ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

DEVELOPMENT MOBILE ROBOT CONTROL ARCHITECTURE WITH INTEGRATED PLANNING AND CONTROL ON LOW COST MICROCONTROLLER

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ABSTRACT

This paper presents new hybrid control architecture-based interval type-2 nuro-fuzzy (IT2NF) for embedded mobile robot navigation where event-driven control is used to handle the dynamically changing of the environment. The proposed hybrid control architecture combining behavior-based reactive navigation and model-based environmental classification has been developed. Weightless neural network (WNNs) in charge of environmental classification, this strategy does not only enable the mobile robot to avoid local minimum points but also eliminates the requirement for prior detailed modeling of the environment. Then, IT2FLC based reactive behavior is utilized to perform mobile robot navigation task use environmental pattern classification. The previous study show that embedded controller on low cost microcontroller is difficult to design due to hardware and software constraints. In this paper, the hybrid control architecture uses hierarchical structure of IT2 fuzzy sets (IT2FS) to avoid the huge rule base due to the embedded platform and modular structure of WNNs to reduce the computational cost and increases processing speed of the controller. Technologies to address these limitations are integrated into hybrid controller architecture to be carried out, thus the autonomous mobile robot navigation system can be executed successfully. Flexibility and performance of the proposed control architecture is validated through experiments on the real embedded mobile robot in a variety of environmental condition. The experimental results show that, the proposed architecture-based IT2NF has dealt in real environment with uncertainties present in the changing and unstructured environments can avoid obstacles at the desired safe distance, follow the desired trajectory in smooth movement and produces minimal computational resources.

Keywords: *Mobile Robot, Control Architecture, Soft Computing, Low Cost*

1. INTRODUCTION

Autonomous mobile robot is a machine able to extract information from its environment and uses knowledge about its world to move safely in a meaningful and purposive manner. It can operate on its own without a human directly controlling it [1][2]. Controlling a mobile robot to navigate autonomously in real world environments is a challenging and difficult task. It has to be equipped with an appropriate control architecture which clearly and systematically. The control architecture is a key issue in the autonomous mobile robot design. Various techniques and approaches have been developed [1]. Recently, mobile robot research community had paid much attention to the development of different control architecture. There are three main classes of control architectures have been developed, there are the hierarchical decomposition-based architecture, behavioral decomposition-based architecture and the hybrid architecture that combines the former two [3].

Each element of hierarchical architecture consists of the functional units, such as sensory processing, world modeling, task decomposition, and value judgment. This implies that deliberate reasoning process based on the world model always exists between perception and action [4]-[6]. However, this architecture is not well acceptable for autonomous mobile robots working under changing environments due to the time consumption in deliberate reasoning. Mobile robot reactivity to the dynamic environments is well achieved in the behavior-based control architecture by connecting the sensors and actuators directly without the world model. The behavior-based control architecture is known as a technique for tightly coupling sensing and action, typically in the context of motor

Journal of Theoretical and Applied Information Technology
15th January 2012. Vol. 35 No.1

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

behaviors, to produce appropriate robotic response in dynamic environments [7]. Furthermore, this behavior has fast response time and modularity because they operate independently with each other [8]-[13].

However it is difficult to construct a control system with suitable arbitration between the outputs of many conflicting behaviors. This is due to the amount of information carries out by an output of a behavior module is not sufficient to represent the internal states of the module and thus their large parts are lost during process [14]. Furthermore, the interaction between behaviors is unknown a priori**,** which may be important to the system robustness. Therefore, the behavior-based control architecture cannot utilize a knowledge base nor perform explicit goals which require a prior planning of multiple tasks.

In recent times, emerging hybrid control architecture utilizes the representational world knowledge to achieve explicit multiple goals as well as maintains the reactive performance to the changing environments. Hybrid architectures take advantage of the hierarchical and behavior-based architecture while minimizing their drawbacks [15],[16]. Intelligent hybrid controller in mobile robot navigation has been exploited to overcome the limitations in individual conventional controller [17]-[19]. However, previous studies show that employing this technique increase computational cost and consume more time in training process due to overhead floating point calculations made in real-time. This problem can decrease the performance of the mobile robot especially when operating on embedded platform with modest capabilities in terms of speed and memory. Therefore this study is concerned with developing an intelligent hybrid controller in mobile robot navigation exploiting computational ability in the embedded controller to get more satisfactory result.

