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Adaptive Fuzzy Urban Traffic Flow Control Using a Cooperative Multi-Agent System based on Two Stage Fuzzy Clustering

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Abstract— The traffic congestion problem in urban areas is worsening since traditional traffic signal control systems cannot provide efficient traffic control. Therefore, dynamic traffic signal control in Intelligent Transportation System (ITS) recently has received increasing attention. This study devises an adaptive and cooperative multi-agent fuzzy system for a decentralized traffic signal control. To achieve this we have worked on a model which has three levels of control. Every intersection is controlled by its own traffic situation, correlated intersections recommendations and a knowledge base which provides its traffic pattern. This study focused on utilizing the prediction mechanism of our architecture, it finds most correlated intersections based on a two stage fuzzy clustering algorithm which finds most intersections effect on a specific intersection based on clustering membership degree. We have also developed a NetLogo-based traffic simulator to serve as the agents' world. Our approach is tested with traffic control of a large connected junctions and the result obtained is promising: The average delay time can be reduced by 42.76% compared to the conventional fixed sequence traffic signal and 28.77% compared to the vehicle actuated traffic control strategy.

Keywords- MAS; Intelligent Transportation System; Fuzzy Control; Fuzzy Clustering; Traffic Light Control,

I. INTRODUCTION

Traffic congestion is a crucial problem in large cities. It is partially caused by improper control of traffic lights, which is not corresponding to the current traffic conditions. To alleviate traffic congestion in urban areas, the concept of Intelligent Transportation Systems (ITS) has been widely accepted in developed countries. ITS is a highly promising system for providing key solutions to current road congestion problems [1].

The problem of intelligent traffic control has been studied in the area of ITS for many years. We will refer to only a few which are related to our work. The first one is the method of Vehicle Actuated Signal Control (VA). This method controls traffic lights by considering the number of cars waiting in the queue to be serviced by a traffic light. When the current green light is going to be changed to red, but the sensor can detect that some cars have come in that range of distance, the duration of the green light is extended further [2, 3]. Some other

methods are based on gathering traffic information during different times of day and year to help agents to make decisions [4, 5]. Using fuzzy control [6, 7], timed Petri Nets [8], SPSSA [9], ant algorithm [10], knowledge based multi-agent system [11, 12], and a mobile agent [13] have also been suggested.

The domain of traffic signal control is well suited for multi-agent based approaches owing to its distributed nature. Researchers and practitioners have now realized that single agent system [14], multi-agent systems and distributed artificial intelligence are attractive because they consider the social aspects of computer systems, ranging from human computer interaction over distributed problem solving, to the simulation of social systems [15].

But recently, multi-agent decentralized strategies for controlling urban traffic networks have attracted considerable attention. Roozmond and Rogier [16] proposed a prototype using agent technology to control traffic signal systems. Srinivasan and Choy [17] used advanced cooperative behaviors to improve individual agent's learning process, Chang-Qing Cai and Zhao-sheng Yang [18] proposed an architecture composed of segment agents, crossing agents and section agents that it can realize an intelligent traffic management by sharing information. Ferreira et al. [19] also presented a multi-agent strategy where its agents optimize a traffic index based on its local state and sensors, and also on information from adjacent intersections.

It appears that all these approaches lack a unified model and use only a fix number of neighbor intersections to predict traffic flow (the neighborhood area in most of them is limited with physical distance). Therefore we have proposed a model with a high abstraction, which considers most correlated intersections to predict traffic volume. Furthermore, each agent has the ability to communicate; enabling each agent to exchange relevant traffic information and cooperative with other multi-agents through a flexible architecture. The flexibility of this architecture is achieved through a modular design. To control the traffic volume in each intersection, we use three parameters:

- 1) *Intersection Traffic volume (number of stopped cars behind red light and flow of cars from green light).*
- 2) *Correlated intersections traffic volume.*

3) Intersection Traffic pattern.

