Efficient Object Motion Prediction Using Adaptive Fuzzy Navigational Environment

Vijay S. Rajpurohit[1] and M.M. Manohara Pai[2]

[1] Gogte Institute of Institute of Technology, Belgaum, India
vijaysr2k@yahoo.com
[2] Manipal Institute of Institute of Technology, Manipal, India
mm.pai@rediffmail.com

Abstract. This paper proposes an adaptive Fuzzy rule based motion prediction algorithm for predicting the next instance position of a moving object. The prediction algorithm is tested for real-life bench-marked data sets and compared with existing motion prediction techniques. Results of the study indicate that the performance of the predictor is comparable to the existing prediction methods.

Keywords: Short Term Motion prediction, Rule base Optimization, Fuzzy Predictor algorithm, Adaptive navigational Environment.

1 Introduction

Short term Object motion prediction in a dynamic Robot navigation environment refers to, the prediction of next instance position of a moving object based on the previous history of its motion. Research literature has addressed solutions to the short term object motion predictions with different methods such as, Curve fitting or Regression methods, Neural network based approaches, Hidden Markov stochastic models, Bayesian Occupancy Filters, Extended Kalman Filter and Stochastic prediction model[1][2][4]6[7]. The design of a navigational model in an automated mobile Robot system is influenced by its specific applications, the environment in which it operates and the sensory system. Many navigational model representations have been proposed, tested and implemented[3].

Based on the literature survey it is observed that i) The existing models lack flexibility in handling the uncertainties of the real life situations. ii) Probabilistic models sometimes fail to model the real-life uncertainties. iii) The existing prediction techniques show poor response time due to their complex algorithmic structure. iv) Most of the approaches validate the results with simulated data.

The present work provides a novel solution for short term motion prediction using adaptive Fuzzy prediction technique. History of moving object motion positions are captured in the form of Fuzzy rule base and the next instance object position is predicted using fuzzy inference process. Because of the multi valued nature of fuzzy logic this approach enjoys high robustness in dealing with noisy and uncertain data.

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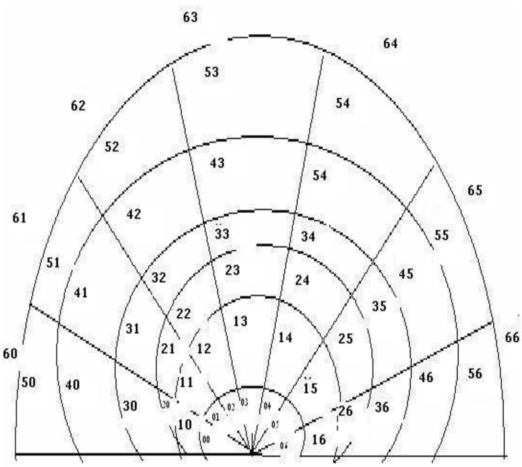
However, direct implementation of the rule base is not suitable for real-life navigation systems due to the formation of huge number of rules. To overcome this drawback rule-base is optimized by adaptive navigational environment.

2 Fuzzy Rule Based Object Motion Prediction

The navigational environment is modeled as Fuzzy World model [3] which can be observed in most of the applications. The Fuzzy representation of the environment is shown in Figure 1 with numerical notation for each region.



Fuzzy Range	Numeric Notation	Fuzzy Angle	Numeric Notation
Vvnear	0	vvleft	0
Vnear	1	vleft	1
Near	2	Left	2
Mod	3	Front	3
Far	4	Right	4
Vfar	5	Vright	5
Vvfar	6	Vvright	6

Fig. 1. Division of Navigation Space into Fuzzy subsets of Range and Direction

In the rule-base formation phase, rules are defined and added to the rulebase using real-life data, expert knowledge base and a simulator. At time t1, the position (Angle and Range) of the moving object from the Robot is read. Using Fuzzification the observed data is converted to Fuzzy value. At time t2 ($t2 > t1$ and $t2 - t1 > \delta$, where δ is threshold time difference greater than or equal to 1 sec), the sensor reads the position of the same object. The read value is converted to Fuzzy value. The same process is followed at time t3 ($t3 > t2$ and $t3 - t2 = t2 - t1$) to get the Fuzzy value of the location of the same object under observation. A Fuzzy rule with the positions of the moving object at time t1 and t2 as the antecedent and the position of the object at time t3 as the consequent is formed and added to the rule-base. Each rule in the rule-base is represented as

$$\text{IF } (R1, \theta 1) \text{ and } (R2, \theta 2) \text{ THEN } (R3, \theta 3)$$

where R1 and $\theta 1$ represent the Range and the Angle respectively of the object at time t1 , R2 and $\theta 2$ represent the Range and the Angle respectively of the object at time t2, and R3 and $\theta 3$ represent the Range and the Angle respectively of the object at time t3.

Similar rules are added to the rule-base for different objects observed at various positions in the navigation environment. In the implementation phase of the predictor, the Robot observes the moving object at time t1 and t2 and sends the data to the Fuzzy predictor algorithm. With the application of Fuzzy inference process, prediction of the next instance position of the moving object is carried out. The complete process of short term motion prediction is represented in Figure 2.

