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Impact of Vehicle Detection Accuracy to the Performance of Intelligent Traffic Control System

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ABSTRACT

Road network is one of the important transport infrastructures demanded for urbanization. Traffic volume of the road network varies from time to time due to daily routine and city development. The fluctuating traffic volumes at different regions of the road network require the traffic management and control to be intelligent and automated. Intelligent Traffic Control System (ITCS) is a key facility developed to control the fluctuating traffic demand efficiently with the capability to perceive the traffic condition around the intersection that it supervises. Traffic condition can be perceived by using vehicle detection system. However, the performance of the ITCS generally reduces when the vehicle detection accuracy reduces. In this paper, a simulation is done for a 4-way intersection in NetLogo environment to determine the impact of vehicle detection accuracy to the performance of ITCS. It is found that the optimality of the ITCS performance is preserved when the detection accuracy is greater than 95%. And, by reasonably compromising the waiting time that a driver waits in a vehicle queue during the red light, a vehicle detection accuracy of 90% is generally acceptable. However, the ITCS results poor user experience when the detection accuracy is reduced below 85%.

INTRODUCTION

Over the past few decades, urbanization has been accelerating all over the world, especially in the developing countries. In 2009, (United Nations 2015) reported that, for the first time, there are more people living in the urban areas than the people in the rural areas worldwide. Generally, rapid urbanization leads to human migration, in which high demand can be expected for transport infrastructures. Road network is one of the transport infrastructures that reflects the usage demand on measurable traffic volume (in vehicle count per unit time). Traffic volume of a road network often varies temporally and geographically. Geographically, property developments such as shopping mall and apartment establishments tend to increase overall traffic volume around specific areas. Temporally, critical hours such as office hours and school hours tend to induce high traffic volume during specific times. Therefore, traffic management and control is necessary to maintain or improve the quality of the road infrastructure in handling the fluctuating traffic demand.

Road traffic planning is an important task to fine tuning the Traffic Management and Control System (TMCS) from time to time. When the traffic demand exceeds the traffic capacity, traffic congestion is incurred. Normally, the bottlenecks of a traffic network are located at the intersections since they need to accommodate the traffic volumes from multiple sides. Some poor user experiences can be observed from traffic congestion are: slow moving cars, increasing queue length and long commuting time. Apart from time consuming, traffic congestion causes fuel wastage on unnecessary vehicle accelerating and decelerating. Moreover, the risk of traffic accident happenings will increase during traffic congestion, when the interactions between drivers have

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become too frequent. According to (Koonce *et al*. 2008), inefficient traffic management will take up the social cost (due to accidents), operating cost (due to depreciation on the infrastructure and facilities) and environmental costs (due to harmful emissions).

Literature Review:

Intelligent Traffic Control System:

Traffic Control System (TCS) is a facility installed at an intersection in the road network to provides traffic signals to the road users, especially the drivers. Traditional TCS uses fixed signalization, in which the traffic signals are generated according to a preprogrammed signal timing in the TCS. The TCS can be considered as an opened loop consider system as there is no sensors equipped for the TCS to perceive the surrounding traffic condition. SIGSET (a computer program for calculating traffic signal settings) and SIGCAP (a computer program for assessing the traffic capacity) mentioned in (Papageorgiou *et al*. 2003) are two examples of signal timing optimizing simulators that implement the traffic flow model developed by (Webster 1958). Meanwhile, MAXBAND (a computer program that finds traffic signal settings to maximize bandwidths on arteries) developed by (Lu *et al*. 2008) is a simulator that implements the traffic model developed by (Little 1966). Considering the traffic conditions at the neighbor intersections for simulation, Little's model has the ability to generate an optimized signal timing that allows continuous traffic flow over multiple intersections along a 2-way arterial. The traffic signals at the intersections are generated and coordinated based on the optimized signal timing. The situation known as green wave.

