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Fuzzy Logic-based Navigation Strategy of Mobile Robots with Obstacle Avoidance
퍼지논리를 이용한 이동로봇의 장애물회피 항법전략

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요 약

이동로봇이 주위환경에 대해서 전혀 알지 못하고 목표점으로 주행할 때, 로봇은 긴 장애물이나 오목한 장애물에 대해서 존재할 수 있는 국부최소점에 빠져 더 이상 진행을 못하는 문제가 발생할 수 있다. 본 논문에서는, 이 문제를 해결하기 위하여 퍼지 이론을 사용하여 효율적인 장애물회피와 안정된 목표점 도달을 달성할 수 있도록하는 알고리즘을 제시한다. 제시된 알고리즘은 상하 2층 구조로 되어 있으며, 하위층은 장애물 회피 알고리즘 및 목표점 접근 알고리즘으로, 그리고 상위층은 로봇이 이동하면서 변화하는 환경에 맞게 앞의 두 알고리즘에 적절한 가중치를 부여하는 가중치 부여 알고리즘으로 구성되어 있다. 본 논문에서 제시된 알고리즘의 타당성을 보이기 위하여 'ㄹ', 'ㅊ' 형태의 장애물 및 여러 가지 형태의 장애물이 복합적으로 존재하는 환경에서 모의실험을 행한 결과, 만족할 만한 결과를 얻을 수 있었다.

Abstract

This paper deals with a fuzzy logic-based local navigation strategy for mobile robots in an unknown and cluttered environment. The proposed algorithm has two-layered hierarchical structure such as a lower layer for collision avoidance and goal approach, and an upper layer for the adaptive combination of these two logics. Fuzzy rules for collision avoidance, goal approach, and those for adjusting a weight to combine the above two behaviors effectively are introduced. Some computer simulation results for a mobile robot equipped with three range sensors show that the suggested navigation algorithm is very effective to escape from local minima under unknown environment.

1. Introduction

The primary goal of navigation of mobile robots in real environments is to reach to their targets without collisions with obstacles on the way. To that purpose, numerous approaches such as potential field methods, roadmap methods (e.g., visibility graph method, Voronoi diagram, freeway net and silhouette) and cell decomposition methods have been proposed and are being studied whether those are global or local [1,2,3,9]. We focus our attention on local navigation, in which the environment surrounding the robot is completely or partially unknown and the robot should avoid the obstacles using information obtained from the equipped sensors, of stationary obstacles.

A reactive approach which is simple to implement and fast in response may be the most conventional approach. In potential field methods which are the most efficient and successful example of the reactive approach, a robot represented as apoint in navigations pace travels in a field of attractive force produced by obstacles, repulsive force by atarget and their combinations. Robot motion commands such as distance and direction are determined by the cumulative effect of all of those forces. However, the potential field methods have their inherent limitations as local minima and oscillations since they are the steepest decent optimization methods[2].

Besides these conventional algorithms to overcome these demerits, some new approaches based on intelligent algorithm such as fuzzy logic, neural networks, expert systems, or genetic algorithms are hot issues on it. Despite of their difficulty to prove stability or convergence, their logical simplicity and flexibility encourage to use them on the navigation strategy of mobile robots. Chohra[4] suggested an efficient multi-layed neuro-fuzzy algorithm. Benreguieg [5] proposed a sensor-based navigation algorithm based on the fusion of elementary behaviors using fuzzy logic and neural networks. Pal[6] applied neural network to avoid long or non-convex obstacles on navigation of the mobile robot. Dubrawski[7] introduced a combined fuzzy and neural network for unknown environment navigation. Qiu[8] suggested a genetic algorithm for the identification of membership functions of fuzzy algorithm.

It is highly recommended to use a simple algorithm for autonomous behavior capability of the mobile robot. Fuzzy logic successfully applied to the control of uncertain and complex processes has provided the paradigm that it would be possible to control uncertain and complex systems without recourse to mathematical models as like as humans do. Robustness of fuzzy algorithm compensates for the data with poor resolution and reliability from range sensors.

