Swarm Intelligence Inspired Adaptive Traffic Control for Traffic Networks

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Abstract. The internet of Vehicles (IoV) technologies have boosted diverse applications related to Intelligent Transportation System (ITS) and Traffic Information Systems (TIS), which have significant potential to advance management of complex and large-scale traffic networks. With the goal of adaptive coordination of a traffic network to achieve high network-wide traffic efficiency, this paper develops a bio-inspired adaptive traffic signal control for real-time traffic flow operations. This adaptive control model is proposed based on swarm intelligence, inspired from particle swarm optimization. It treats each signalized traffic intersection as a particle and the whole traffic network as the particle swarm, then optimizes the global traffic efficiency in a distributed and on-line fashion. Our simulation results show that the proposed algorithm can achieve the performance improvement in terms of the queuing length and traffic flow allocation.

Keywords: Particle swarm optimization · Traffic signal control
Adaptive control

1 Introduction

Internet of vehicles (IoV) has boosted diverse applications with its rapid development. In the transportation network, IoV improves the communication abilities between vehicles, which can help avoid the collision accident, resulting a substantial increase in road safety [1]. Communications between vehicles can provide the real-time vehicle dynamic information [2]. With the rapid development of the city road network, the efficiency of the net-wide traffic system is more significant. IoV enhances the exchange of information between vehicles and the road network [3], and improves the Intelligent Transportation System (ITS) and Traffic Information Systems (TIS). Based on this, we

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can get a better grasp of the real-time dynamic traffic information, and a novel adapted signal control is proposed. The management of the traffic signal control is essential for traffic operation, and numbers of profound research have been done in this hot area.

To ease the traffic pressure, Lin Cao and Bin Hu proposed a traffic signal control based on Action-Dependent Heuristic Dynamic Programming (ADHDP). It is specially adapted to the two intersections traffic model [4]. Daxin Tian and Jianshan Zhou proposed a adaptive signal control model based on the cellular attractor selection, and investigated the robustness and adaptivity of the model [5]. And an adaptive signal control scheme was put forward to prevent intersection traffic blockage [6]. To improve the traffic system performance, a set of algorithms on the traffic signal timing based on the deep neural network (DNN) were also proposed [7]. But with the extension of the city, the road network is becoming bigger, thus a concise and effective traffic signal control model is needed.

We propose a bio-inspired adaptive traffic signal control for the road network with multiple intersections [8, 9]. Due to the topology structure of the road network, inspired by particle swarm optimization, we consider the traffic signal control of an intersection as a particle and the control of the entire traffic network as a networking particle swarm [10, 11]. We propose a adaptive algorithm to improve the traffic conditions.

In this paper, the traffic dynamic model is displayed in the Sect. 2, and in the Sect. 3, we propose the new algorithm on the traffic signal control on the road network with multiple intersections. Section 4 presents the simulation we set up to test our model and discusses the results of it. Section 5 concludes the paper.

2 Traffic Flow Model

Initially, a single intersection is discussed. Considering the straight and left-turn movements, one direction of a intersection is divided into two kinds of flows. One crossroad's four directions are composed of 8 movements, which are controlled by 8 groups of signal lights labeled as Fig. 1 shows.

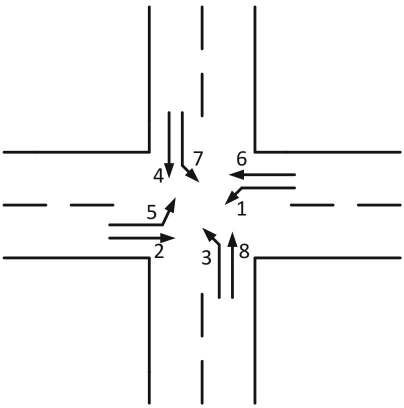

Fig. 1. Typical traffic intersection

Assuming that the signal phases switch with the equal time interval, we get each movement's state transition equation. The current queuing length of each movement is updated by the queuing length of the last time and the varying queuing length. The state of each alignment is updated with every same time interval, which is denoted as t.

