FUZZY LOGIC PATH PLANNING SYSTEM FOR COLLISION AVOIDANCE BY AN AUTONOMOUS ROVER VEHICLE

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ABSTRACT

The Space Exploration Initiative (SEI) of the United States will make great demands upon NASA and its limited resources. One aspect of great importance will be providing for autonomous (unmanned) operation of vehicles and/or subsystems in space flight and in exploration of environments such as the surface of Mars. An additional, and complicating, factor of SEI is that much of the need for autonomy of operation will take place under conditions of great uncertainty or ambiguity. Thus, traditional approaches are less likely to provide satisfactory results for the ambitious goals of SEI. In particular, it is appropriate to consider how control situations (one of the major problem areas) can be handled through emerging technologies such as fuzzy logic, neural networks, and genetic algorithms. The absence of precise mathematical modelling for uncertain environments provides an opening for alternative approaches that are better suited for such problem domains and which in fact may lead to a lower level of computational complexity or even the possibility of customized computer chips that will handle specific control problems.

Systems already developed at NASA/JSC have shown the benefits of applying fuzzy logic control theory to space-related operations. This report is concerned with four major issues associated with developing an autonomous collision avoidance subsystem within a path planning system designed for application in a remote, hostile environment that does not lend itself well to remote manipulation of the vehicle involved through Earth-based telecommunications. A good focus for this is unmanned exploration of the surface of Mars. The uncertainties involved indicate that robust approaches such as fuzzy logic control are particularly appropriate.

Four major issues addressed in this report are:

1. avoidance of a single fuzzy moving obstacle;
2. backoff from a deadend in a static obstacle environment;
3. fusion of sensor data to detect obstacles;
4. options for adaptive learning in a path planning system.

It is likely that the approaches described and references given will be useful for other problems with differing situations but characteristics common to those described here (e.g., autonomy of operation under conditions of uncertainty).

INTRODUCTION

This report addresses four important aspects of autonomous collision avoidance in a path planning system: avoidance of a single fuzzy moving obstacle; backoff from a deadend in a static obstacle environment; the fusion of sensor data from multiple sensor sources for obstacle detection; and, options for adaptive learning in a path planning system. Previous work dealt with various types of stationary obstacle scenarios.

NASA is currently involved with planning a variety of unmanned missions. As a particular focus, this investigation will consider some of the issues associated with unmanned surface exploration of Mars.

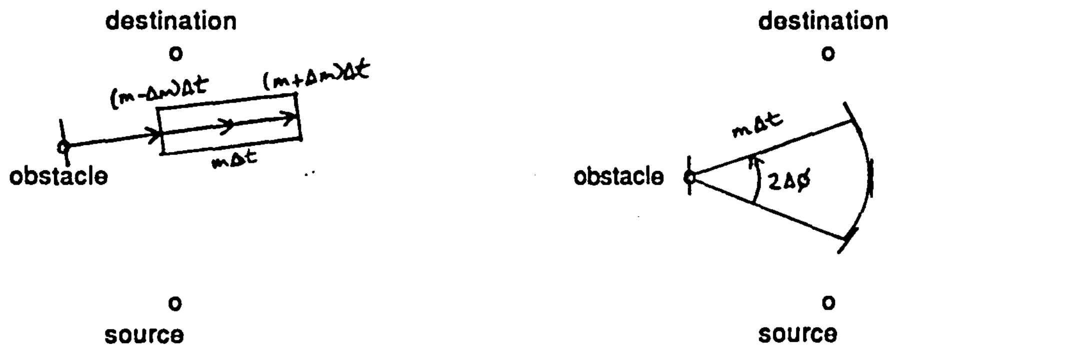
Examples of the need for collision avoidance by an autonomous rover vehicle with a moving obstacle would be: wind-blown debris, surface flow or anomalies due to subsurface disturbances, another vehicle, etc. The other issues of backoff, sensor fusion, and adaptive learning are important in the overall path planning system concept. Fuzzy logic control systems have been shown by Robert N. Lea of NASA/Johnson Space Center and others to be an effective tool in building reliable systems that function well in the presence of uncertainty or ambiguity (1,2,3).

The research into the use of fuzzy logic in the decision and control process for autonomous path planning including collision avoidance is a new aspect of a continuing problem domain (4,5,6,7,8,9). The theory of fuzzy sets and fuzzy logic was introduced in 1965 by L. A. Zadeh of the University of California, Berkeley (10). The book by Klir and Folger (11) gives a good treatment of the fundamentals of this field, while the book by Kosko (12) addresses more advanced aspects as well as the interface between the application of fuzzy and neural approaches to problem-solving. Until the last few years, there has been a dearth of commercial applications of fuzzy logic control (13). At the present, there is a tidal wave of applications coming from Japan, addressing problems in subway systems, process control in industry, automatic transmissions, camera display integrity, washing machines, vacuum cleaners, etc. Togai InfraLogic, Inc., of California has marketed a fuzzy logic expert system shell for ease of fuzzy logic applications development (14).

