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Field implementation feasibility study of cumulative travel-time responsive (CTR) traffic signal control algorithm

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SUMMARY

The cumulative travel-time responsive (CTR) algorithm determines optimal green split for the next time interval by identifying the maximum cumulative travel time (CTT) estimated under the connected vehicle environment. This paper enhanced the CTR algorithm and evaluated its performance to verify a feasibility of field implementation in a near future. Standard Kalman filter (SKF) and adaptive Kalman filter (AKF) were applied to estimate CTT for each phase in the CTR algorithm. In addition, traffic demand, market penetration rate (MPR), and data availability were considered to evaluate the CTR algorithm's performance. An intersection in the Northern Virginia connected vehicle test bed is selected for a case study and evaluated within VISSIM and hardware in the loop simulations. As expected, the CTR algorithm's performance depends on MPR because the information collected from connected vehicle is a key enabling factor of the CTR algorithm. However, this paper found that the MPR requirement of the CTR algorithm could be addressed (i) when the data are collected from both connected vehicle and the infrastructure sensors and (ii) when the AKF is adopted. The minimum required MPRs to outperform the actuated traffic signal control were empirically found for each prediction technique (i.e., 30% for the SKF and 20% for the AKF) and data availability. Even without the infrastructure sensors, the CTR algorithm could be implemented at an intersection with high traffic demand and 50–60% MPR. The findings of this study are expected to contribute to the field implementation of the CTR algorithm to improve the traffic network performance.

KEY WORDS: connected vehicle environment; adaptive traffic signal control; Kalman filter algorithm; market penetration rate; operational efficiency

1. INTRODUCTION

According to the 2015 Urban Congestion Report, average duration of daily congestion—the extra time spent caused by the difference between congested speed and free-flow speed—was approximately 5 hours for January through March in the USA [1]. To deal with congestion in an urban area, various adaptive traffic signal control systems have been developed by traffic engineers and researchers. These systems collect vehicle information in real time to optimize signal timing plans by changing the length and sequence of the phase to serve current traffic demands. Several widely used such systems include Split Cycle Offset Optimization Technique, Sydney Coordinated Adaptive Traffic System, Real-Time Hierarchical Optimized Distributed Effective System, Adaptive Control Software-Lite, Optimization Policies for Adaptive Control, INSYNC, and ATMS.NOW [2].

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While most adaptive traffic control strategies for urban transportation network are designed to deal with traffic congestion, they have two major challenges. First, these systems rely mostly on prediction techniques by using approaching demands, vehicle's arriving pattern, and turning movement rates. Generally, the prediction technique's inaccuracy undermines the performance of traffic control systems. To overcome the inaccuracy, several researchers have tried to apply advanced prediction techniques to control algorithms to improve system performance. For real-time travel time prediction problems, Kalman filter-based algorithms and time-series models have received great attention among parametric models and have been compared with other methods in previous studies. In case of Kalman filter algorithms, several researchers employed advanced Kalman filter to overcome the limitation of Kalman filter that Gaussian noise might not be consistent in field data, such as extended Kalman filter [3–5], adaptive Kalman filter (AKF) [6, 7], and unscented Kalman filter [8]. In addition, neural network model, which is one of the nonparametric prediction models, has been used due to its well-known learning and pattern recognition abilities [9–13]. Currently, k-nearest neighbors approach is widely used as a nonparametric short-term prediction method, and it can be easily extended to handle a multivariate problem by using historical data as well as real-time data [14].

Second, real-time data for the adaptive control systems are collected from infrastructure-based sensors such as video cameras or loop detectors that are fixed point sensors. However, the unreliable prediction of vehicle locations and speeds could lead to suboptimal control. Moreover, travel times could not be directly collected until vehicles completely passed the sensors. Hence, travel times need to be estimated by using an algorithm. Under Vehicle to Vehicle and Infrastructure (V2X) communication environment, connected vehicles (CVs) could send their trajectories to other vehicles and/or infrastructure through communication-based devices in real time and the intersection control algorithm could use directly measured travel-time data regarding vehicle status [15]. Recently, many researchers have studied to take advantage of communication-based traffic data to improve operational efficiency and traffic safety. Several methodologies and algorithms were proposed to allow vehicles to cross safely at an intersection under V2X communication environment. Such algorithms manipulated individual vehicles' maneuvers by using predicted trajectories or calculated crash potential so that vehicles can safely cross the intersection [16, 17]. Guler *et al*. [18] proposed an algorithm that incorporates information from CV to determine the sequence of departures from an intersection and developed an algorithm to evaluate the impacts of autonomous vehicle control and detailed vehicle information. Dujardin *et al*. [19] proposed a multiobjective optimization interactive procedure which is capable of dealing with traffic condition considering total waiting time and the number of stops based on an adaptive optimization system. Feng *et al*. [20] proposed an algorithm to optimize the phase sequence and duration by solving a two-level optimization problem: minimization of total vehicle delay and minimization of queue length under V2X environment. Their traffic control algorithms using communication-based data worked well compared with current adaptive signal control when 100% market penetration rate (MPR) was assumed, but the performance was significantly dropped as MPR decreases. In this study, MPR is defined as the percentage of vehicles equipped with CV technology that reports vehicle's information such as location, speed, and travel time.

