

Memory-based Reasoning Algorithm Based on Fuzzy-Kohonen Self Organizing Map for Embedded Mobile Robot Navigation

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Abstract

Navigation in mobile robot not only avoid obstacles based on the sensor input but also comprehend the nature of its environment, remember over time such comprehended scenarios, recollect them and associate in time perceptions of environment that resemble each other. Such requirements demand spatial and temporal reasoning capabilities, for considering the mobile robot environmental as an experience of a sequence of sensor patterns. Memory-based reasoning must integrate into mobile robot control strategy to produces efficiently movement in unpredictable environment, to achieve robustly and to reduce computational cost. To implement this strategy Fuzzy-Kohonen Network (FKN) technique is utilized by employing small number of rules. The effectiveness of the proposed technique is demonstrated in series of practical test on our experimental mobile robot in structured and unstructured environment. A detailed comparison of the proposed technique with other recent approaches in the specific case of 'local minima' detection and obstacle avoidance is also presented. As results found that mobile robot based on FKN technique has the ability to perform navigation tasks in several environments, it has capability to recognize the environment, suitable for low cost mobile robot due to only produce small resources, provides much faster response to expected events and it allows the mobile robot move without any need to stop for 'danger' situation without suffering from the 'local minima' problem.

Keywords: *Embedded mobile robot, Fuzzy-Kohonen Network, navigation, unstructured environment, memory-based reasoning*

1. Introduction

The two classical motivations of mobile robot navigation are exploration and automation. Therefore, mobile robot requires onboard sensors and processing capabilities in order to bring operability to unknown environment. In such environments it requires a number of heterogeneous capabilities are ability to reach target in real time to unexpected events, to determine the robot's position, and to adapt the environmental changing. Different robot architectures have been developed that level from purely reactive robots which do not keep an internal state to layered architectures with a deliberative layer planning on actions.

Recently, mobile robot is being extensively used in various fields stretching from simple actions to their advanced implementation. Each implementation of mobile robot implies particular concepts and engineering solutions able to deal with problems emerging on the different level [1]. Their main focuses on developing navigation methodologies for realizing accurate, reliable localization and map generation from uncertain data obtained by high sensitive sensors [2-4]. Most studies on such research have explored to design a precise geometric map for identifying their environment [5-7].

Perceiving the environment remains a fundamental task for autonomous mobile systems. In fact it is rather difficult to imagine a robot that is truly autonomous without being capable of acquiring a model of its environment. This model can be built by the robot exploring the environment and registering the data collected with the sensors over time. The visual sensors provide the richer source of useful information about the environmental surroundings. Nevertheless, it have drawbacks such as, slow in processing data, the global information like vision may not be obtained in a dark room and expensive in cost [1, 8].

In the real world, numerous natural agents like animals to recognize their environments just with low sensitive sensors without a geometric map [1], they learn for recognizing new environment by itself. Hence, it is essential to design a simple intelligent robot with low cost sensors, that have capability to recognize environment and adaptive in unknown environments. In the mobile robot navigation design, it is necessary to consider what accuracy is needed in each environmental situation. If the cost of sensing is considered, it may not be optimal in terms of the cost of reaching a target [12]. Moreover, the reactive navigation capabilities are indispensable since the real-world environments are appropriate to change over time [9-11]. It has difficulty handling a modification of the environment, due to some uncertain in each environmental situations.

It needs a method to overcome the uncertainty problem to realize a safe and efficient of mobile robot movement. It means the mobile robot does not collide with obstacles and it can reach a destination in a small amount of time. However, these requirements are usually in a trade-off relationship. If the mobile robot moves quickly to increase efficiency, this most probably decreases safety. If the mobile robot moves slowly to increase safety, efficiency decreases. There are numerous techniques that deal with the uncertainty, cost and efficiency requirements such as fuzzy logic [13, 14], heuristics [15], potential field [16, 17], neural network [18], immunological [4] and their hybrids [19-20]. However, in some cases during the mobile robot traversal cycling between multiple traps (local minima) problem may still occur. Several methods [9, 19, 21, 23] have been proposed, but the computationally is expensive and they cannot guarantee the mobile robot will not trapped [24].

The limitation of computational resources available to an embedded mobile robot often presents challenge. The high computational cost can decrease the embedded controller performance, due to it leads to a strong decrease cost performance in terms of memory and computational resource consumption to achieve speed processing [25]. If these constraints are imposed a priori, the advantages of controllers can be lost [26, 27, 28]. The choice of simple intelligent control algorithm is highly desirable to cope with the memory and time limitations. Intelligent control decisions are a natural consequence of possessing reasoning and cognition properties. It is an essential part of human navigation. Fuzzy-based algorithm comprising of only the two primary modules is unable to functionally replicate such reasoning as far as navigational aspects are concerned. By incorporating self-organizing maps or Kohonen network some of these drawbacks are alleviated. In this work, memory-based reasoning strategy utilizes combination of fuzzy logic and Kohonen network named FKN technique, to realize navigation control on low cost embedded mobile robot.

In this strategy, the mobile robot has capability for building the desired mapping between the perception of the human knowledge and the exact motion control. Satisfactory navigation performance can be achieved using reduced numbers of rules experiences to achieve the necessary spatial and temporal reasoning properties. The proposed algorithm demonstrates in structured and unstructured with 'local minima'

situation. The result founds that it reasonably good performance while navigating in such environments compare to fuzzy and sensor behavior technique.

2. Control Algorithm of Fuzzy-kohonen Self-organizing Map

In order to enable the mobile robot to avoid the obstacle in the navigational path with rapid reaction capacity, the better mapping relation between the sensor data input and the control output must be established. Since this mapping relation is extremely complex and nonlinear, it is very inconvenient to solve this problem using the general control method [29]. Furthermore, an intelligent mobile robot must be self-reliant to perform in complex, partly known and challenging environment using limited physical and computational resources [25], which leads to development of embedded controller.

