Traffic Signal Control Using Fuzzy And Neural Network

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Abstract: This paper presents an adaptive traffic signal method based on fuzzy-neural networks for an isolated four-approaches intersection with through and left-turning movements. This method has the ability to make adjustments to signal timing in response to observed changes. The “urgency degree” term, which can describe the different user’s demand for green time is used in decision-making by which strategy of signal timing can be determined. Using three levels model based on fuzzy-neural networks (FNN), we can determine whether to extend or terminate the current signal phase and select the sequences of phases. Simulation 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, and our proposed controller produces lower vehicle delays and percentage of stopped vehicles than the traffic-actuated controller.

1. Introduction

Traffic signal is an essential element to manage the transportation network. 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. Pappis and Mamdani [1] considered the control of an isolated traffic intersection with simple one-way east-west/north-south traffic control with random vehicle arrivals and no turning movements using fuzzy logic controller. Nakatsuyama et al [2] used fuzzy logic to model the control of two adjacent intersections with one-way movements. Chiu [3] applied fuzzy logic for controlling multiple intersections in a network of two-way streets with no turning movements. Kelsey and Bisset [4] 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 [5]) and also to determine when coordination of junctions is required in order to alleviate the traffic at critical intersections (Tzes et al [6]). 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 [7]) and Zhou et al [8]. The systems of fuzzy logic traffic signal control proposed by Niitymaki and Kikuchi [9] are based on the fuzzy extension principle used in the seminal work by Pappis and Mandani [1]. Mohamed B. Trabia [10] designed a fuzzy logic-based signal controller for a four-approach isolated intersection with through and left-turning movements. Niittymaki and Pursula [11] 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 [12] and Hoogendoorn et al [13].

2. Simulation Environment and Traffic Variables

2.1 Simulation environment

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 through 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.

2.2 Definition of traffic variable
We define following traffic variable:

a) \( D \): the approach jointed the intersection, \( D \in \{EAST, WEST, SOUTH, NORTH\} \), is one of East, South, West, and North four approaches;

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

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

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);

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

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

g) \( Q_{D,P}(t) \): 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 \( D \);

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

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

j) \( Q_{D,T}(t) \): 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

\[
Q_{D,T}(t) = Q_{D,P}(t) + Q_{D,R}(t) + Q_{D,L}(t)
\]

(1)

3. Fuzzy Neural Networks Control for An Isolated Intersection

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.

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 by fuzzy neural network. 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.

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

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. We select following traffic variables: (1) \( P_{D,SLINE}(t) \), (2) \( P_{D,CLINE}(t) \), (3) \( P_{D,BAY}(t) \), (4) \( P_{D,L}(t) \), (5) \( Q_{D,BAY}(t) \), (6) \( Q_{D,L}(t) \), (7) \( Q_{D,R}(t) \). The traffic variables in items (1)-(5) can be detected by sensors. However, the variables in items (6) and (7) cannot be directly obtained by sensors, which need to be calculated or predicted. The sum \( Q_{D,T}(t) \) of \( Q_{D,L}(t) \) and \( Q_{D,R}(t) \) can be simply calculated by the queue length \( L \) and the average length \( l \) of 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 \( P_{D,SLINE}(t) \), \( P_{D,CLINE}(t) \), \( P_{D,BAY}(t) \) to their sum, which is noted respectively, \( K_1(t) \), \( K_2(t) \) and \( K_3(t) \). 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 of \( P_{D,SLINE}^\Delta(t) \), \( P_{D,CLINE}^\Delta(t) \), \( P_{D,BAY}^\Delta(t) \) to their sum, which is noted respectively, \( K_1^\Delta(t) \), \( K_2^\Delta(t) \) and \( K_3^\Delta(t) \). This factor reflects the situation of vehicle distribution within recent time interval \([t-\Delta t, t]\);

c) Change rate of proportion of \( P_{D,SLINE}(t) \), \( P_{D,CLINE}(t) \), \( P_{D,BAY}(t) \) 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 4 is used to predict \( k_1(t) \) and \( k_3(t) \). The architecture of our fuzzy neural network contains four layers. In the fuzzy neural network, Input \( [x_1, x_2, x_3] = [K_1^\Delta, K_2^\Delta, \Delta K_i] \), \( i = 1, 2, 3 \), 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.

\[
f^{(1)}_i = x_i
\]

