A Survey of Intelligence Methods in Urban Traffic Signal Control

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Summary
It is quit difficult to improve the performance of urban traffic signal control system efficiently by using traditional methods of modeling and control because of time-variability, non-linearity, fuzzyness and nondeterminacy in the system. It becomes the research hotspot in this area to apply artificial intelligence methods to urban traffic signal control system. This paper, based on analysis for a general model of urban traffic signal control, makes a summary of the applications of intelligence methods such as fuzzy logic, neural networks, evolutionary algorithms and agent reinforcement learning to urban traffic signal control, and analyzes the superiority and inferiority of these methods in applications. Finally, some points of view about the future research in this area are proposed.

Key words:
Intelligent Transportation Systems; Urban Traffic Signal Control; Fuzzy Logic; Neural Networks; Evolutionary Algorithms; Reinforcement Learning; Pattern Discovery

1. Introduction

In fact, urban traffic signal control is the product of vehicle modernization: in order to separate the traffic flows that may result in traffic conflict, it is necessary to guide and schedule it effectively by using traffic signals. The problem of urban traffic is more and more serious, and many people are trying hard to solve it. On one hand, people are ceaselessly presenting new theories and new methods, and on the other hand, many area coordinated traffic control systems based on computers are developed one after the other. Generally, traffic control methods include fixed-time control, time-of-day control, vehicle actuated control, semi-actuated control, green wave control, area static control and area dynamic control.

As a perfect urban area traffic signals coordinated control system, it is supposed to respond to traffic demand and online-optimize timing plans in time, and then implement real-time control. That is so-called “adaptive” characteristic. However, there is not any system meeting above requirements so far. That is because the traffic control system is non-linear, fuzzy and nondeterministic, and traditional methods of modeling and control can’t work very well. With rapidly developing of computer technology, some significant progresses have been achieved in artificial intelligence (AI) field. AI methods such as fuzzy logic, neural networks, evolutionary algorithms and reinforcement learning are presented and applied in engineering in succession. It can be imagined that a new breakthrough will be achieved by applying artificial intelligence methods to traffic control system. In fact, there are many researchers who have already done some instructive work. This paper makes a summary of the applications of above intelligence methods. Finally, some points of view about the future research in this area are proposed.

2. Traffic control methods based on artificial intelligence

The fundamental principle of urban traffic control is to respond to dynamic changes of the traffic demand. In other words, it is to reduce total traffic delay by adjusting parameters such as cycle, splits, phase sequences and offsets according to changes of the traffic volume. In [1], a general description for the problem of urban traffic control is presented as follows:

$$
\begin{aligned}
&\min PI(k) = \sum_{i=1}^{m} w_i y_i(k) = W^T Y(k) \\
&\text{s.t.} \quad X(k+1) = \boldsymbol{f}(X(k), U(k), \theta, k) + \\
&\qquad\qquad + \boldsymbol{\xi}(k),\ U(k) \in D^U \qquad (1)\\
&\qquad\quad Y(k) = \boldsymbol{g}(X(k), U(k), k) + \Psi(k) \\
&\qquad\quad X(k) = [x_1(k), x_2(k),\ \cdots,\ x_n(k)]^T \\
&\qquad\quad Y(k) = [y_1(k), y_2(k),\ \cdots,\ y_m(k)]^T \\
&\qquad\quad W = [w_1, w_2,\ \cdots,\ w_m]^T
\end{aligned}
$$

where, k is the discrete time instant, $X(k)$ is an n-dimensional vector which denotes traffic volume, vehicle speed and traffic density. $Y(k)$ is an m-dimensional output vector which denotes vehicle delay, number of stops and traffic blockage. $U(k)$ is an l-dimensional control vector which is composed of the cycle, splits and offsets, and belongs to the feasible domain D^U. $\xi(k)$ is an n-dimensional disturbance vector which denotes the influence of external factors to traffic flows. $\Psi(k)$ is an m-dimensional measurement vector of noise usually caused by sensors' systems. W is an m-dimensional weighting coefficient vector. Both $\boldsymbol{f}$ and $\boldsymbol{g}$ are time-variable nonlinear functions. Apparently, the traffic control problem described in formulation (1) is a nonlinear time-variable optimal control problem, and its dynamic characteristics of structure and parameters could be identified hardly, so it is impossible to establish a traditional mathematic model.

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The AI technology may provide another way to solve such a problem.

