A Literature review on finding the K Shortest Path using Dynamic Route Guidance Systems

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Abstract: *The shortest path problem is one of the most fundamental problems applicable in various fields and has close relation to route navigation systems. This is actually quite an established technique for multi-criteria optimization. A literature review on this technique with focus on transportation network would be quite helpful for any research related to dynamicRoute Guidance systems (RGS). Route guidance helps us in providing the path directions based on changing traffic conditions. Given a set of origin-destination (O/D) pairs, there could be many possible routes for a driver. A useful routing system should have the capability to support the driver effectively in deciding on an optimum route to his preference. The algorithm is suitable for finding not only the shortest route but also better routes. The shortest travel time is estimated by applying various shortest path algorithms to the traffic network that has deterministic or dynamic link travel times. Because it is difficult to evaluate these shortest path-finding algorithms in real traffic situations, most of them are evaluated in the virtual traffic networks.*

Index terms: *Route guidance, Dijkstra Algorithm, Navigation, Fuzzy Neural network.*

1. INTRODUCTION

With the recent developments of advanced technologies like communications, microelectronics, sensors, and information technology, the provision of real-time information on traffic conditions to drivers has become technically possible. The new navigation systems will be able to utilize the real-time traffic information by simply adding a receiver.

One functionality of an in-vehicle navigation system is route planning. Here, we represent a road network in the form of nodes (representing junctions) and a set of links

(representing roads). Given an origin-destination (O/D) pair, there could be many possible routes through the network. Generally, the cost functions are related to the links, which could be reflected by the travel time, distance, cost of travel, etc. the problem is understanding the complex evaluation process involved in the route choice and implementing a route selection function for the in-vehicle guidance system.

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. The origin can be input or obtained directly from the use of a differential global positioning system (DGPS). A dynamic route guidance (DRG) system would route drivers using the current traffic conditions such as congestion and roadworks. The system can then provide actual routing advice based on real-time information regarding conditions and incidents of the traffic networks.

The effective transmission of packets is requirement for the provision of advanced communication performance makes finding shortest network paths essential. Routing data packets through the shortest path (SP) is an efficient approach to increase the Quality of Service (QoS) in expanding networks as it minimizes cost or delay while maximizing quality or bandwidth. Therefore, finding the SP is in routing a significant approach for the new and emerging technologies, particularly, video-conferring and video on demand which require high bandwidth, low delay and low delay jitter. A great number of algorithms have been developed for finding the "best" path through a network.
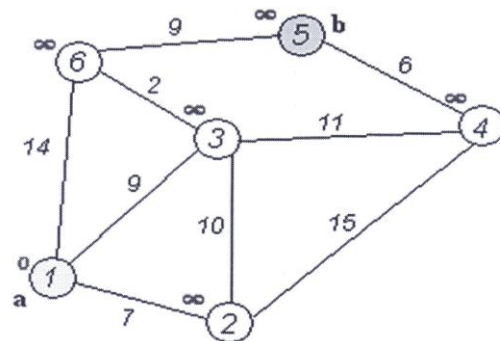

Figure 1.1 Dijkstra Algorithm

As a final example, traffic control systems often need to spread the traffic between two points over multiple paths in order to reduce congestion. So the optimal route is usually calculated by

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International Conference on
Recent Trends in Computer Science & Information Technology (RTCSIT-2016)
21st August 2016
Guru Nanak College Budhlada, Punjab India

139

means of Dijkstra type shortest path or by K-means shortest path algorithm or A* algorithm [1], [2].

2. LITERATURE REVIEW

The study on route choice has been under the topic of traffic assignment. To solve the traffic assignment problem, the rule by which drivers choose routes between their origin and destination of travel must be defined. Usually every driver wishes to minimize his personal travel cost. They have also assumed that time minimization is the only criterion for the driver's route choice. There are a number of factors related to route selection and they fall into four categories: the characteristics/attributes of the feasible routes, the character of the traveler, the nature of that particular trip (e.g., purpose, budget) and other circumstances (e.g., weather, day/night). One study of route choice factors among truck drivers on motorways in Austria has come up with the following order of importance: travel time, width of the road, travel distance, route angularity, and probability of delays, dangerous segments, and slope of the road, multilane, road safety, expected weather and traffic density on the road.

2.1 Route selection by fuzzy logic method

By looking at the problem of route choice between two alternative routes, the driver's perceived travel time on each route is treated as a fuzzy inference. The model consists of rules which indicate the degree of preference for each route given the approximate travel time of the two routes. The approach considers only the travel time criterion and cannot be easily generalized to multiple routes and is based on the driver's perception of attributes of the network, attractiveness of alternate routes as well as models for reaction to information. An example of a fuzzy rule is given at 2.1.1. Such an approach works for a particular O/D set and does not seem general enough for different O/D pairs. Also, for an O/D pair, the inclusion of an additional feasible route means an entirely new set of fuzzy rules.

