GENETIC ALGORITHM-AIDED ROUTING ON 3D DYNAMIC NETWORKS

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KEY WORDS: Topology, Dynamic Network, Network Analysis, 3D, GIS, Navigation, Indoor Navigation

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ABSTRACT:
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3D network analysis for indoor provides strong decision support for users in searching optimal routes on applications such as emergency services, transportation, security and visitor guiding. Genetic algorithm is used to solve non-linear problems with complicated constraints. Therefore, the implementation of genetic algorithm into route finding algorithms is needed. This paper explains the demand using genetic algorithm approach on dynamic network routing problems especially for 3D navigation. Abilities of genetic algorithm is investigated as a search strategy and necessitates of genetic algorithm on use for 3D dynamic network routing is presented.

1. INTRODUCTION

Emergency services, transportation, security, visitor guiding are some of common applications of 3D network analysis applications for indoor. Especially, the problem of evacuating the buildings through the shortest path with safety, has become more important than ever in a case of extraordinary circumstances (i.e. disastrous accidents, massive terrorist attacks) happening in complex and tall buildings of today's world. Conditions that may occur in emergency is not fixed, but rather is a variable structure. During the evacuation of the building in emergency, such cases like damaged areas, gas leaks, power outages etc. are effective beside travel distances on determining the evacuation route dynamically.

When we consider online navigation assisted evacuation systems it may need to solve complex topologies, network analyses, 3D modelling and so on. Currently most of the building plans are represented in 2D with common attributes attached. Therefore, most of the available navigation systems use primarily 2D plans for visualization and communication (Meijers et al, 2005). Since navigation systems concentrate on visualization and data management, there is a need for 3D routing from the research idea.

A few researches on navigation in 3D have been initiated recently. Research of 3D pedestrian navigation model (Lee, 2005; Kwan et al, 2005) shows the intention of using 3D technology for indoor emergency response in a 3D building environment.

In 2006, Ivin et al. had discussed the anticipated and initial requirements for making 3D navigation in 3D-GIS environment possible (Ivin et al, 2006).

In 2007, Ivin et al. tried to model dynamic weight of routes (road networks) and implemented an incremental single sink shortest path (SSSP) algorithm that is used for finding shortest path in dynamic routes which can be extended use for 3D navigation in 3D-GIS (Ivin et al, 2007).

In 2008, Ivin et al. suggested a new spatial analysis function in 3D-GIS; the 3D network analysis for calculating shortest path routes in 3D network data model which supports dynamic changes information on the 3D data (Ivin et al, 2008).

There also had been some approaches based on genetic algorithms for using on dynamic routing. In 2002, Kanoh et al. described a practical dynamic route selection method based on genetic algorithm. Their experiments with the system in a dynamic environment built from a real road map showed that the GA-based method is superior to the Dijkstra algorithm for use in practical car navigation devices (Kanoh et al, 2002)

In 2007, Liang et al. proposed an algorithm for the shortest path problem in dynamic networks by using genetic algorithm. Their genetic algorithm's dynamic adaptation is based on random A* algorithm. The results of the experiments demonstrated the utility genetic algorithm on a very large scale dynamic optimization problem (Liang et al, 2007).

In 2009, Kumar et al. addressed the problem of selecting route to a given destination on an actual map under a static environment and proposed a genetic algorithm based solution for improving the performance of single pair path algorithms such as A* and Dijkstra (Kumar et al, 2009).

In this study, our demand for using genetic algorithm approach on dynamic network routing problems especially for 3D navigation will be explained briefly. In this initial study, we work on improving our previously proposed genetic algorithm presented in section 3 which is suitable for networks with static constraints for enhancing the adaptability of the algorithm under dynamic constraints.