Agent is an entity that has the capability to perceive and act upon the environment to direct the activities towards achieving goals (Russell & Norvig 2003). To illustrate, a driver can be treated as a human agent, which drives on the road with a goal to reach the destination set before the trip. Along the way, the driver may also choose any path to minimize the travel time and expenses, according to the past experience (such as the condition encountered in the previous trips) and present information (such as traffic condition reported by the traffic reporters). The driver is also required to interact with the other drivers to avoid collision, especially when the front cars accelerate or decelerate. After reaching the destination, the driver may evaluate the trip, whether the selected path is efficient or not. In the scenario, it is noted that an agent must have sensors to perceive the environment, a memory to keep knowledge for short-term and long-term durations, a strategy to decide a series of actions to achieve the goals, and an evaluation method for the possible actions.

In contrast to the traditional TCS, an Intelligent Traffic Control System (ITCS) is a machine agent equipped with sensors to perceive the traffic condition. This capability allows the ITCS to implement actuated signalization, in which the traffic signals are generated according to a flexible and adaptive signal timing that is computed according to the traffic conditions from time to time. One cycle of traffic signal is normally time-sliced into multiple phases, in which different vehicle queues are serviced in each phase. In one cycle, all queues will be serviced with different length of green time, according to the perceived traffic conditions of the respective queues. Normally, longer green time is allocated for the phase with higher demand. As a machine agent, the ITCS has a goal to maximize the throughput, which is the count of vehicles serviced per unit time. The goal is also equivalent to the minimization of the average time the drivers wait in the vehicle queues.

Based on the structure of the system, ITCS can be classified into 3 types: isolated ITCS, centralized ITCS and decentralized ITCS (Papageorgiou *et al*. 2003). Isolated ITCS only has the capability to perceive the traffic condition locally, limited to the area around the intersection being controlled. MOVA (Microprocessor Optimized Vehicle Actuation) developed by (Control *et al*. 1988) is an example of isolated ITCS. Centralized ITCS is a hierarchical system, where a group of ITCSs are collectively supervised by a centralized server. The centralized server has the responsibility to generate the signal timings, that will optimized the performance of the system for the entire road network, rather than optimizing the performance of each individual intersection. Some examples of centralized ITCS are SCAT by (Sims & Dobinson 1980), SCOOT by (Zhaomeng 2010), OPAC by (Gartner *et al*. 2001), PRODYN by (Farges *et al*. 1990), CRONOS by (Boillot *et al*. 2006), and RHODES by (Mirchandani & Head 2001). Meanwhile, decentralized ITCS is a modern ITCS that can be considered as an advancement from isolated ITCS. Decentralized ITCS does not only perceive the traffic condition locally within its own intersection, it also interrogates the neighbor ITCSs to understand the nearby traffic conditions. This capability allows a group of decentralized ITCS cooperatively and optimally control the traffic at the network level. The simulations done by (Daneshfar *et al*. 2009) and (Han *et al*. 2015) are based on the decentralized ITCS.

From earlier works until recent works, the researches on ITCS generally demonstrate advancement on the system design complexity requirement to accommodate higher and higher level of 'intelligence'. Many earlier works focus on optimizing signal timings according to mathematical traffic models. However, the mathematical approach becomes difficult as the ITCS has to become more intelligent. Today, ITCS is often developed with the newer approach: agent-based or rule-based method. In this approach, the ITCS is considered as a agent mimicking human reasoning, which issues traffic signals according to a set of rules (Mandava *et al*. 2012).

Vehicle Detection:

Incorporating sensors into ITCS was started in 1930, when Charles Adler, Jr installed the first car-horn-activated TCS at Baltimore intersection. At the same time, in-pavement-based pressure-sensitive sensor was developed by Henry A. Haugh for vehicle detection, in which the sensor was popular for over 30 years. Rather than sensing the vehicle weight, today's technology allows the vehicles to be detected according to various of properties: opacity (optical and infrared sensors, and computer vision), electromagnetic induction (inductive loop detectors), reflection of transmitted energy (infrared laser radar, ultrasonic transceivers, and microwave radar), sound (acoustic sensors), and geomagnetism (magnetic sensors, and magnetometers) (Klein *et al*. 2006).