2.1.1 Fuzzy Rule

IF the perceived travel time on route 1 IS medium AND the perceived travel time on route 2 IS very high, THEN
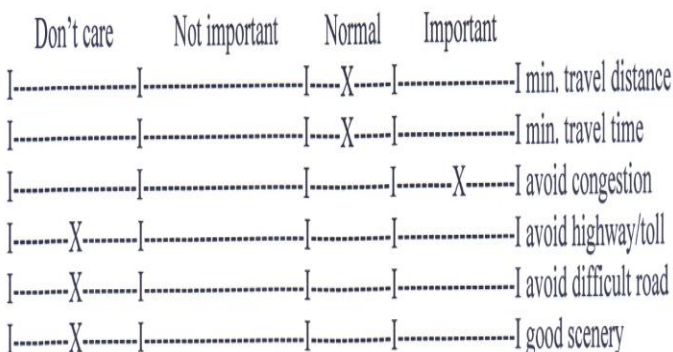
attractiveness of route 1 IS I will probably take route 1 AND I will definitely not take route 2.

3. ROUTE SELECTION BY DECISION ANALYSIS NAVIGATION SYSTEM

Fig. 3.1 describes such a navigation system. The core of such a system is an adaptive route selection algorithm based on a hybrid fuzzy-neural (FN) approach. Each feasible route has a set of attributes associated with it. The attributes are correlated and the final decision by the driver is perceived as a nonlinear function of the attributes.
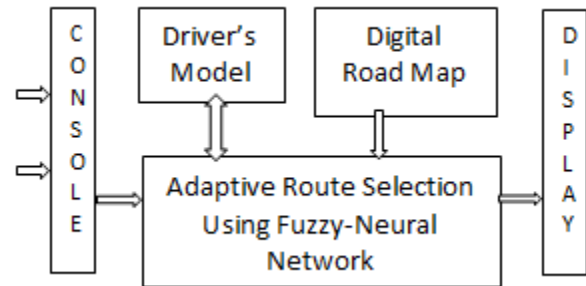

Figure 3.1 Navigation System

3.1 System Description

3.1.1 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)
- Toll (express/highway)
- Degree of difficulty of travel (width of the road, number of lanes, and number of pedestrians and bicycles on the road, etc.)
- Scenery (for long distance trip)

3.1.2 Route Attributes

It is perceived that a feasible 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 feasible route [3]. 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 feasible 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 route can be decided based on a linear scale.

CONFERENCE PAPER
International Conference on
Recent Trends in Computer Science & Information Technology (RTCSIT-2016)
21st August 2016
Guru Nanak College Budhlada, Punjab India

140

- Travel Time: 1 denotes shortest travel time, relative to the set of feasible routes. 0 can be used to denote routes which are 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 whereas 1 denotes the worst situation.
- Toll (Expressway or Highway): 0 denotes no toll and no highway at all. 1 denotes the worst situation.
- Difficulty of Travel: 0 denotes the ideal road situation, very easy to drive. 1 denotes the worst situation.
- Scenery: 1 denotes the best scenery.

3.1.3 Driver's Dynamic Settings

The introduction of these panel weights gives a quick and convenient means for a driver to specify his requirements to the routing algorithm. Effectively, the value of each route attribute is multiplied by its associated panel weight before weight before passing to the route selection algorithm [3], [4]. For example, if a driver is very much concerned with avoiding congestion, and has the usual concern of arriving the destination by a quick route, the settings can be arranged as the panel shown above. In this way, the road attributes "toll", "difficulty of travel", and "scenery" will not be taken into consideration by the routing algorithm. On the other hand, the "degree of congestion" attribute should be given more weight than "travel time" and "travel distance". The suggested values for pi are as follows.

"Don't care"   0.0

"Not important"   0.4

"Normal"   0.7

Fig.3.2 Decision support to the Driver

"Important"   1.0
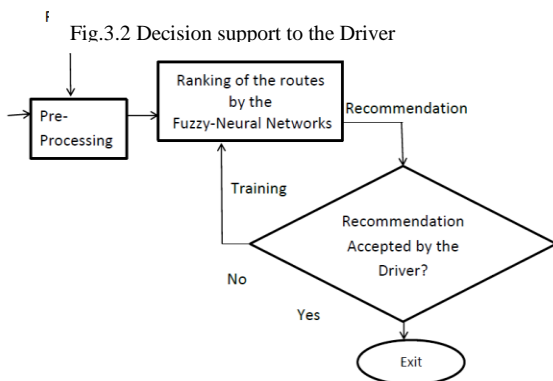
3.1.4 Decision Support

It is perceived that at a particular instance of time, a number of different feasible 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 an in-car navigation system so that it will have the following characteristics.