$$A^i(t) = A^i(t-1) + \Delta A^i(t) \quad i = 1, 2, 3\ldots 8 \tag{1}$$

The varying length of the alignment ΔA is the difference of the incoming flow and the output flow:

$$\Delta A^i(t) = A^i_{in}(t) - A^i_{out}(t) \tag{2}$$

The alignments in an intersection are denoted as the vector:

$$\boldsymbol{A(t)} = [A^1(t), A^2(t), A^3(t)\ldots A^8(t)]^{\mathrm{T}} \tag{3}$$

The incoming flow and output flow are expressed as:

$$\boldsymbol{A_{in}(t)} = [A^1_{in}(t), A^2_{in}(t), A^3_{in}(t)\ldots A^8_{in}(t)]^{\mathrm{T}} \tag{4}$$

$$\boldsymbol{A_{out}(t)} = [A^1_{out}(t), A^2_{out}(t), A^3_{out}(t)\ldots A^8_{out}(t)]^{\mathrm{T}} \tag{5}$$

The signal phase is denoted as an 8 dimensional binary vector $\boldsymbol{s(t)}$, $s^i(t) = 1$ represents that i^{th} signal light is green and the lane is released. $s^i(t) = 0$ represents that the signal light is red.

$$\boldsymbol{s(t)} = [s^i(t)]^{\mathrm{T}} \quad i = 1, 2, 3\ldots 8 \tag{6}$$

The output flow rate is related to the current signal phase $\boldsymbol{s(t)}$ and the current queuing length $\boldsymbol{A(t)}$ which is denoted as:

$$\boldsymbol{A_{out}(t)} = f_{out}(\boldsymbol{s(t)}, \boldsymbol{A(t)}) \tag{7}$$

where the function f^j_{out} is expressed as:

$$f^j_{out} = \begin{cases} \min\left[A^j(t); \frac{\Delta t}{I}\right], & s^j(t) = 1, \\ 0, & s^j(t) = 0 \end{cases} \tag{8}$$

$$\boldsymbol{f_{out}(t)} = [f^j_{out}(t)]^{\mathrm{T}} \quad j = 1, 2, 3\ldots 8 \tag{9}$$

The $A^j(t)$ stands for the current alignment length, I stands for the average passing time between two neighboring vehicles. Δt is denoted as the green light time. $s^j(t) = 1$ represents that the lane is released and $s^j(t) = 0$ represents that the lane is blocked.

Single intersection can be promoted to large road network. We put emphasis on discussing the four-intersection road network. There are $8 \times 4 = 32$ different movements controlled by signal lights which are labeled as the Fig. 2 shows:

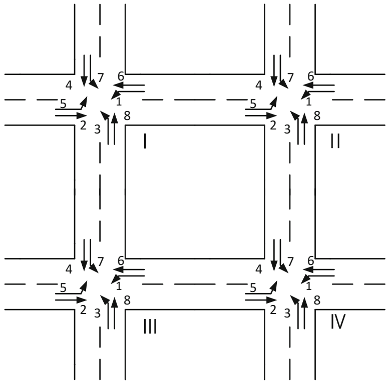

Fig. 2. Traffic network with four intersections

The traffic flow vectors of the four-intersection road network include:

$$\boldsymbol{s(t)} = [s_1(t), s_2(t), s_3(t), s_4(t)]^{\mathrm{T}} \tag{10}$$

$$\boldsymbol{A_{out}(t)} = [A_{out1}(t), A_{out2}(t), A_{out3}(t), A_{out4}(t)]^{\mathrm{T}} \tag{11}$$

$$\boldsymbol{A_{in}(t)} = [A_{in1}(t), A_{in2}(t), A_{in3}(t), A_{in4}(t)]^{\mathrm{T}} \tag{12}$$

$$\boldsymbol{A(t)} = [A_1(t), A_2(t), A_3(t), A_4(t)]^{\mathrm{T}} \tag{13}$$

The directions of the intersections can be categorized into two types:

External direction, which is connected with a node outside the system we consider.
Internal direction, which is connected with the intersection inside the system we consider.