In this paper we propose a cooperative multi agent approach and an adaptive fuzzy inference system based on two stage fuzzy clustering for traffic light control, which efficiently manages the traffic flow according to its current conditions. In addition, we have developed an agent-based traffic simulator in NetLogo [20] that we can easily use to test and evaluate the performance of our approach.

II. PROPOSED MODEL

A. Overview

This section describes the proposed architecture and its components. From Fig. 1, the system architecture comprises of four parts:

- Smart Agent (or SA; each intersection has an SA)
- Traffic Simulator Sensor
- Traffic Simulator Green Light
- Two Stage fuzzy Clustering

The information flow in this model can be described as follows: first, the traffic simulator sensor is used to monitor the traffic volume and forward it to the corresponding SA. Two stage fuzzy clustering module finds all correlated intersections with corresponding intersection and their correlated degrees. Then the corresponding SA communicates and gets traffic flow of correlated intersection's SAs and begins to generate an appropriate traffic signal control strategy for the specific traffic signal using a fuzzy inference system. The data is processed in the SA Traffic Observer Module. SA communicates with other correlated intersections SAs via the Correlation Module.

After gathering all of the necessary information, Knowledge Base Module generates a pattern related to this intersection. The generated results are delivered to Real Traffic Data Preparation Module to prepare the real traffic volume behind the red light, provide a real traffic flow through green light of the corresponding intersection, and send the information to a fuzzy inference engine to set the control parameters of traffic lights. Traffic Observer, Signal Plans Interpreter, Correlation Module, Knowledge Base, and Pattern Module have been written in NetLogo. Real Traffic Data Preparation Module, Fuzzy Inference engine, and two stage fuzzy clustering have been implemented with MATLAB.

Components in SA are shown in Fig. 2. Their functions are briefly summarized below.

B. Traffic Observer

To control the urban traffic, the traffic volume of each intersection's sides should be known, first. The NetLogo programmer API reports raw data about traffic volume for a specific intersection to the Traffic Observer; then it reports the count of the cars that are behind the red light and the count of the cars flowing from the green light of the corresponding intersection every 16 minutes to the Real Traffic Data Preparation Module. Whereas in our Netlogo simulator model the distance between two intersections was 25 patches

(NetLogo's unit) and any turtles (NetLogo's car) move one patch in one minute. Therefore, 16 minutes is a good time to report data without too much redundancy.

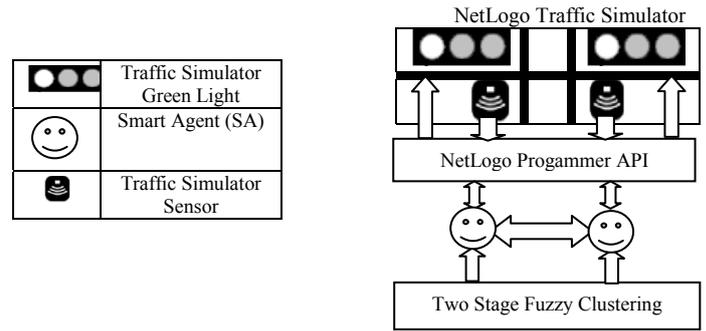


Fig. 1. Overview of the proposed approach.

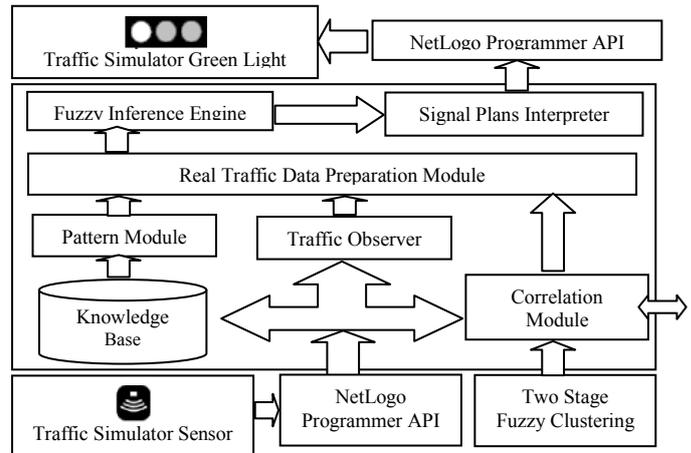


Fig. 2. Structure of Smart Agent.

