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RESEARCH ARTICLE

OPTIMAL DESIGN APPROACH OF WALL FOLLOWING CONTROL OF A ROBOT MOTION USING FUZZY CONTROLLER VIA SUGENO MODEL

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ABSTRACT

This work presents a new strategy for behaviour-based navigation of robots using a fuzzy logic approach. A key feature of the proposed approach is real-time assessment of terrain characteristics and incorporation of this information in the robot navigation strategy. Here fuzzy logic used is Sugeno modelling. The advantage of Sugeno is that it provides sharp response near boundaries with less time. The regional behaviour is complemented by two other behaviour's, local avoid-obstacle and global seek-goal. The detection of a wall by the sensors activates the controller which simply attempts to align the robot with the wall at a specified reference distance. The proposed model performance is compared with Mamdani approach. All simulations are done with the help of MATLAB tool.

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INTRODUCTION

HUMANS have a remarkable capability to perform a wide variety of physical and mental tasks without any explicit measurements or computations. Examples of everyday tasks are parking a car, driving in city traffic, playing golf, cooking a meal, and summarizing a story. In performing such familiar tasks, humans use perceptions of time, distance, speed, shape, and other attributes of physical and mental objects (Klir and Yuan, 1996). Reflecting the bounded ability of the human brain to resolve detail, perceptions are intrinsically imprecise. Perceptions are well beyond the reach of traditional methods, which are based on mathematical modelling and analysis. Instead, perceptions are described by propositions drawn from a natural language, in which the boundaries of perceived classes are fuzzy. For instance, a human can drive a car off-road on a rough terrain using perceptions of the physical environment, rather than with exact information about locations and sizes of objects therein (Gottwald *et al*., 1995).

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The most significant challenges confronting autonomous robotics lie in the area of automatic motion planning. The target is to be able to specify a task in a high level language and have the robot automatically compile this specification into a set of low-level motion primitives to accomplish the task. Navigation of mobile robots in changing and dynamic unstructured environments like the outdoor environments needs to cope with large amounts of uncertainties that are inherent of natural environments. Thus navigation of mobile robots covers a large spectrum of different technologies and applications. It draws on some very ancient techniques, as well as some of the most advanced space science and engineering. The investigation in the field of navigation of mobile robot gained an extensive interest among the researchers and scientists since last two decade. This is due chiefly to the necessity to replace human intervention in dangerous environments (nuclear, space, military mission, harmful material handling, interplanetary explorations. and etc.) or the wish to develop a helpful device for some more classical tasks (Cleaning, supervision, carriage, etc.) (Chia-Feng Juang and Ying-Han Chen, 2015). In today's flexible manufacturing system environment, the autonomous mobile robot plays a very important role.

It is used to transport the parts from one workstation to others, load unloads parts, remove any undesired objects from floors, and so on. Without autonomous mobile robot, the work stations, the CNC machines, machining centres will only be scattered and isolated machine tools, they will never become a manufacturing system. It is the mobile robot that connects the scattered machines tools into an integrated and coordinated unit, which can continuously, automatically and at a low cost, manufacture a variety of parts.

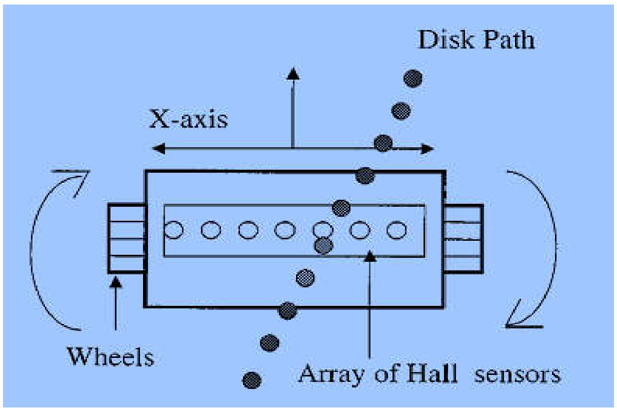

Figure 1. Description of Robot (Klir and Yuan, 1996)

For more efficiency and safety, perception tools have to be increased (several types of sensor including for example cameras) to get more pertinent data of the environment. In fact, some constraints are added to their drawbacks caused by: the difficulties to represent correctly the environment and to locate the robot due to errors in the sensor data that are still far from perfect taking in account the present day technologies.Further, in section II, it represents fuzzy logic modelling with proposed system. In Section III, It defines basics of proposed technique. In Section IV, It defines results of proposed System. Finally, conclusion is explained in Section V.