For internal direction, the entering flow of the alignment is from the other three nodes in the road network. Taking intersection I for example, the entering flow of the movements labeled as 1^{st} and 6^{th} can only be from 3^{rd} and 6^{th} movements of the intersection II. So the increased queuing length of the intersection I is related to the queuing length and the signal control $s_2(t)$ of the intersection II. The flow transition equation of the movements can be expressed as:

$$A_{in\mathbf{1}}^{1,6}(t+1) = f_{in}(A_{\mathbf{2}}^{1,6}(t), s_2(t)) \tag{14}$$

3 Swarm Intelligent Inspired Adaptive Traffic Control Model

Based on the NEMA (National Electrical Manufacturers Association) 8-phase dual-ring control, the signal phases are classified into two types: the west/east direction and the south/north direction. In the real operation process, the green lights which control the release of the lane can only be lighted in one of the types. Additionally, the changing model of the signal lights is limited. According to the NEMA phase, the next-time signal control phase is related to the current phase. For example, if the current control phase $\boldsymbol{s}(\boldsymbol{t})$ is (1 0 0 0 1 0 0 0), which also can be denoted as *1 + 5,* the next-time signal phase $\boldsymbol{s}(\boldsymbol{t}+1)$ can only be selected from the *1 + 6*, *2 + 5* and *2 + 6.* Every intersection in a traffic network faces such choices. We treat this problem as a decision strategy problem (Fig. 3).

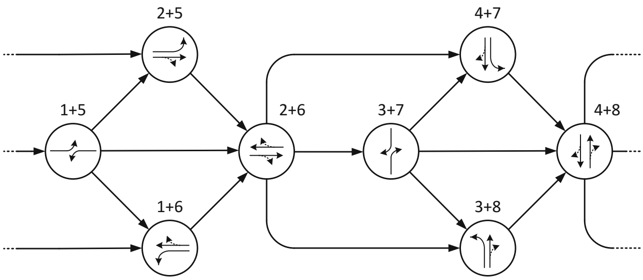

Fig. 3. Primary phasing options for 8-phase dual-ring control

For an eight-phase dual-ring signal control loop, there are four nodes needed to make the decision from three choices to select the next signal phase:

$$\begin{aligned} \boldsymbol{m}_1 &= \left[p_1^1, p_1^2, p_1^3\right]^{\mathrm{T}} \\ \boldsymbol{m}_2 &= \left[p_2^1, p_2^2, p_2^3\right]^{\mathrm{T}} \\ \boldsymbol{m}_3 &= \left[p_3^1, p_3^2, p_3^3\right]^{\mathrm{T}} \\ \boldsymbol{m}_4 &= \left[p_4^1, p_4^2, p_4^3\right]^{\mathrm{T}} \end{aligned} \tag{15}$$

$\boldsymbol{m}_1$, $\boldsymbol{m}_2$, $\boldsymbol{m}_3$, $\boldsymbol{m}_4$ respectively represent the probability vectors when going through the phases of *1 + 5*, *4 + 8*, *2 + 6* and *3 + 7* in the loop.

p^1, p^2 and p^3 respectively represent the probability value, which satisfying the function: $p^1 + p^2 + p^3 = 1$. If the current signal control is *1 + 5*, p_1^1, p_1^2, p_1^3 respectively represent the probability value of choosing the phase of *1 + 6*, *2 + 5* and *2 + 6* as the next-time signal phase. We choose the largest fraction $\max\left\{p_i^1, p_i^2, p_i^3,\right\}$ from the three choices as the next-time signal phase.