Inductive loop is a widely used vehicle detection technology nowadays. To obtain more informative traffic data such as vehicle speed and queue length, multiple loops have to be installed for each lane (Ki & Baik 2006). However, lane closure is required during the intrusive installation and repairing works for the inductive loops. Ultrasonic transceiver is a detection technology that requires non-intrusive installation, in which the technology is commonly used in Japan (Matsuo *et al*. 1999). Comparing to the blind sensors (inductive loop and ultrasonic receiver), a camera provides significantly wider detection area that allows more informative traffic data to be collected. Thus, computer vision for vehicle detection has caught much attentions from many researchers today.

Computer vision is an image analyzing technology that can be consider the duplication of human vision. Preliminary process of vision-based vehicle detection can be done using a background model (Yeo *et al*. 2013). The later process emphasizes on recognizing the vehicles, in which non-vehicle objects are filtered out. In the daytime, vehicles can be apparently seen in the traffic scene. However, vehicle cast shadow was reported to cause inaccurate detection by (Kim & Malik 2003). The cast shadows can be naturally included as a part of the detected vehicels. This makes the detected vehicles significantly larger than its size, especially in the evening, when the cast shadows are long. The oversize detection tends to merge closely separated vehicles as one detected object (Paragios & Deriche 2000). The problem can be solved with shadow elimination process (Li *et al*. 2011). Different problems exist in the nighttime vehicle detection. The first problem is due to the oversize detection due to vehicle headlights, where multiple vehicles can be detected as one object (Yue 2009). Another problem for nighttime vehicle detection is due to low illumination, in which the vehicles are very difficult to be differentiated from the dark scene. By assuming all drivers will turn on the headlights at nighttime, (Zou *et al*. 2015) developed a system to detect the vehicles based on the headlights.

Since the illumination is greatly different between daytime and nighttime, today’s computer vision implements dual schemes for vehicle detection. There is no continuous time response for the accuracy, because there are transitions of the schemes between daytime and nighttime. Thus, a more robust method is required for single-scheme vehicle detection that can solve shadow, headlight and low illumination problems at once. Rather than focusing on visible spectrum, researchers begin to investigate the use of infrared spectrum (which is invincible to human) for vehicle detection (Ducksbury *et al*. 1995). The machine vision operated in infrared spectrum is known as thermal vision, which forms images based on the thermal distribution of the captured objects. Under the thermal vision, there is no vehicular cast shadow in the daytime and the vision in nighttime is clear (Iwasaki *et al*. 2013).

Accuracy is an important measure of the performance of a vehicle detection system. Although vehicle detection is actively researched since 1930, there are few works to relate the vehicle detection accuracy to the performance of ITCS. Research works on ITCS generally assumed that the sensors operate perfectly, which are actually not flawless as demonstrated in the research works on vehicle detection. Recently, (Medina & Benekohal 2015) studied the performance of a traffic network with respect to different amount of inaccurate sensors in the network. In a traffic network, traffic congestion may happen locally at the intersection that is supervised by an inefficient ITCS. The inefficient intersection can be considered as a bottleneck with reduced traffic capacity. Traffic congestion happens because the reduced traffic capacity is insufficient to accommodate the normal traffic demand. Eventually, the congested intersection induces traffic congestion all over the network. Although the process takes time, the larger the congested area built up in the network, the more the time required later to clear the traffic. Thus, it is important to understand the level of compromise on the local performance of ITCS for certain level of the accuracy of the vehicle detection system being incorporated into the ITCS.

Experimental Setup:

In this paper, an ITCS is modeled using NetLogo to study the local performance of a 4-way intersection. NetLogo is a multi-agent modeling environment, which is programmable with Logo-alike programming language (Wilensky 1999). The NetLogo environment has been used in many research area to study the emergence phenomena, in which larger patterns arise through interactions between smaller and simpler entities. In this context, the vehicles are smaller entities and the traffic condition at the intersection is a larger entity. At the intersection, vehicles are not only interacting to each other, but also interacting with the traffic signals generated by the ITCS.

