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APPLICATIONS OF FUZZY SETS TO RULE-BASED EXPERT SYSTEM DEVELOPMENT

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ABSTRACT

In this paper, problems of implementing rule-based expert systems using fuzzy sets are considered. A fuzzy logic software development shell is used that allows inclusion of both crisp and fuzzy rules in decision making and process control problems.

Results are given that compare this type of expert system to a human expert in some specific applications. Advantages and disadvantages of such systems are discussed.

INTRODUCTION

Fuzzy logic was introduced in 1965 by Lotfi Zadeh [Ref. 1] as a method of capturing human expertise and incorporating this expertise into expert systems. The fuzzy set, which allows partial truths of statements as opposed to the classical Boolean logic, more correctly matches real world problems where people are forced into dealing with statements given in natural language. Statements of rules in natural language is a necessary way of dealing with decision making problems of the type typically handled by human experts. The use of the term "fuzzy logic" typically gives erroneous impressions to listeners that "fuzzy thinking" is involved. Actually, fuzzy logic is a mathematical method of dealing with situations that do not conform to Boolean logic. As an example, consider the following problem related to plant control. The condition of temperature being "low" is not a crisp concept, but is a condition that certain plant operators have to deal with on a regular basis. It is also not a probability concept as this operator is not the least bit interested in the probability that the temperature is low or even the question of whether it is likely that, given the current temperature, someone else might call it low. He is interested in evaluating the present situation, i.e., the present temperature that exists now, and deciding if it is low. This brings in the notion of a fuzzy set in a natural way since the condition of being low is a matter of degree. For example it seems to violate all rules of common sense to believe there is a particular temperature that satisfies the criterion that on the low side of that number, the temperature is low, while on the other side, it is not low. Mamdani and Assilian [Ref. 2] dealt with similar problems in their applications to ill-defined industrial processes.

Fuzzy set applications have been particularly successful in dealing with control of ill-defined processes of the type considered by Mamdani and Assilian. Excellent results for systems that are more well-defined but are still so complex that precise modeling is, at best, very difficult and expensive to do. Examples are the studies done at the Johnson Space Center (JSC) that use fuzzy sets in the control of space vehicle simulations and control of sensor data processing [Refs. 3,4]. The controller discussed in the following Control Applications section differs from the work in [Ref. 3] in the following respect. Although that controller is modeled on rules developed through conversations with simulator pilots, it was a hybrid type controller in that it used simple models to determine rates of the active vehicle and assumed that the measurements were smoothed and quite accurate when the controller did its evaluations to determine actions to take. This new variation of the controller uses rules modeled with fuzzy sets only for both rates and positions and uses the data from the sensors directly or with at most, very simplistic smoothing filters.

CONTROL APPLICATIONS

A controller that models the actions of a pilot as closely as is feasible has been modeled. Seven rules are used to control each of the velocities of the vehicle in its body, x, y, and z directions, respectively. As an example, let theta represent the elevation angle of the active vehicle with respect to the target vehicle, d_theta represent the corresponding angle rate, and let x_dot represent the velocity of the active vehicle in the x-direction. Let PS, PM, NS, NM, and ZO represent positive small, positive medium, negative small, negative medium, and zero, respectively. The set of rules are the following.

Rule 1. If theta is PM and d_theta is ZO, then x_dot is PM.

Rule 2. If theta is PS and d_theta is PS, then x_dot is PS.

Rule 3. If theta is PS and d_theta is NS, then x_dot is ZO.

Rule 4. If theta is NM and d_theta is ZO, then x_dot is NM.

Rule 5. If theta is NS and d_theta is NS, then x_dot is NS.

Rule 6. If theta is NS and d_theta is PS, then x_dot is ZO.

Rule 7. If theta is ZO and d_theta is ZO, then x_dot is ZO.

Also, rules for controlling the allowable rates need to be defined. These can be considered to be gain factors. These gain factors are important because allowable maximum rates will be smaller in the vicinity of the desired approach vector. Let A, L, VL, VVL denote average, large, very large, and very very large respectively for the gain factor. The additional fuzzy sets for theta, PL, NL, PVL, NVL, PVVL, and NVVL represent the conditions positive large, negative large, positive very large, negative very large, positive very very large and negative very very large respectively. The additional rules are specified below.

Rule 8. If theta is PS or PM or NS or NM, then gain is A.

Rule 9. If theta is PL or NL, then gain is L.

Rule 10. If theta is PVL or NVL, then gain is VL.

