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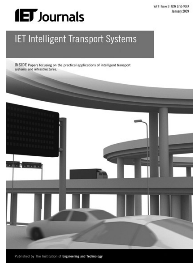

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Dilemma zone avoidance development: an on-board approach

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Abstract: The dilemma zone (DZ) has been discussed in traffic engineering over four decades, because it is positively correlated to potential accidents. The dynamic feature of DZs is indeed difficult resolved and handled only by traffic signal control. This study aims to develop a series of onboard algorithms for DZ avoidance and warning. Three algorithms, DZ estimation, DZ prediction and warning selection are developed. To increase DZ detection accuracy, inputs from roadways, drivers and vehicles are considered. The genetic systematic-rule is used to optimise the prediction of vehicle motion and the dynamical features of DZs. Experimental results show that the accuracy rates of DZ detection for all scenarios are higher than 90%. Such encouraging results show the reliability and operating practicability of the proposed development.

1 Introduction

In general, most accidents occur at intersections. As a statistical result, 21% of all fatal crashes occur at intersections, and about 32% of those are at signalised intersections [1]. Among all possible causes of those related crashes, dilemma problem induced by yellow phase is one of the major puzzles that have not been fully solved yet. Particularly at high-speed intersections, vehicle crashes are usually associated with driver's dilemma decisions. Dilemma zones (DZs) are 'defined in either time or space, as zones where some drivers may decide to proceed through an intersection whereas others may decide to stop at the onset of a yellow indication' [2]. Hence, poor signal timing design may cause some vehicles to be 'trapped' in a DZ and cannot successfully pass the intersection before the conflicting phase starts. In other words, if 'trapped' in a DZ, the driver can neither safely clear the intersection, nor stop comfortably before the stop marking, consequently leads the driver to make wrong decision, resulting in rear-end or right-angle crash [3–5]. Traditionally to relieve the DZ problem, a proper signal timing design is applied. In terms of signal timing design, the intergreen (time) interval, including yellow change and all-red clearance intervals, is the most crucial for preventing crashes at signalised intersections.

In practice, the Gazis, Herman and Maradudin (GHM) model [3] is commonly used by traffic engineers to design intergreen to prevent the formation of the DZ [6]. According to the yellow change interval formula proposed in the ITE handbook, the designed yellow change interval is supposed to allow an approaching vehicle moving at a constant speed to either safely stop or clear the intersection. Thus, the DZ is not supposed to happen. In reality, however, the DZ is difficult to be eliminated because of its dynamic features of location and length [7], resulting from a variety of drivers' behaviour and characteristics, such as the driver's perception–reaction time [2] and vehicle speeds [8]. Hence, current implementation of yellow change intervals still has a potential to form a DZ if a vehicle approaches an intersection at a speed higher than that identified in the ITE formulation. As a result, the static ITE approach might be less helpful for removing DZs in reality.

On the other hand, a most effective manner to improve road safety is to develop an on-board warning system [9–11]. If such an on-board system is functioned with DZ-prevention algorithms, the driver can take timely action to decelerate or pass the intersection to mitigate or even to eliminate the DZ. One of the most related research efforts could be the operational algorithm developed by Moon. Moon's algorithm constituted functional system architecture and established requirements for the development of an on-board DZ warning system. Their integrated system was evaluated and demonstrated its practicability [12, 13]. However, their warning mechanism is decided by the maximum vehicle driving speed (85th-percentile or 95th-percentile speed is used depending on the location). With a fixed maximum speed, the dynamic features of the DZ cannot be reflected in the model as the variation of vehicle speeds is ignored. Later on, Abbas and Li [14] proposed a data collection system specifically designed to evaluate the real-time DZ protection systems. Still, the DZ prevention system is not commonly available in the market or being developed.

With the development of IntelliDrive [15], formerly known as vehicle-infrastructure integration, the need of such on-board algorithms become critical since the IntelliDrive environment provides a networked environment connecting among and between vehicles, the infrastructure and passengers' personal communications devices, to improve transportation safety and mobility. Efforts have attempted to perform more efficiently and less costly IntelliDrive-based applications [16–19] and have attracted increasing attention in the past decade.

This study aims to develop a series of IntelliDrive-ready operational algorithms required for an onboard advanced DZ warning (ADZW) system. In the next section, the system architecture is firstly proposed to identify the functionality of the proposed algorithms and applicable environment. A genetic systematic-rule is proposed for optimising the vehicle motion prediction whereas the Kalman filter is processing. With the understanding of the entire system architecture and the genetic systematic-rule, three algorithms for DZ diagnosis, DZ estimation (DZE); DZ prediction (DZP) and warning selection (WS) are elaborated, then. Finally, the algorithms are tested in various scenarios and determine the reliability and practicability using a costumed simulation programme. A proposed procedure for execution and its accuracy are summarised at the end.

2 System architecture

The system architecture of the avoiding DZ and warning system (ADZW) proposed in this study is illustrated in Fig. 1. The system mainly contains an on-board equipment (OBE) continuously recording the vehicle motion data (e.g. the speedometer); meanwhile, the roadside equipment (RSE) also continuously transmits traffic signal timing information and the configuration (grade and width) of the intersection to the equipped vehicles via wireless communication. Basically, driver preset information (e.g. driver reaction time and vehicle length) is also taken into account in the system. All the information is the input to the developed algorithms processed in the on-board decision mechanism as shown in Table 1.

Owing to the dynamic occasion, the proposed ADZW system should provide following capabilities: (i) predicting risky zones: predict the exact vehicle location and the DZ length when the equipped vehicle is approaching to an intersection, and then determine whether the equipped vehicle will encounter the DZ problem or not, (ii) real-time performance: since all parameters are updated in real time, the collected information and the designed algorithms have to provide the capability of achieving real-time performance and (iii) advanced warning: a warning message should be sent by the ADZW system once the prediction is complete. In other words, the ADZW should issue the warning in advance that the driver is encountering a potential DZ outcome.