2. GENETIC ALGORITHM

Genetic algorithm (GA) is a heuristic technique developed by John Holland in 1975 based on genetic and natural selection principles. In 1989, Goldberg proved that GA is one of the powerful search methods in both theory and practice. GA starts with generating an initial population by random selection of the individuals named chromosomes that each encodes the solution of the problem (Xu et al, 2008). Each chromosome that encodes

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a candidate solution of the problem is made with a combination of significant genes (Whitley, 1994).

GA founded based on two fundamental evolutionary concepts:
1. A Darwinian notion of fitness, which describes an individual's ability to survive
2. Genetic operators, which determine the next generation's genetic makeup based upon the current generation (De Jong, 1988).

The crossover operator generates new individuals called offspring, by recombining the genetic material of two individuals, deemed the parents. Individuals with higher fitness scores are selected with greater probability to be parents and ,,,,pass on'' their genes to the next generation. The mutation operator randomly alters one or more genes in an individual. Mutations add genetic diversity to the population. Through mutation, GAs can search previously unexplored sections of the solution space. Mutations consequently assure that the entire search space is connected (Cedric et al, 2003).

The first step starts with obtaining the values that fitness function returns for each chromosome and selecting the best chromosomes of initial population, which will form the individuals of the next generation. The parents selected for regeneration are replaced by crossover operation and changed by mutation operation to produce child chromosomes. The chromosomes that are not passed through crossover or mutation and newly generated child chromosomes form a new population (Whitley, 1994). The generation of new populations repeats till defined number of times in advance or is being continued until not having better chromosomes (Figure 1).
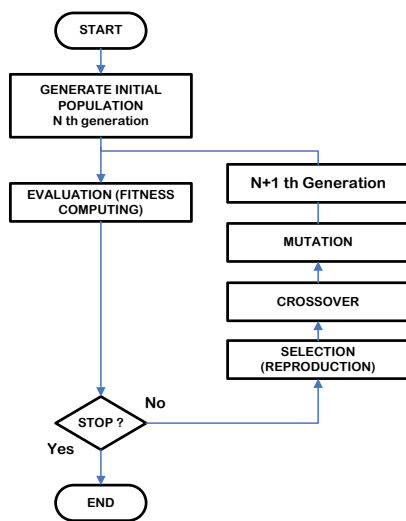

Figure 1. Steps of the Genetic Algorithm

As a high efficient search strategy for global optimization, GA demonstrates favorable performance on solving the combinatorial optimization problems. With comparing to traditional search algorithms, GA is able to automatically acquire and accumulate the necessary knowledge about the search space during its search process, and self-adaptively control the entire search process through random optimization technique. Therefore, it is more likely to obtain the global optimal solution without encountering the trouble of combinatorial explosion caused by disregarding the inherent knowledge within the search space (Kumar et al, 2009).

3. PREVIOUS WORK BASED ON GENETIC ALGORITHM FOR ROUTING PATH

For encoding the problem, chromosomes with constant length have been used. The length of the chromosome is the number of the nodes on the network. The genes of a chromosome represent nodes included in a path between a designated pair of source and destination nodes.

To produce the initial population DFS (Depth First Search), algorithm is reorganized to make random selection of the nodes from source to destination and the same approach is also used in mutation phase to produce alternative paths from mutation point to destination.

3.1 Defining the Routing Problem

It is possible to describe underlying topology of the network with directed graph $G=(N,A)$ where N is the set of the nodes, of cardinality n, and A is the set of the arcs, of cardinality m. There is a cost C_{ij} for each $(i,j) \in A$. These costs are defined in a cost matrix $C=[C_{ij}]$ where C_{ij} denotes a cost of moving on a path (i,j). Source and destination nodes are respectively shown as B and V. The connection information of the nodes with each other is described in an adjacency matrix I_{ij} shown below (Ahn et al, 2002):

$$I_{ij}= \begin{cases} 1, \text{if the link from node i to node j exist in adjacency list} \\ 0, \text{otherwise.} \end{cases}$$