For true autonomy of operation, higher-level path planning is necessary to ensure integrity of the physical system, allow for conservative modification of guidance rules based on experience, and facilitate efficient backoff from deadend approaches that interfere with accomplishing the original goal of the mission. A consideration in this investigation is to seek generalized features that encourage extension and adaptation of this path planning system to other environments (e.g., autonomous collision avoidance for space vehicles with respect to other space vehicles, natural and man-made space debris, etc.) Other types of uncertainty modelling, such as Dempster-Shafer theory, may well be useful tools to complement the strengths of fuzzy logic.

AVOIDANCE OF MOVING OBSTACLES

For purposes of this report, we will address a single, moving fuzzy obstacle; that is, an obstacle with a fuzzy radius w and either a fuzzy speed $[m - \Delta m , m + \Delta m]$ or a fuzzy direction $[ø - \Delta ø , ø + \Delta ø]$. See Figure 1 for a graphic representation of these situations.



a. fixed direction, fuzzy speed

b. fixed speed, fuzzy direction

Figure 1. - Moving Obstacle Scenario

Using the simplest possible approach to a potentially complicated problem, it is best to not try to project the exact path of the moving obstacle. Instead, the best approach is to use fuzzy rules and a fuzzy inferencing mechanism to take an imprecise environment and assess the likelihood of collision based on the current situation. If necessary, collision avoidance techniques are then applied to avoid the danger. Figure 2 contains two key rules for the system and membership functions for key fuzzy linguistic variables. To activate the avoidance system means to make changes as needed in speed and direction to avoid collision.

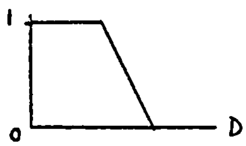
Sample Fuzzy Rules: (fuzzy linguistic variables are underlined)

If the paths of the vehicle and the obstacle <u>cross</u>
and if the time of crossing is <u>similar</u>,
then the obstacle is a <u>hazard</u>.

If the obstacle is <u>close</u> and if the obstacle is a <u>hazard</u>,
then <u>activate</u> the collision avoidance system.

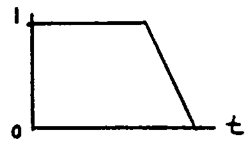
Sample Membership Functions for Fuzzy Linguistic Variables:

<u>cross</u>



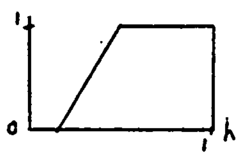
D = closest distance
of paths

<u>similar</u>



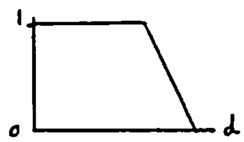
t = difference of time when
closest distance of path is attained

<u>hazard</u>



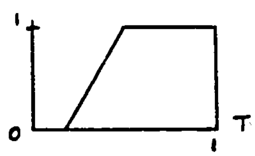
h = degree to which
obstacle is hazard

<u>close</u>



d = critical distance*factor
to adjust for various speeds

<u>activate</u>



T = threshold

Figure 2. - Sample Rules and Membership Functions

Figure 3 has the architecture for a fuzzy avoidance system for a moving fuzzy obstacle. Implementation may well result in modification of this architecture and/or subsystems to enhance performance. In general, this will be a subsystem of a general path planning system for autonomous exploration with collision avoidance.

