Distributed Fuzzy Decision Making System

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ABSTRACT

This paper deals with the decision making process, using fuzzy information, in a distributed environment. In order to deal with the complexity of this problem we have used the agent model approach. In this way, we have apply this model to the problem of transportation in a non-centralized environment. The internal decision process inside each agent is achieved through a fuzzy reasoning system. The agents can share the information using three different communication perspectives: Communication of fuzzy variables, the labels of the variables or the crisp concepts that have got an internal fuzzy interpretation. The communication protocol among the agents is also presented. This protocol has been designed to exchange the fuzzy information, resulting from the fuzzy reasoning tree inside the agents. The system has been modeled in a distributed simulator design ad-hoc and some of the results obtained are presented.

KEYWORDS: Fuzzy, Distribution, Decision-Making

1 INTRODUCTION

Many human systems are designed to solve problems that involve the search of the best subset of pairs composed by the matching of all the points from two sets.

This is the case of the *Transportation Problem* where some goods have to be carried from a set of origin points to a different set of destination points. In this problem it is necessary to obtain the best matching between origin and destination sets, and the amount of goods considering the cost of good transportation. The process to obtain the solution is guided by the cost of the individual pairs Origin/Destination.

A similar problem appears in the analysis of video stereo images where the last step of the computer vision algorithm to obtain a 3-D image. This is the "stereo matching" procedure. In that problem it is necessary to match the points of two cameras to obtain the depth estimation to build the 3-D image. This search is guided by the value of the similarity of the points.

The traditional numerical algorithms obtain the solution using a numerical matrix that define *a priori* cost/benefit to each possible pair. This value is "a priori" knowledge and the algorithm will find the best assignment for this constant information.

Another approach to this kind of problems involve the use of intelligent reasoning. In this case, the problem can be formulated as a consistent labeling problem. The search is representing as a tree of possibilities, where each node describes a tentative solution to the global matching problem. The tree grows from the most promising nodes according to a heuristic function. This function can be numerical or rule based and calculates the distance between the solution and the node.

When the problem is developed in a real environment the a priori knowledge will be the first source of information, but this does not mean that the problem can be solved in a static way. The solution must be adapted to the actual situation. For example, let us consider the problem of carrying some goods from n original points to m destination points. The solution can be obtained using the initial (a priori) cost of carrying a unity of good from the i origin point to the j destination point. Some time later, problems can appear at the i origin point, making the cost (i, j) change. In this case, the solution must be recalculated, but being compatible with the global solution that is being run.

A distributed perspective will consider each node i as an individual agent. In this kind of systems each one of the agents will take care of the events happening in its location. Then, the agents will use its reasoning capabilities to manage those events and take a decision. This decision will involve the negotiation with the other agents in order to get a coherent behavior of the system, which should fulfill the system requirements.

Another problem with the traditional way of solving this problem is the need of considering that all the information that the system manages is numerical and objective. Using techniques from the artificial intelligence it is possible to introduce imprecise and subjective knowledge in the decision making procedure. In this way, a human-like evaluation can be obtained using a fuzzy-symbolic system. Our system will try to reproduce the decisions of a human observer, which is based on subjective and qualitative descriptions of the perceived situations. In order to get this non-crisp information, a fuzzy rule-based system will be used.

In the following sections we will present how we have decomposed the problem into autonomous agents. In this way, the second section show how these agents interact using the properties of the fuzzy logic. The next section presents the fuzzy decision-making process inside each agent is presented. The fourth section is focused in the fuzzy protocol which allows the agents the negotiation. Then, the experiments carried out, the conclusions obtained and the foreseen works are presented.

