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Probabilistic Fuzzy Control of Mobile Robots for Range Sensor Based Reactive Navigation

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Abstract

In this paper, a probabilistic fuzzy approach is proposed for mobile-robot reactive navigation using range sensors. The primary motivation is an integrated reactive navigation control system with good real-time performance under uncertainty. To accomplish this aim, a probabilistic fuzzy logic system (PFLS) is introduced to range measurement and reactive navigation in local environments. PFLS is first adopted to handle the fuzzy and stochastic uncertainties in range sensors and to provide more precise distance information in unknown environments. Consequently these sensor data are sent to a probabilistic fuzzy rule-based inference system with reactive behaviors for local navigation. The feasibility and effectiveness of the proposed approach are verified by simulation and the experiments on a real mobile robot.

Keywords: Mobile Robots, Probabilistic Fuzzy System, Range Measurement, Reactive Navigation

1. Introduction

Reactive navigation control of autonomous mobile robots in the unknown environment is a fundamental and crucial issue in robotics, cybernetics and artificial intelligence [1-4]. In a local environment it is necessary for a robot to possess the capabilities of obstacle avoidance, moving toward sub-goal, escaping from local traps, etc. [5, 6]. Real-time and precise reactive navigation has been a challenging task for mobile robots because the environment may be unpredictable and the sensory information may be incomplete or not accurate enough for decision-making. Several reactive control approaches have been proposed to implement local navigation. For example, occupancy maps have been built using sonar sensors to model the environment and have led to a series of localization and path planning methods [7]. The potential field and virtual force field have been used for navigation in a local environment, respectively, [8]. These methods are mainly employed to deal with stationary obstacles. In the middle of 1990s, some researchers presented behavior-based control methods such as the subsumption architecture [9], where the stimulus-action pairs are defined for the decision and control rules of a robot after a proper coordination if it is necessary. Various soft computing and machine learning methods have been applied to reactive navigation to improve the control performance [2,3,5,6,10,11]. To accomplish the better navigation performance, two problems need to be solved with suitable approaches. One problem is that the data of onboard sensors are always uncertain, which confines the detecting ability of mobile robots in the unknown environments. The other problem is how to make decision using the sensor data to navigate in the unknown and changing environments.

The navigation using range sensors, namely ultrasonic sensors, infrared sensors, laser scanner, etc., has been recognized as one of the most fundamental and important problems in the increasing applications of autonomous mobile robots [2,12-14]. It is well known that all measurement processes are always accompanied by uncertainty [15] and various uncertainties can be classified into nonstochastic uncertainty and stochastic uncertainty [16]. The uncertainties in the range data measured by range sensors with random noises and unpredictable conditions may include incomplete information, vagueness and stochastic uncertainty [17]. In order to handle these uncertainties, probabilistic approaches have been adopted to various robot systems [13,14,18,19]; but most of the existing results focus on sensor fusion, localization and behavior selection. Generally, fuzzy logic systems (FLS) [20] have the capability to deal with multiple uncertainties without a precise mathematical formula [6,10]. The type-2 FLS [21-23] has also been recently studied in detail to better modeling the fuzziness of a fuzzy relation, which could improve the ability to handle inexact information. However, ordinary FLS could not catch the stochastic uncertainty and the traditional fuzzy technique is not the best choice to process the stochastic uncertainty [25,26]. Stochastic uncertainty arises with random probability that cannot be predicted in advance or recognized accurately during the process of measurement. There are various circumstances that are full of stochastic uncertainties. For example, it is possible that random noises, time-varying stochastic uncertainty, stochastic mutative temperature or weather, and the like occur as stochastic uncertainty. It is equally possible that the range sensor data measured by different sensors provide stochastic uncertainty. In addition, random disturbance involving the probability that someone walking around the range sensor will help make serious difference between the measured distance and the real distance. Thus, without ruling out all the possibilities above, the range sensor could not measure the precise distance under various circumstances.

The probabilistic fuzzy logic system (PFLS) [25-27] is different from the ordinary FLS and it uses probabilistic fuzzy sets instead of ordinary fuzzy sets to capture the information with stochastic uncertainties. The main differences between the proposed PFLS approach and most ordinary FLS or probabilistic methods are two-fold. 1) In the proposed PFLS approach, both of the nonstochastic and stochastic uncertainties are processed for sensor fusion and decision-making, while most of the existing results only focus on one of them. So the PFLS method can dramatically improves the performance of the measurement and reasoning for mobile robots, especially in unknown dynamic environments. 2) PFLS bridges the gap of the numerical sensory fusion and fuzzy reasoning, which provides an alternative way for the robot to acquire data-driven human-like intelligence. Hence PFLS will be more valuable for the processing of various uncertainties and the reactive navigation control of mobile robots.

