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FUZZY-GA-BASED TRAFFIC SIGNAL CONTROL

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Abstract:

This paper deals with the traffic signal control using fuzzy logic controller and multi-object genetic algorithm (MOGA). It is not needed to build the traffic flow model for Signal control approach in the intersection using the method based on the fuzzy. Multi-objective Genetic algorithms are used to optimize the parameters in the fuzzy logic controller according to different traffic demand. However, this method can effectively solve the problems of stochastic and unknown in this dynamic system. This method has the adaptive signal timing ability, and can make adjustments to signal timing in response to observed changes.

Keywords:

Traffic Signal Control; Fuzzy System; GA;

1. Introduction

Traffic signal is an essential element to manage the transportation network. A number of traffic signal control methods have been developed in the past. Recently, a major research focus has been on application of artificial intelligence techniques such as expert systems, fuzzy logic, neural networks and genetic algorithms for intersection signal control.

The systems of fuzzy logic traffic signal control proposed by Niitymaki and Kikuchi [2] are based on the fuzzy extension principle used in the seminal work by Pappis and Mandani [1]. Mohamed B. Trabia [3] designed a fuzzy logic-based signal controller for a four-approach isolated intersection with through and left-turning movements. The fuzzy controller will regularly query the traffic conditions in order to decide whether to extend or terminate a current green phase. Niittymaki and Pursula [4] investigated fuzzy control to traffic signals at the individual intersection level. Fuzzy signal group control in their case works in the same way as the traditional control, but a fuzzy extender adjusts the extensions, and a fuzzy selector selects the phase sequences. More thorough reviews of the applications of fuzzy logic to traffic signal control can be found in Sayers [5] and Hoogendoorn et al [6],[7].

With the continuous growth of the available computing resources, the attention of engineers has been directed more and more to the possible use of complex simulations directly in the early stages of the design process. This aspect has underlined the substantial weakness of traditional optimization approaches, which can usually produce only single-objective optimized solutions, and only if the objective function satisfies continuity and often derivability conditions. This fact, together with the need for a multi-disciplinary approach to the design, caused a growing interest into the use of GA as a general purpose optimizer.

This paper deals with the traffic signal control using fuzzy logic controller and MOGA. However, this method can effectively solve the problems of stochastic and unknown in this dynamic system.

2. Fuzzy Logic controller for traffic signal control at intersection

2.1 Simulation environment

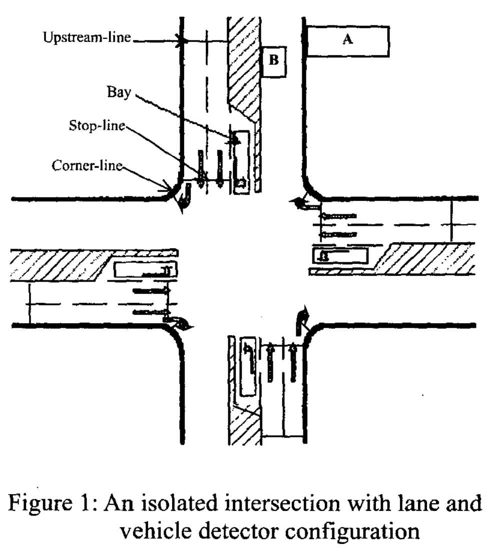

Figure 1: An isolated intersection with lane and vehicle detector configuration

We study an isolated signalized intersection with four approaches and typical vehicle detectors. Figure 1 shows an isolated intersection with lane and vehicle detector configuration. Each approach has through, right-turning and left-turning movements. Inductive loops for vehicle detection are installed on stop-lines, upstream-lines, and right-turning corner-lines. Detectors can count the number of vehicles through the upstream-line, stop-line and corner-line within a given time interval. To detect left-turning vehicles, ultrasonic detectors are placed on side of left-turning bays. These detectors can detect the vehicle appearance and count the number of the vehicles driven into left-turning bays.