- It can model the behavior of the driver by storing his preference and previous decisions/choices.
- It can adapt and learn from the recent decisions of the driver.

4. FUZZY-NEURAL APPROACH

4.1. Artificial Neural Network

Neural networks can be developed to model the driver behavior. 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 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.

4.2. A Hybrid Approach

A hybrid FN approach can combine the advantages of both approaches. This will further enhances the intelligence of the DRG system, especially in the modelling of the driver behavior. The ideas are as follows

- A rule-based fuzzy system is developed which represents model of the driver.
- 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.
- 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.

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21st August 2016
Guru Nanak College Budhlada, Punjab India

141

- After the training procedures, the modified membership functions of the fuzzy systems can be retrieved. This fuzzy system with modified membership functions represents the latest model of the driver. The model of the driver can also be represented by a set of weights of the equivalent neural networks.

5. DYNAMIC AND STOCHASTIC SHORTEST PATH IN TRAFFIC NETWORKS

The dynamic and stochastic shortest path problem (DSSPP) has been the subject of extensive research in the transportation area for many years. In this problem the link travel time is assumed to be a time-dependent random variable. With the advent of Advanced Transportation Management Systems (ATMS), which are designed to improve transportation system performance, an opportunity exists for extending the DSSPP and implementing it on an actual transportation network. In ATMS, real-time travel time information is obtained directly from probe vehicles. Probe vehicles are outfitted with special automatic vehicle identification (AVI) equipment of geographic positioning system (GPS) units. One of the important advantages of probe vehicles is that the travel time of the individual vehicles over each link in their route can be measured and recorded, which has been impossible with the inductive loop data.

Fu and Rilett (1998) et al. proposed approximation models which estimates route travel time mean and variance using the mean and variance of link travel time as a function of time of day. The route travel time variance is defined with respect to individual drivers and therefore, in practice, it is appropriate for estimating individual travel time only for "previous" time periods [5], [6]. Strictly speaking it is not applicable for a forecasting application unless the travel time uncertainty of the forecasting model explicitly considers the mean link travel time forecasting error and individual variance.

5.1 Problem Definition

Consider a traffic network composed of a set of nodes and links. A generalized cost is associated with each link in the network. The travel time will be used to represent this generalized cost. It is assumed that the link travel times on some or all of the links in the network are random variables. In addition, the probability distributions of the link travel times are dependent on the time of a day. Furthermore, this paper assumes that the link travel times are continuous random variables and the only available information about their distribution is their respective means and variances. The problems is to find the minimum path from an origin to a destination with a given departure time in the network. This problem is referred as to the DSSPP.

Figure 5.1 is a representation of a path between an origin node's' and a destination node 'g'. Equations 5.1 and 5.2 represent the approximate relationship between the mean and variance of the arrival times at a pair of successive nodes (node i and node j) on a path in a dynamic and stochastic network.

$$E[Tj] \cong E[Ti] + (E[Ti]) + \mu''(E[Ti])\frac{Var[Ti]}{2} \quad (5.1)$$

$$Var[Tj] \cong \begin{Bmatrix} 1 + \sigma'^2 \ E[Ti] + \\ 2\mu' E[Ti] + \mu'^2 \ E[Ti] \end{Bmatrix} Var[Ti] + \sigma^2(E[Ti]) \quad (5.2)$$

Where,

$[Ti]$ = a random variable indicating the arrival time or departure time at node i;

$E[Ti]$ = the expected arrival time at node i;

$Var[Ti]$ = the variance of the arrival time at node i;

$\mu(T)$ = the mean travel time on link (i, j) as a function of time of day, T. μ' and μ'' are respectively the first order and second order derivatives of μ;

$\sigma(T)$ = the standard deviation of the travel time on link (i, j) as a function of time of day T;

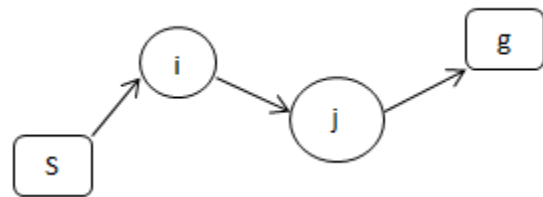σ' first order derivative of σ ;

Fig 5.1 A path from original node s to destination node g including link (i,j)

From equation (5.1) and (5.2), the following properties of the DSSPP may be observed. If the mean link travel time as a function of time ($\mu(T)$) of at least one link in a network is non-linear, the standard shortest path algorithms may fail to find the expected shortest path between two nodes in the network.

