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IMPLEMENTATION OF VARIOUS TYPES OF FUZZY CONTROLS ON A MOBILE ROBOT USING SONAR SENSORS

by

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x_p	Inputs	24
f^l	Firing Level	24
$\mu_F(x)$	Membership Function of Input x in Antecedent Set F	24
$Y_h(x)$	Defuzzified Output Using Height Defuzzification Method	26
$\mu_{B^l}(y)$	Defuzzified Output	26
Ã	Type-2 Fuzzy Set Ã	29
m	Mean	29
σ	Standard Deviation	29
$\overline{f}^l(x')$	Upper Firing Level	30
$\underline{f}^l(x')$	Lower Firing Level	30
$\overline{\mu}_{\tilde{F}_k^l}(x_k')$	Upper Membership Function of Input x_k in Antecedent Set $\tilde{F}_k^l$	30
$\underline{\mu}_{\tilde{F}_k^l}(x_k')$	Lower Membership Function of Input x_k in Antecedent Set $\tilde{F}_k^l$	30
y_l	Left end point	32
y_r	Right end point	32
$C_{\tilde{G}^l}$	Centroid of Consequent	32
w_l^l	Left Weight Interval of Consequent $C_{\tilde{G}^l}$	32
w_r^l	Right Weight Interval of Consequent $C_{\tilde{G}^l}$	32
$Y_{cos}(x)$	Type- Reduction Using Centre of Sets	32
θ_l	Partition of l Points of the Consequent Values (Horizontal Axis)	32

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IMPLEMENTASI PELBAGAI JENIS KAWALAN FUZZY TERHADAP SEBUAH ROBOT BERGERAK MENGGUNAKAN PENDERIA SONAR

ABSTRAK

Dalam penyelidikan ini, sebuah robot bergerak telah digunakan untuk mengimplementasikan kawalan fuzzy jenis ‘Non-Singleton Type-2’ untuk kawalan pergerakan pengemudian dan tepian dinding dengan bantuan penderia sonar. Ini bertujuan untuk membandingkan aksi kawalan fuzzy jenis ‘Non-Singleton Type-2’ dengan jenis ‘Singleton Type-2’ dan ‘Type-1’. Penderia sonar mengukur jarak bahagian tepi serta hadapan dinding untuk memandu robot bergerak itu melalui suatu ‘U Bend’ dan tepian dinding. Di sini, masukan ke penderia sonar dimodel sebagai set fuzzy jenis ‘Type-1’ dan ‘Type-2’ yang mengambil kira faktor ketidakpastian. Sebelum ini kawalan fuzzy jenis ‘Singleton Type-2’, yang menggunakan konsep “Footprint of Uncertainty” pada ‘Antecedent’ dan ‘Consequent’, telah meningkatkan kualiti trek yang dihasilkan berbanding dengan trek jenis ‘Type-1’. Di sini, telah ditunjukkan bahawa aksi kawalan fuzzy jenis ‘Type-2’ boleh dipertingkatkan dengan mengambil kira faktor ketidaklinearan dan ketidakpastian dalam pengukuran masukan. Ini telah disahkan secara kualitatif dan kuantitatif melalui hasil yang diperolehi dalam eksperimen ini. Trek jenis ‘Non-Singleton Type-2’ lebih lancar dan konsisten berbanding dengan trek jenis ‘Singleton Type-2’ dan ‘Type-1’ untuk kedua-dua perlakuan pengemudian dan pergerakan tepian dinding. Tambahan pula, nilai sisihan purata dari laluan yang dikehendaki telah dikurangkan berbanding dengan kes-kes ‘Singleton Type-2’ dan ‘Type-1’. Boleh disimpulkan bahawa, untuk mengoptimumkan aksi kawalan fuzzy jenis ‘Type-2’, alat pengawal fuzzy jenis ‘Non-Singleton Type-2’ haruslah digunakan. Sumbangan dalam penyelidikan ini ialah penggunaan kawalan fuzzy jenis ‘Non-Singleton Type-2’ untuk memahami dan menghayati potensinya sebagai suatu alat kawalan fuzzy yang baru untuk robot bergerak.