C. Traffic Volume Prediction

By using the output of the two stage fuzzy clustering we determined the most correlated intersections to any specific intersection by using a two stage fuzzy membership degree (that show their traffic effects on the specific intersection).

If the two stage fuzzy membership degree of an intersection in relation to a specific intersection is high, it means that its traffic effect on the specific intersection is high and vice versa.

D. Knowledge Base

To Control the urban traffic in each intersection, in addition to the correlated intersection traffic volume, the traffic pattern of the corresponding intersection is also important. To extract an intersection traffic pattern, the traffic volume in seven days of week (in rush and slow hours) should be gathered and be fed to a learning module [5]. Since in the NetLogo traffic simulator it is difficult to simulate different week days, with different traffic conditions (like weekend with rush hours in some intersections and slow hours in other ones), a simplified scheme is considered: we put 400 turtles in an area of 81 intersections as the distance between every two intersections is

25 patches and each turtle length is equal to 1 patch. Every 16 minutes we measured the traffic volume in each intersection and repeated this for 2000 minutes, then calculated the mean and the standard deviation of traffic flow of each intersection in one minute. With this information we could approximately extract the traffic flow pattern of each intersection and create a knowledge base for it.

E. Fuzzy Inference Engine

Another principle in the model is the algorithm chosen to provide the control agents with a decision-making capability. A rule-based approach is suitable if a human expert can describe the control task as a set of rules. In these cases, fuzzy rule-based inference can be a suitable solution [6].

Traffic in general is controlled by rules, which makes rule-based signal control a plausible choice. A rule-based approach gives better control related to how the system should behave [6]. Therefore, this module is a fuzzy rule-based module and it has two inputs: the traffic flow from the green light and the stopped cars behind the red light. These two inputs are prepared through Real Traffic Data Preparation Module. The output of the inference engine gives control parameters that are sent to Signal Plans Interpreter Module. We provided fuzzy sets of this module with use of the mean and the standard deviation calculated in previous section (See Fig. 3).

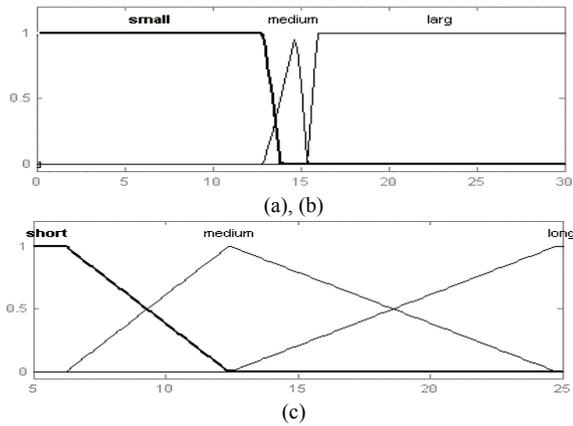


Fig. 3. Fuzzy sets of fuzzy Inference engine. (a) Input: cars behind green light, (b) Input: cars behind red light (c) Output: green light extension

III. TWO STAGE FUZZY CLUSTERING

Data Clustering is one of the most important tools in intelligent information investigation, which belongs to soft computing group [21]. It is to put similar data in one class and different data in different classes [21]. But in real-world, data has not clear boundaries. As a result we cannot separate them, completely. In fuzzy clustering, data can belong to more than one class with different membership degrees; as a result it is more similar to clustering in real world [22].

