AUTONOMOUS NAVIGATION TO PROVIDE LONG-DISTANCE SURFACE TRAVERSES FOR MARS ROVER SAMPLE RETURN MISSION

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ABSTRACT

Knowledge acquisition and representation techniques are developed to allow an autonomous vehicle to negotiate a path over partially unknown terrain, such as the long-distance traverses for the Mars Rover Sample Return Mission.

Terrain navigation is accomplished by the following sequence of steps: The skylines from the visibility map and from the local terrain map are compared and the two 3-D curves in space are stochastically matched to update the vehicle location. A path-segment is selected taking into consideration the goal, overall global topography, obstacles such as craters and boulders derived from the range-finder observations, and a priori constraints related to the mission, fuel consumption, and vehicle stability. The vehicle reaches a new vantage point with relatively broad visibility, but within sight of the last observation point. The skyline is then estimated and approximated again, and the cycle is reiterated for another advance.

INTRODUCTION

One of the first free-wheeling robots was Shaky, the 1960's vintage SRI robot, with whom one of the principal investigators was well acquainted. Shaky's sensor complement included a television camera, a range finder, and tactile whiskers. The Autonomous Land Vehicle built by Martin Marietta under the DARPA Strategic Computing Program recently made headlines when it navigated a 2.5 mile segment of road at 6 mph. Likewise, the six-wheeled CMU Terragator, and its predecessors, the tethered Stanford Cart [1], and tricycles Pluto and Neptune, have demonstrated autonomous outdoor navigation over short road segments. A small three-wheeled robot was exhibited at the University of Massachusetts Perceptual Robotics Laboratory, and others have been built at WPI, U. Maryland and Drexel.

The Stanford Cart gained its experience of its environment entirely through an on-board TV system, using several kinds of stereopsis by correlating features in succession of images. Traversing a 20-meter course took several hours, in spite of the elaborate measures introduced to speed the image processing tasks [1]. The CMU Rover was a small, cylindrical robot with TV camera with pan, tilt and mount, sonar proximity detectors, and contact switches. The rationale for the mechanical design and control strategy are described in [2]. Experience with the sonar-based system which gradually builds a "probability map" of the expected distribution of obstacles in the environment, is described in [3]. The vision system of the Terragator emphasized edge and line finding based on least-squares fit, a modified Huff transform, and curve-following. Current interest in autonomous vehicle navigation is attested by the thirty-nine papers scheduled for presentation at the SPIE Mobile Robots II Symposium.

The highly successful, very substantial ALV enterprises were intended primarily as demonstration projects to discover just what can and cannot be achieved with current technology. The early performance targets were deliberately set modestly, and it is expected that the performance gradually evolve to the level necessary for intended applications.

The research here falls into a different category, both in scale and intent. We are interested in studying the computational problems involved in high-performance vehicle equipped with precision sensors and designed for rough terrain. We intend to verify our ideas using theoretical models and computer simulation.

Among the principal differences are the following. The ALV's are designed to operate at this time primarily over roads: we are interested in a pathless environment. The ALV's are designed to exploit existing technology: we intend to parametrize the stability and control functions of the vehicle, without restriction to a particular implementation. The major sensor in the ALV's is the color camera: we rely primarily on the range-finder, which is not hampered by variations in the ambient light conditions and in directional reflectance properties of the surface. We stochastically estimate the range parameters, which increases the accuracy substantially beyond that possible with single observations. The current systems cannot simultaneously process range-finder and camera information because of computing resource limitations: we investigate the savings possible through synchronized measurements of the delay and amplitude of the directed light beam to obtain simultaneously range and surface reflectance. Finally, we base our work from the start on the availability of coarse map information which is refined by observations of easily detected visual horizons and more difficult to detect surface discontinuities. Hence, the primary problem of the selection of a satisfactory path from point A to point B can be addressed by dynamic programming, a technique inherently suited to breaking down a large problem into manageable segments.

RELEVANT PRIOR WORK BY THE AUTHORS

Our own past research has concentrated on:

(1) Effective methods of processing range-finder returns in a spherical coordinate system to obtain elevation, slope, and slope discontinuity (edge) characteristics of a surface [4-6], and

*Center for Intelligent Robotic Systems for Space Exploration under NASA Sponsorship.
**NSF Grant #IRI-8704718 is gratefully acknowledged.

