Designing Traffic Signal Patterns through Genetic Algorithms

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ABSTRACT

This paper describes a new optimization technique for the design of traffic signal patterns. The proposed method uses a Genetic Algorithm for searching through the better signal patterns. Since the Genetic Algorithm is effective to search directly through a huge binary coded state spaces, the proposed design method has the following advantages over the conventional OR methods: (1) on-line optimization is available within a reasonable time, (2) there is no limitation to the types of signals to be optimized. Some computer simulations are carried out and its ability of getting high quality control in a short period is demonstrated.

1 INTRODUCTION

Optimization of switching patterns for a group of a large number of traffic signals is quite an important problem for relieving today's increasing traffic congestion. This is a difficult combinatorial optimization problem because of the following reasons: (1) the problem spaces, that is, a number of signals are often very large, and (2) the traffic flow is not well formalized because of its complexity and human factors so that the result of optimization using these formulae often does not fit real traffic flow. Much has been proposed in the filed of conventional OR based approaches that are based on traffic models by using such as car following theory [GREE34] and fluid mechanics [WHIT55]. These methods are based on a rough approximation of traffic flow and their solutions are not sufficient as we ordinary experience. If we simulate the traffic flow more precisely, for example, at the level of the movement of each of the cars, and if the best combination of signal patterns could be found by using these simulations, the solution is expected to be better. These simulations are conventionally used to test each of the solutions of traffic flow theories [EBIH85]; there has not been proposed a direct search method from the simulations because the search space is so large that the conventional combinatorial methods have not yet been applicable.

This paper proposes a new combinatorial optimization approach to this problem. The approach uses a *Genetic Algorithm* for the search method through these large state spaces. Genetic Algorithms are recently studied class of optimization methods that are effective to the problems that consist of wide state spaces and that no priori search heuristics are given.

The proposed method observes the real or the simulated traffic flows for a given time interval and evaluates a statistic scalar value that represents the goodness of the traffic flow under control. Mean flow time of cars in the section under consideration is used in this paper. Then, the signal patterns used are combined with the older ones and a new candidate is prepared through Genetic Algorithms.

As is discussed in the following sections, the performance criteria increases throughout these trials and it converges in a maximum value after around 600 trials =14 days. Thus, the system is able to adopt to on-line search of the traffic signal patterns. This means that the method gives the real solutions to the traffic signal designing problems that maximizes/minimizes the desired criteria.

2 GENETIC OPTIMIZATION METHOD

2.1 Traffic signal parameters

Let an i-th traffic signal be L_i. If we can represent all the parameters of the whole signals $\{L_i\}$ of the area under consideration into a binary representation, there is no restriction to the types of signals to be dealt with this method. By this binary representation of parameters, designing signal patterns leads to a combinatorial search problem through binary search spaces. To the simplicity of the following discussions, we settle an exemplified signal configuration as follows. Note that the following restrictions are not essential to this method:

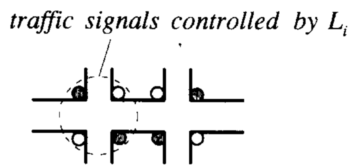

Fig.1. Traffic signals that are controlled by the same parameter.

(1) Two phases control is assumed, that is, only red or blue signs are considered. Let the state of the signal L_i be s_i. We denote each state as s_i=1 for the red sign or s_i=0 for the blue sign, respectively. Yellow sign is neglected by the reason of simplifying simulations. But, by introducing extra control parameters, an yellow sign, that is, more than two phases control, is easily introduced to this method.

(2) A signal L_i is controlled by the following three integer valued constants: a transition time t_i from red to blue or vice versa, an initial time i_i from the starting time of signals until it changes its state, and an initial state l_i that represents the state at the starting time. These constants are assumed not to vary within a trial.

(3) t_i and i_i are both assumed to take a finite variations. Specifically, 4 variations from 10 to 25 unit times by 5 steps are used in the following simulations.

All the parameters for the whole signals are represented in the following form of a string g of bit sequences (**Fig.2**): One set of parameters for i-th signal is represented in 5 bits in this case; 1 bit for l_i, and 2 bits for t_i and i_i, respectively. Each 5 bits are connected each other side by side, which results in a string g of having its bit length a product of 5 with a number of signals.

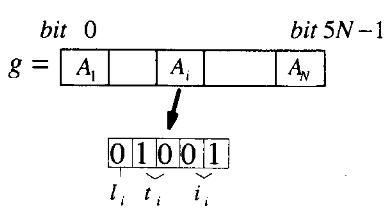

Fig.2. String encoded signal parameters.

Thus, the signal pattern design problem is corresponded to finding the best g that gives the maximum quality of control. The evaluation of the quality of traffic control is a difficult problem because there are a lot of different criteria such as traveling time, waiting time, and fuel consumption rate[HOBA75]. But, these distinct criteria can be combined into a single evaluation function through, for example, a multiple objective optimization methods. Thus, in the following discussions, we assume that the quality of the control by a parameter g is measured by a scalar function $f(g)$. Mean traveling time of the cars that came from the outside of the area and that went out of the area is used as this evaluation function in this paper.

