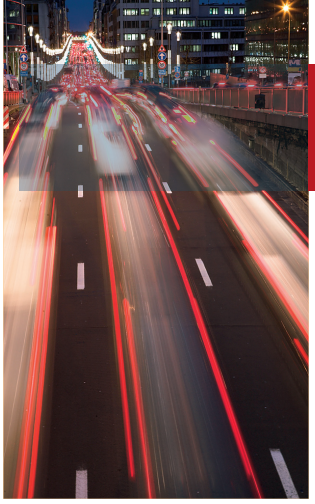

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Agent Recommendation for Agent-Based Urban-Transportation Systems

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The agent computing paradigm has been developing rapidly over the last few decades and is becoming one of the powerful technologies in the development of large-scale complex systems. The characteristics of mobile agents, such as autonomy, mobility, and adaptability, make them a good candidate for a traffic management system because they can deal with the changes and uncertainty in dynamic traffic environments.[1] A review of agent-technology applications in traffic and transportation systems shows that intelligent agent techniques and methods have been applied to many aspects of traffic and transportation systems, including modeling, simulation, dynamic routing, congestion management, and intelligent traffic control.[2] Although researchers in the field have made significant efforts in applying agent technology in traffic and transportation systems, little research has looked at the dynamic selection of the most appropriate control agent to cope with specific traffic states in urban transportation systems.

To address this problem, we proposed a recommendation platform to integrate with an agent-based distributed and adaptive platform for transportation systems (Adapts) to provide an agent recommendation service.[3] Adapts is one of the major components of parallel transportation management systems (PtMS).[4,5] The proposed recommendation system selects the most suitable control agent to meet dynamic traffic-management demands based on the control agent's applicable environment and functions.

Agent-Recommendation Platform

The agent-recommendation platform we present here is a subsystem in the Adapts organization layer. Figure 1 shows the architecture of the recommendation platform and its interactions with Adapts, real-world traffic systems, traffic strategy developers, and traffic managers. The platform consists of three subsystems (the performance-analysis system, traffic-state forecasting system, and the agent-recommendation system), two databases (the traffic-control agent database and traffic-state database), and two servers (the traffic-strategy server and systematic-state server).

Newly developed traffic strategies are submitted to the traffic-strategy server. Each traffic-control strategy is implemented in a control agent, and all the control agents are stored in the traffic-control agent database. The control agents are evaluated by the performance analysis system based on certain evaluation rules. The performance-analysis system includes an artificial transportation system (ATS),[6] which uses real traffic data in the traffic-state database to mimic real-world urban-traffic scenarios. The real-time traffic data are continuously collected by the sensor networks from the actual transportation systems. These traffic data are also used by the traffic-state forecasting system to predict the future states of the actual transportation system and for the systematic-state server to respond to the queries issued by the traffic managers.

The role of the traffic-state forecasting system is to counteract the influence of the transmission delays in the management system and

