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ESTIMATING AND COMPARING RESPONSE TIMES IN TRADITIONAL AND CONNECTED ENVIRONMENTS

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ABSTRACT

Response time (RT) is a critical human factor that influences traffic flow characteristics and traffic safety, and is governed by drivers' decision-making behaviour. Unlike the traditional environment (TE), the connected environment (CE) provides information assistance to drivers. This in-vehicle informed environment can influence drivers' decision-making and thereby their RTs. Hence, to ascertain the impact of CE on RT, this study develops RT estimation methodologies for TE (RTEM-TE) and CE (RTEM-CE), using vehicle trajectory data. Due to the intra-lingual inconsistency among traffic engineers, modellers, and psychologists in the usage of the term RT, this study also provides a ubiquitous definition of RT that can be used in a wide range of applications. Both RTEM-TE and RTEM-CE are built on the fundamental stimulus-response relationship, and they utilise the wavelet-based energy distribution of time series of speeds to detect the stimulus-response points. These methodologies are rigorously examined for their efficiency and accuracy using noise free and noisy synthetic data, and driving simulator data. Analysis results demonstrate the excellent performance of both the methodologies. Moreover, our analysis shows that the mean RT in CE is longer than the mean RT in TE.

Keywords: Connected Environment, Response Time, Human factors, Car-following, Wavelet transform

INTRODUCTION

The connected environment (CE) consists of vehicles enabled to provide the surrounding traffic information to drivers through vehicle-to-vehicle, vehicle-to-infrastructure, and vehicle-to-everything communications. This in-vehicle informed environment can fundamentally transform drivers' decision-making, thereby impacts driving behaviour parameters such as desired speed, desired time gap, and response time (RT) (*1*). Vehicular trajectories embody characteristics of individual driving behaviour and can reflect the change in driving behaviour parameters due to CE. Many useful measures can be easily derived from vehicle trajectories, e.g., individual speed and acceleration profiles, spacing, and time headway. However, to estimate driving behaviour parameter such as RT, sophisticated data analysis techniques are required. Thus, this study develops trajectory data based methodologies to estimate RT in CE and traditional environment (TE) (vehicles in TE receive no information assistance).

Several definitions of RT and reaction time are available in the literature. In human factors literature, Scott and Gray (*2*) defines driver RT as the difference of the time when the stimulus is presented and when the driver responds. Boff and Lincoln (*3*) and Green (*4*) suggest brake reaction time consists of mental processing time (sensation, perception, response selection and processing), movement time, and device response time; and a few studies report that total braking time has two subcomponents namely, brake reaction time and movement time (*5*, *6*). While in traffic flow theory literature, e.g., studies on stimulus-response car-following (CF) models, the reaction time is defined as the time taken by the follower to respond to the leader's stimulus (*7*). Surprisingly, the same phenomenon, i.e., the time from the onset of the yellow light to the time when the brake pedal is pressed, is termed as perception response time (*8*), brake-response time (*9*), and many other names (*10*).

Definitions above reflect inconsistency among researchers, modellers, and psychologists in using the terms RT and reaction time when defining the same stimulus-response phenomena. Starosta and Petrynski (*11*) reports this inconsistency from the perspective of human movement science. They report RT as a combination of latent response time and apparent response time whereas reaction time is equal to the latent response time. They also suggest that "terminology is one of the basic epistemological assumptions of any scientific discipline" and the existence of semantic incoherencies in science can lead to improper building of models. Therefore, in the field of transportation research, there is a need for a universally accepted definition of RT and an unambiguous distinction between RT and reaction time.

RT is a critical driving behaviour parameter that influences traffic flow efficiency and traffic safety. Moreover, it provides a robust measure of the driver attention (*2*). For TE, RT's influence on traffic flow characteristics, and the impact of human factors such as age, gender, distraction on RT are discussed elsewhere (*12*). Previous studies demonstrate that an increase in RT compromises the traffic flow stability in CE and TE (*13*, *14*). Due to CE's novelty, RT's impact on traffic flow characteristics and traffic safety are still elusive.

Motivated by the aforementioned gaps, this study aims to achieve the following objectives:

- To provide a theoretically and practically justified definition of RT with wide applicability in traffic community, and explain how RT differs from reaction time;
- To develop trajectory data based RT estimation methodologies for TE (RTEM-TE) and CE (RTEM-CE);
- To understand CE's impact on RT.

