USING GENETIC ALGORITHMS TO GENERATE ALTERNATIVES FOR MULTI-OBJECTIVE CORRIDOR LOCATION PROBLEMS

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INTRODUCTION

Determining the "best" route or set of routes for linear utilities such as highways, pipelines, and power transmission lines, through a landscape has been the subject of much research in GIS and spatial decision making. Specifying an optimal corridor that connects an origin and destination is analogous to identifying a least-cost-path through a varying space. Extensive research efforts have been executed to solve the problems for many years (e.g. Tomlin, 1990; Eastman, 1989; Douglas, 1994; Berry 2004). Tomlin's (1990) Spread algorithm generates an accumulated-cost-surface iteratively and delineates the weighted shortest path from any location to a destination by tracing back along slope lines. Eastman (1989) implemented a similar, but more efficient, pushbroom algorithm, which is able to produce an accumulated cost surface within three iterations. Many of the existing least-cost-path algorithms in GIS are derived from the Dijkstra's shortest path algorithm and intend to generate a global optimal solution.

However, good decisions in corridor planning usually depend not only on a global optimal solution, but also on how good and reasonable alternative routes are provided to help decision-makers explore the solution space and make compromise among many conflicting objectives. Spatial decision-making problems like corridor location require decision-makers to choose a "preferred" solution from a number of feasible alternatives in the presence of multiple criteria and diverse criterion priorities. Consensus needs to be achieved among stakeholders with different interests and emphases (e.g. engineering cost, environmental impacts, and economic and social values). Such a search for multi-criteria alternatives has often been neglected in the development of corridor locating models. Existing alternative generation techniques, including the k-shortest path algorithm (Yen, 1971; Shier, 1979), the Difference Maximization (Huber, 1980), the Iterative-Penalty Method (Turner, 1968), and Gateway Shortest Path Problem (Lombard and Church, 1993), only consider spatial arrangement as a separate objective and collapse other criteria into a single objective function for optimization using weighting mechanism. They are only useful to search alternatives that are spatially different. There is no comprehensive way in corridor locating model to generate a full range of feasible alternatives, which explore the entire solution space and help decision makers understand possible solutions as well as trade-offs among them when conflicting objectives are in present. Multi-objective genetic algorithms are best approaches developed so far to solve such problems.

Genetic algorithms (GA) are a type of evolutionary algorithms first developed by Holland (1975) in the early 1970s. They are computationally simple yet robust in their search for potential solutions to optimization problems (Goldberg, 1989). By emulating the mechanics of natural selection and genetics, genetic algorithms are able to produce optimal or near optimal solutions within limited computational time, which makes them especially useful for optimization problems with large solution space and complex structure. Moreover, the power of genetic algorithms can exceed traditional single-objective optimization domain by incorporating more than one objective in the fitness functions. Because of the multi-objective nature of most real-world problem, multi-objective genetic algorithms (MOGA) becomes a popular research area and various MOGA methods have been recently developed for decision making problems when multiple objectives or criteria are involved and when the importance of different objectives are difficult to measure. Recent work in MOGA has concentrated on the generation of a set of promising solutions that are Pareto-optimal (Pareto, 1971). For Pareto-optimal solutions, it is impossible to improve the value of one objective without having to give up performance of at least one other objective. Such solutions are usually also termed non-inferior (or non-dominated) solutions. With the introduction of Pareto-optimality concept and MOGA technology, decision-makers are able to generate feasible alternatives that can be studied in-depth to better understand the structure of their problems and the trade-offs among criteria. There is a considerable literature indicating the effectiveness and efficiency of GA-based multi-objective optimization techniques in decision making processes. A comprehensive technical summary of MOGA and related criticism could be found in Coello's survey paper (2000).

The ability of genetic algorithms to search a solution space and selectively focus on promising combinations of criteria makes them ideally suited to complex spatial decision problems. Many researchers have used genetic algorithms to solve spatial problems in different application domains. Promising applications of genetic algorithms in geography could include environmental analysis (Bennett et al., 1999), site selection (Xiao, et al. 2002; Dibble and Densham, 1993; Hobbs and Goodchild, 1996), and spatial modeling (Openshaw, 1998; Wong et al., 1999). However, the power of genetic algorithms as effective alternative generators in multi-objective corridor locating has not been fully investigated.