In this paper, PFLS for range sensor is first proposed to process stochastic uncertainty and can effectively reduce the disturbance caused by stochastic uncertainty, so that the distance information can approximate to the actual measured values more accurately. Then these sensor data are sent to a probabilistic fuzzy rule-based inference system with reactive behaviors for the local navigation to attain better performance under uncertainty. The rest of the paper is organized as follows. The range measurement problem is formulated in Section 2 for reactive navigation of mobile robots. In Section 3, a general probabilistic fuzzy system is designed with range sensor based reactive behaviors for robot navigation. Both the simulative and experimental results on a real mobile robot are shown and analyzed to test the presented approach in Section 4. Conclusions are given in Section 5.

2. Problem Formulation

The robot employed in this study is a MT-R mobile robot. Its main sensors and configurations are shown in **Figure 1**. It is a two-wheel driven robot with 6 pairs of range sensors and each pair of sensors consists of an ultrasonic sensor and an infrared sensor. The detailed specifications of robot MT-R are listed as shown in **Table 1** and the configuration of the 6 pairs of range sensors is shown as in **Figure 1**.

To navigate the robot in a clustered environment, the mobile robot detects the surrounding environment and then decides the motion commands. The robot has six range sensor pairs and can detect the obstacles from six directions (**Figure 1**). So the inputs of the reactive navigation control system are the six obstacle distances d_f, d_{lf}, d_{rf}, d_l, d_r, d_b obtained from the front, left-front, right-front, left, right and back sensor pairs. The outputs are the motion commands to the two wheels with encoders. For MT-R, the sensitive range of the ultrasonic sensor is 0.2 m ~ 7 m and that of the infrared sensor is 0.1 m ~ 0.8 m. These two kinds of range sensors are always combined to detect the obstacles in front of them. As addressed in Section 1, the sensory inputs are always full uncertain. Moreover, the robot control system has to judge the input distance is "far" or "close" and to decide the output motion command is "forward", "turn left" or "back" and so on. To handle these vague and stochastic uncertainties,

Table 1. Specifications of mobile robot MT-R.

Specifications of Robot MT-R	
Dimensions	*Base: d* = 0.490 m *Height*: 0.495 m *Weight*: 30 kg
Motion Control	*DSP + CPLD* 2 *DC motors* (*MAXON* 24 V, 70 W) *with* 2 *shaft encoders* *Max speed*: 2.5 m/s
Exteroceptive Sensors	6 *sonar sensors:* *Resonance frequency* (20 KHz) *Sensitivity Range* (0.2 m ~ 7 m) 6 *infrared sensors*: *Measurement frequency* (100 HZ) *Sensitivity Range* (0.1 m ~ 0.8 m) *CCD camera* 1.3 M *pixel* 30 *frames/s* *USB interface*
Other equipments	*Wireless communication*: 54 M, *etc.*

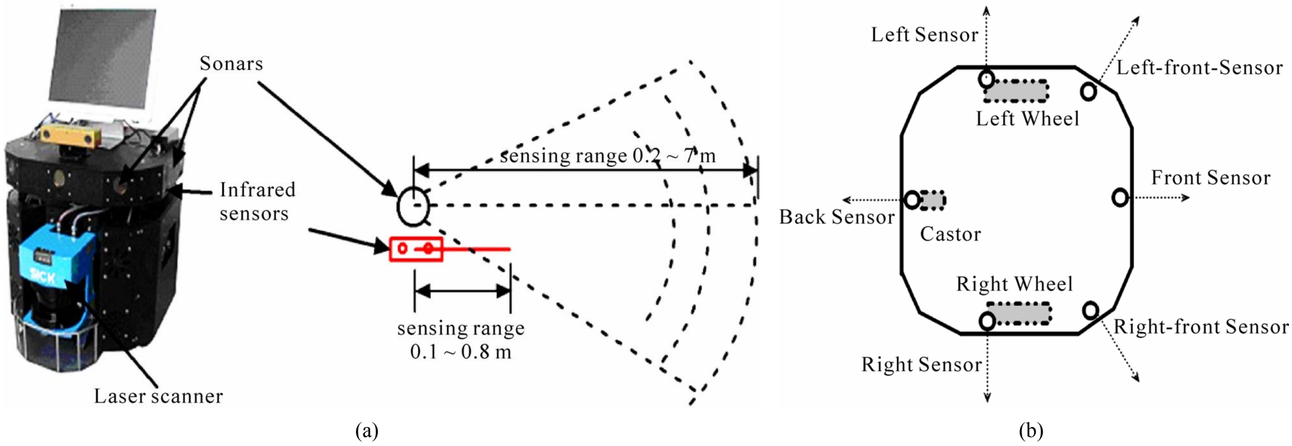

Figure 1. Mobile robot MT-R and its configurations. (a) MT-R mobile robot with rang sensors; (b) Configuration of Range sensors.

the probabilistic fuzzy approach is adopted as an integrated control scheme for the reactive navigation control of mobile robots in unknown environments.