Fuzzy Logic Control

The human brain interprets imprecise and incomplete sensory information provided by perceptive organs. Fuzzy set theory provides a systematic calculus to deal with such information linguistically, and it performs numerical computation by using linguistic labels stipulated by membership functions. A fuzzy inference system (FIS) when selected properly can effectively model human expertise in a specific application. A classic set is a crisp set with a crisp boundary. For example, a classical set A of real numbers greater than 6, where there is a clear, unambiguous boundary 6 such that if x is greater than this number, then x belongs to this set A; or otherwise does not belong to this set. Although classical sets are suitable for various applications they do not reflect the mature of human concepts and thoughts, which tend to be abstract and imprecise (Amiri *et al*., 2014). In contrast to a classical set, a fuzzy set, as the name implies, is a set without a crisp boundary. That is, the transition from "belongs to a set" to "do not belong to a set" is gradual, and this smooth transition is characterized by membership functions that give fuzzy sets flexibility in modelling commonly used linguistic expressions, such as "the water is hot" or "the temperature is high".

The fuzziness does not come from the randomness of the constituent members of the set, but from the uncertainties and imprecise nature of abstract thoughts and concepts. The construction of a fuzzy set depends on two things: the identification of a suitable universe of discourse and the specification of an appropriate membership function. Therefore, the subjectivity and non-randomness of fuzzy sets is the primary difference between the study of fuzzy sets and probability theory (Jamwal *et al*., 2014).

The basic configuration of a fuzzy logic system consists of a fuzzifier, some fuzzy IF–THEN rules, a fuzzy inference engine and a defuzzifier. The fuzzy inference engine uses the fuzzy IF–THEN rules to perform a mapping from an input vector $x = (x1, x2 \ldots\ldots xp)^T$ to an output vector $y = (y1, y2 \ldots\ldots yq)^T$.The ith fuzzy rule is written as

$$Ri: If x1 \text{ is } A1^i and \ldots\ldots xp \text{ is } Ap^i \text{ then } y \text{ is } y^i.$$

Where $A1^i, A2^i$ .... are fuzzy variables andy^i is a Singleton vector.

The four parts of Fuzzy System are

- Fuzzifier (transformation 1);
- Knowledge base;
- Inference engine (fuzzy reasoning, decision-making logic);
- Defuzzifier (transformation 2).

The fuzzifier performs measurements of the input variables (input signals, real variables), scale mapping and fuzzification (transformation 1). Thus all the monitored signals are scaled, and fuzzification means that the measured signals (crisp input quantities which have numerical values) are transformed into fuzzy quantities. This transformation is performed using membership functions. In a conventional fuzzy logic controller, the number of membership functions and the shapes of these are initially determined by the user. A membership function has a value between 0 and 1, and it indicates the degree of belongingness of a quantity to a fuzzy set. If it is absolutely certain that the quantity belongs to the fuzzy set, then its value is 1, but if it is absolutely certain that it does not belong to this set then its value is 0.

The membership functions can take many forms including triangular, Gaussian, bell shaped, trapezoidal, etc. The knowledge base consists of the data base and the linguistic control rule base. The data base provides the information which is used to define the linguistic control rules and the fuzzy data manipulation in the fuzzy logic controller. The rule base defines (expert rules) specifies the control goal actions by means of a set of linguistic rules. In other words, the rule base contains rules such as would be provided by an expert. The Fuzzy Logic Controller (FLC) (Shyong and Mansour Karkoub, 2014) looks at the input signals and by using the expert rules determines the appropriate output signals (control actions). The rule base contains a set of if–then rules. The main methods of developing the rule base are:

- Using the experience and knowledge of an expert for the application and the control goals;
- Modeling the control action of the operator;
- Modeling the process;
- Using a self-organized fuzzy controller;
- Using an artificial controller

Description of proposed system

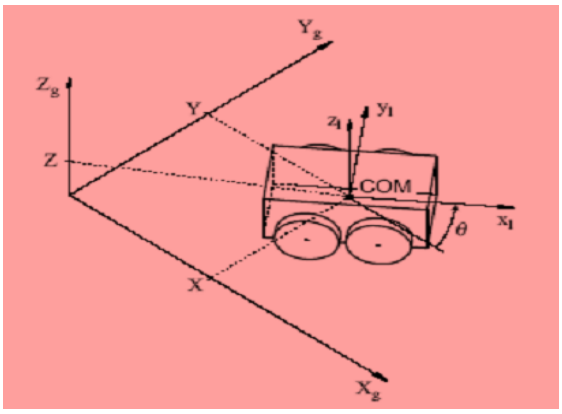

Figure 2. Mobile Robot in Inertial Frame (Chia-Feng Juang and Ying-Han Chen, 2015)

The overall aim of this research is to explore the application of artificial intelligence technique to navigate mobile robot. In this work, fuzzy logic have been used to solve mobile robot navigation problems. The task of the robot is to follow an imaginary path defined by a sequence of disks placed on the floor. The robot for which the fuzzy control system has been designed has two driving wheels. At the bottom of the robot, positioned between the wheels, is an array of sensors. A set of methodologies called qualitative or approximate reasoning have been developed to build a decision making approach in systems where all uncertainties cannot be avoided or corrected. These methodologies attempt to capture some aspects of the human behaviour in system control. Their aim is to incorporate implicitly the uncertainties in the information gathering and reasoning process, rather than to determine explicitly them through numerical calculations or mathematical representations.

The mobile robot system in this study consists of two subsystems. They are driving subsystem and sensing subsystem. Two driving configurations are used in today's mobile robot, steer drive and differential drive. The former uses two driving wheels to make the vehicle move forward and backward, and another separate steering mechanism to control its heading angle. Since the driving action is independent of the steering action, the motion control of the vehicle is somewhat easy. However due to physical constraints, this configuration cannot make turning in a very small radius, which need more floor space for vehicle turning. The differential drive on the other hand has two independent drive wheels arranged parallel to each other. Their speed can be controlled separately. Thus the mechanism is able to not only drive the vehicle forward and backward, but also steer its heading angle by differentiating their speed.Each of these wheels has a separate DC motor. These motors run independently from each other with the help of PWM signals generated. It measures the distance from a wall on its left and protects itself from an obstruction in front. Therefore, it has three ultrasonic sensors. Two of the ultrasonic sensors are on the left side to aid in following a wall and one of the ultrasonic sensors is in front primarily used to detect an obstruction. Low level or data fusion is accomplished immediately on acquisition of the data from the different sensors. Processing at this level involves huge volumes of numerical data and is generally based on techniques developed in the signal fields. This level also exhibits high precision and little intelligence in terms of the final decision making.

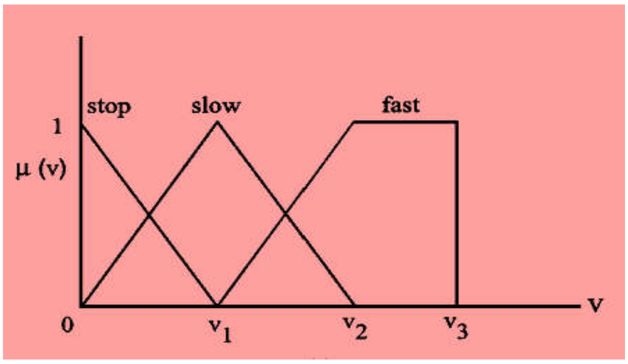

Figure 3. Membership Function for Speed

Linguistic variables like "fast"; "medium" and "slow" are defined for left wheel velocity and right wheel velocity for membership function. Terms like "very slow", "slow", "medium", "fast", and "very fast" are considered for left wheel velocity and right wheel velocity for membership functions. A *normal* fuzzy set is one whose membership function has at least one element x in the universe whose membership value is unity. For fuzzy sets where one and only one element has a membership equal to one, this element is typically referred to as the *prototype* of the set, or the prototypical element.

