Research on Traffic Signal Control Based on Intelligence Techniques

Wei Wu, Wang Mingjun

Abstract--**This paper studies traffic signal control method based on intelligent techniques such as agent, fuzzy logic system (FLS), neural network-fuzzy (NNF) and multi-objective genetic algorithms (MOGA) for intersection. The traffic signal control system of intersections in local area can be built up by using the term of agent, and it comprises four levels: centre command layer, local area coordination layer, isolated intersection control layer, and optimizing layer. This paper focus on discussing isolated intersection control layer and optimizing layer. In an isolated intersection layer, fuzzy logic system is used to control traffic signal, and input parameters of fuzzy system can be forecasted or calculated by neural network-fuzzy. In optimizing layer, parameters in fuzzy system can be optimized by MOGA. The proposed method has the adaptive signal timing ability, and can make adjustments to signal timing in response to observed changes for intersections in local area. Our proposed has the ability to adjust its signal timing in response to changing traffic conditions on a real-time basis.**

Index Terms—**traffic signal control, fuzzy system, neural network, MOGA, Agent**

I. INTRODUCTION

Recently, a major research has been focus on application of artificial intelligence techniques such as expert systems, fuzzy logic, neural networks and genetic algorithms for intersection signal control.

Generally, the Agent is considered as an entity, which possesses knowledge, aim and ability of perception, solving problem and communication with outer environment. From the viewpoint of software implement, it is a computer program, which can communicate with other agents[1][2][3]. The term of agent can used in traffic signal control method. Each area traffic signal system can be considered an agent.

Pappis and Mamdani [4] considered the control of an isolated traffic intersection. Nakatsuyama et al [5] used fuzzy logic to model the control of two adjacent intersections with one-way movements.

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Chiu [6] applied fuzzy logic for controlling multiple intersections in a network of two-way streets with no turning movements. Kelsey and Bisset [7] simulated traffic control of an isolated north-south/east-west intersection using both fuzzy logic and pre-timed control. In a network context, fuzzy logic can be used to calculate cycle length, splits and offset, (Chiu and Chand [8]) and also to determine when coordination of junctions is required in order to alleviate the traffic at critical intersections (Tzes et al [9]). Fuzzy logic is often used to identify and recognize certain patterns of traffic flow, allowing the most appropriate signal timings to be defined and implemented as the traffic situation change (Hoyer and Jumar [10]) and Zhou et al [11]. Many of these proposed systems have been tested on street. Mohamed B. Trabia [12] designed a fuzzy logic-based signal controller for a four-approach isolated intersection with through and left-turning movements. Niittymaki and Pursula [13] investigated fuzzy control to traffic signals at the individual intersection level. More thorough reviews of the applications of fuzzy logic to traffic signal control can be found in Sayers [14] and Hoogendoorn et al [15][16].

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. 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. Genetic algorithms (GA) are optimization techniques based on the principles of natural evolution. GA operates on the population of potential solutions (also called chromosomes) to a problem. A notion of fitness is used in GA to measure the "goodness" of a candidate solution (chromosome). Genetic operators of selection, crossover, and mutation are repeatedly applied to the population to increase the fitness of chromosomes. 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 [17].

II. TRAFFIC SIGNAL CONTROL FOR INTERSECTION IN LOCAL AREA

A. DESIGN OF AGENT FOR TRAFFIC SIGNAL CONTROL

The traffic signal control system for intersection in local area can be built up by using the term of agent, and it comprises four levels illustrated in Figure 1, centre command layer, local area coordination layer, isolated intersection control layer, optimizing layer.

As an autonomous intelligent entity, the agent can response the event of system under some status. That is to say, it can engage some activities, transferring status and yield new event to other agent. An agent can be described from two parts: one is the communication channel, another is its action.

Agent consists of five parts including communication section, inference section, interact members list, database and knowledge base. Here, communication section is the interface of interacting with other agents by uniform communication syntax, in where the massages coming from other agents are analyzed, and messages sending to other agents are attached some information and transmitted. After analyzing messages, the agent employs message function module to process message. The communication section not only provides a channel to interaction and coordination between agents, but also makes agent to improve the intelligence by studying knowledge from other agents. The inference section is the key part of agent, which feature agent as intelligence entity. Some inference algorithm such as data drive, aim guide and bi-direction inference are employed to control the action of intelligent agent and solving problem. The interact members list includes the agent members in activity environment. The other agents communicating with this agent will be registered in the interaction members list. The intelligent agent activities are based on the data base and knowledge base by which the agent can infer, data mining and intelligent computing, furthermore, the agent can study from knowledge and experience. The behavior of an intelligent agent can be described as follows. The communication section receives the messages and requests from outer environment. According to the messages and requests and its status, the agent go on some intelligent activities, such as analysis, understanding and inference etc. After that, some actions are carried out. Meanwhile, the status of agent will change, and may send new requests to other agent. The inference section measures the status, network flow and resource of computer system at regular intervals. According to this information, the agents carry out action or inference.

This paper focus on discussing isolated intersection control layer and optimizing layer.