The research in mobile robots navigation controller and embedded systems are two different areas, if the two areas are combined would produce a very challenging research. However, difficult challenge is to create an implementation that simultaneously optimizes numerous design metrics such as memory resources, power, computation, and sensors that are resident onboard the mobile robot [26]. However, soft computing techniques have the astonishing ability to deal with nonlinear problem and successfully integrated into an embedded controller design [30, 31, 21]. It provides effective techniques and improves the mobile robot navigation performance [32].

Fuzzy-Kohonen clustering network (FKCN) is one type of hybrid technique which is the result of integration between fuzzy logic and Kohonen's self-organizing map network proposed by Huntsberger and Ajjimarangsee (1990). FKCN technique is certainly based on an unsupervised learning; nevertheless, this learning process produces high computational cost, requires intensive processing and needs large storage capacity [34]. In this work, to make this technique simplicity, the originality of unsupervised learning process reduces to supervised named, Fuzzy-Kohonen Network (FKN). In this strategy Kohonen network has the advantage of learning mechanism while the fuzzy logic plays a role in managing the input and output process of pattern recognition [34].

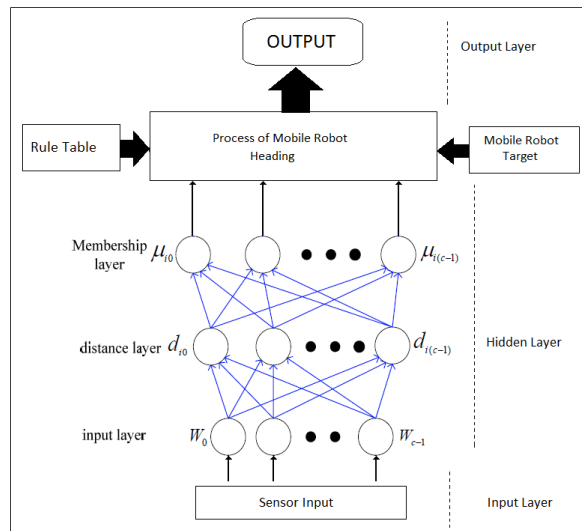


Figure 1. FKN Structure [33]

The FKN structure has the function of pattern recognition and includes three layers: input layer, hidden layer and output layer [33] as shown in Figure 1. In this network, all

initial patterns reflect on weight vector $W_j (1 \leq j \leq c)$ in hidden layer. The weight vector W_j and the number c of initial pattern are determined using Kohonen's self-organizing map algorithm [33]. There are many initial patterns, which represent a characteristic pattern in every layer. To reduce the space complexity and to facilitate fast learning of sample sequences by the FKN, all these patterns are set as a weight in the distance layer and for calculating these weights, the rule base table is utilized instead of being trained. The number of rules equals that of initial patterns and every initial pattern is derived from previous experimental data base.

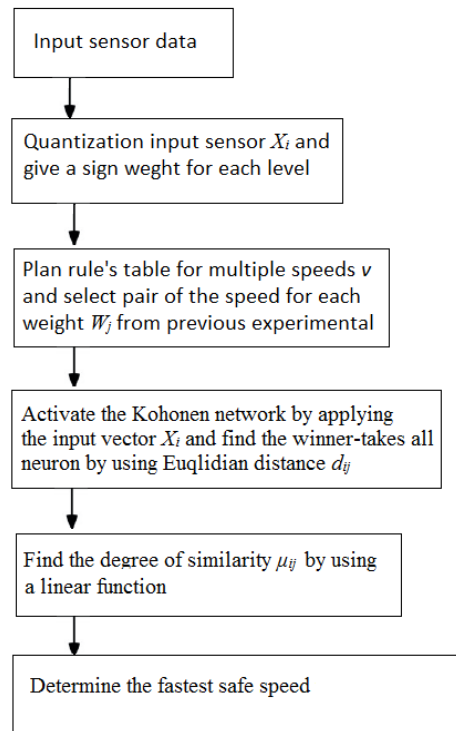


Figure 2. Navigation Control Procedure [34]

The pattern is assigned and associated with a pair of motor speed reference. This research different with works of Song and Sheen (2000) and Tsai *et al* (2010), due to in this research all process of the navigation control uses low cost 8 bits microcontroller and inexpensive infra-red sensor. Therefore, the algorithm must produce simple resources, for making the faster controller in the process and robust in the implementation. The algorithm navigation control procedure to determine the design purpose can be seen in Figure 2.

The starting point of control algorithm construction is a standard Kohonen-Layer [33]. It receives an n -dimensional input $X = (z_1, \dots, z_n)$. Each of the m neurons in the Kohonen-layer processes an n -dimensional weight vector W_j . According to the “winner take-all” (WTA) principle, one neuron is selected as the “winner” pertaining to the current input. In the standard version the neuron c with the smallest Euclidean distance between its weights vectors W_j and X . The method for learning rules to determine the distance and similarity between input pattern and initial pattern are described in the following steps:

Step 1: Create input patterns (X_i) , it constructed from current sensor readings (s_i) . To reduce the measurement error of the sensor and simplify the control algorithm, the

distance input of the every infra-red sensor is divided into 4 grades using equation (1). Where X_i and s_i are the grade value and the distance measured from infra-red sensor, this values is divided into 4 grades.

$$X_i = \begin{cases} a < si \leq b \\ b < si \leq c \\ c < si \leq d \\ si > d \end{cases} \quad (1)$$

Step 2: Activate the Kohonen network by applying the input vector X_i and find the WTA neuron, the values which are most similar to the current input vector. For most application standard way of measuring this similarity is to compute Euclidian distance (d_{ij}). These values responsible for comparing the input pattern X_i with every initial pattern W_j in the hidden layer. When the input pattern X_i and the prototype pattern W_j are completely consistent, the output d_{ij} of j -th node is zero. The output of the hidden layer is expressed in the equation (2).

$$d_{ij} = \|X_i - W_j\|^2 = (X_i - W_j)^T (X_i - W_j) \quad (2)$$

Step 3: The output value u_{ij} in output layer is determined based on d_{ij} , once the similarity value is obtained by using the Euclidean distance, then the degrees of membership μ_{ij} is calculated. To obtain these values, linear function is used, as shown in Figure 3. There are three conditions of d_{ij} values, such as $d_{ij} = 0$, $e \leq d_{ij} < f$ and $d_{ij} \geq f$.

