Path Generation of a Differential Mobile Robot Using Fuzzy Inference system

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Abstract. This paper deals with the development of an efficient Fuzzy Inference System (FIS) based architecture for mobile robot navigation. While developing the system architecture, kinematic constraints have been considered for a differential drive mobile robot. During the analysis, robot chassis is considered as a rigid body and the position of the mobile robot is represented as a point in XY- plane. The developed kinematic models are useful to find out the robot's velocities (X-direction, Y-direction & angular). The proposed fuzzy model requires two inputs: (1) the distance between the robot and the obstacles in the environment and (2) position of the target i.e. the robot heading angle towards the destination. Once the system gets the knowledge from the environment, it will obtain the suitable steering angle for an autonomous mobile robot. This process will be continued until the robot reaches its goal. Simulation and experimental results are presented to verify the effectiveness of the proposed methodology for an autonomous mobile robot.

Keywords: Design For Assembly, Assembly Sequence Planning, Assembly Constraints, Firefly Algorithm, Computer Aided Design (CAD).

1 Introduction

Navigation related to mobile robots is moving towards the goal while avoiding local obstacles. Numerous researches have been devoted to this area within the last decades [1-3]. A fuzzy inference system is a connection of parallel disseminated processing elements in a graph topology. Several researchers have been used fuzzy techniques for solving mobile robot path planning problem [4,5].

This methodology consists of two fuzzy inference: first fuzzy inference is used to determine the "free" space using ultrasound range finder data and the second fuzzy inference "finds" a safe direction for the next robot section of the path in the workspace while avoiding the nearest obstacles. Deepak & Parhi [6] have outlined a new approach to solve mobile robot navigation by formulating it as an optimization problem. Syed et al. [7] have recently developed efficient system architecture for solving motion planning of an autonomous vehicle to navigate in noisy and unknown environments without colliding any obstacles in its path. The proposed system architecture works the help of two multilayer feed forward fuzzy inference controllers namely 'Hurdle Avoidance Controller' and 'Goal Reaching Controller' with back error propagation as training algorithm. Past research found that fuzzy inference system has been integrated with other techniques for obtaining better results in robot motion planning problem [8,9].

In this paper an efficient inference based system architecture has been introduced to solve path planning of a differential mobile robot. Moreover, kinematic model for a differential drive robot have been analyzed in order to obtain the next iterative position of the robot within its unknown static environment. Finally results are presented, how a differential robot can generate a collision-free paths in various robotic unknown environment.

2 Kinematic Model of a Differential Robot

In order to specify the position of a robot on the plane, it is necessary to develop a relationship between the global reference frame of the plane with the robot chassis as shown in Fig.1. Let the global reference frame $\boldsymbol{O}:\{\boldsymbol{X_I},\boldsymbol{Y_I}\}$ to specify the position of the robot. Consider a point P on the robot chassis as its position reference point with respect to the robot's local reference frame $\{\boldsymbol{X_R},\boldsymbol{Y_R}\}$. The position of P in the global reference frame can be specified by the coordinates x and y, and the angular difference between the global and local reference frames is given by θ:

$$\xi_I = [x \quad y \quad \theta]^T \tag{1}$$

And mapping is accomplished using the orthogonal rotation matrix:

$$R(\theta) = \begin{bmatrix} cos\theta & sin\theta & 0 \\ -sin\theta & cos\theta & 0 \\ 0 & 0 & 1 \end{bmatrix} \tag{2}$$

From equation (2) we know that we can compute the robot's motion in the global reference frame from motion in its local reference frame.

$$\xi_R = R(\theta)\xi_I \text{ and } \dot{\xi}_R = R(\theta)\dot{\xi}_I \tag{3}$$

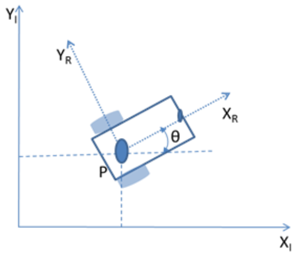


Fig.1 representation of global and local reference frame

1.1 Kinematic Constraints of Wheel Configuration

While a differential robot is in movement, two constraints may possible. The first constraint enforces the concept of rolling contact and the second constraint enforces the concept of lateral slippage. The aim of the designer is to avoid lateral slippage while the robot is motion.