IMPLEMENTATION OF VARIOUS TYPES OF FUZZY CONTROLS ON A MOBILE ROBOT USING SONAR SENSORS

ABSTRACT

In this work, non-singleton type-2 fuzzy control has been implemented on a mobile robot for steering and sidewall movement control with the aid of ultrasonic sensors to compare its performances with the singleton type-2 and type-1 fuzzy control. The ultrasonic sensors measured the distances of the adjacent side and frontal walls to guide the mobile robot along a U Bend and sidewall. Here, the inputs to the ultrasonic sensors were modeled as type-1 and type-2 non-singleton fuzzy sets that took into account factors of uncertainties. It has been previously shown that singleton type-2 fuzzy control utilizing the concept of "Footprint of Uncertainty" in the antecedents and consequents had resulted in improvements in the overall quality of the tracks produced compared to its type-1 counterpart. Here, it has been shown that it was still possible to improve the performance of a type-2 controller by accommodating factors of non-linearity and uncertainties in input measurements. The results yielded in this experiment have confirmed this qualitatively and quantitatively. The non-singleton type-2 tracks were smoother and more consistent compared to the singleton type-2 and also the type-1 tracks, for both the steering and sidewall behaviours. Furthermore the average deviation values from the desired tracks were reduced compared to the singleton type-2 and type-1 tracks. It can be concluded that to optimize the performance of type-2 fuzzy controllers, it is best to use non-singleton type-2 fuzzy controllers. The contribution of this work lies in the utilization of the non-singleton type-2 fuzzy control methodologies to understand and appreciate its potentialities as a new fuzzy control tool for mobile robots.

LIST OF PUBLICATIONS & SEMINARS

"Theoretical Analysis of Fuzzy Control for a Mobile Robot." 4th Mechanical Engineering Research Colloquium, Universiti Sains Malaysia, Penang.

"Simulation of a Mobile Robot For Obstacle Avoidance Using Non-Singleton Fuzzy Control." 5th International Conference on Robotics, Vision, Information and Signal Processing (ROVISP 2005), Penang, pp 145-149.

CHAPTER 1
INTRODUCTION

1.1 Background

One of the great problems faced by mobile robots is the need to exhibit robust performance while operating in a highly uncertain and dynamic environment, which is difficult to model mathematically. The success of implementing fuzzy logic in highly non-linear control systems in which complex mathematical models have been unavailable or unsatisfactory has inspired researches to apply fuzzy logic in studying artificial intelligence behaviours such as navigation, obstacle avoidance and goal seeking (Saffioti, 1997), parking (Gomez et al., 2001) and wall following (Cuesta et al., 2003) on mobile robots.

Fuzzy logic enables the desired behaviour or a combination of behaviours to be encoded in the form of IF-THEN rules. The fusion of these rules enable a certain desired task to be performed based on the sensorial systems that detect the external environment of the mobile robot. The fuzzy IF-THEN rules that consists of the antecedent (input) and the consequent (output) sets enable mobile robots to tolerate uncertainty and imprecision while performing robustly. The antecedent enables the processing of sensorial inputs or fuzzification. The consequent enables defuzzification to produce an output for actuator control. While a well-designed fuzzy logic system tolerates uncertainty and imprecision the antecedents and consequents do not by themselves accommodate magnitudes of uncertainty or imprecision (Mendel, 2003). This fuzzy logic system is categorized as the type-1 fuzzy logic system.

The application of fuzzy logic on mobile robots over the past two decades has progressed along type-1 fuzzy logic control. Recently a new kind of fuzzy logic has been developed as an improvement over the type-1 fuzzy logic system. This is called type-2 fuzzy logic (Karnik et al., 1999). Unlike its predecessor its inputs, antecedents and consequents are able to accommodate uncertainty. A few initial experiments thus far have shown the superiority of the type-2 fuzzy logic over its type-1 counterpart in the control of mobile robots, (Hagras, 2004). This has been achieved by designing antecedent and consequent sets as type-2 fuzzy sets although the input measurements to the sensors were assumed to be crisp or singleton values. In these cases it was assumed that no uncertainties existed in inputs measurements.

In this work the scope of the application of type-2 fuzzy logic in mobile robots is extended a little further in that not only the antecedents and consequents accommodate uncertainties but the inputs are modeled to accommodate magnitudes of uncertainties as well. To achieve this, the sensorial inputs to the mobile robot are modeled as type-1 and also type-2 fuzzy sets.

Figure 1.1 shows the classification of the complete fuzzy logic systems architecture by Mendel (2001). They are based on the type of fuzzy sets and the nature of the inputs. The differences and distinct characteristics of each type will be explained in detail in chapters 3, 4 and 5. In this work the non-singleton type-1 fuzzy logic system is not used since it will not result in significant improvement in performance (Mendel, 2001). Therefore when type-1 fuzzy logic is mentioned it is assumed that the singleton type-1 fuzzy logic system is used. The aim of this work is to see whether there is gradual improvement from the type-1 to the group of type-2 fuzzy logic systems.

The significance of this work is that further improvement in the control of mobile robots could be achieved by accommodating factors of uncertainties in the external environments by modeling the input measurements as non-singleton type-1 and non-singleton type-2 fuzzy sets. It is hoped that the results of this preliminary experiment could pave way towards further improvement for other aspects of mobile robot control such as goal seeking, obstacle avoidance, localization, tracking, navigation and also building of fuzzy maps for perception and identification of its surroundings within the framework of type-2 fuzzy control.

1.2 Problem Statement

The type-1 fuzzy logic enables the representation of behaviours in the form of antecedent (input) and consequent (output) fuzzy sets. The antecedent and consequent fuzzy sets can be encoded in the form of IF-THEN statements.