This observation may be illustrated by the use of the example network shown in Figure 5.2. The network is composed of two sub paths (p1 and p2) from the origin node s to an intermediate node i, and one link (i,j) from node i to the destination node j. Assume that the travel time on p1 is deterministic and that the travel time on p2 is stochastic. The travel time on link (i,j), $\mu(T)$, is deterministic but changes with time in a non-linear fashion as shown in Figure 5.2. if the expected arrival time at node i through p1 (Ti^{p1}), is marginally less than through p2 (Ti^{p2}) then subpath p1 is the minimum expected route from node s to node i. On other hand, it can be seen in equation (5.1) that the expected minimum arrival time at node j not only depends on the expected arrival time at node i, but also on the variance of the arrival time at node i and the

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21st August 2016
Guru Nanak College Budhlada, Punjab India

142

second derivative of the mean travel time on link (ij). Given that the travel time on link (ij) is concave and hence its second derivative is negative and so it is possible that sub path p2 is on the expected minimum path from s to j. In short, Bellman's "principle of optimality" which states that any subpath of a shortest path must be a shortest path, does not hold in a DSSPP [7].
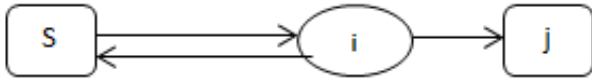

Fig 5.2 A simple dynamic and stochastic network.

Link	Travel Times
A	100 minutes, departing time = 0
B	90 minutes (probability = 0.5), departing time = 0
	120 minutes (probability = 0.5), departing time = 0
C	30 minutes if arrival time at node i < 95 minutes
	100 minutes if arrival time at node i ≥ 95 minutes

5.2 Heuristic Algorithm to calculate the expected shortest path

The heuristic algorithm was developed to identify optimal routes. Theheuristic algorithm proposed in this paper uses this fact to identify the best route without significant additional computation efforts. The algorithm is based on the k-shortest path algorithm and has a parameter K indicating that K shortest paths will be examined [8]. The algorithm proceeds as follows:

Step 1: Find the shortest, the second shortest and up to Kth shortest paths from origin node to destination node, based on the mean travel times over links in the network. These are stored in ascending order in list A.

Step 2: Set k=1 and take the Kth shortest path from A, call it P. Calculate the expected travel time over P by using equations (5.1) and (5.2) denoted by L_{opt}.

Step 3: If k>K: P is the "optimal" path, L_{opt} is the minimum expected travel time, Stop.

Otherwise, go to step 4.

Step 4: Set k=k+1, take the kth shortest path from A, call it P_k. Calculate the expected travel time over P_k by using equations (5.1) and (5.2), denoted by L_k.

If $L_k < L_{opt}$: P= P_k and $L_{opt} = L_k$. Go to Step 3.

There were three issues that needed to be addressed before this algorithm could be implemented. The first issue was to identify the technique for finding the K shortest paths. Here we use k-shortest path algorithm due to its well-known efficiency. The second issue was to identify the value of K. From a practical point of view the appropriate K value can be based on an empirical sensitivity study. The use of larger value for K will increase the chances of finding the optimum expected shortest path, but at same time will require a greater computational effort.

Finally, the proposed heuristic requires applying the approximation formulae presented in section 5.1, which are derived based on the assumptions that the mean and standard deviation of the link travel time are continuous functions of time of day and have at least second order derivatives. A second order polynomial was therefore used to smooth the mean and variance of the link travel times under recurrent traffic congestion.

6. CONCLUSION

The standard shortest path algorithms may fail to find the minimum expected paths in a dynamic and stochastic network. The solution error by the standard shortest path algorithm was shown to be relatively small (5 seconds on average) primarily because of the simplicity of the network and more importantly, because the dynamic travel times changed relatively slowly with time. It is anticipated that a greater impact would be found during incident conditions. While theoretically incorrect the use of standard shortest path algorithms in dynamic and stochastic traffic networks may be applicable from a practical perspective. This will be especially true if the change of travel time in the network is moderate. The route selection algorithm is oriented on the driver's preference. An FN 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 FN net on the driver's choice, the route selection function can be made adaptive to the decision-making of the driver. The methodology paves the way for more intelligent navigation systems.

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21st August 2016
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143

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21st August 2016
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144