Using the above definitions, routing problem can be formulated as a combinatorial optimization problem minimizing the objective function below as follows (Ahn et al, 2002):

minimize
$$\sum_{\substack{i=B}}^{V} \sum_{\substack{i=B \\ i \neq V}}^{V} C_{ij} I_{ij} \tag{1}$$

subject to
$$\sum_{\substack{i=B \\ i \neq V}}^{V} I_{ij} - \sum_{\substack{i=B \\ i \neq V}}^{V} I_{ji} = \begin{cases} 1, \text{if } i=B \\ -1, \text{if } i=V \\ 0, \text{otherwise.} \end{cases} \tag{2}$$

and
$$\sum_{\substack{i=B \\ i \neq V}}^{V} I_{ij} \begin{cases} =0, \text{if } i=V \\ <=1, \text{if } i \neq V \end{cases} \tag{3}$$

3.2 Genetic Representation

In the chromosome structure of proposed GA, node numbers of the route from source to destination are stored as pozitive integer numbers. Each locus of the chromosome represents an order of a node in a routing path. The chromosome length is static. The total number of nodes N is the length of each chromosome in the network. The node numbers that represent the routing path from source (B) to destination (V) are encoded in the chromosome. If the node number of the solution is smaller than the total node number N, unused genes of the chromosome is assigned by zero value. The chromosome encoding of the proposed GA is shown in Figure 2.
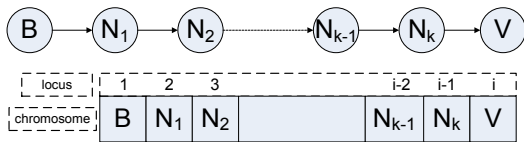
Figure 2. Chromosome encoding of a routing path

3.3 Fitness Function

The fitness function is the object to be optimized. The fitness function must accurately measure the quality of the chromosome in the population and must have computational efficiency; therefore, the fitness function has a critical importance. The fitness function described is as follows (Ahn et al, 2002):

$$f(i) = \frac{1}{\sum_{j=1}^{li-1} Cgi(j), gi(j+1)} \tag{1}$$

where f_i represents the fitness value of the i th chromosome, I_i is the length of the i th chromosome, $g_i(j)$ represents the gene (node) of the j th locus in the i th chromosome, and C is the link cost between nodes.

3.4 Selection (Reproduction) of a New Generation

The selection (reproduction) operator is intended to improve the average quality of the population by giving the high-quality chromosomes a better chance to be copied into the next generation. In this study, roulette wheel selection method, which is a proportionate selection method that picks out chromosomes based on their fitness values relative to the fitness of the other chromosomes in the population, was performed.

3.5 Crossover

In this study a new gene search method named "first-matched gene" is presented in which the first genes matched on two chromosomes as crossover points were selected. Difference of the crossover phase used in this study from classical crossover is that crossover points do not have to be in the same locus of chromosomes. In the end of the crossover operation, two child chromosomes is obtained. If these child chromosomes are infeasible, a repair function for dealing with the infeasible chromosomes is performed.
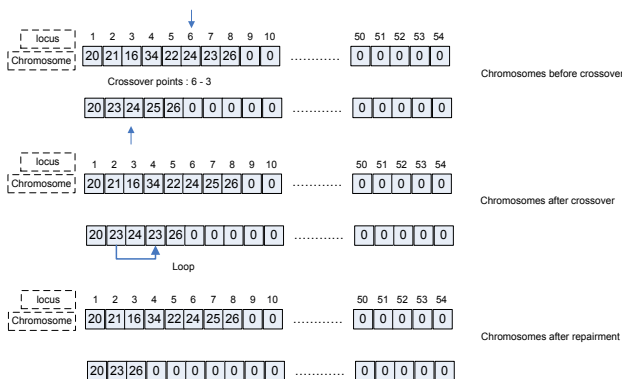Steps of the crossover phase are shown in Figure 3.