A four-phase signal consisting of left turns, right turns and though is shown in figure 2. In a cycle, each approach goes through two time intervals, the green interval during which vehicles on this approach can proceed through the intersection, and red interval during which vehicles on this approach cannot do.

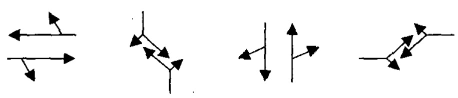

Figure 2:Phase diagram for a four-phase signal

2.2 Definition of traffic variable

We define following traffic variable:

D: the approach jointed the intersection, $D \in [EAST, WEST, SOUTH, NORTH]$, is one of East, South, West, and North four approaches;

$P_{D,ULINE}(t)$: the number of vehicles passed upstream-line with in the time interval $[t-\Delta t, t]$ for approach D;

$P_{D,SLINE}(t)$: the number of vehicles passed through stop-line (not including right-turning vehicles) with in the time interval $[t-\Delta t, t]$ for approach D;

$P_{D,CLINE}(t)$: the number of vehicles passed corner-line with in the time interval $[t-\Delta t, t]$, for right-turning vehicles (East turn to North, South turn to East, West turn to South, and North turn to West), is defined as respectively, $P_{EAST,CLINE}(t)$, $P_{SOUTH,CLINE}(t)$, $P_{WEST,CLINE}(t)$, and $P_{NORTH,CLINE}(t)$;

$P_{D,BAY}(t)$: the number of vehicle which turn left from the bay within the time interval $[t-\Delta t, t]$ for approach D;

$Q_{D,BAY}(t)$: the number of vehicle staying in bay at any time t for approach D;

$Q_{D,P}(t)$: the number of vehicles which will pass through stop-line, but not turn right, and are waiting in a queue at any time t for approach D;

$Q_{D,R}(t)$: the number of only turn-right vehicle, waiting in a queue at any time t for approach D ;

$Q_{D,L}(t)$: the number of vehicles waiting in a queue at any time on the left-turning lanes for approach D;

$Q_{D,T}(t)$: the total number of vehicle waiting in queue at any time t for approach D, $Q_{D,T}(t)$ consist of previous three parts, for approach D, $Q_{D,T}(t)$ can express as

$$Q_{D,T}(t) = Q_{D,P}(t) + Q_{D,R}(t) + Q_{D,L}(t) \qquad (1)$$

$Q_{D,T}(t)$ Can be determined by the queue length L, and the average length l occupied by each vehicle in the queue. L can be detected by detectors such as inductive loop, ultrasonic sensor and CCD camera. l can be approximately calculated by statistic method. However, the proportion of each part in $Q_{D,T}(t)$ is difficult to determine in prior.

2.3 Traffic signal control based on a competitive fuzzy logic

In the case of traffic signal control, the resource in question is green time, and the problem is made more complex by its temporal aspect and the ever-changing and stochastic nature of the demand. This means that the allocation of green time must be constantly reviewed as time passes and the traffic situation changes, in order to distribute it in the desired manner.

An approach to this problem is to derive a value for each user, which reflects their claim on the limited resource, and to use these values to determine the appropriate balance of distribution of the resource. We call this value as the urgency, meaning the urgency with which the stream requires green.

We divided the whole processes into three levels, which are low, middle and high level. The details refer figure 3.

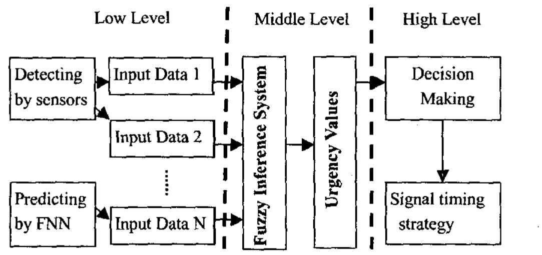

Figure 3: Three levels of Traffic signal control

We divided the whole processes of traffic signal control into three levels (see figure 3), which are low, middle and high level. The low level deals with the traffic variables called input data in which some dates are detected by sensors and others are predicted. The middle level consists of urgency values (or "Urgency degrees"), which are calculated by fuzzy inference system. The high level determines the traffic signal timing strategy called decision-making level.