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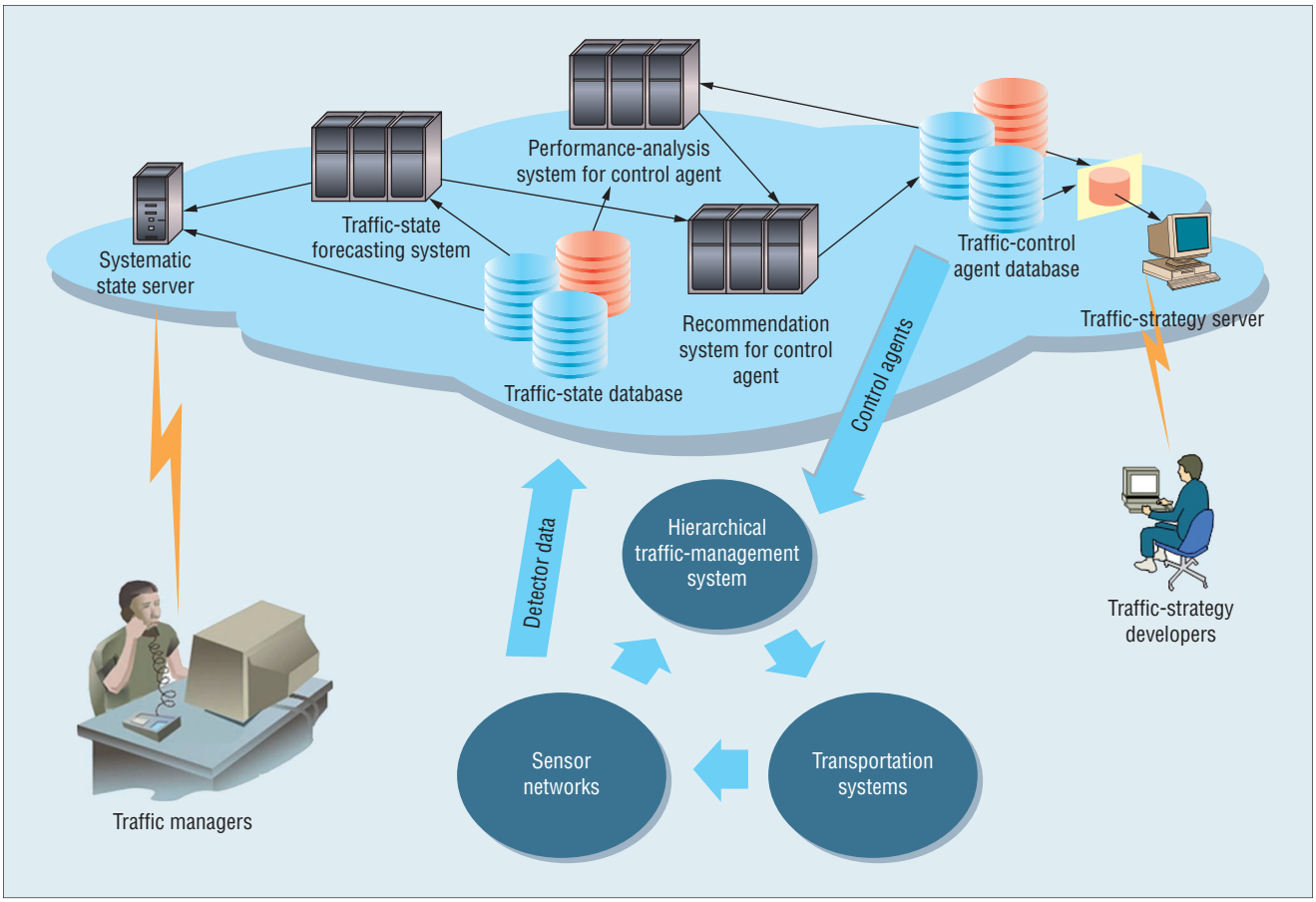

Figure 1. The architecture of the recommendation platform and its interactions with the traffic-management system and the real-world transportation system.

Table 1. Mutative demand of traffic management.

State of traffic environment	Traffic-management demand
Congestion	Balance of vehicle queue
Normal	Low average delay time
Unobstructed	High one-time pass rate

prevent the appearance of a large fluctuation of the traffic states. When the forecasting system predicts the deterioration of a traffic state, the management system's control demand will be adjusted based on the new traffic state. A different control agent is then recommended to the hierarchical traffic-management system. This new control agent will be the most suitable agent for the new control demand based on the performance analysis system's evaluation.

Agent Recommendation

The goal of the agent-recommendation system is to determine the most suitable control agent for a specific traffic state to achieve desired control objectives. The control agent includes two selection criteria. The first criterion is to check if a control agent is applicable to the traffic-control environment. The second criterion is to evaluate a control agent's effectiveness to meet the demand of traffic management. To introduce the recommend mechanism in detail, we first define various traffic-management demands and the modeling of a control agent.