The complete loop of the NEMA phases can be expressed as:

$$\boldsymbol{x} = [\boldsymbol{m}_1, \boldsymbol{m}_2, \boldsymbol{m}_3, \boldsymbol{m}_4]^{\mathrm{T}} \tag{16}$$

The next time signal control transition is defined as:

$$\boldsymbol{s}(\mathbf{t}+\mathbf{1}) = f_s(\boldsymbol{s}(\boldsymbol{t}), \boldsymbol{x}) \tag{17}$$

Inspired by the foraging behavior of birds, we consider the signal selection strategy of one intersection a particle and the selections of the entire traffic network as a networking particle swarm, we map the sequential signal operations of each intersection to the iterative updates of the position and velocity of the corresponding virtualized particle induced by the particle swarm optimization (PSO). Every particle has its own corresponding function. Because the entire traffic is inflow-related, every particle has relation with other particle. Formulating the global objective to optimize the global traffic efficiency as a collection of individual objectives, we implement the iterative PSO in a distributed fashion over the network of particles, in which each particle can sense the surrounding real-time traffic state, share its own signal control and state information with other local particles, and coordinate its own signal control with other particles' controls to get a better traffic condition.

Based on the particle swarm intelligence algorithm, we set the velocity as:

$$\begin{aligned} \boldsymbol{n}_\mathbf{1} &= \left[r_1^1, r_1^2, r_1^3\right]^{\mathrm{T}} \\ \boldsymbol{n}_\mathbf{2} &= \left[r_2^1, r_2^2, r_2^3\right]^{\mathrm{T}} \\ \boldsymbol{n}_\mathbf{3} &= \left[r_3^1, r_3^2, r_3^3\right]^{\mathrm{T}} \\ \boldsymbol{n}_\mathbf{4} &= \left[r_4^1, r_4^2, r_4^3\right]^{\mathrm{T}} \end{aligned} \tag{18}$$

We initialize the fraction of the vector of the velocity as random value. During the process of interating, the values will have adaptive changes.

We can get the general vector of the velocity:

$$\boldsymbol{v} = [\boldsymbol{n}_\mathbf{1}, \boldsymbol{n}_\mathbf{2}, \boldsymbol{n}_\mathbf{3}, \boldsymbol{n}_\mathbf{4}]^{\mathrm{T}} \tag{19}$$

For the network with four intersections

$$\boldsymbol{x}_\mathbf{1}, \boldsymbol{x}_\mathbf{2}, \boldsymbol{x}_\mathbf{3}, \boldsymbol{x}_\mathbf{4} \in \boldsymbol{U}_i \tag{20}$$

The velocity $\boldsymbol{v}$ is updated as:

$$\boldsymbol{v}_{i+\mathbf{1}}(\boldsymbol{t}+\mathbf{1}) = \boldsymbol{v}_i(\boldsymbol{t}) + \omega\left(\boldsymbol{x}_i^{best}(\boldsymbol{t}) - \boldsymbol{x}_i(\boldsymbol{t})\right) + (1-\omega)(\boldsymbol{x}_{U_i}^{best}(\boldsymbol{t}) - \boldsymbol{x}_i(\boldsymbol{t})) \tag{21}$$

$\boldsymbol{x}_i^{best}(\boldsymbol{t})$ stands for the optimal value of the single intersection, and $\boldsymbol{x}_{U_i}^{best}(\boldsymbol{t})$ represents the optimal value of the four intersections in the whole network. ω is the inertia coefficient.

Based on the particle swarm intelligence algorithm, $\boldsymbol{x}$ is updated as the sum of the old position $\boldsymbol{x}$ and the velocity $\boldsymbol{v}$. To satisfy $p^1 + p^2 + p^3 = 1$, we use $\boldsymbol{f_x}$ to correct the interation function:

$$\boldsymbol{x}'(\boldsymbol{t}+\boldsymbol{1}) = \boldsymbol{x}(\boldsymbol{t}) + \boldsymbol{v}(\boldsymbol{t}+\boldsymbol{1}) \tag{22}$$

$$\boldsymbol{x}(\boldsymbol{t}+\boldsymbol{1}) = \boldsymbol{f_x}(\boldsymbol{x}'(\boldsymbol{t}+\boldsymbol{1})) \tag{23}$$