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 each term node is trapezoidal, as shown in figure 5, and can be described as follows:

\[
f^{(2)}_i = \begin{cases} 
\frac{x_i - w_{1,i}}{w_{2,i} - w_{1,i}} + 1, & w_{1,i} \leq x_i \leq w_{2,i} \\
1, & w_{2,i} < x_i \leq w_{3,i} \\
\frac{w_{3,i} - x_i}{w_{4,i} - w_{3,i}} + 1, & w_{3,i} \leq x_i \leq w_{4,i} \\
0, & \text{otherwise}.
\end{cases}
\]

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:

\[
f^{(3)}_i = \prod_i f^{(2)}_i
\]

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 5.
is the learning rate. Output value at this layer can be defined as follows:

\[ y = f^{(4)} = \frac{1}{4}(v_{1,i} + v_{2,i} + v_{3,i} + v_{4,i})f^{(3)}_i \]  

(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

\[ E = \frac{1}{2}(y_d - y)^2 \]  

(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 \([v_{1,i}, v_{2,i}, v_{3,i}, v_{4,i}]\). Using expression (7) and expression (5), four parameters in vector \([v_{1,i}, v_{2,i}, v_{3,i}, v_{4,i}]\) can be updated by expression (8), where \( \eta \) is the learning rate.

\[ \frac{\partial E}{\partial v_{k,i}} = \frac{\partial E}{\partial f^{(4)}_i} \cdot \frac{\partial f^{(4)}_i}{\partial v_{k,i}} = -(y_d - y) \cdot f^{(3)}_i \cdot \frac{1}{4\sum f^{(3)}}, k = 1,2,3,4 \]  

(7)

\[ v_{k,i}(t + 1) = v_{k,i}(t) + \eta(y_d - y) \cdot f^{(3)}_i \cdot \frac{1}{4\sum f^{(3)}}, k = 1,2,3,4 \]  

(8)

In layer 3, the error signal is computed by

\[ \delta_i = -\frac{\partial E}{\partial f^{(3)}_i} = -\frac{\partial E}{\partial f^{(4)}_i} \cdot \frac{\partial f^{(4)}_i}{\partial f^{(3)}_i} \]  

\[ = \frac{1}{4} \cdot \frac{(y_d - y)}{(\sum f^{(3)}_i)^2} \cdot \left[ (v_{1,i} + v_{2,i} + v_{3,i} + v_{4,i})\sum f^{(3)}_i - \sum (v_{1,i} + v_{2,i} + v_{3,i} + v_{4,i}) f^{(3)}_i \right] \]  

(9)

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 whose updated procedure is described as follows.

\[ \frac{\partial E}{\partial w_{k,ij}} = \frac{\partial E}{\partial f^{(3)}_i} \cdot \frac{\partial f^{(3)}_i}{\partial f^{(2)}_i} \cdot \frac{\partial f^{(2)}_i}{\partial w_{k,ij}}, k = 1,2,3,4 \]  

(10)

where

\[ \frac{\partial f^{(2)}_i}{\partial w_{1,ij}} = \begin{cases} \frac{x_i - w_{1,ij}}{(w_{1,ij} - w_{2,ij})^2}, & w_{1,ij} \leq x_i \leq w_{2,ij} \\ 0, & \text{otherwise} \end{cases} \]  

(11)

\[ \frac{\partial f^{(2)}_i}{\partial w_{2,ij}} = \begin{cases} \frac{x_i - w_{1,ij}}{(w_{2,ij} - w_{1,ij})^2}, & w_{1,ij} \leq x_i \leq w_{2,ij} \\ 0, & \text{otherwise} \end{cases} \]  

(12)

\[ \frac{\partial f^{(2)}_i}{\partial w_{3,ij}} = \begin{cases} \frac{-(x_i - w_{1,ij})}{(w_{3,ij} - w_{2,ij})^2}, & w_{3,ij} \leq x_i \leq w_{2,ij} \\ 0, & \text{otherwise} \end{cases} \]  

(13)

\[ \frac{\partial f^{(2)}_i}{\partial w_{4,ij}} = \begin{cases} \frac{x_i - w_{3,ij}}{(w_{4,ij} - w_{3,ij})^2}, & w_{3,ij} \leq x_i \leq w_{4,ij} \\ 0, & \text{otherwise} \end{cases} \]  

(14)

\[ \frac{\partial f^{(3)}_i}{\partial f^{(2)}_i} = \prod_{k=1}^{n} f^{(2)}_k, n = 1,2,3,4 \]  

