Adaptive Route Selection for Dynamic Route Guidance System Based on Fuzzy-Neural Approaches

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Abstract

The objective of this work is to model the driver behaviour in the area of route selection. The research focus on an **optimum route search function** in a typical in-car navigation system or dynamic route guidance (DRG) system. In this work, we want to emphasize the need to orientate the route selection method on the driver's preference. Each route candidate has a set of attributes. A fuzzy-neural approach is used to represent the correlation of the attributes with the driver's route selection. A recommendation or route ranking can be provided to the driver. Based on a training of the fuzzy-neural net on the driver's choice, the route selection function can be made adaptive to the decision-making of the driver.

1 Introduction

A route guidance system is a routing system that provides instructions to drivers based upon "optimum" route solutions. A driver can make the destination known to the system. A dynamic route guidance (DRG) system would route drivers using the current traffic conditions such as congestion and roadworks. The system can provide actual routing advice to the driver in light of the real-time traffic conditions. It will be based on real-time information regarding conditions and incidents of the traffic network. It is conceived as the integration of the routing and the traffic control functions. With the recent advances in the micro-electronics technology and informatics, the development of DRG systems has been made possible.

One objective of such a dynamic route guidance system is to balance the level of service on all major network links so as to increase the efficiency, speed, safety and quality of travel (e.g. to minimize travel time). Such a system would be particularly useful when accidents or roadworks occurred in the traffic network. Also, the system is highly beneficial to the motorist when driving in unfamiliar areas. A DRG system would act as the driver's assistant and try to reduce his tension.

The issue of driver behaviour in terms of route choice and response to guidance is complex. One focus in this paper is on the modeling of driver behaviour in route choice on the DRG system. Here, we assume that the DRG system has a voluntary choice scheme and the driver has the option of not following the advice from the DRG system. The driver's preference is modeled as a fuzzy expert system, and his reaction to the advice and information provided by a DRG system is stored. The previous choices of the driver, in particular the deviation from the recommendation, are then used for the training of the system so that it is made adaptive to the driver.

1.1 Decision-support in Route Selection

The success of a DRG system will depend on how the human being, as a driver, will be taken into account from the very early stage of the work. Hence, topics like driver characteristics, driver decision-making, driver response to guidance advice and driver capacity are important, and must be treated.

The most modern information technology will allow the introduction of real-time data exchange and real-time control as new functions in road traffic. The information system must also support the driver effectively in decisions (i.e. information in the form of advice for proper action). The general information should be screened for decision-making whilst driving, so that the system does not overload the driver with information.

In this paper, the focus will be on route selection, i.e. the capability to support the driver effectively in deciding on an optimum route to his preference. Figure 1 describes such a navigation system. The core of such a system is an adaptive route selection algorithm based on a hybrid fuzzy-neural approach. Each route candidate has a set of attributes associated with it. The attributes are correlated and the final decision (choice) by the driver is perceived as a nonlinear function of the attributes.

1.2 Routing Algorithm

So far, the idea of "**optimum**" has been taken in a very limited sense. Most route guidance systems nowadys compute the "best" route for the driver based on either the shortest time [1, 2] or the shortest distance [3]. Some systems would provide information on congestion of the road as well [4]. Hence, the route selection function makes use of the distance data (static) and information on average travel speed (dynamic). In the Vehicle Information and Communication System (VICS) project announced by the National Police Agency in 1991, **optimum route selection** was a focus but the focus was based only on travel distance and travel time reduction based on empirical and real time information. Also, it was not clear how the two criteria can be resolved or compromised to give the optimum route. For example, in the driver's route selection logic in [5], it is not clear how to tradeoff the relative importance of minimum distance route and minimum time route.

From a survey carried out in 1989 [6], respondents were asked to choose between guidance systems that chose routes on the basis of shortest time, shortest distance or some combination of the two. In London, 42% of the respondents would prefer a system that can perform a tradeoff between travel time and travel distance. 56% said they would choose route based on the shortest travel time. A similar result is obtained in Paris. In Munich, 71% would prefer a tradeoff between travel time and travel distance, and only 27% would choose route based just on the shortest travel time. Therefore, it can be observed that a routing algorithm that can accommodate the various route selection criteria and their tradeoff would be highly desirable.