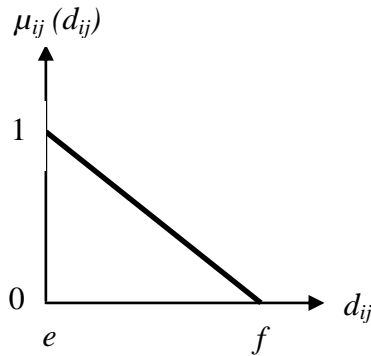


Figure 3. Linear Function

Each kind of initial pattern W_j is corresponding to a fuzzy control rule, and each fuzzy control rule is corresponding to a speed vector. In this paper to simplify the algorithm, the max value f of Euclidian distance is obtained from experimental result due to the sensor reading by using Equation (3),

$$f = \sqrt{(w_{maksimum} - x_{minimum})^2 \times c} \quad (3)$$

where : $x_{minimum}$ as minimum of weight sign, $w_{maksimum}$ as maximum of weight sign, c = number of input .

To describe a linear function utilize Equation (2) and (3) as a membership degree μ_{ij} . If the input pattern does not match any initial pattern, then the similarity value is represented by membership value μ_{ij} from 0 to 1, by using Equation (4),

$$\mu_{ij} = \begin{cases} 1, & d_{ij} = 0 \\ \frac{f-d_{ij}}{f-e}, & e \leq d_{ij} < f \\ 0, & d_{ij} \geq f \end{cases} \quad (4)$$

The membership degree μ_{ij} represents the similarity between X_i and W_j , and $\mu_{ij} \in (0,1)$ and the sum of membership degree output μ_{ij} equal to 1, the algorithm as shown in Figure 4.

```

    FKN Function: real
    declaration
    integer : y[4], w1, w2, w3, w4
    real : distance (s),  $\mu_{ij}$ , bound
    description
    -----
     $d_{ij} \leftarrow \sqrt{(y[1]-w1)^2 + (y[2]-w2)^2 + (y[3]-w3)^2 + (y[4]-w4)^2 + (y[5]-w5)^2}$ 
     $\mu_{ij} \leftarrow (d_{ij} - \text{threshold})/d_{ij}$ 
    return ( $\mu_{ij}$ )
    
```

Figure 4. Simple Algorithms to Obtain Similarity Value

3. Mobile Robot Navigation Platform

Mobile robot navigation must be reactive in the changing and in the unknown environment for achieving a goal. The most important property of a reactive control system is its fast reactions and it should be capable of reacting unexpected environment simultaneously. In this work, the experimental test illustrates the application of the proposed algorithm. Figure 5 shows a block diagram of embedded mobile robot platform and control system based on FKN technique, it responsible for generating motor steering and speed command in response to embedded controller. Operational data from infra-red sensors are processed in real-time by the on-board controller mounted on the mobile robot platform.

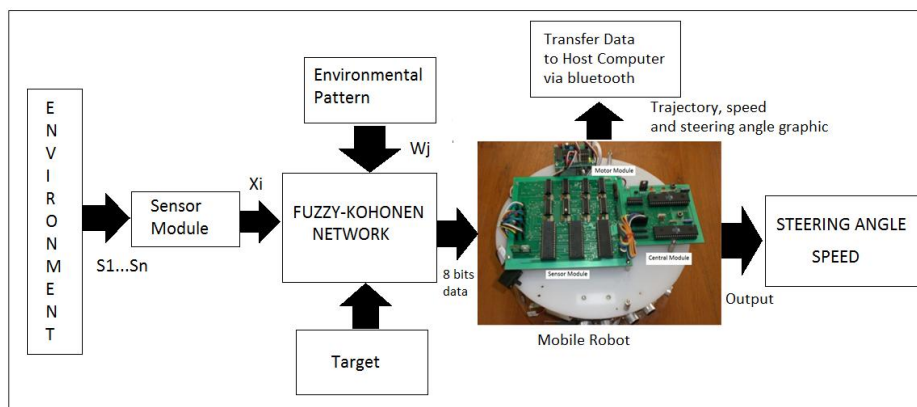


Figure 5. Block Diagram of Mobile Robot System

To perform several navigation tasks, mobile robot uses five infra-red low cost sensors are mounted in a circle on the mobile robot 45° apart to extract more information about surroundings. To reduce the space complexity and to facilitate fast learning of sample sequences by FKN is used that maps each sample u_s to a particular class. Initially the five infra-red sensors are grouped into three groups namely left, center and right. Only one sensor s_3 in group 1 is used to detect obstacles at the front of mobile robot. Two sensors s_1 , and s_2 , in group 2 are used to detect obstacle at left side and two sensor s_4 and s_5 in group 3 are used to detect obstacles right side of the mobile robot. The minimum reading of the sensors in each group is considered as the reading of that group.

The FKN classifies the readings of such groups into one of the 21 classes as shown in Table 1. To provide discrete samples for training, before sending into neural network, the sensor value quantization is performed. The formulas for three groups are;

$$X_{1,2} = \begin{cases} 1 & \text{For } 0 \text{ cm} < s_i \leq 15 \text{ cm,} \\ 2 & \text{For } 15 \text{ cm} < s_i \leq 20 \text{ cm,} \\ 3 & \text{For } 20 \text{ cm} < s_i \leq 25 \text{ cm,} \\ 4 & \text{For } s_i > 25 \text{ cm} \end{cases} \quad X_3 = \begin{cases} 1 & \text{For } 0 \text{ cm} < s_i \leq 20 \text{ cm,} \\ 2 & \text{For } 20 \text{ cm} < s_i \leq 25 \text{ cm,} \\ 3 & \text{For } 25 \text{ cm} < s_i \leq 30 \text{ cm,} \\ 4 & \text{For } s_i > 30 \text{ cm} \end{cases}$$

where, X_i are the grade value and s_i are the minimum distance value from infra-red sensor of the i_{th} group and $s_1, s_2 \dots s_i$ are threshold values for quantization. Evidently there can be other ways of classifying the range reading to classes. The reason to have specified the range readings in terms of far is 4, medium is 3, near is 2 and very near is 1. There are essentially due to the same kind of partitioning employed in the fuzzification part of the inference scheme for collision avoidance.

