four sensors, hence, the values of the four weighting factors are all equal to 1 (see Figures 11b. Consequently, the robot will be in the free-heading mode. The immediate reaction of the robot will be biased to turn towards the side at which the target sensor is located at that instant; since the Turn to Left and Turn to Right sets are equally scaled.

The variation of the steering angle and its influence on speed are Figure 11c and 11d. The value of the steering angle depends on the location of the center of the Turn to Target set, which is allowed to move in the range [-30, 30] depending on which side the target is at that instant.



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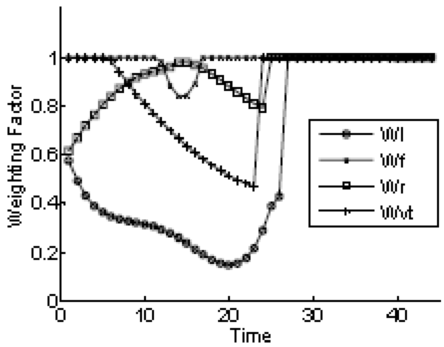

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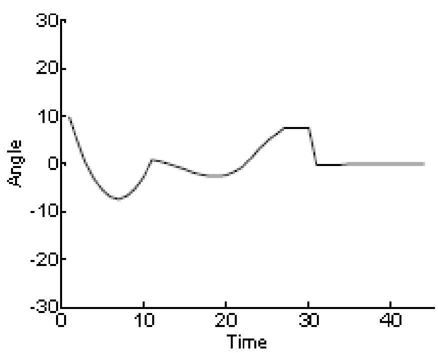

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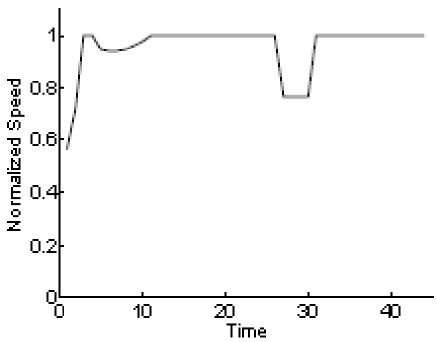
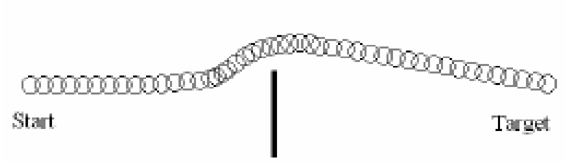


(d)

Fig-10: a): Robot Trajectory; b) Variation of weighting factors; c) Variation of steering angle; d) Variation of speed with time for case 2.

In the second case, Figure 10, the robot can be assumed as passing through an empty tunnel where the only present obstacles are the parallel bounding walls of the tunnel. The response of the robot towards these two lines will be influenced by the instantaneous variation of all the weighting factors as shown in Figures 12b. At the first instant the level of cautions towards the obstacles at both sides are equal, while both the weighting factor resulted from the front and target sensors indicate that there are no obstacles in either direction, thus the robot will turn towards the target. As the robot proceeds in moving towards the target the steering angle will be gradually reduced because of the continuing increase in the difference between the right and left weighting factors and the fall of both front and target weighting factors. Once the robot becomes close to the left obstacle, the right weighting factor will rebalance the left and target weighting factors. Thus, the robot will slightly turn to the right until it aligns itself to move later in parallel with the left obstacle. When reaching the end of the tunnel, the target-weighting factor will rapidly increase to 1. Hence, the robot will noticeably reduce its speed for a short while until it is completely turned in the direction of the target.



