TERRAIN NAVIGATION THROUGH KNOWLEDGE-BASED ROUTE PLANNING

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ABSTRACT

The advent of advanced computer architectures for parallel and symbolic processing has evolved to the point where the technology currently exists for the development of prototype autonomous vehicles. Control of such devices will require communication between knowledge-based subsystems in charge of the vision, planning, and conflict resolution aspects necessary to make autonomous vehicles functional In a real world environment. This paper describes a heuristic route planning system capable of forming the planning foundation of an autonomous ground vehicle.

An effective route planner must address two levels of planning. At the high level, the planning algorithm usually exploits some form of map data to generate a global route which avoids mountains, valleys, and canyon areas. Depending upon the map resolution, Individual pixel path points at this level vary from a representation area of 100 by 100 meters to 12.5 by 12.5 meters. At the low level, the planning algorithm must deal with local planning inside these individual path points so that obstacles such as trees, rocks, and holes may be avoided.

A consensus exists that global information in the form of a digitized terrain map Is essential in the operation of an autonomous vehicle, at least at the global level of route planning [1-4]. The terrain map required must be capable of representing huge amounts of multi-dimensional data In a format easily exploited by the route planner. In order to make it suitable as a basis for real-time decision making during vehicle operation, the data should also be preprocessed Into a more compact and manageable format. Two Interesting approaches to this problem are the rule-based creation of a "composite map" [3] and the transformation of a polygonal obstacle map Into a relational graph database [1]. It Is to the second concept that our current approach to preprocessing map data Is more closely aligned.

This paper describes a dynamic route planning and execution system called TREK (Tech Route Execution Kale doscope). TREK consists of four distinct processing phases: (1) scene recognition, (2) route generation, (3) scene matching, (4) and knowledge-based validation. Each of these processes Is discussed in the following sect lons.

The recognition of objects in an image is central to the concept of local route planning. Given that a global route can be generated through a large area of terrain, scene recognition must be capable of interpreting the objects contained within the current fleld-of-view so that they may be avoided during the traversal of the actual terrain. Without a capability to determine what is in its local environment, low level route planning would not be able to avoid threatening objects or objects obstructing the vehicle's path.

Scene classification in the TREK system exploits a hierarchical classification tree consisting of objects and regions divided Into natural or man-made categories. Efforts in scene classification to date have concentrated on detection and classification In video imagery. This work will be extended to infrared imagery In the near future.

The goal of a route planning system Is to analyze all available information to produce a route that Is optimal in light of predetermined mission requirements. The TREK route planning system consists of three stages: A) point generation, B) graph generation, and C) heuristic search.

A. Point Generation

The TREK system generates three different types of path points: two-sweep points, convex terrain points and crossover exposure points. The two-sweep point generation algorithm Is a humanistic approach to terrain traversal assuming that the system possesses a map and a compass. The central Idea of two-sweep is the assumption that the direction of the goal point can always be determined through simple geometry. The algorithm Initially scans forward from Its current location until It locates the goal point or encounters an obstacle. The underlying heuristic Is the simple strategy that a person uses when there Is an obstacle In front that prevents him/her to go to the desired destination. The Individual usually goes around the obstacle following Its contour until the destination Is visible. This approach can be used both at the local and global level In route planning, but only the global application Is discussed In this paper.

The convex points of Interest for an obstacle are defined as the set of points on the obstacle's boundary such that: a) each point In the set Is a convex point, b) for each point P In the set, p's curvature Is a local maximum, and c) the set of points forms a convex polygon.

A set of convex points Is generated for each obstacle In the terrain Image. An obstacle Is represented as a list of (x,y) coordinate pairs which define Its boundary. This set of points does not have to be of a continuous nature, but It Is assumed that the distance between adjacent points Is uniform.

The combination of two-sweep and convex point routes produces an extensive route graph with a number of route segment Intersections. These Intersections or crossover points actually represent high traffic areas of maximum exposure. By connecting all crossover points with a Ilne-of-sIght algorithm, a number of offensive route options are created. When merged with defensive path points produced by two-sweep and convex point generation, an unbaslsed route graph Is generated. In this mode the TREK system Is capable of non-military route planning as would be the case In a robot vehicle patrolling a national park looking for stranded motorists.

B. Graph Generation

A global terrain Image graph based upon the aforementioned point sets Is generated using a line-of-sIght computation Is made to determine If a path exists between Individual obstacles polnts-of Interest. A cost Is then assigned to each edge In the graph. This cost Is computed as a weighted function of distance, terrain, scenario threats and vehicle constraints as fol lows:

$$F(c) - \text{Distance} * W1 + \text{Tarrain} * W2 + \text{Threats} * W3 + \text{Constraints} * W4$$

This criteria edge graph forms the search space for the A* algorithm.