(2) Data structures for efficient retrieval of terrain characteristics, including visibility maps, from a digital elevation model, [7-10].

1. Autonomous Navigation on Rough Terrain

The research originally initiated by C.N. Shen and his colleagues for the project NASA Mars Rover and refined over more than a decade may be summarized as follows. The range finder, mounted at a height of about 2m, scans the terrain in front of the vehicle in concentric arcs. The standard deviation of the positioning angles (azimuth and elevation) are assumed to be of the order of 1 arc minute and the ranging accuracy is about 0.05m.

The matrix of range data is the input to a procedure called the Rapid Estimation Scheme, which models sudden changes in the range or in its first differences by means of a Kalman filter [11]. Such differences, if consistent, correspond to the boundaries of obstacles. Consistency is established by hierarchical recursive clustering of the candidate edge points into subsets of continuous edges corresponding to planar facets. The method is designed to be invariant with regard to the observation point, so that obstacles may be detected regardless of the relative position of the vehicle and the obstacle [12].

Once the obstacles have been "mapped", the in-path and cross-path surface slopes are estimated. Hermite polynomials are then used to obtain a smooth model [13] of the terrain along the corridors that are candidates for the path of the vehicle. The estimation is complicated by the fact that uniformly distributed observations in the original spherical coordinate system of the range finder correspond to non-linear loci in the cylindrical coordinate system required for terrain slopes. Furthermore, any tilt in the vehicle due to terrain roughness is magnified in the movement of the top-mounted range finder.

In the next phase, the terrain variable at discrete sections along each corridor are computed using the estimated slopes. A path selection scheme then evaluates the risk index by means of a two-step dynamic programming algorithms [14-15]. The cost function is a convex combination of individual cost elements.

The research findings are summarized in various technical papers for the following tasks: (1) feature extraction employing edge detection [16], (2) gradient estimation using spline functions [4,17], (3) identification and recognization of objects/targets using a model based recognition process[18], and (4) performance evaluation of probability of success in finding given objects/targets [5,6,19].

The major advantage of the method is that since it is solidly based on probability theory, the reliability of the path selection may be readily calculated.

2. Data Structures for Terrain Representation and Visibility Maps

Nagy has conducted research on remote sensing and on geographic information processing since 1972 [20-24]. In a collaborative US-Italy project initiated in 1979 on the application of computational geometry to geographic problems, he and his Genova colleagues have developed a hierarchical data structure for surface approximation by means of nested planar triangular patches [7-9]. The resulting terrain model is well suited for irregularly distributed data points and for surface approximation by linear interpolation. It naturally provides a variable-resolution coverage. Triangular meshes also render it convenient to work with nonconvex and multiply connected regions, such as elevations near bodies of water.

More recently, this joint project has resulted in an algorithm that extracts the visibility regions of selected points from a triangulated irregular network model of the terrain [10]. One goal of the current visibility research is the identification of significant topographic features, but applications to navigation, orientation, location of observers, and to the disposition of transmitters and receivers in line-of-sight communications systems are more immediate. How much of the terrain is visible from any given point on the path of an autonomous vehicle is clearly an essential aspect of the design of the control and path selection system of such a vehicle.

STATEMENT OF THE PROBLEM

The scanning laser range finder determines the radial distance to points on the terrain surface. This determination is highly accurate when the surface reflectance is unimodal and the slope is nearly normal to the line of sight of the laser. The computed range has a high variance when the surface gives rise to multiple reflections or if the slope is at a glancing angle to the beam. The observations are obtained in a spherical coordinate system and transformed into a vehicle-centered cylindrical system for computing the path. From these observations boundaries of "smooth" surface patches and their gradients can be obtained by 3-D edge extraction schemes. The surface of the terrain within a boundary is determined by a 3-D smoothing algorithm and represented as a bicubic Hermite polynomial which can be made continuous in second partial derivatives at all node points.