Figure 3. Crossover phase

3.6 Mutation

Mutation operation maintains the genetic diversity of the population and changes the genes of the selected chromosomes and keeps away from local optima. A random path is generated using reorganized DFS algorithm from the mutation node to the destination node which is also used for creating initial population. This random generated path is exchanged with the genes starting from mutation point. The mutated chromosome may be feasible. In this case, a repair function for dealing with these infeasible chromosomes is performed.
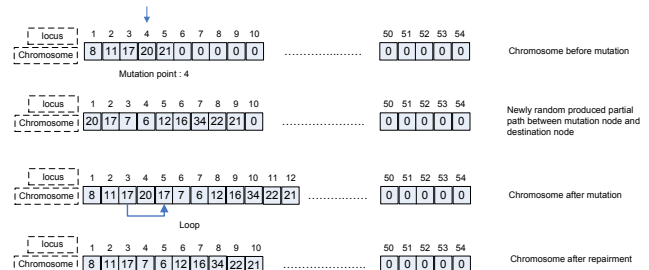Steps of the mutation phase are shown in Figure 4.

Figure 4. Mutation phase

3.7 Steps of the Genetic Algorithm and Termination

To terminate the genetic algorithm, the fitness value of the best chromosome on each generation is checked. If the fitness value of the best chromosome obtained does not change for 10 generations, the algorithm is stopped. The pseudo code of the algorithm is as follows:

Repeat as population size

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Step-1 : Generate a random number between 0 and 1.

Step-2 : If the random number is smaller than crossover rate go to Step-3, otherwise go to next cycle of the loop.

Step-3 : Select two chromosomes randomly from population.

Step-4 : Search for the matching gene starting from the gene of second locus of the first chromosome. Select the locus numbers of the chromosomes in which the first matched genes included as crossover points.

Step-5 : Starting from the crossover point, exchange the genes between the chromosomes.

Step-6 : If the newly generated chromosomes have loops(feasible), remove the loops.

Step-7 : Move the possible zero gene values which may occur after removing loops to the highest locus numbers of the chromosomes.

Step-8 : Pass the newly generated chromosomes to the population

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3.8 Experimental Results

The genetic algorithm was tested on a static 2D network with different sizes of 10, 50, 250 and 1000 nodes.

As given in Table 1, even the number of nodes grows to 1000, the average generation to find the optimum path is not much then 36.4 in worst case and by increasing the population size it is seen that the algorithm finds solutions in less generations. When the number of nodes grows by 10 times from 10 to 1000,

the time needed for finding the solution grows only by nearly 2 times.

		Number of Nodes			
		10	50	250	1000
Population Size	30	17,05	19,43	33,09	36,4
	50	14,16	19,41	30,57	33,2
	100	12,45	16,13	27,53	28,2
	200	12,01	13,22	25,24	27,6
	400	12	12,21	21,37	23,43
	800	12	12,01	18,14	20,12

Table 1. Average generations to find the optimum path

Average fitness values of the proposed genetic algorithm that converges the exact solution found by Dijkstra algorithm is shown in Figure 5.
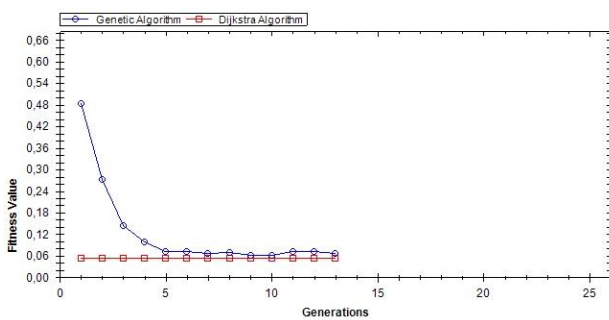

Figure 5. Convergence property of the proposed genetic algorithm and Dijkstra algorithm

Table 2 shows the average difference of the exact routes and approximate routes found by the proposed genetic algorithm.

