

Issues of Optimization of a Genetic Algorithm for Traffic Network Division using a Genetic Algorithm

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Keywords: Genetic Algorithm, Traffic Network Division, Parameters Optimization.

Abstract: In this paper, we describe an approach to optimization of the genetic algorithm for division of road traffic network, which we developed. The division of road traffic network is necessary to enable to perform the road traffic simulation in a distributed computing environment. The optimization approach is based on a genetic algorithm, which is employed to find best settings of the optimized genetic algorithm for road traffic network division. Because such an optimizing genetic algorithm is expected to be extremely computation- and time-consuming, its distributed implementation is discussed as well.

1 INTRODUCTION

Utilization of a distributed computing environment, where combined power of multiple interconnected computers (nodes) is utilized, is a common way how to speed up a detailed simulation of road traffic. Prior to the distributed simulation itself, the simulated road traffic network must be divided into sub-networks, which are then simulated on particular nodes of a distributed computer. To achieve a good speedup of the simulation, two issues should be considered during the division – the load-balancing of the resulting sub-networks and the minimization of the inter-process communication.

In our previous work, we have developed a method for division of road traffic network based on a genetic algorithm, which considers both the mentioned issues (Potuzak, 2011b). The method gives good results (Potuzak, 2012). However, the parameters of the genetic algorithm have been set manually based on preliminary testing. Hence, it is likely that the settings of the parameters are not optimal and can be tuned to achieve better performance of the division method.

In this paper, we discuss the usability of a genetic algorithm for optimization of the parameters of the genetic algorithm for road traffic network division, which we developed. Because the optimizing genetic algorithm is expected to be extremely computation- and time-consuming, we discuss its distributed implementation as well.

2 GENETIC ALGORITHMS

Genetic algorithms are evolutionary algorithms, which mimic natural genetic evolution and selection in nature in order to solve a problem. Developed by John Holland in 1975 (Holland, 1975), they are widely used for solving of optimization and searching problems in many domains, including multi-objective optimization (Farshbaf and Feizi-Darakhshi, 2009).

2.1 Basic Notions of Genetic Algorithm

There are several basic phases and notions, which are commonly present using a typical genetic algorithm.

A single solution of the solved problem is considered to be an *individual* (usually represented by a vector of binary or integer values). At the start, a set of individuals (so-called *initial population*) is most often randomly generated (Menouar, 2010). Then, the *fitness function* is calculated for each individual. The fitness function represents an objective assessment of each individual depending on the solved problem. Then, a number of individuals with highest fitness value are selected as the parents of a new generation. The new generation is created using the selected individuals and the *crossover* and *mutation* operators (Menouar, 2010).

The entire process repeats until a preset number of generations is created or a stop condition is met.

3 GA NETWORK DIVISION

The method for division of road traffic network, which we developed, is based on a genetic algorithm. It will be briefly described in this section.

3.1 Issues of Network Division

There are two issues, which should be considered during the road traffic network division – the load-balancing of the resulting sub-networks and the minimization of the inter-process communication.

The load-balancing is necessary in order to maximally utilize the computational power of all nodes of the distributed computer. The minimization of the inter-process communication, which is used for the transfer of vehicles among the sub-networks and for the synchronization, is necessary, since it is much slower than the remainder of the simulation computations.

3.2 Description of Division Method

The method for road traffic network division, which we developed, considers both the load-balancing of the sub-networks and the minimization of the inter-process communication. It utilizes a less-detailed road traffic simulation for assigning of the weights to particular traffic lanes (Potuzak, 2011a). These weights correspond to the numbers of vehicles moving in particular lanes of the divided road traffic network (Potuzak, 2012).

Once the weights are assigned, the traffic network can be considered as a weighted graph with traffic crossroads acting as nodes and the sets of lanes connecting particular traffic crossroads acting as weighted edges (with weights equal to sum of weights of particular traffic lanes of the set). The road traffic network (i.e. weighted graph) is then divided using a genetic algorithm (GA) into required number of load-balanced sub-networks with minimal number of divided traffic lanes.