Table 1. Rule Base for Distance Linguistic Variables

L_Distance	R_Distance
Near	Near
Medium	Medium
Far	Far

Table 2. Rule Base for Velocity Linguistic Variables

L_Velocity	R_Velocity
Slow	Slow
Medium	Medium
High	High

Table 3. IF-THEN Rules for Linguistic Variables

IF	THEN
L_Dist is Far and R_Dist is Far	R_Vel is high, L_Vel is high
L_Dist is Near and R_Dist is Near	R_Vel is Slow, L_Vel is high
L_Dist is Near and R_Dist is Medium	R_Vel is Slow, L_Vel is Slow
L_Dist is Near and R_Dist is Far	R_Vel is Slow, L_Vel is Slow

In this section, we used the Sugeno, or Takagi-Sugeno-Kang, method of fuzzy inference. The first two parts of the fuzzy inference process, fuzzifying the inputs and applying the fuzzy operator, are exactly the same. The main difference between Mamdani and Sugeno is that the Sugeno output membership functions are either linear or constant.

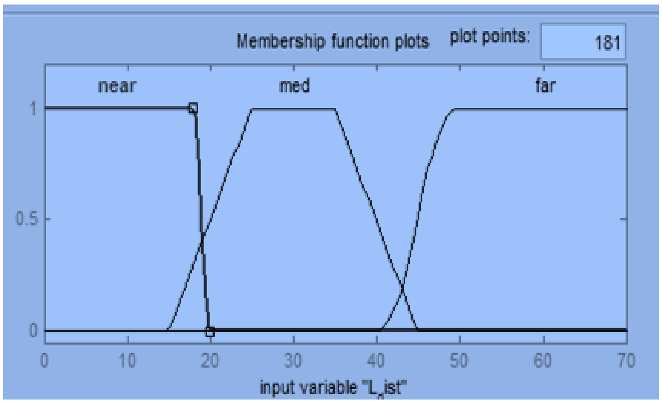

Figure 4. Membership Function of 1st Input

The steps in designing a fuzzy control system are as follows

- Identify the variables (inputs, states, and outputs) of the plant.
- Partition the universe of discourse or the interval spanned by each variable into a number of fuzzy subsets, assigning each a linguistic label (subsets include all the elements in the universe).
- Assign or determine a membership function for each fuzzy subset.
- Assign the fuzzy relationships between the inputs' or states' fuzzy subsets on the one hand and the outputs' fuzzy subsets on the other hand, thus forming the rule-base.
- Choose appropriate scaling factors for the input and output variables in order to normalize the variables to the (0, 1) or the (−1, 1) interval.
- Fuzzify the inputs to the controller.
- Use fuzzy approximate reasoning to infer the output contributed from each rule.
- Aggregate the fuzzy outputs recommended by each rule.
- Apply defuzzification to form a crisp output.