2.1 Fuzzy control technology

Fuzzy logic is a powerful tool for processing nondeterministic and non-linear problems. It can represent fuzzy and qualitative knowledge, and so it can imitate human to reason. As we know, a seasoned traffic police can lead traffic quickly and effectively. Actually he just reasons and makes decisions by making use of interrelated qualitative knowledge. The process of reasoning and decision-making can be described as follows: for a lane, if there are many vehicles arriving in, more green time is allocated. Otherwise, less green time is allocated or the phase turns to next one. Of cause, at the same time it is necessary to consider traffic demands in other lanes when change the phase. The control process is shown in figure 1. The traffic intensity can be denoted by queue length before stop line or traffic density on the approaches in the current or next phase.

approach. Simulation results showed that fuzzy logic control reduced average delay significantly.
Above methods only take the flow of the through movement flows into account, however, in practice, turning (especially left-turning) movement flows should be considered. In [8], Mohamed et al. presented a two-stage fuzzy logic control method. The controller was designed to be responsive to real-time traffic demands. The fuzzy controller used vehicle loop detectors, placed upstream of the intersection on each approach, to measure approach flows and estimate queues. These data were used to decide, at regular time intervals, whether to extend or terminate the current signal phase. In the first stage, observed approach traffic flows were used to estimate relative traffic intensities in the competing approaches. In the second stage, these traffic intensities were then used to determine whether the current signal phase should be extended or terminated.
In [9], Liu et al. designed a new traffic controller for a single intersection based on the people's strategic decision process to the multi-phase signal traffic control. The

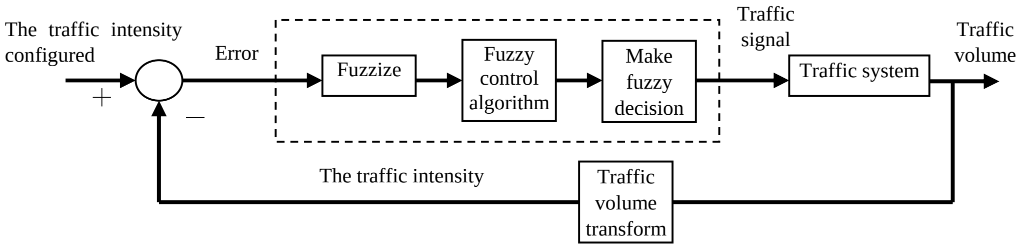

Fig. 1 The block diagram of fuzzy control

In [5], a fuzzy logic controller was designed for an isolated two-phase intersection, which had three inputs and one output. From 7 seconds after green time, decisions were made every 10 seconds to decide whether to extend green time (not exceeding maximum green time) of current phase or change the wayleave to the next phase according to traffic volume of all approaches. Simulations had shown that the above method was effective. This is the earliest example applying fuzzy logic to traffic controls.
In [6], Nakatsuyama et al. designed a fuzzy logic phase controller. It only considered traffic volume of one approach. The fuzzy control rule was: for an approach of a trunk, whether to extend or end green time of local intersection depended on traffic volume of the upstream one. Considerable effect could be received when traffic volume changed greatly, for example, during the peak period.
In [7], Chiu presented fuzzy logic to control multiple intersections in a network of two-way streets with no turning movements. The fuzzy rules were used to adjust parameters such as the cycle time, offsets and splits according to the degree of saturation on each intersection

inputs of controller were the queue lengths on the contiguous phase lanes and the differences between the current queue lengths and the ones in next phase lanes. The outputs of one were extending green time of the current phases or changing into the successional phases. Fuzzy reasoning rulers are created according as experiences of traffic police. This controller had been applied practically and worked very well.
In [10], Liu et al. proposed a hierarchical fuzzy control method, and applied it to the arterial coordinated control. Its fundamental principle was to use hierarchical structure and fuzzy theory to solve real time coordinated control problems of traffic trunk road. It regarded all intersections on the trunk as subsystems. According to the cycle length provided by a coordinator, it adjusted the splits of all approaches on line by using fuzzy control methods. Traffic volumes detected at all intersections were sent to the coordinator. The cycle length and splits were determined by using fuzzy control method. The goal of the coordinator and subsystems was to minimize the queue length. Simulation results shown that it could shorten the queue, and reduce total traffic delay.

