A JOINT HIERARCHICAL FUZZY-MULTIAGENT MODEL DEALING WITH ROUTE CHOICE PROBLEM
RoSFuzMAS

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Keywords: Transportation Route Choice problem, Intelligent Transportation System, MultiAgent System, Fuzzy Controller.

Abstract: Nowadays, multiagent architectures and traffic simulation agent-based are the most promising strategies for intelligent transportation systems. This paper presents a road supervision model based on fuzzy-multiagent system and simulation, called *RoSFuzMAS*. Thanks to agentification of all components of the transportation system, dynamic agents interact to provide real time information and a preliminary choice of advised routes. To ensure the model rationality, and to improve the route choice make decision, we propose to use a hierarchical Fuzzy inference including some pertinent criteria handling the environment as well as the driver behavior. A multiagent simulator with graphic interface has been achieved to visualize, test and discuss our road supervision system. Experimental results demonstrate the capability of *RoSFuzMAS* to perform a dynamic path choice minimizing traffic jam occurrences by combining multiagent technology and real time fuzzy behaviors.

1 INTRODUCTION

In view of the enormous increase of vehicle number, accidents and traffic jam situations become widespread in all road networks in the world. A solution for these problems is to develop and invest in *Intelligent Transportation System* (*ITS*) which is capable of managing in a better way the existing capacity and encouraging more efficient vehicle routing over time and space, in order to improve safety, traffic efficiency, etc. Varied applications of *ITS* currently under development represent a real opportunity to advance toward a best future.

Furthermore, a number of ITS based on multiagent approach came recently into being to improve performances dynamic routing and traffic management by employing collaborative driving system (Hallé and Chaib-Draa, 2005) or by route guidance system (Adler *et al.* 2005).

Since the nineties, the use of fuzzy logic in *ITS* is marked. Research in soft computing field has been exploring the application of fuzzy set theory as a framework solving many transportation problems (Teodorovic, 1999), as route choice problem, traffic assignment problem, traffic control at the intersection, accident analysis and prevention, and traffic light controller. The majority of authors are based on a comparison of fuzzy values representing the routes' costs. The corresponding rules are of the type: "*If times on route 1 and 2 are very high, I will probably take route 3*".

In this sense, this paper presents a joint hierarchical fuzzy-multiagent model dealing with transportation route choice problem. Our model called *RoSFuzMAS*, acronym for "*Road Supervision based on Fuzzy MultiAgent System*" is poised between two different philosophies: the distributed and parallel *ITS* and the uncertain reasoning. To ensure the model rationality, and to improve the route choice make decision, we propose to use a hierarchical Fuzzy inference including some pertinent criteria handling the environment as well as the driver behavior.

The paper is organized as follows: Next section presents our road supervision system. The third section describes the improvement of decision making for route choice problem by adding other decision criteria structured in a hierarchical fuzzy controller. The simulation part detailed in the forth section gives an idea about the environment and discusses some results.

2 A ROAD SUPERVISION DISTRIBUTED UNDER MULTIAGENT APPROACH

Since some years ago, *multiagent systems* (*MAS*) took hold data processing (Wooldridge, 2002). Indeed, a cooperative interaction always leads to an increase of quantitative and qualitative system performances (Kallel *et al.*, 2002), (Kammoun *et al.*, 2005), (Kallel and Alimi, 2006).

In this sense, our system has as objectives to ensure an efficient network capacity allocation and decrease the number of congestion situations. Accordingly, the system proposes a best road choice to help drivers' vehicle to attempt their destinations.

We propose a model involving three kinds of agents: *City Agent* (*CA*), *Road Supervisor Agent* (*RSA*) and *Intelligent Vehicle Agent* (*IVA*). Figure 1 presents three levels of the proposed system as well as the acquaintance links between *CA*, *RSA* and *IVA*. Each agent use the organizational model *AGRE* (*Agent-Group-Role-Environment*) (Ferber *et al.*, 2005) and lives according to a cycle bound to an iterative process of reception / deliberation / action detailed in (Kallel *et al.*, 2006).

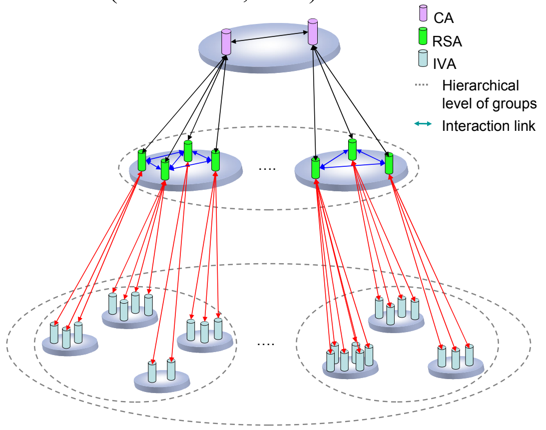

Figure 1: Hierarchical organizational architecture.

