A MULTI-MODAL ROUTE PLANNING APPROACH WITH AN IMPROVED GENETIC ALGORITHM

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KEY WORDS: Route Planning, Multi-modal, Multi-criteria, Genetic Algorithm

ABSTRACT:

The purpose of multi-modal route planning is to provide the traveler with optimal, feasible and personalized route between origin and destination, which may involve public and private transportation modes. The strategy driven approach (i.e. routing by certain predefined transfer order) is useful but can hardly provide free combination of multiple travel modes and some feasible results may be consequently missed. A genetic algorithm (GA) is proposed in this paper to solve the multi-modal route planning problem. Variable length chromosomes with several parts (subchromosome) are utilized to represent routes in multi-modal travel environment, where each part describes a kind of transportation mode. Crossover and mutation operators are redefined in single mode; two new operators, hypercrossover and hypermutation, are defined as inter-mode operation. A multi-criteria evaluation method using a p-dimensional vector to represent multiple criteria is adopted in the fitness function for selecting the optimal solutions. The experimental results show a various mode combination, and some results conform experience well.

1. INTRODUCTION

Multi-modal transportation systems are designed to provide various travel approaches. However, problems yield accompany with the convenience of so many travel mode choices including public and private transportation. How to make a sensible decision among these travel modes or the combination of certain kinds is becoming a Gordian knot. The multi-modal route is defined as a route involves two or more different modes among which the traveler has to make a transfer (van Nes, 2002). Free combination of different travel modes is an essential characteristic. However, rare researches are concentrating on it. With the consideration of free mode combination, the time consumption of strategy drive approach is a hard burden. How to combine different modes to meet the travelers' individual needs with least computational cost is a bottleneck of optimal multi-modal route planning.

Route planning problem is used to be represented as an optimal problem which is aiming at providing feasible route under certain needs. In single criterion era (the shortest path problem), Dijkstra algorithm has been considered as a representative solution. It is an exact algorithm which always determines the exact shortest one. However, real-world optimization problems can hardly be expressed with just one criterion, one result neither. When considering multi-criteria, conflict appears often, that is, improve in one criterion could lead to deteriorate in another. The exact algorithms could not handle it well. As genetic algorithms (GA) handle a set of solutions simultaneously and have multiple various solutions during one process, it is an effective algorithm to deal with multi-criteria optimal problems.

This paper presents a multi-modal route planning approach utilizing an improved genetic algorithm to solve the multi-modal route planning problem. Variable length chromosomes with several parts (subchromosome) are utilized to represent routes in multi-modal travel environment, where each part describes a kind of transportation mode. Crossover and mutation operators are redefined in single mode; two new operators, hypercrossover and hypermutation, are defined as inter-mode operations. A p-dimensional vector representing multiple criteria with the concept of *dominate* is adopted for selecting the optimal solutions.

The remainder of this paper is organized as follows. Some related work introduced in Section 2. Section 3 describes the problem we are concentrating on. Then a multi-modal network model is introduced, and an improved GA for multi-criteria route planning approach is proposed in Section 4. The implementation with experiment and result are shown in Section 5. Finally, conclusion and future work is introduced.

2. RELATED WORK

In the past decades, a growing number of multi-modal route planning systems are available either on the internet or on desktop which appear as spatial decision support tools to provide available travel suggestions for travellers. Most of the online route planning systems (e.g. Google Map, Bing Map, *etc.*) support multiple travel modes. Nevertheless, few could provide free combination of travel modes.

Utilizing Genetic Algorithm to solve route planning has been reported for years. Gen and Cheng *et al.* (1997) proposed a priority-based encoding method to represent all possible paths in a graph. The chromosomes are of the same length, and the encoding is also complex, but their work provided a new approach to such kinds of difficult-to-solve problems. Delavar

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and Samadzadegan *et al.* (2001) proposed a genetic algorithm with a part of an arterial road regarded as a virus to select route to a given destination on an actual map under a static environment. They generated a population of viruses in addition to a population of routes. Crossover and virus theory of evolution were used to improve the rate of search, but mutation did not used. The length of the route was taken as fitness. Davies and Lingras (2003) presented a GA based strategy to find the shortest path in a dynamic network, which adapted to the changing network information by rerouting during the course of its execution. In their case the problem was no longer the shortest path, but the shortest walk. Crossover operator was used when walking condition changed to bad and spliced the new walk into the old one. All these researches concentrate on single criterion problems.