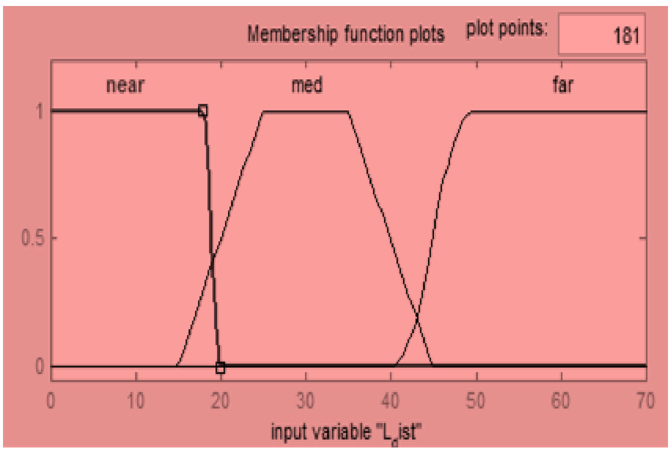

Figure 5. Membership Function of 2nd Input

RESULTS AND DISCUSSION

In this, it presents the results of robot moving in obstructed path using Sugeno technique. The mobile robot designed in this work is a wheeled robot intended for indoor use as opposed to other types. This robot type is the easiest to model, control, and build. The control strategies of mobile robots can be divided into open loop and closed loop feedback strategies. In open loop control, the inputs to the mobile robots (velocities or torques) are calculated beforehand, from the knowledge of the initial and end position and of the desired path between them in the case of path following. This strategy cannot compensate for disturbances and model errors. Closed loop strategies however may give the required compensation since the inputs are functions of the actual state of the system and not only of the initial and the end point. In this, the fuzzy output is then considered as the fuzzy input into a fuzzy controller, which consists of linguistic rules. The output of the fuzzy controller is then another series of fuzzy sets. Since most physical systems cannot interpret fuzzy commands (fuzzy sets), the fuzzy controller output must be converted into crisp quantities using defuzzification methods. These crisp (defuzzified) control-output values then become the input values to the physical system and the entire closed-loop cycle is repeated.

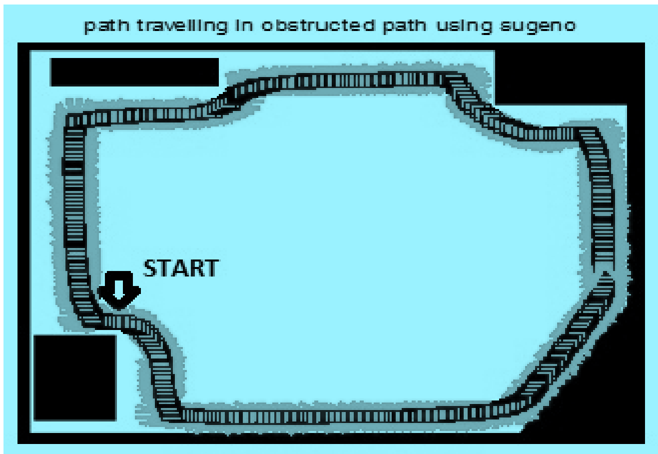

Figure 6. Response of Robot Navigation using Sugeno Model

The mobile robot considered in this thesis is a point robot for simulation mode. Each robot has an array of sensors for measuring the distances around it and locating the target i.e., front obstacle distance (FD), left obstacle distance (LD), right obstacle distance (RD) and detecting the bearing of target (HA). The distance between the robots and obstacles act as repulsive forces for avoiding the obstacles, and the bearing of the target acts as an attractive force between robots and target. Linguistic variables such as "far", "medium" and "near" are taken for membership function. Since all information contained in a fuzzy set is described by its membership function, it is useful to develop a lexicon of terms to describe various special features of this function. For purposes of simplicity, the functions shown in the following figures will all be continuous, but the terms apply equally for both discrete and continuous fuzzy sets.