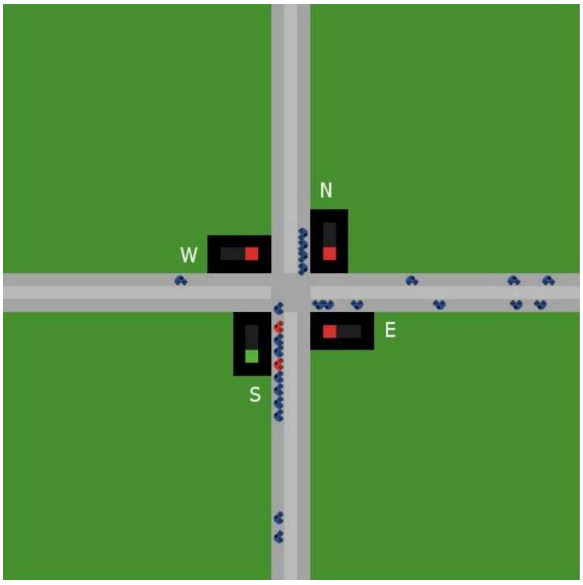

Fig. 1: 4-Way Intersection Model in NetLogo Environment. The intersection connects to 4 roads and all vehicles on the roads are driven on the left. The vehicles are colored in blue if it is detected, otherwise they are colored in red.

The 4-way intersection to be studied is modeled in NetLogo environment, in which the graphical interface of the model is shown in Figure 1. The intersection services traffics from 4 roads: North (N) road, East (E) road, South (S) road, and West (W) road. On the roads, all vehicles are driven on the left. The ITCS issues traffic signals in green, yellow and red to respectively service, slow down and stop the vehicles approaching from different roads. By assuming an inaccurate vehicle detection system is used, vehicles entering the intersection can be either detected or non-detected. The detected vehicles and the non-detected vehicles are respectively colored in blue and red. During the simulation, NetLogo updates the status of every agent in the model at once every tick, which is a time unit that is synonym to second in the real world. Every vehicle is considered as an moving agent that is known as 'turtle' in the Netlogo environment. At every tick, the vehicles move on the roads according to the behavior governed by the following rules (ordered from high priority to low priority).

i. If there is a vehicle ahead, then decelerate.
ii. If red light is encountered, then stop.
iii. If yellow light is encountered, then decelerate.
iv. If there is no vehicle ahead, then accelerate.

In the model, there is a probability of 0.07 that a new vehicle enter the intersection from each road in every tick. This probability will produce a traffic volume of about $0.0616\ vpt$ (Vehicle Count per Tick) for each road. With a highly accurate vehicle detection system, the traffic volume will drive the intersection to operate under unsaturated traffic condition, in which the traffic control at the intersection is stable and the queue length is steady in every traffic signal cycle. This setup leaves a gap for accuracy adjustment to study the compromise of ITCS performance before the intersection is driven into the saturated traffic condition, in which the traffic control is unstable and the vehicle queues are continuously developed cycle to cycle to occupy the entire roads.

Figure 2 illustrates the simulation response of a road traffic condition with 10 vehicles in the queue, after the green light is issued to the queue for 80 ticks. Then, it follows with the yellow light for 5 ticks. Every vehicle is counted once it leaves the road and entering the intersection. Let n and t denote the vehicle count and tick. Figure 2(a) is presents the a smoothen curve for vehicle count n over the time duration. At the beginning of the green time, the first vehicle in the queue takes time to accelerate from rest and enter the intersection. 2 ticks are taken before the first vehicle is counted. The saturation asymptote in the figure indicates the linear dependency of the vehicle count n to the time t, when the queue is serviced at the optimum and stable rate, which the slope of the asymptote. After the queue has been cleared, the intersection is still servicing the continuous incoming traffic, which is indicated by the slope of the volume asymptote in the figure.