Table 1. Rule Base [34]

Rule number	If-part (W_i)					Then-part	
						motor speed (v) references	
						v_{refleft} (%) pwm)	v_{refright} (%) pwm)
1	4	4	1	4	4	87	60
2	4	4	4	2	4	80	90
3	4	2	4	4	4	90	80
4	4	4	4	4	1	90	73
5	1	4	4	4	4	73	90
6	1	4	4	4	1	87	87
7	1	2	1	4	4	85	55
8	4	4	1	2	1	55	85
9	4	4	4	4	4	90	90
10	1	4	4	1	1	77	87
11	1	2	4	4	1	87	77
12	4	1	1	4	4	85	57
13	4	4	1	2	4	57	85
14	1	1	4	4	4	90	83
15	4	4	4	1	1	83	90
16	4	2	4	2	4	85	85
17	1	3	2	3	4	85	53
18	4	3	2	3	1	53	85
19	1	3	2	4	1	85	58
20	1	4	2	3	1	58	85
21	1	3	4	3	1	86	86

In order to enable the mobile robot to avoid the obstacles with reactive action, the better mapping relation between the sensor data as input and the speed control as output must be established; due to the distribution of obstacle is complex. Since the obstacle exists in mobile robot direction and the width of obstacle is less than the measurement width of sensors, the mobile robot can recognize the environmental pattern. If the mobile robot detects an obstacle in the front, left, right or two sides, it can determine the navigation path. However, the ‘danger’ condition like u-shape is always occurred, therefore special control scheme has to be given. The mobile robot will reduce the speed first and then turn to the right/left, when it detects simultaneously an obstacle in all direction.

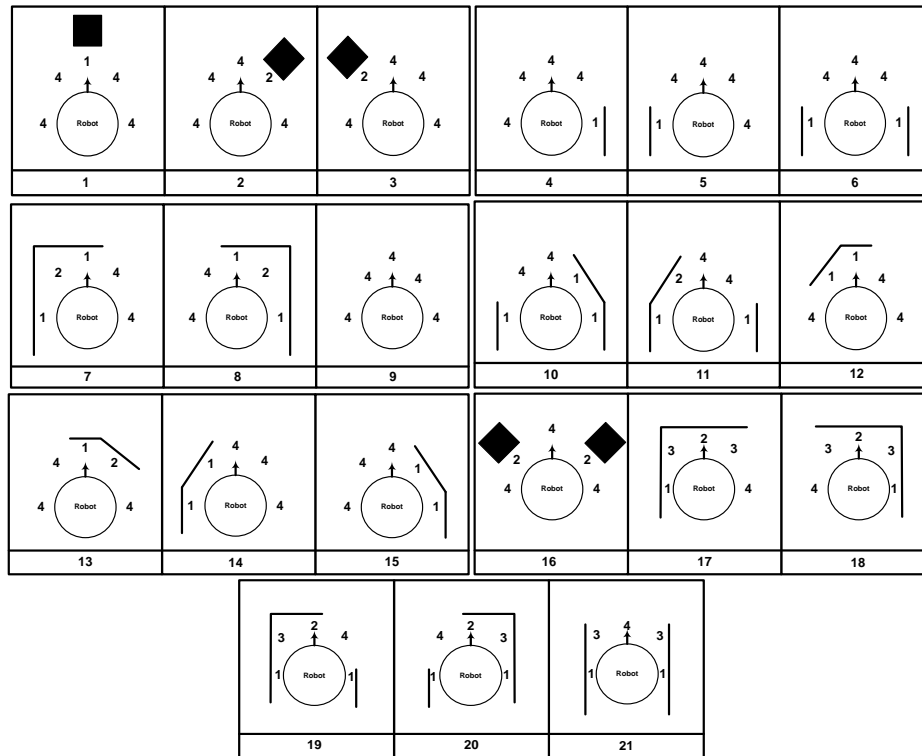


Figure 6. Several Typical of Environments [34]

In this work infra-red sensors installed in mobile robot can be classified as 21 of environmental pattern categories as shown in Figure 6. All possibilities of mobile robot environmental are considered through fuzzifying process and combining these 21 classes of rule base in Table 1. The rule table is constructed exploiting the sequence of environmental pattern and speed levels. In this strategy 21 rules are employed to kept few compare to conventional fuzzy control technique. Our mobile robot is equipped with two wheels on both side and one free wheel at the front of mobile robot. The two parallel wheels are driven by direct current (dc) motors. Its sequence is determined by the relative references speeds of the left and right wheels. Therefore, each initial pattern is associated with a couple of reference speeds. In this work mobile robot target is assigned to kept simplicity.

In mobile robot navigation, speed control analysis gives information about and mobile robot’s left and right speed over the time. By using FKN technique, after the rule base and similarity patterns (μ_{ij}) are known, the mobile robot speed (v) is determined by finding rule that has the highest level of similarity (μ_{\max}). The final value is calculated with

multiplied by level similarity with the speed references (v_{ref}). The simple algorithm for generating DC motor speed can be seen in Figure 7. The results of mobile robot speed than conversion to pulse width modulation (PWM) data, namely the duty cycle. Duty cycle is determined within a few percentage points, to obtain some value. By regulating the duty cycle of PWM, the speed of DC motor and steering angle are obtained for controlling mobile robot movements. The formula of PWM as follows,

$$PWM = \text{duty cycle (\%)} \times 255 \quad (5)$$

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declaration
real    :  $\mu_{max}$ ,  $v_{right}$ ,  $v_{left}$ ,  $v_{refright}$ ,  $v_{refleft}$ ,  $\mu_1$ ,  $\mu_2$ ,  $\mu_3 \dots \mu_{21}$ 
description
 $\mu_{ijmax} \leftarrow (\mu_1, \mu_2, \mu_3 \dots \mu_{21})$ 
if (  $\mu_{ijmax} = 1$  ) then
     $v_{right} \leftarrow v_{refright}$ 
     $v_{left} \leftarrow v_{refleft}$ 
else
     $v_{right} \leftarrow (\mu_{ijmax} * v_{refright})$ 
     $v_{left} \leftarrow (\mu_{ijmax} * v_{refleft})$ 
end if
    
