Cognitive Decision Making for Navigation Assistance Based on Intent Recognition

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Abstract. Within rehabilitation robotics, machines are being designed to help human in activities of everyday life. Mobility is an essential component for independent living. Autonomous machines with their high degree of mobility are becoming an integral part of assistive devices leading to a number of developments in mobility assistance. This is primarily in terms of smart wheelchairs embodied with agents. Autonomous agents keep an eye on irregularities during navigation and trigger corrections whenever required. They behave as teammates for the human wheelchair user. Such agents will be more effective if it's behavior is closer to human or it is intelligent enough to understand the possible course of action taken by the human user. Therefore recognizing intention of the human driver and surrounding vehicles is an essential task. We have formulated a fuzzy model for the prediction of intention. A qualitative distance and orientation mechanism have been adopted, where few environment features are taken to show how the prediction of intention can improve the ability of decision making.

Keywords: Intent recognition · Autonomous vehicle navigation
Motion planning · Obstacle avoidance

1 Introduction

Autonomous decision systems in outdoor navigation represent a convergence of diverse areas of research. The central objective is to effectively work in a real world environment that has not been specifically engineered. The evolution of such system is challenging. For a truly autonomous robot, systems designed with a preformed sequence of operations within a highly constrained environment are not acceptable. Such robotic systems usually fail to work in an unexplored scenario. Many methods have been proposed for robot navigation. A very basic inertial navigation method which provide dynamic information through direct measurements was proposed in 1995 [3]. The system calculates distance at real time and avoid collisions. A force based potential field navigation method was proposed [1]. Here obstacles exert repulsive forces onto the robot, while the target applies an attractive force. The resultant force determines the subsequent

A. Ghosh et al. (Eds.): MIKE 2017, LNAI 10682, pp. 81–89, 2017.
https://doi.org/10.1007/978-3-319-71928-3_9

direction and speed of travel. Vector field histogram [4], Robust Monte Carlo Navigation [19], occupancy grids [7], map matching, and many others techniques have been used for navigation. Despite recent advances in autonomous robots, a number of difficulties need to be sorted to achieve a true autonomous system. The wide variety of uncertainty arising out of an unstructured environment is a major barrier for such systems. We require a methodology which can provide the probabilistic future events within its immediate environment and take a deliberate decision.

We believe that adding cognitive reasoning into intelligent systems can lead to more natural and human compatible behavior of the resulting system [9]. Recognition of 'intent' of the teammates or other agents in the vicinity is one such cognitive ability. Intent recognition involves prediction of intentions of an agent, usually by observing an agent or a group of agents [12] in a dynamic environment. It is a proactive approach for decision making [17] and have been successfully used in service robots designed for assistance [2,10,16]. In this paper, a fuzzy model for prediction of intention is presented. Under the assumption of availability of few environmental features, we apply a fuzzy based prediction of turning behavior of surrounding vehicles in order to find a safe and smooth path for the subject vehicle. Combination of two qualitative spatial reasoning methods [5] are incorporated to deal with the distance and orientation.

2 Model of Intention Prediction

Any approach used to control dynamic system needs to use some knowledge or model of the system to be controlled. The kinematics and dynamics of a subject vehicle may be complex and nonlinear [8]. Further, the interaction between the surrounding vehicles is hard to model in general. This motivated several communities to use fuzzy control techniques [11,13,15]. We have designed an intention based decision system to model the behavior of an autonomous mobile agent (Fig. 1).

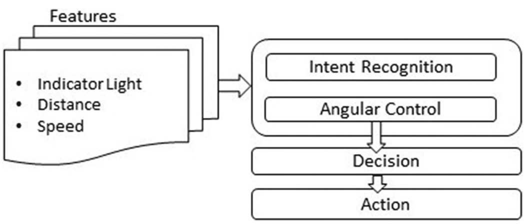


Fig. 1. Model of intention based system

The Model Consists of few predetermined features which are available to the system and a fuzzy module to predict intention of motion of surrounding vehicles. The angular control module finds a safe direction and angle of the subject vehicle exploiting qualitative orientation $OPRA_m$ [14] and an absolute distance calculus [6].

2.1 Features

Three features related to surrounding vehicles are analyzed, which is available to the system as input parameters. Two quantitative features *distance* and *velocity* and a qualitative "*Indicator*" signal is considered to model the behaviour of system. Though only these number of features are not sufficient to justify a robust system however, taking few provide simplicity. And suffice for a first step towards establishing a claim that intention based approaches have a significant impact on cognitive decision making.