2. PROBLEM BACKGROUND

Recently, autonomous 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. Each mobile robot has the basic of the control system with different architecture. They differ in deciding method and process. For a completely robot, its control system must be able to deal with a large amount of comply information, uncertainty environment and imprecision. Therefore, the concept of suitable control architecture is designed exclusively for the problems being analyzed [20].

Control architecture is one of the important issues in the research of autonomous mobile robot, which aims at organizing and controlling systems of the robot to achieve a certain function [21]-[23]. It defines the principles involving organizing hardware and software function modules, integration methods and supporting tools and it must manage the interaction between each module [21]. Under certain given resources, control architecture design must decide whether the mobile robot can react timely and correctly to dynamic environment to achieve the designed purposes. An instance of control architecture must guarantee the accomplishment of its own tasks in a robust-stable way [22].

Currently, the lack of a compact, modular, and flexible instrumentation infrastructure that supports a wide variety of connectivity options, while preserving robust performance leads to the development of a new integrated design for mobile robot control architecture [23]. Hence, control architecture must ensure the mobile robot will achieve its task despite all these constraint. Strategy control system describes what the system components should have, how the interaction of each components, and how the processing of these components to provide functionality of the mobile robot control [24].

Purely reactive system may have many limitations when applying to a domain which needs long term goal planning [25]. Deliberative reasoning support long term goal planning but the computational cost may cause the mobile robot behavior to execute improperly in the rapidly changing environment [26]. In recent times, the use of artificial intelligent (AI) to design control architecture has grown rapidly with successful applications in mobile robot areas [27]. However, some literatures indicate that most control architecture employed conventional AI methods are weak in their learning capability [28]-[34]. It accumulates all achievements of implementation soft computing techniques are connected with creating of mobile robot.

Mobile robot need to be equipped with learning capabilities as an essential prerequisite in order to adapt effectively to dynamic and varying environments. Control architecture integrating soft computing techniques such as, fuzzy logic and neural network are proving to be effective and

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

improves the intelligence in mobile robot control [35]. Even though fuzzy logic can mimic experts, nevertheless, deriving and fine-tuning the entire rule set and membership functions are often tedious and difficult. Neural network learn the training patterns are usually difficult to obtain, and training time for the whole dynamic range is very long. These limitations have been a central driving force behind the design of intelligent hybrid control architecture, where two or more techniques are combined in a manner that overcomes the limitations of individual techniques.

Type-1 fuzzy logic system (T1FLS) is promising technique in handling problem of mobile robot application that contains uncertain and incomplete information [36]. However there are limitations in the ability of T1FLS to model and minimize the effect of uncertainties [37]. Recent development has been introduced an improvement of T1FLS called interval type-2 fuzzy logic system (IT2FLS) [38]. This technique in mobile robot application indicates good result [38]-[40]. Nevertheless, the IT2FLS involves a computational overhead associated with the inference engine and type-reduced fuzzy sets computation [41]. This computational overhead makes complexity and difficult to implement in embedded application [42]. Due to the mentioned problem, it is desirable to exploit a learning capability to enhance the performance of IT2FLS in embedded mobile robot navigation.

As a propose solution, this research utilizes hybrid control architecture combining a problem solver which is neural network as a deliberative part and fuzzy logic as the reactive part. Compared to the conventional neuro-fuzzy methods [6],[43]-[45], in this work the architecture combines the interval type-2 fuzzy logic (IT2FL) and weightless neural network (WNNs) technique named interval type-2 neuro-fuzzy (IT2NF). This hybrid technique provides the flexibility in modular design while retaining a systematic structure, enabling an easy design process in hardware by using parallel microcontroller and simple in software structure. The modular structure permits different combination of the modules with other hardware and software, therefore new mobile robot architectures can be generated. This allows future work to be carried out by modifying the existing mobile robot to perform different, more complex tasks.

3. A NEW HYBRID CONTROL ARCHITECTURE

In this paper, control architecture is proposed combines advantages of deliberative computations and reactive actions. It takes advantage of IT2FL [46] and weightless neural network (WNNs) [47] assimilating human expertise with continuous representation, combining with learning capability. The architecture is made up of WNNs as behavior-classification block and IT2FL as behavior-control block. The control architecture device implemented within multi-processing of microcontroller unit (MCU) as shown in Fig. 1. It consists of a multi-processor unit and memory, interfacing the other units throughout input and output (I/O) ports. The modular structure of control architecture is implemented over a low cost microcontroller platform. There are three programmable modules are utilized such as sensor module, the navigation module and motor drive module in modular structure. In this work, the software is implemented into a microcontroller-based system due to it afford flexibility in the software design. However, the realization is limited by hardware capability and can also lead to high computational [48]. The efficiency and flexibility in this architecture can be simultaneously met other requirements using modular approach in the architecture of processors.