The primary objectives of this paper are (i) to analyze effectiveness of a cumulative travel-time responsive (CTR) algorithm by incorporating MPRs, traffic demand, and types of available data (i.e., data from both CV and infrastructure sensors vs. CV's data only) and (ii) to verify a feasibility of field implementation in a near future. The CTR algorithm proposed by Lee *et al*. [21] was modified by adopting AKF to improve prediction performance under variable MPRs. Furthermore, this study evaluated the CTR algorithm by using a calibrated VISSIM simulation environment. The performance of CTR algorithm was compared with current traffic signal control algorithm based on infrastructure sensors considering MPRs in terms of mobility and environmental sustainability.

The remainder of this paper is organized as follows. A concept of the CTR algorithm and the prediction technique in the CTR algorithm are introduced in section 2. The prediction technique in the CTR algorithm and proposed analysis procedure based on microscopic simulation are presented in section 3. The effectiveness of the CTR algorithm is evaluated via simulation in terms of mobility and environmental sustainability by using an existing intersection in section 4, followed by the findings and future studies in section 5.

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2. CUMULATIVE TRAVEL-TIME RESPONSIVE TRAFFIC SIGNAL CONTROL ALGORITHM

2.1. A concept of the CTR algorithm

The CTR algorithm is a real-time intersection control strategy. The CTR algorithm determines the optimal green split for the next time interval by identifying the maximum cumulative travel time (CTT) measured or estimated by both CV and infrastructure-based sensors under V2X communication environment. CTT, employed as a real-time measurement for the CTR algorithm, is defined as the summation of the elapsed time spent by individual vehicles for each phase at an intersection, thereby enabling to capture instantaneous delays caused by queues and waiting time at the intersection. Thus, the CTR algorithm could rapidly respond to traffic congestion condition to reduce delay and total travel time of the intersection.

Figure 1 depicts the CTR algorithm. The travel-time data of individual vehicles equipped with a communication device are collected to implement the CTR algorithm. Consequently, the CTT for each phase is calculated and the highest CTT phase can be determined among the calculated CTTs. Then, the phase with the highest CTT is compared with the current green time phase. The CTR algorithm decides whether the current green time phase should be kept or not and updates traffic signal every 5 seconds. Additionally, the impacts of update intervals were investigated by using various intervals (i.e., 4–7 seconds). It turned out that the results under these intervals were not statistically significant. Thus, the CTR algorithm under 5-second update interval was used throughout this paper.

The CTT is a key factor when the CTR algorithm determines the next signal phase. In other words, the performance of the CTR algorithm depends on the accuracy of CTTs. As the CTTs depend on MPR, low MPR would likely undermine the CTR algorithm's performance. Hence, advanced prediction technique can be employed to improve the estimation accuracy of CTTs. To this end, this paper applied Kalman filter algorithms to compensate imperfect market penetration.

Taking into consideration the variety of MPRs, this paper evaluates the performance of the CTR algorithm in comparison with current signal control by conducting the following steps. First, this paper selected a study area and established a simulation environment by using VISSIM [22], a microscopic simulation package. Second, field data (i.e., traffic volume and signal timing plans) were collected during both peak and off-peak hours for VISSIM model calibrations. Third, in the simulation environment, real-time CTTs were collected from calibrated VISSIM models and estimated by Kalman filter algorithms under imperfect MPR conditions. It is worth noting that AKF was employed to improve the prediction performance as the AKF could dynamically adjust coefficients for the system and observation noises under the congested situation. This paper also considered two distinctive types of data availability: (i) data from both CV (e.g., travel time) and infrastructure sensor (e.g., total

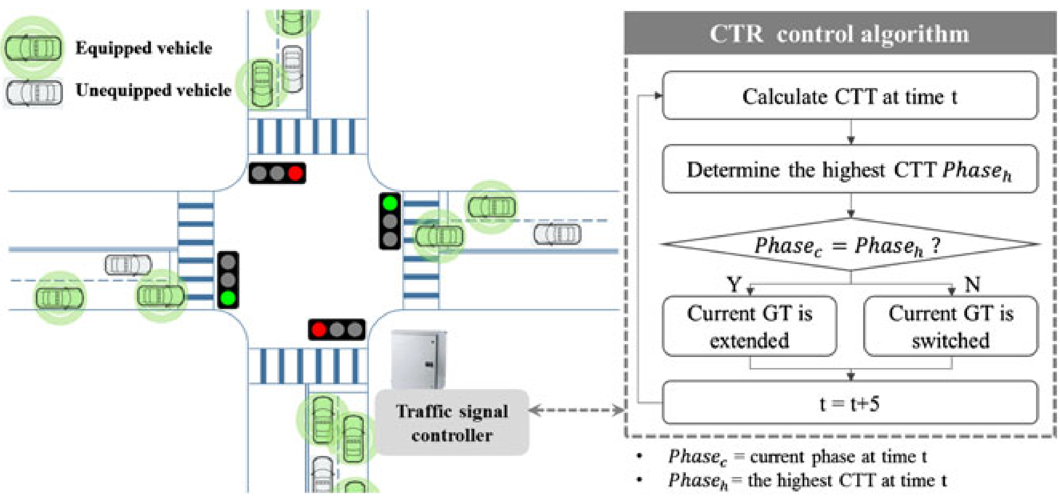

Figure 1. Concept of the cumulative travel-time responsive algorithm.

