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The Design of Route Planning for Travel Demand based on Fuzzy Multi Valued Bayesian Network

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Abstract

For recent decades, as transportation means and environment are converged with intelligent technology, the importance of technologies using them is increasing. Route planning methods that can recommend efficient routes to users have been studied. Most of Route planning methods are to find the shortest path from the starting point to destination. They are focusing on searching a route that minimize distance, time and cost issues. However in order to maximize user satisfaction, it is necessary to consider not only the distance, time and cost issues, but also the purpose of travel when we use the transportation system. In this work, considering travel demand, purpose, internal/external infrastructure, road congestion and user's preference, we proposed travel demand based Fuzzy Multi Valued Bayesian Network which has the functions of route extraction, selection of optimal route according to the user's demand & travel purpose and Bayesian revision by new information. The proposed system was tested with the traveling data.

keywords : Route Planning,Travel demand, Fuzzy MVB node, Future simulation, Bayesian Revision

1. Introduction

The transportation environment created along with the development of transportation is coveraging with information technology, making human life more convenient. Moreover, as autonomous vehicle technology becomes a reality, it is accelerating the evolution of intelligent transportation system related infrastructure to utilize it. As a lot of roads are being built and computer technology are developing quickly, a smart environment with intelligent technology is being created together.

The common purpose is to increase the efficiency and satisfaction of human life as much as possible by utilizing intelligent transportation technology and infrastructure. For recent decades, many studies have been conducted on the transportation system for this purpose. One of such approaches is the study on route planning[1]. Most of the research on route planning is to find the shortest path. The focus has been on finding a route that minimize distance, time and cost issues[3,5,6]. However in order to maximize user satisfaction, it is necessary to consider not only the distance, time and cost issue, but also the purpose of travel when we use the

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transportation system[7]. For example, if purpose of travel is simple movement from start point to the destination, it is best way to select a route that can minimize the distance time and cost. However if the purpose of travel is tourism, it would be a different story. Perhaps the user will choose a route that can tour the tourist spots according to the purpose of tourism, even if it takes more time.

Travel demand models use current travel behavior to predict future travel patterns. The models are critical tools for planner to forecast transportation needs. There are many ways to build a model requires detailed information about:

- Where people to go (Starting point and destination)
- The ways their travel behavior changes during the specific conditions

Traditionally, travel demand models use a four-step process of travel generation, distribution, mode choice and trip assignment for analyzing regional transportation planning.

However, for making a system more sophisticated it needs to consider the following factor:

- Transprtation Demand Management (the purpose of trips to be made)
- Internal/External transportation infra structure
- Road Congestion
- Intelligent information control

Considering these factors, we designed Route planning system for travel demand based Fuzzy Multi Valued Bayesian(MVB) Network which has the functions of route extraction, selection of optimal route according to the user's demand & travel purpose and Bayesian revision by new information. As a transport Network, Fuzzy MVB network is designed to be composed of multi valued Fuzzy MVB nodes for supporting the user's service. Fuzzy MVB node contains multi values which represent user's travel purpose, for example business or Sightseeing purpose and probability of occurrence.

In section 2, Route planning related studies are explained and in section 3 Future simulation mechanism of Route planning for travel demand optimal path is proposed. We applied the proposed system to the problem of selecting the optimal routing path and tested with data.

2. The techniques for Route Planning

The approaches for Route planning are classified to several categories : Public Transit Route Planning, Multi Modal Route Planning, Customizing Route Planning in road networks and Computational of jogging routes[1]

2.1 Public Transit Route Planning

In public Transit Route Planing, the input is given as a time table which defines stops and trips operating along sequences of stops at certain times of day. They ask for a set of optional journey all departing within a certain time range from one stop to all other stops of the network and the algorithm is based on a graph model. The precomputation of full distance table over a subset of important stops of the network is possible. Another criterion besides travel time is the number of transfer. State-of-art approaches use variants of Dijkstra's algorithm. It exploits the fact that the vehicles operate on well defined routes, which allows for a dynamic program that successively constructs the Pareto set. Because it does not require preprocessing, it can be directly used in dynamic scenarios, easily handling delays and trip cancellations.