Figure 2 shows three distance data measured by range sensor under different stochastic circumstances, respectively. For instance, Situation 1 represents the distance data under normal condition without any disturbance. Situation 2 expresses the data under man-made disturbances such as the movement of someone around the range sensor during measurement. Situation 3 presents the distance information with the disturbance of random noises. Under each of these stochastic conditions, the error $\varepsilon_i (i = 1,2,3)$ between actual measured distance and precise distance can be used for fuzzification with diverse membership function. In addition, each of the stochastic situations possesses a probability with a certain probabilistic distribution function in continuous case or discrete case. Due to the specific probability held by each of the stochastic uncertainties, PFLS for range measurement can be implemented to effectively reduce the measurement error caused by stochastic uncertainty.

3. Reactive Navigation with PFLS

Range sensors are most widely used for mobile robots to move autonomously with obstacle-avoidance. In this section, PFLS method is first introduced for processing the sensory inputs, and then an integral control scheme is designed and implemented to achieve robust and precise reactive navigation for mobile robots.

3.1. Probabilistic Fuzzy Logic System

Ordinary fuzzy logic is based on the theory of fuzzy set which is composed of discrete or continuous elements possessing degree of membership. An ordinary fuzzy set can be represented as a set $S = (I,U)$, where an input variable $x \in I$ and $u(x) \in U \subseteq [0, 1]$ is its fuzzy membership grade. If $I = \{x_1, x_2, \cdots, x_n\}$ and n is the number of the elements in fuzzy set, then the fuzzy set $S = (I,U)$ can be expressed as

$$S = (I,U) = \frac{u(x_1)}{x_1} + \frac{u(x_2)}{x_2} + \cdots + \frac{u(x_n)}{x_n} = \sum_{i=1}^{N} \frac{u(x_i)}{x_i}.$$

In comparison with the ordinary fuzzy logic system (FLS), a probabilistic fuzzy logic system (PFLS) similarly includes fuzzification, fuzzy rules, fuzzy inference and defuzzification. Nevertheless, the distinct difference of PFLS to FLS is that the fuzzification and defuzzification procedure are based on probabilistic fuzzy sets instead of ordinary fuzzy sets [25-27].

3.1.1. Fuzzification in PFLS

Definition (Probabilistic Fuzzy Set) *The probabilistic fuzzy set* $\tilde{S}$ *can be donated as a probability space of* $\tilde{S} = (S,P)$, *where* $S = \{S_j\} = \{(x, u_j) \ \ j = 1,2,\cdots,m\}$ *is the set of all possible events and* $x \in I$ *is the input variable. For all element event* $S_j \in S$

$$P(S_j) \geq 0,\ P(\Sigma S_j) = \Sigma P(S_j),\ P(S) = 1.$$

The probabilistic fuzzy set can be formulated as the union of the finite space as follows:

$$\tilde{S} = \bigcup_{x \in I} ((I,U),P)$$

In PFLS, the fuzzy membership grade $u(x)$ is a random variable with a certain probabilistic distribution function (PDF) $P(x,u(x))$. For example, **Figure 3** presents an instance of a discrete probabilistic fuzzy set $\tilde{S}$ in a three-dimension ordinary fuzzy space.