The *RSA* computes the traffic index for road *i* (RFI_i) according to equation (1).

$$RFI_i = \frac{N_v}{N_{v\max}} * \frac{\overline{T_j}}{T_t} = \frac{\sum_{j=1}^{N_v} T_j}{N_{v\max} * T_t} \quad (1)$$

$$\text{with } \overline{T}_j = \text{Average}(T_j) = \frac{1}{N_v}\sum_{j=1}^{N_v} T_j$$

with N_v is the number of *vehicles* in road *i*, N_{vmax} is the maximum number of vehicles in this road, T_j represents the time in jam state for vehicle *j* calculating in T_t period.

Equation 2 presents the *Path Flux Index* (*PFI)* as a sum of RFI_i average with the route length pondered by a coefficient *α*.

$$PFI = \overline{RFI}_i + \alpha \sum_{i=1}^{nb} l_i \quad (2)$$

with *nb* is the number of road in the path, l_i is the length of road *i* and *α* is the length importance coefficient.

3 HIERARCHICAL FUZZY ROUTE CHOICE CONTROL

Modelling route choice behaviour is a complex activity if we add other inputs. We try to improve our route choice model by using fuzzy logic (Zadeh, 1965). Furthermore, the use of hierarchical fuzzy controller in several applications' areas showed a real improvement in precision and interpretability (Alimi, 1997), (Kallel *et al.*, 2005) especially in multi-choice problem.

As shown in figure 2, we select only the *k* first paths as *k* alternatives for fuzzy choice, while fuzzifying their *PFI* values. The hierarchical controller uses other inputs fuzzy representations of route characteristic depending on *n* criteria. It provides the recommended route *R* to follow by the vehicle driver.

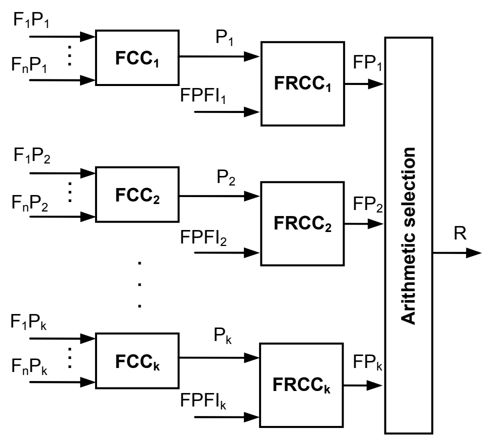

Figure 2: Hierarchical fuzzy route choice model.

with *FiPj* is the fuzzy representation of path *j* corresponding for criteria *i* and R is the recommended route.

3.1 Fuzzy Criteria Controller *FCC*

Let suppose that *k*=3 and *n*=5, we will compare 3 alternative routes depending on 5 factors in urban environment. These factors are the most important criteria, more used, and accessible from the vehicle information system.

The *FCC* allows a better road evaluation according to criteria concerning the vehicle state, the driver behavior and the environment.

- **Inputs parameters:** these criteria are presented in descending order of their importance for route choice makes decision.
  - RWInformation (road work information, the highest important criteria): NoRoadWork, RoadWork
  - TimeOfDay: Morning, Midday, Evening, Night
  - Familiarity: Unfamiliar (with a route), Medium, Familiar. This parameter takes in account the driver's experiences and will be updated in each trip
  - WeatherConditions: Bad, Medium, Good
  - Speed: Slow, Medium, High
- **Output parameters:**
  - Preference: Weak, Strong

The figure 3 draws the membership function used in this case.

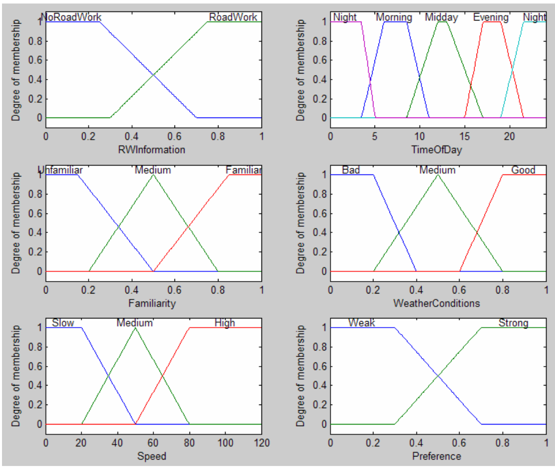

Figure 3: Fuzzification of inputs and output used in FCC.

- **Rule base of *FCC* model:** The rule base of *FCC* model is built by combination of input and output variables. This base is generated by experts in the transportation area and formed initially by 216 rules. As an example of rule, we can cite: "*if RWInformation is NoRoadWork and TimeOfDay is Night and Familiarity is Familiar and WeatherConditions is Good and Speed is Medium then Preference is Strong*".
- **Fuzzy Inference and defuzzification of the *FCC* model:** For the inference process, Mamdani (max–min) inference method is used in FCC model. The Center of Gravity (*COG*) method is used for defuzzification of the *FCC* model.

In view of the fact that the number of rules is high, we propose to model this controller by a hierarchical fuzzy architecture in order to gain in interpretability without decreasing efficiency. We regroup by pairs the criteria having some correlation.