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number of vehicles), denoted as Case 1: CV and infra and (ii) data from CV only, denoted as Case 2: CV only. Therefore, this study investigated the impacts of insufficient information on the performance of CTR algorithm. Fourth, the effectiveness of the CTR algorithm was evaluated by comparing with the actuated signal control under various values of MPR in terms of mobility and environmental sustainability. The selected performance measurements include travel time, average speed, throughput, delay, CO_2 emissions, and fuel consumptions.

2.2. *Kalman filter algorithms*

The Kalman filter technique has been widely implemented to estimate future traffic conditions by using collected data [7, 23–25]. This method relies on stochastic and dynamic models that describe the behavior of the state-space vector and the relationship between the state-space and the measurement vector. The algorithm works in a two-step process: (i) time update and (ii) measurement update. In the first step, the algorithm estimates of the current state variables, along with their uncertainties. Once the outcome of the next measurement is observed, these estimates are updated by using a weighted average in the second step, with more weight being given to estimates with higher certainty. In addition, this algorithm can run in real time by using only the present input measurements and the previously calculated state and its uncertainty matrix because of the algorithm's recursive nature.

The state-space equation in Equation (1) explains the current state (x_k) that is the result of the previous state (x_{k-1}), the previous input action (u_{k-1}), and the noise from the previous time step. The measurement equation presented in Equation (2) explains the current measurement (z_k) that resulted from the current estimated states with noise. w_k and v_k are process noise and measurement noise with variance of Q and R and assumed to have a Gaussian noise. The observation matrix, H in Equation (2), is employed to adjust the difference between the measured states (the collected CTTs from CV) and the predicted states (the obtained CTTs from state-space equation). If MPR is 100%, then the observation matrix should be an identity matrix.

- State-space equation: $x_k = Ax_{k-1} + Bu_{k-1} + w_{k-1}$

  A: transition matrix for state mapping.
  B: transition matrix for input mapping.

$$w_k \tilde{} N(0, Q) \tag{1}$$

- Measurement equation: $z_k = Hx_k + v_k$

  H: observation matrix.

$$v_k \tilde{} N(0, R) \tag{2}$$

The transition matrices, A and B in Equation (1), are employed to account for the relationship between control activities and the results. These matrices need to be determined by considering road and traffic characteristics such as geometric condition (i.e., the number of lanes for each phase), volume (i.e., the number of approaching vehicles), and signal status because the CTT could be affected by various external activities. Hence, this paper utilized an equation in a previous study [21] described in Equation (3). As noted, when MPR is 100%, the observation matrix becomes an identity matrix. If infrastructure sensors are not installed (e.g., loop detector), then the total number of vehicles (q_i in Equation (3)) is not available. In this case, this equation is modified as Equation (4).

- Case 1: CV and infra

$$\begin{aligned} t_{i,k} &= \alpha t_{i,k-1} + \beta q_{i,k-1} + \mu g_{i,k-1} + \sigma NL_i \\ t_{j,k} &= \gamma t_{i,k-1} + \delta t_{i',k-1} + \varepsilon q_{j,k-1} + \tau g_{j,k-1} \end{aligned} \tag{3}$$

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- Case 2: CV only

$$
\begin{aligned}
t_{\mathrm{i,k}} &= \alpha t_{\mathrm{i,k-1}} + \mu g_{\mathrm{i,k-1}} + \sigma NL_{\mathrm{i}} \\
t_{\mathrm{j,k}} &= \gamma t_{\mathrm{i,k-1}} + \delta t_{\mathrm{i',k-1}} + \tau g_{\mathrm{j,k-1}}
\end{aligned} \tag{4}
$$

where

t_{k}	CTT at time interval k
$q_{\mathrm{i,k-1}}$	vehicle counts of phase i at $k-1$
$g_{\mathrm{i,k-1}}$	length of green time of phase i at $k-1$
NL_{i}	the number of lane of phase i
i, j	the number of phase for through and left turn based on the National Electrical Manufacturers Association standard, respectively
i'	the number of through-traffic phase corresponding left-turn traffic
j	the number of phase for left turn
$\alpha, \beta, \gamma, \delta, \varepsilon, \mu, \tau, \sigma$	coefficients.

The covariance matrices in standard Kalman filter (SKF) could be estimated by using Minimum Norm Quadratic Unbiased Estimation [26]. However, the Minimum Norm Quadratic Unbiased Estimation is an offline tuning process; this is not suitable for real-time implementation. The estimation of the noise variance is very important in order to correctly tune the filter because it determines the Kalman gain. In this study, AKF was considered to address this issue. The basic idea of the AKF is to update the covariance matrices at every time interval by using a covariance matching technique called multiple model adaptive estimation [27] to reduce uncertainty in the error of covariance. Generally, the procedure of the AKF is as follows: (i) State propagation and prior state estimation error covariance are estimated; (ii) observation errors are computed; (iii) observation process covariance matrix is updated; (iv) Kalman gain is calculated; (v) posterior state estimation and posterior state estimation error covariance are estimated; (vi) state estimation errors are computed; and then (vii) state process covariance matrix is updated. More details about the Kalman filter algorithms are available in previous studies [6, 7].