Traffic-management demand

Traffic management demands vary with the traffic environment's state. Table 1 shows the traffic-management demands for the congestion, normal, and unobstructed traffic states. In the congestion state, a traffic-management system's most important objective is to avoid a long waiting time or vehicle queue. Hence, the goal is to balance the vehicle queue in all links of an intersection. In the normal state, a traffic-management system tries to shorten the travel time as much as possible. As a result, the average delay time is given the highest priority.

In the unobstructed state, there are only a few cars on the road, so it is

hard to shorten the travel time by adjusting the control mode. In this case, we pay special attention to the energy consumption of the transportation. The high one-time pass rate is chosen as the demand of the traffic management system to reduce the number of times vehicles must restart in intersections.

Once the traffic-management demands at different traffic states are defined in a computer, the aims of a traffic-management system are interpreted in a way that can be understood by the computer. These measurable traffic management demands are then used by the recommendation system for dynamic agent selection.

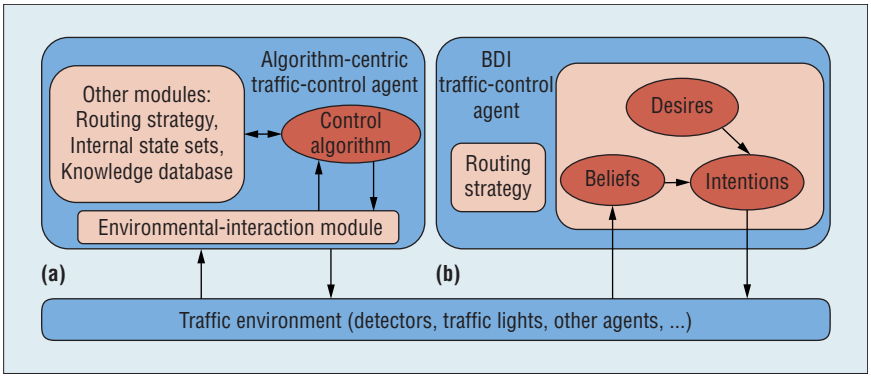

Figure 2. Two types of agent models for control agents. (a) The control agent's architecture includes the environmental-interaction and the algorithm module. (b) The BDI control agent includes three major components: beliefs, desires, and intentions.

Agent Modeling

For most existing traffic management systems, a control agent usually acts as the carrier of traffic-control algorithms or strategies.[7–10] The control agent's architecture includes two major components: the environmental-interaction module and the algorithm module (see Figure 2a). The environmental-interaction module's main function is to allow a control agent to exchange information with the outside world. The algorithm module is a core module that processes traffic information and performs decision making.

This type of agent structure is called an algorithm-centric structure. In addition to the environmental-interaction module and the algorithm module, an algorithm-centric traffic-control agent might also include modules such as a routing module for mobile agents. From the traffic-control point of view, there is no difference between a traffic-control agent and the control algorithms wrapped by the agent. As a result, the performance evaluation of a control agent is the same as the evaluation of control algorithms carried by the agent. The typical measures of effectiveness (MOEs) of a control agent include average speed, average delay time, one-time pass rate, and so on.

Although an algorithm-centric control agent can provide basic functions for traffic control and the interactions with traffic systems, additional characteristics are needed to achieve autonomy. An autonomous agent is defined as a system within and part of an environment that senses the environment and acts on it over time, in pursuit of its own agenda, to affect what it senses in the future.[11] According to this definition, an autonomous agent should be reactive, autonomous, goal-oriented, and temporally continuous. The Belief-Desire-Intention (BDI) software model is a good fit for implementing these properties in a software agent.[12] Figure 2b shows the architectural components of a BDI control agent, which includes three major components: beliefs, desires, and intentions.