The terrain model is a triangulated irregular network derived from a set of (x,y,z) observations of the area. It is assumed that a coarse terrain model, obtained from prior observations (infrared satellite scanners, aerial photographs, sideways looking radar or existing topographic maps) is available to the vehicle control system for gross path calculations. The model allows computation of the approximate visibility region and local horizon of the vehicle at any point. This terrain model is not, however, sufficiently detailed to allow the vehicle to perform detailed path calculations for avoiding local obstacles. Local obstacles are considered large compared to the wheel or track dimensions, but small compared to the mapped topographic features.

The visibility regions can be updated locally by estimates obtained from the laser range finder. On the other hand, to observe the terrain ahead of the vehicle with the range finder, maximum possible visibility is desirable for path selection purposes. Therefore the estimation of surface features with a range finder and the visibility problem are combined in an adaptive learning paradigm.

The intersection of two smooth surfaces yields a curve, which is to be detected as an edge. Using the range finder alone, the probability of detection decreases rapidly as the dihedral angle between the surfaces approaches pi. However, edges represent discontinuities both in the reflected illumination and in the directional derivative of the range readings. Therefore edge location can be improved using surface reflectivity measured directly by a receiver sensitive to reflected ambient illumination and synchronized with the receiver of the range finder.

The constraints imposed on acceptable paths may be of a number of types. For instance, one may restrict the maximum in-path angles for ascent and descent according to the climbing and braking capabilities of the vehicle. One may limit the minimum distance that the vehicle may approach unseen terrain to ensure that it does not fall into a ravine that is invisible to the range finder. It would be necessary to also limit the cross-path slope according to the lateral stability of the vehicle. Once these essential constraints are satisfied, it would be desirable to find the shortest or the fastest path between two specified points. Alternatively, if the purpose of the vehicle is reconnaissance, one may wish find the trajectory that would maximize the total area visible to the vehicle in a given region. Any of these constraints could be readily accommodated by means of an expert system, which would constitute an extensible and modular knowledge base incorporating goal, terrain, vehicle, and instrument characteristics.

As the vehicle moves from place to place, it extends its fine (local) model of the terrain and updates its visibility information. One must therefore evaluate the benefit drawn from the laser measurements over the previously obtained information contained in the coarse terrain model. The evaluation of the selected path can incorporate any of the following criteria: minimum fuel, minimum risk, minimum deviation from direct course, or minimum time.

The paradigm we have adopted for terrain navigation can be summarized in the following sequence of steps:

1. At the vantage point of the vehicle, a forward sector view is determined from the visibility map extracted from the terrain model. The visibility map also provides a skyline in the forward sector.

2. The same skyline is estimated and approximated from the on-site measurements of the laser rangefinder. The skyline is obtained by segmentation of the locally observed terrain map at points of large range discontinuities.

3. The skylines from the visibility map and from the local terrain map are compared and the two 3-D curves in space on the maps are stochastically matched to update the vehicle location. The matching can also be achieved by clustering the first partial derivatives and the mixed second partial derivatives in a 3-D space.

4. The local portion of the visibility map is improved and revised using the local observations and the registration parameters derived in the previous step.

5. A path is selected taking into consideration the overall visibility information, locally observed obstacles such as boulders or craters, and the a priori constraints.

6. The vehicle moves a short distance by dead-reckoning along the chosen path without taking any observations. Once it arrives to a new and relatively high location, i.e., a new vantage point with broad visibility, the entire procedure is iterated.

METHOD OF APPROACH

It is assumed that a coarse terrain model obtained from prior observations is available to the vehicle control system for coarse path calculations. This model allows the determination of the approximate visibility region and local horizon of the vehicle at any point. The visibility region can be refined locally by estimates derived from a vehicle-mounted laser range finder. This allows for a more accurate location of the vehicle than is possible by dead reckoning alone and also allows the path selection algorithm to avoid local obstacles not represented in the global model. The study investigates the interrelation of surface feature estimation with a range finder and the visibility problem in a partially unknown environment.

In the current paper, we plan to combine several research strands in order to evaluate a complete path-optimization system based on range estimation and imperfect prior knowledge of the topography. The entire system is simulated by means of a computer program to allow assessment of the effects of diverse parameters. The task consists of the following components [Figure 1]:

(1) Model the laser range-finding instrument, including specification of its pointing accuracy and signal-to-noise ratio, as a function of reflectance parameters.