This paper is outlined as follows. Section 2 gives a description on how a route selection system is setup based on some important attributes of a route. Section 3 presents a hybrid fuzzy-neural approach and the basic ideas behind such an approach. The details on the construction of a fuzzy-neural network is given in section 4. Section 5 describes a modeling of the driver's route selection behaviour using fuzzy rules, which is then used for determining the weights of the fuzzy-neural network. Section 6 gives the details on the training of the fuzzy-neural network. The paper is concluded in section 7.

2 System Description

2.1 System Setup

2.1.1 Route Characteristics

It is perceived that a driver may select a route based on many different factors which include :

- travel distance
- travel time
- degree of congestion (number of cars on the road, queue length)
- toll (of expressway or highway)
- degree of difficulty of travel (width of the road, number of lanes, number of pedestrians and bicycles on the road etc.)

- scenery (esp. for long distance trip)

2.1.2 Route Attributes

It is perceived that a candidate route has many different attributes. These attributes coincide with the factors which are used by the driver in route selection. Below is a set of some of the most important attributes of a candidate route. Note that each attribute has a range from zero (0) to one (1).

- travel distance
  1 denotes the route with the **shortest travel distance**, relative to the set of candidate routes. **0** can be used to denote routes which are x km longer than the shortest route, where x is a system parameter. The attribute value for other routes can be decided based on a linear scale.

- travel time
  1 denotes **shortest travel time**, relative to the set of candidate routes. **0** can be used to denote routes which are y minutes longer than the quickest route, where y is a system parameter. Again, the attribute value for other routes can be decided based on a linear scale.

- degree of congestion
  0 denotes **no congestion** at all. **1** denotes the worst situation.

- toll (of expressway or highway)
  0 denotes **no toll and no highway** at all. **1** denotes the worst situation.

- difficulty of travel (narrowness and winding of the road, number of traffic lights, road work, number of pedestrians and bicycles on the road etc.)
  0 denotes the **ideal road situation**, very easy to drive. **1** denotes the worst situation.

- scenery (esp. on long distance trip)
  1 denotes the **best scenery**. The higher, the better.

2.1.3 Types of attribute

It can be noticed that for the attributes travel distance, travel time and scenery, a driver would like those attribute scores to be as close to 1 (i.e. as large) as possible for an ideal route. These three attributes are therefore called "positive attributes". As for attribute scores for congestion, toll and degree of difficulty, a driver would prefer them to be as close to 0 (i.e. as small) as possible and they are called "negative attributes".

It can also be perceived that some attributes of a candidate route are dynamic while some can be considered as static. The dynamic ones are travel time, degree of congestion and degree of difficulty of travel. The static ones are travel distance, toll and scenery.

2.1.4 Decision-support (Figure 2) :

It is perceived that at a particular instance of time, a number of different candidate routes which have different set of attributes should be considered by the driver. The driver has to make a decision based on the relative importance of the different factors for route selection. Each decision is based on a combination of different factors. There could be some heuristics in route selection but some preferences could be difficult to express in words. The objective here is to design an **optimum route search function** in a typical in-car navigation system so that it will have the following characteristics :

- It is a decision-making assistant to the driver in route selection. In other words, it embodies a route selection algorithm.

- It can model the behaviour of the driver by storing his preference and previous decisions/choices.

- It can adapt and learn from the recent decisions of the driver.

3 Fuzzy-neural Approach

3.1 Artificial Neural Net (ANN)

Neural networks [7] can be developed to model the driver behaviour. It is chosen for this study for their ability to learn from examples, to generalize, to predict and to cope with incomplete input data. A neural network is a parallel distributed information processing system. It consists of a large number of highly interconnected but very simple processing elements known as neurons. Each neuron has a number of inputs and one output which branches out to inputs of other neurons. The output of a neuron is a nonlinear function of the sum of all inputs through the weighted links. Hence, the knowledge of a network is distributed throughout the weighted links.

For our application, the inputs will be the various attributes of a route and the output will be an acceptance measure of the route. The ANN can be trained off-line. The real-time execution of the ANN will be extremely fast. It also has the ability to adapt to different users of the car. Any new user can train the network to learn his preference.

3.2 Fuzzy systems

It is well-known that the decision-making of the driver is fuzzy. The aim is to develop a fuzzy expert system [8] which can be used to rank the route candidates. At the beginning of the system, heuristic rules on how the driver evaluates the route attributes can be specified.

3.3 Advantage of Fuzzy systems

Rule-based fuzzy systems are based on fuzzy theory, with expert knowledge represented explicitly using a set of fuzzy if-then rules. They offer a high degree of transparency into the system being modeled.