In multi-criteria research, Chakraborty (2004, 2005) proposed a GA based algorithm with a novel fitness function for simultaneous multiple routes searching for car navigation to avoid overlap. The alternate routes considered some attributes such as distance, number of turns, passing through mountain and passing by the side of river, and use penalty for fitness. In the work of Huang and Cheu, *et al.* (2004), GA introdueced for determining the weights of different criteria, which eventually achieve a series value of each criterion and sum the up as the final cost. Hochmair, H. H. (2008) utlized GA for Pareto Optimal route set searching in order to reduce the number of route selection criteria. In this work, fitness function was not included. Instead, the distinct solutions were kept. Random walking was used to generate initial population in single criterion and two parents to create a mutated offspring and replaces one parent approach is not as the traditional. However, the specific detail is not introduced. The GA based solution for multimodal shortst path problem presented by Abbaspour, R.A. and Samadzadegan, F. (2009) shown the robustness of this approach through an experiment and concluded that proposed algorithm can efficiently explore the search space to find the shortest multimodal path. Two criteria, length and waiting time, were summed in order. However, the time cost calculation is time-table based and estimated. Nevertheless, these researches are useful exploration.

For multi-criteria problem, some label setting algorithms (e.g. Martins, 1984; Corley and Moon, 1985) and label correcting algorithms (e.g. Skriver and Andersen, 2000) are reported. However, these labeling methods may cause exponential running time. As a high efficient search strategy for global optimization, genetic algorithm demonstrates favorable performance on solving the combinatorial optimization problems. GAs for dealing with multi-criteria optimal problem has been considered as an effective approach in Multi-objective Optimization. It can process a set of solutions simultaneously, and obtain various effective ones. According to these, we introduce GA in multi-modal route planning field considering multiple evaluation criteria in order to provide optimal alterable routes with free combination of travel modes.

3. PROBLEM DESCRIPTION

The single mode road network is often represented as a directed graph model $G=(V,E)$, in which $V=\{1,...,n\}$ represents a set of nodes *n*, and *E* is the set of direct arcs. Each arc is denoted by a pair (edge) $e=(i,j)$ connecting node *i* to node *j*, $\forall i,j \in V$. Weight of each edge $w(e)$ is assigned on *e* in graph *G*. A route $R(s,t)$ in the road network between two distinct nodes is defined as $R(s,t)=\{s=i_1,(i_1,i_2),i_2,...,i_{j-1},(i_{j-1},i_j),i_j=t\}$. The length of a route from *s* to *t* is calculated as the sum of the weight that assigned on edges along $R(s,t)$. The shortest path problem is to get the minimal value of $\sum w(e_{i,j}), e_{i,j} \in R(s,t)$.

In the multi-modal case, *G* can be considered as the union of multiple subgraphs, representing different travel modes respectively. The graph is not simple, that is for any two nodes $n_1, n_2 \in V$ there may be more than one edge. In a three modes involved travelling network, $G=G_D \bigcup G_P \bigcup G_W$ where $G_D=(V_D,E_D)$, $G_P=(V_P,E_P)$, $G_W=(V_W,E_W)$ represent driving network, public transportation mode (i.e. bus, subway, tram etc.) and pedestrian walking. The subgraph nodes V_D,V_P,V_W are defined with $V_{DW}=V_D \bigcap V_W \neq \varnothing$ as well as $V_{PW}=V_P \bigcap V_W \neq \varnothing$, which describe the connection among different transportation modes. Similarly, E_{DW},E_{WD} define the transfer between driving mode and walking mode; E_{PW},E_{WP} between public mode and walking mode.

Associated weight of each edge $w(e)$, in multi-criteria environment is represented as a p-dimensional vector of criteria $C(e)=(C_1(e),C_2(e),...,C_P(e)), e \in R(s,t)$. The value of any criterion $k \in (1,...,p)$ for the given route $R(s,t)$ is defined as $C_k^{R(s,t)}=\sum_{e\in R(s,t)} C_k^e$. So the optimal problem can be stated as $\min C^{R(s,t)}$. Criteria such as time, transfer, fare etc. can be described together in multi-criteria problem.