2.2 Search through a Genetic Algorithm

Finding the string g that maximizes $f(g)$ is a search problem for a large state spaces. For example, assuming that there are 36 signals, the bit length of g becomes 180 so that the total search space becomes as much as 2^{180}.

Suppose the traffic condition does not vary substantially with days, it should cost a day to gather the traffic data through sensors to evaluate the criteria $f(g)$. This means that one evaluation, which we refer to a *trial*, costs a day in an on-line optimization. Thus, we should limit the search steps to a sufficiently small amount, for example, up to a week trials.

From this discussion, it is impossible to search through the state by using conventional combinatorial optimization methods. But recently developed class of optimization methods - *Genetic Algorithms* [GOLD89] - is reported to be effective to this type of large optimization problem because a fairly good solution is often given within a small amount of trials. Thus, we discuss the application of a Genetic Algorithms to find g that maximizes $f(g)$.

Genetic Algorithms are stochastic search methods that are inspired by Darwinism evolution theory: a natural evolution of selection by fitness. It represents the variables in search into a binary coded string, which is referred to as a *chromosome*. In this case, g is regarded as a chromosome. A population of chromosomes are prepared and their performances are evaluated by actually applying these binary encoded parameters to the objective system. The performance measure is a real number and this is referred to as a *fitness values*. In this application, $f(g)$ is used as a fitness value for g.

After the evaluation of each fitness values, all the chromosomes are combined each other through *genetic operators* to reproduce a new set of chromosomes to be evaluated. Genetic operators are prepared as the following three variations:

(1) *Reproduction* operator is firstly called and it selects two chromosomes to be candidate chromosomes until the number of the reproduced chromosomes reaches the upper limit. Specifically, let

$$F = \sum_{i=1}^{N} f(g_i), \tag{1}$$

be the total fitness of the chromosomes. Each g_i is selected at the probability

$$\Pr(g_i) = f(g_i) \,/\, F, \tag{2}$$

which means that the chromosomes of having higher performances can get higher probability of producing their offsprings.

(2) *Crossover* operator swaps arbitrary bit intervals of two chromosomes selected by the reproduction operator. The number of cutting points are previously determined.

(3) *Mutation* operator alters arbitrary bits of the reproduced chromosomes. This is done by a fixed probability r_m, which means that approximately one bit from every $1/r_m$ bits are reversed during crossover operations.

This renewal of the whole chromosomes is referred to as a *generation*. As the generations goes on, the chromosomes are resembling to each other so that they converge into a near optimal solution.

The application of the Genetic Algorithms for this signal design problem is summarized as follows;

(1) Prepare a randomly initialized set of signal parameters g_i for $i=1,...,N$.

(2) By using g_i, traffic signals are controlled for a given interval T and the criteria $f(g_i)$ is evaluated by the statistic data given from sensory input. Here, T may be a sufficiently long time interval such that the $f(g_i)$ is stably evaluated; a day may be recommended. Thus, it takes $T*N$ unit times for the evaluation of one generation.

(3) Genetic operators are applied to g_i according to $f(g_i)$ and a next generation of g_i is prepared.

(4) Repeat from step 2 and step 3 until the whole $f(g_i)$ converges to a similarly high value. The given g_i is the optimized result of the signal pattens of the area under consideration.

3 SIMULATION EXPERIMENTS

To ensure the effect of the proposed Genetic Algorithm based signal design method, some computer simulations are carried out. To the simplicity, the signals are simulated under the restrictions exemplified in section 2.

The traffic is described at the level of the movement of individual cars. These cars are simply simulated as follows:

(1) A car arrives the area at the edge location directing inside of the area according to the Poisson arrival of having previousely settled mean interval. Each car is given its own speed s and s does not vary through the movement of that car. Maximum number of cars that can stay in the area is previously settled.

(2) To each direction d_i, $i=1,...,4$, at each of the corners L_j, the direction of the car passing through the corner obeys the probability $p(i,j,k)$ of the direction d_k. These probabilities are basically settled to take the maximum value at $d_k=d_i$ and 0 at d_k is opposite to d_i. The probabilities does not vary through time.

(3) A car stops at a red sign at the center of the corner. All the locations of the cars waiting for the same signal are assumed to overlap. When the signal turns blue, the car that arrived earliest moves again at its speed s, and the next car moves again W unit times after the departure of the previous car.

(4) If a car c_i reaches the edge of the section, it disappears and its travelling time T_i is recorded so as to evaluate the mean travelling time $f(g)$ such that,

$$f(g) = \sum_{i=1}^{N} T_i \,/\, N, \tag{3}$$

where N is the number of cars that disappears outside the area.

Fig.3. shows the result of a simulation; its vertical axis corresponds to the inverse of the mean travelling time. **Table 1** shows the traffic simulation parameters and **Table 2**

denotes the parameters for the Genetic Algorithm. Suppose an interval between two signals is 100m, and suppose the average speed of a car is 36 km/h, a unit time corresponds to 1 second.