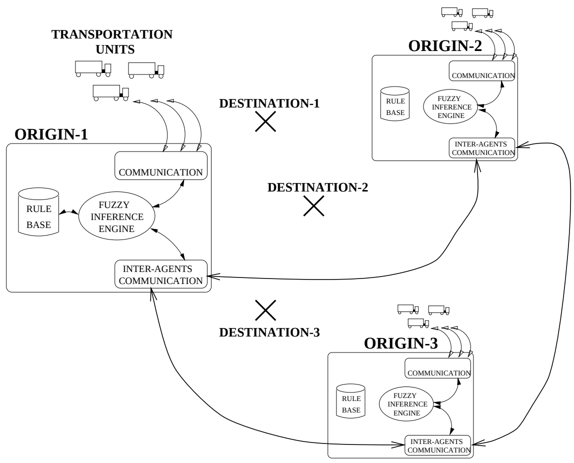

Figure 1 Agent Architecture

2 A FUZZY DISTRIBUTED SYSTEM

The agent architecture for these kind of problems will have to integrate the information about the current situation at its location, the informs received from the transportation units, the request and infos received from other agents and the inferred data. This architecture of the agent is shown in figure 2. These agents use a knowledge representation based on fuzzy logic in order to cope with the uncertainties of the information supply to the agent and the inaccuracies due to failures in communication, hardware, etc..

Fuzzy systems offer higher robustness to those problems using different levels of abstraction. The first level corresponds to the rough data directly acquired from the world. This information is fuzzified from the crisp values into linguistic variables. The next levels consist of decision-making processes able to manage fuzzy variables [12]. This agent architecture will provide a consistent action based on a fuzzy rule-based decision-making system.

When attempting to define such a distributed system two different approaches emerges:

Centralized: In this kind of systems one of the autonomous agents is configured as the team-leader. It will split up the task in charged to the group and it will send the subtask to the other agents. These agents will send the leader its decisions or needs and the chief would recalculate the solution if it is

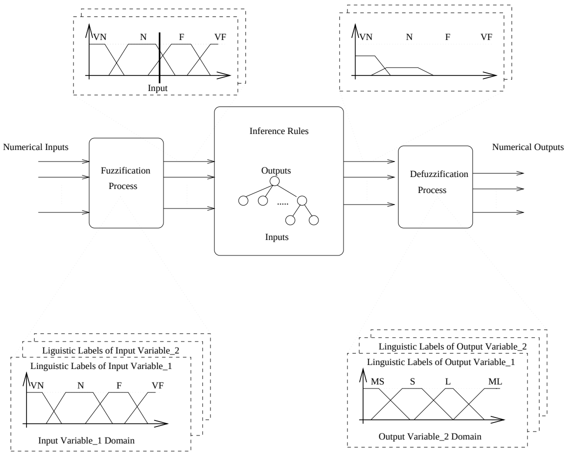

Figure 2 Fuzzy Logic Controller

needed. These systems can be hierarchical, this means that a large group of agents can be split up into subgroups, each of them with its own leader.

Decentralized: The classical metaphor [4] is a group of human experts working together. If we assume that no one of the experts has a higher status than the others. In such situation, each expert will spend most of his time working alone on various subtasks that have been partitioned from the main task, pausing accidentally to interact with the other experts. These interactions generally involve requests for assistance on subtasks or the exchange of results.

Each of the methods has got its own advantages, for instance, the second one is more fault-tolerant (this means that the system would degrade if some of the agents crash), while the first one can be more efficient. The decision of what kind of architecture has to be used is problem-dependent.

To work with a unknown environment it is used a decentralized approach where each node has its own view of the problem and try to obtain its own solution. When a problem appears and the fuzzy reasoning process decides that to obtain the solution the agent needs the help from the other agent, a communication of the problems that have emerged is transmitted to all the agents that can give their resources to resolve them. Through a negotiation process among the nodes a solution is achieved.

3 THE FUZZY DECISION-MAKING PROCESS

The decision making process can be defined [6] as the study of how decision are actually made and how they can be made better or more successfully. This process can be made by one or more decision entities. And also the decision can be taken in one or more stages. As we have shown in the previous section, the decision in our system is taken by a group of autonomous agents.

The use of fuzzy techniques in the problem we have previously described let us use more vague and undetermined information

The construction of a fuzzy motor of inference requires some steps:

1. Define input and output variables, that is, determine which phenomenon will be observed and which control action have to be considered.