```

Figure 7. Simple Algorithms to Control Motor Speed

4. Experimental Results and Discussion

In order to evaluate the performance of the proposed autonomous exploration strategy, several experiments are conducted employing a self-constructed embedded mobile robot. The effectiveness, robustness and comparison of various systems are done using single stage fuzzy behavior, sensor behavior and our proposed simple FKN technique. Experimental is set-up on real embedded mobile robot. Low cost microcontroller 8 bits Alf and Vegard's Risc processor (AVR) 8535 with 8 Kbytes flash memory is designed for central navigation as onboard controller. The specified traveling nominal speed in these experiments is 20 cm/s. The mobile robot has maximum speed of $v_{max} = 90\%$ of duty cycle of PWM. The data from experimental result is obtained by using embedded bluetooth strategy in a real time. For evaluating our proposed technique, experiments are implemented including structured, unstructured environment and unstructured obstacle as 'danger situation'.

4.1 Structured Environment

This section, the experiments in complex environment is conducted utilize twenty one environmental patterns, for investigating the influence of FKN technique in terms of steering, speed and movement performance. The input data from sensor is created from the sensing of a structured environment. After learning process, the training data are given to the FKN as initial data. In this experiment, we dealt with more noise like unstructured obstacles, as depicted in Figure 8 (a) and (b). As stated earlier, mobile robot performance based on FKN is compared to other technique are fuzzy behavior in red line and sensor behavior in green line.

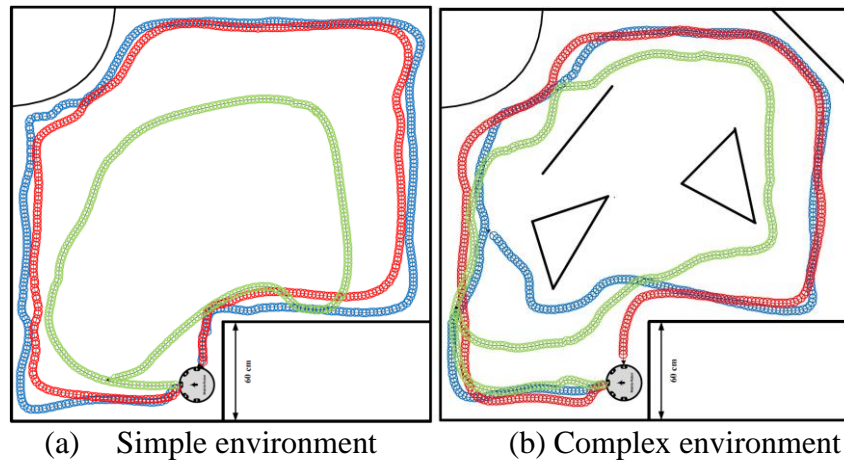


Figure 8. Mobile Robot Movement on Structured Environment

In order to verify the effectiveness of the proposed technique, mobile robot is set up in several environments. It can be seen in Figure 8 (a), all technique that use in mobile robot successfully to perform navigation tasks. However, mobile robot based on FKN is able to recognize the environment and produce smooth movement; due to it has demand spatial and temporal reasoning capabilities in memory of mobile robot. Fuzzy logic has the ability to follow the wall behavior and it has smooth movement too. In contrast to mobile robot based sensor behavior, it does not smooth in movement, due to it runs only based the sensor perception. The decision for the proper turn angle of the mobile robot is taken based on sensory information and the angular difference between the mobile robot's current direction of motion and the goal orientation with respect to origin of the reference frame.

Figure 8(b) shows the mobile robot in complex environment, by applying the off-line data and supervised training method to this network, the pattern mapping relation between sensory input and velocity command is established. Proposed technique indicates that efficiently realize the mobile robot navigation. In fuzzy behavior technique, mobile robot starts wall-following behavior at the same position for the same environment. However, the largest length of mobile robot path from the wall is obtained compare to FKN technique. Different with sensor behavior performance, the mobile robot moves only keep the distance from the wall.

In Figure 9, presents the experimental result of the mobile robot performance in structured environment, indicating the effectiveness and applicability of the proposed technique. The same fact is observed from the outputs of various experiments performed in different environmental conditions. The results highlight the fact that by adding the Kohonen self-organizing map stage enhances environmental sensing capacity of the mobile robot system. Figure 9(a) and 9(c) shows the mobile robot trajectory in two environments such as simple and complex environment, the mobile robot will not move into the concave region and move successfully to the target.