2.4 The Derivation of Urgency Values

The Urgency degrees depended on traffic variables calculated or predicted, and also depend on traffic date detected by detectors such as inductive loop, infrared, ultrasonic and video image processing detectors.

For a, b, c, and d (see figure 2) four phases, we define urgency degrees as respectively $U(a)$, $U(b)$, $U(c)$ and $U(d)$. In same phase, the urgency consists of two parts which reflect different "urgency degree" on two approaches whose relationships are described as : a) $U(a)$:{$U(a)$_East, $U(a)$_West}; b) $U(b)$:{$U(b)$_South, $U(b)$_North}; c) $U(c)$:{$U(c)$_South, $U(c)$_North}; and d) $U(d)$:{$U(d)$_East, $U(d)$_West}.

In our research, the traffic variables $P_{D,ULINE}(t)$, $P_{D,SLINE}(t)$, $P_{D,CLINE}(t)$, $P_{D,BAY}(t)$, $Q_{D,BAY}(t)$, $Q_{D,P}(t)$ and $Q_{D,L}(t)$ are described using Trapezoidal fuzzy memberships set (see figure 4). These fuzzy sets provide an analogy to human characterization by assigning truthfulness value, μ, to linguistic terms. These terms are "Small", "Medium" and "Big". For example, in fuzzy membership function $\mu_{Big}(P_{EAST,ULINE})$, "Big" is a fuzzy set and $P_{EAST,ULINE}(t)$ is a universe of discourse. In figure 4, for each traffic variable, we use four parameters a, b, c and d to describe Trapezoidal shape. The four parameters can be determined by expert knowledge, or optimized by Genetic Algorithms. In this paper, fuzzy neural networks are used to update and optimize these parameters.

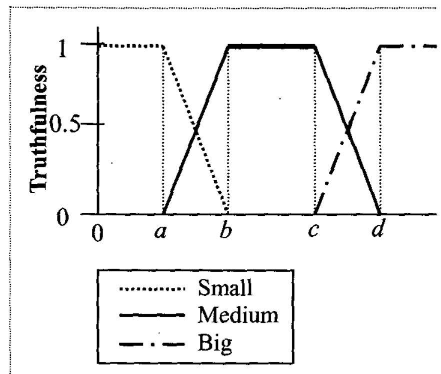

Figure 4: Trapezoidal fuzzy memberships sets for traffic variables

The "urgency degrees" of four phases can be determined by fuzzy inference system. In this paper, we adopt fuzzy inference system. In our fuzzy inference system, 36 fuzzy rules are adopted. Fuzzy rules are divided to three groups with respective to "Big", "Medium", and "Small" for urgency degree of each phase. As examples, for "a" phase, the fuzzy rules can be described as follows.

If {{ $P_{EAST,ULINE}(t)$ is big} and {{ $P_{EAST,CLINE}(t)$ is small} and { $P_{EAST,BAY}(t)$ is small}}} or { $Q_{EAST,P}(t)$ is big}, then {$U(a)$_East is big} (2)

If {{ $P_{WEST,ULINE}(t)$ is big} and {{ $P_{WEST,CLINE}(t)$ is small} and { $P_{WEST,BAY}(t)$ is small}}} or { $Q_{WEST,P}(t)$ is big}, then {$U(a)$_West is big} (3)

If {{$U(a)$_East is big} or {$U(a)$_West is big}}, then {{$U(a)$ is big}} (4)

In expression (2)-(4), we define the operation method of each symbol. "and" means "Min", "or" means "Max".

3 The multi-objective optimization of parameters for fuzzy logic controller

The GA is an optimization technique inspired by the evolution process of natural life. The GA provides a very flexible framework and, recently, has been expected to be not only a global optimization method but also a multi-objective optimization method in various areas.