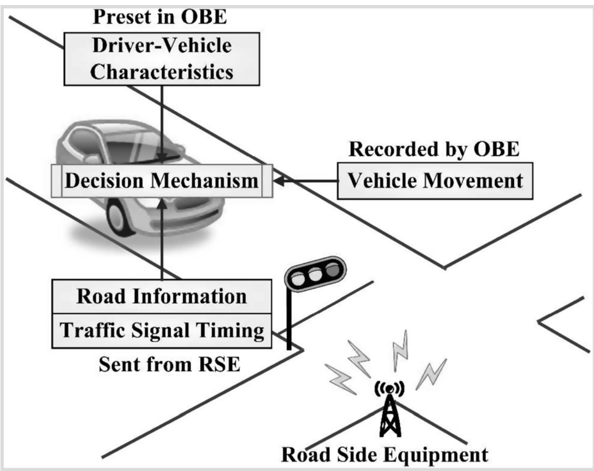

Fig. 1 *System architecture*

Table 1 System input messages

Type	Factor	Unit	Update frequency
vehicle motion	distance from the stop line (x)	m	10 Hz
	speed (v)	ms^{-1}	
traffic signal timing	remaining green time (G_R)	s	
	intergreen time (I_G)	s	
roadway configuration	grade of the approach lane (G)	0.01%	
	width of the intersection (W)	m	
driver–vehicle characteristics	vehicle length (L)	m	preset value
	typical deceleration (D)	ms^{-2}	
	Jerk rate (J)	ms^{-3}	
	Driver perception–reaction time (τ)	s	

3 Vehicle motion prediction methodology

The Kalman filter is a set of mathematical equations that provides an efficient recursive means to estimate the state of a process [20]. It is herein utilised for predicting the equipped vehicle motion from time to time

$$\hat{\boldsymbol{X}}_{k+1}^{-} = \boldsymbol{A}\hat{\boldsymbol{X}}_k + \boldsymbol{W}_k \tag{1}$$

$$\boldsymbol{P}_k^{-} = \boldsymbol{A}\boldsymbol{P}_k\boldsymbol{A}^{\mathrm{T}} + \boldsymbol{Q} \tag{2}$$

$$\boldsymbol{K}_k - \boldsymbol{P}_k^{-}\boldsymbol{C}^{\mathrm{T}}[\boldsymbol{C}\boldsymbol{P}_k^{-}\boldsymbol{C}^{\mathrm{T}} + \boldsymbol{R}]^{-1} \tag{3}$$

$$\boldsymbol{P}_k = [\boldsymbol{I} - \boldsymbol{K}_k\boldsymbol{C}]\boldsymbol{P}_k^{-} \tag{4}$$

$$\hat{\boldsymbol{X}}_k = \hat{\boldsymbol{X}}_k^{-} + \boldsymbol{K}(k)[\boldsymbol{Y}_k - \boldsymbol{C}\hat{\boldsymbol{X}}_k^{-}] \tag{5}$$

where k is the time-step, $\hat{\boldsymbol{X}}_k^{-}$ is the priori estimate of the system state, $\hat{\boldsymbol{X}}_k$ is the updated state estimate and $\boldsymbol{A}$ is the state transition matrix. $\boldsymbol{W}_k$ is the random error state vector, $\boldsymbol{P}_k$ and $\boldsymbol{P}_k^{-}$ are error covariance for posterior parameters and predicted parameters, respectively; $\boldsymbol{Q}$ and $\boldsymbol{R}$, respectively, represent the noise covariance of motion and measurement; $\boldsymbol{K}_k$ is the Kalman gain; $\boldsymbol{C}$ is the observation matrix; and $\boldsymbol{Y}_k$ is the measurement.

The predicting physical quantities include the displacement s, the vehicle speed v and the acceleration a. Then, the state vector $\boldsymbol{X}$ is set as $[s\ v\ a]^{\mathrm{T}}$. Supposing that the vehicle motion approaching to an intersection can be regarded as a rectilinear motion, the state transition matrix can be represented as

$$\boldsymbol{A} = \begin{bmatrix} 1 & h & \dfrac{h^2}{2} \\ 0 & 1 & h \\ 0 & 0 & 1 \end{bmatrix} \tag{6}$$

in which h denotes the predicting period (s).

During the recursive computations, the vehicle distance from stop line at time $(t+h)$, $x(t+h)$, can be determined by (7).

$$x(t+h) = x(t) - s(t+h) \tag{7}$$

where $x(t)$ is the vehicle distance from stop line at time t and

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$s(t+h)$ is the predicted displacement at time $(t+h)$. Based on $x(t+h)$ and the predicting vehicle speed $v(t+h)$, the exact location of DZ can be determined if the dilemma problem occurs.

In the Kalman calculation, the noise matrices, $\boldsymbol{Q}$ and $\boldsymbol{R}$ are usually tuned experimentially by a trial-and-error method. However, it is much dependent on an experienced operator [21]. To overcome the difficulty, a genetic systematic-rule is involved in searching optimal $\boldsymbol{Q}$ and $\boldsymbol{R}$ to yield better motion estimation and prediction.

The genetic systematic-rule is a stochastic global search method that mimics the metaphor of natural biological evolution [22]. In general, the algorithm consists of five steps: encoding, fitness evaluation, selection, crossover and mutation [23]. In this research