2.2 Multimodal Route Planning

This method combines different modes of tranport in reasonable way. A common approach to obtain feasible mode sequence is label constrained shortest path problem, which models mode sequences by regular languages. A variant Dijkstra's algorithm that run on the union of each modal subnetwork computes optimal solutions, but too slow in practice. This work presents a faster approach based on the concept of vertex contraction. It preprocesses the input such that arbitrary mode sequences are retained. This enables the user to specify mode sequence constraints at query time, a problem considered challenging before. This approach is considered that combines multimodal and multi criteria route planning[4]. Instead of following specific modal sequence, it identify a convenience criteria for each mode of transportation. These criteria are used to compute Pareto sets of alternative journeys.

2.3 Customizable Route Planning in Road Networks

It considers the classical problem of computing optimal routes in road networks. For most efficient algorithms, an update of the matric requires rerunning a costly preprocessing phase. This approach addresses that it is based on multi lavel overlay graphs. The key idea is to split the preprocessing phase : In a first metric independent stage. The graph is partitioned into loosely connected regions of roughly equal size. This defines the topology of overlay graphs. The second metric dependent stage quickly computes weights on the arcs of the overlay graphs. Intergrating a new metric only requires reruning the second stage.

2.4 Computation of jogging Routes

It considers computing 'good' jogging routes: Given a source vertex in a pedestrian network and length of the desired route, it asks to compute a cycle containing the source vertex that approximates the given length. An ideal route might have a rather circular shape and travel through good areas such as parks and forest of the map. In this work, two approaches to solve the problems. The first one successively extends a given route by joining adjacent faces of the network. The second one transfer the intuition of constructing equilateral polygons to graph in order to obtain jogging routes. The algorithm can compute sensible alternative routes.

3. Future Simulation of Route Planning for Travel Demand Optimal Switching Path

In this work, we designed Fuzzy MVB(Multi Valued Bayesian) Network and proposed future simulation system for Route planing which may be classified to combination method and closed to multimodal Route planing model among the various approaches which are explained in section 2, in the viewpoint of that has a structure of multi valued processing.

3.1 Basic Fuzzy MVB network

1) Fuzzy MVB network

Fuzzy MVB Network as a basic frame of Knowledge Base has constraint form of Directed Acyclic graph which consists of nodes and arcs as shown in Fig.1.

Fig. 1. A basic frame of Fuzzy MVB network

The node of Fuzzy MVB network consists of ID(Identified Name), x_i, its probability, $P(x_i)$, and its value $V^c(x_i)$ as shown in Fig.2. $V^c(x_i)$ represents a vector of multi values of a fuzzy MVB node which has fuzzy value. A Fuzzy MVB node has multiple values of categories, c, depending on the point of view. For example, business, sightseeing and etc.. $V^c(x_i)$ is denoted by a vector of fuzzy values.

$$V^c(x_i) = [F_B(V^B(x_i)), F_s(V^S(x_i))],$$

where $F_B(V^B(x_i))$ is fuzzy value of Business degree for x_i and $F_S(V^S(x_i))$ is fuzzy value of sightseeing degree for x_i because two factors of Business and sightseeing purpose are considered in this proposed system[10]. If it is generalized, more trms can be added.

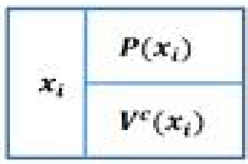

Fig. 2. The structure of a node of Fuzzy MVB network

The membership function of $F_B(V^B(x_i))$ is denoted by equation (1)-(3) in Fig.3.