The series of IF-THEN statements form a fuzzy rule-base that fuses or blends multiple behaviours for flexible decision making in the control actions of a mobile robot. However the two-dimensional nature of the type-1 fuzzy sets does not account for uncertainties in the antecedents and consequents that make up the IF-THEN rule base. Furthermore any amounts of uncertainties in

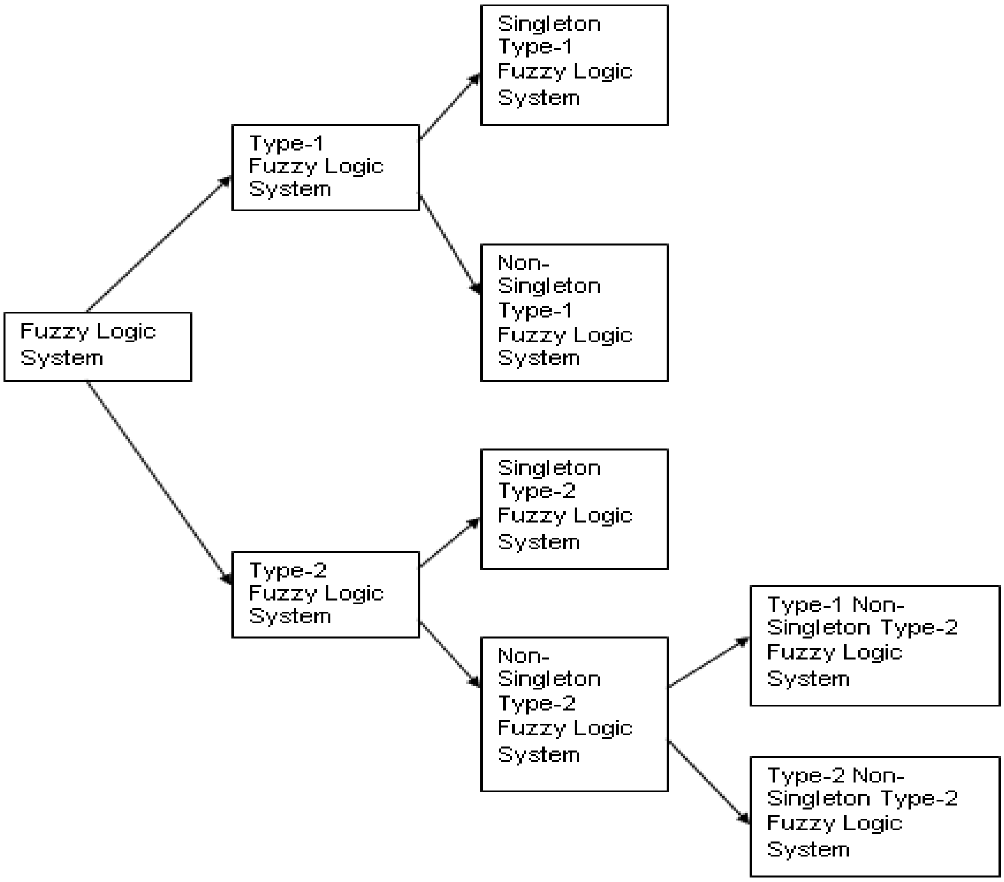

Figure 1.1 Classifications of Fuzzy Logic Systems

input measurements are also not accounted for. It is well known that noise is inherent in ultrasonic sensors which can distort the accuracy of distance measurements by a mobile robot. Also the crisp outputs do not fully account for uncertainties in actuator control actions. In short, although type-1 fuzzy control has shown good results in studying the behaviors of mobile robots they do not fully account for all uncertainties that occur in the inputs, antecedents and consequents representative of the control actions and also the external environments of a mobile robot in action. As a result type-1 fuzzy control brings about the problems of inconsistent tracks and large deviations from straight paths of a mobile robot. Several researches such as Wu (1996), Hagras (2004), Figueroa, et al., (2005) and Coupland, et al., (2006) have mentioned this problem when utilizing type-1 fuzzy control.

Previous works in the type-2 fuzzy control of mobile robots have only accommodated the factor of uncertainties in the antecedents and the consequents but not in the sensorial input measurements (Hagras, 2004). This is an inadequate model in that it has not accounted for all uncertainties in the external environments of the mobile robot. Coupland, et al. (2006) showed that singleton type-2 fuzzy control for a mobile robot could occasionally produce inconsistent tracks with some amount of deviations from desired paths for wall following tasks.

1.3 Research Objectives

In previous works involving type-2 fuzzy control on mobile robots, the antecedents and the consequents were modeled as type-2 fuzzy sets to accommodate the uncertainties that occur in the IF-THEN rules. However the sensorial input measurements were assumed to be crisp and singleton. This model is known as the “Singleton Type-2 Fuzzy Logic Systems” (Mendel, 2001).