1. *Encoding or chromosome representation:* The noise covariance $\boldsymbol{Q}$ and $\boldsymbol{R}$ are coded into a real-valued string, known as a ‘chromosome’. A typical coding example of a chromosome is given as: chromosome = $[\boldsymbol{Q}, \boldsymbol{R}] = [0.01, 0.023]$.
2. *Initial population:* The initial population of the chromosomes is randomly generated on the preset population size n.
3. *Fitness evaluation:* In a generation, each of the chromosome is decoded back to the values of $\boldsymbol{Q}$ and $\boldsymbol{R}$. Based on these values, the Kalman filter works for the prediction. After that, the mean squared error of the predictions is calculated for the fitness evaluation. Then, the chromosome is ranked based on the fitness with a linearly ranking arrangement.
4. *Selection for reproduction:* Reproduction is dealt with a mating-pool process that the parent chromosomes are selected to produce their new offsprings. In this research, parent chromosomes are selected and copied to a ‘mating pool’ where the highly fit chromosomes are more likely to receive more than one copy, and unfit chromosomes are more likely to receive no copy.
5. *Crossover:* In order to combines two parent chromosomes to produce a new chromosome (offspring), the arithmetic crossover is applied, where every two different chromosomes in the mating pool are selected as parents and linearly combined to produce a new offspring. Let $u = (u_1, \ldots, u_n)$ and $w = (w_1, \ldots, w_n)$ be the parent strings, then the offspring $o = (o_1, \ldots, o_n)$ is computed by $o_i = \alpha * u_i + (1-\alpha) * w_i$, $i = 1,\ldots, n$; where α is the weighting factor, randomly generated from the uniform interval of $[-1.0, 1.0]$.
6. *Mutation:* After the crossover is done, limiting chromosomes are randomly chosen for mutation. The offspring string after mutation $\hat{o}_\iota$ is computed accordingly: $\hat{o}_j = o_j * \gamma$, $j = 1,\ldots, m$; where γ is a mutation factor randomly generated from the uniform interval of [0.1, 10] and m is the number of offspring for mutation in a generation.
7. *Iteration:* Procedures (3)–(7) are iteratively processing until a given convergence condition is achieved.

4 Algorithms development for the ADZW system

4.1 DZ determination

Referring to the GHM model [3] described in previous two parameters are important to determine DZ: the critical stopping distance S_{stop} and the continuation distance S_{con}. Let x be the distance of an approaching vehicle to the stop line (a.k.a. stop bar) before entering an intersection. S_{stop} is the minimum x required by an approaching vehicle with fully braking and stopping at the stop line. S_{con} is the shortest distance x required by an approaching vehicle with an comfortable acceleration passing through the intersection at the onset of yellow indication. In this study, S_{stop} is formulated as [24]

$$S_{\text{stop}} = v \times \tau\left(v\frac{D}{J} - \frac{1}{6}\frac{D^3}{J^2}\right) + \frac{(v - D^2/2J)^2}{2(D + G \times g)} \tag{8}$$

where v is the approaching speed at the onset of yellow indication (ms^{-1}), τ is the driver perception-reaction time (s), D is the typical deceleration rate for stopping on level pavement (ms^{-2}), G is the grade of the approach lane (in percentage), g is the acceleration due to gravity (9.81 ms^{-2}) and J denotes the jerk rate (ms^{-3}) of the equipped vehicle in fully braking.

S_{con} is defined as

$$S_{\text{con}} = v \times I_{\text{G}} - (W + L) + \frac{1}{2}a_{\text{pass}}(I_{\text{G}} - \tau)^2 \tag{9}$$

where I_{G} is the intergreen time (s), W is the span width of an intersection (m), L is the length of the equipped vehicle (m) and a_{pass} is the acceleration rate of the equipped vehicle at crossing an intersection (ms^{-2}). As shown in Fig. 2, once $S_{\text{stop}} > S_{\text{con}}$ and the vehicle falls in the range of $S_{\text{stop}} > x > S_{\text{con}}$, the driver will encounter the DZ. Otherwise, the vehicle falls in the range of $0 < x \le S_{\text{con}}$, called the clearance zone (CLZ), in which the driver can pass through the intersection. If the driver wants to stop at the CLZ, the vehicle would be stopped in the middle of the intersection. Therefore situations where a vehicle is trapped in either DZ or CLZ are considered risky. In this paper, CLZ and DZ are both regarded as ‘risky zones’ and the developed algorithms aim to assist driver in avoiding the risky zones.

According to (8) and (9), one can find the DZ is a function of many contributing factors, such as vehicle’s distance from the stop line, vehicle speed and remaining green time. Table 1 has listed all the factors and their updating requirements. In the past, collecting such messages in real-time was technically difficult. Now, with the improved communication technology, obtaining such information and real-time data become easy.

The determination of DZ is executed as the decision mechanism illustrated in Fig. 3. This mechanism is composed of three different algorithms: DZE, DZP and WS. Once real-time data flow feeds into the decision mechanism, the DZE and DZP algorithms are responsible for determining the occurrence of the DZ. Then, the WS algorithm decides a proper warning for drivers to prevent the DZ.

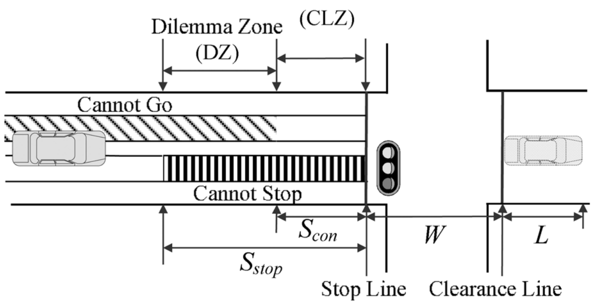

Fig. 2 *Definition of DZ at a signalised intersection*

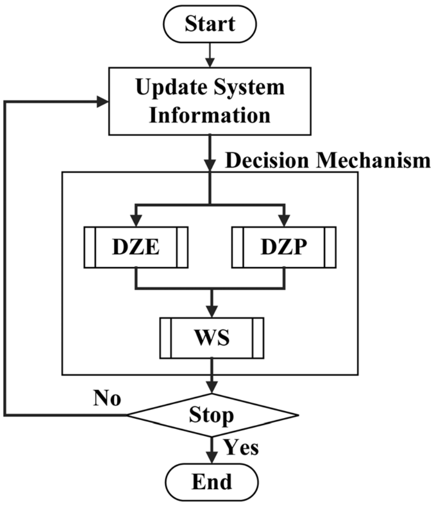

Fig. 3 *Flow diagram – decision mechanism*

4.2 DZE algorithm

The DZE algorithm assumes that the speed of the equipped vehicle approaching an intersection is constant. In other words, the vehicle speed measured at the time t, $v(t)$, is equal to that at the onset of yellow indication $v(t+G_R)$, that is, $v(t) \simeq v(t+G_R)$. Fig. 4 shows the steps of estimating the vehicle position and determining if the vehicle will be trapped in a risky zone:

Step 1: Obtain system information (collecting parameters in Table 1).
Step 2: Employ (8) and (9), respectively, to estimate the critical stopping distance, S^E_{stop} (the estimated critical stopping distance) and the continuation distance, S^E_{con} (the estimated continuation distance).
Step 3: If $S^E_{stop} > S^E_{con}$, the risky zone occurs, and go to Step 4; otherwise go to Step 7.
Step 4: Estimate the vehicle position at the onset of yellow indication: $x(t+G_R) = x(t) - v(t) \times G_R$; where $x(t+G_R)$ and $x(t)$ are the distance from stop line (m) at the onset of yellow and at time t, respectively. G_R is the remaining green time (s).

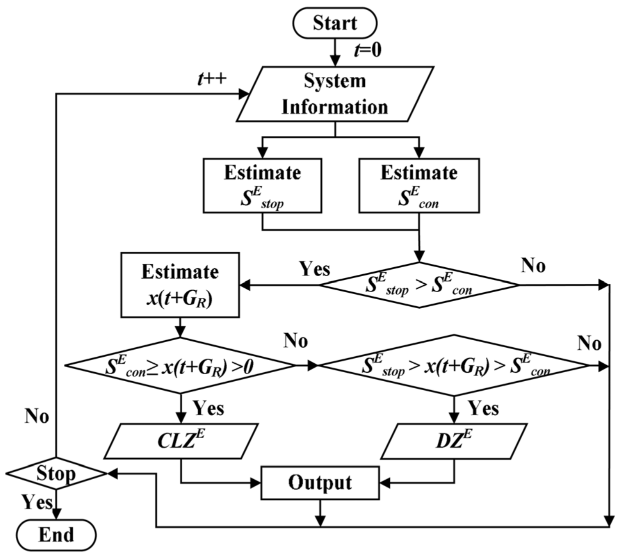

Fig. 4 *Real-time DZE algorithm*

Step 5: If $S^E_{con} \geq x(t+G_R) > 0$, then outputs CLZ^E (the estimated clearance zone) and back to Step 1; otherwise go to next step.
Step 6: If $S^E_{stop} > x(t+G_R) > S^E_{con}$, then outputs DZ^E (the estimated DZ) and back to Step 1; otherwise go to the next step.
Step 7: If the ADZW system is 'on', go back to Step 1.

4.3 DZP algorithm

The DZE algorithm is generally utilised for estimating risky zone and easy to implement. However, the assumption of constant vehicle speeds might not be realistic in real situation and would decrease the accuracy and reliability of the ADZW system, particularly in the term of the green indication near to the end. Thus this research proposes another useful algorithm for DZ prediction, DZP, to improve this condition as shown in Fig. 5. The motion of the equipped vehicle approaching to an intersection is predicted by the Kalman filter with a genetic systematic-rule (called as GAKF) described in previous section, where the genetic systematic-rule is employed to optimise the noise covariance, $\boldsymbol{Q}$ and $\boldsymbol{R}$, to yield better prediction results.

Two issues are noticed for using the GAKF. The one is that if the DZP algorithm starts late as the vehicle is approaching the DZ, there would be too few recursions to support precise prediction. The other issue is that if the DZP algorithm is executed far early before the vehicle approaching the risky zones, the output is generally redundant for the driver and the processing makes the RSE/OBE having extra computational burden. Hence the optimal actuation distance, D_{AC}, the distance upstream from the stop line to trigger the algorithm, needs to be determined in the DZP algorithm to ensure enough recursions but reduce the computational burden. When $x(t) \leq D_{AC}$, the DZP algorithm should start the recurrence of the GAKF. Otherwise, the recursion will stop to avoid redundant computations.

In the GAKF, optimising or evaluating $\boldsymbol{Q}$ and $\boldsymbol{R}$ should be processed offline on the data of just passing period. Therefore the evaluating is triggered at lower speeds or stopping to avoid interfering the ADZW-urgent working of the OBE. A threshold for triggering the evaluation, v_{stop}, is set at 10 kph. The values of $\boldsymbol{Q}$ and $\boldsymbol{R}$ are updated for the Kalman

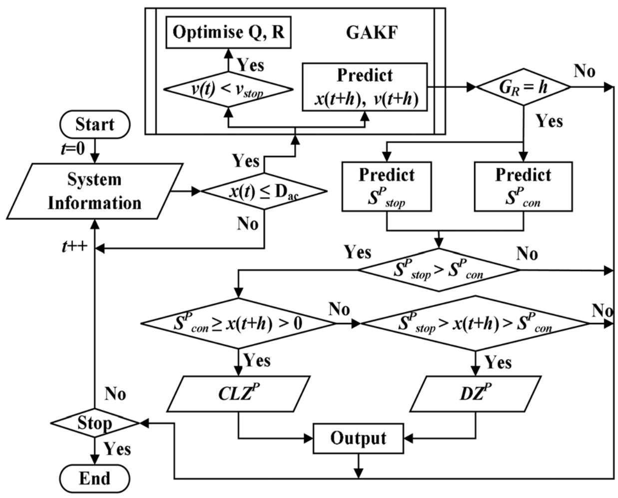

Fig. 5 *Real-time DZP algorithm*

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filter operation once the improved $\boldsymbol{Q}$ and $\boldsymbol{R}$ come out. The DZP algorithm's operation is as following:

Step 1: Obtain system information (collecting parameters in Table 1).
Step 2: If $x(t) \le D_{\rm AC}$, then go to Step 3. Otherwise, go back to Step 1.
Step 3: Predict vehicle motion: $x(t+h)$ and $v(t+h)$. Meanwhile, if $v(t) < v_{\rm stop}$, execute $\boldsymbol{Q}$ and $\boldsymbol{R}$ evaluation and update them with improved values.
Step 4: If $G_{\rm R} = h$, the predicting period (s), then go to Step 5, else go to Step 9.
Step 5: Employ (8) and (9), respectively, to determine the critical stopping distance, $S^{\rm P}_{\rm stop}$ (the predicted critical stopping distance) and the continuation distance, $S^{\rm P}_{\rm con}$ (the predicted continuation distance).
Step 6: If $S^{\rm P}_{\rm stop} > S^{\rm P}_{\rm con}$, the risky zones occurs and go to Step 7. Otherwise, go to Step 9.
Step 7: If $S^{\rm P}_{\rm con} \ge x(t+h) > 0$, outputs CLZ$^{\rm P}$ (the predicted clearance zone) and back to Step 1. Otherwise, go to Step 8.
Step 8: If $S^{\rm P}_{\rm stop} > x(t+h) > S^{\rm P}_{\rm con}$, output DZ$^{\rm P}$ (the predicted DZ) and back to Step 1. Otherwise, go to Step 9.
Step 9: If the ADZW system is 'on', go back to Step 1.

Since the DZP algorithm can predict the vehicle motion one time period ahead, the driver can be warned early if the dilemma situation happens. Therefore the length of this time period is defined as a pre-warning period. This time period will affect the effectiveness of the ADZW system to the driver. If the pre-warning period in the system is insufficiently long, for example, 1 s, the driver may not have enough time to take proper action to prevent the dilemma problem whereas the vehicle is closing to an intersection. On the contrary, if the pre-warning period is too long, the algorithm may be sensitive to uncertainty, increasing the number of false alarms and reducing the reliability of the ADZW system. According to Taoka' [25] study, most drivers' reaction time is in the range between 1.1 and 1.3 s when they drive vehicles with high speeds (i.e. >64 kph) approaching to an intersection. Hence, 3, 4 and 5 s are preset for the pre-warning period in this study. Accordingly, the DZP algorithm can determine the occurrence of the DZ in time from 3 to 5 s before the onset of the yellow indication.

4.4 Warning selection

One should note that the DZP algorithm is only executed on the pre-warning periods: 3, 4 and 5 s. Hence, the DZP algorithm will do nothing when $G_{\rm R} > h_{\rm max}$, where $h_{\rm max}$ is the maximal pre-warning period. As the plan in this study, the algorithms of DZE and DZP are integrated in the ADZW system to combine the strengths of both algorithms. During little early periods, $G_{\rm R} > h_{\rm max}$, the ADZW system issues warnings solely handling by the DZE. During the urgent periods, $G_{\rm R} \le h_{\rm max}$ (the green indication will be ending) the ADZW system issues warnings handling by DZE and DZP concurrently. Therefore during the periods of $h_{\rm min} \le G_{\rm R} \le h_{\rm max}$, the outputs may come out two distinct warning levels. In order to incorporate two distinct outputs, the WS algorithm is developed to conclude a final warning message and its corresponding urgent level. It should be noted that the warning is mainly based on the outputs of the DZP algorithm. In other words, if there is a conflict between the DZP and DZE algorithms, the system will adopt the output from the DZP algorithm.

Table 2 WS algorithm

Warning type	Warning from DZE DZ$^{\rm E}$/CLZ$^{\rm E}$	Warning from DZP DZ$^{\rm P}$/CLZ$^{\rm P}$	Verbal warning	
			Message (visual)	Beeper (vocal)
1	DZ$^{\rm E}$	none	slow down!	none
2	CLZ$^{\rm E}$ none	DZ$^{\rm P}$	slow down!	lowly frequent beeping
3	DZ$^{\rm E}$	DZ$^{\rm P}$	warning!	highly frequent
4	DZ$^{\rm E}$ CLZ$^{\rm E}$ none CLZ$^{\rm E}$	CLZ$^{\rm P}$ none	please drive carefully to pass the intersection	none
5	none	none	none	none

As shown in Table 2, there are five types of warning messages. Each type of warning includes both visual and vocal information to represent different conditions and urgent levels a driver would encounter. This WS algorithm is considered effective and, meanwhile, conservative to avoid triggering/interfering any unnecessary driving action.

5 Experimental test and analyses

The performance of the ADZW system depends on how accurately the warning can successfully prevent the DZ. To verify the reliability and accuracy of the proposed algorithms, this study conducts experimental tests with different mimic scenarios.

5.1 Experimental design

Table 3 listed all the parameters used in the experiments. Among these parameters, driver and vehicle characteristics, roadway configuration and system parameter are assumed constant in the simulation. The parameters regarding vehicle motion and traffic signal timing are measured and generated based on the traffic conditions at that certain time.

In order to realistically simulate an equipped vehicle approaching a signalised intersection, effects of traffic

Table 3 Parameters preset for the experiments

Parameter type	Factor	Value	Unit
driver and vehicle characteristics	vehicle length	5	m
	typical deceleration	3	ms^{-2}
	jerk rate	3	ms^{-3}
	perception reaction time (τ)	1.0	s
	acceleration range	[−0.5, 0.5]	ms^{-2}
traffic signal timing	inter-green interval	4	s
roadway configuration	grade of the approach lanes	0.0	%
	width of the intersection	30	m
	prevailing speed	65	kph
system parameter	activation distance	600	m
genetic systematic rule	initial population size	300	–
	maximum number of generations	150	–
	mutation probability	0.05	–
	range of real-value string	[0.001, 1000]	–

signals on driver behaviours should be considered. Thus, a simplified driver behaviour model is proposed as follows:

1. When the signal indication is green and the vehicle's speed is over the upper bound of the range of desired speed, R_{DS}, the vehicle will be decelerated to the speed within R_{DS}. If the speed is below the lower bound of R_{DS}, the vehicle will be accelerated to keep speed within it. In the experiments, R_{DS} is allocated in the range of $[V_P - 3.6,\ V_P + 3.6]$ kph, where V_P denotes the prevailing speed.
2. When the signal indication is green and the vehicle speed is within R_{DS}, the acceleration of the vehicle will vary randomly in the range of $[-0.5, 0.5]$ ms^{-2}, to simulate the speed fluctuation because of the traffic interaction and driver behaviour.
3. When the signal indication turns yellow, if the distance between the vehicle and the stop line is greater than the critical stopping distance, the driver will slow down the vehicle with constant deceleration; otherwise the driver will clear the intersection at a constant speed.