2. Define the way in which the events of the world are expressed in fuzzy terms.

3. Design the rule base.

4. Determine the way to which fuzzy outputs can be transformed into agent actions.

A fuzzy system is presented in figure 2. This figure presents the whole fuzzy reasoning process. In first place, the numerical values are fuzzified using the *linguistic labels* defined on the variables domain. Then, the fuzzy inference rules get the fuzzy action, which is translated into crisp actions through a defuzzification process. The system can be composed of more than one level, as is represented in the central box of the figure 2. In this case, the fuzzy labels of the output of the first level of rules would be the fuzzy inputs of the next level. Therefore, the inputs of the global reasoning system would be the inputs of the first level and the output variables would be the outputs of the last level.

Let us consider a simplified example as the one in figure 3. In this figure only two origin points, named A and B, have been considered. Each of the origin points would have got 10 units of the good considered. The destination points have

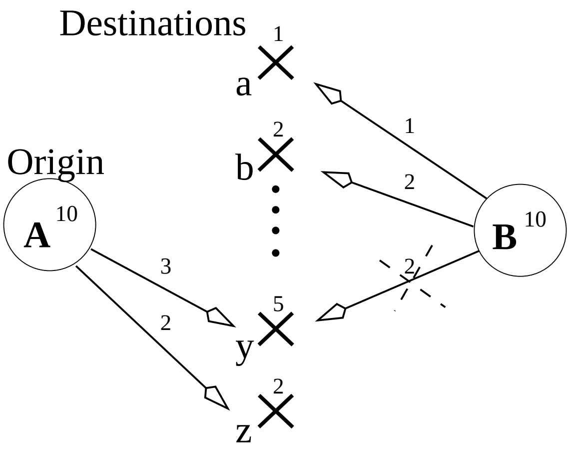

Figure 3 A simplified Example

been named from a to z and have been represented by one "X". The number over the "X" indicates the number of units that have to be sent to that point. The arrow between an origin i and a destination j indicates the number n of good units that the origin i have decided to send to the destination j. In this example we have reduce the origins and destination points to the minimum and also the transportation costs have not been considered.

Let us suppose that the decided solution to the problem, which would had been negotiated among the agents, is the one represented in figure 3. Let us also suppose that for any reason the delivery between the origin B and the destination z is delayed. Then, the agent b will receive a piece of information from the transportation unit of the kind *Delay will be very long*. Then, agent B can perform one of these actions:

1. **Wait** till the delivery can be accomplished by the actual transportation unit, which can disturb destination z.

2. **Re-send** another transportation unit, which means that the cost is increased and the stock of goods is reduced.

3. **Ask** A for sending the goods.

The information from agent A to B about the problem is transmitted in a fuzzy way. This representation to includes subjective information.

4 FUZZY PROTOCOL

We have described how the agents take advantages of the fuzzy reasoning to cope with the uncertainties of their situation. In the same way, fuzzy techniques can be used in the communication protocol among agents. The use of a fuzzy protocol will leave more opened the content of the messages than the crisp one. When the design of the protocol is considered, three possibilities arise:

1. The first one is based in the communication of fuzzy variables stored in the data-base. These variables are defined by a set of labels each one representing a function defined over the domain of its variable. The labels in all the agents will be defined by the same function and over the same domain.

2. The previous one can be modified in order to use the same labels but defined over different domain ranges in each agent.

3. The third one is based in the interpretation of the linguistic variables by different agents. This interpretation is carried out by a rule-base where the concepts are share among all the agents. But these concepts will not be defined in the same way. Each concept will be interpreted from each agent point of view. This protocol will be similar to human communication. If one person has a perfect image of a situation that he has lived. When he wants to communicate this information he uses a rule base to translate his experience into words, which implies a reduction in the global information he has got in his brain. Then, these words are received by other person, who translates them into thoughts using his own rule base.

