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Constraint Based Probabilistic Determination of Object State for Autonomous Robots

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Abstract: ***This paper presents a probabilistic determination algorithm for dynamic objects. Gaussian model is used along with path balancing. The predictive system uses state estimate and covariance of the tracking system and map of the environment to compute the probability distribution of the future obstacle state over a specified area. Here the system is assumed to be nonlinear. The core of this approach is a weighing matrix that balances the contribution of each vector constraint used for prediction of object state. The constraints are considered as additional feature which is injected into control law. The computed object state is integrated with navigational behaviours to enable a robot to reach its navigational goal, avoiding any hazards. All the posture is represented by polar coordinates and the dynamic equation is feedback-linearized. After determining the object state a novel sliding mode control law is used for asymptotically stabilizing the mobile robot to a trajectory so it can navigate by avoiding any hazards.***

Keywords: Gaussian model, sliding mode control, trajectory tracking, nonlinear systems, navigational behaviour

1. Introduction

Autonomous driving is one of the widely growing field in mobile robotics. Intelligent vehicles aim in improving road safety, vehicle efficiency and convenience. Most of the autonomous cars are based on reactionary planners that rely on rapid replanning in order to respond to dynamic environment in which they operate. One way to handle the autonomous cars more intelligently is to incorporate probability based determination of object state into path planning. The potential field method is a common technique for generating collision-free trajectories.

The problem of prediction is inherently probabilistic, as it is impossible to know the true future behaviour of any dynamic obstacles that make their own independent decisions. In addition, the behavioural model used to predict the obstacle behaviour are often highly nonlinear. Several algorithms have been proposed to simplify the problem, such as assuming no uncertainty in future obstacle behaviour. These algorithms are well suited for cooperative situations, where the obstacles can communicate their intentions to the robot, or for short anticipation horizons. However, they do not provide sufficient information for reasoning about an obstacle with unknown intentions over a significant anticipation horizon. Several of this proposed methods consider only a subset of obstacle uncertainty, such as along track error. These approaches reduce the complexity of the problem to a manageable level, while still considering the probabilistic aspects of obstacle anticipation, but are typically very simple and narrow in their application.

The stabilized movement of a mobile robot on a pre-determined trajectory has several difficulties. One of the problem is that, nonholonomic systems cannot be applied to methods of linear control theory, and they are not transformable into linear control problems. Another difficulty in controlling nonholonomic mobile robots is that, in the real world there are uncertainties in their modelling.

Some other algorithms applies standard estimation filters to the problem of anticipation. Such approaches assume a model for the behaviour of the obstacle, and provide mathematically rigorous, probabilistic estimates of that obstacle’s state over the anticipation horizon. These approaches are well suited to obstacles that are accurately described by linear models because they maintain a single Gaussian to represent the uncertainty. For obstacles with more complex behaviours, such as those based on nonlinear dynamics like car, truck, etc. and those that make discrete decisions like crossing, passing, etc., the uncertainty of the anticipated obstacle state becomes inaccurate very rapidly.

2. Existing System

Most of the algorithm used to determine the future state of dynamic obstacle in an operating environment addresses the complex uncertainties by avoiding the linearization problems of standered filters. For example, Monte-Carlo (MC) methods. These approaches consider complex, non-Gaussian uncertainties and allow for the use of nonlinear obstacle models to capture complex obstacle behaviour. However, the accuracy of prediction scales with the number of particles, and there is no guarantees that the particle set effectively covers the true distribution of possible future obstacle states. Because the assumed dynamics model for the obstacle has to be evaluated at every particle used in anticipation, increasing confidence in the estimate is strongly traded with computational resources.

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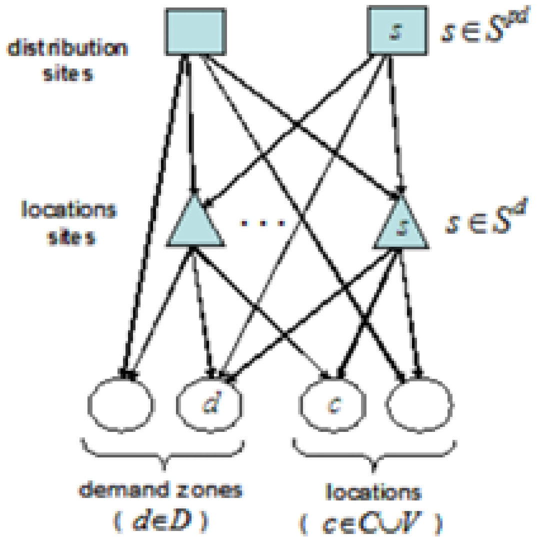

Figure 1: MC model Network Structure

3. Proposed System

The algorithm presented in this paper is designed to predict the probability distribution of dynamic object over the state of tracked obstacle forward in time. The main aim is to make accurate, probabilistic information about future obstacles behaviour available for use in path planning. The obstacle model includes nonlinear behaviour and discrete variables to capture higher level decisions. After determining the future state of dynamic objects a collision free trajectory is constructed by planning the trajectory in image space allowing the visibility and the navigation constraints.

