Intelligent Path Prediction for Vehicular Travel

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The problem of predicting the motion of a vehicle has been investigated by several researchers. Many have used Kalman filter techniques based on the equations of vehicle motion; these techniques most accurately predict short-term motion. In contrast, my dissertation (Krozel 1992)[1] presents a methodology for intelligent path prediction, where predicting the motion of an observed vehicle is performed by reasoning about the decision-making strategy of the vehicle's operator. With intelligent path prediction, the long-term mission objective of the vehicle is being predicted in addition to the short-term motion. Thus, when applied to predicting the motion of a car, an intelligent predictor will attempt to predict the final destination—say, for example, the vehicle appears to be going to the post office or the art museum—in addition to predicting which streets will be used. The theory is also applicable to predicting air vehicle travel, so that for a military application, the target (from a set of plausible targets) and the threat-avoidance policy (from a set of plausible policies), in addition to the route, can be predicted.

Predicting a Mission Objective

The first investigation is to develop a method for identifying a decision-making strategy that seemingly explains the vehicle's motion. Assume that the operator of the vehicle is executing a solution to the FindPath problem from robotics: Find a path from a start location s_0 to a goal location g guided by the cost criteria c.

The goal location g is assumed to be from the set $\{g_1, g_2, ..., g_m\}$. The cost criterion c is assumed to be from the set $\{c_1, c_2, ..., c_n\}$. Research in the field of intelligent planning assists in the synthesis of candidate cost criteria; for example, the methods of Donald and Xavier (1988), Kanayama and DeHaan (1988), Lee and Preparata (1984), Mitchell (1986, 1988), Sharir and Schorr (1986), and Suh and Shin (1988) investigate path planning with the cost criteria of distance, safety, visibility, and time. A candidate *mission objective* (g,c) describes a transit mission decision-making strategy. In intelligent path prediction, one seeks the particular candidate mission objective that best explains the observed motion. After establishing the predicted mission objective, the future path leading to the goal location is predicted.

An optimal path from any point in the environment to a particular goal location g can be obtained by propagating a reverse search based on a cost criterion c from the goal location g; Dijkstra's algorithm is applicable (Dijkstra 1959; Hart, Nilsson, and Raphael 1968; Mitchell 1986, 1988; Nilsson 1980). The search pointers indicate the optimal solution paths from any location within the search frontier to the goal location g. Reverse-search results maintained in a gradient field representation have utility in path-planning applications for mobile robots (Payton 1990); in this dissertation, reverse-search results provide useful information for the purpose of path prediction.

A gradient field representation of a route plan provides, for each location in the map, the best direction to trav-

el to reach a goal location. For each different candidate mission objective (g,c), a different gradient field can be obtained. Given a cost criterion that defines a cost per unit length c to a point ζ in the environment, we define the path cost to be the integral of the cost over the path π. For each point ζ in the environment, there is an optimal path to the goal location g with the minimum cost $C^*(\zeta)$. The scalar function C^* suggests a gradient direction that can be defined to be the unit tangent vector in the direction of an optimal path from the point ζ to the goal location g.

The candidate mission objective that best explains the observed motion is selected based on a path similarity correlation measure. A local and global measure are created. First, the local path correlation measure is the dot product between the optimal direction to proceed at a point and the path tangency direction indicated by the observed vehicle path π. The global path correlation measure is referred to as the path similarity value. The path-similarity value σ is the integral of the local path-similarity value, integrated over the path π and normalized with respect to the total path cost $C\pi$. The path-similarity value σ has a range between –1 and 1. Path similarity gives a means for correlating a possible mission objective (g,c) with the observed path π. If the observed path tangency information strongly correlates with (i.e., near 1) the reverse-search gradient information, then the mission objective (g,c) explains the observed motion reasonably well and can be a sound basis for predicting future motion.

In the dissertation, other path-similarity correlation measures are also defined. A moving data window establishes a path-similarity value using a limited amount of data, disregarding path information outside the moving window. If either the goal location or the cost criterion used for travel changes while the vehicle is being observed, then the path-similarity measure might be biased by old data, data that might deceive the predictor from correlating the path with the new goal location or new cost criterion. A moving-window predictor

will forget data that are outside a window, thus considering only the latest path information in making a prediction. Additionally, the data within the moving window can be weighted. For example, in a fading-memory predictor, the most recent data are weighted highest. Moving-window predictors have utility when the vehicle does not have a constant mission objective.

The solution approach proposed for intelligent path prediction initially establishes a collection of results from several reverse searches. For each possible candidate mission objective (g,c) with $g \in \{g_1, g_2, \ldots, g_m\}$ and $c \in \{c_1, c_2, \ldots, c_n\}$, a search is performed from the goal location g back to the start location s_0 governed by the cost criterion c. These searches establish the gradient direction information for each candidate mission objective (g,c). Because computing these searches is the most computationally expensive task in the prediction process, this gradient direction information is computed offline (before processing any data describing the vehicle's motion) and is stored so that the path-similarity values can quickly be computed (linearly with respect to the path data) as observed path data become available. As the history of the observed path evolves, a predicted mission objective (g,c) is selected based on maximizing the path-similarity value over all candidate mission objectives. The process repeats recursively for all incoming data, so that at any time, the best prediction is provided based on the latest available information. Finally, after a predicted mission objective (g,c) is selected, the predicted future path is established by following the gradient direction information from the current vehicle location to the predicted goal location g.

Proposing a Goal Location

The second investigation is to develop a method for automatically proposing a candidate goal location for the observed vehicle. For intelligent prediction, if candidate goal locations are not readily available, then a prudent selection of a candidate goal location might be necessary. Given a particular cost criterion c, a region of plausible goal locations is proposed, and these locations are ranked based on some heuristic merit.

The definition of a region of plausible goal locations is developed based on forward-search results. Based on the optimal-path map, a generalization of the shortest-path map (Lee and Preparata 1984; Mitchell 1986), a region of plausible goal locations is defined for a given cost criterion. A critical assumption is that the vehicle arrives at its current location using an optimal path and will maintain an optimal path in the future. Alternatively, if the observed path is suboptimal, then the region of plausible goal locations can be defined, assuming that the future motion might also be suboptimal. To this end, an additional technique for defining the region of plausible goal locations is developed based on ε-optimal paths. A *suboptimal path* is a path that is within some tolerance ε of optimal with respect to cost criterion c. An *ε-optimal path* is a path that is no more than $(1 + \varepsilon)$ times the optimal cost for traveling between two given points. Using the tolerance ε observed in the past motion, a region of plausible goal locations is defined to account for suboptimal motion in the future.

Heuristic methods for specifying a particular goal location from the region of plausible goal locations are described next. Two criterion for ranking plausible goal locations are given: One integrates the results from the region of plausible goal locations for some or all of the history of the path data; if desired, weighting data can be performed. An alternative heuristic method is to rank a point based on how many of the predicted future paths lead through the point. The point in the environment that has the highest heuristic value is then proposed as the candidate goal location.

Note

1. A copy of this dissertation can be obtained by writing the author at the Hughes AI Center, RL 96, 3011 Malibu Canyon Road, Malibu, CA 90265.

A copy of this dissertation can also be obtained from University Microfilms International.

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