Three states of WNNs process are read, write and idle. The three control signals that determine these states are *'we'* (*write enable*), *'rce'* (*ram chip enable*) and '*oe*' (*output enable*) as shown in Fig. 1. By considering the two situations that exist and the absence of the obstacles then the reactive strategy is designed. The fundamental principle of reactive mobile robot navigation is the target that attracts the mobile robot while the obstacles keep away from it. In this work, the mobile robot moves toward the target and avoid a collision by changing the motion direction and speed are varied according to the desired level.

3.1 Proposed Control Architecture

Sensor module is configured using parallel microcontrollers where its controls the sensor pulse as shown in Fig. 3. It calculates sensor readings, and selects which sensors are active according to their position in the robot periphery. The sensor module enable the mobile robot to interpret the external environment in two ways: providing the distance between the mobile robot and the obstacles indicating where the collisions have occurred. The sensors allow the mobile robot to determine object

Journal of Theoretical and Applied Information Technology
15th January 2012. Vol. 35 No.1

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

locations of the obstacles, walls and target without physical contact, therefore it could avoid and reach the goal successfully. Ultrasonic and infra-red range finder sensors are chosen to implement the detection of obstacles and target because it simple and low-cost solution that can provide a fairly accurate distance sensing [48].

To acquire the information about the environment around the mobile robot, 8 ultrasonic sensors mounted on the front of mobile robot are used. The maximum effective detection distances under short distance pattern and long distance pattern are 10 cm to 3 m. In order to reduce the computing data then 8 ultrasonic sensors are divided into 4 groups to arrange at the four environmental situation and four sides of mobile robot as shown in Fig. 2. The groups are left obstacle, front obstacle, right obstacle and back obstacle respectively. The sensor ultrasonic positions in all arrays are fixed; one on back side, and seven facing outwards at 30 degree intervals starting from sensor 1 up to sensor 7. The placement of the sensors permits the detection of an obstacle in different positions. Sensor 8 is used to detect obstacle at the back of the mobile robot for backward movement.

The central of the architecture is navigation module that captures high-level linguistic based human expertise in a set of IT2 fuzzy rules. The set of feature vectors generated by the WNNs for a given behavior state is used as input data to the IT2FL to choose an appropriate output for making navigation decision. The WNNs, whose inputs are pre-processed by ultrasonic sensor readings, informs the mobile robot of the environmental situation. WNNs algorithm consists of two phases: the learning phase and the recalling phase. During the first phase the network is trained under some training regime with representative data, to perform navigation task. The recalling phase is the stage in which the network is actually used. Data is fed in the WNNs and the output is summed to get its response.

In designing IT2NF algorithm every components utilize random access memory (RAM) and flash memory of the microcontroller due to each component processor that produces any temporary variables is stored in memory. Fuzzyfication process is done by indexing the memory where the membership function is stored as a look-up table to produce a fast calculation. The inference engine, the antecedent and the consequent sets are stored in memory microcontroller respectively. While the type-reduction process requires a sum operation, subtraction and division can be achieved in RAM. WNNs is built using dedicated parallel microcontroller to reduce the computational cost, and IT2FL is integrated in the software solution.

Motor driver module exclusively generates the pulse width modulation (PWM) signals to run the two dc motors. The module composed of two dc motors, encoder, and all circuitry for the steering and speed control. Several peripheral features are available including: timer or counter, two serial ports, 8 bit wide parallel port and 8 channels high speed 8 bit analog to digital converter. Attached to each dc motor is an optical encoder which is used for distance and speed calculation. The motor driver circuit constitutes a power driver that converts the low current signals provided from the processor to high current pulses. It describes the speed level of the mobile robot intercepts the command and activates the corresponding routine. The signal generate from the motors are controlled by PWM. The rotation angle is determined uses PWM with frequency 50 Hz or 20 m sec. Output from navigation module is 8 bit, as input of motor driver module. In this work, the output divides into two functions which are 4 bit to control the steering angle and 4 bit to control the speed levels of the motor.