Let dn/dt denotes the vehicle flow rate. Figure 2(b) presents the flow rate over the time duration. The saturation and volume asymptotes are now appear horizontally at different level in the figure. The value indicated by the saturation asymptote is known as saturation flow rate, $s = 0.3866\ vpt$. Meanwhile, the value indicated by the volume asymptote is known as traffic volume, $v = 0.0616vpt$. (Koonce *et al.* 2008) suggests the traffic condition with total volume-to-capacity ratio v/c lesser than 0.85 to be unsaturated. The ratio v/c can be calculated according to Equation (1), in which C and g denote the cycle time and effective green time respectively. The effective green time includes the green time and the total loss time such as yellow time and the time for the first vehicle to enter the intersection. If the 4 roads have equal traffic volume, an optimized ITCS must be able to allocate equal effective green time for each roads, making $g = C/4$. Thus, the optimally controlled intersection in this simulation gives the ratio $v/c = 0.6374$.

$$\frac{v}{c} = \frac{v}{s} \cdot \frac{C}{g} \tag{1}$$

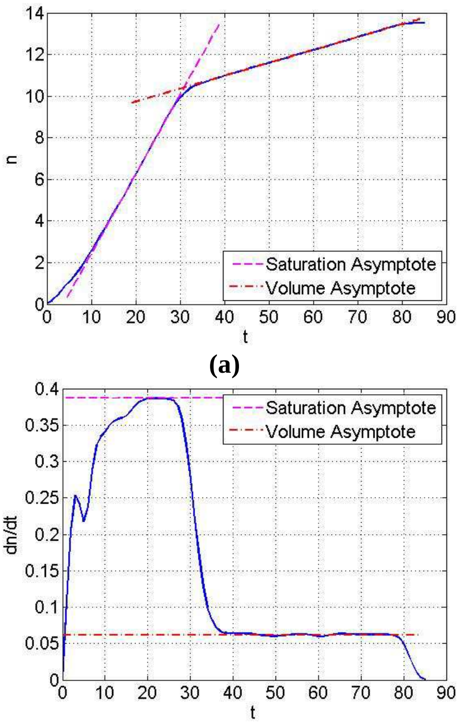

Fig. 2: Traffic Condition during a Signal Phase. (a) Saturation and volume asymptotes indicate the linearity of the of the curve during queue clearance and ongoing traffic servicing respectively. (b) Horizontal saturation and volume asymptotes indicates the saturation flow rate and traffic volume respectively.

An efficient ITCS must be able to properly allocate green time according to the varying traffic condition. And, a fuzzy control system can be used to generate the traffic signals for the 4 roads. Fuzzy control system is a control system that implements fuzzy logic, which represents logical variables with continuous function rather than discrete values like 0 and 1 only (Passino & Yurkovich 1998). In the simulation, the fuzzy control system takes in two parameters generated by vehicle detection system with tunable accuracy. The two parameters that reflect the traffic conditions are the traffic volume v and queue length q. For the 4-way intersection in the study, the ITCS divides a signal cycles in to 4 phase. Within one cycle, the traffic from all roads will take turn to be serviced. In each phase, different green time may be allocated. Table 1 is the fuzzy decision table for the ITCS to compute the green time allocated in each phase. Traffic volume and queue length are each distributed in 3 condition levels: low, medium and high. Meanwhile, the green time is distributed in 5 condition levels: short, moderate short, moderate, moderate long and long. The roads with higher traffic volume and higher queue length are considered to demand more on the capacity. Thus, longer green time should be allocated for the roads. Consequently, the roads with lower traffic volume and queue length will have shorter green time.

Table 1: Fuzzy Decision Table for Green Time Allocation.

		Traffic Volume		
		Low	Medium	High
Queue Length	Low	Short Green Time	Moderate Short Green Time	Moderate Green Time
	Medium	Moderate Short Green Time	Moderate Green Time	Moderate Long Green Time
	High	Moderate Green Time	Moderate Long Green Time	Long Green Time

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RESULTS AND DISCUSSIONS

In this paper, the simulation is executed for different vehicle detection accuracy values, ranging from 0% (worst detection performance) to 100% (perfect detection performance). For each selected accuracy, the simulation is run for 50000 ticks to assure the simulation comes to a steady state. Also, the time duration assures sufficient number of signal cycles being considered. Let i denotes a number to identify each road. At the end of the simulation, the traffic volume v_i, average queue length $q_{avg,i}$, and average green time $g_{avg,i}$ for each road are recorded. $q_{avg,i}$, and $g_{avg,i}$ are respectively the average values of the queue length and the green time collected in all signal cycles. In addition, the waiting time per vehicle W is recorded. It is the average of total time, in which the vehicles rest in a queue. The simulation is repeated for every 1% of accuracy and the performance results are presented in Figure 3.