This driving behaviour model simplifies the simulation process not only can reflect the effects of traffic signals and surrounding traffic but also considers the simulation efficiency. The simulated vehicle would continue to pass through several intersections, not encountering more than one light indication changeover at each intersection. Once the yellow indication turns on, warnings determined by the WS algorithm will be recorded and compared with the actual situations in simulation.

The signal timing parameters include the inter-green interval and remaining green (G_R). The former is assumed to be consistent for all intersections, and the latter is intentionally generated to have the simulated vehicle approach the risky zone as close as possible at the onset of the yellow indication. Therefore the activation distance D_{ac} is utilised to represent the distance between the stop line and an upstream point where the DZP algorithm is activated. The timing of G_R at the moment when the vehicle is passing the point at D_{ac} is defined as the initial remaining green, denoted as G_R^I. If G_R^I satisfies (10), the simulated vehicle will be close to the risky zone when the green indication turns off

$$G_R^I = \frac{3.6 * (D_{ac} - S_{stop})}{V_L} + \frac{1.8 * (V_P - V_0)^2}{a \times V_L} + \mathrm{RV} \qquad (10)$$

where V_0 is the initial speed of the vehicle entering activation zone (ms^{-1}), a is the acceleration rate (ms^{-2}), V_P is the prevailing speed (kph), RV is a random value in $[-10, 10]$ to avoid identical stopping position occurring for each randomly generated vehicle when the remaining green ends. By (10), the occurrences of DZs in the simulation are more frequent than those in reality. Therefore the simulation can effectively reflect the robustness of the proposed algorithms.

5.2 Sensitivity analysis

The prevailing speed and the acceleration range are two most sensitive parameters to driver's behaviour. The prevailing speed affects driver's practical speed and the acceleration range affects the variation of speeds in simulation. The activation distance, D_{ac}, also affects the performance of the ADZW system since the DZP algorithm is based on the historical data of the vehicle motion; that the longer D_{ac} is, the more historical data can be obtained. Table 4 shows the composition of these parameters in different ranges for the sensitivity analysis.

Table 4 Composition of the parameters for sensitivity analysis

Prevailing speed, kph	Acceleration range, ms^{-2}	Activation distance, m
50	−0.1–0.1	400
55	−0.3–0.3	500
60	−0.5–0.5	600
65	−0.7–0.7	700
70	−0.9–0.9	800
75		
80		

The DZE algorithm is performed in the entire process, but the DZP algorithm only outputs prediction results at specific time stamps, (e.g. 3, 4 and 5 s) before the onset of the yellow indication. The simulation was continuous till that the equipped vehicle has passed through 1000 intersections where their signal indication changeovers match the condition of 'green to yellow'. The warnings that concluded by the WS algorithm were recorded for the sensitivity analysis.

Two measures of effectiveness, pre-warning period's warning accuracy Acc_h (%) and system warning accuracy Acc_S (%) are used to evaluate the system performance and defined as

$$\mathrm{Acc}_h = \frac{\mathrm{CW}_h}{N} \times 100\% \qquad (11)$$

$$\mathrm{Acc}_S = \frac{\mathrm{CW}_S}{N} \times 100\% \qquad (12)$$

where CW_h is the total number of correct warnings specifically when the pre-warning period is at $h = 3$, 4 and 5 s, respectively. CW_S is the total number of correct warnings for all pre-warning periods in each encountering intersection and N is the number of experimental runs. Therefore Acc_S is always lower than Acc_h.

The effect of prevailing speeds on prediction accuracy is shown in Fig. 6*a*. Results show that both Acc_h and Acc_S decrease when the prevailing speed is >65 kph. Acc_S achieves to 93.8% when the prevailing speed is 70 kph and it decreases to 92.4% as the prevailing speed is raised to 80 kph. This is because that the vehicle is set to drive at the prevailing speed in simulation. It would require less time for a vehicle to go through D_{ac} at a higher prevailing speed; therefore the reduction of historical motion data would decrease the prediction accuracy.

The acceleration range in simulation is to represent different driver behaviours (e.g. aggressive or moderate) in response to the effect of surrounding traffic. A larger range of acceleration varied indicates that the driver steers his/her vehicle more aggressively. Fig. 6*b* shows the different acceleration ranges and their corresponding accuracy rates. As expected, Acc_S decreases as the acceleration range is expanded. The lowest Acc_S is 91.6% when the acceleration range is $[-0.9,\ 0.9]$ ms^{-2}, whereas the scenario with the range $[-0.1, 0.1]$ ms^{-2} has the highest Acc_S 98.8%. The results show that the accuracy rate is sensitive to the acceleration range. However, such aggressive drivers are rather rare and can be considered as a special case. Overall, Acc_S still remains above 90% even in the extremely scenarios and this proves the prediction capability of the ADZW system.

As mentioned, the vehicle motion is predicted by the GAKF. Hence, sufficient historical motion data, depending on D_{ac}, are essential for providing highly accurate