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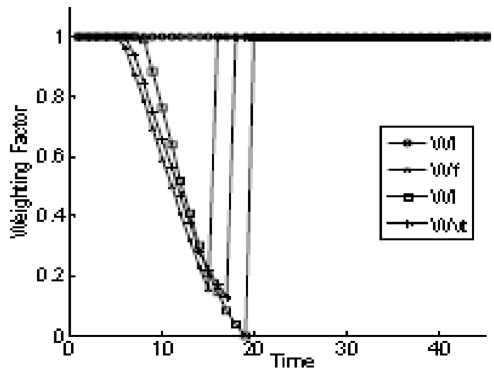

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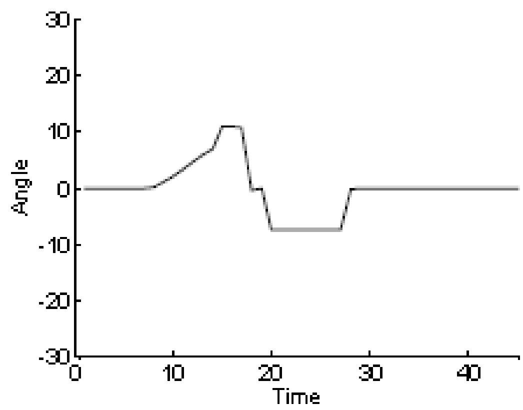

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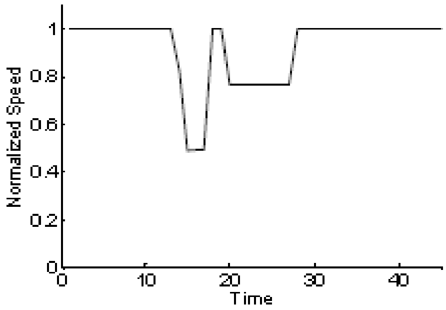

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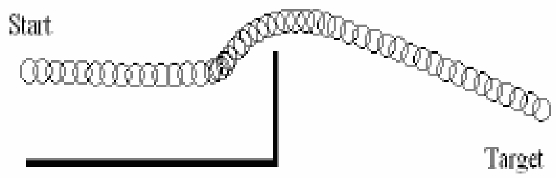
Fig-11: a): Robot Trajectory; b) Variation of weighting factors; c) Variation of steering angle; d) Variation of speed with time for case 3.

In the third case, Figure 11, the robot is assumed to be initially heading towards the target with full speed. A simple obstacle appears not far from the initial location of the robot. The obstacle totally blocks the robot from the right direction and it is slightly extended over the line that connects the locations of the robot and the target. As can be seen in Figures 13b the first apprehension is from both the front and target sensors through the decreasing values of their corresponding weighting factors. However, the robot does not respond immediately since both the right and left weighting factors have the same values. This is due to the lag in detecting the total obstruction by the right sensor. The reason for this lag is due to the location of side sensors and their orientation. This issue is outside the scope of this paper and is part of ongoing research by the authors. After moving a few steps ahead, the right sensor detects the presence of the obstacle, and the robot immediately reacts by turning gradually to the left while reducing its speed due to the dominance of the left weighting factor. Once the robot passes the obstacle both the front and the target weighting factors increase sharply. The right weighting factor follows and rises sharply to indicate the absence of any obstacle in all directions. Reacting immediately to this situation, the robot reduces its speed and turns to the right side to align itself again with the target direction.



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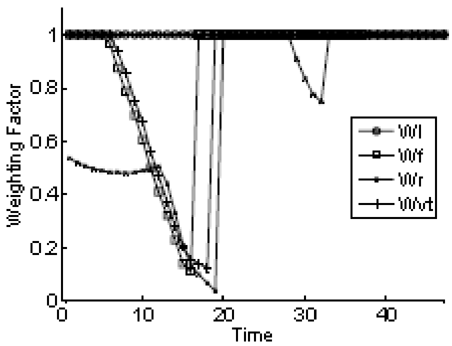

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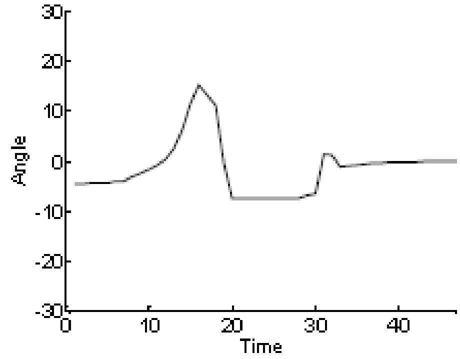

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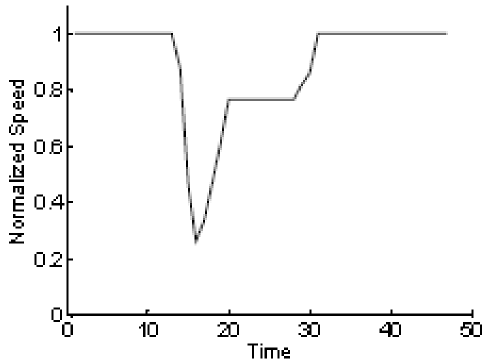

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Fig-12 : a): Robot Trajectory; b) Variation of weighting factors; c) Variation of steering angle; d) Variation of speed with time for case 4.