The process of designing a GA consists of two parts: (1) designing a representation and a crossover operator, and (2) designing a generation-alternation model. In designing a representation and a crossover operator, we determine how to represent a solution on the computer and how to generate a new solution from two or more solutions. The performance of GAs heavily depends on a representation and a crossover operator. It is important to consider characteristics of problem domain when designing a representation and a crossover operator. In designing a generation-alternation model, we design the way of choosing pairs of parents for generating children by crossover and the way of selecting individuals to survive in the next generation. By devising a generation-alternation model, we can allow a GA to effectively search on a multi-modal search space or to find a set of non-dominated solutions in a single run by explicitly handling multiple criteria.

In traffic signal control, there are a number of diverse criteria or control objectives, such as maximize safety, minimize delays and minimize environment disadvantage et al. The problem is that the optimum of each objective is achieved in different cycle times. These objectives are not completely coincident. We use the three objectives as an example to explain the relationship among different criteria. If the minimizing of delays is the main goal, the effects to other goals are little negative. The only positive effect is between the environment and safety. In other words, the environmentally effective traffic signal control can also be safe, because the cycle times of the environmentally effective traffic signals are quite long. The long average cycle time means that the number of amber intervals is smaller, and the risk of rear-end collisions is smaller. The biggest problem is that environmental or safe control strategy does not give a good delay result. The average delay can be even 40% bigger than the optimum delay.

In order to achieve the desired flexibility, the parameters of the signal controller must be optimized with respect to different objectives or criteria. The multi-objective genetic algorithms (MOGA) can effectively solve this problem.

Each optimal solution reflects a different trade-off between the desired objectives. When implementing the controller in a particular context, the solution that performs best with respect to the desired objectives for that context may be chosen from the optimal set by the user. The MOGA uses the Pareto ranking method to rank the solutions of each generation by the number of other solutions which dominate them. This technique is described more fully in Horn et al [8].

In our proposed method, 7 types of traffic variables $P_{D,ULINE}(t)$, $P_{D,SLINE}(t)$, $P_{D,CLINE}(t)$, $P_{D,BAY}(t)$, $Q_{D,BAY}(t)$, $Q_{D,P}(t)$ and $Q_{D,L}(t)$ are described using Trapezoidal fuzzy memberships set, and for each traffic variable, we use four parameters a, b, c and d to describe Trapezoidal shape, therefore, the total number of parameters are 7*4=28. In most case, the value of traffic variable is integer, so the parameters optimized are suitably described using integers. To reduce the range of parameter space, and decrease the computational cost, expert knowledge is often adopted so that the range of each parameter is in a smaller interval.

Classical optimization algorithms are capable, under strict continuity and derivability hypothesis, of finding the optimal value only in the single objective case and therefore the problem of finding the group of non-dominated solutions (the Pareto set) is reduced to several single objective optimizations.

While traditional optimization algorithms do need the use of a utility function, the particular structureof GA can face the multi-objective optimization problem in a more direct way, developing populations in which the diversity follows the conflicting objectives.

Pareto-GA algorithms mainly differ from classical GA in the selection process, even though other specific operators might be constructed. In particular in this paper a novel crossover operator is introduced, together with a quick review of several other Pareto-GA techniques.

Pareto tournament selection: the tournament selection can consider the Pareto concept as a basis for the tournament: the selected individual is the one that dominates the individuals taking part to the tournament. Most profitable implementations of this method are usually coupled with sharing.

Local Pareto selection. As shown in [10] an effective way of maintaining diversity in the population able to follow the conflicting objectives, can be the use of local selection schema based on the Pareto dominance concept. In this case the population is placed on a toroidal grid and the members of the local tournament are chosen by means of a random walk in the neighborhoods of the given grid point.