The first objective of this research is to model the inputs as type-1 non-singleton and type-2 non-singleton fuzzy sets. Therefore the factor of uncertainty is not only accounted for in the antecedent and the consequents but also the inputs from the ultrasonic sensors as well. The inputs in this case are the measured distances of the adjacent walls surrounding the mobile robot. For the case of type-1 non-singleton input the architecture is known as the "Type-1 Non-Singleton – Type-2 Fuzzy Logic System" (Mendel, 2001). For the type-2 non-singleton input, it is known as the "Type-2 Non-Singleton – Type-2 fuzzy Logic system" (Mendel, 2001).

The second objective, by utilizing the non-singleton type-2 fuzzy logic systems, is to see whether they are able to outperform singleton type-2 fuzzy controller in terms of yielding smoother tracks with less deviation from ideal paths. In particular it is to find out if fully accounting for uncertainties in the inputs, antecedent and consequent sets does result in any further marked improvement in the quality of the tracks. In fact this is a more realistic representation of the external environment in which the mobile robot has to operate in. Furthermore the ultrasonic sensors used by the mobile robot as input transducers are corrupted by noise. This factor has to be to taken into account in order to create a model that is able to tolerate high levels of imprecision and uncertainty in its surroundings.

In order to achieve this, two behaviours have been chosen namely, steering through a U-Bend and moving along a sidewall. For the steering task the mobile robot has to steer itself in between the U-shaped bend which is made up of left and right sidewalls. For the sidewall following, the mobile robot traverses along the side of a wall while maintaining a certain distance along it.

1.4 Assumptions and Scopes

In this simple experimental setup, due to budget constraints, no procurement of expensive equipment such as CMOS cameras, global positioning systems (GPS), compasses or D.C motors equipped with high resolution encoders were made.

Therefore additional behaviours such as simultaneous goal seeking, obstacle avoidance and precise navigation such as odometry or dead reckoning could not be performed. However at this initial stage of study a simple experimental setup in which the mobile robot has to rely solely on the low cost but reliably accurate Devantech SRF04 ultrasonic sensors is sufficient. Some navigational tasks such as obstacle avoidance, goal seeking and wall following have been achieved by being reliant mainly on ultrasonic sensors without the aid of vision systems, for example the sonar behaviour-based fuzzy control of the Helpmate mobile robot by Thongchai, et al. (2000)

In this case no simulation model of the possible tracks of the type-1 and type-2 fuzzy control algorithms were made. The highly non linear nature of the mobile robot's external environment such as noise presence in the ultrasonic sensors would have made the task of modeling the external environment of the robot highly unrealistic and difficult. The success of simulation models usually does not translate to successful operations in actual settings. The more realistic approach would be to create and tweak the fuzzy control models to enable the mobile robot to function in an actual and real world setting. Pioneering research by Sugeno (1984), Saffioti, (1997) and Goodridge (1994) involved the fuzzy control of mobile robots in actual and real-time environments.

The limited amount of memory available in the PIC18F452 micro-controller, which has 16K RAM capacity, ruled out the possibility of integrating multiple behaviours such as wall following and navigation. Even the encoding of the type-2 fuzzy algorithms for single behaviours such as steering and sidewall following has almost stretched the memory capacity of the PIC18F452 to its limit. (For a complete explanation of its memory capacity please consult the website http://www.microchip.com).

In this study we optimized the fuzzy sets by experimentally tuning two main parameters of the fuzzy sets namely, the standard deviation and mean values. This was done on a trial and error basis. The on-line tuning of the fuzzy sets using neural network architectures such as backpropagation was not done, as this would have increased the amount of code. This was not possible due to the limited amount of the memory of the PIC18F452 micro-controller. Also the on-line tuning of the fuzzy sets does not necessarily translate into better control in real-time setting.

1.5 Approach

Extensive literature review showed that fuzzy logic control for mobile robots have been based mainly on the type-1 fuzzy logic for the past two decades. Hagras (2004) also mentioned the inadequacies of using type-1 fuzzy logic for control of mobile robots. The approach taken in this work is to improve upon previous works by using a new fuzzy control architecture, namely the type-1 and type-2 non-singleton type-2 fuzzy logic systems based by Liang and Mendel (2000). It is believed that the theoretical foundations laid down by Liang and Mendel (2000) and Mendel (2001) offer a better way to accommodate factors of uncertainty and non-linearity in the inputs, antecedents and consequents.

The initial part of this work is to build a mobile robot .The design is based on simplicity and the availability of the accessories that make up the mobile robot such as d.c motors, the H-Bridge driver, the PIC18F452 micro-controller and the SRF04 DevanTech ultrasonic sensors. The PIC 18F452 micro-controller acts as the central control system to control the steering action of both the d.c motors based on the inputs from the ultrasonic sensors. The inputs are the distances of the adjacent walls to the ultrasonic sensors.