By using fuzzy logic with 35 rules, starts its journey from initial position to the final position and mobile robot successes follow the wall and avoid the obstacle in complex environment. Nevertheless it cannot recognize the environment. Therefore, the mobile robot needs more data to reach the target. The same situation with mobile robot based on sensor behavior. In contrast to the mobile robot based on FKN technique only use 21 rules, it can recognize the environmental pattern by considering navigation memory; therefore it reaches the target faster. Mobile robot's steering angle during its journey can

be seen in Figure 9 (b) and (d). Steering angle is the difference between target and mobile robot heading and provides information about current mobile robot orientation.

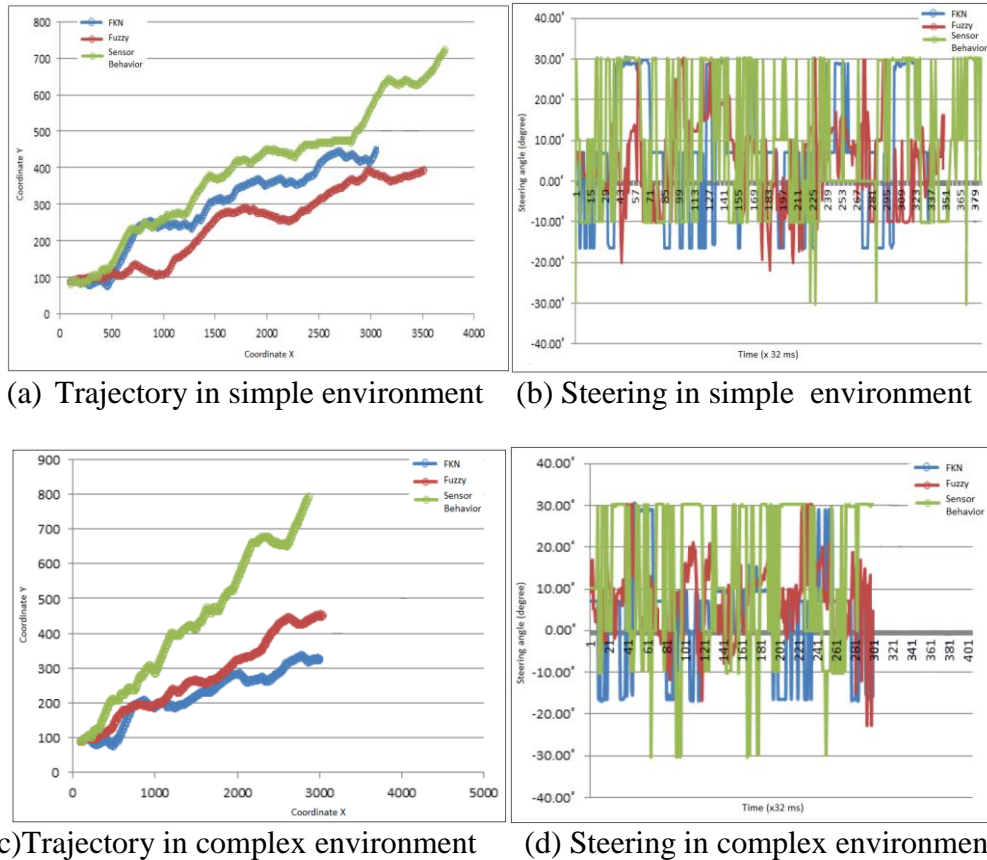


Figure 9. Mobile Robot Performance in Structured Environment

4.2 Unstructured Environment

The second experiment is performed in unstructured environment. An unstructured environment is a type of environment that has no specific pattern. Traps can be created by a variety of obstacle configurations. A well-known drawback in unstructured environment is that the mobile robot suffers from ‘danger’ problems in that it uses only locally available environmental information without any previous memorization. The key issue to that problem is the detection of the ‘danger’ situation during the mobile robot’s traversal.

Figure 10 (a) and 10 (b) presents an experimental result in which the mobile robot navigating in unstructured environment in two environmental situations. The mobile robot have been explored an unknown environment employing its onboard controller, the trajectory is recorded reveals that the mobile robot can avoid the obstacles safely. In the experiment 1 as depicted in Figure 10 (a), the mobile robot based on fuzzy logic will move into the concave region and be trapped. The same situation with mobile robot based on sensor behavior. In the acute angle situation due to concave and convex corner mobile robot based two techniques cannot continue move to the target. The mobile robot trapped in the acute angle, due to the nature of the fuzzy algorithm and sensor process. In the absence of spatial cognition followed by memorizing and retrieval leads to the following reasoning the mobile robot gets into the traps. Care should be taken to note that in this

instance the mobile robot actually does not detect a 'danger situation' by correlating similar experiences.

In contrast to mobile robot based on FKN technique can recognize the entire environmental situation and can reach the finish without trapped in the concave and convex environment. The same with experiment 2 as shown in Figure 10 (b), these results suggest that in the case of unstructured environment FKN technique are preferred. This is due to of the fact the fuzzy logic output in the unexplored regions of inputs is not predictable and error at each stage gets accumulated and hence do not give stable movements. However, in 'danger situation', FKN technique by considering memory-based reasoning brings the mobile robot out of the trap.

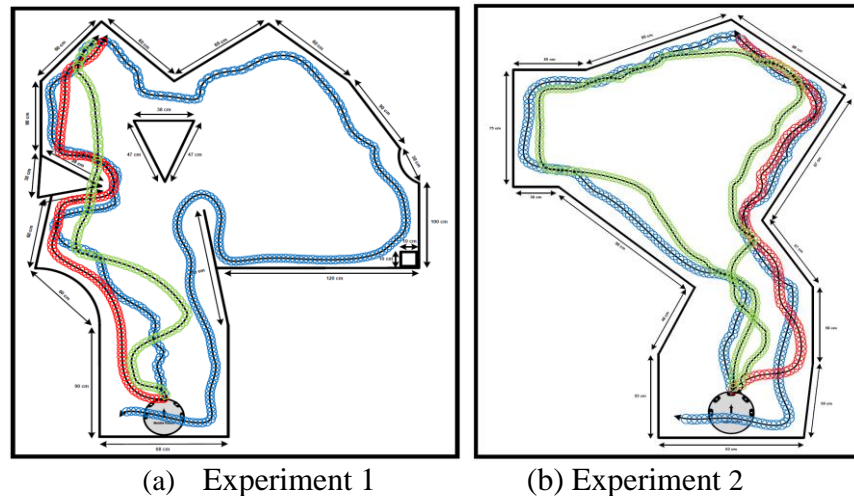


Figure 10. Mobile Robot Movements in Unstructured Environment