(2) Represent the fine model of the terrain, in the form of an irregular triangulated network. This allows computation of the expected signal for the range finder. The fine model represents perturbations on the gross terrain model described below. It includes reflectance characteristics for each planar facet. These perturbations are terrain features that are too small to appear in the gross terrain model but yet large enough to affect the motion of the vehicle: examples are boulders and craters. The fine terrain features must be estimated from the range-finder signals. (Figure 2).

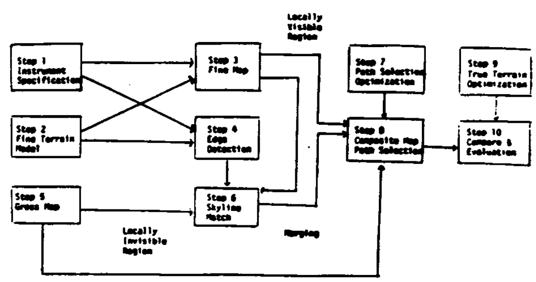

Figure 1. Block Diagram Model for an Autonomous Vehicle Navigation System

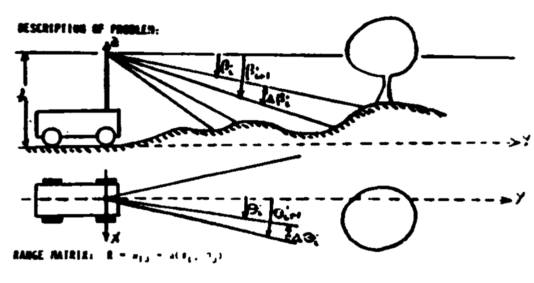

Figure 2. Range-Finder Signals

(3) Develop a set of algorithms for conversion of raw signals derived from items 1 and 2 to C1-continuous polynomial (spline) functions of elevation values in cylindrical coordinates. This constitutes a local visible map from a range finder.

(4) Develop algorithms for edge determination for the fine model, i.e. discontinuities in the low-order functional description of the terrain into space-curves. These space-curves are completely unstructured, and can be estimated by using spline functions, each grid point of which registers in 3-D space its position, the inpath slope and cross path slope. For example, the skyline thus obtained shows many layers of ridges, near or distant. They also yield local boulders and crates anywhere on the terrain.

(5) Represent the gross model of the terrain provided to the system in the form of a triangular irregular network. It is assumed that the gross topography is available to the autonomous vehicle control system as a result of previous satellite or aerial maps. The level of detail given in the gross terrain model may vary all the way from zero, in which case the path is selected entirely on the basis of local range observations, to the full detail of the fine terrain model, in which case the observations are irrelevant. The skyline is estimated from the visibility map with the current position of the vehicle, using the direction of motion as reference azimuth.

(6) Develop algorithms for gross-fine skyline matching. We first look for the discontinuity of the skylines, i.e., one ridge in front of another in a cascade of mountains. The space curves thus generated are in separate branches. These separate curves are arbitrary in shape or size. For a reference point on any one branch of the gross visibility map there are locally many possible points on the fine navigation map for matching. A Euclidean or other norm is used for the errors introduced in 3-D of the position and slope. Local matching is accomplished in minimizing the errors by moving the points in the fine minimizing navigation maps along the fixed reference point in the gross visibility map. Thereafter, a global matching is performed by a stochastic fit of the space curve for the entire branch. Here an expert system with the A.I approach will be investigated.

(7) Postulate a set of path specifications [Figure 3] which describe desirable features of the selected path such as maximum rate of climb and descent, maximum lateral slope, and minimum distances for altering direction, and the initial and terminal points of the path. Criteria to be minimized may also include fuel consumption, time, and risk (of damage to vehicle). The various components of the desirable path specification may carry arbitrary weights.

(8) Develop path selection algorithms which allow combining the gross terrain data (item 5), the goal information (item 7), and the results of the range-finder observations (from items 3, 4 and 6) to determine successive segments of the path as the vehicle progresses from the initial to the terminal point. Currently the optimal path is computed with a two-stage dynamic programming code [Figure 4], with the visible navigation map at the first stage and the invisible gross map at the second. However, we will also use an expert system for this purpose.