The next step is to design the type1- and type-2 fuzzy control architectures for the mobile robot. The type-1 fuzzy architecture consists of the fuzzification, IF-THEN rule bases, inferencing and defuzzification modules. The type-2 fuzzy architecture has an added task module called the type reduction module prior to defuzzification. The fuzzification processes the sensorial inputs from the ultrasonic sensors. The inferencing module fuses the set of behaviours in the IF-THEN rule base. Finally type reduction and defuzzification produce a crisp output to steer both the d.c motors. These modules are initially written in the form of pseudo-codes.

In order to save time the Pro Compiler program is used to encode the pseudo-codes to implement the type-1 and type-2 fuzzy control algorithms to perform the steering movement of the U shaped bend and also the sidewall following movement. Since encoding the algorithms using the PIC assembly language is a cumbersome and time-consuming task, its use has been avoided. The straightforward manner of the BASIC syntax language of the Pro Compiler program makes the task of debugging much easier.

For the experimental stage the U shaped bend and a wall portion made of thick cardboards are used for the steering and the sidewall following. The mobile robot is run from the right to left direction and vice versa. The tracks are then photographed and documented according to the behaviour and fuzzy architecture categories.

1.6 Organization of Thesis

The thesis is organized into seven chapters. Chapter one gives a brief introduction of the overall scope of the study. In addition the problems of inconsistent tracks with deviations from desired paths were addressed based on results and findings of previous researchers. The non-singleton type-2 fuzzy control architecture is proposed to overcome this problem by accommodating uncertainties in the inputs, antecedents and consequents.

Chapter two gives a historical perspective on the use of fuzzy logic in studying artificial behaviours in mobile robots over the last two decades. The fuzzy control of mobile robots thus far has been based on type-1 fuzzy logic architectures. Until recently attempts have been made to use type-2 fuzzy logic on mobile robots to improve the performance in navigation, obstacle avoidance, tracking and goal seeking. The literature review provides the justification on the use of the non-singleton type-2 fuzzy controller, particularly in the modeling of the inputs as non-singleton type-1 and non-singleton type-2 fuzzy sets as a further step.

Chapter three describes the type-1 fuzzy control architecture. Detailed explanations are given on aspects of the usage of Gaussian fuzzy sets, fuzzification, defuzzification and the IF-THEN rule base and fuzzy inferencing engines.

Chapter four discusses the three types of type-2 fuzzy logic systems namely; the singleton, type-1 non-singleton and type-2 non-singleton fuzzy logic systems in detail. For a start this chapter discusses the singleton type-2 inputs. The processes of fuzzification, fuzzy inferencing, type reduction and defuzzification are explained. Here the differences between the type-2 fuzzy control architecture and its type-1 counterpart will be obvious.

Next, the inputs are then modeled as type-1 and type-2 non-singleton inputs. This forms the type-1 and type-2 non-singleton type-2 fuzzy logic systems respectively. For both cases the modeling of the inputs in this manner enable accommodation of uncertainties in inputs measurements, for instance in the case of ultrasonic sensors corrupted by noise. The methods of fuzzy

Inferencing, type-reduction and defuzzification are similar to the case of the singleton type-2 fuzzy logic system.

Chapter five provides the methodology and the experimental setup of the whole study. It starts with the description of the physical make up of the mobile robot with its mechanical and electronics accessories. In particular a brief description is provided for the functions of the SRF04 ultrasonic sensors, the H-Bridge controllers, the PIC18F452 micro-controller and the DC motors. The building blocks of the Pro Compiler program for the type-1 and type-2 fuzzy controllers and also the interfacing between the ultrasonic sensors, DC motors and the H-Bridge controller with the PIC18F452 micro-controller are explained in detail. Functional differences between the type-1 and type-2 fuzzy controller is clearly shown. The complete fuzzy IF THEN rules for the U Bend steering and the sidewall following tasks are shown. The parameters for the antecedent and consequent fuzzy sets (type-1 and type-2) used are also shown. The detailed procedures of the experimental set up for the U Bend steering and the sidewall following tasks are explained.

Chapter six discusses the results by making a qualitative and quantitative comparison of the various tracks produced by the type-1, singleton type-2 and the non-singleton type-2 fuzzy control algorithms for both the steering and sidewall movements of the mobile robot. Qualitatively the non-singleton type-2 tracks showed a higher degree of smoothness and consistency compared to the singleton type-2 and type-1 tracks. Quantitatively, the average of the root mean square and the largest deviation distances, from the desired paths, of the non-singleton type-2 tracks were smaller compared to the singleton type-2 and the type-1 tracks. However there were not significant differences in the quality and deviation values between the type-1 and type-2 non-singleton type-2 tracks. The most important result here was that when the inputs were modeled as type-1 and type-2 fuzzy sets to accommodate factors of uncertainties and non-linearity, this resulted in better performance within the framework of type-2 fuzzy control. Theoretical explanations were also given to show why the non-singleton type-2 fuzzy architecture could outperform the singleton type-2 and also the type-1 fuzzy control architecture, in terms of the simulated control surfaces and the number of design parameters.