Generally, a differential mobile robot has two motorized fixed standard wheels and one non-motorized caster wheel. The fixed standard wheel has no vertical axis of rotation for steering. Its angle to the chassis is thus fixed, and its motion is limited to back and forth along the wheel plane and rotation around its contact point with the ground plane. Fig.2 depicts a fixed standard wheel and its position is expressed in polar coordinates by distance l and angle α. The angle of the wheel plane relative to the chassis is denoted by β.

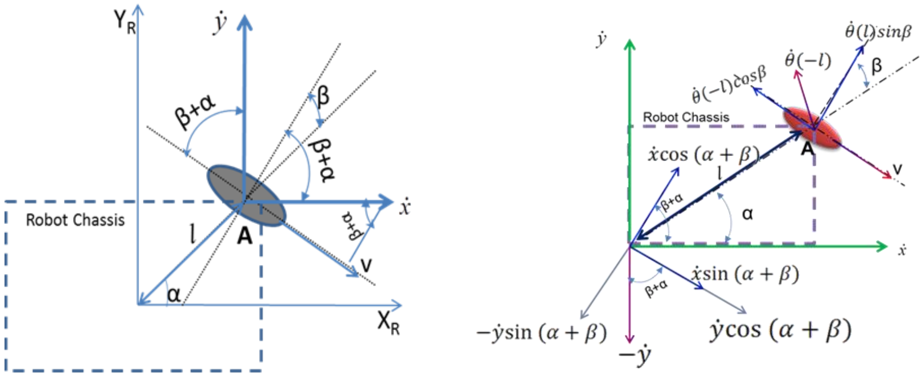


Fig.2 Fixed standard wheel and its parameters

The fixed standard wheel has two motion constraints as follows:

i). The rolling constraint for this wheel enforces that all motion along the direction of the wheel plane must be accompanied by the appropriate amount of wheel spin so that there is pure rolling at the contact point:

$$[\sin(\alpha+\beta) \quad -\cos(\alpha+\beta) \quad (-l)cos\beta] * R(\theta)\dot{\xi}_I - r\dot{\varphi} = 0 \qquad (4)$$

ii). The sliding constraint for this wheel enforces that the component of the wheel's motion orthogonal to the wheel plane must be zero:

$$[\cos(\alpha+\beta) \quad \sin(\alpha+\beta) \quad l\, sin\beta]R(\theta)\dot{\xi}_I = 0 \qquad (5)$$

The configuration of the robot can be expressed1 by the following vectors of coordinates.

Posture coordinates: $\xi_I = [x(t) \quad y(t) \quad \theta(t)]^T$

Angular coordinates: β_{f1} and β_{f2} are the wheels of differential respectively

Rotational coordinates: $[\varphi_{f1}(t) \quad \varphi_{f2}(t)]^T$ for the rotation angles of the wheels around their horizontal axis of rotation.

The rolling constraints of all wheels can now be collected in a single expression:

$$J_1(\beta)R(\theta)\dot{\xi}_I - J_2\dot{\varphi} = 0 \qquad (6)$$

Where, J_2 is a constant diagonal matrix $N\ x\ N$ whose entries are radii r of all standard wheels. $J_1(\beta)$ denotes a matrix with projections for all wheels to their motions along their individual wheel planes.

We use the same technique to collect the sliding constraints of all standard wheels into a single expression with the same structure.

$$C_1(\beta)R(\theta)\dot{\xi}_I + C_2\dot{\beta}_S = 0 \qquad (7)$$

From equation (6), the rolling constraints of all wheels can be expressed. Therefore the velocity of the robot can be determined by using equation (8).

$$\Rightarrow \xi\ I = R\ (\theta)^{-1} j_{1f}^{-1} j_2\ (\varphi) \qquad (8)$$

3 Sugeno Fuzzy Model

The fuzzy inference system is a popular computational method developed based on the concepts of fuzzy set theory, fuzzy if-then rules, and fuzzy reasoning. The basic configuration of a fuzzy inference system comprises of three theoretical components:

- a rule base - which contains a set of fuzzy rules;
- a database - which identifies the membership functions used in the fuzzy rules
- a reasoning mechanism - which performs the inference process for the rules and gives details to derive a suitable conclusion.

The fuzzy inference system can receive either fuzzy inputs or crisp inputs but the outputs it obtains are almost fuzzy sets as shown in Fig.4.