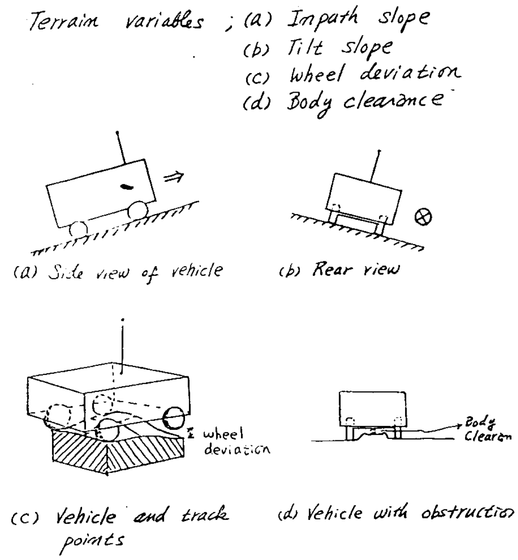

Figure 3. Terrain Features

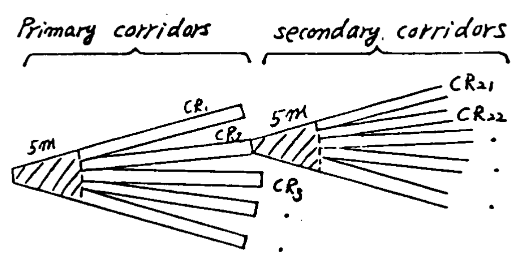

Figure 4. Path Selection Corridors

(9) Build a new composite map at a new vehicle location. After the vehicle has moved into a new location and measurements are made again for the fine map, one can use a filtering and smoothing technique by combining the present fine measurements with the old gross visibility map and the trace of the vehicle location. A hidden point in the gross visibility map may happen to be seen for the first time after the vantage point of the vehicle advances by a discrete increment. A triangle is formed in the old composite map where the dead reckoning of the motion of the vehicle is used as a base and the directions of the corresponding departure of the azimuth headings are intersecting to form these points. A modified 2-D Kalman filter is employed to follow the plant noise in the prior estimate at the old vehicle location and the measurement noise in the new estimate for the new composite map at the new location of the vehicle. More accurate estimates of the data can be thus expected.

(10) Develop an optimal path determination algorithm which operates on the actual true terrain model. The output of this algorithm is not, of course, available to the vehicle control system and is computed strictly for evaluation purposes.

(11) Derive an evaluation function which compares the optimal (or reference) path computed in item 9 with that computed in item 8 on the basis of gross terrain data and range finder observations. In the evaluation the weights given to the various types of deviation from the optimal path may be weighted by the experimenter.

The output of the simulation is a measure of the deviation of the path determined by the vehicle control system from the reference path, and a tabulation of the selection criteria (fuel, etc.) for both the reference path and the selected path.

Scientific advances to be derived from this research include stochastic merging of information from a global model and a sequence of local range observations, advances in constrained path selection using the combined model, and robust computational-geometric methods of deriving visibility information from both digital elevation models and panoramic range data. The work links conventional signal-processing approaches with knowledge-based AI methods learning and uncertainty reduction using efficient search techniques.

SUMMARY

We are interested in studying by means of theoretical models and computer simulation the computational problems of a high-performance autonomous vehicle equipped with precision sensors and designed for rough terrain.

We are considering a pathless environment and intend to parametrize the stability and control functions of the vehicle without restriction to a particular implementation. We rely primarily on the range-finder, which is not hampered by variations in the ambient light and in the directional reflectance properties of the surface. We stochastically estimate the range parameters. We base our work from he start on the availability of coarse global topographic data which is refined by observations of easily detected visual horizons and more difficult to detect surface discontinuities. The primary problem of selecting a satisfactory path from point A to point B is addressed by dynamic programming, a technique inherently suited to breaking down large problems into manageable segments.

The information to obtain terrain variables for path selection are generated from the observations of the range-finder in the visible corridors in front of the vehicle, augmented by the global information about the invisible regions behind hills and in chasms. The local observations register the course map and provide detailed information about boulders and craters, while the global topography helps to avoid invisible traps. Combining the two sources of information requires matching the skylines as seen from both maps. The composite map is then used for path selection.

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