We consider the fuzzy logic-based navigation of a mobile robot equipped with three range sensors to measurethe distance between the robot and obstacle in an unknown environment. The mobile robot is assumed to be a point for simplicity without loss of generality.

2. Fuzzy Logic-based Navigation

As stated in the previous section, the major draw back of potential field methods is that they can be trapped into local minima when the robot runs into a dead end (e.g., inside a U-shaped obstacle), since they are the steepest decent optimization methods. One approach for dealing with local minima is to design potential functions that have no local minima except only one global optimum. But it is difficult to apply itto problems involving uncertain and high-complex navigation space due to the unknown, cluttered and dynamic environments. Another approach is to complement the basic potential field method with mechanisms (e.g., random motions at local minima, motion commands based on the context encountered by the mobile robot, and heuristic recovery rules) to escape from thelocal minima.

In this paper, the latter approach is applied to the navigation of mobile robots. Among four behaviors developed so far, obstacle avoidance and goal reaching behaviors will be used for the navigation with avoiding obstacles. As shown in Fig. 1, the proposed navigation algorithm has two-layered hierarchical structure such as a lower layer for collision avoidance and goal approach, and an upper layer for thead aptive combination of these two behaviors. Fuzzy rules for collision avoidance, goal approach, and those for adjusting a weight to combine the above two behaviors effectively are introduced. The basic concept of the proposed algorithm may be summarized as the emulation of human-like qualitative reasoning scheme with adaptive combination of elemental behaviors.

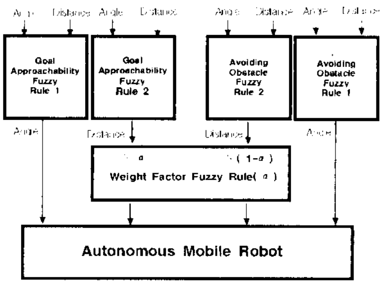


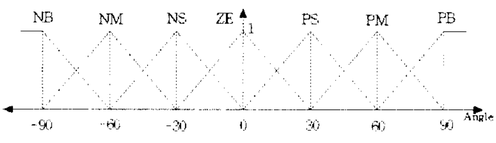
Fig. 1. Block diagram of the proposed algorithm.

2.1 Fuzzy rules for goal approach

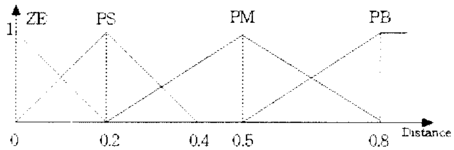
This rules enable the robot to approach its goal point without obstacles directly by reducing its mobility around its destination. We consider two variables such as observability variables and adjustment variables. The observability variables consist of the angle and distance between the robot and the goal point. The adjustment variables are the angle and the distance for the robot to move. The basic idea for the rules is as follows. The robot tries 1) to face onthe goal point 2) to approach to the goal point with a rate which is proportional to the distance between the robot and the goal point.

2.1.1 Angle generating fuzzy rules for goal approach

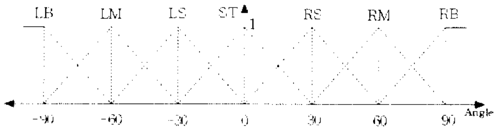
The first observability variable is the angle between the robot and the goal point. Just for simplicity, clockwise angle is assumed to be positive. The next observability variable is the distance between the robot and the goal point. The adjustment variable describes for the angle for the robot to rotate. Fig 2 shows membership functions for the each observability variables and the adjustment variable. Angle generating fuzzy rules for goal approach is summarized in Table 1.



(a) Membership function of the angle between the robot and goal point.



(b) Membership function of the distance between the robot and goal point.



(c) Membership function of the adjustment variable.