RTEM-TE and RTEM-CE are built on the fundamental stimulus-response relationship. The wavelet-based energy distribution (WED) of time series of speeds is utilised to detect the stimulus-response points. Both RTEM-TE and RTEM-CE are rigorously tested at three stages. Moreover, this study utilises high quality trajectory data for CE (with information assistance) and TE (without information assistance) collected from a carefully designed driving simulator experiment. RTEM-CE and RTEM-TE are applied to CE and TE trajectory data, respectively. Afterwards, estimated RTs are compared to gain valuable insights on how participants react to leader's hard deceleration and to an advanced message about the same in CE.

The remainder of the paper is organised as follows. The next section provides the definition of RT, discusses the difference between RT and reaction time, and reviews previous RT estimation studies. After this, the data collected from a driving simulator experiment are briefly described. Thereafter, RTEM-TE and RTEM-CE is presented. The following two sections assess the performance of the two methodologies and present the RTEM-TE and RTEM-CE implementation results. The final section summarises the main conclusions and suggests future research directions.

DEFINING RESPONSE TIME (RT)

This section provides a more theoretically and practically justified definition of RT, and presents our view on how RT is different from reaction time. From the RT definitions reported in the previous section, it is clear that the driver RT is a complex process; its definition is modified or adjusted as per the research question and the researchers' disciplines, and the terms RT and reaction time are often used interchangeably. Driver's response in traffic is essentially a type of human response to a stimulus. Not surprisingly, human response time has been extensively studied in many other disciplines, e.g., human computer interaction (*15*), ergonomics (*16*), psychology (*17*), etc. While these studies are not reviewed here due to space limit, it is important to explore and learn from the literature in other relevant disciplines rather than traffic engineering only. Particularly, in the information theory literature, Fitts' law (*18*) and the Hick-Hyman law (*19, 20*) are two famous theoretic laws of human RT that are widely applicable in the field of ergonomics, engineering, psychology, and human-computer interaction. For brevity, this study excludes descriptions of these laws. How RT is defined in human factors and in human movement science is discussed previously.

Built upon the knowledge gained from the studies (cited in this paper) belonging to different research disciplines, we define RT as: the time taken by a driver to adjust his/her speed against a stimulus, with or without deliberately delaying his/her decision. In TE, a change in the leader's speed, the onset of a traffic light, a road closure sign, etc., are some examples of different stimuli to the driver. While in CE, the information about stimuli act as a stimulus to the driver, e.g., advisory messages about speed of the leader, a road closure, a lane change opportunity, warnings such as speed limit warning, tailgating warning, rear-end collision warning, and advanced messages (early warning) about leader decelerating hard, the onset of red light, etc. The proposed definition of RT is ubiquitous because it can incorporate all the driver responses including no response. Note that the present study focusses only on CF scenarios in TE and CE.

RT is a measurable characteristic of human drivers. As discussed by Koppa (*21*), we also consider reaction time as a part of RT. Having said that, we interpret reaction time as a latent characteristic of human drivers, which is approximated by the minimum value of RT for a given stimulus. The measurable reaction time is defined as the time taken by a driver to adjust his/her speed against a stimulus, without deliberately delaying his/her decision. To comprehend the difference between RT and measurable reaction time, consider a leader-follower vehicle pair travelling on a road. After some time the leader starts decelerating. The follower, after sensing and perceiving the change in leader's speed, can delay his/her reaction deliberately if there is no urgency to maintain a safe gap, and responds only when a safe gap is desired. On the other hand, for the same situation, the follower can also respond as soon as he/she has perceived the stimulus. The time difference between the stimulus and the response in the former case represents RT and in the latter case represents the minimum RT, i.e., the reaction time.

Following the aforementioned definition, RTs can be estimated using trajectory data (as demonstrated in this paper). Furthermore, as shown in Figure 1, RT has two components, namely Latent Response Time and Observable Response Time, which are defined below.

Latent response time (LRT) is the time between when the stimulus is presented and when the driver initiates the detectable muscle activity. LRT involves Sensation, Perception, Decision, Initiation, and Delay. *Sensation* is the time required to detect the stimulus (*4*). *Perception* is the time required to interpret the stimulus (*4*). *Decision* is the time taken by the driver to finalise the course of actions against the stimulus. *Initiation* is the time needed to initiate the muscle activity. No movement is observed during initiation, though the muscle activity can be recorded (*11*). Finally, *Delay* is the time period for which a driver is intentionally delaying the desired response against the stimulus.