We consider the indicator signal of surrounding vehicle as one of the features to understand the qualitative intention of surrounding vehicles. Usually an indicator signal is mounted as a uni-colour light on both end of vehicles. We assume F_I which denote the indicator feature, which may have status ON or OFF. Where status ON means light in "on" and OFF indicate the absence of light signal. Quantitative values for each qualitative status can be defined as;

$$F_I = \begin{cases} 1 & Indicator\ is\ ON \\ 0 & Indicator\ is\ OFF \end{cases}$$

In addition to the Indicator, two quantitative features of surrounding vehicles are considered - *distance* and *orientation*. Both the features are kept in an array, Where a distance array F_D consists of the distance of surrounding vehicle from the subject vehicle and another F_O holds orientation information.

$$F_D = [F_{D1}, F_{D2}, ..., F_{Dn}]$$
$$F_O = [F_{O1}, F_{O2}, ..., F_{On}]$$

2.2 Intention Recognition

Navigation intent can be determined by the function, structure and behavioural aspect of the environment object [18]. The behaviour of taking a turning or going straight could be one of the functional property of surrounding vehicles, which is captured in a fuzzy set of having membership for each such surrounding vehicle. A Fuzzy based Intention prediction is used to capture the intention of all the neighbour vehicles via two membership functions τ_t and ξ_t, where the functions are related to each other. ξ_t determines the membership value for moving straight and τ_t represent membership value for taking turn. 'α' is rate of change of membership functions with respect to Acceleration and 'β' is rate of change of membership functions with respect to Indicator signal. 'a' is acceleration of neighbour vehicle.

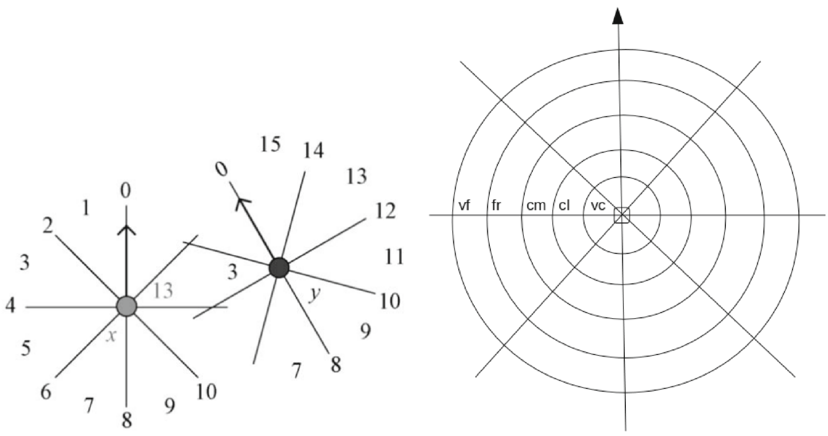
$$\xi_t = \begin{cases} 1 & t = 0 \\ 1 - \tau_t & F_I = 0 \\ \beta\xi_{t-1} & F_I \neq 0 \end{cases}$$

Membership value of going straight is maximum and membership value of turning is minimum initially as there is no need to take turn without any obstacle in the path. Membership value of going straight is changing with respect to turn by subtracting the τ_t from the maximum value. Here α is greater than β because in this scenario impact of indicator is much more than the impact of variation in speed.

$$\tau_t = \begin{cases} 0 & t = 0 \\ 1 - \xi_t & F_I \neq 0 \\ \dfrac{\tau_{t-1}}{\alpha} & F_I = 0 \wedge a > 0 \\ \alpha \tau_t & F_I = 0 \wedge a < 0 \end{cases}$$

If a surrounding vehicle intends to come into the path, i.e. indicator signal F_I is ON, indicating the possibility of crossing the way of automated vehicle then membership function of going straight is decreased by the factor β and membership value of turning is increased by subtracting the ξ_t from maximum value.

Membership values also varies with acceleration of neighbour vehicle as if neighbour vehicle is retarding down their is a possibility of taking turn and it may come into the path of automated vehicle so membership value of turn for automated vehicle should be increased by the factor inverse of α. If neighbour vehicle is speeding up (i.e. accelerating) then membership value of taking turn is decreased by the factor α.



(a) $OPRA_4$ (b) Absolute Distance Scale

Fig. 2. Representation of orentation and direction scheme. **(a)** A basic relation in $OPRA_4$. **(b)** A combined illustration of orientation and direction.

2.3 Orientation and Distance

Apart from the prediction of intention of surrounding vehicle based on a qualitative feature, orientation and distance would also play a significant role. For orientation information the Orientation Point Algebra ($OPRA$) [14] is used to describe the relative direction information, where $OPRA_m$ signifies the uses of m number of lines going through the object point and can be visualised in Fig. 2(a), in which orientation point x lies on the third part of the space divided by lines going through oriented point y, whereas y lies on 13th part of space divided by the lines going through x under the assumption of m = 4.