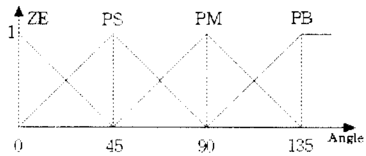
Fig. 2. Membership functions of the angle for goal approach.

Table 1 Fuzzy rules for the angle and the distance between the robot and goal point

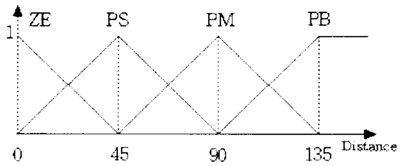
Dist / Angle	ZE	PS	PM	PB
NB	LB	LB	LB	LM
NM	LB	LM	LM	LS
NS	LM	LM	LS	LS
ZE	ST	ST	ST	ST
PS	RM	RM	RS	RS
PM	RB	RM	RM	RS
PB	RB	RB	RB	RM

2.1.2 Distance generating fuzzy rules for goal approach

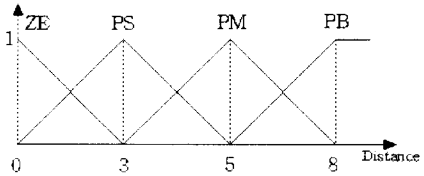
It consists of two variables such as absolute angle and distance between the robot and the goal point. The adjustment variable describes for the distance for the robot to move. Fig.3shows their membership functions respectively. Table 2 shows the distance generating fuzzy rules for goal approach.



(a) Membership function of the angle between the robot and goal point.



(b) Membership function of the distance between the robot and goal point.



(c) Membership function of the distance between the robot and goal point.

Fig. 3. Membership functions of the distance for goal approach.

Table 2 Rules for the angle and distance between the robot and goal point

Angle \ Dist	ZE	PS	PM	PB
ZE	PS	PM	PB	PB
PS	PS	PM	PB	PB
PM	ZE	PS	PS	PS
PB	ZE	PS	PS	ZE

2.2 Fuzzy rules for avoiding obstacle

This fuzzy rule is for the robot to avoid the obstacles on its navigation. The robot is equipped with three sensors to measure the distance between the robot and obstacle. The observability variables are the distance between the obstacle and the robot and the angle between the goal point and obstacle from the robot. The adjustment variables consist of the angle and the distance for the robot to move for avoiding the obstacles.

2.2.1 Angle generating fuzzy rules for avoiding obstacle

The collision avoidance rule is motivated by the human knowledge obtained from cases between the robot and obstacle as shown in Fig. 4.

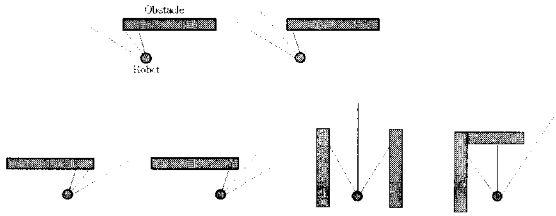
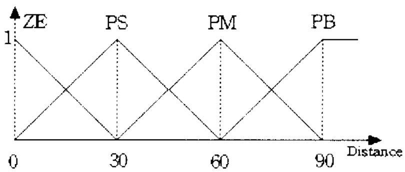
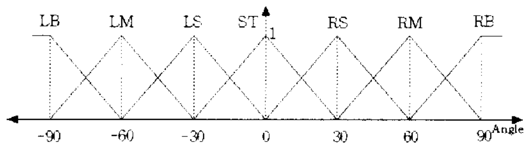


Fig. 4. Some cases between the robot and obstacle.

Fig. 5 shows the membership function of the distance measured with each sensor, and the membership function of the adjustment variable of the angle to avoid collision with the obstacle.



(a) Membership function of the distance measured with a sensor.



(b) Membership function of the adjustment.

Fig. 5. Membership functions of the angle to avoid collision with the obstacle.