The reaction time is LRT minus the delay time i.e., the reaction time is equal to LRT if the driver does not delay his/her decided response deliberately.

Observable response time or movement time is the time between when the foot movement starts and when the foot movement ends (*11*).

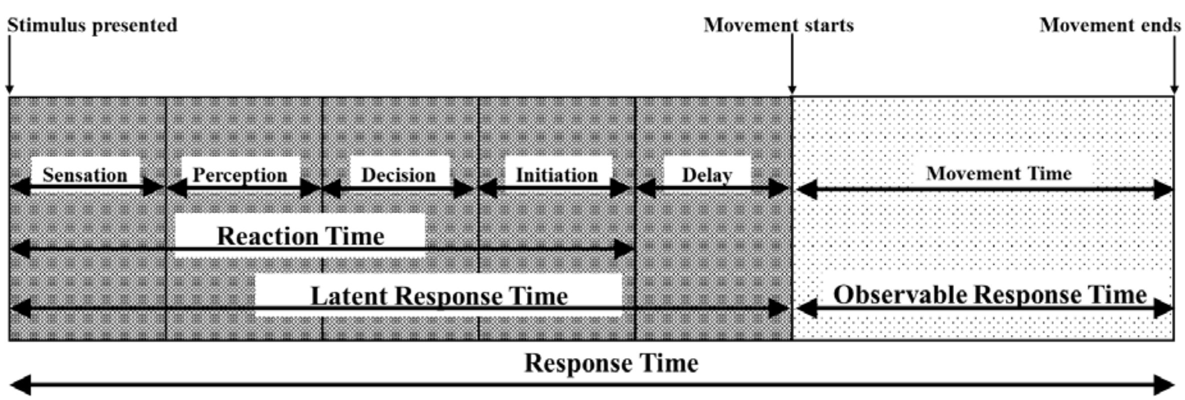

FIGURE 1 RT and its different components (figure not to scale).

A REVIEW OF RT ESTIMATION METHODOLOGIES

In general, RT is estimated either using trajectory data or using physical responses recorded in driving simulator experiments/controlled field experiments. Estimating RT using physical responses is straightforward, e.g., in response to collision warning, Lee et al. (*22*) estimated RT as the sum of accelerator release time from the collision warning, accelerator-to-brake transition time, and brake-to-maximum brake press time.

Contrarily, estimating RT using trajectory data can be complex. The literature lacks RT estimation techniques for CE. To the best of the authors' knowledge, only Ali et al. (*23*) have estimated RT to a road closure message using segmentation. Contrary to CE, a few approaches have been proposed to estimate RT in TE. The first approach is the cross-correlation method (*24*), which approximates RT as the time lag that results in the highest correlation between the relative speed and the corresponding follower's acceleration. The second approach is based on identifying the corresponding peaks on the relative speed time series and the follower's acceleration time series using a graphical method, and the time difference between the peaks is termed as RT (*25*). The third (*26*) and fourth (*27*) approaches are improved versions of the second approach in which the process of identifying peaks is automated using a computer program (no description) and Fourier analysis, respectively. The fifth approach estimates RT as the time difference between when a change in space headway is noted after steady-state CF and when the follower's deceleration is greater than 0.15 m/s^2 (*28*).

Previous studies directly applied the aforementioned approaches to trajectory data without rigorously assessing their capability and reliability in estimating RT. Moreover, it is unclear how sensitive these approaches are to different levels of noise in trajectory data. Recently, Sharma et al. (*29*) demonstrated a dynamic time warping (DTW) based method to estimate RT. One limitation of DTW is singularity (i.e., one to many mapping), due to which a few data points have to be removed from the analysis (*29*).

DATA

High quality trajectory data were collected for CE and TE from a carefully designed driving simulator experiment. The experiment was divided into two scenarios, namely baseline (represent TE) and connected (represent CE). In each scenario, participants had to follow a platoon of vehicles on a single lane motorway for 3 km. In the baseline scenario, no information assistance was provided to the participants, and in the connected scenario, to simulate vehicle-to-vehicle and vehicle-to-infrastructure information dissemination, continuous and uninterrupted information assistance was provided to participants using driving aid. Specifically, three categories of information were delivered (a) continuous information such as the speed of the leading car, (b) on time event-triggered information such as speed limit warning, and (c) advanced event-triggered information such as the warning message 'leader braking hard.'