In the overall control architecture, both the software and hardware implementation are dealt with. The proposed control architecture has to provide the flexibility of modular design while retaining a systematic structure, enabling an easy design process in hardware and software structure. The modular architecture permits different combination of the modules with other hardware and software, so that new mobile robot architectures can be generated. This allows future work to be carried out by modifying the existing mobile robot to perform different, more complex tasks.

3.2 Simple WNNs Structure

WNNs must be trained to recognize the correct patterns from incorrect ones and it works by generating all the possible input combination [49]. To train WNNs, one must provide a suitable quantity of data. This allows the network to generalize previously unseen cases, as well as make correct approximation. Training is a single-pass process in which each discriminator is trained individually on a set of patterns that belongs to it. For a given training that belongs to what class, all

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

the sites of discriminator that are addressed by this pattern are set to 1. This process is repeated until all pattern of set are trained and when the process is complete, the WNNs has encodes the information in its memory register about the training subset, neuron structure of the WNNs as shown in Fig. 3.

During learning, the input vector from sensor module $s_1 \ldots s_n$, which is an n-bit binary number, where n defines the length of the input vector from $0<n<\infty$. Every location in RAM addressed is a signed register. Initially all of the registers are set to *0* or all RAM register stores *0*. When all training pattern are presented to the networks data stored to all RAM addressed register which is in write mode. The network is counting the frequency of a bit pattern sequence encountered in the binary matrix. Each neuron $N_{m,n}$ has n address lines of memory and 2^n single bit storage locations. The WNNs will generate a feature vector *(x)* when an unknown pattern is detected to the networks that describes the class of the input vector. The outputs $O_{m,n}$ of all discriminator are summed together to give its response.

The data is stored in the discriminator after all training patterns are presented to the network and give the generalization ability. This means that it is possible to extract the general features of a given concept based on the input information. The training set consists of an equal number of patterns from each class. In this work, generalization is introduced by considering the hamming distance from training patterns. The Hamming distance between two binary patterns is the number of bit positions in which they differ [51]. It is simply defined as the number of bit that is different between two bit vectors and this gives a rough idea of how similar the two patterns are [52].

3.3 Hierarchical IT2FL

The number of differences in perception of the mobile robot can encounter grows exponentially with the number of sensors it possesses, thereby making the task of hardwiring behaviors cumbersome and error-prone [53]. To cope with the huge rule base, in this works, fuzzy behavior structure is decomposed into hierarchical system by breaking down the input space amongst multiple behaviors. Hierarchical partition of space sensors allows the mobile robot to learn the input-output mapping corresponding to each layer independently from other layers. Each layer must be responsible for one aspect of behavioral objectives. This strategy significantly reduces the search space and allows for the implementation where all the learning can be done by experimenting with the physical world [54],[55]. As shows in Fig. 4, IT2FL structure and each reactive behavior uses IT2 fuzzy sets to represent the input and output variables.

In the designing of hierarchical IT2 fuzzy structure, the behavior of mobile robot navigation can be divided into a limited part of a special task to achieve all behaviors. Therefore the operation alone would insufficient to perform the complex tasks. The navigational tasks is decomposed into five sub-tasks such as, obstacle-avoidance, left and right-wall-following, goal-seeking and emergency situation. Four IT2FL sub-controllers connected in a parallel configuration are designed to achieve each sub-goal. All the fuzzy rules based on 4 types of behaviors are defined by WNNs as different control policy as shown in Fig. 5.

The capabilities of each behavior can be combined through synergistic coordination to produce composite behaviors suitable for navigational tasks. All IT2FL behaviors are produced preferences to the same outputs therefore each behavior will map different inputs to outputs steering and speed. Each behavior is an independent and self-contained IT2FL with a small number of inputs and outputs and a small rule base and it serves a single purpose such as, obstacle-avoidance, right or left-wall-following and goal-seeking behavior.

4. EXPERIMENTAL RESULT

The proposed control architecture-based IT2NF is validated and experimented in our laboratory by using the riel embedded mobile robot on 8 bits low cost microcontroller. Corners and doors in the corridor are asymmetric and unstructured. Obstacles in different shapes and sizes are also used as walls to configure the environmental pattern. The mobile robot estimates the world coordinate based on the environmental pattern from the WNNs output. Experimental results showed that the control architecture is dynamically reorganized according to the changes in the environment. While mobile robot navigates, the steering and speed error increases by wheel sliding and sensor noise. Therefore, IT2FL strategy is to make control decision with respect to pattern information in mobile robot. Furthermore, the performance of proposed architecture is evaluated in several experiments involving mobile robot navigational tasks. A 3.0 m x 4.0 m area containing walls and

Journal of Theoretical and Applied Information Technology
15th January 2012. Vol. 35 No.1

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

obstacles is created as the mobile robot working domain.