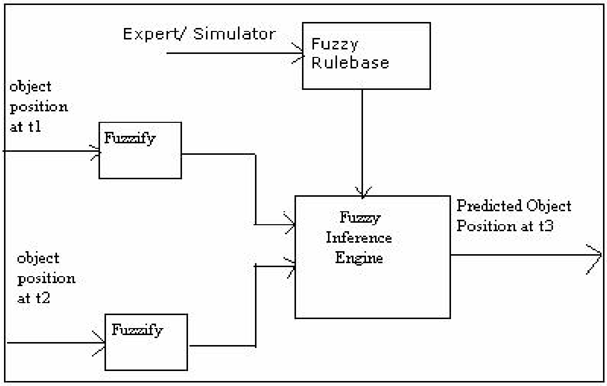
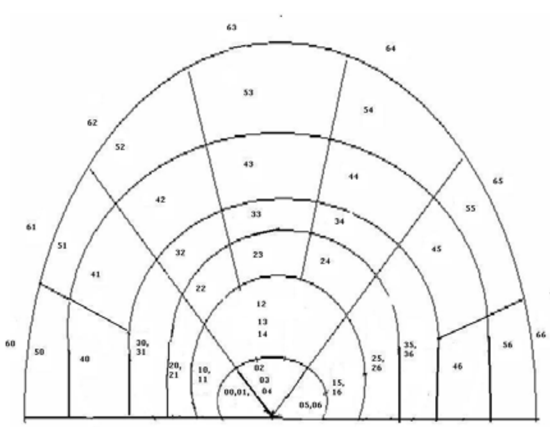


Fig. 2. Short term motion prediction

3 Rulebase Optimization Using Adaptive Navigational Environment

To enhance the performance of the predictor algorithm, the basic navigation environment is altered such that at nearer distance only three, at moderate distance five



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a. Division of space in Fuzzy subsets of Range and Direction

b. Numeric notation for Fuzzy range and Angle Values

Fig. 3. Adaptive division of navigation space into Fuzzy regions

and at the far distance seven Fuzzy membership functions are defined for angular subset by merging adjacent members in the angular subset(Fig. 3). By defining Adaptive navigational environment, the number of Fuzzy rules can be decreased as well as the accuracy of the results can be further improved.

4 Experimental Results

The Fuzzy predictor algorithm is developed in C++ language. The algorithm is tested on 1.66 GHz machine in VC++ environment. The tests are carried out for real-life benchmarked datasets [5]. Figure 4 represents the movement of the objects from left to right direction and the corresponding short term motion prediction path. Pi and Ai represent the predicted and the actual path traversed by the moving object. Pi(G) and Ai(G) represent the predicted goal and the actual goal of the object. A1 is the actual path observed and A1(G) is the actual goal reached by the object A1.

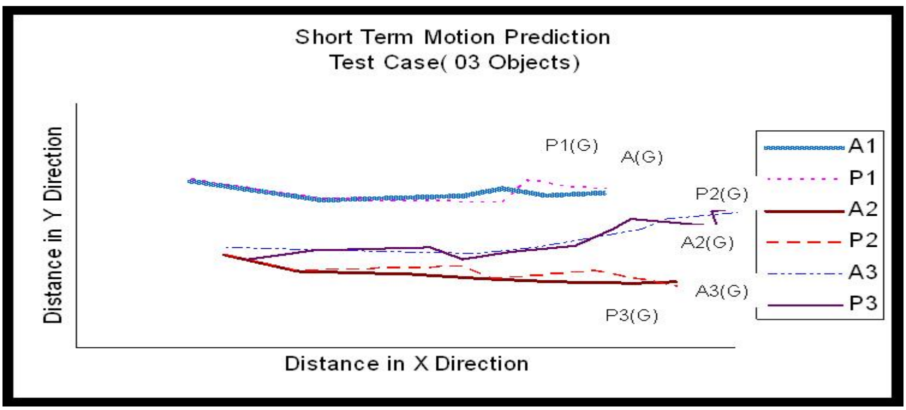

Fig. 4. Prediction graphs showing the few of the path prediction solutions for Short term motion prediction

Table 1. Comparison of Short term predictors

Short Term Predictor	Relative Error	Response time in seconds
Neural Network predictor	6-17%	560×10^{-3} sec
Bayesian Occupancy Filters	1-10%	100×10^{-3} sec
Extended Kalman Filter	1-20%	0.1 sec
Proposed Fuzzy Predictor Algorithm	1-10%	02×10^{-3} sec to 05×10^{-3} sec

Table 1 compares a few of the well known prediction techniques which are re-implemented and compared with the developed Fuzzy predictor in respect of response time and relative error. From the table it can be observed that the performance of the predictor is comparable with regard to relative error but better than the other prediction methods as far as response time is concerned.

5 Conclusion

In a dynamic navigation system the Robot has to avoid stationary and moving objects to reach the final destination. Short Term motion prediction for moving objects in such an environment is a challenging problem. This paper proposes a simplified approach for predicting the future position of a moving object using fuzzy inference rules derived from expert knowledge. Fuzzy based prediction is more flexible, can have more real life parameters, comparable to the existing approaches and suited for real life situations. The results of the study indicate that, the Fuzzy predictor algorithm gives comparable accuracy with quick response time when compared to existing techniques.

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