There performance to the traffic control is measured according to 3 categories: traffic volume serviced by the intersection (the higher the better), queue length developed in every signal cycle (the lower the better), and the waiting time a vehicle rests in a queue (the lower the better). Let α denotes the detection accuracy. The performance indexes for the traffic volume, queue length and waiting time are calculated with Equation (2), (3) and (4) respectively, in which k denotes the number of road being considered. In this paper, $k = 4$. If the 3 performances are treated to be equally important, the overall performance $P(\alpha)$ of the traffic control will be the average of the 3 performances as shown in Equation (5). At $\alpha = 100\%$, the performance $P(\alpha = 100\%) = 1$, which is assumed to be a perfect performance with the optimized traffic control. However, as the accuracy α reduces, the performance $P(\alpha)$ reduces also. In Figure 3, $P_W(\alpha)$ reduces at the highest rate among the performance curves. Thus, extra care has to be considered for the performance $P_W(\alpha)$.

$$P_V(\alpha) = \frac{V(\alpha)}{V_{max}}; \quad V(\alpha) = \frac{1}{k} \cdot \sum_{i=1}^{k} v_i(\alpha); \quad V_{max} = \max_{\alpha} V(\alpha) \tag{2}$$

$$P_Q(\alpha) = \frac{Q_{min}}{Q(\alpha)}; \quad Q(\alpha) = \frac{1}{k} \cdot \sum_{i=1}^{k} q_{avg,i}(\alpha); \quad Q_{min} = \min_{\alpha} Q(\alpha) \tag{3}$$

$$P_W(\alpha) = \frac{W_{min}}{W(\alpha)}; \quad W_{min} = \min_{\alpha} W(\alpha) \tag{4}$$

$$P(\alpha) = \frac{1}{3}\left(P_V(\alpha) + P_Q(\alpha) + P_W(\alpha)\right) \tag{5}$$

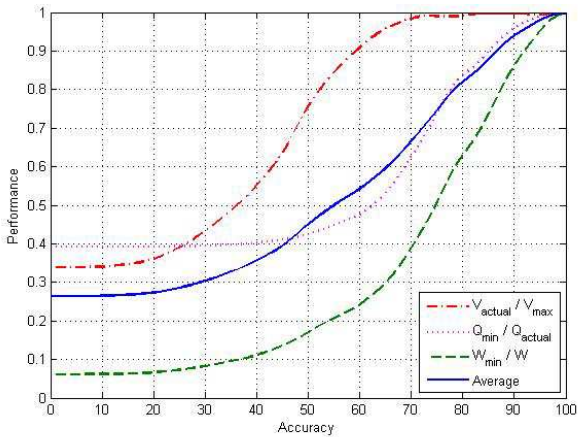

Fig. 3: Performance of Traffic Control with Different Vehicle Detection System Performances. Generally, the performance curves drop as the accuracy is reduced.

Table 2 highlights the values of the performances in the accuracy region $75\% \leq \alpha \leq 100\%$. When the accuracy is reduced to 95%, the overall performance is 0.9810, in which only 1.9% of the optimized overall performance is compromised. When the accuracy is further reduced to 90%, 5.8% of the optimized overall performance is compromised, majorly due to the reduction in $P_W(\alpha)$. At this accuracy, every driver is expected to spend 15.62% more time to stuck in the queue. In the real world, if the optimized waiting time is 60 seconds at an intersection, 90% accuracy will makes the driver to wait for additional 9.372 seconds, which is generally acceptable. However, when the accuracy α is reduced to 85%, 35.06% extra waiting time (about an additional of 21.036 seconds for the real world scenario) is required. Higher rate of performance reduction is observed when the accuracy α is further reduced. At $\alpha = 75\%$, the waiting time is almost double of the optimized waiting time. Thus, it is important to assure highly accurate vehicle detection system is used for traffic control. Generally, an accuracy of more than 90% is acceptable. Meanwhile, an accuracy of more than 95% makes almost no lost in the overall traffic control performance.