|		Number of Nodes			
		10	50	250	1000
Population Size	30	% 0,6	% 20,7	% 140,1	% 159,3
	50	% 0	% 9,1	% 79,8	% 87,3
	100	% 0	% 3,6	% 57,1	% 71,2
	200	% 0	% 0,3	% 34,7	% 52,8
	400	% 0	% 0	% 20,2	% 33,1
	800	% 0	% 0	% 4	% 12,4

Table 2. Average difference of the exact routes and approximate routes in %

According to the results given in Table 2, approximate solutions found by the proposed genetic algorithm are very close to exact solutions with the node number 10 and 50. On a graph with 10 nodes, exact solutions obtained when the population size is 50 or greater. When the node number grows to 50, the exact solutions obtained with population starting from 400. By increasing the population size, it is seen that the algorithm gets closer to exact solutions. When the node number is 1000, average difference of the exact and the approximate routes is cut from 159.3% to 12.4% with the increase of population size from 30 to 800.

4. GENETIC ALGORITHM BASED ROUTING ON 3D DYNAMIC NETWORKS

Network analyses processes for indoors require 3D models of the buildings. The initial model is called "Building Model (BM)" which provides 3D visualization of the building. 3D BM is stored only for visualization and representation purposes, since it does not contain any topologic information. The main objective of BM is enabling user to see the geometry of the buildings on the screen (Figure 6a).

3D Network model is called "Network Model (NM)" which represents the network in the building based on a graph representation. NM contains the paths between the entities in a building. Each entity is defined as a node, and the links between the nodes are also stored in this model. Therefore, NM is a topological model, since it contains connectivity information (Figure 6b). Besides, it contains geometric information such as coordinates of the nodes and the link lengths for providing visualization and the cost (the shortest/optimum path) computation. The model, which is represented both geometrically and topologically, is called "Geometric Network Model" by Lee (2001) (Figure 6c).
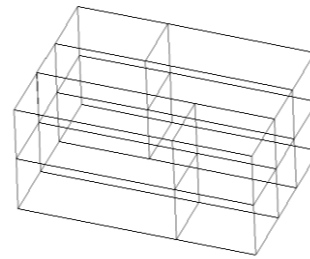
(a)
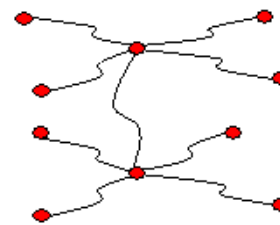
(b)
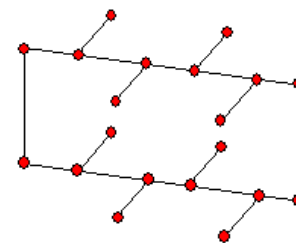
(c)

Figure 6. (a) 3D Building Model (b) 3D Topologic Model (No geometry) (c) Network Model (Topology + Geometry)

We are currently studying on a GA based routing model for 3D dynamic networks. 3D Network model that is intended to be used in routing will be generated using MUSCLE Model

(Multidirectional Scanning for Line Extraction) developed by Karas (2007). This method can be applied on images of floor plans that can be represented as an image on GUI (Figure 7a). Models are generated automatically by analyzing and processing those images.