$$\tilde{S} = \bigcup_{i=1,2,3,4} ((I,u_i),P_i)$$

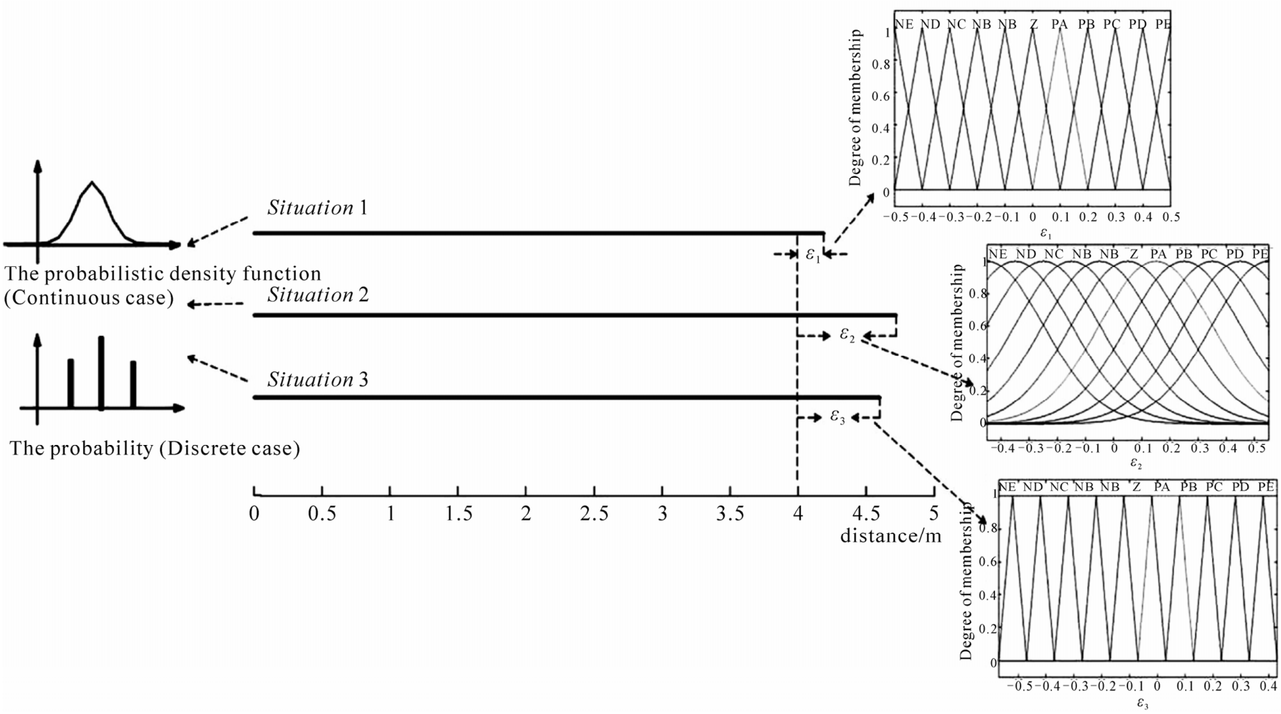

Figure 2. Demonstration of three measured distance data under different stochastic circumstances.