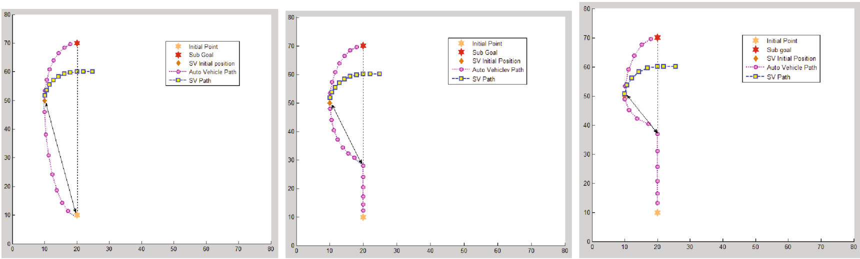
Distance in spatial domain can represent by either absolute scale or some relative measurement. We consider distance on an absolute scale where notions such as *very close*, *close*, *commensurate*, *far*, and *very far* could be used. In general, the distance relation has meaning only when combined with direction relation. Therefore distances are used together with $OPRA$.

3 Implementation and Results

The objective to design a fuzzy model was to analyze the effect of intention based method in navigation. Where we are interested only on the path obtained by the autonomous agent in the different scenario. Therefore, instead of exhaustive implementation and considering many features and real scan data, a sample set of data is used in Matlab to fulfill the objective. Demonstrative results of the path taken by the integrated autonomous vehicle in different circumstances are shown. A comparison of this integrated approach with potential field navigation method is done for the analysis. Results represented here can broadly divide into two categories *Navigation Path* in different surrounding scenarios and *Comparison and Analysis* with other existing methods.

3.1 Navigation Path

A different surrounding environment scenario requires a different navigation path strategy. Autonomous navigation vehicle should follow the navigation according to the present surrounding scenario. It should avoid the collision and achieve the goal by keeping the motion smooth. Few scenarios and respective navigation paths are demonstrated in Fig. 3, which presents the navigation path in presence of one vehicle in the surrounding and shows the path followed by the autonomous vehicle with different values of the effective range. Where the effective range is that distance from which vehicle starts observing the surrounding objects. Figure 3(a) shows the path of the vehicle when the effective range is large where Vehicle observed the presence of a surrounding vehicle and starts taking a curve turning to avoid the sharp turn. This proactive observation gives machine more time to take the turn and make the motion smoother. Similarly, in Fig. 3(b), effective range is medium and the vehicle starts taking turning after covering some distance from the initial point. Figure 3(c) shows a small value of range and observation of surrounding vehicle starts when they are very close. In this scenario vehicle gets a very small time to take action and path becomes curved.

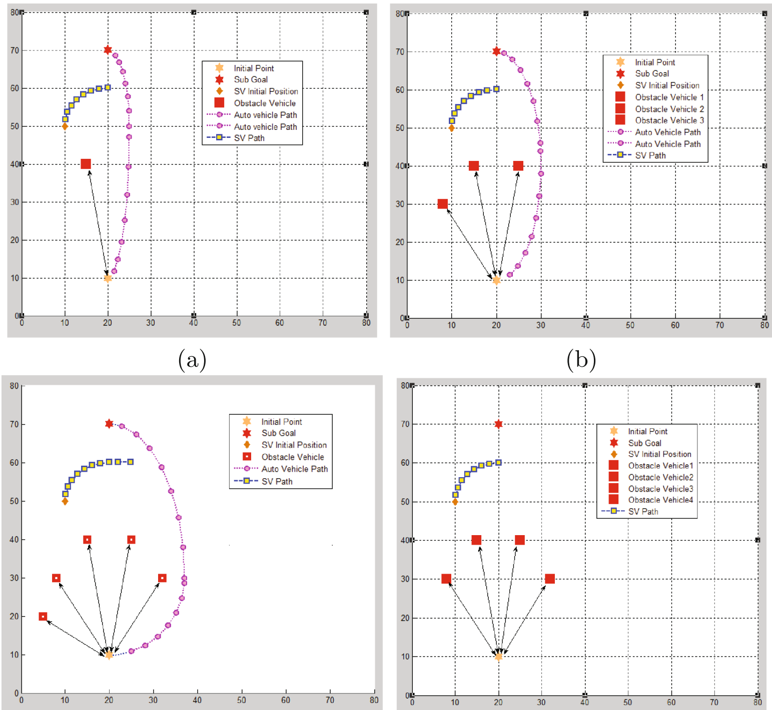


(a) (b) (c)

Fig. 3. Navigation Path for different effective range of Autonomous Vehicle. **(a)** Large effective range. **(b)** Medium effective range. **(c)** Small effective range.