3. ANALYSIS

3.1. Study area for simulation experiments

Lee highway and Nutley Street within the Northern Virginia's connected vehicle test bed [28] were selected as shown in Figure 2. The intersection operates according to the actuated signal control. The Nutley Street is connected to I-66, which is an interstate highway in the eastern USA as well as Lee highway, and there are high inbound traffic volumes during peak hour. To establish and calibrate a simulation environment of study area, field data (e.g., traffic volume, geometrical characteristics, and signal timing plans) were collected during peak hour (7 AM–8 AM) and off-peak hour (3 PM–4 PM). The eastbound and westbound approaches have permitted exclusive left-turn signals; southbound and northbound approaches have protected through left-turn signals.

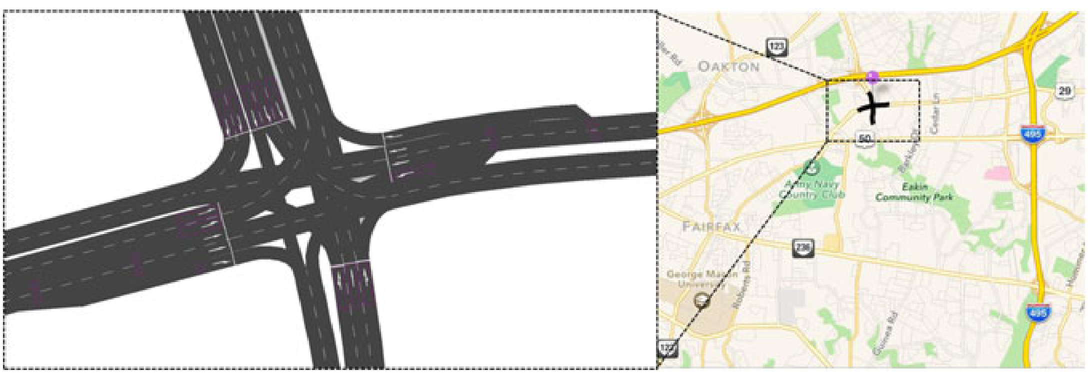

Figure 2. VISSIM network for study area.

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Two volume data were collected in the study area during peak and off-peak hours. In both volume data, higher traffic volume rates were found at Lee highway (i.e., east–west directions) than at Nutley Street. The left-turn traffic in southbound and right-turn traffic in westbound had higher volume rates than through traffic due to the traffic volume going in and out of I-66.

To establish a simulation-based environment for analysis of the CTR algorithm, VISSIM is used in this study. To reflect field condition of the study area within the simulation environment as a base case, VISSIM model was developed by using field data such as traffic counts and traffic signal timing plan and was calibrated in terms of total travel time and average speed by mean absolute percentage error (MAPE). As described in Table I, the calibrated VISSIM simulation results showed 5–15% error when compared with the field measurements. The CTR algorithm was evaluated by using the calibrated VISSIM simulation model, and measures of effectiveness (MOE) regarding operational efficiency and environmental sustainability analyzed 10 replications to assess the performance of the CTR algorithm.

In addition, a C# programming language on VISSIM's COM interface, which allows additional external control of simulation model, is used to implement the CTR algorithm. Figure 3 describes the simulation-based analysis procedure in this study by using VISSIM COM interface for the CTR algorithm. At time interval *t*, VISSIM collects elapsed time information of equipped vehicles as travel-time measurements for each phase and sends the information to the CTR algorithm. If MPR is 100%, then the CTR algorithm immediately calculates CTTs. If MPR is imperfect, then CTTs are estimated from Kalman filter algorithms, the SKF, or the AKF. To calculate the matrices in the Kalman filter algorithms, this paper used the dynamic linked library in MATLAB. Once the highest CTT phase is determined as next green phase by using the estimated CTTs, the current green signal is either extended or switched by the CTR algorithm. It is noted that the signal control information is updated for every 5 seconds even though it can be adjusted.

3.2. Model estimation in Kalman filter algorithms

In the state-space equation, coefficients were estimated by considering external traffic characteristics such as number of lanes, existence of left-turn bay, and signal status. These estimated coefficients should be statistically significant because these coefficients would affect the accuracy of estimated CTTs. To estimate coefficients by a regression model, this study collected 2880 data records including CTTs, the number of vehicles, and length of green time from the calibrated VISSIM simulation and used SPSS 22 that is one of statistical analysis packages. The geometric characteristics, the number of lanes for each phase, were also used. Considering data availability, two types of state-space equation were developed as shown in Table II: (i) CV and infrastructure sensors (i.e., CV and infra) and (ii) CV only (i.e., CV only). All parameters are statistically significant with a 95% significance level for both equations, and R^2 values, which represents model performance, are close to 1.0. Using coefficients for each equation, Equations (3) and (4) can be written as Equations (5) and (6), respectively.