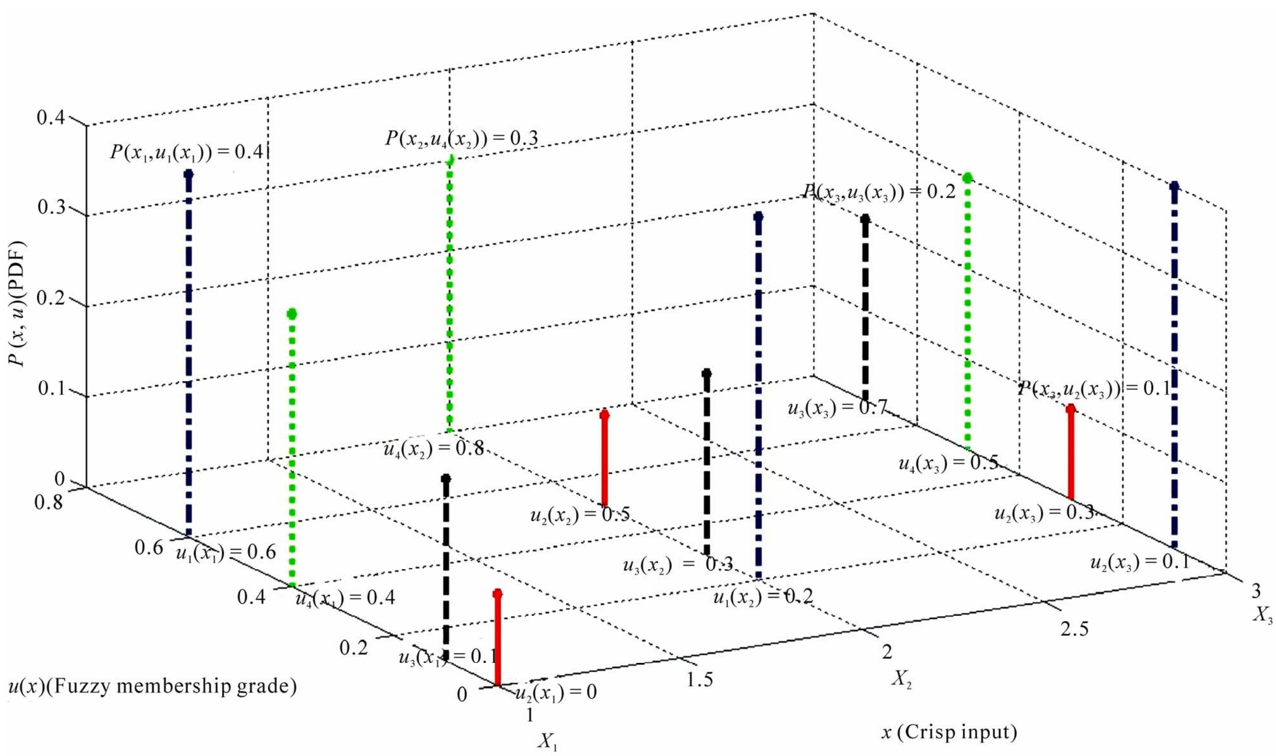

Figure 3. An instance of discrete probabilistic fuzzy set in three-dimension coordinate.

where $I = \{x_1, x_2, x_3\} = \{1, 2, 3\}$
$P_1 = 0.4$, $u_1 = \{0.6, 0.2, 0.1\}$; $P_2 = 0.1$, $u_2 = \{0, 0.5, 0.3\}$
$P_3 = 0.2$, $u_3 = \{0.1, 0.3, 0.7\}$; $P_4 = 0.3$, $u_4 = \{0.4, 0.8, 0.5\}$.

3.1.2. Inference in PFLS

The *j*th rule of a PFLS is usually expressed as follows:

Rule *j*: *IF* x_1 *is* $\tilde{A}_{1,j}$ *and* x_2 *is* $\tilde{A}_{2,j}$ *and* $\cdots$ *and* x_n

is $\tilde{A}_{n,j}$; *Then* q *is* $\tilde{B}_j$.
where $\tilde{A}_{i,j}(i=1,2,\cdots,n)(j=1,2,\cdots,m)$ *and* $\tilde{B}_j$ are probabilistic fuzzy sets. For more details, please refer to [25-27].

3.1.3. Defuzzification in PFLS

The method of probabilistic defuzzification is deduced from ordinary fuzzy sets. In ordinary FLS, it is usually used for defuzzification with a centroid calculation. However, the operation of defuzzification in PFLS is realized by computing centroid calculation with the association of the mathematical expectation.

For each possible input event, the output has a fuzzy set which has L elements that each element is assigned a value $v_k(k=1,2,\cdots,L)$ and every number is corresponding to a membership grade $u_v(x,v_k)(k=1,2,\cdots,L)$ where the input variable $x \in I=\{x_1,x_2,\cdots,x_n\}$. Thus, with the centroid calculation, the centroid output is obtained

$$v_d = \frac{\sum_{k=1}^{M} v_k u_v(x,v_k)}{\sum_{k=1}^{M} u_v(x,v_k)}$$

There are M possible events that each of them has an output $v_d(d=1,2,\cdots,M)$ through the defuzzification of centroid calculation, and accordingly the probability distribution is $P_d(d=1,2,\cdots,M)$. In the stochastic circumstance, the mathematical expectation v from v_d is used as the terminative output of PFLS

$$v = E(X(v_d)) = \sum_{d=1}^{M} v_d \times P_d$$

3.2. PFLS for Reactive Navigation

Generally, reactive navigation refers to the navigation control without map-building and global planning. In this paper, the reactive navigation system is designed to help the robot moves in a local area freely and safely. The robot used in our study is called MT-R as shown in **Figure 1**. It is a two-wheel driven mobile robot and takes range sensory data as inputs to detect the surrounding environment and try to seek free regions after processing these range data. So to achieve effective reactive navigation, firstly we have to adopt a range sensor data processing method to get more accurate range information; secondly suitable reactive behavior and decision-making approach should be designed to navigate the robot. In [28], the probabilistic fuzzy system has been shown to be effective to deal with both the nonstochastic and stochastic uncertainties in range measurement. In addition, PFLS is also a good candidate for the behavior control of mobile robots. Hence we present an integral reactive navigation approach based on range sensors using PFLS.