Table 2: Performance of Traffic Control for Vehicle Detection Accuracy Ranging between 75% and 100%.

α	75%	80%	85%	90%	95%	100%
$P(\alpha)$	0.7486	0.8215	0.8799	0.9413	0.9810	1
$P_V(\alpha)$	0.9919	0.9931	0.9995	0.9982	0.9965	1
$P_Q(\alpha)$	0.7429	0.8391	0.8998	0.9607	0.9926	1
$P_W(\alpha)$	0.5109	0.6322	0.7404	0.8649	0.9538	1
$\frac{W(a)}{W_{min}}$	1.9573	1.5818	1.3506	1.1562	1.0484	1

Conclusion

Road network is one of the important transport infrastructures for country development. The ever increasing traffic demand in the road network has made the traffic management and control to be an important research. ITCS is a key facility developed to handle the fluctuating traffic demand efficiently. It controls the road traffic according to the traffic condition perceived from vehicle detection system. However, the performance of the ITCS generally reduces when the vehicle detection accuracy reduces. In this paper, it is found that the optimality of the ITCS performance is preserved with the detection accuracy greater than 95%. With a reasonable compromise on the performance for waiting time, the detection accuracy of 90% is generally acceptable. However, an accuracy lower than 85% is not advisable, as the traffic control results poor user experience. Below 85% detection accuracy, every driver is expected to spend extra 35.06% time to wait during the red light, comparing to the time required for the optimized signal timing. At the 75% detection accuracy, the waiting time is almost doubled of the optimized waiting time. Thus, it is important to assure highly accurate vehicle detection system being used for optimized traffic control.

REFERENCES

Boillot, F., S. Midenet, J.C. Pierrelee, 2006. The Real-Time Urban Traffic Control System CRONOS: Algorithm and Experiments. *Transportation Research Part C: Emerging Technologies*, 14(1): 18–38.

Control, I.S., R. Developments, V. Actuation, 1988. MOVA Isolated Signal Control - Recent Developments. In *IEE Colloquium on UK Developments in Road Traffic Signalling*. London: IET, 1–4.

Daneshfar, F., 2009. Adaptive Fuzzy Urban Traffic Flow Control Using a Cooperative Multi-Agent System Based on Two Stage Fuzzy Clustering. In *IEEE Vehicular Technology Conference*. Barcelona: IEEE, 1–5.

Ducksbury, P.G., D.M. Booth, C.J. Radford, 1995. Vehicle Detection in Infrared Linescan Imagery Using Belief Networks. In *Fifth International Conference on Image Processing and its Applications*. Edinburgh: IET, 415–419.

Farges, J.L., I. Khoudour, J.B. Lesort, 1990. PRODYN: On Site Evaluation. In *Third International Conference on Road Traffic Control*. London: IET, 62–66.

Gartner, N.H., F.J. Pooran, C.M. Andrews, 2001. Implementation of the OPAC Adaptive Control Strategy in a Traffic Signal Network. In *IEEE Intelligent Transportation Systems*. Oakland: IEEE, 195–200.

Han, Z., 2015. An Urban Traffic Simulation System Based On Multi-agent Modeling. In *Chinese Control and Decision Conference*. Qingdao: IEEE, 6398–6403.

Iwasaki, Y., M. Misumi, T. Nakamiya, 2013. Robust Vehicle Detection under Various Environmental Conditions Using an Infrared Thermal Camera and Its Application to Road Traffic Flow Monitoring. *Sensors*, 13(6): 7756–7773.

Ki, Y.K., D.K. Baik, 2006. Model for Accurate Speed Measurement Using Double Loop Detectors. *IEEE Transactions on Vehicular Technology*, 55(4): 1094–1101.