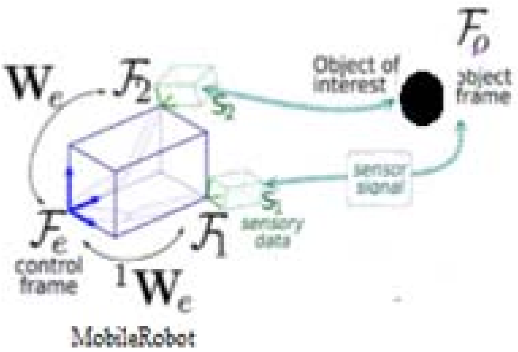

Figure 2: Object State Determination Model

Gradient projection method (GPM) is used to draw a hierarchy between the different tasks and to build a control scheme that prevents lower subtasks from disturbing higher ones. However, a common issue with this approach is, when upper tasks constrain all the robot's degrees of freedom (DOF), it prevents the lower subtasks from being performed. A solution can be to build a new operator that projects a subtask on to the norm of the main tasks, freeing some DOF that can then be used by secondary tasks. Task sequencing technique is used to make the task hierarchy dynamic.

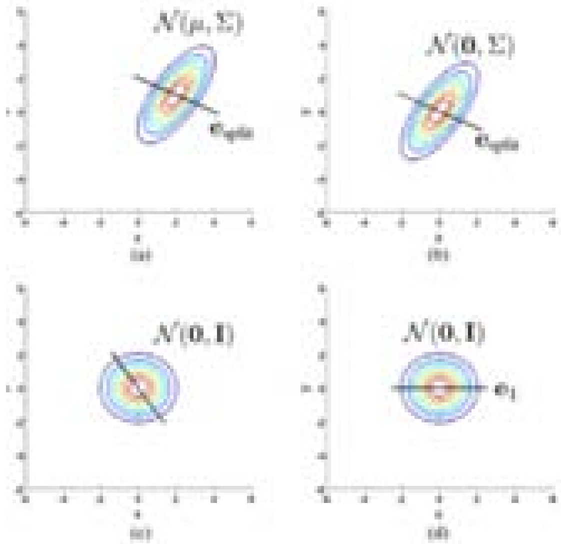

Figure 3: Transformation of Gaussian axis to offline problem. (a) Single Gaussian. (b) Translated to origin. (c) Transformed to unit variance. (d) Rotated splitting axis.

Here the Gaussian model is used to uniquely include discrete state elements that capture complex, high-level obstacle behaviours. Accurate anticipation of a wide variety of dynamic obstacles is ensured using a novel method for detecting linearization errors using sigma-point methods, and adjusting the mixture accordingly by optimally splitting inaccurately propagated mixands

A novel sliding mode control law for solving trajectory tracking problems of nonholonomic mobile robots is used. Dynamic models of mobile robots is used to describe their behaviours with bounded disturbances in system dynamics. The posture variables of mobile robots is represented in polar coordinates and is feedback linearized with a sliding mode control law which is applied for stabilizing the robots to a reference trajectory and compensating for existing disturbances.

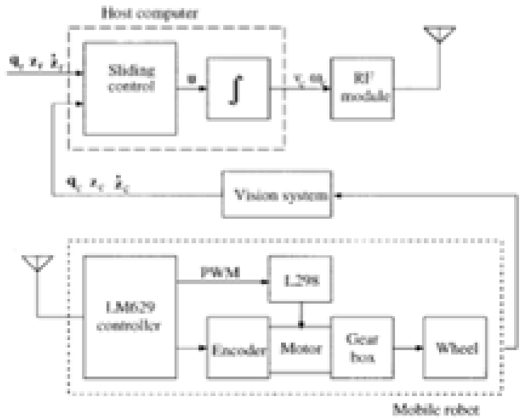

Figure 4: Schematic diagram of robot control system

4. Algorithm Used

This algorithm is invoked at sensory node when a new obstacle is seen along the duty path trajectory to determine its future state. Algorithm: DYNAMIC OBSTACLE STATE This program at node is invoked when a new obstacle is seen {e;w;B}.

1: if (the current object is on the duty path) then
2: Search pq's record and put the qualified records in FoundList;
3: if (FoundList !=empty) then
4: Send FoundList to the LCM computation node;
5: Return;
6: else
7: if (new record) then;
8: add record to ForwardList;
9: Send the query message with ForwardList to the selected path trajectory;
10: end if
11: end if
12: else
13: Forward the query message {e;w;B} based on PSM Slice Handler rules;
14: Compute weighing matrix;
15: end if

The core of this approach is a weighing matrix that balances the contribution of each vector constraint used for prediction of object state. Denoting s=(s1,s2,…..,sn) as the m-dimensional signal of a multiple obstacle nonlinerized system, the signal time variation is given by

$$s` = J_s q` \quad (1)$$

The weighing matrix is given by

$$J_s = L W_e^{\,e} J_q \quad (2)$$

$$= \begin{bmatrix} \mathbf{L}_1 & \cdots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \cdots & \mathbf{L}_k \end{bmatrix} \begin{bmatrix} {}^1\mathbf{W}_e \\ \vdots \\ {}^k\mathbf{W}_e \end{bmatrix} {}^e\mathbf{J}_q$$

Figure 5: Full rank matrix

The weighted error is given by

$$e_H = He \quad (3)$$

where e is the sensor error defined as

$$e = s - s^* \quad (4)$$

and H is the diagonal positive semi definite weighing matrix that depends on the current value of s.