The overall reactive navigation system is described as **Figure 4**. For each control step, the range sensory date $\{d_f, d_{lf}, d_{rf}, d_l, d_r, d_b\}$ are first sent to a PFLS, after being processed, the outputs of range data are used for the reactive behavior control. For the details of the PFLS based method for range measurement, please refer to [28]. As for the reactive behavior, the decision-making is based on the range information $\{d_f, d_{lf}, d_{rf}, d_l, d_r, d_b\}$. Here three kinds of primitive behaviors are designed for the local navigation control: emergency behavior, obstacle-avoidance and goal-seeking. The reactive navigation task is decomposed in terms of all these primitive behavior that respond to the immediate sensory inputs.

Emergency behavior is directly added to the control system without probabilistic fuzzy inference to avoid collision with a dynamic obstacle or a stationary wall when a possible sensing failure. The emergency behavior has the priority to guarantee very safe navigation. When an obstacle is closer than a threshold and the robot has no time to avoid it while moving, the robot has to stop immediately and retreat from the imminent danger. The threshold distances are selected online according to the robot velocity.

Obstacle-avoidance has always been the basic ability to navigate in a local area. The distance information for obstacle-avoidance is gained by detecting the environment with range sensors $\{d_f, d_{lf}, d_{rf}, d_l, d_r, d_b\}$. If the threshold value $\delta = 0.15$ m is set as the safe distance and the maximum sensing range $L = 7$ m, then the obstacle-avoidance behavior is controlled by using a probabilistic fuzzy inference engine within the range $\delta \sim L$.

As for goal-seeking behavior, an autonomous robot has the ability of recognizing or knowing where the goal is. For the behavior of turning to goal or subgoal, the key is to recognize the goal and measure the distance between the robot and the goal. In this paper, the location of the goal is assumed to be known to the robot.

As shown in **Figure 4**, all of the behavior are implemented using the probabilistic fuzzy controller and the output data m_1 and m_2 refer to the control output after defuzzification for the two DC motors with encoders.

4. Experimental Results

To demonstrate the performance of the presented reactive navigation system based on PFLS, several groups of experiments are carried out using a simulated navigation platform and the real mobile robot MT-R, respectively.