C. Heuristic Search

Once the search graph has been constructed, a suitable search procedure must be used to find an optimal route. Given the expected size of the graph, It Is Important to have cost estimate functions to help Improve the efficiency of the search.

The A* algorithm was chosen as the heuristic search mechanism In TREK. A* Is basically a best-first tree search algorithm augmented to handle cycles and duplicate paths between nodes. If a recently discovered path to node N Is found to be an Improvement over a previous path to the same node, the pointer from N to Its predecessor Is updated and the Improvement Is propagated to other paths that have N as an Intermediate node.

One of the most Important aspects of an autonomous vehicle system Is Its ability to maintain and follow the routes that It generates. If a vehicle Is Incapable of performing this task. It wtll eventually wander aimlessly through terrain that It can not recognize as nothing will match Its global map. For this reason, an accurate scene matching algorithm must be Incorporated Into the system.

The symbolic processing nature of the TREK system readily lends Itself to a syntactic pattern recognition approach to scene matching As the goal In scene matching Is to perform an Image-to-Image mapping, pixel correlation techniques are probably the most accurate method available. The difficulty for autonomous vehicle applications Is that the local sensor Image Is guaranteed to have a different perspective than that of the global altitude data map being matched. Such a perspective Invariant requirement Is the shortcoming of most conventional scene matching approaches.

The key to determining and maintain the vehicle's position Is to match objects and regions detected during scene classification to objects and regions In the map. This can be accomplished by representing each object and region as a classified point, constructing a perspective Invariant graph of the local Image points, and comparing the local graph as a subgraph to be located In a global map graph which has been created In the same manner [5]. This time of a local-to-global scene matching Is accurate In light of obscurations and other possible terrain permutations and easily performed using a symbolic processing language such as LISP.

Scene recognition, route planning, and scene matching Information constitute the global database of the TREK system. This Information Is processed by the system as a preliminary representation of the current vehicle environment. Tasks or mission goals are provided to the system through communicating problem requirements via the control strategy. For a military scenario, example mission goals would be as follows:

PRIMARY GOAL: patrol zone 410
SECONDARY GOAL: neutralize Intruders
SECONDARY GOAL: maximize survivability
SECONDARY GOAL: maximize kill ratio

TREK Interprets these mission requirements and determines the optimal mission parameters which are passed to the scene recognition, route planning, and scene matching algorithms. An Initial plan of action Is then generated and represented In the global database. Decisions the on validity of the scene Interpretation and the current plan of action are made through knowledge base processing. The TREK knowledge base contains three types of rules : scene rules, mission rules, and survIvability rules.

Scene rules are used to validate and further Interpret the Information provide by scene recognition. In natural terrain Images, object classification confidences can be enhanced through the utilization of positive and negative evidence provided by scene context. For example,

SCENE RULE 98
IF [1] an object Is man-made and
[2] It Is on a road or In a field and
[3] It has a high confidence of motion,
THEN [1] hypothesis the object Is a vehicle
[2] Increase target confidence

Mission rules Interpret the generated plan In light of high level mission goals. For example, the detection of three threats will generate a plan of action to engage and neutralize the threats based upon the previously entered mission plan. Mission rules further analyzed the system goals by examining the requested survivability and kill ratio levels and creating a modified plan through system feedback. For example,

MISSION RULE 132
IF [1] multiple threats are detected and
[2] they are In a column and
[3] they are In possess motion and
[4] they are approaching an area that will maximize kill and survivability
THEN [1] generate a defensive route to that area and
[2] determine the threat time of arrival to that area and
[3] generate an offensive route to maximize kill to be executed on threat arrival

Mission plans are also used to repair plans based on Invalid Interpretations or changes In a scene.

Survivability rules are rules that maximize the vehicles chances of survival based on the Interpretation of the current environment. For example,

SURVIVABILITY RULE 122
IF [1] an object Is detected and
[2] avoidance will delay accomplishment of mission goals
THEN [1] determine Its probability of threat and
[2] replan to avoid If threat Is greater than (.5)

Based upon the results of knowledge base processing, the control strategy will feedback adjusted parameters to scene recognition, route planning, or scene matching algorithms for updated Information, or execute the plan and communicate this decision to the user for approval.

SUMMARY

This paper has presented a high level view of the TREK terrain navigation system. TREK [1] analyzes a digital terrain map to generate a global route, [2] performs scene Interpretation to generate local routes, [3] maintains a track of Its position through scene matching, and [4] uses knowledge base processing to validate and Improve preliminary plans In light of predetermined mission goals. The entire TREK system was written In LISP on a Symbolics 3600 and Is currently being enhanced to Increase It visual recognition capabilities, broaden Its Interpretation of mission goals, and advance Its temporal reasoning process. Near term plans Include the transportation of the entire TREK system Into a two functional mobile robots (possessing additional sensory Inputs) that has recently been donated by IBM for research In materials handling and flexible manufacturing applications.

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