Rule 11. If theta is PVVL or NVVL, then gain is VVL.

Similar rules, as defined for elevation angle, are defined for the azimuth angle including gains since they typically will be different than for elevation control. Relative range rate, R_dot, control is specified by rules that make rate proportional to the relative range R, i.e., R_dot = k*R.

The value of k may be specified by a function of range, position, elevation angle, etc. However, for this study, k is a simple constant. The nominal value is .001 since this corresponds closely to rates maintained during manned rendezvous missions. It may be varied depending on the desired rate of approach and the relative range of the active and target vehicles. For R_dot control, rules are defined as a function of certain range gates. For example if r0, r1, r2, ... , rn are n-values of relative range and r0_dot, r1_dot, r2_dot, ..., rn_dot are n-values or relative range rate, then the range rate rules are defined as follows.

Rule 12. If R is less than r0, then R_dot should be approximately k*R.

Rule 13. If R is between r0 and r1, then R_dot should be about r0_dot.

Rule 14. If R is between r1 and r2, then R_dot should be about r1_dot.

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Rule (12 + n). If R is between r(n-1) and rn, then R_dot should be about r(n-1)_dot.

Rule (13 + n). If R is greater than rn, then R_dot should be about rn_dot.

Typically, these values for range rate will be a function of the mission scenario, e.g., if the closing maneuver must be completed in a certain amount of time, then this will obviously affect the required closing rates. On the other hand, if the primary constraint is fuel usage then closing rates will be based on that consideration.

For this specific application development
r0 = 1000, r1 = 1500, r2 = 2000,
r3 = 4000, and r0_dot = 1.0,
r1_dot = 2.0, r2_dot = 3.0,
r3_dot = 4.0.
Therefore, there are 27 fuzzy rules for this simulation.

RESULTS

This version of the fuzzy controller has been compared to several other control sources. The results have been quite favorable although considerably more testing needs to be done. The current fuzzy pilot version more nearly conforms to rules that are adhered to by actual pilots of shuttle vehicles or simulators used for pre-mission analysis or training. The major problem that has not been completely solved as yet is the problem of noisy sensors where the noise is greater than the range in which the parameter under control needs to be maintained. This applies almost exclusively, for shuttle problems, to range rate control. Here the shuttle radar has a range rate 1-sigma noise of ±.3 ft/sec. One can easily understand the problems encountered when trying to control the system to .2 ft/sec when the noise is ±.3 ft/sec.

In comparisons with actual engineers and pilots flying the simulators using no additional aids than those available to the pilots, i.e., the modeling assumed no additional smoothing or massaging of the data, the fuzzy pilot performed perfectly acceptable so far as maintaining the desired trajectory and used within 5% of the propellant used by manned trajectory profiles. Some results from an early version of this controller [Ref. 5] support the above statement. With very unsophisticated smoothing of sensor data the automated controller will outperform the manual case. This is especially noticeable in stationkeeping maneuvers.

Further studies have been made to verify that fuzzy set models give results that are better than models using specifically crisp rules. Simulation tests for 40 cases, twenty which used crisp rules and twenty which used fuzzy rules, were made. Comparisons of the fuzzy and crisp cases were made based on propellant usage. In these runs the fuzzy rule-based controller performed, on the average, 20% better than the crisp rule-based controller. In cases where shuttle body rates were included in the simulation, which is the realistic case, the fuzzy controller performed better by 28%.

OTHER APPLICATIONS AND CONCLUSIONS

Rule-based controllers have been shown to be useful in control problems here at the JSC and also in numerous other studies and applications primarily in other countries. However, it should not be inferred that fuzzy controllers are always the best. When a process can be modeled quite accurately, and when this model can be used for estimating responses to actions in real-time there certainly seems to be merit for doing so. Bernard, and his associates at MIT, studied fuzzy rule-based versus analytic controllers in the control of a nuclear reactor power plant [Ref. 6] and came to the reasonable conclusion that each approach has its particular area of usefulness. For his particular application area he claims to get slightly better results with analytic controllers when data is close to the expected but that the fuzzy controller is more robust, i.e., it will tolerate much more unexpected situations and respond favorably. Thus it seems that fuzzy rule-based and analytic controllers may be best used together when modeling of the process is feasible. This is basically the philosophy taken in [Ref. 4] where fuzzy rules are used to control flow of data from various shuttle navigation sensors to an analytically derived Kalman filter, that does not perform well on data for which it has not been tuned.

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