- Case 1: CV and infra

$$\begin{aligned} t_{\mathrm{i,k}} &= 0.85\cdot t_{\mathrm{i,k-1}} + 3.33\cdot q_{\mathrm{i,k-1}} - 22.90\cdot g_{\mathrm{i,k-1}} + 8.13\cdot NL_{\mathrm{i}} \\ t_{\mathrm{j,k}} &= 0.92\cdot t_{\mathrm{i,k-1}} - 0.01\cdot t_{\mathrm{i',k-1}} + 4.11\cdot q_{\mathrm{j,k-1}} - 22.48\cdot g_{\mathrm{j,k-1}} \end{aligned} \tag{5}$$

- Case 2: CV only

$$\begin{aligned} t_{\mathrm{i,k}} &= 0.92\cdot t_{\mathrm{i,k-1}} + 22.81\cdot q_{\mathrm{i,k-1}} + 13.68\cdot NL_{\mathrm{i}} \\ t_{\mathrm{j,k}} &= 0.98\cdot t_{\mathrm{i,k-1}} + 0.02\cdot t_{\mathrm{i',k-1}} - 19.06\cdot g_{\mathrm{j,k-1}} \end{aligned} \tag{6}$$

When the regression models were adopted in the KF models, the KF algorithms' performances were analyzed by using MAPE under 100% MPR with comparison between measured CTTs by CV in VISSIM and estimated CTTs by KF algorithms. The average MAPEs of SKF and AKF were

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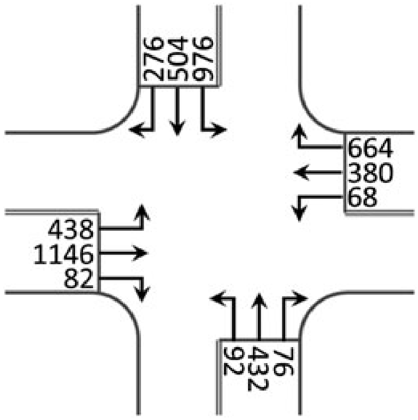
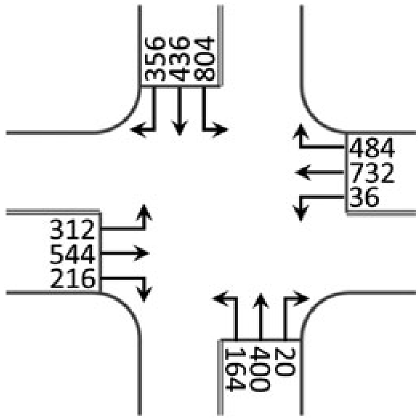
Table I. Simulation results using existing traffic signal timing and traffic volume.

Parameters	Peak hour	Off-peak hour
Volume (vph)		
Total travel time (h)	169.089 (MAPE 5%)	98.659 (MAPE 13%)
Average speed (mph)	11.040 (MAPE 15%)	16.697 (MAPE 8%)
Delay (s)	92.310	48.214
CO_2 (kg/unit)	0.787	0.473
Fuel (kg/unit)	0.615	0.315

MAPE, mean absolute percentage error.

investigated as 18.15% and 15.31%, respectively. It is noted that the key to the success is not about the prediction accuracy but the correct identification of an approach with the highest CTT. The prediction accuracies to identify the highest CTT of the SKF and AKF were 89.6% and 92.1%, respectively. In addition, there are a few factors affecting the travel-time prediction accuracy. These include communication errors, vehicle types, MPR, etc. This paper only considered MPR in evaluating the performance of the Kalman filter because it is generally understood that communication errors are important for safety critical applications (i.e., not critical for travel-time estimation) and the vehicle mix on this corridor has less than 2% trucks. In addition, the Kalman filter used in this paper predicted quite well even without considering vehicle types.

3.3. Scenarios and measures of effectiveness

Eleven different MPR values are applied to the simulation scenarios to evaluate the CTR algorithm. The MPRs were ranged from 0% (current signal control) to 100% (perfect CV environment) incrementing by 10%. This study used two sets of traffic volume data including peak hour and off-peak hour. In addition, two types of communication technique and two types of Kalman filter were considered. Thus, total 88 scenarios were developed to evaluate CTR algorithm and 5 replications were made for each scenario.

For comparison purpose, this study employed the following MOE: total travel time (h), average speed (mph), and delay (s) as mobility measures and amount of CO_2 emissions per vehicle and fuel consumption as environmental sustainability measures. In addition, Virginia Tech microscopic energy and emission model [29] was employed to estimate the emissions and fuel consumptions of each scenario by using speed and acceleration in vehicle trajectory data collected by VISSIM simulation.

3.4. Hardware in the loop simulation configuration for the CTR algorithm

Given that CV technology has not been deployed, the Bluetooth technology could be used as a CV surrogate and simulations of a fully implemented CTR algorithm in a V2X environment under various MPRs. This paper developed a hardware in the loop simulation (HILS) [30] environment to evaluate the field implementation feasibility of the CTR algorithm. The HILS consists of 2070L traffic signal