$$\mu_{B_{high}}(x,a,b) = \begin{cases} 0, & if\ x \le a \\ 2 * \left(\frac{x-a}{b-a}\right)^2, & if\ a \le x \le \frac{a+b}{2} \\ 1 - 2 * \left(\frac{b-x}{b-a}\right)^2, & if\ \frac{a+b}{2} \le x \le b \\ 1, & if\ x \ge b \end{cases} \quad (1)$$

$$\mu_{B_{middle}}(x,\alpha_1,c_1,\alpha_2,c_2) = \frac{1}{1+e^{-\alpha_1(x-c_1)}} - \frac{1}{1+e^{-\alpha_2(x-c_2)}} \quad (2)$$

$$\mu_{B_{low}}(x,a,b) = \begin{cases} 1, & if\ x \le a \\ 1 - 2 * \left(\frac{x-a}{b-a}\right)^2, & if\ a \le x \le \frac{a+b}{2} \\ 2 * \left(\frac{b-x}{b-a}\right)^2, & if\ \frac{a+b}{2} \le x \le b \\ 0, & if\ x \ge b \end{cases} \quad (3)$$

Fig. 3. The membership function of $F_B(V^B(x_i))$

Similarly, the membership function of $F_S(V^S(x_i))$ is denoted by equation (4)-(6).

$$\mu_{S_{high}}(x,u,v) = \begin{matrix} 0, & if\ x \le u \\ 2*\left(\frac{x-u}{v-u}\right)^2, & if\ u \le x \le \frac{u+v}{2} \\ 1-2*\left(\frac{v-x}{v-u}\right)^2, & if\ \frac{u+v}{2} \le x \le v \\ 1, & if\ x \ge v \end{matrix} \quad (4)$$

$$\mu_{S_{middle}}(x,\beta_1,r_1,\beta_2,r_2) = \frac{1}{1+e^{-\beta_1(x-r_1)}} - \frac{1}{1+e^{-\beta_2(x-r_2)}} \quad (5)$$

$$\mu_{S_{low}}(x,u,v) = \begin{matrix} 1, & if\ x \le u \\ 1-2*\left(\frac{x-u}{v-u}\right)^2, & if\ a \le x \le \frac{u+v}{2} \\ 2*\left(\frac{v-x}{v-u}\right)^2, & if\ \frac{u+v}{2} \le x \le v \\ 0, & if\ x \ge v \end{matrix} \quad (6)$$

Fig. 4. The membership function of $F_S(V^S(x_i))$

In Fig. 1, we denote 'Fuzzy MVB path' for the routing links as $[x_i \rightarrow x_j \rightarrow x_k]$.

The link between x_i and x_j is denoted by equation (7).

$$P(x_i,x_j) = P(x_j|x_i) \quad (7)$$

where it represents the congestion degree in this application system.

The joint probability $P(x_i,x_j,x_k)$ of Fuzzy MBV path in Fig.1 is as following equation (8).

$$P(x_i,x_j,x_k) = P(x_k)P(x_k|x_j)P(x_j|x_i) \quad (8)$$

If we generalize this, given any joint distribution $P(X_1,\ldots,X_n)$, a Fuzzy MVB Network is constructed by a recursive procedure starting from X_1 as a root and assigning marginal probability $P(x_1)$. If X_2 is connected and dependent to X_1, one node is added and quantified by $P(x_2|x_1)$. Otherwise, X_1 and X_2 are disconnected and assigned the prior probability $P(x_2)$. At the i_th stage, the node X_i is formed and a group of directed links to node X_i from a parent set π_{x_i}, quantified by the conditional probability $P(x_i|\pi_{x_i})$.

The conditional probabilities, $P(x_i|\pi_{x_i})$ on the links of the Directed Acyclic graph contain the information for reconstructing the distribution function. Using the chain rule we can get the following the product:

$$P(x_1,x_2,\ldots,x_n) = \Pi_i P(x_i|\pi_{x_i}) \quad (9)$$

2) Bayesian Revision in Fuzzy MVB network by new information

When new information as an evidence comes in, the Bayesian values and structure of Fuzzy MVB network can be revised [2,8,9].