Figure 12 shows the behavior of the robot when moving towards a target that is located to the right side of the robot. The present environment consists of two obstacles one at the right side of the robot obscures it from turning immediately towards the target, while the second one prevents the robot from going in straight line direction. At the first stage the robot will be slightly attracted towards right direction, in spite of the obscuration at that side, due to the overwhelming balance of both the right and target weighting factors against the left one. As the robot get closer to the second obstacle the front, the right and the target weighting factors will be dropped to a low level thus engulfing the domination of the turn to left behavior. Therefore, the robot will turn quickly away from the target to the left side to escape from this trap until it passes over the vertical obstacle, at which it will appreciably reorient itself towards the target again because of the target attraction. As the robot is totally aligned with the target, a small sharp falling in the right weighting factor is resulted due to the short distance between the robot and the vertical obstacle, but it want greatly affects the turning to target behavior of the robot.

Figures 13 and 14 present two similar obstacle arrangements. In Figure 13 the vertical obstacle is made wider, while in Figure 14 the obstacle is replaced by a circular one. The attitude of the robot towards the obstacle in Figure 13 is almost similar to that of Figure 12 except that the robot keeps on turning away from the target while it is passing around the obstacle. This is due to the repulsion effects of the obstacle. Also, the sharp falling of the left weighting factor noticeably reduces the steering angle and hence the turning to target behavior.

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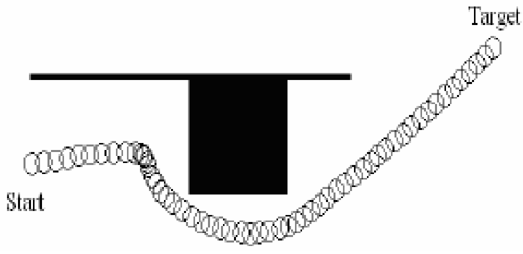

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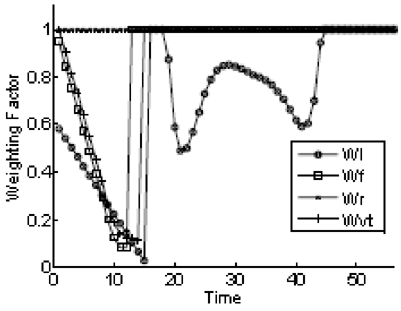

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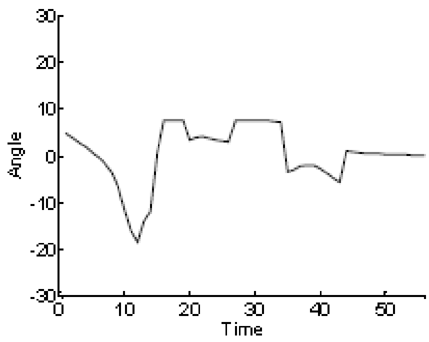

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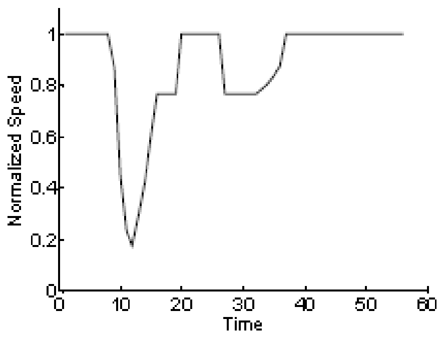

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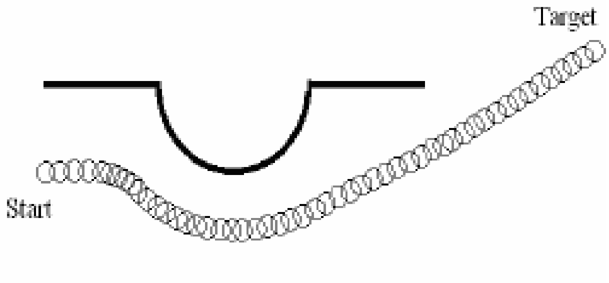
Fig-13 : a): Robot Trajectory; b) Variation of weighting factors; c) Variation of steering angle; d) Variation of speed with time for case 5.