4. MODELING APPROACH

4.1 Data Modeling

Before introduce the proposed GA, the data model has to be declared in advance, for the later evolution operators depend on it. The multi-modal network used in our research is organized on the concept of subgraph. The subgraph approach is a widespread method considering several existing single modes independent representation, which lays the gaps for modeling mode transfer, and further makes the route guidance inaccurate and unclear. In order to remain the independence of each network and maintain the connectivity of each other simultaneously, transfer nodes and transfer links are proposed. Note that transfer nodes are those belonging to or could be attached to both source and target travel modes. In multi-modal network each mode is represented as a horizontal layer, while transfer links or nodes connect each of them. The transport modes concerned in our research involve both public and private transportations. Driving, bus, subway and walkway networks are established separately.

Road network using navigation dataset consists of roadways of different classes, and is represented as a directed graph. In this road network, *Node* denotes the intersection, roadway start and end, entry and exits. *Roadway Section* states a directed path between two neighbor nodes. A series of *Vertex* constitute a *Roadway Section*. *Roadway* is a part of a road over which vehicles travel. One *Roadway* contains several *Roadway Sections*. The start and end of a trip as well as the transfer node could be any point of interest (POI), bus stops and subway stations. *Nodes* and *Roadway Sections* have been attached with *ID* attribute for identification, which would be used in transfer relationship representation. *Roadway Sections* also have *Fnode*, *Tnode* attributes to express the direction from Node *i* to Node *j*.

A feasible pedestrian walking network should comprise walking facilities such as crosswalk, overpass, underpass etc. In our earlier work (see Yu, H. and Lu, F. 2009) walking network is automatically built based on the road network data and the walking concerned facilities data with spatial manipulation and semantic analysis on the involved dataset. It has similar attributes as road network. Besides, the associated roadway ID has been taken as an attribute, which could make connection between these two modes. The transfer defined here is critical as they provide an access to other travel modes and connect them together.

Bus network encompasses different bus routes (such as Bus No. 839) and is built with dynamic segmentation technology. The opposite direction of the same bus route is defined as two bus lines and assigned with different *ID* value. Bus stops are assorted as physical stops and logical stops. The former denotes the actual bus stop location with ID as its only identity. Physical stops with the same stop name but different direction are identified separately. The latter denotes the logical relationship among physical stops. Through logical stops, we can identify stops with the same coordination, name, bus line assigned, and roadway ID attached. By doing this, the relationship of bus network and road network has been established. That is, these two modes could make transfer at bus stops. So does the walking network.

Subway network is represented as an undirected graph with timetable-based attributes. The node here is represented as subway station, which is the access to transfer to other modes. Each subway station has calculated the available roadway ID, walkway ID and bus stops for transfer. These are one to more relations.

In our research, POIs are taken as the origin and destination spots and the transfer nodes, which could be easily attached to the modes mentioned above. For most of the time, transfer links defined as a virtual one. In order to represent the transfer cost between modes, transfer links also assigned weight of everyone the same as those defined in single mode. This definition is useful in calculating routes in multi-modal network, such as waiting time, transfer delay and so on.

Note that the multi-modal network is independent in physical, which can be maintained and managed separately, but connected in logical, which can be easily rebuilt when single mode data updated. This approach ensures the independency and connectivity simultaneously.

4.2 The Proposed GA

We assume the reader is familiar with the simple GA. For detailed information please see Goldberg (1989). As the simple GA does not support evolution in multi-modal environment, an improved one is proposed in this paper to solve the multi-modal route planning problem. The proposed GA (Figure 1) have the similar procedure as the simple one, but differ at representation and evolution operators and using p-dimensional vector to represent environment pressure.

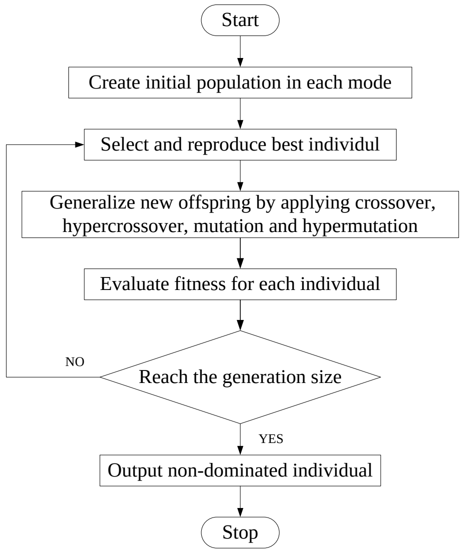


Figure 1. Flowchart of proposed genetic algorithm

4.3 Genetic Representation

To represent multi-modal routes as genes is critical for developing a genetic algorithm. Special difficulties arise from a) a route contains multiple modes and for each mode encompasses different number of genes, b) a random sequence of edges usually does not correspond to a route (Gen and Cheng *et al*. 1997), and c) allowing evolution operators among multiple modes in one route may cause deficiency.