Before intersections clustering, we should determined metrics for it. Distance between intersections is not a sufficient metric for clustering because sometimes two near intersections do not impact on each other's traffic volume. Therefore, we used intersection positions (x,y) , traffic volume mean, and standard deviation in each intersection together as metrics for fuzzy clustering [26]. These three factors create better result

because if two close intersections have similar traffic volumes, means and standard deviations, then their traffic volume changes are predictable from the traffic volume of the neighbor.

In the first stage, we clustered intersections by using the above metrics (four dimensions). But in the second stage we clustered again by adding the first stage membership degree of each intersection as a new metric to the previous metrics.

A. Fuzzy C-mean Clustering Algorithm

We use the following notations in our approach:

Equation (1) denotes data that is used in clustering [23]:

$$z_k = [z_{1k}, \dots, z_{nk}]^T \quad z_k \in \mathfrak{R}^n, \quad Z = \{z_k \mid k=1,2,\dots,N\} \quad (1)$$

Each vector has n elements (N is the number of data vectors), and the matrix of whole vectors is [23]:

$$Z = \begin{bmatrix} z_{11} & z_{12} & \dots & z_{1N} \\ z_{21} & z_{22} & \dots & z_{2N} \\ \vdots & \vdots & \ddots & \vdots \\ z_{n1} & z_{n2} & \dots & z_{nN} \end{bmatrix} \quad (2)$$

In this paper, vector elements are intersection coordinates (x,y) , intersection mean, and standard deviation.

The limitations of fuzzy clustering are [23]-[25]:

μ_{ik} : The membership degree of each data vector to each cluster

$$\mu_{ik} \in [0,1] \quad 1 \leq i \leq N, \quad (3)$$

$$\sum_{i=1}^c \mu_{ik} = 1 \quad 1 \leq k \leq N,$$

$$0 < \sum_{k=1}^N \mu_{ik} < N \quad 1 \leq i \leq c.$$

$$M_{fc} = \left\{ U \in \mathfrak{R}^{c \times N} \mid \mu_{ik} \in [0,1], \forall i, k; \sum_{i=1}^c \mu_{ik} = 1, \forall k; 0 < \sum_{k=1}^N \mu_{ik} < N, \forall i \right\}$$

Where matrix U contains membership degrees of all elements to all clusters.

The main goal of clustering is to minimize a cost function. In this approach we use (4), as a cost function [23, 24]:

$$J(Z; U, V) = \sum_{i=1}^c \sum_{k=1}^N (\mu_{ik})^m D_{ikA}^2, \quad D_{ikA}^2 = \|z_k - v_i\|_A^2 = (z_k - v_i)^T A (z_k - v_i) \quad (4)$$

that

$$A = \begin{bmatrix} (1/\delta_1)^2 & 0 & \dots & 0 \\ 0 & (1/\delta_2)^2 & \dots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \dots & (1/\delta_n)^2 \end{bmatrix} \quad (5)$$

V : Cluster center vectors and δ_i : is the variance of the i^{th} cluster.

Finally the following C-mean algorithm is iteratively used to find the intersection fuzzy clusters:

1) Find the distance between vectors and each cluster center using (6).

$$D_{jkA}^2 = (z_k - v_i^{(l)})^T A (z_k - v_i^{(l)}) \quad 1 \leq i \leq c, 1 \leq k \leq N. \quad (6)$$

2) Find membership degree of each element by (7).

for $1 \leq k \leq N$ (7)

if $D_{ikA} > 0$ for all $i=1,2,\dots,c$

$$\mu_{jk}^{(l)} = \frac{1}{\sum_{j=1}^c \left(D_{ikA} / D_{jkA} \right)^{\frac{2}{m-1}}},$$

otherwise

$$\mu_{ik}^{(l)} = 0 \text{ if } D_{ikA} > 0 \text{ and } \mu_{ik}^{(l)} \in [0,1] \text{ with } \sum_{i=1}^c \mu_{ik}^{(l)} = 1.$$

3) Find cluster centers by (8) again.

$$v_j^{(l)} = \frac{\sum_{k=1}^N (\mu_{jk}^{(l-1)})^m z_k}{\sum_{k=1}^N (\mu_{jk}^{(l-1)})^m} \quad 1 \leq j \leq c. \quad (8)$$

4) Repeat all above steps until $\|U_{(l)} - U_{(l-1)}\| > \epsilon$

Clusters obtained from this algorithm have oval or circular shapes [23].