3.2 Avoiding Obstacle

Figure 4(a) shows the navigation path followed by the subject vehicle when one obstacle is present, where it observe the surrounding vehicle at initial point



(a) (b)

(c) (d)

Fig. 4. (a) shows the path followed by Autonomous Vehicle with one obstacle. **(b)** shows the path followed by Autonomous Vehicle with three obstacles. **(c)** shows the path followed by Autonomous Vehicle with five obstacle. **(d)** shows the Vehicle can not move forward due to obstacles.

and starts turning to avoid it but at the same time it observe the indication of turning intention of an another vehicle, which command to calculate a new path. Therefore it select the control from the decision making module to predict the next optimal path and pass it to the action module. Multiple obstacles can also be their as shown in Fig. 4(b) and (c), where it every time when an obstacle is found in the path it calculate the new optimal path with the help of decision tree. Figure 4(d) represents a different situation where all possible directions are obstructed by the obstacles and vehicle has no way but to stop. In this situation decision maker will return all possible directions one by one and if it will not find any clear path then it signals the stop command to the vehicle.

4 Analysis

Although exact comparison could be made only in the dynamic environment, a comparison study is shown here to give an idea to differentiate between the results of reactive and proactive approach. Here potential field navigation

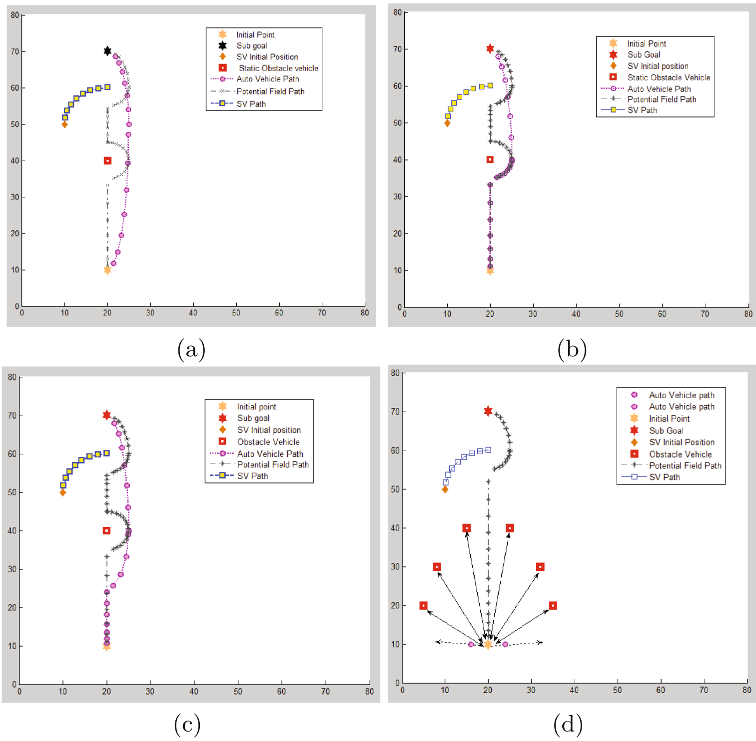


Fig. 5. Path obtained **(a)** when effective range is large **(b)** when effective range is small **(c)** when effective range is medium **(d)** shows the Vehicle can not move forward due to obstacles.

method is compared with the presented method. Figure 5(a) represents the comparative path of both the methods. Line with crosses shows the path followed by potential field navigation where the other line with circles shows the path of new proactive approach. Effective distance taken here is large and it is clear from the graph that new approach gives a much smooth path with less number of curves. This approach becomes closer to the reactive approaches as the size of effective distance is decreased as shown in Fig. 5(b). As the size of effective range is decreased the proactive power of vehicle also decreased. Small effective range leads to the late prediction of intents of surrounding vehicles hence reduces the pro-activeness. Vehicle follows the same path as followed by potential field method because in this case intents of surrounding vehicle (SV) can be calculated at approximately same time when it comes into the path of vehicle. So both the techniques take turn at same time. Apart from this Fig. 5(a) represents the comparison with a medium value of effective range. In this case path produced by novel approach has lesser number of curves and it avoids the obstacles more smoothly as shown in graph.

5 Conclusion

In this paper integration of intent recognition with decision making for navigation assistance of a mobile robot have been presented. Implementation of the approach strengthens the claim to consider intention based decision making for mobile robot navigation. Such a framework can predict the future course of action much before the reactive systems. Conclusively, it can be observed that the approach proposed in this paper has many advantages over the existing reactive techniques. Nevertheless, there are certain scenarios where reactive methods may perform better. Implementation within a robotic platform like ROS (Robotic Operating System) may provide a better way to evaluate the claim. This is part of on-going research.

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