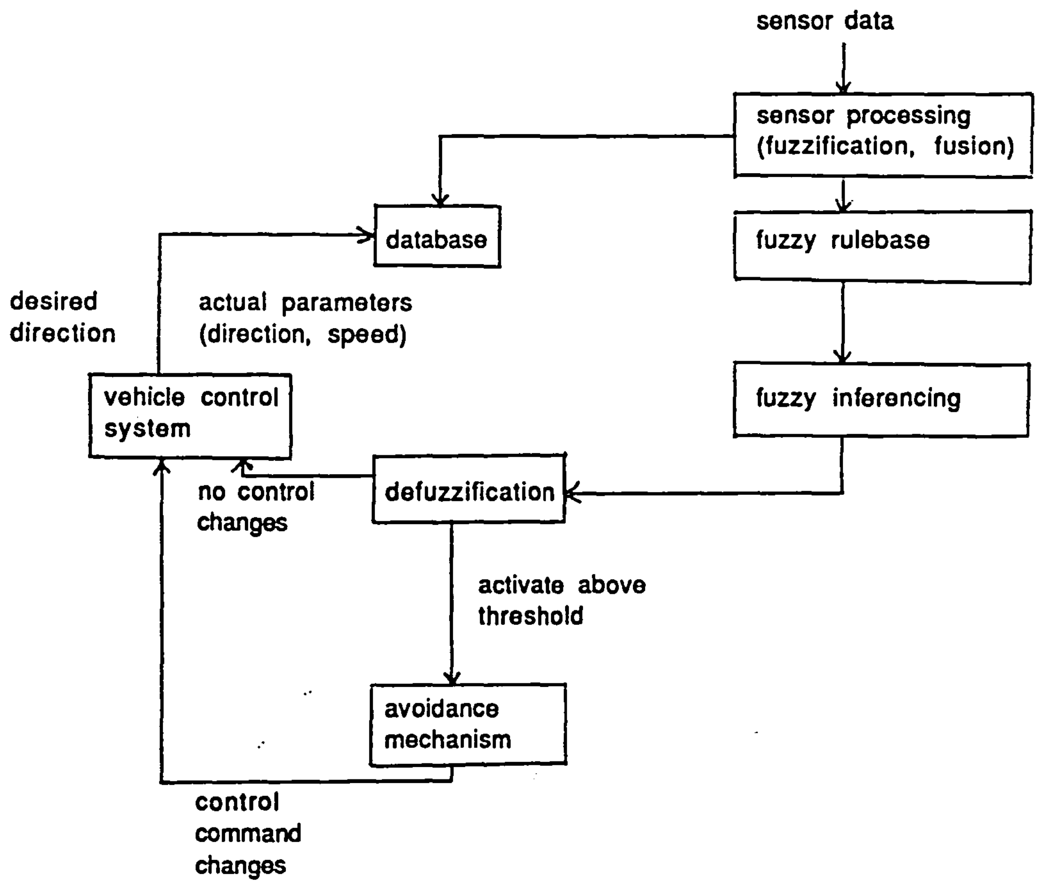


Figure 3. - Architecture for Fuzzy Collision Avoidance Sysem

SENSOR FUSION

Sensor fusion, in the sense of combining information based on more than one sensor operating simultaneously, promises to give a significant improvement in object detection over the use of a single sensor source (4,8). The problem, of course, is to have a computationally reasonable means of combining and interpreting sensor data from dissimilar sources. Dempster-Shafer Theory is a good candidate for giving useful combinations and interpretations of such data, but it is computationally intense (15,16). A formation of information in a hierarchical structure can be used to give a significant improvement in computational complexity. Our search here has been exploratory in nature, and we see directions for further work, but it is clear that nothing definitive has been established to date.

BACKOFF TECHNIQUES

Basically there are two viable techniques for backoff from deadends in a static environment that is not fully mapped and where uncertainty of information is a regular element of the environment. The first technique is based on reversing direction coupled with extending the critical distance for sensor processing and synthesis so that oscillatory travel patterns are avoided. A possible concern with this approach is that the algorithm is essentially a greedy heuristic that works under the premise that most of the time making a local optimal choice will yield a successful path. The second approach is to store a modified world model that would map known (or approximate) information regarding the explored environment so that a repeat of that exploration would be prevented. The problem with this second approach is the need for significant memory to store the model and increased processing capability for subsequent path development in backoff situations. With neither choice being a clear winner, it is likely that the first approach may have an advantage in the sense of a lesser degree of complexity. Other possibilities are: storing a limited map of the explored region or blocking one or more sectors from being chosen for the direction of the vehicle until an obstacle threshold has been passed and new data is available to evaluate path options. These are desired directions and alternatives for expanding and improving the algorithms previously reported (5,6,7).

OPTIONS FOR ADAPTIVE LEARNING IN A PATH PLANNING SYSTEM

One of the most promising options for adaptive learning in control environments has been the use of neural networks (5,12,17,18,19,20,21,22,23). A difficulty with applying neural networks to adaptive learning in fuzzy environments is the transfer of techniques from one application to another. Many of the neural approaches to control are very domain specific and require extensive modification (when possible) to use in conjunction with fuzzy systems. One particular approach which is promising is to use neural nets (or even neurons) to tune (adjust) the membership functions of fuzzy variables. Attempts to find general approaches or modify existing designs to accomplish this have been less than successful to date, but it is too early to write off this approach. A bigger problem will be to develop an adaptive system that will operate on data being generated as the system performs and continually (or periodically) update parameters of the system to improve or maintain optimal (or near optimal) performance. Even though this appears to be feasible, it is still unsolved and appears to be more difficult than originally viewed and will still face the test of convincing skeptical engineers that a new technology that adapts to changing circumstances in uncertain environments is a viable choice for mission critical problem-solving. A different adaptive technology that seems possibly suited for training a fuzzy logic control system is genetic algorithms (24).

CONCLUSION AND FUTURE DIRECTIONS

Fuzzy logic control provides significant opportunity for application to uncertain and/or ambiguous control environments such as autonomous collision avoidance. Many areas have been identified in this report that warrant further investigation. In brief, areas of promise are simulation of avoidance of a moving obstacle, use of various approaches to sensor fusion, validation of backoff techniques for static collision avoidance environments, and further development of adaptation techniques to improve/maintain system performance under conditions of uncertainty. Integrating these concepts into a viable path planning system is a worthy, if difficult, goal. Finally, identification of general concepts that transfer to other problem domains is a side goal that may be even richer than the application to collision avoidance and path planning.

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