As shown in figure 3, the maximum, mean, and minimum fitnesses are almost monotonically increasing according to generations. Maximum performance is given after 30 generations. Although there still exist some differences among parameters that gives maximum, mean, and minimum fitnesses, the fact that these populations saturates at their maximum values shows that the differences shoule be considered as the drift caused by the simulation. Thus, we should conclude that the Genetic Algorithm could optimize the signal parameters in a short period of trials; in this case, 30*20=600 trials and 33.3 minutes (=2000 unit times) for each trial sums up to about 14 days.

Fig.4. shows the result of a simulation by another parameters. **Table 3** describes the parameters modified from Table 1 and 2. In this case, the number of cars, populations of chromosomes, and the interval of one trial are shortened to 20, 4, and 80 unit times, respectively. This causes the traffic simulation more sensitive to signal patterns. As is illustrated in figure 4, it saturates to a better maximum fitness value in a shorter time; 13 generations in this case. Thus, we can conclude that the Genetic Algorithm should be effective under the condition that sensitively be effected by signal parameters, in such cases as the traffic is not uniformly distributed.

Table 1: Simulation parameters (1).

Mean interval of car arrival	5 unit times
Average car speed	0.1 unit interval / unit time
Maximum number of cars	90
Interval between two signals	1 unit interval
Number of signals	6*6=36
Interval of state transition of a signal	10 to 25 unit times, varies by 5 unit times

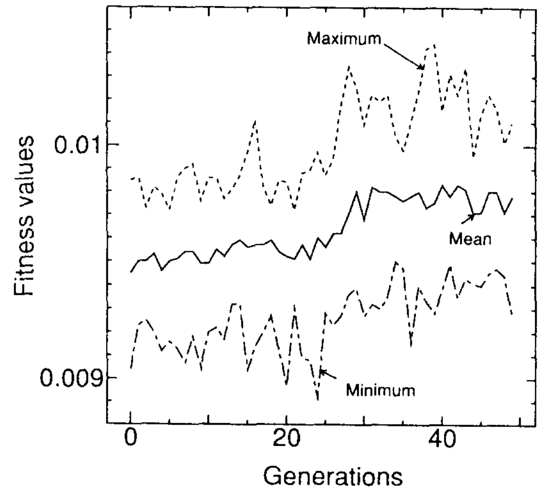

Fig.3. Change of quality of control by signal parameters through the Genetic Algorithm (1).

Table 2: Parameters for a Genetic Algorithm (1).

Trials per one chromosome	2000 unit times
Number of chromosomes	20
Cutting points for crossover	8
Crossover ratio	0.5
Mutation ratio	0.1

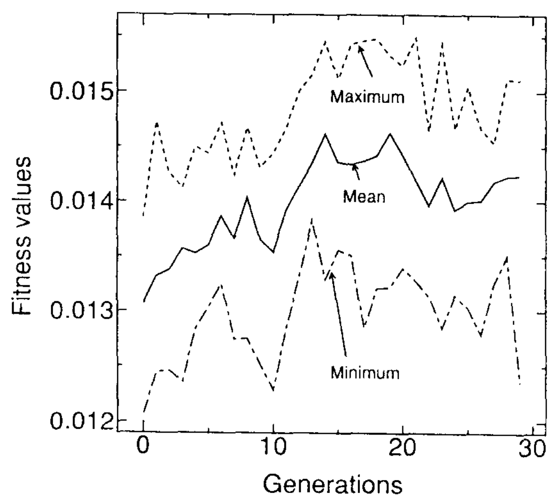

Fig.4. Change of quality of control by signal parameters through the Genetic Algorithm (2).

Table 3: Parameters for simulation and the Genetic Algorithm (2).

Maximum number of cars	20
Trials per one chromosome	80 unit times
Number of chromosomes	4

4 CONCLUSION

A new optimization technique for the design of traffic signal patterns has been proposed. The proposed method has an advantage over conventional OR methods at the point that there is no limitation to the types of signals to be optimized. It has been also pointed out that the method can on-line optimize the signals within a reasonable duration. From computer simulations, we can expect that the on-line application of the method to 40 signals in a real traffic environment will optimize the parameters within a week.

REFERENCES

[EBIH85] Ebihara, K., and Okamoto, H., *Traffic Systems Engineering* (2), Corona pub. (1985)(in Japanese)

[GREE59] Greenberg, H., An analysis of traffic flow, *J. Op. Res. Soc. Am.*, Vol.7, No.1, pp.79-85 (1959).

[GOLD89] Goldberg, D.E., *Genetic Algorithms in Search, Optimization, and Machine Learning*, Addison-Wesley (1989).

[HOBA75] Hobara, T., and Nakahara, T., *Traffic control*, Corona pub. (1975).(in Japanese)

[WHIT55] Lighthill, M.J., and Whitham, X.Y., A theory of traffic flow on long crowded roads, *Proc. Royal Soc.*, Series A229, pp.317-345 (1955).