Let H denote a hypothesis, $d_n = d_1,d_2,\ldots,d_n$ be a sequence of past data and e notes a new evidence. $P(H|d_n,e)$ would be changed as appending the new data e to the past data d_n. The entire data set is $d_{n+1} = \{d_n,e\}$. We can calculate $P(H|d_n,e)$ by discarding the past data and the computing the new data impact by equation (10).

$$P(H|d_n,e) = P(H|d_n)\frac{P(e|d_n,H)}{P(e|d_n)} \quad (10)$$

where $P(H|d_n)$ is the prior probability, that is past experience. For Bayesian revision, it needs to be multiplied by the likelihood function $P(e|d_n,H)$, which measures the probability of the new evidence, e , given hypothesis H and past observations.

3.2 The design of Future Simulator and optimal switching path for Route Planning

1) The structure of Future Simulator

The structure of Future Simulator proposed in this work is as following Fig.3. This future simulator for selecting the optimal routing path is mainly operated by Bayesian revision and Future simulation cycle.

Bayesian Revision cycle is a procedure that updates the Bayesian value and structure of fuzzy MVB network with new evidence. The main function of Bayesian Revision cycle lies in keeping Fuzzy MVB network up to date by the incoming new information. If the new evidence is acquired, the cycle adjusts Fuzzy MVB network according to the new relations. The Bayesian value and structure of the network are adjusted by the Bayesian Revision.

Future Simulation cycle is a procedure which extracts the reachable reasoning paths starting from keyword and simulates the future solution. The objective of Future Simulation is to make the most successful decision by selecting the optimal routing path with highest evaluated value.

The workflow of Future Simulator proposed in this work is as follows: It starts from input stream which consists of user's demand and the related data prepared for extracting phase. Incoming input streams to I/O interface are analyzed through PREPROCESS, this module categorizes the incoming stream into simple keyword and fuzzification. As a result of analysis, Input keywords and fuzzified data are produced. The produced Input keywords and data flows into next step. There are two paths to flow. If it is a new evidence, data stream comes into Bayesian Revision mechanism to update Fuzzy MVB network. If it is for extracting the routing paths, data stream goes into Routing Path Extraction module. After the routing paths are retrieved, evaluation procedure for selecting the optimal path is performed and the selected path is recommended for best decision making with explanation through I/O Interface.

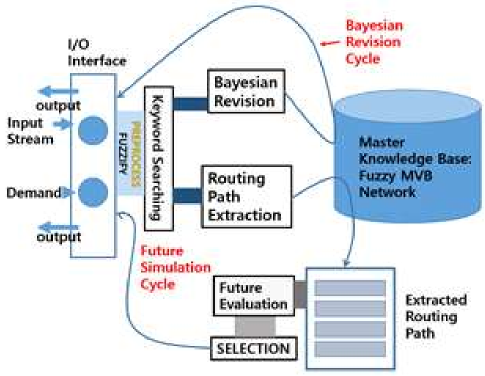

Fig. 5. The structure of Future simulator for selecting the optimal Routing path

2) Future Evaluation

In order to find the optimal path that best fits the goal among the extracted reasoning paths, the evaluation for each path is required. Provided that the extracted path, $path_i$, is $x_p \rightarrow x_q \rightarrow x_r$, the joint probability of path is obtained by equation (11).

$$P(x_p, x_q, x_r) = P(x_r|x_q)P(x_q|x_p)P(x_p) \quad (11)$$

The evaluation value, $E(Path_i)$ is calculated by equation (12).

$$E(Path_i) = \ln(1 - P(x_r|x_q)) + \ln(1 - P(x_q|x_p)) + \ln(1 - P(x_p)) \tag{12}$$

Evaluation value represents how the routing path is optimal. During the evaluation process, the total value of the path for Travel Demand is also produced by equation (13).

$$T(Path_i) = \sum_{j=1}^{n} \mu_c(V^c(x_j)) \tag{13}$$

where $V^c x_j$ is a value of j^{th} node of extracted reasoning path.

- Selection of optimal path

There are three cases to choose the optimal reasoning path. These are to select the path which has maximum value of related strength (evaluation value), maximum total value and considering both terms. The system selects the optimal path by using the following equation (14)-(15) for each case.