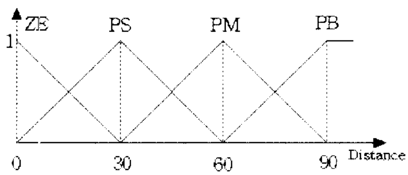
Table 3 describesthe fuzzy rules to avoid the collision with the obstacle. The observability variables consist of distance between the robotand the obstacle measured by three sensors. The adjustment variable is the angle for the robot to move to avoid the collision with the obstacle.

Table 3 The fuzzy rule to avoid the collision with the obstacle

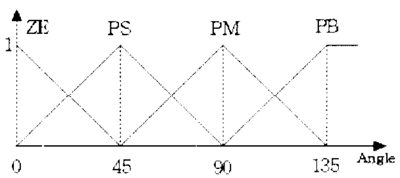
S0		ZE				PS				PM				PB			
S2		ZE	PS	PM	PB	ZE	PS	PM	PB	ZE	PS	PM	PB	ZE	PS	PM	PB
S1	ZE	RB	RB	RM	RM	LM	LM	RS	RM	LM	LM	LS	RS	LB	LM	LS	ST
	PS	RM	RM	RS	RM	LM	LS	RS	RM	LM	LS	ST	RS	LM	LM	LS	ST
	PM	ST	RS	RS	RS	LS	ST	RS	RS	LS	LS	ST	RS	LS	LS	ST	ST
	PB	ST	ST	ST	RS	LS	ST	ST	RS	ST	ST	ST	ST	LS	ST	ST	ST

2.2.2 Distance generating fuzzy rules for avoiding obstacle

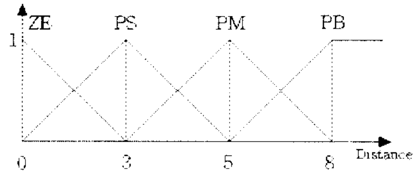
The observability variable of the rule is the angle between the goal point and the closest point of the obstacle measured by three sensors. Fig. 6 shows the membership function of the closest distance measured by the sensors, that of the angle between the goal pointand the closest point ofthe obstacle measured by the sensor from the robot, and that of the adjustment variable to avoid the collision avoidance with the obstacle, respectively.



(a) Membership function of the closest distance measured by the sensors.



(b) Membership function of the angle.



(c) Membership function of the adjustment variable.

Fig. 6. Membership functions of the distance to avoid collision with the obstacle.

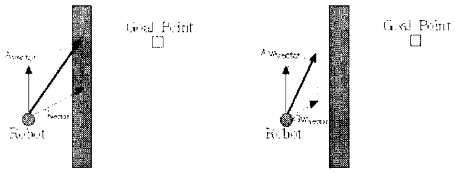
Table 4 depicts the fuzzy rules to generate the distance to avoid the collision with obstacle.

Table 4 Fuzzy rules of the distance to avoid collision with obstacle

Dist / Agle	ZE	PS	PM	PB
ZE	ZE	PS	PS	PM
PS	ZE	PS	PM	PM
PM	ZE	PM	PM	PB
PB	PS	PM	PB	PB

2.3 Fuzzy rules for combination of elemental behaviors

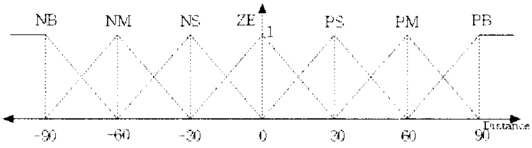
When the robot is moving for successful navigation, the appropriate weight factor to the fuzzy rules of the goal approach and collision avoidance is given by the rules. Depending on the existence of obstacles, the size of weight factor is adjusted for both goal approach and obstacle avoidance rule. Both of the fuzzy rules for goal approach and collision avoidance generate angle and distance. The robot navigation command is based on the sum of their vectors such as approaching vector (Gvector) and collision avoidance vector (Avector) as shown in Fig. 7.



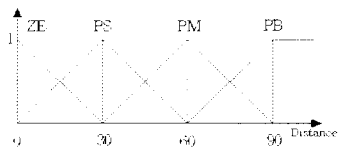
(a) (b)

Fig. 7. The sum of the two vectors.