In this study, variable length chromosomes have been used for encoding the problem. A chromosome or an individual (route) encompasses several sequences of positive integers which represent the IDs of the representative modes and the same number of negative integers that identify the mode of the following genes. In other words, mode tag has been added in front of its genes as a negative integer (Figure 2). The precondition of this encoding approach is that the values of genes (IDs) are positive integers. The ID coded chromosome contains arc IDs in road and walking modes and node IDs in bus and subway modes. The reasons that we do not use node for all modes are as follows. First, arc feature to represent road is more reasonable in logical and so does the point feature to denote bus stops and subway stations. Second, it is easy to attach a point feature to the surrounding arc which makes modes transfer more apparent. Third, when calculating on road network, turning impedance, temporal regulation, even real-time dynamic traffic information are base on arc feature, which makes it possible to apply this approach in dynamic environment.

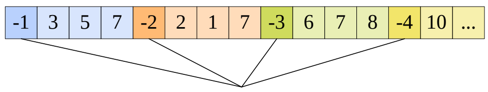


Figure 2. An example of a chromosome

4.4 Evaluation Function

An evaluation function plays the role of the environment, rating solutions in terms of their “fitness” (Michalewicz, 1996). The fitness is not a scalar value as in single criterion problem. It is represented as a p-dimensional vector, each dimension associated with one evaluation criterion. In multi-objective optimization, conflicting objectives (criteria) functions result in a set of optimal solutions, instead of one. These optimal solutions are known as Pareto-optimal solutions, that is, no reduction can be made to one of its cost components, without increasing at least one of the others. Dominate concept is using to identify the relationship of vectors. In our case, for two routes *R1* dominates *R2*, are represented as $f(R1) \preceq f(R2)$, when $C_i^{R1} \le C_i^{R2}$ for each $1 \le i \le p$ and $C_i^{R1} < C_i^{R2}$ for at least one *i*. Then, *R1* is called the non-dominated solution. Multi-objective ranking method proposed by Goldberg (1989) has been used. In this method, all non-dominated individuals are assigned as rank 1. Besides the current non-dominated ones, compare the rest individuals and assign the non-dominated as rank 2, repeat until finish all individuals. Each criterion has its own fitness function calculated independently. The rank values identify the optimal solutions.

4.5 Population Initialization

The composition of initial population is remarkably different compare to the simple GA. As we are looking forward to getting free mode combination of travel modes, the initial population has been generated in each mode respectively. Thus, the initial population encompasses four sets of sub-population in our study, and in each sub-population, random generalization is applied.

Note that in some travel mode such as subway there is not always available route from the input *Origin* to *Destination* (*O-D*). We allow these incomplete solutions but only in initial population, with the precondition that these incomplete solutions are a part or would be a component of complete ones in later evolution. One incomplete solution must generate in the possible reaching space decided by the *O-D* position and through evolution operators it could generate a complete one. This could insure the pureness and diversity of initial population.

4.6 Evolution Operators

Conventionally, evolution operations are achieved through *selection*, *crossover* and *mutation* operators. Another two operators created in this case to adjust to multi-modal environment. The *Crossover* operator and *Mutation* operator are defined in intra-modal environment, i.e., in single mode. Accordingly, *Hypercrossover* operator and *Hypermutation* operator are defined in inter-modal environment, and achieve new individuals from different travel modes.

The *Selection* operator reproduces the best individual. Those selected ones are the current optimal with the lowest rank value, i.e. the Pareto-optimal solutions, which guarantee the elite genes keeping in the next generation. On other hand, to avoid large numbers of similar solutions, individuals with the same chromosome are taken as a “single” one. If the count of “single” non-dominated does not satisfied the purpose selection size (decided by the selection probability), the next rank value has to be taken into account, until finish the target. On the country, random select the target number of individuals into the next generation.

Single point crossover strategy is being utilized in both *Crossover* operator (Figure 3) and *Hypercrossover* operator (Figure 4). For two randomly selected (according to crossover probability) individuals (parents): first, detect all the possible operational modes (with the same mode tag), and select one randomly as the current crossover mode; then, for the current operation mode utilize the corresponding single point crossover operation; if failed, return to select other modes; if all failed turn to *Hypercrossover*. The detailed procedures of single point crossover are as follows:

a) Detect all the candidate crossover genes;
b) Select a pair of candidates and make crossover;
c) Loop detection and repair.