Most researchers work at control an isolated intersection with fuzzy control method (see [5,8,9, 11~16]). Few of them apply this method to the coordinated control of arterial or area traffic. Area traffic coordinated control system is a complex large-scale system. There are many interactional factors, and it is difficult to describe the whole system using some qualitative knowledge. It is just the limitations of fuzzy control methods. In a word, it is more appropriate to use fuzzy control methods for traffic signal control of the isolated intersection.

2.2 Artificial neural networks

Artificial neural network (ANN) has been widely used in many fields such as signal and information processing, pattern recognition, automatic control because of its capabilities such as non-linear mapping (or generalization), self-adapting, self-organizing and self-learning. The traditional methods of modeling can't work well in the traffic control owing to its' non-linear characteristics. Of course, it is a natural choice to utilize these capabilities of ANN to solve traffic control problems.

In [17], Spall et al. presented a system-wide traffic-adaptive control (S-TRAC) method based on ANN. As figure 2 shows, S-TRAC is composed of two close loops. The loop below is based on a well-trained neural network. This neural network controller created the best timing plan according to real-time information of traffic system detected by detectors and some other information such as weather conditions and statuses of all timing durations. The loop above, which should be executed at least once a day and can be closed or opened depending on whether it is necessary to add a neural network controller or self-tuning controller for adapting long-period variation of the system, used neural network to make weight estimation. S-TRAC usee simultaneous perturbation stochastic approximation (SPSA) method which didn't need to calculate the gradient of PI. Simulation at a road with 9 intersections had shown this method was effectual.

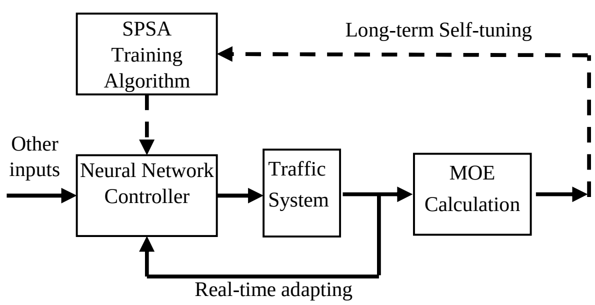

Fig.2 the block diagram of S-TRAC

In [11], the ANN was used to implement fuzzy reasoning. This method can improve the precision of fuzzy controller and accordingly improve the effect of control. In [18], neural networks and fuzzy control methods were combined, and used to a special FDP algorithm for improving its computing speed. This method has been applied to the PRODYN system. In [19], neural networks were used to map fuzzy relations in arterial coordinated control for improving the precision of fuzzy controller.

In [20], a self-learning control method based on neural networks was applied at an isolated intersection. The control system was composed of two neural networks and a performance evaluation unit. Two neural networks were always alternatively in the state of learning or working during the process of self-learning according to the decision of the performance evaluation unit on the traffic conditions of intersections. After complete self-learning, the neural network can act as a controller. Simulation results showed it could increase traffic capacity of multi-phase intersections and was highly adaptive to changes of traffic flows.

In [21], a self-tuning predictive control method for urban area traffic signal control based on the ANN was proposed. The strong coupling between adjacent signaled intersections was fully considered, based on which a traffic model for queues was established. The number of approaching vehicles in the next cycle at this intersection was predicted by using ANN and the traffic parameters ware obtained to decide the optimal cycle length. By using real measured data, the feedback tuning method was used to process all the above prediction values. The constrained predictive control algorithm was given to determine the control tactics. Simulation results showed that the proposed method was effectual.

In [22], the multi-layer chaotic neural networks involving feedback (ML-CNN) were developed based on Hopfield networks and chaos theory. Its inputs were saturation flow rate and real-time traffic volume of all lanes, and outputs were cycle length and green time of every phase. Simulation had been implemented at an isolated intersection. The results showed that the new method was better than traditional timing methods.

In [23], the fuzzy neural networks (FNN) were used to solve the real time arterial coordinated control problem. An arterial road could be regarded as a large-scale system, and the subsystems were the intersections in the arterial road. Each intersection had itself FNN controller in which the fuzzy relations were generalized by neural networks. This controller could manage dynamically the phases and the green time according to the traffic status in local and adjacent intersections. The simulation showed this method had better performances in the cases of time-varying traffic patterns and heavy traffic conditions than the vehicle actuated method.