An individual of the utilized genetic algorithm represents a single assignment of the crossroads to particular sub-networks. The fitness function consists of two parts – the *equability* representing the load-balancing and the *compactness* representing the minimization of inter-process communication. The ratio of these two parts can be changed, but is set to 0.75 in favour of the equability by default. Each generation has 90 individuals, from which 10 individuals with highest fitness value are selected to be parents of the next generation. The crossover is performed using each combination of two parents

producing two offspring. Each offspring can be mutated using up to five random changes. The entire process repeats for preset number (from 1000 to 100 000) of generations (Potuzak, 2011b).

4 OPTIMIZING GA USING GA

The values of particular parameters of the genetic algorithm were set based on preliminary testing. So, it is possible that the settings are not optimal. Hence, we utilize another genetic algorithm for the optimization of the particular parameters of the genetic algorithm for road traffic network division.

The genetic algorithm for optimization of the parameters of the genetic algorithm for road traffic network division will be referred as *optimizing genetic algorithm* or OGA further in the text.

4.1 Parameters of GA to Optimize

The most obvious parameters of the genetic algorithm for road traffic network division, which should be optimized, are the number of individuals in a generation, the number of individuals selected based on the fitness function, and the number of generations. Another parameter, which can be optimized, is the maximal number of mutations (i.e. random changes), which can be applied to each individual during the creation of a new generation.

Besides the mutation, the crossover and selection of the parent individuals can be considered for the optimization as well. In our genetic algorithm for road traffic network division, only one type of selection (simple truncation selection) and one type of crossover (see Section 3.2) have been employed.

However, there are more types of selection and crossover, which can be utilized as well. For example, the fitness proportionate approach (Bäck, 1996) or the reward-based approach (Loshchilov et al., 2011) can be used for selection. For the crossover, one-point or two point segment approach or the uniform crossover can be utilized (Ahmed, 2010).

The parameter, which will not be optimized, is the ratio in the fitness function (see Section 3.2) due to its direct influence on the quality of the road traffic network division.

4.2 OGA Individual Representation

The representation of an individual of the OGA must incorporate all parameters described in previous section. All the parameters can be expressed as

integer numbers but of different maximal size. Hence, the bits of particular integer values will be used in the individual directly. More specifically, each individual will consist of 52 bits. First 20 bits will be used for number of generations (i.e. 0 to 1 048 576 generations), 10 bits for number of individuals in one generation (i.e. 0 to 1024 individuals), 10 bits for number of selected individuals from each generation (i.e. 0 to 1024 individuals), 8 bits for maximal number of mutations per individual (i.e. 0 to 256 mutations), 2 bits for type of selection (i.e. up to 4 types of selection), and 2 bits for type of crossover (i.e. up to 4 types of crossover). An example is depicted in Fig. 1.

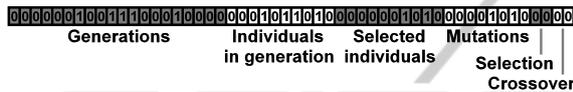


Figure 1: Example of an OGA individual.

The initial population will consist of 90 individuals (similar to the optimized genetic algorithm for road traffic network division), which will be randomly generated. Although a larger number of individuals could be more appropriate, we have to have in mind that the OGA will be extremely time-consuming and the computation time would increase with increasing number of individuals in one generation.

4.3 OGA Fitness Function

The OGA fitness function will be calculated for all individuals. For each OGA individual, the parameters of the genetic algorithm for road traffic network division will be set accordingly. Then, 3 road traffic networks (regular grids of 64, 256, and 1024 crossroads) will be divided into 2, 4, 8, and 16 sub-networks. So, 12 complete optimized genetic algorithms will be used for each OGA individual to keep the optimization as universal as possible.

The OGA fitness function will be then calculated using the maximal achieved fitness values for each combination of the divided network and the number of sub-networks as:

$$F_{OGA} = \frac{\sum_{i=1}^3 \sum_{j=1}^4 F_{ij}^{\max}}{12}, \quad (1)$$

where F_{OGA} is the OGA fitness function, F_{ij}^{\max} is the maximal achieved fitness function of the optimized genetic algorithm for i th traffic network and j th number of sub-networks.