The weighing matrix for sensor S is given by

$$\mathbf{H} = \begin{bmatrix} \mathbf{H}_1 & \cdots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \cdots & \mathbf{H}_k \end{bmatrix}$$

Figure 6: Diagonal positive Semi definite weighing matrix

The two state stochastic obstacle state determination in nonlinear system with fixed logistics takes following form
Max f(X,Y,Z) $=\sum_{\Omega} p(\beta)[\max qF(\beta)] - (cX+aY+kZ)$

$S_t = A[X,Z] < b$,
$-T(\beta)Z + UF(\beta) = 0$, β € Ω
$-V[X,Y] + WF(\beta) = h$, β € Ω
$X > 0$; Y,Z binary; $F(\beta) > 0$, β € Ω

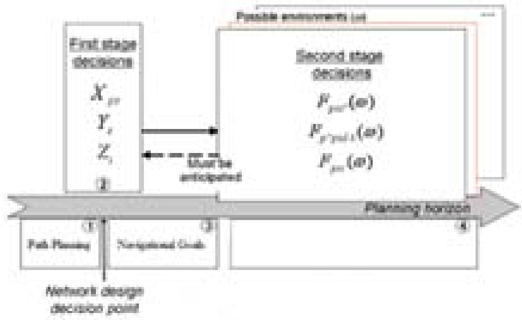

Figure 7: Logistic obstacle state determination

5. Performance Analysis

The proposed system was analysed for performance and efficiency with existing anticipation and path balancing techniques. The result of performance analysis is visualized in the form of a graph to provide a clear insight on the improvements achieved. This analysis was carried out on the following metrics: state estimate, path optimization, DOF, fairness index, efficiency. The resultant values is graphically plotted below, for comparison of the existing and the proposed system. Series 1: Existing System, Series 2: Proposed System.

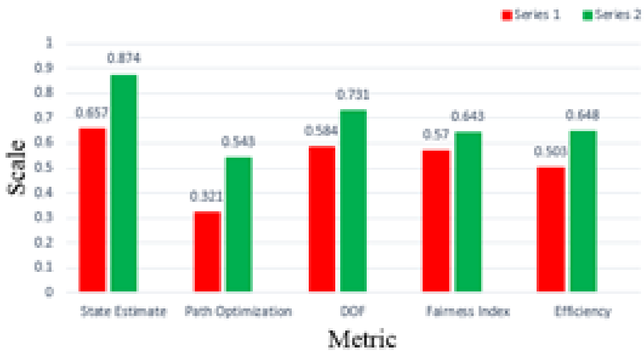

Figure 8: Performance analysis of proposed system vs existing system

The path balancing is viewed as a step function where the path between intermediate nodes from source to destination is developed in an iterative manner.

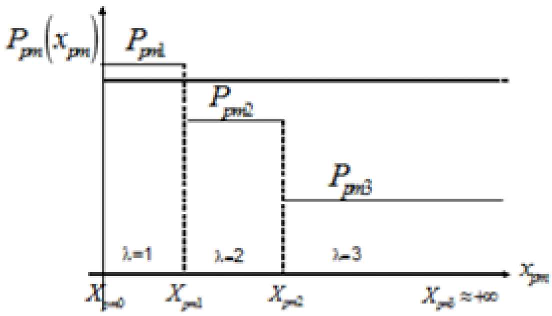

Figure 9: Path generation as step function

6. Conclusion

This entire work is based on creating an efficient and light weight constraint based probabilistic determination algorithm for determining the future state of dynamic objects in the operating environment. Technically speaking, the solution is to modify the predictive system to use state estimate and covariance of the tracking system and map the environment to compute the probability distribution of the future obstacle state over a specified area. For this, Gaussian model along with path balancing is used. The system was assumed to be nonlinear during the entire project. The core of this approach is a weighing matrix that balances the contribution of each vector constraint used for prediction of object state where the constraints are considered as additional feature which is injected into control law. The computed object state is integrated with navigational behaviours to enable a robot to reach its navigational goal, by avoiding any hazards. The accuracy of state estimate in the proposed system has increased to 87.4 % from 65.7 % of the existing system and at the same time the degree of freedom (DOF) of the proposed system has increased to 73.1% from 58.4% Using LMI optimization the path optimization has increased from 32.1% to 54.3% with an increase in fairness index of 29.5%. Thus the overall efficiency of the system has increased from 50.3% to 64.8%.

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