Figure 11 presents the mobile robot experimental result in unstructured environment with several acute angles. The trajectory in first environment is illustrated in Figure 11 (a). By using fuzzy logic and sensor behavior technique, mobile robot stop in concave situation and cannot continue move. In contrast to mobile robot based on FKN technique success traveling to the target because it has the ability to recognize the environment. It allows continuous, fast motion of the mobile robot without any need to stop for 'danger situation'. From Figure 11 (b) shows that the recorded of mobile robot steering angle performance based on FKN, fuzzy logic and sensor behavior technique respectively. The steering angle can be used to check the maneuvering of the mobile robot as it encounters obstacles. The results reveal that the proposed technique is capable of smoothly steering the mobile robot over this unstructured environment.

The recorded of mobile robot speed of both wheels as shown in Figure 11 (c), and 11 (d). By using fuzzy logic system, the mobile robot reduces the speed and stop the processes in second 14, thus the controller does not send the command to the motor. The same situation with mobile robot based on sensor behavior. Otherwise mobile robot based on FKN technique successfully travelling the environment, after escaping from the recursive concave environment, the mobile robot reaches target. The experimental result shows that memory-based reasoning indicates the improving mobile robot navigation performance.

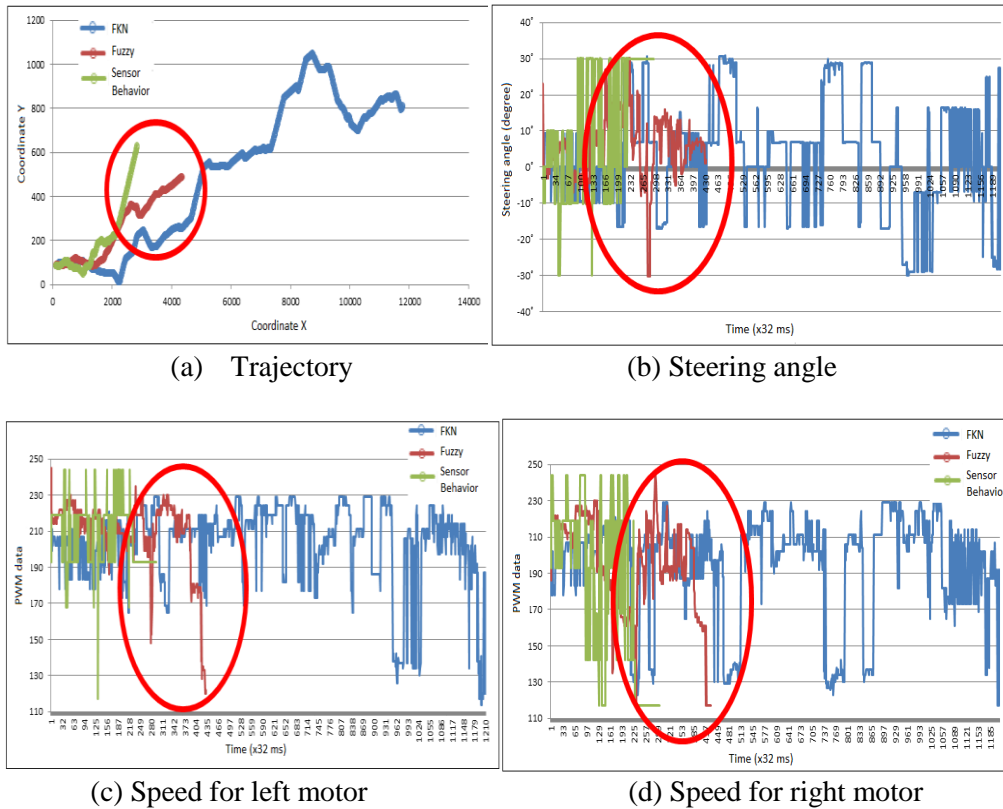
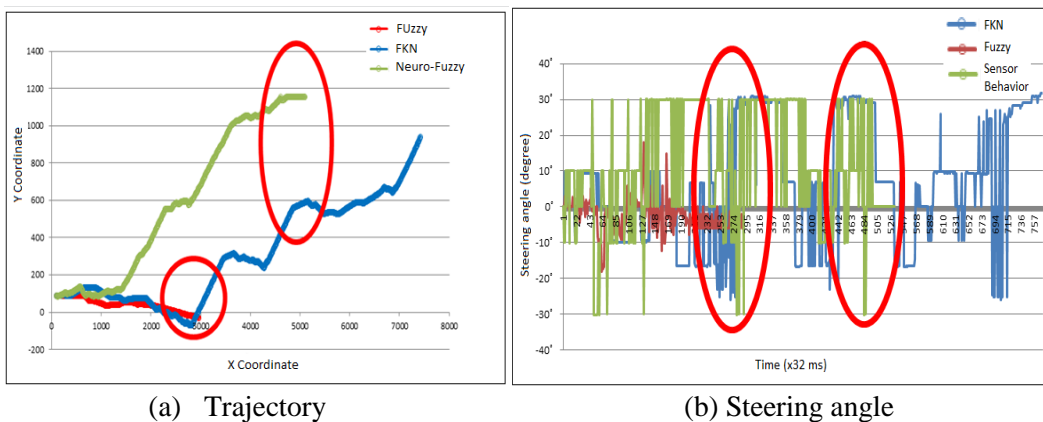


Figure 11. Mobile Robot Performance in Unstructured Environment 1

Figure 12 demonstrates the other possible trajectories when the environment is changed due to there are some acute angles (concave and convex corner) in the environment. In Figure 12(a)–(d) the mobile robot performance is recorded such as trajectory, speed and steering angle respectively. Notably, mobile robot based on FKN algorithm has the ability to explore the environment safely in this long journey without collision and ‘dead lock’ in danger situation. In contrast to the mobile robot-based fuzzy logic system and sensor behavior, it cannot continue move due to the ‘danger’ situation in the environment. The mobile robot based on FKN technique to respond promptly to its surroundings, for instance, to avoid unexpected obstacles and continue traveling toward the target.



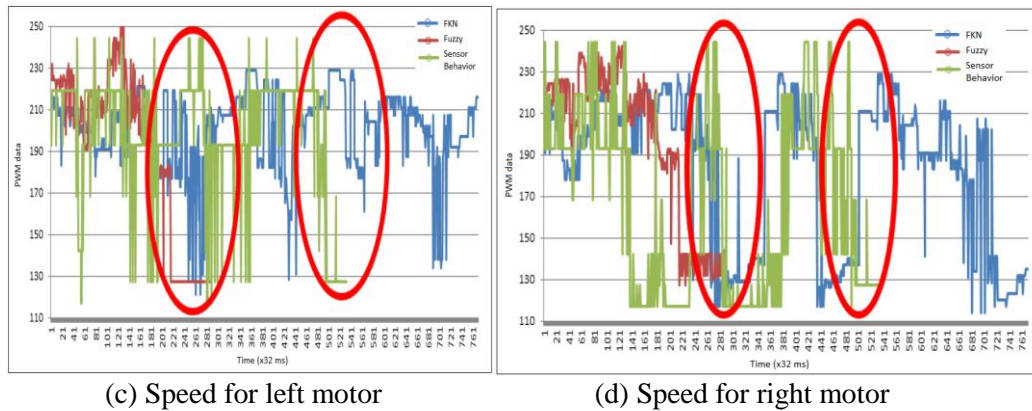


Figure 12. Mobile Robot Performance in Unstructured Environment 2

4.3 Local Minima Situation

The basic objective of this experiment is to enable the mobile robot to autonomously identify all environmental situation (that is to identify each corner) in real-time while exploring this completely unknown environment using 21 environmental pattern, starting with no prior knowledge about environmental shape, specifics, corner description, any or any global coordinates. The navigation strategy is based on the recognizing of local sensed environment, thus the FKN actively selects a movement direction from sets of possible direction in a rule base table. Once initial pattern in the rule table have been established the FKN network will produce desired robot heading for escape the trap.

Numerous experiments are conducted to demonstrate the performance of mobile robot navigation employing FKN technique to various complex unstructured environments, in particular, the capability of escaping from the traps or the wandering situations described. Several researchers have proposed the control strategy to overcome the problem by designing several control strategy (Luh and Liu, 2006; Zhu and Yang, 2007), however, the ‘local minima’ may still happen. For example, a mobile robot wanders in definitely in a loop inside a U-shaped obstacle, because it does not has memory about the initial pattern of the environment, and its navigation is only based on the local sensed environment. In this paper, using the information acquired from the sensor array, the memorizing control strategy in tends to find a safe way to circumvent any collision to guide the mobile robot out of the traps.