Fig. 6 and 7, shows the plotting of mobile robot trajectory on the simple and complex environment. Fig. 6 shows mobile robot trajectory in simple environment, the mobile robot makes trajectory by enabling the wall-following behavior. Initially, mobile robot with the three controller run with the same movement and direction, however when detecting the front wall architecture-based IT2NF able to perform deflection with a more smooth motion than T1NF and T1FL.

In Fig. 7 shows that by using proposed control architecture-based IT2NF always keeps the farthest distance from the obstacle with smoother movement compared to T1NF and T1FL. Thus, when close to the target, IT2NF is able to reach the target with the closest coordinate points than T1NF and T1FL. In this works, the environmental effect on training to the generalization abilities is also investigated. The numbers of neurons are determined based on the patterns formed in the environment of form behaviors including obstacle-avoidance, right or left-wall-following and goal-seeking.

To evaluate the performance of WNNs structure, 160 bit neuron structure is chosen with 8 bit per neuron in 11 chips processor. The proposed WNNs structure then compared to WISARD in monolithic structure and WNNs structure proposed by Simoes (2008) [56]. The experiments have been done for different number of WNNs neuron and the number of neuron inputs can be modified by rearranging the connectivity to the sensors. Fig. 8 shows the percentage of success recognition in both simple and complex environment. The generalization ability shows how large the Hamming distance between the training and the current input affects to recognition level. The results show the ability of the proposed architecture has successfully recognized the environment.

Reliability is defined as repeatability or consistency. If an experiment is repeated many times it will give identical results if it is reliable or consistent [57]. In this work experiments are performed to compare the reliability performance in terms of collision per minute and time to reach the goal for T1FL, T1NF and IT2NF control architecture using simple environment and complex environment.

As shows in Fig.8, control architecture-based IT2NF has achieved the smallest collision due to its capable to minimize the effect of uncertainty in sensor error and recognize the environmental pattern before making the action. The T1FL has the largest collision number compared to T1NF, due to the effect of uncertainty in environment and more collisions are introduced. Furthermore, IT2NF reduces the computation time because of using WNNs to recognize the environment and activate the rule in current condition. However, IT2NF can lead to incorrect response, depending on situation and condition of the environment.

Table 1
Reliability performance of mobile robot navigations

Experiment	T1NFC Success	T1NFC Relia-bility (%)	IT2NFC Success	IT2NFC Relia-bility (%)
One obstacle	18	84	19	95
simple environment	17	88	19	95
corridor environment	16	80	17	85
complex environment	15	70	17	85

The reliability performance is evaluated on the whole environmental patterns. This is observed when the mobile robot tries to recognize several environments. The summary of the result is present in Table 1. It is proven IT2NF has better reliability compared to T1NF. This is because of architecture-based IT2NF has the ability to incorporate uncertainty values in the IT2 fuzzy sets, which leads to better performance. From the result, combination IT2FL and WNNs classifier responses show good reliability when the mobile robot starts from different starting positions or when tested with changing geometrical settings as they deal in real time are involve dynamic changes in the environment.

5. CONCLUSION

In this paper control architecture-based IT2NF for mobile robot is proposed. Some methodological aspects of the control architecture implementation are described and the modular structure of control architecture is implemented over a low cost microcontroller platform. It is new structure with learning ability using WNNs approach which has solved the computational bottleneck in the IT2NF involved. The proposed control architecture are simple to construct, and do not necessitate a significant amount of storage, making them a

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

sufficient choice for an embedded mobile robot with an adequate processor and small fixed storage. According to the environmental situation, the result shows that mobile robot navigate successfully in tight corridors, avoiding obstacles and reach the goal, dealt with all the irregular shapes that are presented to it. Mobile robot can dynamically recognize the environment situation and it able to initiate adaptive action to the changing environment and achieve good performance. Embedded mobile robot-based IT2NF is suitable in unknown, unstructured and dynamic environments. 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 environmental condition taking into considerations both static and dynamic obstacles.

6. ACKNOWLEDMENT

Author thanks to Higher Education General Director (DIKTI) Nation Education Department, Indonesia for their financial support in Competitive Grants Project.