There are three cases of applications of ANN in traffic signal control. In the first case, ANN is solely used for modeling, learning and controlling (see [15,18]). In the second case, the generalization capability of ANN is used based on other methods. For example, in order to improve the precision of fuzzy control, ANN is used to map the fuzzy relations or implement fuzzy reasoning (see [11, 18, 19, 23]). In [21], ANN was regarded as a forecast model for the traffic system based on predictive control, where it is hard to get results for the traditional forecast model. In the third case, ANN is combined with other methods to improve their generalization capability (see [22]). The applying effect of ANN depends on its generalization capability. So the samples should be ergodic and the learning process should converge to the global optimal point. In fact, it is hard to meet these conditions for a real application. Therefore, further development of ANN is needed for applying this method to traffic signal control really.

2.3 Evolutionary algorithms

The optimization of timing plans is very important for the area traffic coordinated control. A typical optimization model of timing plans is static, and can be regarded as a static non-convex nonlinear programming problem. At present it is hard to find its global optimal solution by using traditional mathematic methods. Evolutionary algorithms have advantages in evidence to resolve such problems.

In [24], a genetic algorithm was used to optimize timing plans. The application object was an octothorpe-shaped traffic network with 4 intersections. Every intersection can run a two-phase plan. This method used 9 decision variables including the total green time of all phases, phase orders and splits. These 9 decision variables were coded with 24 bits. Objective function was the reciprocal of total waiting time. A simulation model was used to evaluate the optimizing method. Results showed that genetic algorithm was indeed a parallel global optimizing method compared with traditional search methods.

In [25], a new traffic signal timing optimization method based on genetic algorithm was proposed. It could optimize cycle, offsets, splits and phase orders at the same time (genetic algorithm of TRANSYT-7F can't optimize them at the same time, thus the global optimal solution may be missed). Therefore, it was more effectual.

In [26], an urban area traffic coordinated control method based on an improved immunity genetic algorithm was proposed. A two-level hierarchical distributed construction was adopted. The parameters were optimized hierarchically with an interval of 5～30 minutes. The Cycle and offsets were optimized in the central controller in each interval and splits were optimized in intersection controller in each cycle. For a given performance index, such as minimizing the mean vehicle delay or number of stops etc., an improved immunity GA was used to optimize the cycle, offsets and splits. Simulation results showed that the new method proposed in this paper was feasible and effectual.

In [27], a logistic chaotic mapping was applied to mutation operation of genetic algorithm and then a chaotic mutation was implemented. In this way chaotic genetic algorithm was built. Concretely 5 percent individuals were selected randomly from the group and used to search according to chaotic dynamic searching process. Then the results of searching replaced previous individuals to be part of the group. Simulations in CORSIM showed that the new algorithm could converge more quickly, and avoid local optimization and premature convergence.

In [28] and [29], chaos-particle swarm optimization algorithm (C-PSO) and catastrophe-particle swarm optimization algorithm (Ca-PSO) were proposed respectively to solve the problem of local optimization. The fundamental principle of C-PSO can be described as follows: it randomly selects N D-dimensional vectors from the community composed of m particles in an N-dimensional space to compose another smaller community. The chaotic mutation based on logistic mapping is adopted. Because of the ergodicity of chaotic mapping, C-PSO algorithm is good at global searching. The fundamental principle of Ca-PSO can be described as follows: firstly it searches according to PSO algorithm, then judges whether it satisfies the catastrophic critical condition. If the condition is not satisfied, it outputs the results of optimization. Otherwise it implements catastrophe operation: it reserves current best particles, and randomly creates other particles, then searches once again. The times of implementing catastrophe operation can be configured. C-PSO algorithm and Ca-PSO algorithm are compared with the genetic algorithm proposed in [24]. CORSIM simulation showed they could remarkably improve the speed of convergence.

In [30], the ant algorithm was used to optimize timing parameters in area traffic coordinated control. In order to solve the dimensional disaster problem, a reduced-order rolling horizon optimization algorithm based on an improved ant algorithm was proposed. A rolling horizon optimization model of area traffic coordinated control problem was formulated. A large-scale region was divided into a series of sub-regions with a reduced-order method, and a compound layered construction graph was designed to describe and search the solution space of the reduced-order model. Simulation results showed that the reduced-order algorithm could improve the total computational efficiency, reduce the total stop delay remarkably, and then suitable for the rolling horizon optimization of large-scale traffic regions.