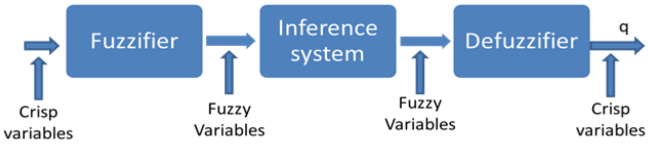


Fig.3. The structure of the fuzzy logic control

The Sugeno fuzzy inference system was introduced as the first effort to control a steam engine and boiler arrangement by a set of linguistic control rules obtained from human experience. Basic two-rule Sugeno fuzzy inference system is shown in Fig.4 which derives the overall output z when subjected to two crisp inputs 1 and 2.

The rules for Sugeno fuzzy model are considering as follows:

If input-1 is A and input-2 is B then z=f(x,y)

Defuzzification means the way of a crisp value is takeen out from a fuzzy set as a representative value. For Sugeno fuzzy system, defuzzification approach is not necessary and the weighted average can be calculated as follows:

$$z = \frac{W_1 * Z_1 + W_2 * Z_2}{W_1 + W_2} \quad (9)$$

Where Z is the weight aggregated output membership function

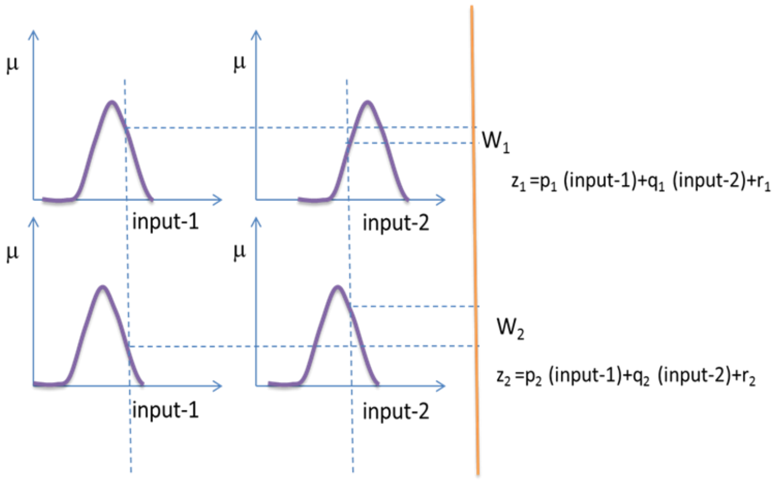


Fig.4 Sugeno Fuzzzy inference system with two inputs and one output

4 Generalized Bell Membership Functions

This type of membership functions (MF) are indicated by three parameters {a, b, c}:

$$\mathrm{bell}(\mathrm{a}, \mathrm{b}, \mathrm{c}) = \frac{1}{1+\left|\frac{x-c}{a}\right|^{2b}} \quad (10)$$

The parameters ‘a’ for width of the MF, and b is a positive value for representing slope of the curve and ‘c’ for centre of MF. In this paper, two inputs and one output are considering; the membership values for these are the bell-MF.

4.1 Member Ship for First Input

The fuzzy system is taking the sensory information as the inputs from the environment and the suitable steering angle gives as the output. The first input parameter is the distance between the nearest obstacle and the robot. Let us assume the maximum possible distance can be sensed by the robot is 180cm. So the MF values are varying from 0cm to 180cm and is represented by 'ROB'. Five linguistics are considered for this variable varying from V_high to V_low to form the rules.

4.2 Member ship for second input

Let the system is working in first quadrant so the target angle is varying from 0^0 to 90^0 ($\Pi/2$) and the membership functions are represented by T_angle. Five linguistics are considered for this variable varying from V_high to V_low to form the rules.

4.3 Member ship for output

Like the same condition output as the steering angle also varying from 0^0 to 90^0 ($\Pi/2$) and the membership functions are represented by S_angle. Five linguistics are considered for this variable varying from V_high to V_low to form the rules.

5 Simulation Results

Fuzzy logic controller for the motion planning of a mobile robot has been developed in MATLAB 2008 version. Figs. 5-6 represent collision free trajectories of an intelligent mobile robot in unknown environment.