Beliefs. In a BDI model, an agent's beliefs represent the information about its world. The beliefs of a traffic-control agent include the applicable operating environment and real-time environmental information. The first part is predefined for a specific control agent where it can be applied. It includes the information of the applicable intersections (the type of intersections or their traffic state), the minimum operational requirement, the traffic-management system architecture, and so on.

The second part represents the real-time traffic information perceived by a control agent and the communication of this agent with other system components. It includes detector data (the traffic-flow data), agent-coordination information, the state of the entire traffic-management system, and the agent's internal state.

Desire. The desires represent a BDI agent's motivational state. It reflects the goals of a control agent. The desires of a traffic-control agent can have single, multiple, or subperiod objectives. These objectives correspond to the reference indexes of the MOEs. A control agent's desires can be a single index or a combination of multiple indexes of the MOEs for the applied intersection or area. We expand MOEs to include some new indexes, such as the balancing vehicle queue in all links of an intersection. The objectives of a control agent are used as the evaluation indexes in the performance analysis. We assume that a control agent with desires that match the control objectives will perform better compared to others.

Intentions. Intentions are desires that an agent has chosen to achieve by executing plans. This component describes the details of the process an agent uses

in pursuit of its certain desires. A traffic-control agent's plan is a sequence of operations defined by control algorithms. This component provides a mechanism for a control agent to act on the environment where it resides.

With a BDI model, a traffic-control agent's goal-oriented characteristic can be implemented with the three components we discussed earlier. The performance evaluation of a control agent is based on an agent's beliefs and desires rather than several fixed indexes of the MOEs. In addition, only those agents with an applicable operation environment and performance indexes that match the state of traffic environment and the traffic-management demands will be evaluated. For example, a control agent designed to handle the state of congestion on a ramp will not be evaluated for the traffic control at a crossroad in the normal state. This approach allows more efficient and better-targeted performance analysis of control agents.

Recommend Mechanism

The recommendation system selects the most suitable control agent for a traffic-management system by scoring control agents through a two-stage filtering process. The most suitable agent has the highest score among the agent candidates. Let S_i denote the score of the ith agent. The value of S_i is equal to $S_{1i} * S_{2i}$, where S_{1i} is the agent score assigned from the first filtering stage and S_{2i} is from the second filtering stage. In the first stage, the actual environment is compared with the assumption and modeling of the applicable environment of a control agent defined in the beliefs component. The agent score in the first stage only has two possible values: 0 or 1. If the agent-applicable environment matches the actual environment, the value 1 is assigned to S_{1i}; otherwise, 0 is assigned to S_{1i}. The same scoring rule also applies to the comparison of the management system's demand and the control agent's desire. If the desire module does not contain the management system's demand, the value of S_{1i} is set to 0; otherwise, it is set to 1. If the value of S_{1i} of a control agent is equal to 1, it will enter into the second filtering stage.

The second stage will score the agent's control effectiveness based on its performance report obtained from the performance-analysis system. A control agent's performance index can be a single index or multiple indexes. For each index, the performance of all the agents is normalized to the best performance. The value of S_{2i} for a control agent can be expressed as follows:

$$S_{2i} = \sum s_{2ij} * w_j$$

where s_{2ij} is the normalized performance of the control agent i on the jth performance index and w_j is the weight of the jth performance index. After these two stages, the most suitable control agent is the one with the highest score. This agent will be recommended for the traffic management by the recommendation system.

> Our goal is to enable dynamic selection of the most appropriate control agents for a specific traffic state in urban-transportation systems.

The agent recommendation mechanism and platform we present here provide a guideline to enable dynamic selection of the most appropriate control agents for a specific traffic state in urban-transportation systems. With this recommendation platform, newly developed or legacy traffic-control algorithms can be dynamically incorporated into existing traffic-management systems through mobile agent technology and the recommendation system ensures that the deployed control agent has the best performance for a specific traffic-management demand among available control agents. Future work will focus on the integration of this recommendation platform into real-world traffic-management systems and the further development of a performance-analysis system to include more performance indexes and evaluation rules.

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