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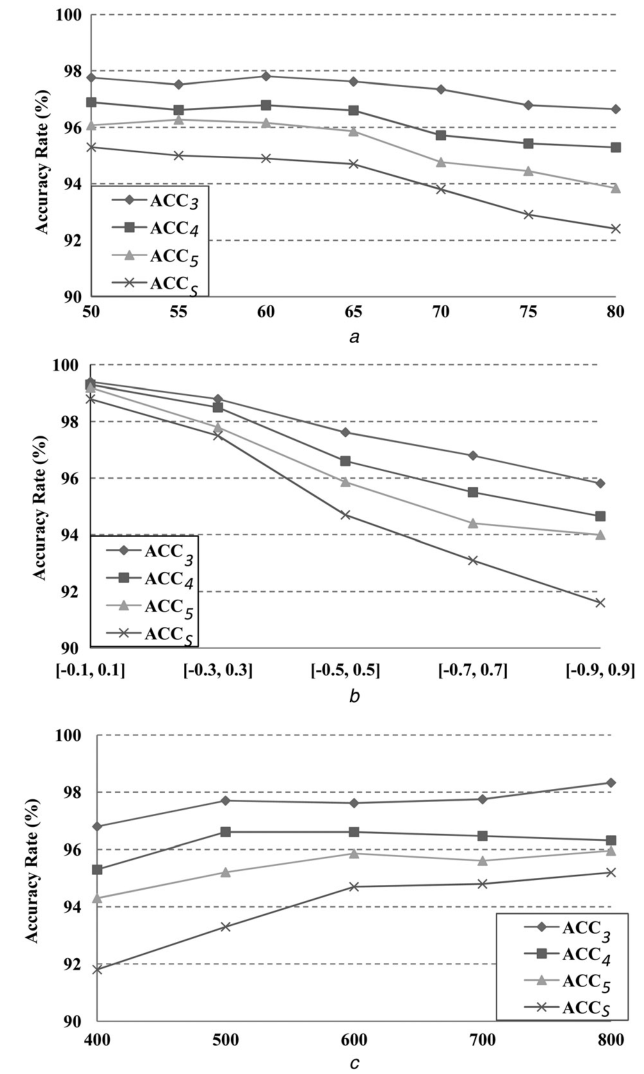

Fig. 6 *Results of sensitivity analysis*

a Prevailing speed (kph)
b Acceleration range (ms^{-2})
c Activation distance (m)

prediction. Fig. 6*c* shows the accuracy decreases as D_{ac} decreases. Acc_S descends obviously when D_{ac} is <600 m. Acc_S is 91.8% as D_{ac} equals 400 m. Acc_S reaches 95% when D_{ac} is >600 m. However, Acc_S does not improve significantly as D_{ac} is >600 m. It is concluded that the reasonable threshold of D_{ac} is 600 m.

5.3 System applicability

In practice, the prevailing speed is statistical refereeing to the roadway and traffic conditions and cannot be influenced by any vehicle. D_{ac} is a preset parameter in the ADZW system. In order to improve the applicability of the ADZW system, proper selection of D_{ac} is critical for improving warning accuracy and minimising computational burden of the OBE in different prevailing speed conditions. Hence, the analysis for system applicability is of great importance before field implementation. Thirty-five scenarios are generated based on different combinations of prevailing speeds and D_{ac}.

To better visualise the results of analysis, Fig. 7 illustrates the contour plot of Acc_S of given 35 scenarios, in which 10 scenarios have $Acc_S > 95\%$ and 24 scenarios have Acc_S between 90 and 95%, and only one scenario has $Acc_S <$

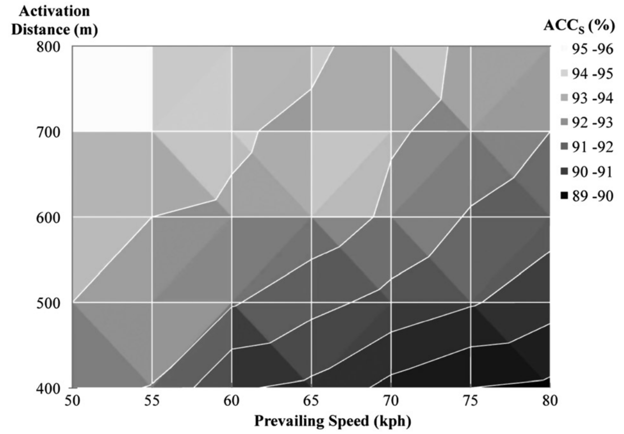

Fig. 7 *Contour plot of system warning accuracy (Acc_S)*

90%. Fig. 7 clearly illustrates that the Acc_S increases as prevailing speed decreases and/or D_{ac} increases. This figure also shows that Acc_S is determined by the D_{ac} in high prevailing speeds. As we can see that, when the prevailing speed is 80 kph and D_{ac} is preset as 400 m, as shown at the bottom right corner of Fig. 7, the Acc_S is relatively lower (89.8%). That is, in high prevailing speed scenarios (prevailing speed $\geq$80 kph), Acc_S falls to exceed 90% unless the D_{ac} is extended at least to 500 m. Therefore the condition where the equipped vehicle passes through an intersection with high speeds and short D_{ac} is preset, will potentially induce inaccurate warning results.

One can find that the shorter the D_{ac} is, the more sensitive the Acc_S is to the variation of prevailing speeds. For example, when $D_{ac} = 800$ m and the prevailing speed increases from 50 to 80 kph, the reduction of Acc_S is only about 2%. However, this reduction increases to 5% when D_{ac} is 400 m. Therefore in the situation where the driver may experience large variation of speeds, D_{ac} should be set as longer as enough to avoid the instability of Acc_S. This instability is not only diminish system reliability, but also increases the risk of trapping the equipped vehicle into DZ. Likewise, Acc_S in scenarios with higher prevailing speeds are more sensitive to the variation of D_{ac} than Acc_S in scenarios with lower prevailing speeds. Hence, the modification of D_{ac} should be treated carefully especially driving with high speeds along a country road. Furthermore, Fig. 7 can be a meaningful reference by users in determining a proper D_{ac}. For example, if the prevailing speed is 65 kph and the required Acc_S is anticipated at 94%, D_{ac} should be set at least 600 m.

6 Conclusions

The dynamic feature of DZs cannot be handled by the static roadway design and might cause potential risks for vehicle safety. In this study, three algorithms, DZE, DZP and WS algorithms for DZ prevention are developed for an in-vehicle system, the advanced ADZW system, potentially equipped in an IntelliDrive-ready vehicle. The attributes of driver, vehicle and roadway are considered in the algorithm development to increase the accuracy of determining the DZ and the CLZ. Besides, in order to capture the dynamical feature of DZ, a genetic systematic rule improving the prediction capacity of the Kalman filter is integrated into the DZP algorithm.