In C-mean clustering algorithm, we must determine the number of clusters before clustering [23]. Natural data cluster's number is the best candidate for the cluster's number, but it is difficult to find it. Therefore, we define criterion (9) to evaluate the clustering that are done with specific number of clusters [23].

$$\chi(Z; U, V) = \frac{\sum_{i=1}^c \sum_{k=1}^N \mu_{ik}^m \|z_k - v_i\|^2}{c \cdot \min(\|v_i - v_j\|^2)} \quad (9)$$

The best cluster number has the least χ value; therefore, we did clustering with different cluster numbers and selected the cluster number with the minimum χ value.

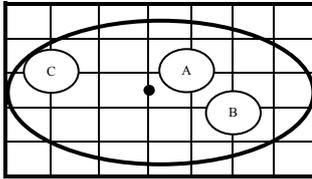


Fig. 4. Intersections B, C have the same membership degrees. A, B have not equal membership degrees, but they have more near correlated data rather than B and C.

B. Two Stage Fuzzy Clustering Algorithm

At the first stage of fuzzy clustering, we divided intersection coordinates, mean and standard deviation values to

c clusters and found the best c clusters number using Equation (9) (in the proposed approach c is 12).

Whereas the C-mean fuzzy clustering algorithm calculates the data membership degrees to the cluster centers. Therefore if two data have equal membership degrees, it does not mean they are correlated, rather it means they have equal distance to the center of the cluster (see Fig. 4). Therefore, the membership degree of this stage cannot precisely determine the data correlations, therefore, at the second stage we clustered each above cluster again in the following manner to find correlated data:

1) For each cluster we selected the intersection that had the most membership degree to it.

2) We added membership degree to each intersection's data vector as a new dimension.

3) We clustered each cluster again with the new data.

Equation (10) shows the second stage of the sub cluster's number for each c cluster.

$$\begin{aligned} \text{for } 1 \leq i \leq c \\ \text{if } n_i > 4 \\ \quad c_{i2} = \lfloor n_i / 4 \rfloor \\ \text{else} \\ \quad c_{i2} = \lfloor n_i / 2 \rfloor \end{aligned} \quad (10)$$

C_{i2} : The sub cluster number of cluster i in the second stage.

K_i : The set of all vectors which their maximum membership degree belongs to cluster i .

n_i : The number of K_i members.

We found Equation (10) by using Equation (9), experimentally. We wrote another application that used the above results to calculate the correlation between the two intersections' traffic as in Equation (11).

$$\begin{aligned} \text{if } x \in K_i, y \notin K_i \\ \quad \lambda = 0 \\ \text{else} \\ \quad \lambda = 1 - |\mu_x - \mu_y| \end{aligned} \quad (11)$$

x, y : two intersections.

λ : the correlation between intersections.

μ_x, μ_y : x, y membership degrees

Whereas we want to calculate the correlation of x in relation to y ; therefore, we found a sub cluster that has the most membership degree of y and determines the x membership degree to it, then subtract them to calculate the correlation.

IV. EXPERIMENTATION

We performed some experiments using the Knowledge Base section assumptions in order to compare our approach with other works. The experiment aimed at determining the simulated average delay time of a specific urban traffic

network and achieved by the proposed architecture, when compared to the conventional fixed sequence and VA signal control strategy. In the present definition, average delay time is the average of all cars waiting times in front of all traffic lights in a specific traffic network.