We organize the formula and get the expression of the $\boldsymbol{x}(\boldsymbol{t}+\boldsymbol{1})$:

$$\boldsymbol{x}_i^j(\boldsymbol{t}+\boldsymbol{1}) = \left[\left(p_i^j + r_i^j\right) \Big/ \sum\nolimits_{j=1}^{3} \left(p_i^j + r_i^j\right)\right] \; i = 1, 2, 3, 4 \quad j = 1, 2, 3 \tag{24}$$

Through interative computing, we hope to get a better condition of the road network which is quantificated as the fitness of the alignment. The fitness is defined as:

$$\text{fitness} = \max\left\{A^i(t)\right\} \quad i = 1, 2, 3\ldots 8 \tag{25}$$

To avoid the congestion of the single direction in an intersection, we set the biggest current alignment length as the fitness value. In the process of iteration, the smaller fitness value is considered to be better.

During the iteration, $\boldsymbol{x}_{U_i}^{best}$ continues to evolve, globally coordinating the signal phase control in the road network. The four intersection will achieve the coordinate and optimized traffic flow distribution.

The computational flow chart is showed in the Fig. 4:

4 Performance Evaluation

By using distributed interactions and PSO, the signal control strategies of the particles are induced co-evolutionary, self-organized, and self-adaptive to varying environmental conditions. Finally, simulation results have also been supplemented to show that our proposed method can better benefit the global traffic network than the conventional fixed-time control in term of robustness and traffic efficiency regardless of its large-scale complexity and dynamic nature.

We simulate our bio-inspired algorithm based on the road network with four intersections. To compare with the conventional fixed-time control, we set the same initial value and parameter for our algorithm. We initially set every movement as empty. For every movement, the maximum passing capacity is 3600 vehicles per hour. We differentiate the entering traffic flow to see the performance of the algorithm under different conditions. If the outflow rate is lower than the inflow rate, the condition is defined as unsaturated, and conversely it is defined as saturated.

For one single direction, the inflow of whole network with 4 intersections is differentiated as 1600, 2400, 3200, 4000, 4800 vehicles per hour. And we set the ratio of the flow rate in the left-turn movement and straight movement as 1.0 and 0.5 to test the

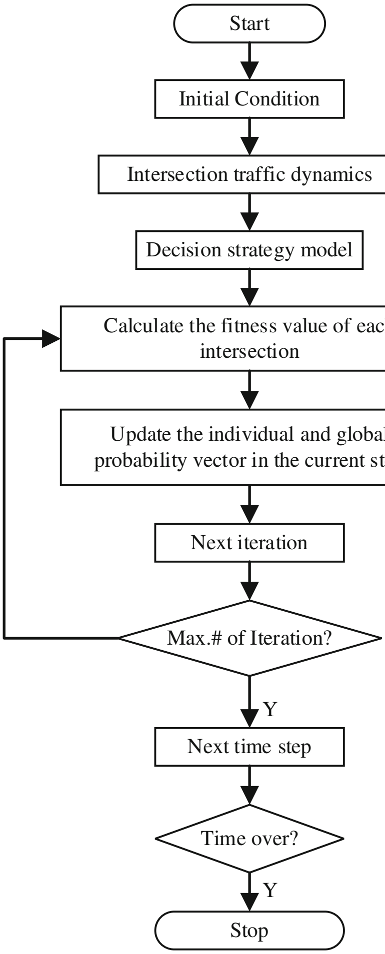

Fig. 4. Computational flow chart

algorithm under different conditions. We set the same time interval to be 30 s. Inertia coefficient $\omega = 0.3$.