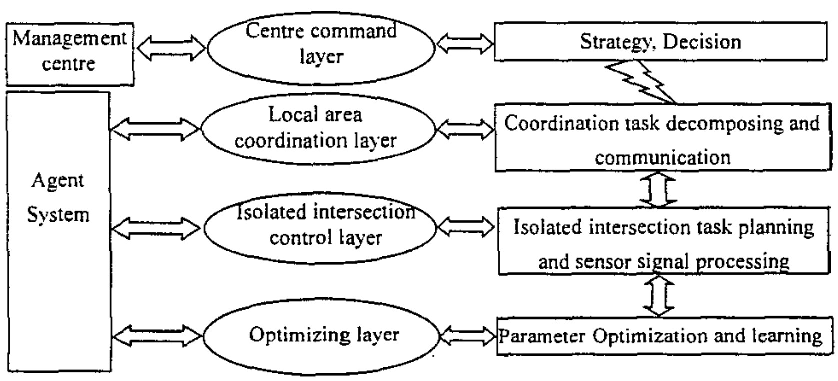

Figure 1: Four levels of the traffic signal control system for intersection in local area

B. TRAFFIC PARAMETER OF ISOLATED INTERSECTION

We study intersections with four approaches and typical vehicle detectors. 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.

Detectors can count the number of vehicles through the upstream-line and stop-line within a given time interval.

For each intersection, 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.

Traffic variables can be obtained by detectors or calculating. However, the ability of the controller to estimate the traffic variables is limited by its detectors' configuration. So, it is very important to take full use of traffic variables. Some traffic variables can be detected by sensors. However, other variables cannot be directly obtained by sensors, which need to be calculated or predicted, these variables are very important input data for fuzzy logic controller such as following variables:

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

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

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 sensor. 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.

The sum $Q_{D.T}(t)$ of $Q_{D.P}(t)$, $Q_{D.R}(t)$ and $Q_{D.L}(t)$ can be simply calculated by the queue length L and the average length lo f vehicle, however the proportion of each part to the sum $Q_{D.T}(t)$ is not known a prior, needs to be estimated or predicted. We can predict the proportion of each part to the sum $Q_{D.T}(t)$ noted respectively, $k_1(t)$, $k_2(t)$ and $k_3(t)$ considering following three factors:

a) During previous three cycle, the proportion of $P^{3T}_{D.SLINE}(t)$, $P^{3T}_{D.CLINE}(t)$, $P^{3T}_{D.BAY}(t)$ to their sum, which is noted respectively, $K^{3T}_1(t)$, $K^{3T}_2(t)$ and $K^{3T}_3(t)$. This factor describes the situation of vehicle distribution within recent three cycle time;

b) Within the current time interval $[t-\Delta t, t]$, the proportion

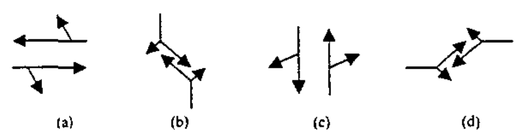

Figure 2:Phase diagram for a four-phase signal

of $P^{\Delta t}_{D.SLINE}(t)$, $P^{\Delta t}_{D.CLINE}(t)$, $P^{\Delta t}_{D.BAY}(t)$ to their sum, which is noted respectively, $K^{\Delta t}_1(t)$, $K^{\Delta t}_2(t)$ and $K^{\Delta t}_3(t)$. This factor reflects the situation of vehicle distribution within recent time interval $[t-\Delta t, t]$;

c) Change rate of proportion of $P^{\Delta t}_{D.SLINE}(t)$, $P^{\Delta t}_{D.CLINE}(t)$, $P^{\Delta t}_{D.BAY}(t)$ to their sum in the current time interval $[t-\Delta t, t]$ comparing to previous time interval $[t-2\Delta t, t-\Delta t]$, which is noted respectively, $\Delta K_1(t)$, $\Delta K_2(t)$ and $\Delta K_3(t)$. This factor reflects the situation of vehicle distribution within recent time interval $[t-\Delta t, t]$;

For $k_1(t)+k_2(t)+k_3(t)=1$, by $k_1(t)$ and $k_3(t)$ we can calculate $k_2(t)$.

In this paper, fuzzy neural network shown in figure 3 is used to predict $k_1(t)$ and $k_3(t)$. In the fuzzy neural network, Input $[x_1, x_2, x_3] = [K^{3T}_i, K^{\Delta t}_i, \Delta K_i]$, $i = 1,2,3$, respectively output $y = k_i(t)$. The function of each layer is described below.

a) Layer 1: nodes at layer 1 are input nodes with crisp input and crisp output.

$$f^{(1)}_i = x_i \qquad (2)$$

b) Layer 2: nodes at layer 2 compute the value of the membership function. Each of nodes represents a term of an input-linguistic variable. The membership function of