The method, actually, depends on generating middle points of the lines. The algorithm of the method implements the line thinning and the simple neighbourhood methods to perform generation. BM and NM are generated and stored in a geodatabase after a series of processes including generating and vectorizing the lines and optimisation. 3D BM and 3D NM generated by MUSCLE method is shown in Figure 7b and Figure 7c.
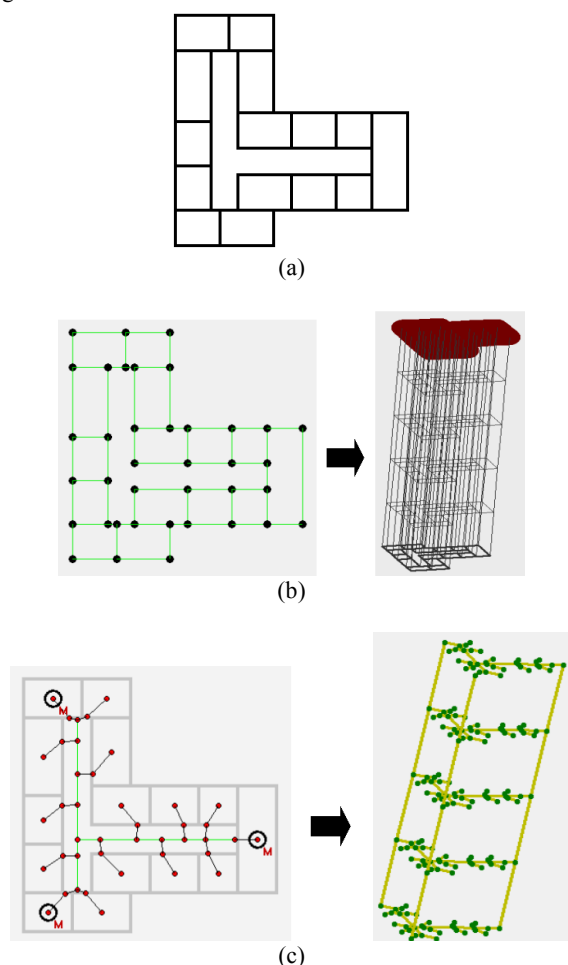

(a)

(b)

(c)

Figure 7. (a) Floor plan of building (b) 3D Building Model (c) 3D Network Model

The GA model that we want to propose will be implemented on an automatically extracted 3D network model of a building (Figure 8a). GA based model will satisfy the need of dynamic routing purposes and network analysis. (Figure 8b). Our aim is to utilize the adaptation ability of GA to the changing situations and improve the performance of shortest path algorithms such as A* and Dijkstra.
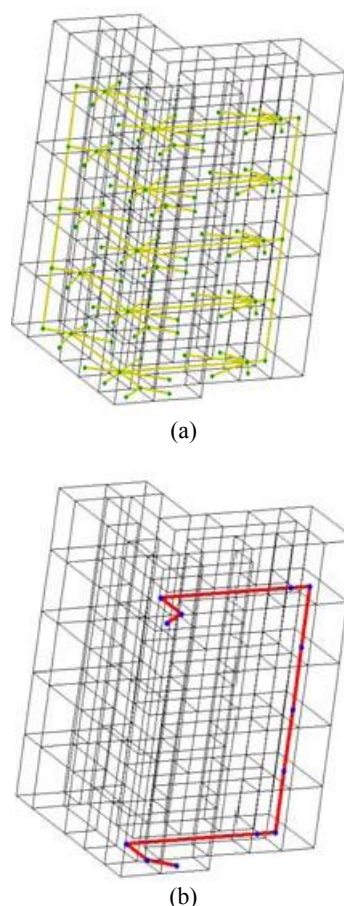

(a)

(b)

Figure 8. (a) 3D Visualization of Building and Network Model (b) 3D Visualization of Optimum Path Between Two Entities

GA is used to solve combinatorial optimization problems and non-linear problems with complicated constraints or non-differentiable objective functions. It necessitates the application of GA into GIS route finding algorithms (Kumar et al, 2009). We want to improve the performance of single pair path algorithms such as A* and Dijkstra by adapting the GA on dynamic networks. That is why we want to use GA on 3D dynamic network analysis.

5. CONCLUSIONS

Searching optimal path is an important advanced analysis function in GIS. Unlike traditional search algorithms, GA is able to automatically obtain and gather knowledge about the search space during its process. Therefore, integration of GA into shortest path algorithms may improve the quality of solutions on dynamic routing. Dynamic routing problems in network analysis may be solved using genetic algorithm through efficient chromosome encoding and genetic operators.

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