Further investigations shows our approach reduced average delay time by 42.76% compared to the fixed sequence traffic signal and 28.77% compared to the VA control strategy (see Fig. 5).

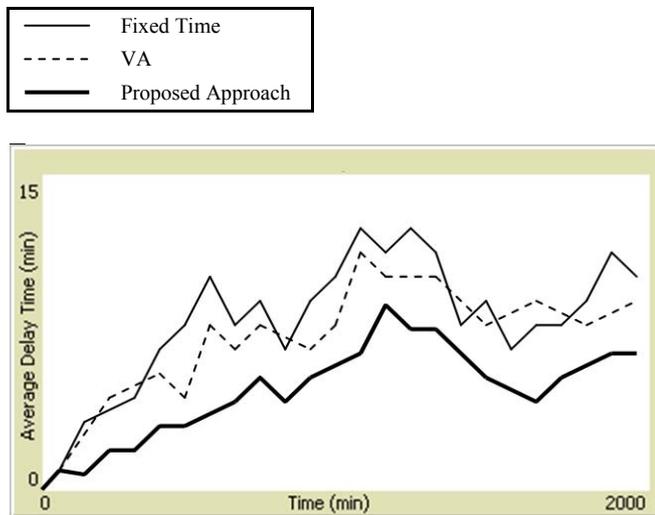


Fig. 5. Average delay time comparison of fix sequence, VA traffic signal control strategy and our approach.

V. CONCLUSIONS

We have presented a multi-agent approach for decentralized fuzzy traffic signal control which efficiently manages the traffic according to the current traffic condition, correlated intersections traffic condition, and pattern traffic conditions. It predicts traffic flow in each intersection by considering most correlated intersections as neighbors and implies their traffic volume by the correlation degree which is extracted from a two stage fuzzy clustering. Our model also enhances flexibility and extensibility owing to its modular design. Modular design means that the module within the architecture can be substituted using better and newer modules when necessary. A decentralized control strategy achieves improved scalability by adopting a multi-agent system, since each agent oversees the local optimization problem and no master controller is required. Thus, adding new intersections to the network only increases the computational loading on fuzzy clustering stage. Also agent fuzzy decision-making capability can be used to achieve a balance between efficiency, safety, and environmental objectives in traffic control.

The simulation results demonstrate that the model outperformed the conventional fixed sequence and VA traffic signal control strategy.