Figure 5 shows the range measurement results for the

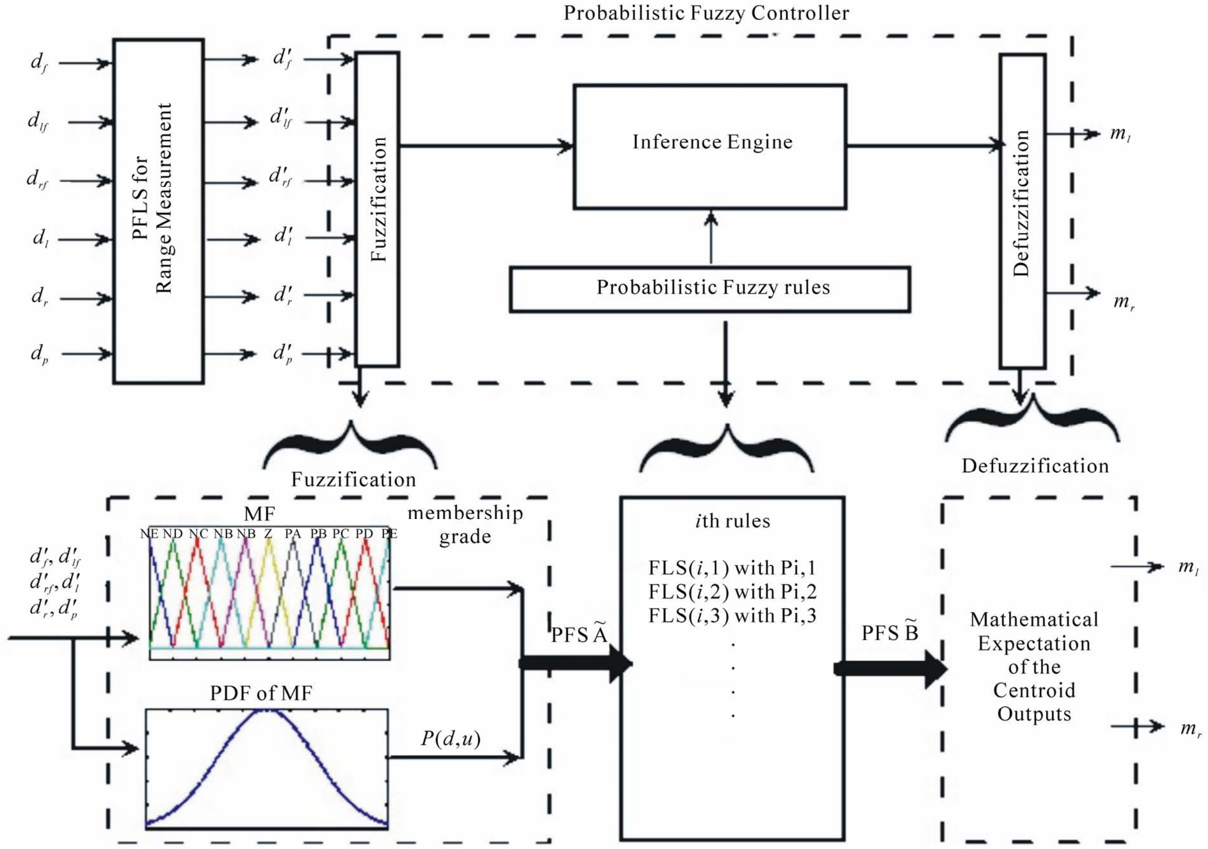

Figure 4. The PFLS controller for reactive navigation.

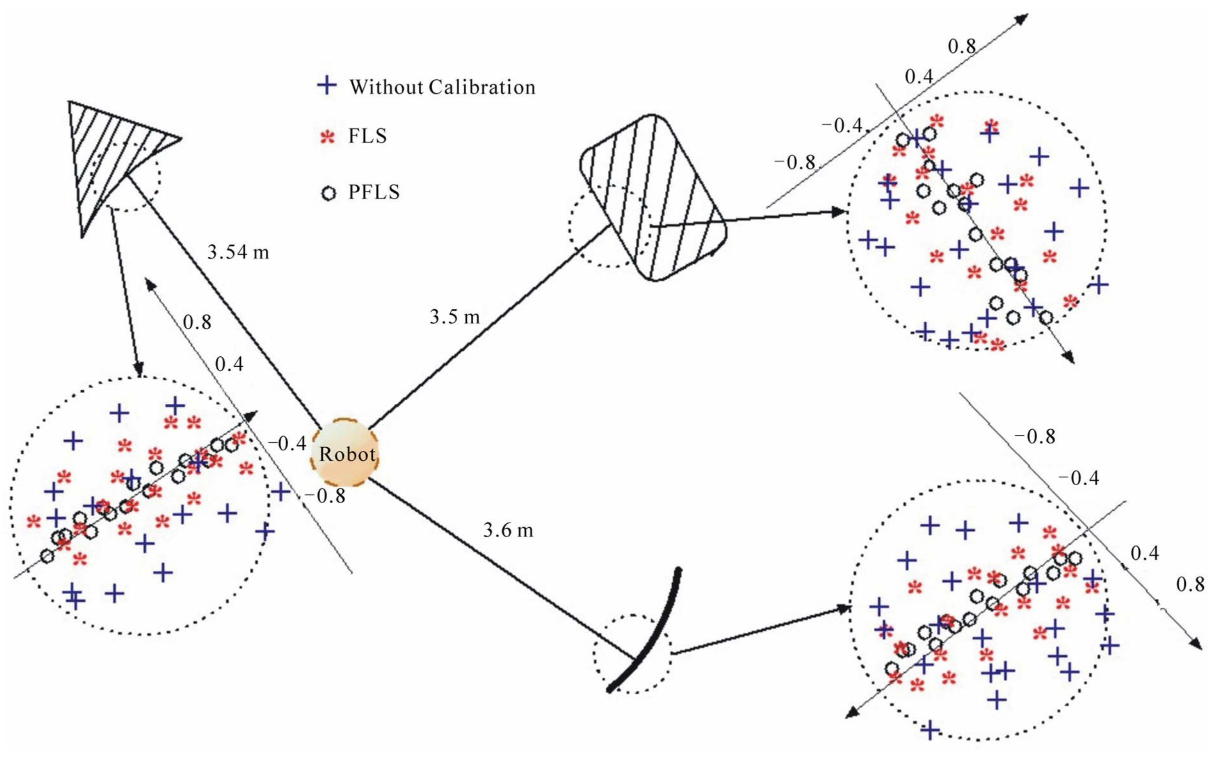

Figure 5. Experimental results of range measurement for mobile robots.

reactive navigation in a local environment. The performance of range measurement using PFLS is compared with the ordinary FLS method. It is clear that FLS can reduce the distance errors, but it can not process the stochastic errors and is difficult to further improve the range measurement performance. On the contrary, PFLS based range data processing method works better.

Figure 6 demonstrates the navigation results in the simulation environment, which is built up using Visual C++ with the setting of 600 × 400 (Grid representation). In each case, the environment is assumed to be completely unknown for the mobile robot except the start and goal states. The robot has to explore the environment using onboard range sensors. It is shown in **Figure 6** that the PFLS method navigates the robot more safely and effectively. Then we further test the reactive navigation performance on the real robot MT-R in our office building. As shown in **Figure 7**, the robot walks through a corridor with clustered obstacles quickly and safely. All these results also demonstrate the success and practicability of the proposed reactive navigation control approach.