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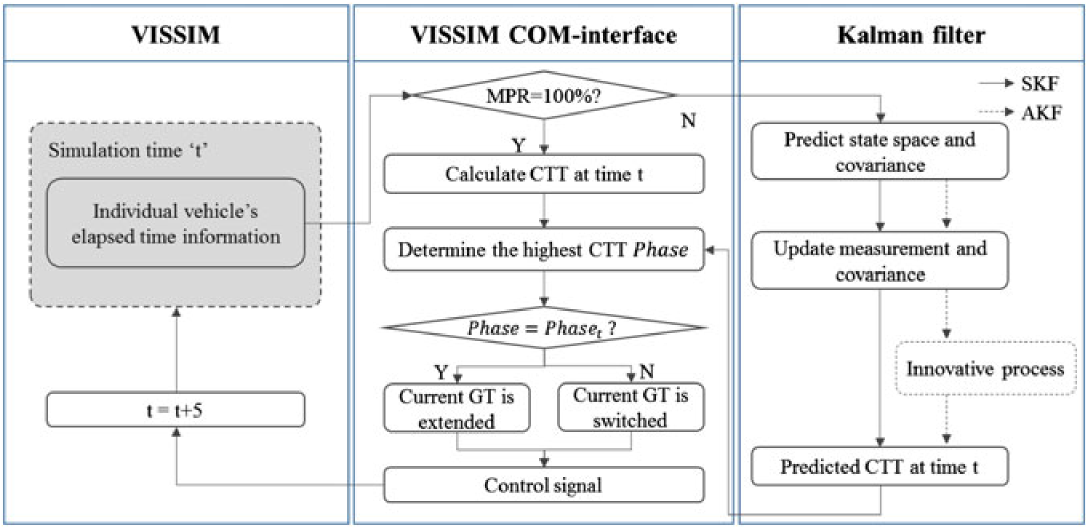

Figure 3. Simulation-based analysis procedure.

Table II. Regression model to estimate coefficients in Kalman filter by using simulated data.

		Model summary					Performance		
Scenario	Equations	Parameter	B	Std. error	t	Sig.	R	R^2	Adjusted R^2
CV and infra	Equation for THRU	α	0.85	0.01	67.81	0.00	0.976	0.953	0.953
		β	3.33	0.49	6.72	0.00			
		μ	−22.90	0.89	−25.81	0.00			
		σ	8.13	1.12	7.23	0.00			
	Equation for LT	γ	0.92	0.01	109.61	0.00	0.975	0.951	0.951
		δ	−0.01	0.01	−2.20	0.03			
		ε	4.11	0.28	14.83	0.00			
		τ	−22.48	0.74	−30.41	0.00			
CV only	Equation for THRU	α	0.92	0.01	167.64	0.00	0.976	0.952	0.952
		μ	−22.81	0.89	−25.52	0.00			
		σ	13.68	0.77	17.79	0.00			
	Equation for LT	γ	0.98	0.01	132.81	0.00	0.973	0.947	0.947
		δ	0.02	0.01	2.78	0.01			
		τ	−19.06	0.73	−26.16	0.00			

Note: CV, connected vehicle; THRU, through; LT, left turn.

controller hardware; controller interface device (CID); Bluetooth readers developed by Lee, Zhong, Du, Gutesa, and Kim [31]; communication devices between a server computer and Bluetooth readers; and VISSIM. Figure 4 illustrates HILS configuration to operate the CTR algorithm under CV environment.

First, Bluetooth readers capture Medium Access Control (MAC) addresses of Bluetooth devices in approaching individual vehicles in each direction for every 5 seconds. Second, the collected MAC addresses are transmitted from Bluetooth readers to a remote server computer through Zigbee-based short range communications [29]. The MAC address data are stored in a database in the server computer. Third, a program in the server computer matches the MAC addresses from downstream and upstream for each direction and computes the travel time of equipped vehicles in real time. Fourth, using these travel times, the CTR algorithm determines the next green time phase and sends this information to the CID. At last, the CID switches digital signals to analog signals, and this signal is sent to controller hardware. In addition, the controller sends the signal

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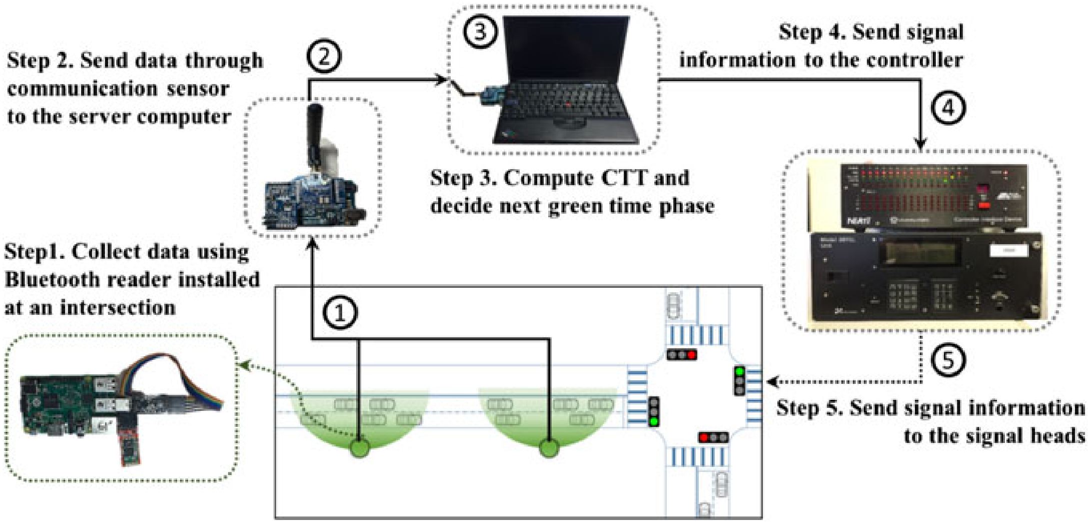

Figure 4. Hardware in the loop simulation configuration for the cumulative travel-time responsive algorithm.

information to the signal head. Note that step 5 is not available to consider for indoor experiments. Thus, this study analyzed the CTR algorithm in the HILS configuration implementing step 1 through step 4.