3.4 Advantage of Neural systems

Neural networks have very strong learning capability. Given some numerical data on how a system should behave, there are many neural network algorithms which try to learn this system behaviour. Knowledge is stored implicitly in the weights of a neural network. However, the neural network offers no insight to internal dynamics and relationships.

3.5 A Hybrid Approach

A hybrid fuzzy-neural approach can combine the advantages of both approaches. This will further enhance the intelligence of the DRG system, especially in the modeling of the driver behaviour.

The ideas are as follows :

1. A rule-based fuzzy system is developed which represents a preliminary model of the driver.
2. The rule-based fuzzy system is then implemented using a neural network. A method of constructing a neural network which is equivalent to the fuzzy system is developed. It is constructed so that the procedures and membership functions of the fuzzy system can be retrieved from the implementation of the neural network.
3. A special learning algorithm is then used to learn and adapt itself to the recent choices of the driver. The weights of the network will be adjusted. The derivation of the learning algorithm is based on a gradient descent algorithm.
4. After the training procedure, the modified membership functions of the fuzzy systems can be retrieved. This fuzzy system with modified membership functions represent the latest model of the driver. The fuzzy system has now been tailored to the particular driver. The model of the driver can also be represented by a set of weights of the equivalent neural network.

4 Construction of Fuzzy-Neural Network

In this section, the architecture of a kind of fuzzy-neural network is described. The network is essentially a parallel implementation of a fuzzy system using a particularly structured neural network. The structure involves the construction of a fuzzification sub-network and a defuzzification sub-network. The two sub-networks will be integrated in such a way that the structure and decision-making process of the original fuzzy system can be fully retrieved from its network implementation. The corresponding neural network should have similar performance as the original fuzzy system.

Figure 3 shows the structure of the system. Each sub-network performs a different function explained as follows :

- fuzzification sub-network : to represent the membership functions of the linguistic terms of the input attributes

- defuzzification sub-network : to generate a defuzzified value which represents the acceptance level of a candidate route

4.1 Fuzzification sub-network

The inputs of the system go to the first layer which is consisted of a number of fuzzification sub-networks. The input x_i to each fuzzification sub-network is the same as the input to the fuzzy logic system. The outputs from the fuzzification sub-network correspond to the degree of membership μ_{ik} where k is the number of linguistic terms corresponding to the x_i. Figure 3 shows some two-layer fuzzification sub-networks for this purpose. It should be noted that the number of hidden layers in a fuzzification sub-network is not important as long as it can represent the membership function of the linguistic term of the input attribute. Initially, each sub-network should be trained with the specified membership functions of x_i. If two inputs have the identical set of linguistic terms, then the same fuzzification sub-network can be used at the beginning. During the sub-network learning stage described later on, the membership functions of the linguistic terms will be changed subsequently using the training data.

4.2 Defuzzification sub-network

This is the most important stage in the construction of the fuzzy-neural network. The aim is to compute the acceptance value of a candidate route. The main issue concerns with ways to represent membership functions of output linguistic terms using a network implementation and to perform defuzzification. The defuzzification sub-network consists of two layers. The first layer is introduced to represent the membership functions of output linguistic terms. The number of inputs α_i to this layer is the same as the number of fuzzy rules r. Let n be the number of discrete values in the output range u. Let $U = \{u_1, u_2, ..., u_n\}$ be a set of discrete output values. The initial weights of this layer are calculated from membership functions of the output as

$$w_{ij} = \mu_{C_j}(u_i) \tag{1}$$

where $i = 1, ..., n$ and $j = 1, ..., r$. Note that C_j is the linguistic label of rule j. Essentially, it means that the weight w_{ij} equals the degree of membership of C_j at $u = u_i$. The second layer in this sub-network performs the task of defuzzification. Here a center-of-area method is used. In this case, the weights of the second layer is given by

$$\beta_i = \frac{u_i}{\gamma} \tag{2}$$

where

$$\gamma = \sum_{i=1}^{n} \mu_i \tag{3}$$

The defuzzified value u is given by

$$\sum_{i=1}^{n} \beta_i \mu_i \tag{4}$$

Again, the initial weights in the first layer of the defuzzification sub-network can be changed later by the learning algorithm and the training data. However, the learning process will only change the membership functions of the output linguistic terms in the first layer and not the defuzzification operations in the second layer.