The purpose of this paper is to present a genetic algorithm based approach to the multi-objective corridor locating problems on raster surface datasets, with a focus on the geographical representation of corridor selection problems in genetic algorithms and the special design of genetic operators like crossover and mutation. The superiority of GA-based approaches for complex and ill-structured problems has been widely recognized. The MOGA corridor selection model proposed in this paper will outperform the conventional methods both in computation intensity and in optimal or near optimal alternative generation, thus demonstrating the effectiveness and efficiency of this GA-based approach to geographical analysis and multi-objective decision making.

This paper is organized into five sections. These cover the background information about the least-cost-path algorithms and existing approaches for corridor selection problems; details about the proposed GA-based approach for multi-objective corridor selection; an experiment and related discussion to illustrate the effectiveness of the proposed approach through a comparative study with GSP method for corridor selection problems. The paper will conclude with some summary remarks and recommendations for further work in GA-based corridor locating models.

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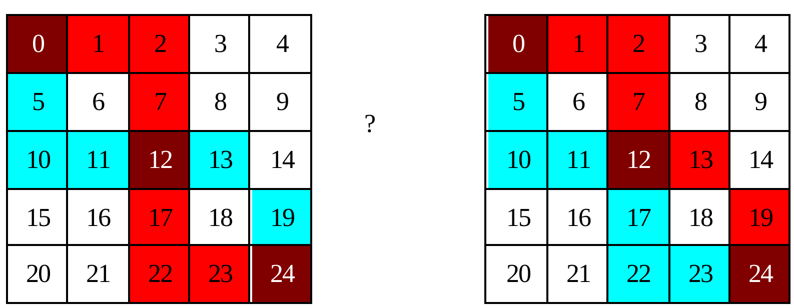
1. Development of Genetic Algorithm

There are four basic components in a GA: 1) representation of individuals, 2) design of the genetic operators, 3) determination of the probabilities controlling the genetic operators, and 4) determination of the fitness function. In this section, these issues are addressed within the framework of a new GA-based approach for solving the multiple objectives corridor selection problems. Furthermore, comparisons of the proposed algorithm with other known methods, particularly gateway shortest paths, for the same problem are also made.

- **Chromosome representation:** In our method, a feasible corridor, represented as a chromosome, is a continuous sequence of integers and each integer (gene) represents the node ID through which it passes. A node ID refers to the location of a corresponding cell on a raster surface. For example, integer 110 refers to the cell [2, 10] in a 100 by 100 cell region, using row ordering. Variable-length chromosomes (route) and their genes (nodes) have been used for encoding the problem. Every valid chromosome starts with a source cell and ends with a destination cell, connecting links that stretches from the origin to the destination along a constrained network. A valid chromosome should not have duplicated integers in the sequence, which would indicate a circular path.

- **Population initialization:** An appropriate size of population is initiated at the beginning of the procedure. Each individual is generated using a random manner. The algorithm starts with the source cell and randomly chooses a valid gene (cell) based on topological information (connectivity) of the network. This encoding process keeps selecting a valid cell that is connected with the last cell of the current chromosome (route), until the destination is reached. The encoding process executes repeatedly until the whole population is generated. When random selection mechanism results in poor performance, heuristics is introduced into population generation process. In heuristic method, a biased walk instead of random selection is used. Cells in the favorable direction from the origin to the destination have a higher probability to be selected as the next gene in a chromosome.
- **Selection:** The selection operation of GAs is straightforward. It selects chromosomes from the current population for genetic reproduction, crossover, and mutation operations, according to probability proportional to the relative fitness of each individual. Hence, high-quality chromosomes have a better chance to be copied into next generation. Two chromosome selection schemes are used in this study: roulette wheel and tournament. Roulette wheel selection is conducted by spinning a biased roulette wheel, which is sized in proportion to the fitness of each chromosome. Therefore, individual with high quality occupies a bigger proportion of pie in the wheel and has higher probability to be selected. Tournament selection is performed by means of choosing non-overlapping random sets of s chromosomes (s tournament size) from the population and then selecting the best chromosome from each set to serve as a parent for the next generation. The chromosomes with the better fitness, called elitists, are copied directly into the next generation.
- **Crossover:** The crossover operation of conventional genetic algorithm is based on an exchange between two chromosomes of fixed length when a bit string representation is used. In the proposed crossover scheme, the two chromosomes chosen for crossover can have different lengths. However, they must have at least one gene (cell) in common except for the origin and destination cells. When two chromosomes have more than two common genes, the proposed GA will randomly choose one of them as the crossover point. For example:

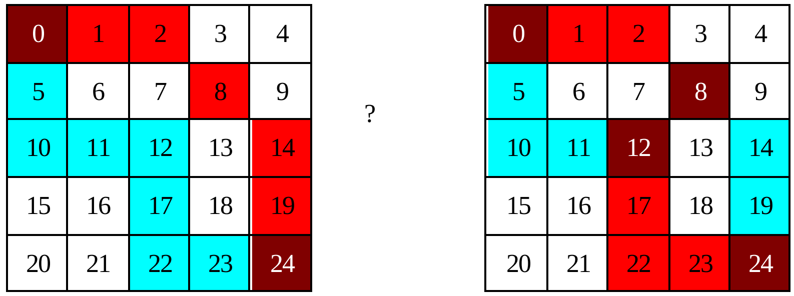
Parent chromosome 1: 0 – 1 – 2 – 7 – **<u>12</u>** – 17 – 22 – 23 – 24
Parent chromosome 2: 0 – 5 – 10 – 11 – **<u>12</u>** – 13 – 19 – 24
A valid crossover point D5 exists. The result after crossover will be:



Child chromosome 1: 0 – 1 – 2 – 7 – **<u>12</u>** – 13 – 19 – 24
Child chromosome 2: 0 – 5 – 10 – 11 – **<u>12</u>** – 17 – 22 – 23 – 24

This crossover pre-condition of commonly-shared genes between two chromosomes might be so strict that the performance of resultant GA suffers great degradation. If that is the case, the pre-condition can be loosened to allow crossover operation when two parent chromosomes have a pair of genes within the same neighborhood (neighboring cells). The pair of genes is included in both child chromosomes after crossover. For example,

Parent chromosome 1: 0 – 1 – 2 – 8 – 14 – 19 – 24
Parent chromosome 2: 0 – 5 – 10 – 11 – 12 – 17 – 22 – 23 – 24
Node 12 and node 8 are in the same neighbor. The result after crossover will be:

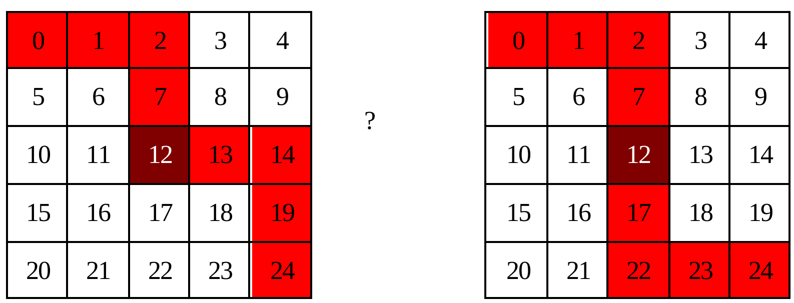


Child chromosome 1: 0 – 1 – 2 – **8 – 12** – 17 – 22 – 23 – 24
Child chromosome 2: 0 – 5 – 10 – 11 – **12 – 8** – 14 – 19 – 24

It is possible that loops are formed in resultant routes after crossover. The crossover may generate infeasible chromosome that includes the same nodes twice. Hence, a repair function is needed to eliminate any loop in a possible route. The simplest way to deal with infeasible chromosome is detecting the loops in the route by searching duplicated nodes and eliminating the loop by getting rid of genes between duplicated nodes.

- **Mutation:** Mutation is used to make a random change to a chromosome to increase or maintain population diversity, and also to avoid the premature convergence of the population. In the proposed GA, a gene in a parent chromosome is selected randomly as the break point. Mutation process will generate a partial-route starting from the mutation break point to the destination in a random manner and combine it with the partial-route from the origin to the mutation break point in the parent's chromosome. The example below indicates how a new chromosome is created by mutation:

Parent chromosome: 0 – 1 – 2 – 7 – 12 – 13 – 14 – 19 – 24



Randomly choose node 12 as the mutation point. The mutation operation generates a sub-route starting from 12 to the destination (12-17-22-23-14) and combines it to the sub-route staring from source to node 12 (0-1-2-7-12).