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Journal of Theoretical and Applied Information Technology
15th January 2012. Vol. 35 No.1

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

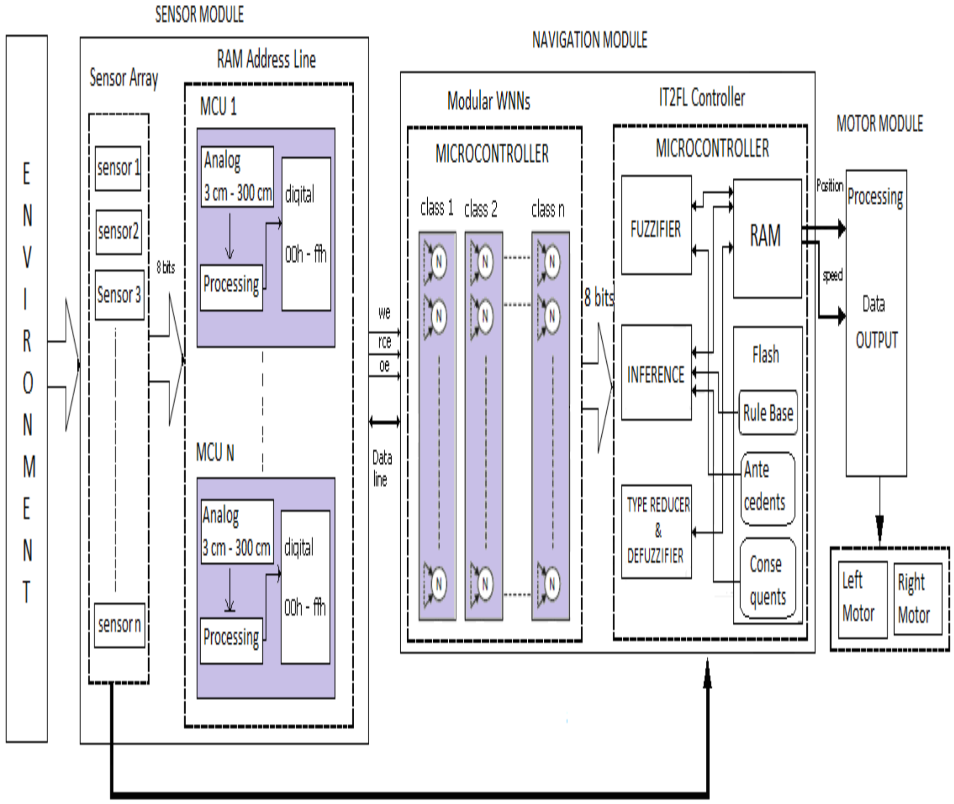
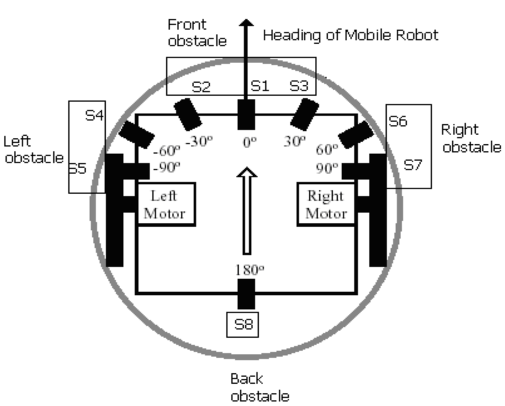