Case 1 : Evaluation value

$$Choice^e = \underset{i}{\arg max}\, E(Path_i) \tag{14}$$

Case2 : Total value

$$Choice^T = \underset{i}{\arg max}\, E(Path_i) \tag{15}$$

Case 3: Both Evaluation value and Total value

$$S(Path_i) = \mu_c(V^c(x_r))*\ln(1 - P(x_r|x_q)) + \mu_c(V^c(x_q))* \ln(1 - P(x_q|x_p)) + \mu_c(V^c(x_p))*\ln(1 - P(x_p))$$
$$Choice^{eT} = \underset{i}{\arg max}\, S(Path_i) \tag{16}$$

If the optimal routing path is selected, system recommends the optimal path with total value for best decision making through I/O interface.

4. Experiments

In experiments, we applied the proposed system to optimal path searching problem. As shown in Fig.6, provided user wants to reach the goal city, Busan, starting from Seoul, and there are several routes between Seoul and Busan, the problem is to search the optimal path satisfying the user's demand in various viewpoints. Users may want to find a route for sightseeing purpose even if it takes long way around. For building Fuzzy MVB network, in the first step we mark the cities as nodes and connect nodes along the routes. The created Fuzzy MVB network is following Fig. 7. Then Fuzzy MVB node specification is made as shown in Fig. 8 which consists of ID, Name, Probability of node, $P(x_i)$, its value, $V^c(x_i)$ where c is sightseeing or business category. Fig. 9 shows the congestion degree between nodes which represents as conditional probability.

Fig. 6. The map for selecting the optimal routing path

Congestion degree	value	Congestion degree	value
$P(x_1\|x_0)$	0.1	$P(x_{10}\|x_6)$	0.6
$P(x_2\|x_0)$	0.6	$P(x_{11}\|x_9)$	0.4
$P(x_3\|x_0)$	0.7	$P(x_{12}\|x_{10})$	0.5
$P(x_4\|x_1)$	0.1	$P(x_{13}\|x_{10})$	0.5
$P(x_5\|x_2)$	0.8	$P(x_{14}\|x_{13})$	0.7
$P(x_5\|x_3)$	0.6	$P(x_{14}\|x_7)$	0.2
$P(x_6\|x_4)$	0.5	$P(x_{14}\|x_8)$	0.2
$P(x_7\|x_4)$	0.3	$P(x_{14}\|x_{11})$	0.3
$P(x_8\|x_4)$	0.1	$P(x_{14}\|x_{12})$	0.8
$P(x_9\|x_5)$	0.5		

Fig. 7. Congestion degree of link

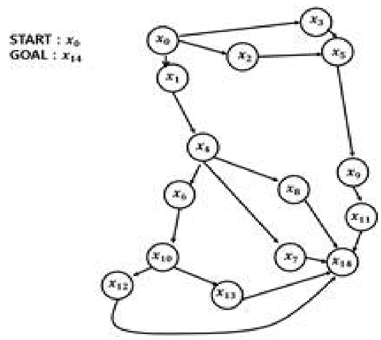

Fig. 10. Fuzzy map MVB network

ID	name	$P(x_i)$	$V_B^C(x_i)$	$V_S^C(x_i)$
x_0	Seoul	1.0	10	10
x_1	Suwon	1.0	10	5
x_2	Wonju	1.0	2	7
x_3	Kangnung	1.0	5	10
x_4	Taejeon	1.0	9	5
x_5	Youngdong	1.0	4	10
x_6	Cheongju	1.0	8	5
x_7	Masan	1.0	5	6
x_8	Taegu	1.0	10	4
x_9	Pohang	1.0	10	8
x_{10}	Kwangju	1.0	9	5
x_{11}	Ulsan	1.0	10	8
x_{12}	Mokpo	1.0	3	8
x_{13}	Yeosu	1.0	3	9
x_{14}	Busan	1.0	10	8