5 Modeling of Driver Behaviour

5.1 Fuzzy ranking rules

Each driver would have his own perspective of a desirable route. The system is designed so that a driver can specify his preference using fuzzy rules with some pre-defined linguistic terms. Below is an example of a set of fuzzy rules that may be used by a typical driver for route ranking :

If **travel distance** is <**averagely**> short, then route is <**good**>.

If **travel time** is <**averagely**> short, then route is <**very good**>.

If **congestion** is <**averagely**> heavy, then route is <**very bad**> .

If **toll** is <**averagely**> high, then route is <**not good**>.

If **degree of difficulty** is <**averagely**> high, then route is <**bad**>.

If **scenery** is <**averagely**> good, then route is <**fair**>.

The linguistic terms are in brackets. In the rule antecedent part, the driver can choose from the term set { very, averagely, slightly }.

5.2 Linguistic terms and rule firing

The numeric value of a route attribute is the crisp input to the associated fuzzy rule. The fuzzification sub-network will compute the degree of match between the crisp input and the fuzzy set describing the meaning of the rule-antecedent. The fuzzy set describing the meaning of the rule-antecedent is scaled to the same degree to which the rule-antecedent has been matched by the crisp input. Finally, the scaled fuzzy sets of each rule are aggregated to obtain the defuzzified value, which is a performance measure of the route candidate.

In graphical representation, the firing of each fuzzy rule will contribute an area to the defuzzification procedure. The algorithm adopted in this paper is the center-of-area (COA) method, which is the best well-known defuzzification method.

6 Training of the Fuzzy-Neural Network

In this section, an algorithm to train the fuzzy-neural network is described. The objective is to train the neural network so that it will refine the membership functions of the fuzzy systems. A set of learning rules similar to the backpropagation learning algorithm can be derived from the gradient descent method.

The back-propagation learning algorithm developed for standard multilayer feedforward neural networks can be extended for the training of the fuzzy-neural network. Here, we assume that a set of desired or optimal input/output pairs is available. Let u be the output of the network and u^d be the desired value. The error function is defined as

$$E = \frac{1}{2}(u^d - u)^2 \tag{5}$$

During the training process, the defuzzification algorithm needs to be maintained and hence the β_i are calculated from equation (2) using μ_i. The rule for updating w_{ij} in the first layer of the defuzzification sub-network can be shown as :

$$w_{ij}(t+1) = w_{ij}(t) + \epsilon\alpha_j(u^d - u)(\beta_i - \sum_{l=1}^{n} u_l\mu_l/\gamma^2) \tag{6}$$

where ϵ is a learning rate between 0 and 1. β_i and γ are defined as in equation (2) and (3) respectively. α_j represents the degree of firing of fuzzy rule j in the fuzzification sub-network. Note that $w_{ij}(t+1)$ is updated only if μ_i is within the range [0,1]. The error term e_j that is back-propagated to the output of the fuzzification sub-network is :

$$e_j = (u^d - u)\sum_{i=1}^{n} w_{ij}(\beta_i - \sum_{l=1}^{n} u_l\mu_l/\gamma^2) \tag{7}$$

This error term is used to adjust the weights of the fuzzification sub-network using the back-propagation algorithm.

When the training process has been completed, the new membership functions can be recovered from individual sub-network. From the fuzzification sub-network, we can obtain the modified membership functions for each linguistic label of input x_i. To obtain the modified membership functions for the output linguistic labels, we have to set α_i to 1 (where $i = 1, ..., r$), all others to zero, and obtain μ_i (where $i = 1, ..., n$).

6.1 Summary of the Intelligent Route Selection Procedures

1. The system is setup by a driver inputing his fuzzy rules on route selection using a set of pre-defined linguistic terms. This is the initial setup of the system and a fuzzy-neural network is formed. The weights of the fuzzy-neural network are determined from the shape of the linguistic terms.

2. When planning a trip or during a trip, the driver can modify the relative importance of the various route attributes using some settings on a panel. This is a convenient way for specifying driver's preference, which could be useful for planning a special purpose trip.

3. The driver inputs his origin and destination to the system, and a set of route candidates is obtained.

4. For each route candidate, the attribute scores are inputs to the fuzzy-neural network, and the output is an overall score of that route candidate. With the computation of this overall score, a ranking of the set of route candidates is performed.
5. The driver can accept the recommendation from the system. Alternatively, he can choose an alternate route. Any derivation from the recommendation will be stored, and this information is used for forming the training pairs of the fuzzy-neural network. Hence, the system can be made adaptive to the decision-making of the driver.

