A FUZZY APPROACH TO SIMULATE THE USER MODE CHOICE BEHAVIOUR

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1 INTRODUCTION

In recent years the use of fuzzy theories have became a common practice in the transportation field and different applications have been made to simulate various aspects of the transportation system.

Very shortly, the Fuzzy Logic approach to identify the nature of the problem can be resumed as follows:
- the use of linguistic variables either in place or in addition to numerical variables;
- the characterisation of links among variables by using fuzzy conditional statements;
- the implementation of complex relations by using fuzzy algorithms and calculus.

The fuzzy Inference Systems (FIS) are very good tools as they hold the nonlinear universal approximation. They are suitable to handle experimental data as well as a priori knowledge on the unknown solution, which is expressed by inferential linguistic rules in the form IF-THEN whose antecedents and consequents utilize fuzzy sets instead of crisp numbers.

Whichever the application is, the inputs of the procedure are interpreted as fuzzy variables. Each fuzzy value carried out by a fuzzy variable is characterized by a fuzzy membership function (FMF). Each FMF expresses a membership measure to each of the linguistic properties. FMF are usually scaled between zero and unity, and they overlap. Gaussian FMFs has been used to improve the flexibility of the applied model. A FIS is usually designed according to the following procedure:
- fuzzification of the input-output variables;
- fuzzy inference through the bank of fuzzy rules;
- defuzzification of the fuzzy output variables.

In FIS generation the input-output pairs are used without exploiting the concept of learning: as a result, the estimation accuracy was found to be invariably not good enough. However, the design of such a “naïve” FIS can turn out to be useful as a first guess model and when real time systems are concerned. Results can be improved either by using an algorithm of automatic extraction of FIS from numerical data [4] (MATLAB® GENFIS System) and possibly by introducing learning (MATLAB® ANFIS).
2 MODE CHOICE AND FUZZY SET APPROACH

The concepts reported in the previous section have been used in order to evaluate the decisional criteria followed by users when they choose a transportation mode. In fact, a simple decision rule could be expressed in the form:

\[ \text{IF time on mode } m \text{ is less than time on mode } r \text{ THEN choose mode } m. \]

This kind of behaviour can be well simulated by a fuzzy approach.

Generally the user mode choice follows a more complex decision rule, for example of the form:

\[ \text{IF run time on mode } m \text{ is less than run time on mode } r \text{ AND access/egress time on mode } m \text{ is less than access/egress time on mode } r \text{ AND comfort on mode } m \text{ is greater than comfort on mode } r \text{ AND....THEN choose mode } m. \]

The construction of the decision rule set is a trial-and-error process, till a correct fit of the input-output set is reached. Particularly, the construction of artisan banks of fuzzy rules arises from the possibility to cover the input-output space took up by samples whit overlapping patches: each patch represents a fuzzy rule. The total covering of the samples, even if the behaviour of the system can be considered itself linear, is practically impossible because a lot of samples are not covered by any patch. To fulfil this demand, we operate a sort of weighed average exploiting fuzzy curves and surfaces.

In order to show how a fuzzy curve works, let us consider a Multiple-Input Single-Output (MISO) system, as in the case of mode choice, where more variables specify the mode (input) and one choice is made by user (output) as results of a crossed comparison among different attributes.

We assume that \( n \) training data are available, thus \( x_{ik} \) (\( k=1, \ldots, n \)) are the \( i \)th co-ordinate of each of the \( n \) training patterns. The fuzzy curve is defined as follows:

\[
c_i(x_i) = \frac{\sum F_{ik}(x_i) \cdot y_k}{\sum F_{ik}(x_i)}, \quad k=1, \ldots, n,
\]

where \( F_{ik}(x_i) = \exp \left[-\left(\frac{(x_{ik} - x_i)}{s} \right)^2\right] \) is a Gaussian function (other different local functions could advantageously be introduced). The importance of the input in affecting the estimation of the output is determined on the basis of a figure of merit defined as the range of the fuzzy curve, \( (c_{i \text{ max}} - c_{i \text{ min}}) \).

A natural extension of the fuzzy curves are the fuzzy surfaces which structure is as follows:

\[
c_i(x_i, y_j) = \frac{\sum F_{ik}(x_i) \cdot F_{ik}(y_j) \cdot y_k}{\sum F_{ik}(x_i) \cdot F_{ik}(y_j)}, \quad k=1, \ldots, m,
\]

In this case the fuzzy rules are with double antecedents which connective is “and”. In this way, the transformation occurs into a particular space in which the application of fuzzy patches (and then fuzzy rules) is easier. Of course, fuzzy curve results as a particular section
of fuzzy surface; consequently the extraction of a bank of rules directly from fuzzy surfaces is very useful: firstly, the writing of rules with double antecedent reduces the cardinality of the system and eliminates the risk of explosion of the system and, secondly, the rules extracted by fuzzy surfaces contain the rules extracted by fuzzy curves.

In order to extract the mode choice decision rules of users different models have been tested, by evaluating different sets of rules and different membership functions; this process also allows to recognize the most important rules taken into account by users when they choose a particular mode.

In the application five modes have been considered: feet, car-driver, car-passenger, motorcycle, bus. The best model considers as input variables the runt time, the sex, the family condition of the user, the parking difficulty.

As an example, figure 1 reports the membership function for the car run time; the three curves correspond to the linguistic rules: low run time, medium run time, high run time.

![Figure 1. The five-steps method representation](image)

The results obtained by the different models have been compared on the basis of the percentage error, i.e. the number of correct reproduced choices as regards the failures.

The response of the fuzzy system corresponds to the code of the chosen mode. Particularly, the codes of each mode are the integer numbers among 1 and 5, while the output is a continuos number among 1 and five. So in order to match the mode code and the continuos output, this latter has been approximated to the nearest integer, except that for the number of the kind integer+0.5: in this case the fuzzy result cannot be interpreted.

Figure 2 reports the results of the simulation. As it can be seen, the fuzzy rules allows to reproduce correctly practically all the chosen modes, showing a great capability of
rebuilding human behaviour from a reduced set of rules (and in effect only a limited number of rules affect the human behaviour).

3 CONCLUSIONS

In this paper the fuzzy approach has been used to simulate user choice behaviour, starting from the hypothesis that the complex human decision mechanism can be well represented by fuzzy sets. In fact, human decisions are based on a set of limited rules and they are fuzzy in nature because the users decide on the basis of rules such as “if time on mode m is low and comfort is high and cost is medium than choose mode m”, rather then on the basis of exact rules (time is x, comfort is y, cost is z then choose mode m, where x, y, z assume exact numerical values). The good results obtained in this paper confirm the initial hypothesis and suggest more research work in this field.

REFERENCES