(15)

considering expressions (2) and (4), four parameters \( w_{1,ij} \), \( w_{2,ij} \) and \( w_{4,ij} \) can be updated by

\[ w_{n,ij}(t + 1) = w_{n,ij}(t) + \eta \cdot \frac{\partial f^{(2)}_i}{\partial w_{n,ij}} \cdot \delta \cdot \prod_{k=1}^{n} f^{(2)}_k, n = 1,2,3,4 \]  

(16)

3.2 The derivation of urgency degrees

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

![Figure 6: Trapezoidal fuzzy memberships sets for traffic variables](image)

In our research, the traffic variables \( P_{D,ULINE}(t) \), \( P_{D,SLINE}(t) \), \( P_{D,CLINE}(t) \), \( P_{D,RAY}(t) \), \( Q_{D,RAY}(t) \), \( Q_{D,P}(t) \) and \( Q_{D,L}(t) \) are described using Trapezoidal fuzzy memberships set (see figure 6). These fuzzy sets provide an analogy to human characterization by assigning truthfulness value, \( \mu \), 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 5, 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 multi-objective genetic algorithms (MOGA). The “urgency degrees” of four phases can be
determined by fuzzy inference system. In this paper, we adopt fuzzy inference system described in [14]. 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. We take a group to explain fuzzy rules, in which the urgency degree of phase is “Big”. For example:

If \{P_{\text{EAST,ULINE}}(t) \text{ is big}\} and \{P_{\text{EAST,BAY}}(t) \text{ is small}\} or \{Q_{\text{EAST,F}}(t) \text{ is big}\}, then \{U(a)_{\text{East is big}}\}  \hspace{1cm} (17)

Where “and” means “Min”, “or” means “Max”. So, expression (17) can be operated

\[
\mu_{\text{Big}}(U(a)_{\text{East}}) = \text{Max}(\text{Min}(\mu_{\text{Big}}(P_{\text{EAST,ULINE}}(t)), \mu_{\text{Small}}(P_{\text{EAST,CLINE}}(t))),
\mu_{\text{Small}}(P_{\text{EAST,BAY}}(t)), \mu_{\text{Big}}(Q_{\text{EAST,F}}(t)))
\]

(18)

The high level determines the traffic signal timing strategy called decision-making level. As the high level of fuzzy controller, the aim of Decision-making level is to decide whether to extend the current phase and decide the next phase. For each phase, if in current green phase, the controller is activated after \(T_{\text{min}}\) Seconds from the start of the green phase, where \(T_{\text{min}}\) ensures that the green signal stays long enough for safe passage of a single vehicle to clear the intersection, and the total green time cannot exceed \(T_{\text{max}}\), so, the green time is an value between \(T_{\text{min}}\) and \(T_{\text{max}}\). In this paper, the proposed decision-making method based on urgency degrees can effectively solve this problem. It is noted that the next phase is determined according to the maximum urgency degree in all rest phase, and only chosen in six type sequences. For example, during the fuzzy logic decision-making, suppose “a” phase is the current phase, the phase sequence can be one of “a-b-c-d-a”, “a-b-d-c-a”, “a-c-b-d-a”, “a-c-d-b-a”, “a-d-b-c-a”, “a-d-c-b-a”. “Urgency degree” of each phase is obtained by previous fuzzy inference system.

4. The multi-objective optimization of parameters for fuzzy logic controller

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. 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 [15].

Figure 7 describes the procedure of fuzzy logic controller parameter optimization. In our proposed method, 7 types of traffic variables \(P_{\text{D,ULINE}}(t)\), \(P_{\text{D,SLINE}}(t)\), \(P_{\text{D,CLINE}}(t)\), \(P_{\text{D,BAY}}(t)\), \(Q_{\text{D,F}}(t)\), \(Q_{\text{D,R}}(t)\) and \(Q_{\text{D,L}}(t)\) 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.

5. Simulation and conclusions

The situations of simulation for the effects of the fuzzy controller are described in the previous section on an intersection with four approaches (fig.1), that uses four-phase signal with leading left turns, as shown in fig.2. The intersection has two through lane and one left turn bay on each approach. The 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 smaller 15-30% than the extension principle in the test area100-1500vph. The results also indicated that the application area of our proposed algorithm is wide including saturated/un saturated traffic volumes, however the extension principle only fit 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 “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.

References