5. Conclusions

PFLS has been demonstrated to be an effective approach to map the typical non-linear relation of input-output model with stochastic and fuzzy uncertainties. In this paper, PFLS is further extended to a general method for range measurement based reactive navigation. First, PFLS for range sensor is proposed to process stochastic uncertainty and can effectively reduce the disturbance caused by stochastic uncertainty, so that the distance information can approximate to the actual measured values more accurately. Then these sensor data are sent to a probabilistic fuzzy rule-based inference system with designed reactive behaviors for the local navigation. Both of the simulated experiments and the experiments on a real mobile robot MT-R show that the presented probabilistic fuzzy approach can help obtain more precise sensory information robustly and improves the performance of the reactive navigation in uncertain environments.

Our future work will focus on the application of PFLS to more sensor systems and the combination of robot learning systems. The probabilistc fuzzy rules of behavior-selection are mostly configured by experiences. It will be more useful and practical for the robot to adjust the existing control rules through learning.

6. Acknowledgements

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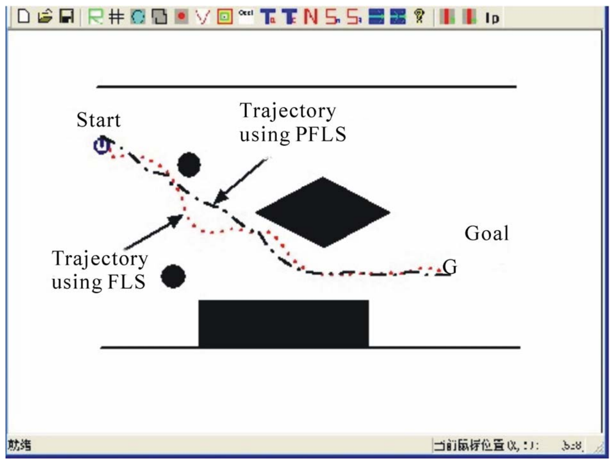

Figure 6. Simulated results of reactive navigation.

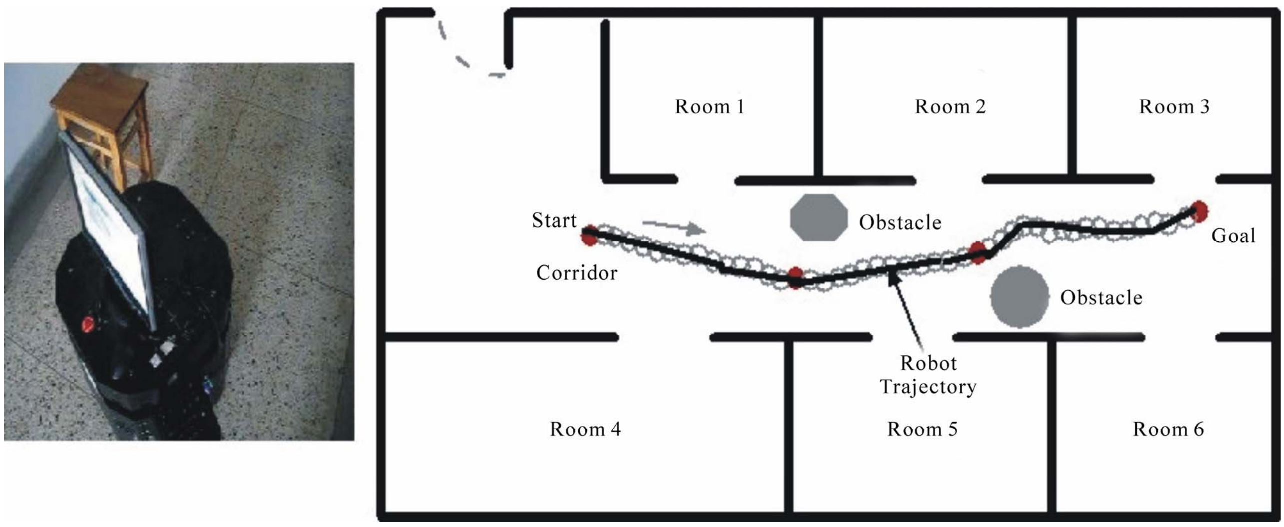

Figure 7. Performance demonstration of reactive navigation in a local environment using MT-R.

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