Figure 1: New hybrid control architecture



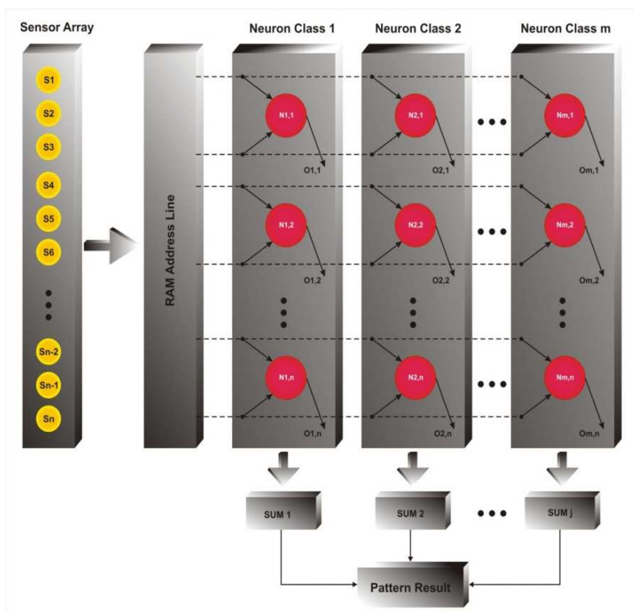


Figure 2: Arrangement of ultrasonic sensors **Figure 3: Neuron structure**

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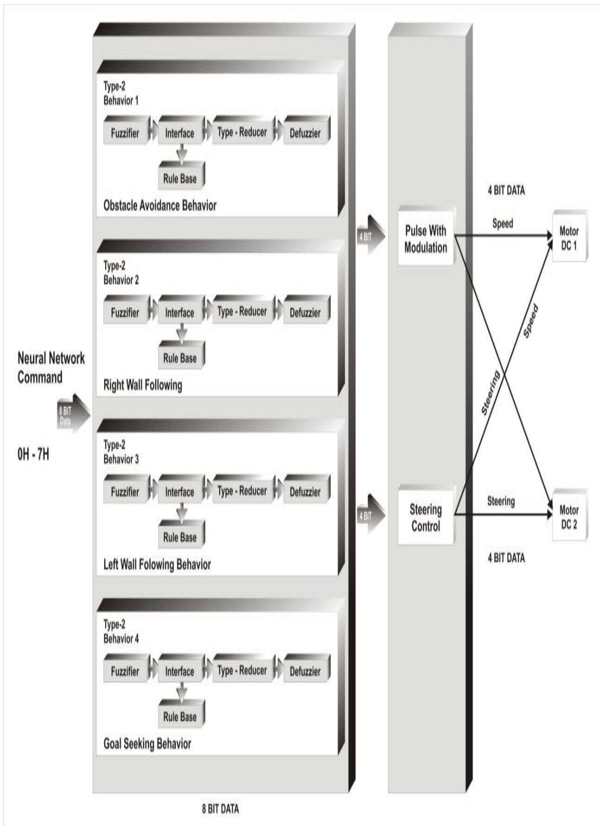