Figure 5 shows the performance of the algorithm under Left-turn/straight = 1.0 condition:

In the unsaturated part where the inflow rate is relatively small, the conventional fixed-time control is capable to coordinate the traffic situations. We can see that the performance of the bio-inspired algorithm and the conventional control is relatively close. In the saturated part, we can see a good improvement compared with the conventional control. When the inflow rate reaches 4000 vehicles per hours, the algorithm can optimize the maximum queuing length for about 26%. When it reaches 4800 vehicles per hours, the improvement is more obvious.

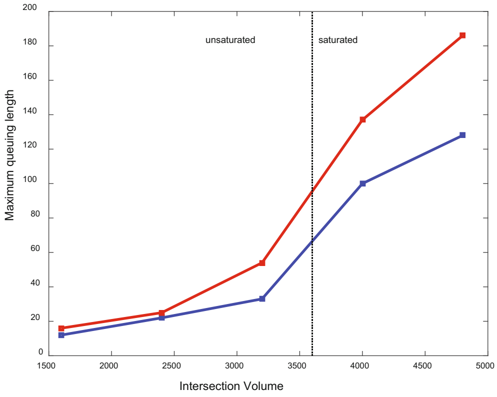

Fig. 5. Algorithm performance comparison

For the ratio of Left-turn/straight = 0.5 condition, generally both controls have better performances than the Left-turn/straight = 1.0 condition. Analogously we still can see that our bio-inspired algorithm has a good improvement on the traffic conditions (Fig. 6).

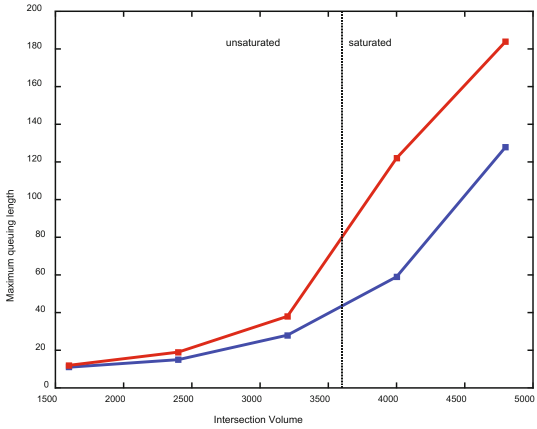

Fig. 6. Algorithm performance comparison

As for the general situation of the intersection, since we set the fitness as the maximum of the queuing length. As the algorithm trying to reduce the value of the maximum queuing length, the vehicles need to be distributed to the rest of the movements, which will greatly help to reasonably coordinate the traffic flows. We selected the inflow rate of the 3200 vehicles per hour situation to see the performance. We can see that the distribution of the traffic flow is more reasonable than the conventional control (Fig. 7).

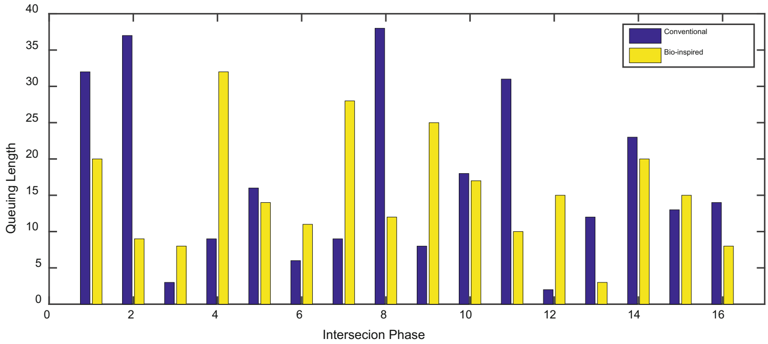

Fig. 7. Queuing length comparison

5 Conclusions

We use the particle swarm intelligent inspired algorithm to find the rational proportion of the signal lights, and map the sequential control way to promote the condition of the traffic intersection. We simulate the four-intersection situation in this paper. As the results show, the algorithm has a good progress under different situations. For larger road network, the algorithm will show good reliability and efficiency of the traffic control.

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