In fact evolutionary algorithms such as genetic algorithm, ant algorithm and particle swarm optimization are all biomimetic methods for global optimization. Evolutionary algorithms are not apt to be trapped in local optima because of their characteristics of random search and implicit parallel computing. However, encountering a large-scale problem, these methods will spend overmuch time to converge to the optima. It is disadvantageous for on-line optimization of area traffic coordinated control. Moreover the convergence rate is sensitive to parameters selected, which depend on practical problems to be solved. And so applying the evolutionary algorithm to area traffic coordinated control is limited.

2.4 Reinforcement learning

Unlike supervised or unsupervised learning, reinforcement learning is to learn the optimal policy by perceiving states of environment and receiving nondeterministic information from the environment. It is one of the basic technologies of intelligent agent. This method considers learning to be a trial-and-error process. The agent can only obtain the evaluation of actions implemented just now. It is not told how to do. Because little information is provided, the agent must optimize its policy by using information of states, state transitions, actions and rewards. It can be described as the formulation below:

$$\pi^*(s) \equiv \arg\max_a [r(s,a) + \gamma V^*(\delta(s,a))] \tag{2}$$

where s belongs to a set S of possible states; a belongs to a set A of actions; r belongs to a set R of rewards; d (s, a) denotes the state resulting from applying action a to the state s; g is called discounted rate. V *(×) is called evaluation function (or cumulative reward). In a complicated system it is impossible to obtain the exact model of d (s, a) and r, so the agent can’t learn by using (2). To solve the problem above, a Q-learning algorithm for deterministic Markov decision processes (MDP) was proposed (see [33]):

$$\hat{Q}(s, a) \leftarrow r + \gamma \max_{a'} \hat{Q}(s', a') \tag{3}$$

where s '＝d (s, a), s ' is the state after applying action a to the state s; a ' denotes every possible action which can be applied to the state s '. After iterated repeatedly converges to V *. Combining the Q-learning with temporal difference learning, Sutton (see [32]) proposed a new Q-learning algorithm for non-deterministic Markov decision processes.

$$\hat{Q}_n(s, a) \leftarrow (1-\alpha_n)\hat{Q}_{n-1}(s, a) + \alpha_n[r + \gamma \max_{a'} \hat{Q}_{n-1}(s', a')] \tag{4}$$

where an is the learning rate. Reinforcement learning methods are still under development (see [34,35]).

Urban traffic signals should be supposed to response the changes of traffic flow constantly. According to this characteristic, the basic framework of traffic signal control based on agent was proposed (see [36~38]). Ou et al. (see [39]) proposed a multi-agents based method. In [39], an agent represented a signal intersection controller, and multi-agents realized coordination of multiple intersections to eliminate congestion. Because the modified Bayesian learning was combined with recursive modeling method, a better simulation results were achieved.

Ma et al. (see [40]) applied Q-learning to dynamically control the traffic signals at an isolated intersection. The states include the index of green phase, the lasting time of green light, traffic volume during green phase, mean number of queuing vehicles during red phase, and the prediction of the trend of traffic flow; the action is to change the green phase to red phase, or extend green phase until next decision point. The reward is denoted by traffic volume during green phase between successive decision points divided by the waiting time increased during red phase. Simulation results indicate the effect of the method. Later Ma et al. (see [41]) extended the method to coordinately control at a road with two intersections.

Abdulhai et al. (see [42]) presented a basic framework of applying Q-learning to traffic signal control system. In the case of the isolated intersection, the states include the queue lengths on the four approaches and the elapsed phase time; actions include extending the current phase and changing the wayleave to the next one. The reward (actually a penalty in this case) is defined to be the total delay incurred between successive decision points by vehicles in the queues of the four approaches. And the delay is denoted by a power function of queue length. For a road with multiple intersections, some other states may be added, for example the splits between two intersections. The reward is the weighted summation of rewards of all isolated intersections, where the reward of main road should be weighted more heavily.

In [43] and [44], the evolutionary game theory and reinforcement learning were introduced to the agents. Intersections in an arterial are modeled as individually-motivated agents or players taking part in a dynamic process in which not only their own local goals but also a global one has to be taken into account.

In [45] and [46], Wiering et al. utilized multi-agent reinforcement learning algorithm to train traffic signal controller. The goal is to minimize the overall waiting time of cars in a city. Where the states include the traffic nodes where cars stand, orientation of cars, positions in the queue and destination addresses. The action is to set the light to green or red. The reward function is used as follows: if a car stays at the same place, the reward r =1. Otherwise r=0 (the car can advance). This reinforcement system learns the assignment function (which is used to estimate overall waiting time of cars) under different setting of lights. Apparently, changes of traffic lights will result in a new combination of waiting time predicted. In paper 42, a traffic signal control system is developed based on the ideas above. Because the signal controller relates to uniparted vehicle (only consider vehicles waiting in the queue before an intersection), the optimal control strategy for area traffic control can be obtained by using this method. At the same time, the strategy of every vehicle is also optimal. That is to say, drivers can choose the shortest path while costing the least waiting time.