Kim, Z., J. Malik, 2003. Fast Vehicle Detection with Probabilistic Feature Grouping and its Application to Vehicle Tracking. In *Ninth IEEE International Conference on Computer Vision*. Nice, France: IEEE, 524–531.

Klein, L.A., M.K. Mills, D.R.P. Gibson, 2006. *Traffic Detector Handbook* 3rd ed.

Koonce, P., 2008. *Traffic Signal Timing Manual*, Washington, DC: Federal Highway Administration, U.S. Department of Transportation.

Li, Y., 2011. Vehicle Detecting and Shadow Removing Based on Edged Mixture Gaussian Model. In *IFAC World Congress*. Milano, 800–805.

Little, J.D.C., 1966. The Synchronization of Traffic Signals by Mixed-Integer Linear Programming. *Operations Research*, 14(4), pp.568–594.

Lu, S., X. Liu, S. Dai, 2008. Revised MAXBAND Model for Bandwidth Optimization of Traffic Flow Dispersion. In *International Colloquium on Computing, Communication, Control, and Management*. Guangzhou: IEEE, 85–89.

Mandava, V., 2012. Knowledge Based Agent for Intelligent Traffic Light Control – An Indian Perspective

State of Art. In *Advanced Intelligent Computing Theories and Applications with Aspects of Artificial Intelligence*. Springer Berlin Heidelberg, 491–501.

Matsuo, T., Y. Kaneko, M. Matano, 1999. Introduction of Intelligent Vehicle Detection Sensors. In *IEEE/IEEJ/JSAI International Conference on Intelligent Transportation Systems*. Tokyo: IEEE, 709–713.

Medina, J.C., R.F. Benekohal, 2015. Vehicle Detection Design (Coverage and Accuracy) and the Performance of Congested Traffic Networks. In *IEEE 18th International Conference on Intelligent Transportation Systems*. Las Palmas: IEEE, 179–184.

Mirchandani, P., L. Head, 2001. RHODES: A Real-Time Traffic Signal Control System - Architecture, Algorithms, and Analysis. *Transportation Research Part C: Emerging Technologies*, 9(6): 415–432.

Papageorgiou, M., 2003. Review of Road Traffic Control Strategies. *Proceedings of the IEEE*, 91(12): 2043–2067.

Paragios, N., R. Deriche, 2000. Geodesic Active Contours and Level Sets for the Detection and Tracking of Moving Objects. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 22(3): 266–280.

Passino, K.M., S. Yurkovich, 1998. *Fuzzy Control*, Addison-Wesley.

Russell, S., P. Norvig, 2003. *Artificial Intelligent: A Modern Approach* 2nd ed., New Jersey: Pearson Education.

Sims, A.G., K.W. Dobinson, 1980. The Sydney Coordinated Adaptive Traffic (SCAT) System Philosophy and Benefits. *IEEE Transactions on Vehicular Technology*, 29(2): 130–137.

United Nations, 2015. *World Urbanization Prospects The 2014 Revision*, New York.

Webster, F.V., 1958. Traffic Signal Settings. In *Road Research Technical Paper*. London: Great Britain Road Research Laboratory.

Wilensky, U., 1999. NetLogo. *Center for Connected Learning and Computer-Based Modeling, Northwestern University*,. Available at: http://ccl.northwestern.edu/netlogo/.

Yeo, B.C., W.S. Lim, H.S. Lim, 2013. Scalable-Width Temporal Edge Detection for Recursive Background Recovery in Adaptive Background Modeling. *Applied Soft Computing*, 13(4): 1583–1591.

Yue, Y., 2009. A Traffic-Flow Parameters Evaluation Approach Based on Urban Road Video. *International Journal of Intelligent Engineering & Systems*, 2(1): 33–39.

Zhaomeng, C., 2010. Intelligent Traffic Control Central System of Beijing - SCOOT. In *International Conference on Mechanic Automation and Control Engineering*. Wuhan: IEEE, 26–28.

Zou, Q., 2015. Robust Nighttime Vehicle Detection by Tracking and Grouping Headlights. *IEEE Transactions on Intelligent Transportation Systems*, 16(5): 2838–2849.