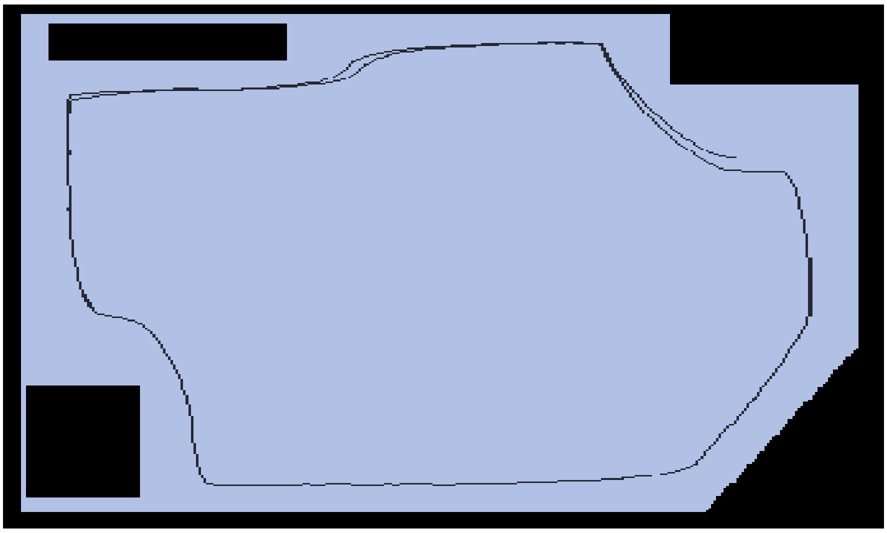

Figure 7. Response of Robot under Different Behaviour

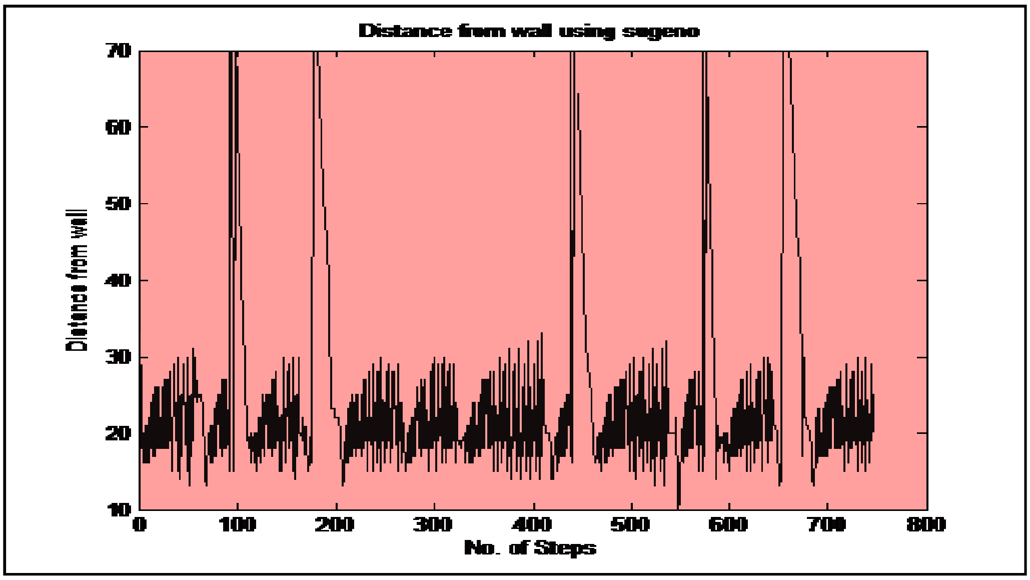

Figure 8. Distance Optimization from Wall

Fuzzification is the process of making a crisp quantity fuzzy. We do this by simply recognizing that many of the quantities that we consider to be crisp and deterministic are actually not deterministic at all: They carry considerable uncertainty. If the form of uncertainty happens to arise because of imprecision, ambiguity, or vagueness, then the variable is probably fuzzy and can be represented by a membership function. Defuzzification is the conversion of a fuzzy quantity to a precise quantity, just as fuzzification is the conversion of a precise quantity to a fuzzy quantity. The output of a fuzzy process can be the logical union of two or more fuzzy membership functions defined on the universe of discourse of the output variable.

Conclusion

The proposed behavior-based robot navigation strategy using fuzzy logic rules has major advantages over existing analytical methods. First, the fuzzy logic rules that govern the robot motion are simple and easily understandable, and can emulate the human driver's perception, knowledge, and experience. Second, the tolerance of fuzzy logic of imprecision and uncertainty in sensory data is particularly appealing for outdoor navigation, because of the inherent inaccuracy in measuring and interpreting the terrain quality data, such as slope, roughness, and discontinuity.

The new regional behavior introduced in this paper complements the local avoid-obstacle and global seek goal behaviours commonly used in behavior-based navigation systems.

From the simulation results, it is concluded that the developed simple fuzzy controller with membership is able to control the navigation of mobile robot. By using kinematics of mobile robot right wheel velocity and left wheel velocity of the robot is calculated.

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