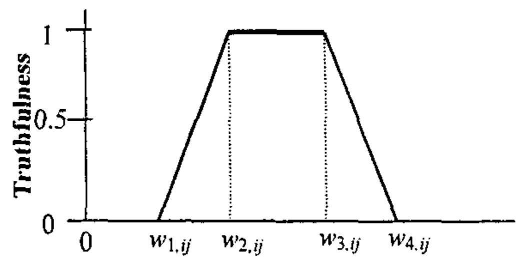

Figure 3: Trapezoidal fuzzy memberships sets for parameters in fuzzy neural network

each term node is trapezoidal, as shown in figure 4, and can be described as follows:

$$f^{(2)}_i = \begin{cases} \dfrac{x_i - w_{1,ij}}{w_{2,ij} - w_{1,ij}} + 1, & w_{1,ij} \le x_i \le w_{2,ij} \\ 1, & w_{2,ij} \le x_i \le w_{3,ij} \\ \dfrac{w_{3,ij} - x_i}{w_{4,ij} - w_{3,ij}} + 1, & w_{3,ij} \le x_i \le w_{4,ij} \\ 0, & \text{otherwise.} \end{cases} \qquad (3)$$

c) Layer 3: This layer is called the rule layer and each node in this layer represents one fuzzy logic rule. The output of a rule node in this layer is calculated by the product operation as follows:

$$f^{(3)}_i = \prod_i^n f^{(2)}_i \qquad (4)$$

d) Layer 4: This layer is noted the output-linguistic layer and provide the output value to the outside world. They act as the defuzziers. Likely, the membership function of each term node is trapezoidal, as shown in figure 3 (change w into v). Output value at this layer can be defined as follows:

$$y = f^{(4)}_i = \frac{\sum_i \frac{1}{4}(v_{1,i} + v_{2,i} + v_{3,i} + v_{4,i}) f^{(3)}_i}{\sum_i f^{(3)}_i} \qquad (5)$$

When the structure of the network is built, the learning phase can be done. In this phase, we intend to minimize errors with the gradient descent method, by adjusting the parameters associated with membership functions. The error function is defined to be

$$E = \frac{1}{2}(y_d - y)^2 \qquad (6)$$

where y_d is the desired output value and y is the actual output value.

In the layer 4, we adjust four parameters in vector $[v_{1,i}, v_{2,i}, v_{3,i}, v_{4,i}]$. In layer 2, four parameters $w_{1,ij}, w_{2,ij}, w_{3,ij}$ and $w_{4,ij}$ of each membership function have to be trained

III. INSOLATED INTERSECTION CONTROL LAYER

A. FUZZY LOGIC CONTROL METHOD

Traffic signal control is one of a class of problems where a limited resource is required by a number of potential users, and the quantity of that resource is not always sufficient to meet demand. The users are competing against each other for a share of the resource, and thus the control problem could be termed "competitive".

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 solve 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 degree.

In different traffic states (or traffic parameters, such as the number of vehicles waiting for queue), the urgency degree for green time is different among different phases. Urgency degree can be described by linguistic terms, such as "Small", "Medium", and "Big", therefore, urgency degree is suitable to be expressed in fuzzy set. In this paper, we solve the problem of traffic signal control using the method based on fuzzy neural networks control.

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 (refer 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 $\vec{x} = (x_1, x_2, \Lambda, x_n)$ (for example, x_i is the number of vehicles passed upstream-line with in the time interval $[t-\Delta t, t]$ for one approach) are described using Trapezoidal fuzzy memberships set (see figure 2). These fuzzy sets provide an analogy to human characterization by assigning truthfulness value, μ, to linguistic terms. These terms are "Small", "Medium" and "Big". In figure 4, for each traffic variable, we use four parameters p_1, p_2, p_3 and p_4 to describe Trapezoidal shape. The four parameters can be determined by expert knowledge, or optimized by Genetic Algorithms.

The "urgency degrees" of four phases can be determined by fuzzy inference system. In this paper, we adopt fuzzy inference system.

B. MOGA-BASED OPTIMIZATION OF PARAMETERS

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.

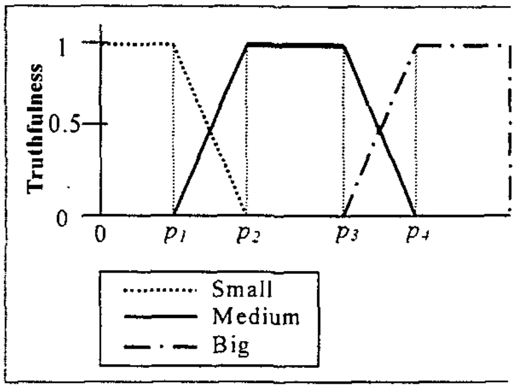

Figure 4: Trapezoidal fuzzy memberships sets for traffic variables

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.

Genetic algorithms (GA) are optimization techniques based on the principles of natural evolution. GA operates on the population of potential solutions (also called chromosomes) to a problem. A notion of fitness is used in GA to measure the "goodness" of a candidate solution (chromosome). Genetic operators of selection, crossover, and mutation are repeatedly applied to the population to increase the fitness of chromosomes.

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 [17].

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 structure of 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.

When optimizing fuzzy logic controller parameters using MOGA, more criteria can be added such as maximize safety, delays and minimize environment disadvantage et al.

IV. CONCLUSION

In our simulation, to optimize the performance of the controller, "minimize delays" is used as the primary criteria for MOGA, and "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 to 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.

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