The algorithms are tested with a variety of scenarios to demonstrate the system reliability and performance. The results show that the highest accuracy rate (Acc_S) of the proposed algorithms is 98.8%. In other words, the algorithms can accurately prevent 98.8% of vehicles from trapping in the DZ or CLZ in 1000 simulation runs. According to the sensitivity analysis, the warning accuracy is sensitive to the variation of prevailing speed, range of acceleration rate and activation distance (D_{ac}). That is, the accuracy decreases as either prevailing speed or acceleration range increases, or as D_{ac} lessens. In our tests, the Acc_S, however, is over 90% for all scenarios, consequently demonstrating the noteworthy reliability of the proposed algorithms. A contour plot of Acc_S is presented to assist in selecting a proper D_{ac} based on the prevailing speed and/or the Acc_S. These results of analysis can help the accomplishment of the algorithms more practical for preventing dilemma problem, and enhance the safety of IntelliDrive-ready vehicle approaching signalised intersections.

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8 References

1 Fatality Analysis Reporting System (FARS): Available at http://www-fars.nhtsa.dot.gov/Main/index.aspx, accessed December 2010
2 Rakha, H., El-Shawarby, I., Setti, J.R.: 'Characterizing driver behavior on signalized intersection approaches at the onset of a yellow-phase trigger', *IEEE Trans. Intell. Transp. Syst.*, 2007, **8**, (4), pp. 630–640
3 Gazis, D., Herman, R., Maradudin, A.: 'The problem of the amber signal light in traffic flow', *Oper. Res.*, 1960, **8**, (1), pp. 112–132
4 Sheffi, Y., Mahmassani, H.: 'A model of driver behavior at high speed signalized intersections', *Transp. Sci.*, 1981, **15**, (1), pp. 50–61
5 Liu, C., Herman, R., Gazis, D.C.: 'A review of the yellow interval dilemma', *Transp. Res. A*, 1996, **30**, (5), pp. 333–348
6 Institute of Transportation Engineers (ITE): Traffic Engineering Handbook. (ITE, 1999, 5th edn.)
7 Li, Z.: 'Modeling dynamic dilemma zones using observed yellow-onset trajectories', *ITE J.*, 2009, **79**, (11), pp. 24–31
8 Moon, Y.J., Coleman, III, F.: 'Dynamic dilemma zone based on driver behavior and car-following model at highway-rail intersections', *Transp. Res. B*, 2003, **37**, pp. 323–344
9 Adell, E., Varhelyi, A., Alonso, M., Plaza, J.: 'Developing human-machine interaction components for a driver assistance system for safe speed and safe distance', *Intell. Transp. Syst., IET*, 2008, **2**, (1), pp. 1–14
10 Amditis, A., Floudas, N., Kaiser-Dieckhoff, U. *et al.*: 'Integrated vehicle's lateral safety: the LATERAL SAFE experience', *IET Intell. Transp. Syst.*, 2008, **2**, (1), pp. 15–26
11 Lu, X.-Y., Madanat, S.: 'Truck adaptive following distance based on threat assessment under variable conditions', *IET Intell. Transp. Syst.*, 2009, **3**, (2), pp. 138–147
12 Moon, Y.J.: 'Functional requirements for in-vehicle dilemma zone warning system at signalized intersections', *Transp. Res. Record*, 2002, (1800), pp. 62–68
13 Moon, Y.J., Lee, J., Park, Y.: 'System integration and field tests for developing in-vehicle dilemma zone warning system', *Transp. Res. Record*, 2003, (1826), pp. 53–59
14 Abbas, M., Li, P.: 'Advanced real-time intersection data collection system for safety evaluation'. Proc. 12th Int. IEEE Conf. ITS, St. Louis, MO, USA, October 2009, pp. 510–515
15 U.S. Dept. Transp. (USDOT): IntelliDrive^{SM}—Safer, Smarter, Greener, 2010. Available at http://www.intellidriveusa.org, accessed December 2010
16 Ma, Y., Chowdhury, M., Jeihani, M., Fries, R.: 'Accelerated incident detection across transportation networks using vehicle kinetics and support vector machine in cooperation with infrastructure agents', *IET Intell. Transp. Syst.*, 2010, **4**, (4), pp. 328–337
17 Dion, F., Oh, J.S., Robinson, R.: 'Virtual testbed for assessing probe vehicle data in Intellidrive systems', *IEEE Trans. Intell. Transp. Syst.*, 2009, **PP, 99**, pp. 1–10
18 Arnaout, G.M., Khasawneh, M.T., Zhang, J., Bowling, S.R.: 'An IntelliDrive application for reducing traffic congestions using agent-based approach', *IEEE Syst. Inf. Eng. Design Symp.*, 2010, pp. 221–224
19 Doshi, A., Trivedi, M.M.: 'Communicating driver intents: a layered architecture for cooperative active safety applications'. Proc. 13th Int. IEEE Conf. ITS., 2010, pp. 373–378
20 Kalman, R.E.: 'A new approach to linear filtering and prediction problems', *Trans. ASME J., Basic Eng.*, 1960, **82D**, pp. 35–45
21 Shi, K.L., Chan, T.F., Wong, Y.K., Ho, S.L.: 'Speed estimation of an induction motor drive using an optimized extended Kalman filter', *IEEE Trans. Ind. Electron.*, 2002, **49**, (1), pp. 124–133
22 Holland, J.H.: 'Adaptation in Natural and Artificial Systems' (MIT Press, Cambridge, 1992)
23 Michalewicz, Z.: 'Genetic Algorithm + Data Structure = Evolution Programs' (Springer–Verlag, New York, 1996, 3rd edn.)
24 Fenton, R.E.: 'A headway safety policy for automated highway operations', *IEEE Trans. Veh. Technol.*, 1979, **VT-28**, (1), pp. 22–28
25 Taoka, G.T.: 'Brake reaction times of unalerted drivers', *ITE J.*, 1989, **59**, (3), pp. 19–21

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