The case presented in Figure 14 may seem for the first instance as if the robot will behave in a similar manner as in the previous two cases. In fact it is a real challenging problem for any fuzzy navigation system. The behavior of the robot at the first stage when it is approaching the circular obstacle almost follows the same trend as that of the previous case.



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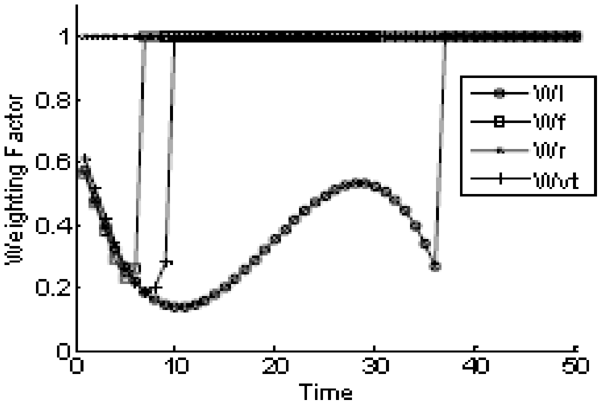

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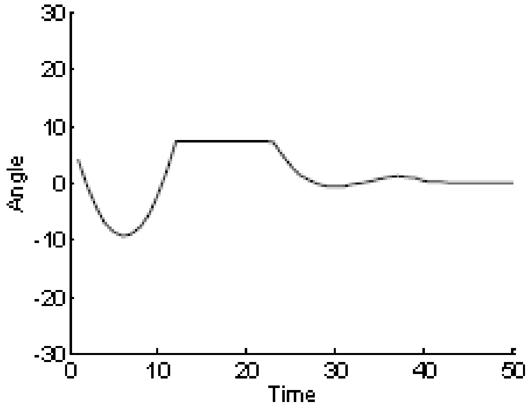

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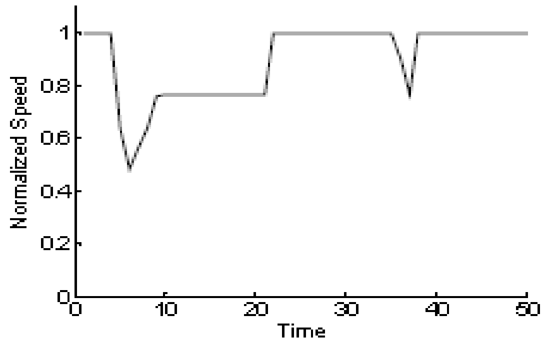

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Fig-14 : a): Robot Trajectory; b) Variation of weighting factors; c) Variation of steering angle; d) Variation of speed with time for case 6.

The next two cases show the reaction of the robot due to the presence awkward obstacles that can lead to total malfunctioning of the fuzzy navigator because of their total obstruction to the robot.

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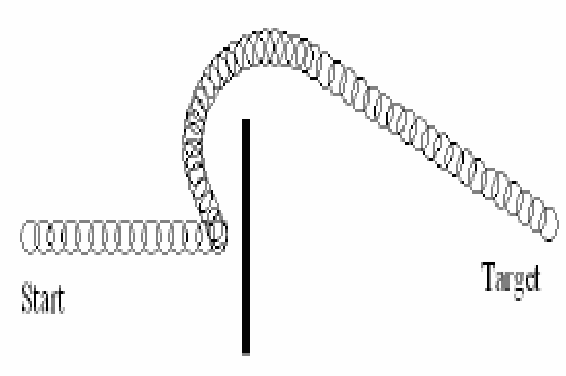
In fact such types of obstacles are classified as traps. It is noted that trap situations in having normal reactive fuzzy navigators to fail to provide a solution under. This is due to the limited information perceived by the robot and the disability in memorizing previous states. Normally, a reactive fuzzy navigator requires assistance to provide the robot with the capability to escape from trap situations. This could be achieved by adding some additional rules based on certain heuristics or a special system dedicated to detect traps and supervise the reactive fuzzy navigator system. In this study a single heuristic rule have been added to the second stage of the fuzzy steering angle controller, which is only activated when all the weighting factors get to be VL, and its inferred decision is to turn the robot 90・ to the left (or right) direction. This additional rule helps only in escaping from simple traps, and the problem of escaping from any trap situation needs a special treatment that will be presented in a future study.