REFERENCES

- [1] N. Fujimoto, M. Moriya, A. Ishizuka, and M. Goto, "Intra- and inter vehicle communication network using low-cost POF links", *IEICE Trans. Inf. & Syst.*, Vol. E85-D, no.11, Nov. 2002, pp.1839–1850.
- [2] H. Taale, "Comparing methods to optimize vehicle actuated signal control", in *IEE conference publication Road Transport Information and Control*, 2002, 486, pp. 114-119.
- [3] R.T. van Katwijk, "Multi-agent look-ahead traffic-adaptive control", Ph.D. thesis, TRAIL Research School, The Netherlands, 2008.
- [4] Sascha Ossowski, Jose Uena and Ana Garcia-Serrano, "A case of multiagent decision support: using autonomous agents for urban traffic control", *IBERAMIA* 1998: 100-111.
- [5] Marjan Kaedi, Naser Movahhedinia and Kamal Jamshidi, "Traffic signal timing using two-dimensional correlation, neuro-fuzzy and queuing based neural networks", *Neural Comput & Applic*, 2008 17:193–200.
- [6] I. Kosonen, "Multi-agent fuzzy signal control based on real-time simulation", *Transportation Research, Part C*, pp. 389-403, 2003.
- [7] P. Hsu and H. Liu, "The MAS with an adaptive fuzzy algorithm for flow control of traffic networks", *National Science Council*, 2007.
- [8] A. Th. Van den Bosch, M. R. Menken, M. V. Breukelen, and R. T. Van Katwijk, "A test bed for multi-agent system and road traffic management", *Proc. 15th Belgian-Netherlands Conf. on Artificial Intelligence (BNAI'03)*, Vrije Universiteit, Amsterdam, 2003. URL: <http://www.cs.vu.nl/~mrmenken/BNAI03.php>
- [9] M.C. Choy, D. Srinivasan, and R.L. Cheu, "Simultaneous perturbation stochastic approximation based neural networks for online learning", *Proc. 7th IEEE Int. Conf. Intelligent Transportation Systems*, October 2004, pp. 1038–1044.
- [10] C. Bertelle, A. Dutot, S. Lerebourg, and D. Olivier, "Road traffic management based on ant system and regulation model", *MAS conference*, 2003. URL: <http://www.liophant.org/mas2003/index.html>
- [11] K. Dresner and P. Stone, "Multiagent traffic management: an improved intersection control mechanism", *AAMAS'05*, July 2529, 2005, Utrecht, the Netherlands.
- [12] V. Hirankitti and J. Krohkaew, "An agent approach for intelligent traffic-light control," *First Asia International Conference on Modeling & Simulation (AMS'07)*, pp. 496-501, 2007.
- [13] H. Kheyruri, A. Z. Jahangiri and A. Pardakhtchi, "Independent agents for urban traffic control problem with mobile-agent coordination," in *Proc. 7th WSEAS International Conf. Computer Science*, Venice, Italy, 2007, pp. 372-376.
- [14] Y Hong, G Lee, C Kim and JW Kim, "Traffic signal planning using a smart agent system," *Computer Science, KES-AMSTA 2007*, Springer LNAI 4496, pp. 938–947, 2007.
- [15] R. Schleiffer, "Intelligent agents in traffic and transportation," *Transportation Research Part C: Emerging Technologies*, Vol.10, no.5–6, pp.325–329, Oct.–Dec. 2002.
- [16] D.A. Roozmond and J.L.H. Rogier, "Agent control traffic lights," *ESIT2000*, Aachen, Germany, Sept. 2000.
- [17] D. Srinivasan and M.C. Choy, "Cooperative multi-agent system for coordinated traffic signal control," in *Proc. IEEE, Conf. Intelligent Transport Systems*, March 2006, Volume: 153, Issue: 1, pp 41–50.
- [18] C.Q. Cai and Z.S. Yang, "Changchun study on urban traffic management based on multi-agent system," presented at the *2007 Int. Conf. Machine Learning and Cybernetics*.
- [19] E.D. Ferreira, E. Subrahmanian, and D. Manstetten, "Intelligent agents in decentralized traffic control," in *Proc. IEEE, Conf. Intelligent Transportation System*, Aug. 2001, pp. 25–29.
- [20] Uri Wilensky, *NetLogo User Manual version 4.0 3*, Center for Connected Learning and Computer-Based Modeling, Northwestern University, Evanston, IL. Available at: <http://ccl.northwestern.edu/netlogo/>. As accessed on August 21, 2008.
- [21] D. Man and M. Tosa-abrudan, "Fuzzy Clustering Algorithms: A Survey," *7th Joint Conference on Mathematics and Computer Science*, July 2008.
- [22] J. Jantzen, "Neurofuzzy Modelling," University of Denmark, Denmark, Rep. 98-H-874 (nfmode), 1998.
- [23] X. L. Xie and G. A. Beni, "Validity measure for fuzzy clustering," *IEEE Trans. on Pattern Anal. and Machine Intell.* 3(8), 841–846, 1991.
- [24] J. Valente de Oliveira, W. Pedrycz, *Advances in fuzzy clustering and its applications*, John Wiley & Sons, 2007, pp. 5-10.
- [25] W. Pedrycz, *Knowledge-based clustering*, John Wiley & Sons, 2005, pp. 1-27.
- [26] W. Weijermars, "Analysis of urban traffic patterns using clustering," Ph.D. dissertation, University of Twente, 2007.