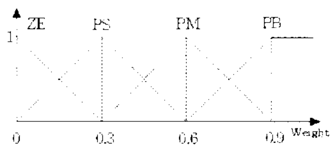
By applying the weight factor to the basic fuzzy rule, the rule is enhanced to avoid the collision as shown in Fig. 7(b) differently form (a). It helps the robot escape from its local minima. Besides, it enables the robot to arrive at its destination safely by diminishing its mobility around goal point. The observability variables are the closest distance between the robot and the obstacle, and the difference between the distance to the goal point and the closest distance to the obstacle. Fig. 8 shows the membership function of the observability variable of the fuzzy rules for weight factor, and that of the adjustment variable of the fuzzy rule for weight factor which has the value between 0 and 1.



(a) Membership function of the difference between the distance to the goal point and the closest distance to the obstacle



(b) Membership function for the closest distance to the obstacle.



(c) Membership function of the adjustment variable.

Fig. 8. Membership functions of fuzzy rules for combination of elemental behaviors.

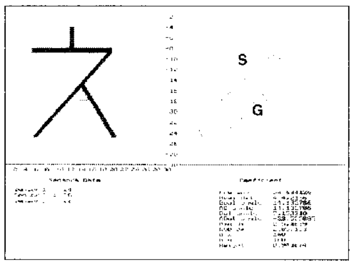
Table 5 describes the fuzzy rules for combination of elemental behaviors.

Table 5 Fuzzy rule for combination of elemental behaviors

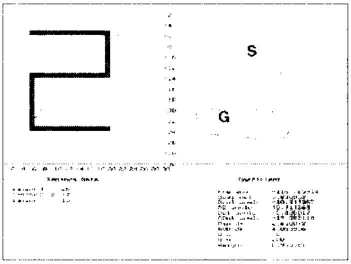
Dist1 \ Dist	NB	NM	NS	ZE	PS	PM	PB
ZE	ZE	ZE	PS	PS	PM	PM	PB
PS	ZE	PS	PS	PM	PM	PB	PB
PM	PS	PM	PM	PM	PB	PB	PB
PB	PM	PB	PB	PB	PB	PB	PB

3. Simulation results

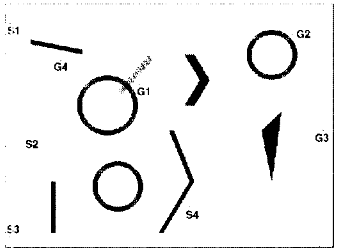
In the simulation, therobot is assumed as a point and equipped with 3 range sensors whose maximum measuring distance is 100 pixel and the angle between adjacent sensors is 30 degree. As shown in Fig. 9, in which S denotes a starting point, G denotes a goal point and the dotted line from S to G denotes the trajectory of the mobile robot, the robot approaches to its goal point when it confronts the non-convex obstacles such as ㅊ, ㄹ types andlarge non-convex or scattered obstacles. As expected, the robot successively navigates without collision among large non-convex or scattered obstacles with local minima as shown in Fig. 9.



(a) Navigation for ㅊ type obstacle.



(b) Navigation for ㄹ type obstacle.



(c) Navigation for variously shaped obstacles.

Fig. 9. Simulation results.

4. Concluding Remarks

A fuzzy logic-based local navigation strategy to avoid local minimain the navigation of mobile robots under unknown and cluttered environments has been proposed. The proposed algorithm had two-layered hierarchical structure such as a lower layer for collision avoidance and goal approach, and an upper layer for the adaptive combination of these two logics. Fuzzy rules for collision avoidance, goal approach, and those for adjusting a weight to combinethe above two behaviors effectively were introduced. Some simulation results show that the suggested algorithm is very effective in avoiding the local minima. Combining fuzzy algorithm with other intelligen tones such as neural network or genetic algorithm is highly recommended as a further research. The navigation research on moving obstacles is on the way.

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