Accordingly, the eighth case presented here, Figure 15, tests the reaction of the robot when trapped by a wide obstacle while the target lies along the robot heading direction. In this situation the effects of both the right and the left weighting factors will cancel each other, and the robot will continue moving along its initial heading direction. As the robot gets very close to the obstacle all the weighting factors fall to zero. Hence, the assisting rule will be activated and the robot will turn to the left by 90・. Immediately after activating the rule, the left weighting factor rises to 1, while the other factors remain zero for a short while. This results in getting the robot to turn to the left until it is away from the obstacle by a safe distance. The effect of the target weighting factor rebalances the turn to the left behavior. Once the critical situation is overcome, the robot behaves in a similar manner to the case of Figure 12.



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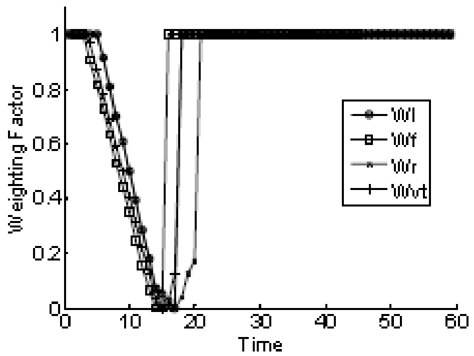

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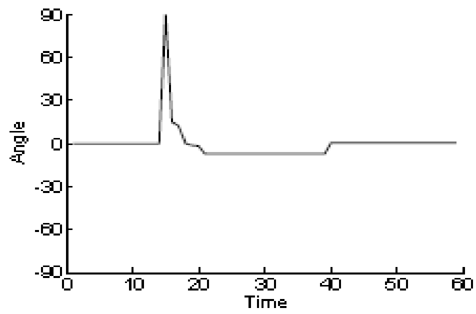

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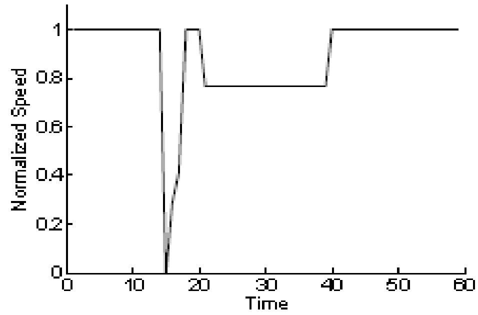
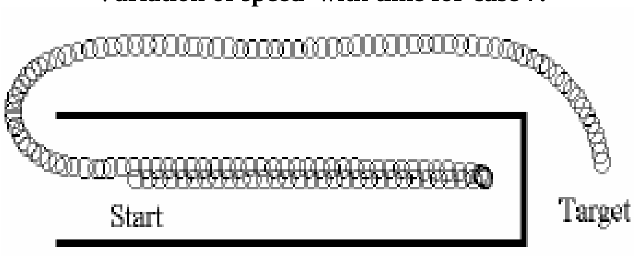
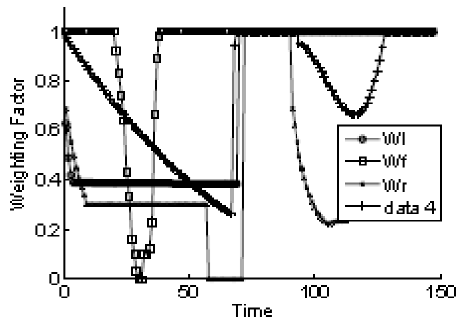


(d)

Fig-15 : a): Robot Trajectory; b) Variation of weighting factors; c) Variation of steering angle; d) Variation of speed with time for case 7.