Chapter seven concludes the findings of this work by emphasizing that type-2 fuzzy control is fully optimized if all the inputs, antecedents and consequents accommodate uncertainties. Type-1 and type-2 non-singleton type-2 fuzzy logic control systems possess this feature. The resulting tracks by the type-1 and type-2 non-singleton type-2 fuzzy control algorithms were comparatively smoother with less deviation from desired paths. In the future a type-2 based neural-fuzzy network could be used for a vision-based navigational guidance system for a mobile robot.

CHAPTER 2
LITERATURE REVIEW

2.1 Introduction

Since its inception by Zadeh (1965), fuzzy logic has begun to see extensive use for control of mobile robots in recent years. By using fuzzy logic a certain or combinations of behaviours for a mobile robot can be encoded as a set of IF THEN rules. The IF-THEN rules not only act as a linguistic representation of the behaviours of mobile robots but enables control of a mobile robot in a mathematically simple manner. Its simplicity and flexibility has enabled mobile robots to tolerate imprecision in such a way as to exhibit robust behaviour despite operating in highly unstructured and non linear external environments. Fuzzy logic also enables fusion or blending of multiple behaviours in a mobile robot.

2.2 Previous Works on Type-1 Fuzzy Logic for the Control of Mobile Robots

Sugeno and Nishida (1984) experimented with fuzzy control on a toy car, which was fitted with a rotating ultrasonic sensor and a microprocessor to execute the encoded fuzzy rules. By controlling the steer angles of the wheels the toy car successfully negotiated a crank shaped bend.

Goodridge (1994) developed the mobile robot MARGE using a distributed, heterogeneous (different) network of fuzzy controllers, each independent and concurrent. Fusion of several individual behaviours was achieved by means of pre-processing and multiplexing (switching). MARGE was able to perform tasks such as goal seeking, wall following, obstacle avoidance, docking and also escaping local minima (trap).

Saffiotti (1995) devised a hierarchical fuzzy controller in their famous robot Flakey, as a series of behaviours that are assigned a context of applicability. By means of context dependent blending a certain or a series of blended behaviours can be exhibited to fulfill a certain navigational task. Flakey was also aided in its navigational tasks by the use of fuzzy topological maps that incorporated fuzzy sets in order to identify stable features of its environment. In one experiment Flakey managed to successfully navigate a corridor, while avoiding obstacles, in order to reach a room.

Yen and Pfluger (1995) incorporated fuzzy logic to Payton and Rosenblatt's (1990) method of command fusion, which combines outputs of multiple behaviours in the control of mobile robot navigation. The usage of linguistic fuzzy rules enabled the mobile robot to cope in dynamic environments. Successful path navigation and obstacle avoidance were demonstrated. An important contribution was a new defuzzification method called centroid of largest area that enabled smoother control compared to existing defuzzification techniques such as centroid and mean of maxima.

There are also variations of techniques associated with purely fuzzy control such as automatic generation of fuzzy rules by Pin and Watanabe (1995), fuzzy interval control methods by Wu (1996), real time reactive fuzzy control by Xu and Tso (1996), fuzzy sonar maps by Gasos and Martin (1996), tangent algorithm method by Lee et al. (1997), adaptive fuzzy control by Barfoot and Ibrahim (1998), a hybrid fuzzy potential method by McRetridge and Ibrahim (1998), and sliding control methods by Rigatos and Tzafestas (2000), fuzzy perception by Cuesta et al. (2003). Most of this research utilized either sonar sensors or cameras or a combination of both for obstacle avoidance, mapping and navigation purposes.

Recently there has been a trend in using neural network and genetic algorithms to tune the fuzzy sets for optimization of performance. These are called neuro-fuzzy, genetic-fuzzy or soft computing methods. A few examples are backpropagation by Watanabe et al. (1995), radial basis function by Godjavec and Steele (1999), Kohonen clustering network by Song and Sheen (2000), genetic fuzzy methods by Hoffmann (2001), a three layer neuro-fuzzy network by Marichal et al. (2001) especially for obstacle avoidance tasks, Kohonen Self Organizing Map by Krishna and Kalra (2001).

There are many similar research works that abound in the literature of fuzzy or neural-fuzzy control of mobile robots. Thus far, all these works have been based on type-1 fuzzy logic systems. Being two-dimensional fuzzy type-1 sets do not account for uncertainties in input measurements. It is well known that noise is inherent in ultrasonic sensors. This can distort the accuracy of distance measurements. Also the crisp outputs do not fully account for uncertainties in actuator control actions. Ambiguities also occur in describing the linguistic variables. In short although type-1 fuzzy control has shown good results in the control of mobile robots they do not fully account for all uncertainties that occur in the inputs, antecedents and consequents that are inherent in the external environments of a mobile robot in action. Quite a number of researchers such as Hagras (2004) mentioned these problems when comparing type-1 and type-2 fuzzy controllers for mobile robots.