Figure 4: Hierarchical structure of IT2FL

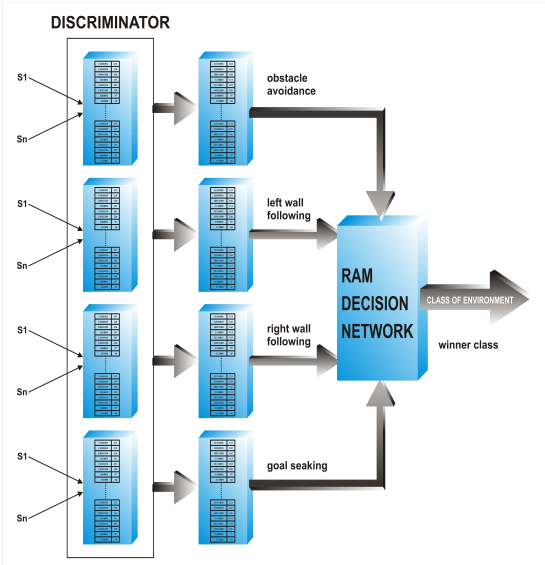

Figure 5: WNNs modular structure

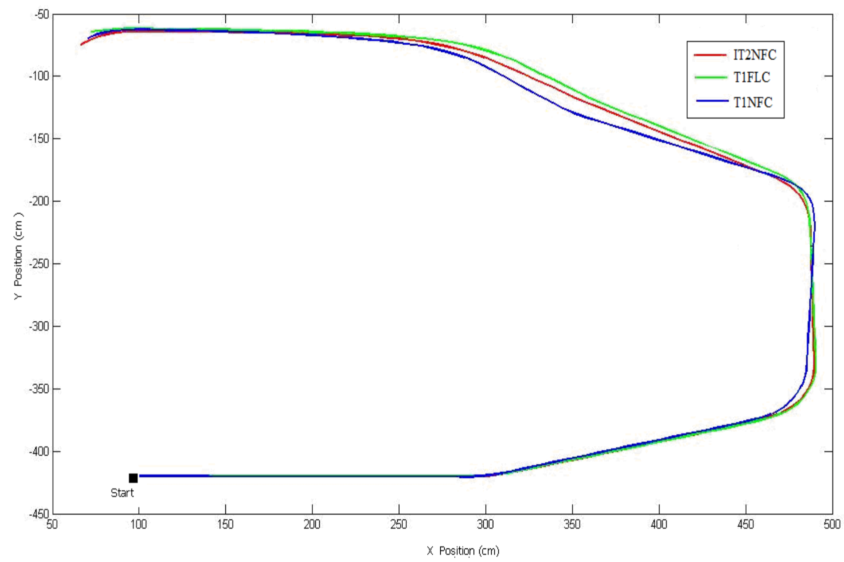

Figure 6: Wall following behavior

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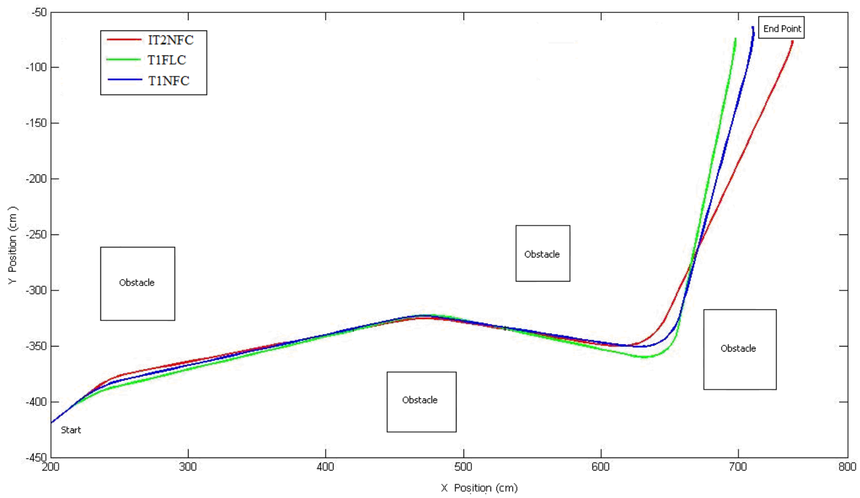

Figure 7: Obstacle avoidance behavior

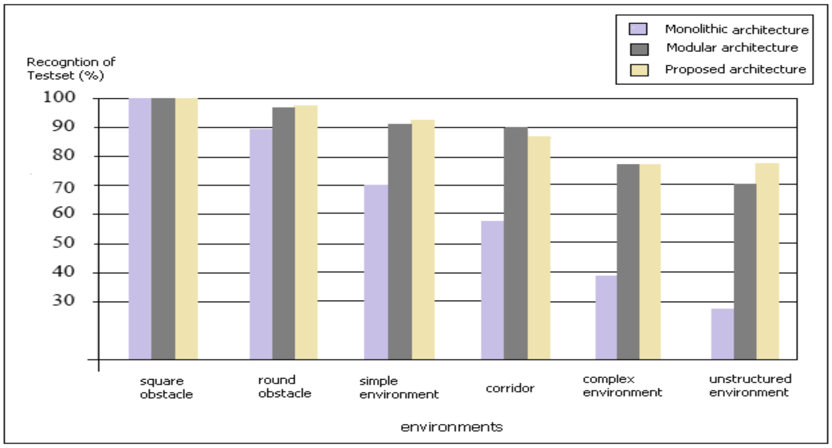

Figure 8: Comparison of generalization ability

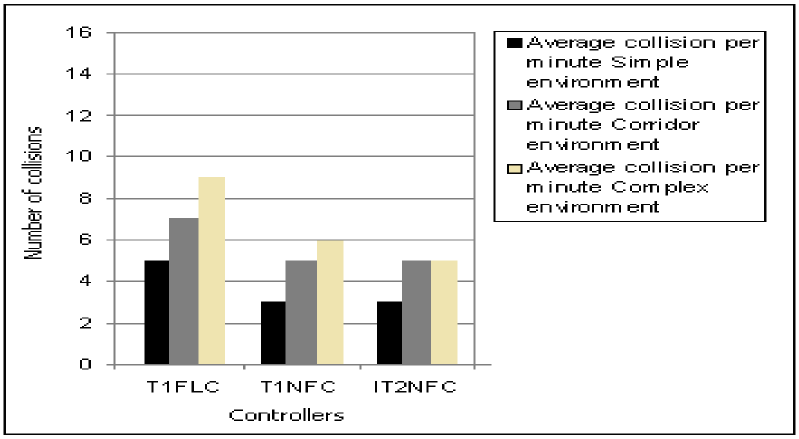

Figure 9: **Average collision per minute**