Fig. 8. Fuzzy MVB nde specification

```
evaluation ...
path 1 3.40
path 2 3.50
path 3 3.30
path 4 3.50
path 5 2.40
path 6 2.50
Optimal path : path 2
Optimal path : path 4
evaluation + Sightseeing Value...
path 1 2.91
path 2 3.04
path 3 2.96
path 4 2.90
path 5 2.92
path 6 3.14
Optimal path : path 6
evaluation + Business Value...
path 1 3.82
path 2 3.92
path 3 3.86
path 4 4.41
path 5 3.04
path 6 3.11
Optimal path : path 4
```

Fig. 11. Evaluation and Selection of optimal routing path

```
path 1 x0 x1 x4 x6 x10 x12 x14
path 2 x0 x1 x4 x6 x10 x13 x14
path 3 x0 x1 x4 x7 x14
path 4 x0 x1 x4 x8 x14
path 5 x0 x2 x5 x9 x11 x14
path 6 x0 x3 x5 x9 x11 x14
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Fig. 9. Future simulator: Routing path criteria

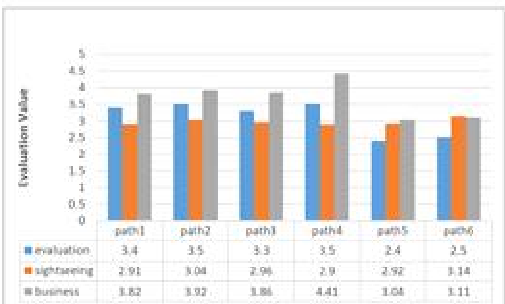

Fig. 12. Routing path evaluation(Initial case)

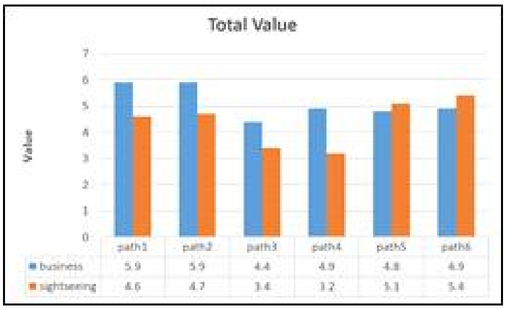

Fig. 13. Total value of Routing path(Initial case)

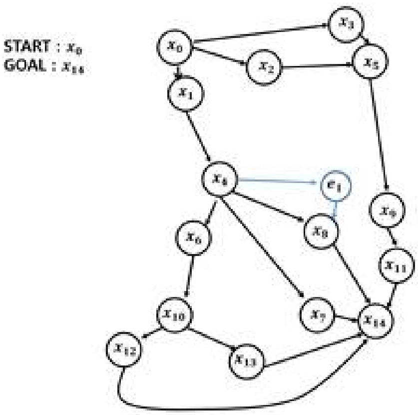

Fig. 14. The changed structure by Bayesian revision

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path 1 x0 x1 x4 x6 x10 x12 x14
path 2 x0 x1 x4 x6 x10 x13 x14
path 3 x0 x1 x4 x7 x14
path 4 x0 x1 x4 x8 x14
path 5 x0 x1 x4 e1 x8 x14
path 6 x0 x2 x5 x9 x11 x14
path 7 x0 x3 x5 x9 x11 x14
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Fig. 15. Bayesian revision and routing path extraction

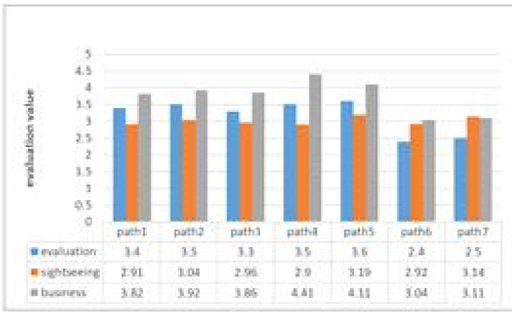

Fig. 16. Routing path evaluation (new evidence case)

Fig. 17. Total value of routing path (new evidence case)

The higher this value, the more crowded the link is. In other words, it means that the infrastructure such as road conditions, required time and etc.. is more crowded and inefficient. The simulation results of Future simulator in the initial state and depicted in Fig. 10 and Fig.11. Especially Fig.11 explains the output of the routing paths. The reachable reasoning paths are extracted by Routing Path Extraction module in Future Simulation cycle. The evaluation process for selecting the optimal routing path are made and two paths are selected. The evaluated values of both paths are same as 3.50, so both paths od path2 and path4 were selected. This results are recommended to the user for better decision making through I/O interface in this system. Considering the value in the viewpoint of purpose, in the case of sightseeing Path6 which has maximum value as 3.14 is selected as an optimal routing path. In the same way. as a result of business viewpoint part4 having maximum value of 4.41 is selected for optimal path. The graphs shown in Fig. 15 and Fig. 16 represent the results of Routing path evaluation and Total values respectively. When reliable evidence comes in, the structure of Fuzzy MVB network is changed based on this new information by Bayesian revision cycle as shown in Fig. 16. This time 7 reasoning paths are extracted as shown in Fig. 15. By analyzing the evaluation results, it can be confirmed that the selected path as an optimal routing path has been changed path 5 for sightseeing purpose because a new evidence has high value for sightseeing purpose. It can be seen that total value has also been changed. Therefore, from the results we can see the structure of Fuzzy MVB network was revised as a new evidence has come in.