2.3 Development of Type-2 Fuzzy Logic Systems

The concept of a type-2 fuzzy set was first proposed by Zadeh (1975).Subsequently Mizumoto and Tanaka (1976) developed and discussed some properties of type-2 fuzzy sets but no work was done to further develop it into a useful and practical tool. Karnik, et al. (1999) introduced the concept of "*Footprint of Uncertainty*" and the upper and lower membership functions to describe type-2 fuzzy sets. Using interval type-2 fuzzy sets they developed the singleton and non-singleton type-2 fuzzy architectures for practical applications in engineering. A simple and straightforward treatment of type-2 fuzzy sets was given by Mendel and John (2002). The three dimensional nature of type-2 fuzzy sets suggest that uncertainties could be better accommodated compared to the two dimensional type-1 fuzzy sets.

2.4 Comparison between Type-1 and Type-2 Fuzzy Logic Control of Mobile Robots

From literature review the first known attempt to use type-2 fuzzy control on a mobile robot was by Hagras (2004). The type-2 controller was a hierarchical reactive type that was able to operate in real time. It consists of a series of low level behaviours integrated by a high-level behaviour coordinator. Each low level behaviour is self-contained with its own input, output and rule base. Each low level behaviour has a certain truth-value of context to determine when it should be activated. The high level coordinator, which coordinates the low level type-2 behaviours, has a rule base that determines when a certain low level behaviour should be activated. Besides achieving economy in the number of rules needed the type-2 fuzzy control architecture outperformed the type-1 fuzzy controller for goal seeking, obstacle avoidance, right edge and left edge behaviours despite navigating in challenging external and unstructured environments. For both indoor and outdoor experiments the hierarchical type-2 fuzzy controller demonstrated its superiority over its type-1 counterpart.

Phokharatkul and Phaiboon (2004) conducted a comparison between a type-2 fuzzy controller and the on-off and type-1 fuzzy controller for obstacle avoidance and corridor following to reach a goal point. By training and fine-tuning the parameters of the type-2 fuzzy logic by means of backpropagation techniques the type-2 controller enabled the mobile robot to reach its goal point in slightly faster time in comparison to the on-off and type-1 fuzzy controller.

Figueroa et al. (2005) utilized type-2 fuzzy control to track a mobile object for robotics soccer games. Image processing was used to estimate the angle between the moving object and target. In static ball tests, the ball was located in a fixed point and the robot tried to reach it. The robot with the type-2 fuzzy controller exhibited a series of more regular paths with smaller deviations compared to the type-1 fuzzy robot. In the mobile ball tests the robot tried to track a moving ball whose desired trajectory was defined. Results showed that the robot with the type-2 fuzzy controller maintained a smaller average distance between it and the moving ball compared to the robot using type-1 fuzzy controller. This meant that the type-2 fuzzy controller produced a path closer to the desired trajectory.

Recently Coupland, et al. (2006) performed a comparative study to evaluate the performance between the type-1, interval type-2 and general type-2 fuzzy controller in following the edge of a curved wall. Statistical analysis and visual inspection of the produced paths indicate that the general type-2 controller was more consistent in performance compared to the interval type-2 and type-1 fuzzy controllers.

Wagner and Hagras (2007) utilized Genetic Algorithm based architecture to facilitate the task of tuning the type-2 membership functions for an outdoor mobile robot. Manually tuning the type-2 fuzzy membership functions to obtain optimal performance is a time consuming and difficult task. After only a small number of iterations the type-2 controller evolved into a robust controller that enabled it to outperform the type-1 and manually designed type-2 controller.

The first three experiments used the interval type-2 fuzzy sets in order reduce computational overhead while achieving a consistently better performance than the type-1 fuzzy controller. The type-2 fuzzy rule bases accommodate uncertainties in the antecedents and consequents with the "*Footprint of Uncertainty*" inherent in their type-2 fuzzy sets. In the fourth experiment the non-uniform distribution of the fuzzy type-2 sets resulted in better performance of the general type-2 controller as compared to interval type-2 and type-1 fuzzy controllers. In the fifth case genetic algorithm was used to tune the parameters of the type-2 fuzzy sets automatically to enable the mobile robot to learn to navigate in an outdoor environment. In all these cases the inputs were modeled as singleton inputs. Despite promising results these experiments have not accounted for uncertainties in the inputs measurements.