Thorpe (see [47]) presented a traffic signal control method based on SARSA reinforcement learning algorithm. The method uses a discrete state-action space to represent the states and actions. The current state is characterized for SARSA by the queue length, positions of vehicles in the queue, and the elapsed time current light lasting. The action for a given state is to keep previous color or set it to its opposite color. The reward is defined as follows: there are four vehicle detectors near the stop line at every intersection. If one of the detectors corresponding to a green (or red) light is activated, the reward is incremented (or decreased) by 1. If both detectors corresponding to green (or red) light have been activated, the reward is decremented (or incremented) by 2. The reward is initially -3. Apparently the reward varies between -5 and -1. Simulation is made in a 4´4 network with different parameters. The simulation result showed this method was better than fixed-time control.

The advantage of reinforcement learning is that it is not necessary to establish the mathematic model for external environment. However, there is also a disadvantage of converging slowly. It can be easily understood: comparing with those methods requiring mathematic model for external environment, it is provided fewer information about environment. So it is impossible to converge quickly. If mathematic model of external environment or enough samples can be obtained, we needn't use reinforcement learning methods. From this standpoint, the reinforcement learning methods are more suitable for strategic control of traffic system, such as arterial and area coordinated traffic control.

3. Prospect

The traffic system is regarded as a nondeterministic object in the urban traffic adaptive control system, and it can continuously measure the states such as traffic volume, speed, and density (queue length) and gradually understand and grasp the object. After compare with expected dynamic characteristics, it makes use of their differences to adjust the adjustable parameters of the system or to implement control directly. In this way, no matter how the environment changes, the control effect is optimal or sub-optimal (see [2,4]). Singh et al. (see [48]) regarded this problem as a dynamic optimal control one following the definition of industrial control. In fact, comparing with industrial system, the traffic control system has its own particular characteristics. Because traffic trip behaviors relate to human directly, the randomicity, fuzzyness and nondeterminacy of traffic system is more distinct than which in industrial process. So the breakthrough can't be achieved by copying methods of industrial control. Apparently, modeling and optimization are the two main problems that traffic adaptive control system encounters. Yet no satisfying modeling method and traffic model are found so far. A general timing optimization problem is essentially a nonconvex mathematic programming problem. But how to find the global optimal solution is a problem unsolved theoretically, which is still on the exploring stage. Ceaseless development of artificial intelligence theory brings hopes to solving the problem above. Two further considerable research directions are proposed as follows:

3.1 Pattern discovery methods

A number of practical experiences have shown that operation states of urban traffic can be divided into different patterns, and the patterns are often recurrent (see [49,50]). There should be an optimal timing plan corresponding to each traffic pattern. This optimal timing plan can be obtained by using theoretical analysis or traffic analysis software. These traffic patterns and corresponding plans can be stored in the control system. When running, the system detects real-time traffic data, and then judges that which pattern the current traffic condition should belong, for example, D-S evidential theory can be used to solve this problem (see [51]). So the system runs the corresponding optimal timing plan. Now, the problem is how to find these patterns. Andrew presented a basic method for pattern discovery (see [51]). However some special researches on urban traffic system should be made. There are still a lot of things to do before solving this problem, for example, processing mass data. The rough set theory is used to make attribute reduction for traffic volume (see [52]), and make patterns discovery more efficient.

3.2 Reinforcement learning methods

Since the application framework of traffic control system based on agent was presented in [36], many fruitful researches have been made. As one of the basic technologies of the agent, reinforcement learning is still under development (see [34,35]). So far it has become the research hotspot in many fields such as process control, task scheduling, robot design and games. When using reinforcement learning, the state transitions of environment must be a Markov decision process (MDP). Otherwise, the reinforcement learning algorithm may not converge. So if want to apply reinforcement learning to traffic control system, first we must find out whether this system is a MDP. In the field of urban traffic control, the researches on this method are just beginning. Because of its good performance in a large space and complex nonlinear system, we should make further researches on urban traffic control theories and methods based on reinforcement learning.

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