(a)



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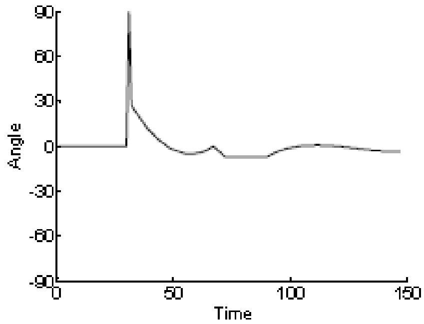

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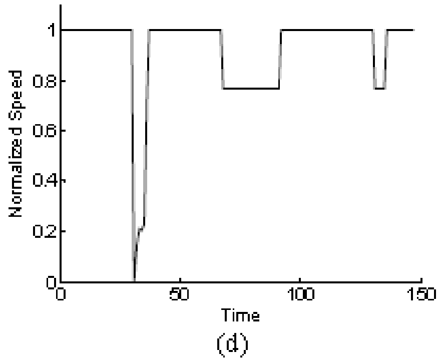

Fig-16 : a): Robot Trajectory; b) Variation of weighting factors; c) Variation of steering angle; d) Variation of speed with time for case 8.

The behavior of the robot in Figure 16 will be almost the same as that of the previous case during the period when the robot is heading towards the target. Similar action by turning to the left side will be taken when the robot faces the vertical part of the concave obstacle and this will overwhelm the effect of the left weighting factor over the others. Because of the concavity of the obstacle the domination of the left weighting factor will last until the robot is totally heading away from the target. Furthermore, due to the narrowness of this obstacle the robot will keep on moving away from the target until it gets close to the wide opening, at which time the target attraction behavior will be the dominant factor in spite of the fluctuations in the right weighting factor.

Finally, Figures 17 and 180 present two more complicated simulation cases to show the performance of the proposed reactive fuzzy navigator system towards more realistic situations.

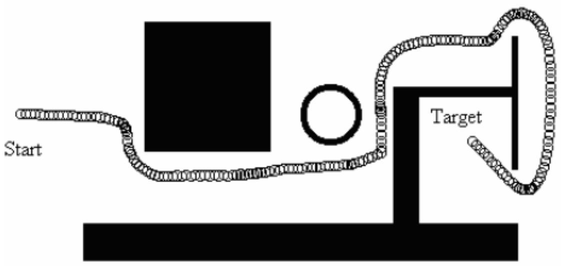

Fig-17: Simulated Trajectory of a MR in a maze 1.

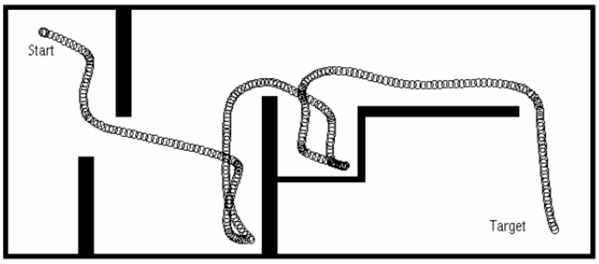

Fig-17: Simulated Trajectory of a MR in a maze 2.

IV. EXPERIMENTAL PROTOTYPE

SALIM, Simple Autonomous LIght weight Mobile robot, which was constructed at the authors' universities, has been used to conduct practical experiments. SALIM has a cylindrical shape with a radius of 30 cm, and travels at a maximum speed of 8m/min. The robot has two independent wheels, driven by geared PM DC motors, located at the ends of an axis near to one of the ends of the circular base, and one free caster at the at the other end of the base. Such arrangement provides a simple and effective differential-velocity steering control by varying the applied voltage to the motors. The motion control of the two PM DC motors is accomplished by a simple motion control board designed by the authors, which consists a full bridge chopper circuit, and PIC16f877A micro-controller. The advantage of using this micro-controller is that it accepts velocity commands from the onboard computer and to control two DC motors independently.