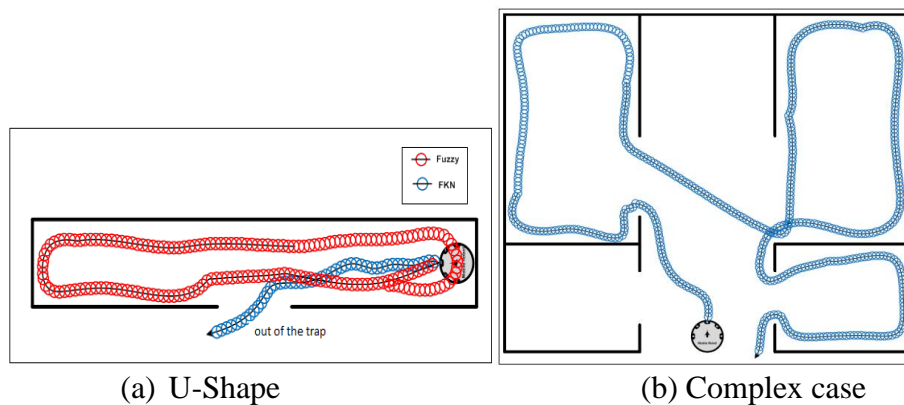


Figure 13. Mobile Robot in Complicated Situation without Suffering from the ‘Local Minima Problems

Figure 13 (a) and (b) show the mobile robot in local minima situation, due to a long wall with U-shaped area is located in the complex environment. When the obstacles are long and goal repulsing fuzzy behavior conflict and the mobile robot gets itself into an infinite loop as shown in Figure 13(a). This continues ad infinitum and is termed the local minima problem. By using mobile robot memory based on FKN, a possible means by which the mobile robot can come out of this loop is to recognize its repeated traversal in the same environment and execute a sequence of steps that pulls it out of the trap. The fuzzy inferencing method has been shown to be successful in real-time navigation with cluttered environments. But when the environment is filled with obstacles in the form of loops, concave corner, convex corner, and other complicated structures the mobile robot tends to lose track of direction and gets trapped.

It can be seen from Figure 13 (b) that the mobile robot meets infinite loops, which are a loop inside U-shaped obstacle, without suffering from the 'local minima problems. To come out of the loop the robot must comprehend its repeated traversal through the same environment, which involves memorizing the environment already seen. In the experiment, memory-based reasoning strategy is developed for the system in navigation chips. The mobile robot change the strategy if the distance between the mobile robot and obstacle in current situation same as the distance in navigation memory for solving local minima.

5. Conclusion and Future Work

This paper presents memory-based reasoning algorithm for embedded mobile robot, through the combination of heuristic fuzzy rules and the Kohonen self-organizing map network. This technique also builds up pattern mapping relation between sensors input and velocity command by applying the off-line and supervised training method to this network. The proposed FKN techniques are simple to construct, and do not necessitate a significant amount of storage, making them a sufficient choice for an embedded mobile robot with an adequate processor and small fixed storage. The results show that, the mobile robot has the ability to memorize and recognize the structured and unstructured environment and produce satisfactory performance. Furthermore, proposed simple FKN technique is adaptive to the environmental changing and can overcome the sensor noisy compare to fuzzy logic and sensor behavior technique. FKN structure has been proven to be effective in reducing the number of the fuzzy rules so that the simple navigation strategy has been proposed to steer the mobile to reach the target. The proposed technique is presented in this work is promising and is able to predict the mobile robot in unstructured environment, to make the collision avoidance system more robust or flexible and it has capability to escape from U-shaped situation.

Using the merit of combination hybrid soft computing technique, we successfully establish the mapping relations in embedded mobile robot, due to by using FKN technique in mobile robot can recognize and memorize the environmental situation. This strategy produces good action to guide the mobile robot to achieve the goal. It has a great potential in the fields of machine learning, computer science and engineering due to it has the following features: self-organizing, memorization, recognition, adaptation, and learning. For the future work, we need to investigate on how to extend and expand the proposed technique that is to make it more general to all unstructured environments taking into considerations both static and dynamic obstacles.

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