New chromosome: 0 – 1 – 2 – 7 – **12** – 17 – 22 – 23 – 24

2. Multi-criteria evaluation:

The assignment of land suitability score is an application-oriented operation. Different applications may favor different sets of cost items in the evaluation of corridor configurations. Generally, two types of costs are associated with corridor location problems (Jong and Jha 2000): (1) location-dependent cost, which is sensitive to the spatial location of the corridor in region. For example, the unit cost of wetland and flood plain are usually assigned with relatively high values so that alternatives passing through these lands are prohibited in corridor planning. (2) length-dependent cost, which is a sensitive to the length of generated alignments. For example, the pavement cost and maintenance cost are a linear function of corridor length. There is a large literature in transport system dealing with cost estimates of corridor planning (Sadek et al. 1999, Jha and Schonfeld 2004, Jong and Jha 2000). For simplicity, only a few cost items are considered in this study since the main purpose of the paper is not to present a throughout real-world case study but to demonstrate the validity of the GA -based corridor location model based on a highway selection example. Geographic data from multiple sources are acquainted for cost evaluation. Some of those include geology, topography, land use and land cover, soil types, and flood plains. The suitability score assigned to each cell is scaled to a value between 0 and10, with low score value depict high suitability and high score values depict low suitability. 0 indicates complete compatibility and 10 indicates high degree of conflict. Complete exclusion is possible by the assignment of an arbitrary high value, say 1000. Suitability scores for different criteria are specified in the following table as an example.

Land Type	Engineering cost	Environment cost	social costs
Fault	1000	5	5
Water plain	1000	5	5
Slope		5	5
> 20%	1000		
8-20%	10		
5-8%	5		
< 5%	0		
Soil		5	5
Strong rock	0		
Weak rock	3		
Dense sands	5		
Loose sands	10		
Land use and Land cover			5
Urban & built up	10	0	
Agriculture	3	3	
Grass and shrub	5	5	
Forest	7	7	
Water	10	7	
Wetland	10	10	
Barren	0	0	
Population Density	5	5	
> 500 person/ km2			10
200-500 person/km2			5
50-200 person/km2			3
< 50 person/km2			0

The suitability score assignment proposed above may be too simple. Another way to illustrate the functionality of the GA -based corridor location model is using artificial maps, assuming preliminary data gathering is completed and suitability surfaces are created.

In either way, three suitability surfaces are created for study. Each represents the land suitability of corridor development in terms of engineering cost, environmental impacts, and social cost. The multi-objective corridor selection problem could be stated as the determination of a route that simultaneously optimizes all three objectives below using Pareto non-inferior solution concept.

- minimize Z(c) = ? z(ci), total engineering cost of the chosen route.
- minimize Z(e) = ? z(ei), total environmental impact of the chosen route.
- minimize Z(s) = ? z(si), total social costs.

Different from single -objective GA, in which the fitness function of GAs is generally the objective function of the indicated optimization problems. In multi-objective scenario, the fitness function of GAs reflects the supreme of solution in each of the objectives. Therefore, the Pareto optimum concept is introduced. The fitness value of a solution is based not upon the values from objectives function, but upon its Pareto rank within the population.

I. Experimental Results:

The MOGA approach described above are coded in Microsoft Visual C++. The program runs on a Pentium IV processor PC (2600-MHz clock with 512 MB memory). In all the experiments, the parameters of GA are set as follows:

II. Conclusion and Further Research:

This paper presents and implements a novel genetic algorithm to generate alternatives for multi-objective corridor location problems. To the best of my knowledge, no comprehensive studies involving the use of genetic algorithm and multi-objective decision methods has been attempted before in the field of corridor selection. To my knowledge a similar algorithm has not been designed and implemented in commercial off-the-shelf GIS software packages, nor has a few found in academic research. Findings in this paper will make a contribution to GIScience based spatial analyses in general, and to intelligent corridor decision making in particular.

The method proposed in this research can be extended to other applications such as finding alternative route for car navigation system. The methods are relatively independent of problem types for almost all source-destination pairs.

1. Visualization: computer visualization can help decision maker to investigate the effects of some intangible parameter, such as unusual land and environmental characteristics that are not considered in optimization process. It can also be used to illustrate the performance of GA -based corridor location model.
2. Constrained GA optimization. Some applications may have particular constraints in corridor location. For example, minimum radius constraints for road segments, as required by highway design standards, need to be considered in GA optimization to ensure smoothness.
3. More specific land suitability assignment for different corridor location applications could be investigated in detail.
4. dynamic network topology
5. Distributed GA algorithms. Natural evolution is a massively parallel search process, working on different species at different locations simultaneously. Many works using island model have been done in parallel GA. A distributed GA not only can take the nature of evolution into account but also able can reduce the computation time significantly. GA is well suited for highly