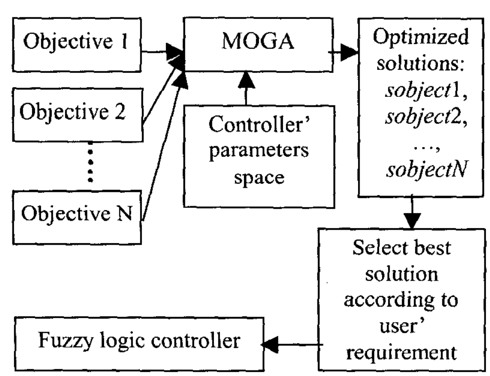

Figure 5: Procedure of fuzzy logic controller parameter optimization

Ranking-based selection (non-dominated sorting GA). With this approach, the classical fitness function is substituted by a ranking value. To all the non-dominated members a rank of one is assigned, and then removed from the population. The non-dominated members in the remaining part of the population are then assigned a rank of two and this process is continued until the entire population is ranked. To each individual is then assigned a fitness value based on its non-domination ranking.

Vector evaluated genetic algorithm. In this approach, proposed by Schaffer and referred to as VEGA algorithm, the population of size P is subdivided into N sub-populations, with each of them addressing one of N criteria. Typically, as done in [9], the different criteria are expressed as different utility functions with N different weighting. Multi-directional crossover. While usually one or two point classical cross-over operator is employed, in this work a new cross-over operator first introduced in [11], called multi-directional crossover, suitable both for single and multi-objective optimization is presented.

In our research, the following parameters governing the operation of the MOGA are suitable:

A chromosome consists of 28 integers; each constrained to lie between the range which is estimated using the expert's knowledge;

The population size is 150;

Two-point crossover is used to create two new chromosomes from two parent chromosomes;

The mutation rate is 0.08 meaning that mutation has a 0.08 chance of occurring in each new chromosome created by crossover;

The MOGA is run for at least 30 generations;

Elitism is enabled, permitting solutions of high rank (cut-off point can be specified) to pass directly into the next generation without modification;

Primary criteria: minimize delays;

Secondary criteria: minimize the number of vehicle stop;

The parameters in fuzzy logic controller should be optimized to satisfy user demand. In traffic signal control, there are a number of diverse criteria or control objectives, such as maximize safety, minimize delays and minimize environment disadvantage et al. The problem is that the optimum of each objective is achieved in different cycle times. These objectives are not completely coincident. We use the three objectives as an example to explain the relationship among different criteria. If the minimizing of delays is the main goal, the effects to other goals are little negative. The only positive effect is between the environment and safety. In other words, the environmentally effective traffic signal control can also be safe, because the cycle times of the environmentally effective traffic signals are quite long. The long average cycle time means that the number of amber intervals is smaller, and the risk of rear-end collisions is smaller. The biggest problem is that environmental or safe control strategy does not give a good delay result. The average delay can be even 40% bigger than the optimum delay.

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Multi-directional crossover. While usually one or two point classical cross-over operator is employed, in this work a new cross-over operator first introduced in [21], called multi-directional crossover, suitable both for single and multi-objective optimization is presented.

4 Simulation and conclusions

The situations of simulation for the effects of the fuzzy controller are described in the previous section in an intersection with four approaches, which uses four-phase signal with leading left turns. The intersection has two through lanes and one left turn bay on each approach.

The simulation results show that the percentage of stops of our algorithms is smaller 15-25% than the traditional extension principle, and using our proposed algorithm, the average delay is also 15-30smallerthan the extension principle in the test area 100-1500vph. The results also indicate that the application area of our proposed algorithm is wide including saturated/un saturated traffic volumes, however the extension principle only fits to traffic signal mode in the area of very low traffic volumes.

In our simulation, to optimize the performance of the controller, "minimize delays" is used as the primary criteria for multi-objective genetic algorithms (MOGA), and "to minimize the number of vehicle stops" is used as secondary criteria for MOGA. To evaluate the performance of the controller, average vehicle delays and percentage of stopped vehicles are compared with those of a traffic-actuated controller. These results show that the fuzzy controller has the ability to adjust its signal timing in response to changing traffic conditions on a real-time basis. Our proposed controller produces lower vehicle delays and percentage of stopped vehicles than the traffic-actuated controller

Acknowledgements

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