5. Conclusion and future works

We designed Route planning system for travel demand based Fuzzy MVB network which has the functions of route extraction, selection of optimal route according to the user's demand & travel purpose and Bayesian revision by new information. As a Transport network, Fuzzy MVB network is designed to be composed of multi valued Fuzzy MVB node contains multi values which represent user's travel purpose, for example business or sightseeing purpose, and probability of occurrence. In experiments, the proposed system was applied to the problem of searching the optimal routing path from starting point and destination. The functions of future simulation and Bayesian revision were tested with data. As a result of simulation, the proposed mechanism is found to be working well. It is expected that the proposed mechanism can be used for the design of recommendation system which can give a service of reacting on user's travel demand.

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References

[1] Thomas Pajor," Algorithm Engineering Journey Planning in Transportation Network". Doktors der Naturwissen Schaften, KIT, Nov 15, 2013.

[2] Judea Pearl, " Probabilistic Reasoning in Intelligent Systems: Networks of Plausible Inference, revised second printing", MORGAN KAUFMANN Publisers ISBN: 0-934613-73-7

[3] Abraham. I., Delling.D, Fiat A., Goldberg A.V., Werneck R.F," VC-dimension and shortest path algorithms",ICALP 2011, LNCS, vol. 6755, pp. 690-699. Springer,

Heidelberg(2011)
doi:10-1007/978-3-642-2206-7-58
[4] Aifadopoulou G., Ziliaskopoulos A, Chrisohoou E, " Multiobjective optimum path algorithm for passenser pretrip planning in multimodal transportation networks", Transp. Res., Board 2032(1), 26-34 (2007)
doi:10 3141/2032-04
[5] Allulli L., "Exploiting GPS data in public transport journey planners", LNCS, vol. 8504, pp 295-306. Springer, Heidelberg (2014)
doi : 10.1007/978-3-319-07959-2_25
[6] Rusell Lyons, Yuval Peres, "Probability on Trees and Networks", Cambridge University press, 2016.
ISBN : 9781107160156
[7] Brandes U, Schulz F, Wagner D, Willhalm T, " Travel Planning with self-made maps", LNCS, vol. 2153, pp 132-144, Springer, Heidelber(2001)
doi: 10.1007/3-540-44808-X_10
[8] Russell Lyons, Yuval Peres, " Probability on Trees and Networks - Cambridge Series in Statistical and Probabilistic Mathematics", Cambridge University Press, 2016, ISBN:9781107160156
[9] Thomas M. Cover, Joy A. Thomas, " Element of Information Theory", Wiley-Interscience, 2005, ISBN : 13-978-0-471-24195-9
[10] Paul P. Wang, S.K.Chang, "Fuzzy Sets Theory and applications to Policy Analysis and Information System", Prenum press, 1980. ISBN: 0−306-40557-1

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