Three groups of ultrasonic sensors are mounted at the front, and at the two ends of the central axis of the robot, where the right and the left sensors are directed at 45・ from the central axis as shown in Figure 19. Target's orientation with respect to the center of the robot is obtained by an electronic compass. The actual angle between the robot frontal axis and the target can be found by simple manipulation to the robot's heading angle, which is updated instantaneously by the microcontroller, and that measured by the electronic compass. According to instantaneous value of this angle another ultrasonic sensor is utilized to detect the existence of any obstacle in the virtual target direction. This sensor is allowed to rotate, using a small stepper motor, in the range (-5・ to 5・) with respect to the frontal axis of the robot. The reason in mounting the ultrasonic sensors in such arrangement has been mentioned previously. The error eliminating rapid ultrasonic firing (EERUF) method [32] is used to minimize the error in distance measurements due to the noise that affect the ultrasonic sensors, and the crosstalk problem was eliminated by using alternating delays method. A number of simple experimental tests were performed on the mobile robot to test the validity of the proposed strategy. Figure 20 provides a snapshot of the robot during its navigation in one of the simple environments that were investigated.

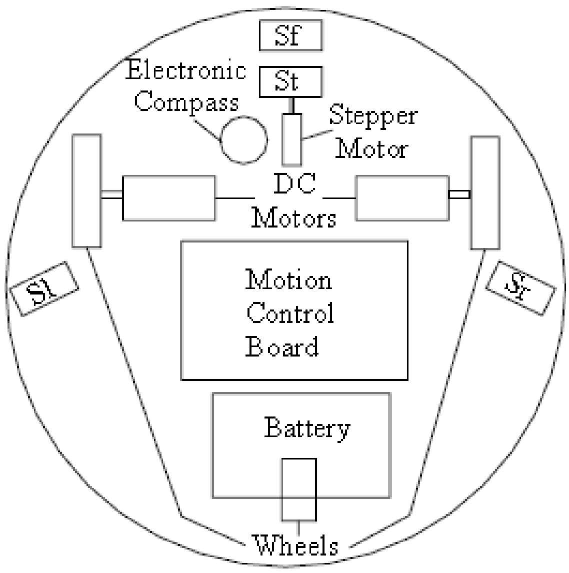

Fig-19: Schematic of SALIM with sensor locations.

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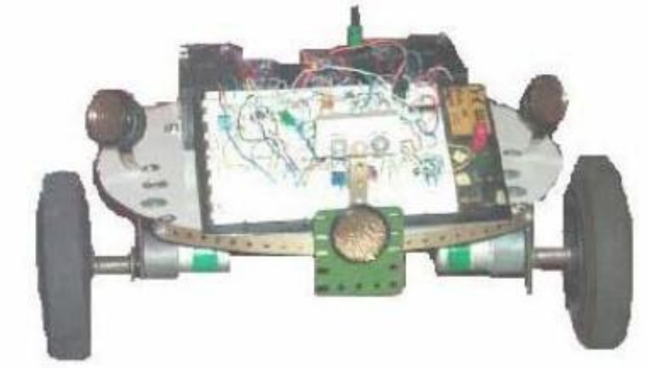

Fig-20: Snapshot of SALIM

V. CONCLUDING REMARKS

A simple real-time fuzzy control scheme for mobile robot navigation has been presented in this work. The approach is based on decomposing multidimensional fuzzy system into a set of simple one dimensional fuzzy systems by the inference break-up method. This method relies upon finding quantifiable means to represents the expert's experience, and determines a mapping from current state of a system to the fuzzy measures with which the expert's knowledge is quantified. Therefore, it has the advantage of greatly reducing the number of "If-Then" rules when compared with classical fuzzy controllers. With slight modification to the decomposed multivariable fuzzy controller concept, two interconnected fuzzy controllers are designed, in which the concept of using weighting factors for the sensor inputs inferring the reflexive conclusions from each input rather than having to go through a huge list of rules to infer a single conclusion is introduced here for the first time. The approach was tested in a number of simulated case problems to demonstrate its effectiveness, and it was found that the results compromise with reasonable satisfaction the obstacle avoidance and target reaching requirements. In addition to that the proposed controller showed the capability of a mobile robot to escape from simple traps.

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