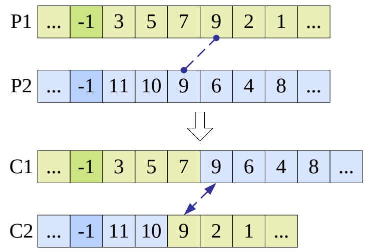


Figure 3. Crossover operator

The detected candidate crossover genes are those with the same gene value. One point crossover could generate loops or other illegal path, which have to be eliminated.

Hypercrossover operator is more complex than the above one. The combination mode set formed by the permutation of all the modes of each parent individual. Determination of the current mode combination is achieved by random selecting. Then, crossable candidates are detected and selected one pair. This function execute on the bases of the relationship among multiple modes, which established in Network Modeling Section. The detected crossable candidates are those with mode transfer relationship or within certain distance (walking) or have some connection in attribute, which could make a transfer. Besides loop path, incomplete solutions could be generated (a certain gap between two crossover genes). Thus, gene repair is used to amend this kind of problem by adding appropriate genes in certain mode, such as walking.

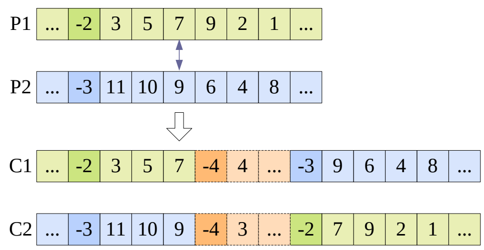


Figure 4. Hypercrossover operator

The *Mutation* operator and *Hypermutation* operator (Figure 5, 6) are similarly defined in different environment. Unlike the crossover operators, mutation operators are unary operations, that is, with one individual each time. In mode detection step, the length of the mode (the size of genes), has to be taken into account, and neglected the too short one, because those one can hardly make operation. For the random selected two mutable genes, another route (genes) is generated and replaces the original one. Make sure that the lengths between the two selected genes are long enough to generate another path. In some mode such as subway, mutability detect is recommended, for there’s not always other route existing between two stations.

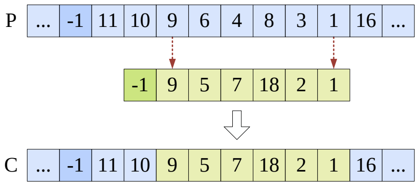


Figure 5. Mutation operator

Hypermutation operator is designed to achieve performance improvement in at least one criterion. Therefore, each mode has defined certain target mutation modes to reduce cost in some criterion. Walking mode is seldom taken as target mode except the select genes are within walking distance, and fulfils the probability. Like hypercrossover operation, gene repair method is mostly used, for there would be many gaps in inter-mode transfer or intra-mode transfer (bus transfer).

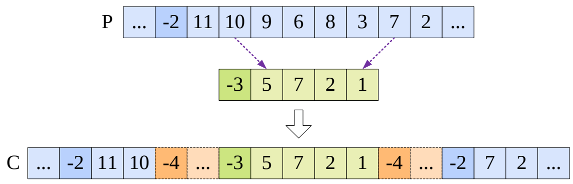


Figure 6. Hypermutation operator

5. EXPERIMENT AND RESULT

To evaluate the performance of the proposed approach, we implement the improved GA in our multi-modal, multi-criteria route planning system. Data utilized in this prototype comprise detailed road network navigation dataset with 53,997 *Roadway Sections* (arcs) and 33,402 nodes, 786 bus lines with 23,590 logical bus stops organized by dynamic segmentation technology, 7 subway routes with 113 subway stations, and walkway with 52,509 arcs and 33,225 nodes. And 839 POIs distribute in Beijing downtown. Those data stored separately as arc, node or point features. Network topology built on each single mode firstly; then, the topology of the multi-modal network built according to the relationship among various travel modes.