4. RESULTS

The effectiveness of the CTR algorithm over the actuated signal algorithm is summarized in Table III in terms of MPRs, volume scenarios, communication types, and Kalman filter algorithms compared. It is noted that the existing actuated signal control is considered to be up to date as the Northern Virginia traffic engineers well maintain the timing plans in the area. Because the existing signal control was considered as the base case, we observed the changes of MOEs between the base case and the proposed control scenarios (with the CTR algorithm). In Table III, when the MOE of the scenario is greater than that of the base case, the value of change is positive. For example, if a change of total travel time is −20%, then it means that the CTR algorithm reduced total travel time by 20% compared with the actuated signal control.

Generally, the CTR algorithm's performance improved as the rate of equipped vehicle increased. With 100% MPR under V2X communication environment, the CTR algorithm significantly improved the mobility when compared with the actuated signal control at peak hour; total travel time decreased by 45–47%, average speed increased by 96–101%, and delay decreased by 71–73%. Moreover, at off-peak hour, travel time decreased by 37–42%, average speed increased by 57–70%, and delay decreased by 61–69%. In terms of environmental sustainability, the amount of CO_2 emission slightly increased by 1–2% and fuel consumption decreased by 3–6%; however, it was not significant. We found a large drop of fuel consumption under low MPR.

4.1. Effectiveness of prediction technique

An interesting finding is that the CTR algorithm showed different performance by the type of Kalman filter algorithm under low MPR conditions. At off-peak hour, the performance of the CTR algorithm with the SKF denoted as rectangle marks was about 5–10% better than that with the AKF denoted as circle marks. Moreover, the minimum required MPR of the SKF (10%) was lower than that of the AKF (20%). However, the AKF's results were slightly better (2–7%) than the SKF's results at peak hour. In addition, the minimum required MPR of the AKF (20%) was lower than the SKF (30%). Therefore, to guarantee the CTR algorithm's performance for both traffic

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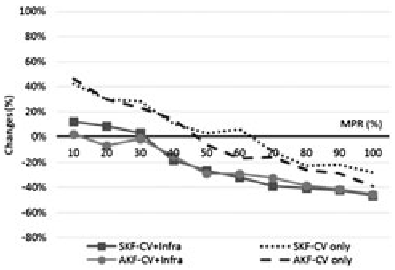
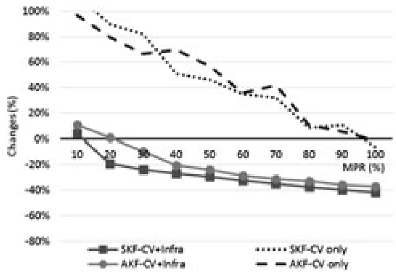
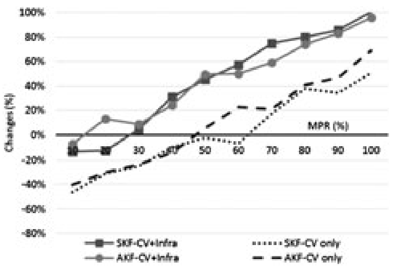
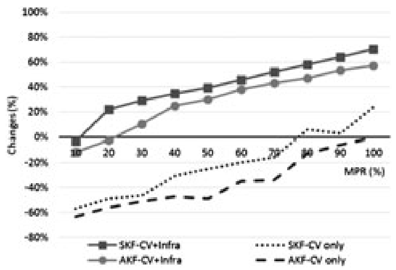
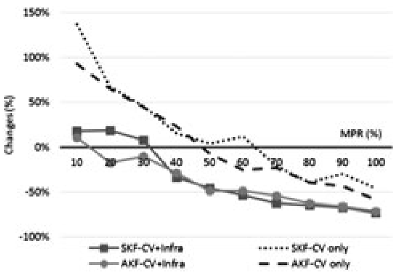
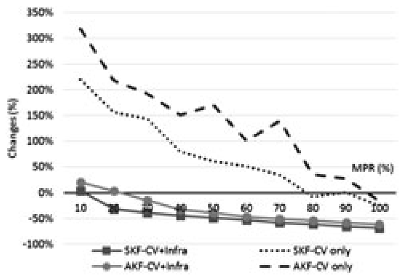
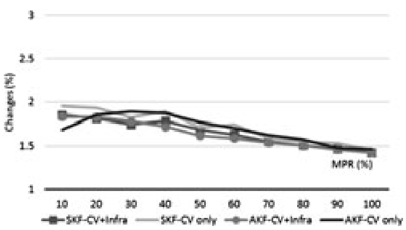
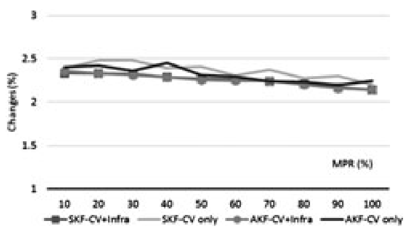
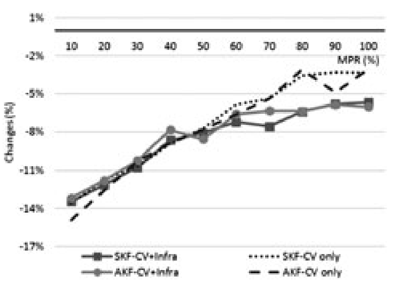
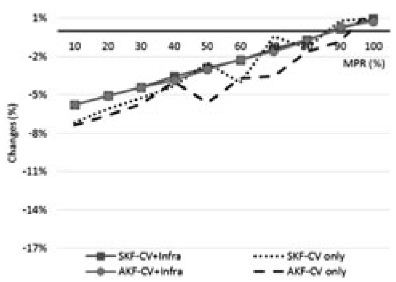
Table III. Evaluation results.