2.5 Justification on the Usage of Non-Singleton Type-2 Fuzzy Logic Systems

To put it in historical perspective, the period between the mid 80's to late 90's saw a proliferation in the application of type-1 fuzzy logic and type-1 based neural fuzzy techniques in the control of mobile robots. With the introduction of the concept of type-2 fuzzy logic by Karnik, Mendel and Liang (1999) as an improvement over the type-1 fuzzy logic, it is only natural that researches will start to look for improvements for the control of mobile robots within the paradigm of type-2 fuzzy logic once the application of type-1 fuzzy logic has reached full maturity. The pioneering work by Hagras (2004) has demonstrated practically and convincingly that type-2 fuzzy control architecture is superior to type-1 fuzzy control for mobile robots. Although still a relatively new control methodology it is expected that many more variations of fuzzy, neural fuzzy and genetic-fuzzy techniques within the framework of type-2 fuzzy logic will be devised and used in the future for mobile robots.

In this work we further extended the scope of the usage of type-2 fuzzy control by modeling input measurements by the ultrasonic sensors as a type-1 non-singleton and type-2 non-singleton inputs. Mendel (2001) has mentioned the modeling of inputs as type-1 and type-2 fuzzy sets that result in additional design parameters, which provides more degrees of freedom compared to singleton inputs. Therefore the non-singleton type-2 fuzzy architectures should be able to outperform the singleton type-2 fuzzy architecture. Liang and Mendel (2000) performed simulations to show that non-singleton type-2 fuzzy systems outperformed not only the type-1 fuzzy logic systems but also its singleton type-2 counterpart for the time-series forecasting in the presence of noise. They mentioned the possibility of utilizing the group of the non-singleton type-2 fuzzy logic systems for robust control in the presence of uncertain information.

In the light of this, we wish to test the performance of the non-singleton type-2 fuzzy logic systems in comparison to the singleton type-2 and the type-1 fuzzy logic systems. In particular it is to see how well the ultrasonic sensors, which are corrupted by noise, will be able to aid the movement of the mobile robot when the inputs (distance values) to the ultrasonic sensors are modeled as type1- and type-2 fuzzy sets to accommodate uncertainties.

CHAPTER 3
SINGLETON TYPE-1 FUZZY LOGIC SYSTEM

3.1 Introduction

Figure 3.1 shows the block diagram for the type-1 fuzzy logic system. The crisp inputs or singleton inputs are first fuzzified to obtain membership function values. The inferencing of the IF-THEN rule-base produces output values, which are defuzzified to produce a crisp output value for control.

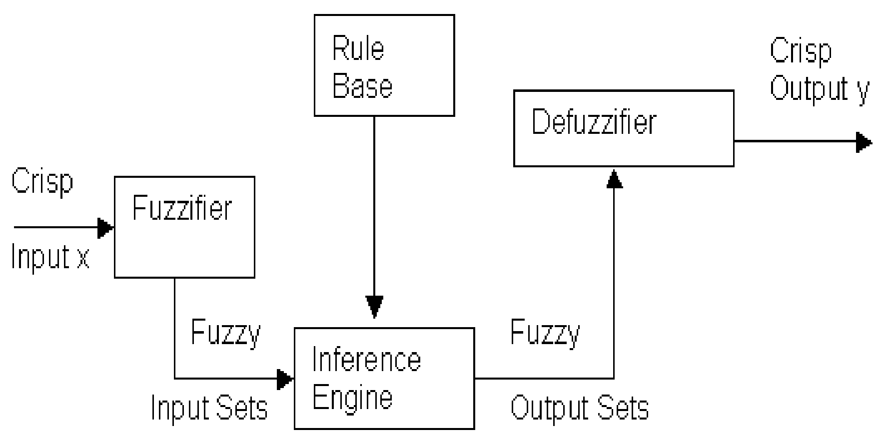

Figure 3.1 Block Diagram of a Singleton Type-1 Fuzzy Logic Architecture (Mendel, 2001)

3.2 Fuzzification and Inferencing

The fuzzifier consists of the antecedent Gaussian fuzzy sets that map the singleton input values into membership function values. The singleton inputs mean that it is assumed that there are no uncertainties in the distance measurements by the ultrasonic sensors. When a singleton input x is mapped into the Gaussian fuzzy set F_X, a membership function value $\mu_F(x)$ is produced.

Fuzzy inferencing involves the t-norming of membership function values to obtain the firing levels. T-norming involves minimum and product t-norms. For example, for a single rule that involves two inputs and two antecedent fuzzy sets the minimum t-norm firing level is represented by:

$$f^l = \mu^l = \min [\mu_{F_1^l}(x_1'), \mu_{F_2^l}(x_2')] \tag{3.1}$$

For the product t-norm the firing level is:

$$f^l = \mu^l = \mu_{F_1^l}(x_1') \times \mu_{F_2^l}(x_2') \tag{3.2}$$

The min t-norm is used to avoid the multiplication operation that will increase computational load of the micro-controller as a result of using product t-norm operations. Figure 3.2 and Figure 3.3 show the fuzzification and also the minimum t-norm and product t-norm operations respectively.