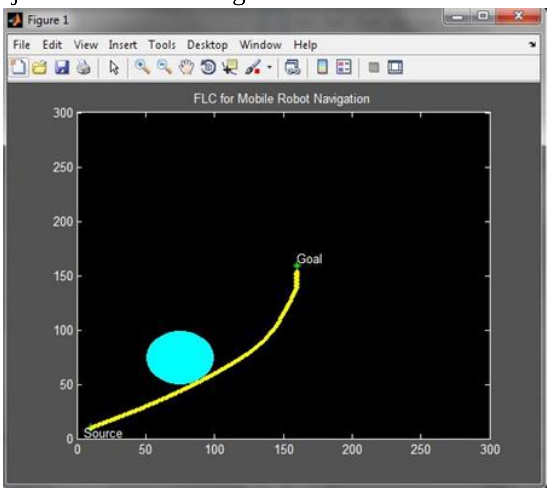


Fig.5 Single obstacle – single target environment

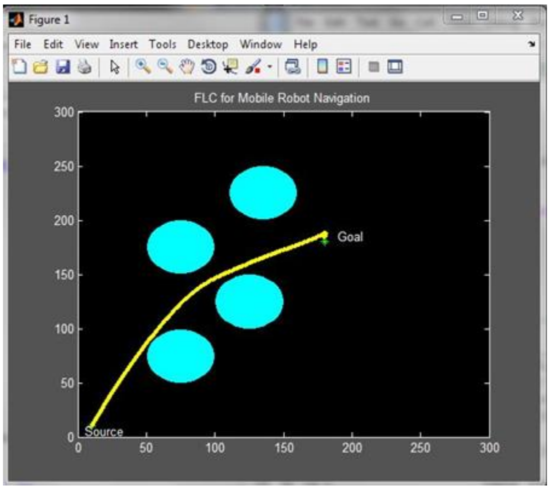


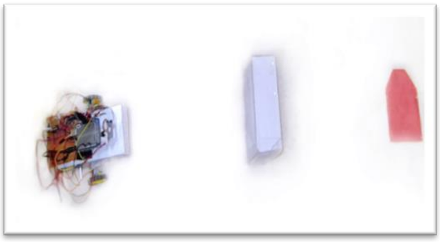
Fig.6 Multi obstacle – single target environment

6 Experimental Results

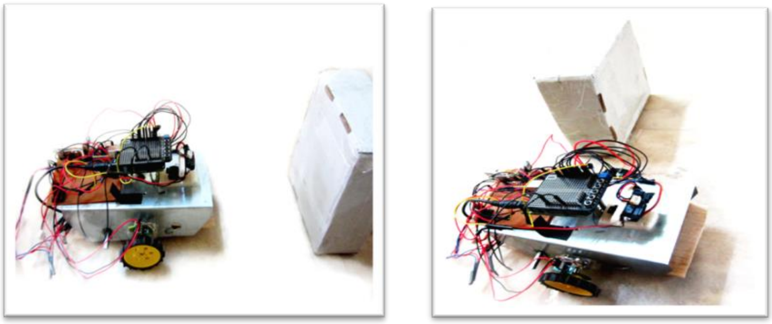
Experimental analysis has been conducted in order to validate the feasibility of the proposed methodology. The necessary equipment used for modeling an autonomous mobile robot:

- *Microcontroller* – ATMEGA 328 is used for PWM generation for servo motor control, data acquisition, sensor reading and data transferring.
- *Obstacle Sensor* - GP2DY Infrared Distance sensor is used, which can detect the obstacles based on the triangulation method.
- *Position Encoder* – It is used for determining position and velocity of the wheel.
- *Magnetic Compass* – It is interfaced using I2C communication which determines the direction of the robot.
- *L2938* – It's a motor driver which helps in controlling the speed of the DC motor.

The developed differential drive robot and its operation in real time environment is represented in Fig.7. The robot reached its target position in 100sec. while moving with a velocity of 10cm/sec.

a) Developed differential mobile robot and b) its source, goal and obstacle in



c) Obstacle avoidance in robotic search space

d) Robot reached its target within its search space

Fig.6 Path generated in real robotic environment and its different positions.

7 Conclusion

New efficient system architecture has been modelled based on fuzzy inference system for solving mobile robot navigation. The proposed system architecture works on the Sugeno fuzzy type and bell shape membership functions has been considered. To obtain feasible path within the robotic work space, fuzzy inference system has modelled with two input parameters and one output parameter. By obtaining the proper steering angle, the mobile robot reaches its goal by avoiding obstacles within its free environment. From the simulation results it has been concluded that the robot can generate optimal collision free paths using the proposed methodology. Although the developed algorithm is suitable for generating collision free trajectories within its environments, it is required to apply more number of rules and fine tune of membership values in order to obtain better results.

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