MOEs	(a) Peak hour	(b) Off-peak hour
Total travel time (h)		
Average speed (mph)		
Delay (s)		
CO_2 (kg/unit)		
Fuel consumption (kg/unit)		

MOE, measures of effectiveness.

demands, 30% and 20% MPR should be needed for the SKF and the AKF, respectively. Because the AKF showed better performance than the SKF under imperfect MPR, the AKF is recommended as prediction technique for the CTR algorithm.

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4.2. Effectiveness of data availability

If information from infrastructures is not available, then high MPR should be ensured for operating the CTR algorithm. According to the comparison results between “CV and infra” with solid line and “CV only” with dotted or dashed line, the minimum required MPRs for the CTR algorithm were 50–60% at peak hour and 90% at off-peak hour to outperform the current actuated traffic signal control. According to the results of *t*-tests to compare effectiveness of data availability, travel-time, average speed, and delay of “CV and infra” were significantly reduced than those of “CV only” at off-peak hour ($\alpha < 0.05$). In case of peak hour, the results of *t*-tests were not statistically significant at peak hour. However, the differences in terms of travel time, average speed, delay, and CO_2 were statistically significant when the AKF was adopted ($\alpha < 0.05$).

Even at the same MPR for peak and off-peak hour, the performance of the CTR algorithm shows a big difference because the quality of information for operating the CTR algorithm is influenced by the number of equipped vehicles. Therefore, the infrastructure sensor data should be needed for stable algorithm performance. On the other hand, even though there is no infrastructure sensors at the intersection, the CTR algorithm could be considered where high traffic demand is found with 60% MPR. Furthermore, the CTR algorithm could improve the mobility than actuated control even in under 50% MPR when the AKF is considered.

5. CONCLUSIONS

To verify the feasibility of field implementation in a near future, this research enhanced and evaluated a cumulative travel-time responsive (CTR) real-time intersection control algorithm under various conditions considering MPR, traffic demand, and types of data availability. An existing intersection within the CV test bed in Virginia, USA, was simulated within a microscopic traffic simulation model, VISSIM, under the current traffic signal timing plans and volumes of peak and off-peak hours. Two CTT estimation techniques, SKF and AKF, were applied for each phase in the CTR algorithm. In addition, HILS configuration, which utilizes actual traffic signal controller, was proposed to test the feasibility of implementing the CTR algorithm in the field.

The CTR algorithm improved the mobility in comparison with actuated traffic signal control when MPRs exceed 30% with the SKF and 20% with the AKF. At 100% MPR, total travel time, average speed, and delay were significantly enhanced when compared with the current actuated traffic signal control. Without utilizing infrastructure sensors, the CTR algorithm could be considered at the intersection when traffic demand is high and MPR is 50–60%. We found that the AKF outperformed the SKF at peak hour because it reduces the uncertainties with the process and observation noise statistics. Although the environmental sustainability was not improved as much as mobility, the CTR algorithm is highly expected to improve mobility performance under CV environment.

As expected, the CTR algorithm’s performance largely depends on the MPR because the information of CV is a key factor of the CTR algorithm. However, we found that the perfect MPR requirement of the CTR algorithm could be relaxed (i) when the data were collected from both CV and the infrastructure sensors and (ii) when the AKF was adopted in the CTR algorithm.

For successful implementation of the CTR algorithm in the field, there are several challenges. The performance of communication devices should be considered because it could affect reliability of collected data from CV. It can be accomplished with a field experiment by using Connected Vehicle Roadside Equipment and On-board Equipment. For reliable information, advanced communication devices might be needed to minimize packet losses and latencies of data delivery such as Dedicated Short-Range Communications. To explicitly consider vehicle mixes, Kalman filter model should include vehicle type (e.g., % of heavy vehicles) as a variable for estimating/predicting the CTTs. In addition to enhancing the applicability of the results shown in this study, it needs to configure the CTR algorithm for multiple intersections. To consider the progression along the corridor, we propose to apply weights on the movements along the main corridor based on the platoon dispersion factor. The findings of this study are expected to be of great use in trying to implement the CTR algorithm with minor modifications in the field to improve network performances.

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