6.2 Implementation

The fuzzy-neural network described above and the adaptive route selection algorithm has been implemented using the C programming language. This work will form an important component of an intelligent route navigation system.

7 Conclusions

A useful routing system should have the capability to support the driver effectively in deciding on an optimum route to his preference. In this paper, an **optimum route search function** in a typical in-car navigation system is developed. The routing algorithm is orientated on the driver's preference. A **fuzzy-neural approach** is used to represent the correlation of the attributes with the driver's route selection. A recommendation or route ranking can be provided to the driver. Based on a training of the fuzzy-neural net on the driver's choice, the route selection function can be made adaptive to the decision-making of the driver. This methodology paves the way for more intelligent navigation systems.

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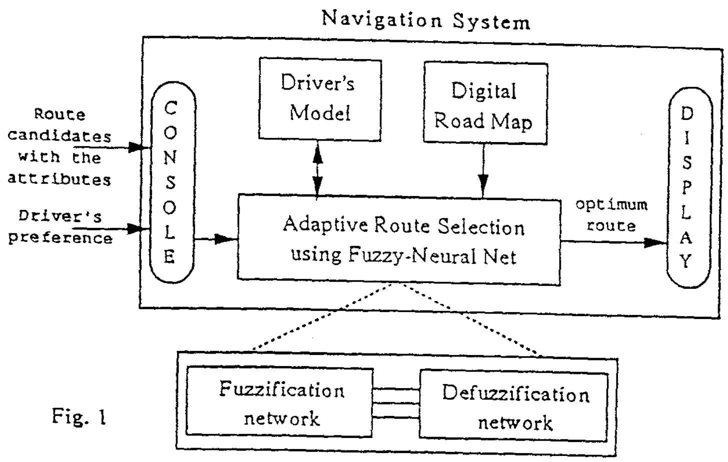

Fig. 1

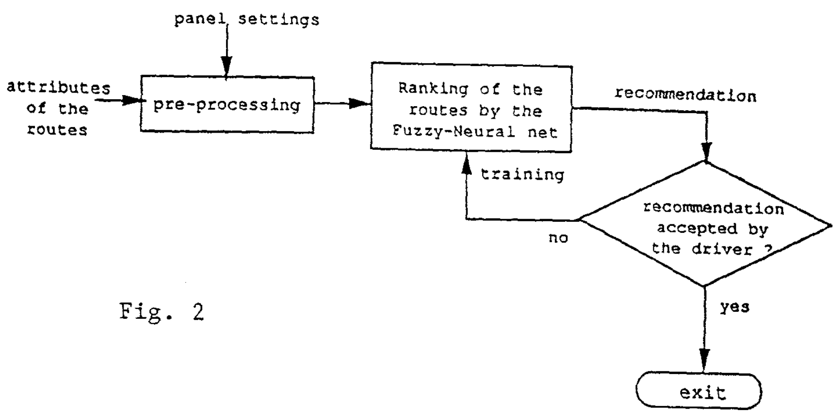

Fig. 2

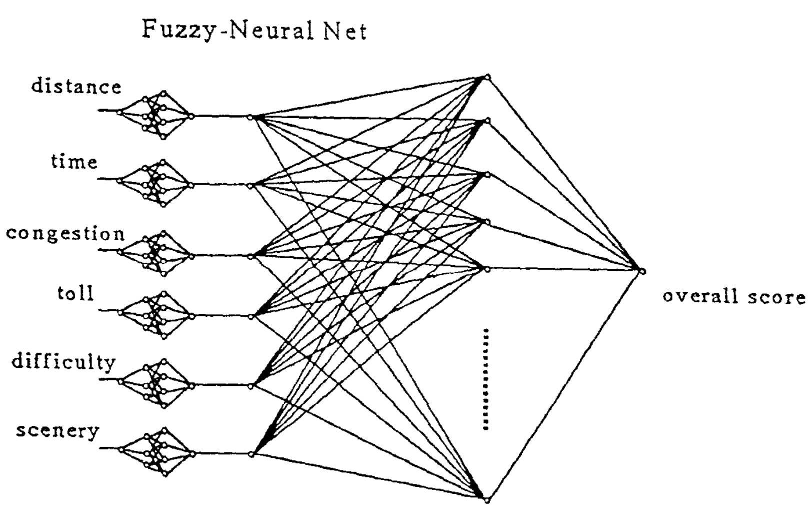

Fig. 3