3.2 Fuzzy Route Choice Controller *FRCC*

The *FRCC* uses as inputs, the outputs of *FCC* and a Fuzzy representation the *PFI*, called *FPFI*.

- **Input parameters:**
  - Preference: Weak, Strong
  - FPFI: Low, Middle, High
- **Output parameters:**
  - FP: VeryUnrecommended, Unrecommended, Undecided, Recommended, VeryRecommended
- **Rule base of *FRCC* model:** The rule-base is formed initially by 216 rules. As an example of rule, we can cite: "*if Preference is Strong and FPFI is Low then FP is VeryRecommended*".

4 SIMULATION EXPERIMENTS

Figure 4 presents some virtual maps, created by agent observer of TurtleKit tool (Michel *et al.*, 2005), in order to apply several tests varying vehicles' positions, environment conditions and drivers' behaviour factors.

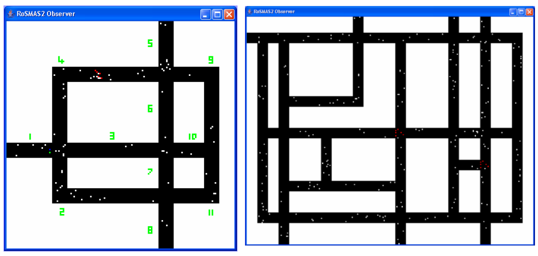

Figure 4: Examples of simulation environments.

The simulator recognizes three kinds of vehicles named *classic vehicle*, *bad vehicle*, and *intelligent vehicle*. The first one is a vehicle without intelligent module; the second one is a vehicle stopped in jam situation; the third one is intelligent, that means it is a part of *RoSFuzMAS*. With several tests, we try to compare intelligent vehicle route choice behaviour with a classic vehicle leaving from the same position in the same time and having the same destination. The first road network presented is a virtual map holding eleven roads numbered from 1 to 11 in only one city, and a variable number of cars circulating with random and autonomous way. The network state in defined time intervals is known as well as the traffic load intensity to be forwarded from road 1 to road 5. Figure 5 shows the road flux index in the different alternatives from road number 1 to road number 5. The *IVA* chooses the first alternative (by road 4) because it has the smallest flux index compared with second and third alternatives. The flux index in the second alternative is high because of jam situation in road 6. The flux index in the third alternative is high because of the route length. The *RFI* was from 0 to 100 %. The simulation has been done every 450 seconds when updating the road flux index table after every 60 seconds.

Second series of simulations was performed using the fuzzy rule base with the same parameters of the first simulation. Figure 6 confirms that after the work information, bad weather condition, and driver's unfamiliarity of the road 4, the controller proposes the third alternative to follow.

Various other simulations are applied with other maps, other positions of clutters, and different criteria. The results show that the fuzzy logic application for route choosing gives a better management of road network in all cases.

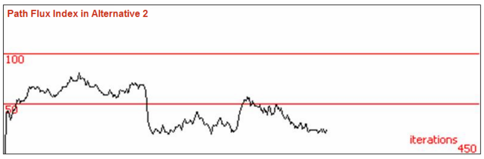

Figure 5: Viewer of Path Traffic Index.

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[turtle 213]  I'm in road 1. I want to get to Road 5 ?
[IVA 213] 3 possible Paths:
[IVA 213] alternative 1: by Road 4
[IVA 213] alternative 2: by Road 3 + Road 6
[IVA 213] alternative 3: by Road 3 + Road 10 + Road 9
[RSA 1] the flux index in Road 4 is 21 %
[RSA 1] the flux index in Road 3 is 35 %
[RSA 1] the flux index in Road 6 is 73 %
[RSA 1] the flux index in Road 9 is 32 %
[RSA 1] the flux index in Road 10 is 46 %
[IVA 213] alternative 1: RFI = 21 %
[IVA 213] alternative 2: RFI = 54 %
[IVA 213] alternative 3: RFI = 47.66 %
[IVA 213] the recommended path: alternative 1
[IVA 213] the recommended path using Fuzzy controller: alternative 3
[IVA 213] follow alternative 3
[IVA 213] follow road 3
[turtle 213]  to move forward
```

Figure 6: Example of communication messages between IVA and RSA.

5 CONCLUSION

In this paper, we presented a hierarchical architecture as well as a model and a simulation of road supervision system based on joint fuzzy logic and multiagent approach. The route choice algorithm developed shows acceptable results, but it become very complex if we add other criteria for route choice make decision.

The originality of this model resides on:

- A hierarchical fuzzy controller in the multi-route choice problem.
- Generic architecture, without limit for the number of factors to use.
- A hierarchical multiagent architecture handling fuzzy inference for the route choice problem.

As perspectives, we intend in the near future to add other options such as the factor of variant speed for *IAV*, an advancement treatment of crossroads, an environment with double way, and the change lane problem. Applying learning methods such as (Kallel *et al.*, 2006) become a necessity in order to reduce rule numbers and adjust membership functions. Furthermore, paths learning and multiobjective optimization of vehicle path planning can be added.

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