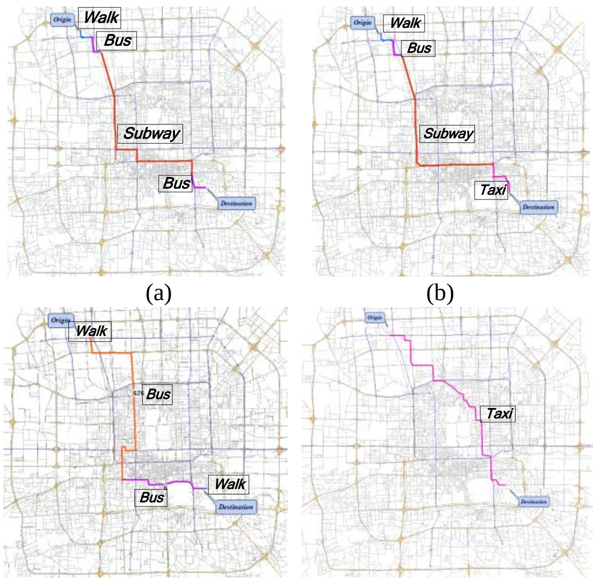
In our experiment, the initial population size is 100, with 13 taxi routes, 40 in bus and subway each, and the rest in walking mode. Table 1 lists the parameters of the proposed GA. The testing *Origin* and *Destination* (*O-D*) are located in the northwest and southeast of Beijing with Euclidean distance over 1,300m.

Parameter	Value
Initial population size	100
Selection size	10~20
Crossover probability	0.25
Hypercrossover probability	0.2
Mutation probability	0.25
Hypermutation probability	0.2
Max generation number	30

Table 1. Parameters of proposed GA

Evaluation criteria vector is calculated as the cost of each route. Criteria considered are travel time, fare and transfer numbers. The shortest path is not taken because in practical environment it could not lead to direct value representation as the other criteria. Time cost encompasses different modes. In pedestrian walk, length of connected edges and average walking speed (5 km/h) are included; in bus mode, besides length and velocity, the interval in bus route line and the entrance and exit platform time are considered; subway mode is schedule based, and the transfer time is counted; driving mode has the similar representation as walking, however, the velocity is fluctuated with time and provided by traffic velocity prediction on historical traffic reasoning with real-time traffic information. The fare structures of taxi, bus and subway systems are different. In Beijing, taxi fare depends on both travel distance and waiting time (velocity less than 10km/h); bus is distance and bus line related with 60% discount for Travel Card users; a fixed amount of 2 RMB is charged per trip for subway. Inter-mode and intra-mode transfers are counted together to represent transfer times including walking.

Figure 7 shows the routes provided for alternation: (a) a bus-subway-bus transfer route, with walking guidance; (b) the fastest route with bus-subway-taxi transfer; (c) a bus-bus transfer route; (d) a taxi route, which is faster but more expensive than (c).



(a) (b)

(c) (d)

Figure 7. Alternative results

Table 2 lists the routing results of each non-dominated individuals. In this table, the least time route using bus-subway-taxi mode combination, which conforms the experience well. In other mode combination, except the common bus-bus transfer, bus-subway-bus, walk-subway-bus and bus-subway-taxi transfer also achieved.

Time	Fare	Transfer	Modes
29.2’	2.8	3	WBSB
29.9’	2.4	2	WSB
48.7’	0.8	1	WB
28.2’	17.4	3	WBST
29.8’	32	0	T
183.1’	0	0	W
43.2’	0.8	2	WBB

Table 2. Routing Result List

6. CONCLUSION

The purpose of multi-modal route planning is to provide the traveler with optimal, feasible and personalized routes between origin and destination, which may involve public and private transportation modes. This paper proposed an improved GA for route planning in multi-modal, multi-criteria environment. Crossover and mutation operators are redefined in single mode; hypercrossover and hypermutation are defined as inter-mode operation. In order concerning various requirement, Vector based evaluation has been utilized to represent multiple criteria. Through applying multi-objective ranking method, the optimal solutions are provided.

This approach implements a free combination of travel modes with concerning various individual needs, which has little manipulation and more intelligence. An experiment has been conducted on the base of our multi-modal network. And the results show a various mode combination, which could adapt to different situations and the results conform experience well.

In the future, multi-objective optimization has to be studied in order to improve the evolution operation for non-dominated solutions. The current multi-objective ranking method is useful but consumes much running time. Other time consuming aspect should be studied further. The performance of the proposed approach in dynamic environment has not tested yet, which leaves a lot work to do.

ACKNOWLEDGEMENTS

This research is supported by the Hi-Tech Research and Development Program of China under grant No. 2007AA12Z241; Chinese NSFC program under grant No. 40871184; The Knowledge Innovation Project of CAS under grant No. KZCX2-YW-308. Their supports are gratefully acknowledged.

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