4.4 OGA Selection

Once the fitness value will be calculated for every individual of the current generation, 10 individuals with highest fitness value of the 90 individuals of the current generation (see Fig. 2) will be selected to be parents of next generation. This selection is the same as the one used in the optimized genetic algorithm for road traffic network division (Potuzak, 2012).



Figure 2: Simple truncation selection used in OGA.

4.5 OGA Crossover and Mutation

Once the parents are selected, a new generation is produced using the crossover and mutation in the same way as in the optimized genetic algorithm for road traffic network division (see Fig. 3).

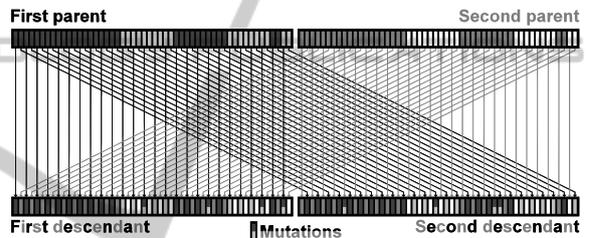


Figure 3: Crossover of two individuals and four mutations.

Using the crossover and mutation, a new generation is produced. The entire process then repeats until the preset number of generations is reached. Since the OGA is very computation- and time-consuming (see Section 5), the number of created generations will be limited by the computational power and time at our disposal.

4.6 Distributed OGA

To achieve a feasible computation time, the OGA will be performed on a distributed computer consisting of 24 desktop PCs. Each PC incorporates one Intel i5-2400S Quad-Core processor at 3.1 GHz, 8 GB of RAM, and 250 GB HDD.

The calculation of the fitness value is by far the most time-consuming part of the OGA (see Section 4.3). Hence, the individuals of an OGA generation will be uniformly distributed among all available processor cores where the fitness values will be calculated by working processes. The selection, crossover, and mutation will be then performed by a control process.

5 TESTS AND RESULTS

In order to predict the feasibility of the distributed OGA and its time requirements, we have performed a set of tests. These tests were performed directly on one of the computers, on which the distributed OGA is planned to be performed (see Section 4.6). On the computer, the DUTS Editor, which is a system containing implementation of the optimized genetic algorithm for road traffic network division, was installed together with the described road traffic networks (see Section 4.3). Then, the networks were divided into four (one of the four numbers of sub-networks used by the OGA – see Section 4.3) sub-networks using from 1000 to 1 000 000 generations of the optimized genetic algorithm.

In order to test the usability of multiple cores simultaneously, the division was performed on one and four cores. The results are depicted in Table 1.

Table 1: Results of the testing.

Gen.	Cores	Computation time [ms]		
		64 crossroads	256 crossroads	1024 crossroads
10^3	1	830	3296	15310
	4	859	3631	15834
10^4	1	7982	32859	139753
	4	8699	35825	149127
10^5	1	79661	320038	1396286
	4	86248	348558	1492700
10^6	1	805411	3063346	12309876
	4	853462	3499342	14851707

As can be seen in Table 1, the simultaneous usage of more cores increases the computation time, but only by roughly 7 %. Hence, it is possible to utilize all four cores simultaneously.

The time necessary for calculation of the fitness value of an OGA individual is the sum of the times necessary for division of particular networks into 2, 4, 8, and 16 sub-networks (i.e. four times sum of one row of Table 1). Considering simultaneous usage of all cores, the total time necessary for computation of the fitness value of one OGA individual using one core is summarized in Table 2 in the dependency on the number of generations of the optimized genetic algorithm for road traffic network division.

Table 2: Computation of an OGA individual fitness value.

Number of generations	Computation time [ms]
1000	81296
10000	774608
100000	7710024
1000000	76818044

6 CONCLUSIONS

In this paper, we described the OGA and its possible distributed implementation for multi-core personal computers. Considering usage of 24 quad-core computers (i.e. 96 cores), the predicted computation time of the OGA ranges from 21 to $2 \cdot 10^6$ hours depending on the number of generations of the OGA and the optimized genetic algorithm. Hence, only lower numbers of generations are feasible.

In our future work, we will focus on implementation of the distributed OGA and its testing.

ACKNOWLEDGEMENTS

Author wishes to thank to Jakub Smid for the inspiration for the main idea of this paper.

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