These three possibilities can be illustrated as in figure 4

5 EXPERIMENTS

In order to probe the ability of our system to get a solution for the *Transportation Problem* we have used a new version of the distributed simulator [9] developed at the *Lab. de Agentes Inteligentes.* This simulator was originally designed to simulate

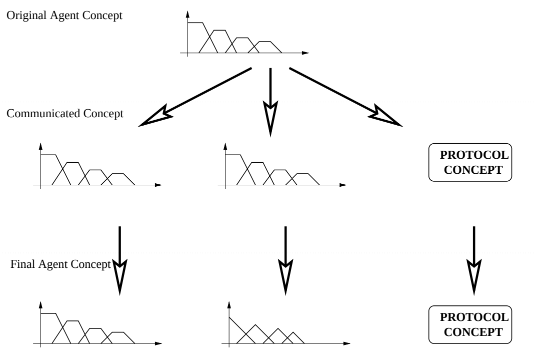

Figure 4 Three Communication Protocols

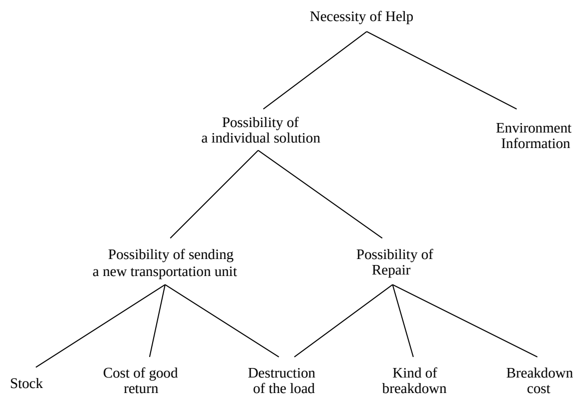

Figure 5 Decision Tree

autonomous robots and it has been adapted to simulate the agents defined in previous sections.

Each agent will be a process in a time-sharing, multi-processes computer. Therefore, the simulator allows the agents to be running autonomously in different computers or in the same one. The agents communicates to each other through another process named *The World*. This configuration let us simulate the real world, where messages can be lost, modified, send to wrong destination or returned to sender. The simulator is a multi-platform software (nowadays running on HP-UX, Sun-OS, Net-BSD and LINUX) and soon will be available as free software.

In order to illustrate the internal operation of the system, let us suppose that a problem is defined through a cost matrix, as in 1, where three origin points, marked as O_i, and three destination nodes, marked as D_i, are considered. The total amount of goods that have to be transported to each destination appears in the last row, and the stock in the origins appears in the last column.

	D_1	D_2	D_3	Stock
O_1	1	4	6	10
O_2	3	2	5	8
O_3	4	1	6	5
Transported	4	3	6	

Table 1 Cost Matrix

The numerical solution to the problem is : (O_1 to D_1, 4 units), (O_2 to D_3, 3 units), (O_3 to D_2, 6 units). Let us suppose that during the execution a transportation unit is broken down.

For instance, let's suppose that the transportation between O_2 and D_3 breaks down. The node will try to solve the problem by itself. The evaluation of this possibility is considered through a fuzzy decision tree, representing in figure 5. In this case, the stock in this node is 2, and the influence of this value results in a high activation grade of the variable *HELP NECESSITY*.

After this conclusion the information flow from O_2 to O_1 and O_3, using the standard acts of cooperation [8] is:

Step 1: $O_2 \longrightarrow O_1$, $O_2 \longrightarrow O_3$:

- Request-To-Do(Send(D_3, 6 units))
- Inform(I can help with Few Units)
- Inform(Available nodes O_1, O_3)

Step 2: $O_1 \Longleftrightarrow O_3$:

- Inform (Its own stock)

Step 3: The decision heuristic would say: "It is better to group the load". So the decision taken would be: O_1 will send 6 units to D_3

6 CONCLUSIONS AND FURTHER WORK

In this paper, we have shown that a distributed approach to the *Transportation Problem* can get advantages over a centralized one. We have also shown that it is possible to use fuzzy reasoning in the definition of the agents in order to use the subjective knowledge that human experts have got about the way of solving this problem.

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