In the CF section of the experiment, the leading cars (programmed vehicles) followed the speed profile displayed in Figure 2 whereas the driven car's (car driven by the participant) speed profile was governed by the participant's CF behaviour. Note that the vehicle interactions remain the same in the baseline and in the connected scenario.

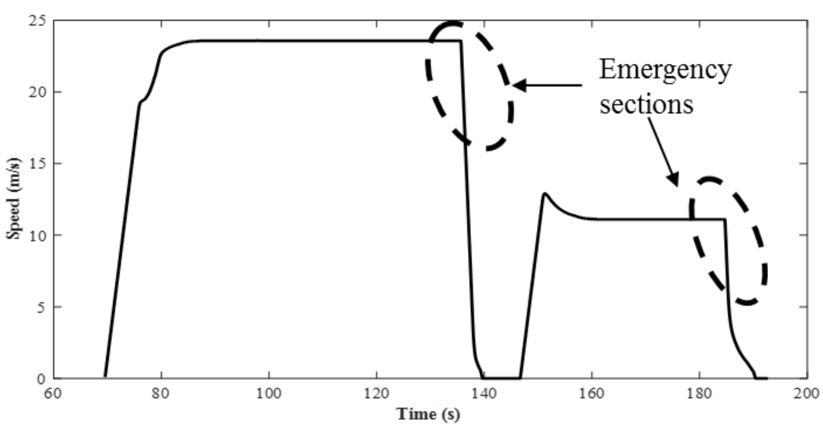

FIGURE 2 Speed profile of the leading car.

This study focusses on the emergency sections of the experiment. Emergency sections denote those road sections of the simulator experiment where leading car decelerated hard. Importantly, advanced event-triggered information ('leader braking hard') was provided to the participants 3 s before the actual hard braking in CE's emergency sections. We opted for 3 s to ensure that the full impact of connectivity in assisting drivers' decision making can be captured (average RT of 2 s and additional 1 s to cater for the time needed for perceiving and understanding the text message displayed on the screen).

Seventy eight eligible participants from the diverse background drove the simulator car resulting in the 78 leader-follower trajectory pairs in each scenario. For details regarding the simulator experiment, refer to Sharma et al.(*1*).

METHODOLOGY

Wavelet Transform: an introduction and its application in detecting changes

The wavelet transform decomposes a signal[1] into scaled and shifted genres of the mother/original wavelet. Popular applications of the wavelet transform in traffic engineering include traffic incident detection (*30*), bottleneck activations and traffic oscillations analysis (*31*), and short-term traffic volume forecasting (*32*).

A wavelet is a short-lived wave with zero mean and non-zero norm, and represented using a real or complex mathematical function. There are hundreds of wavelets available in the literature and a few widely used wavelets are Haar, Daubechies family, Mexican hat, Morlet, and Coieflets family. Zheng and Washington (*33*) presents a comprehensive examination of different wavelets' suitability in analysing traffic engineering related research topics, and concluded that the Mexican hat wavelet provides satisfactory performance in detecting traffic state change points, the start and the end of lane change manoeuvres, start points of acceleration (deceleration) waves, and discontinuity of the fundamental diagram. This study also prefers the Mexican hat wavelet because RT estimation is based on change point detection.

The wavelet transform coefficient of a continuous signal $S(t)$ is provided in Equation (1):

$$T(a,b) = \frac{1}{\sqrt{a}}\int_{-\infty}^{\infty} S(t)\psi\frac{t-b}{a}dt \tag{1}$$

where $T(a,b)$ is a wavelet coefficient, $S(t)$ is a continuous signal (time series of speeds in this case), $\psi\frac{t-b}{a}$ is a wavelet function, and a and b are scale and translation parameters of the wavelet function, respectively.

As demonstrated by Zheng and his collaborators (*31, 33*), the temporal distribution of wavelet-based energy E_b can assist in identifying significant speed changes. The formulation of E_b is presented in Equation (2). A sharp increase in the WED (Figure 3(b)) is noticed corresponding to an abrupt change in the time series of speed (Figure 3(a)). Thus, this approach is adopted in this study for accurately estimating RT. Note that WED is unitless and is produced after averaging E_b across all scales and this averaging can sometimes cause an early or late detection of abrupt changes. To avoid it, we can limit the range of scales within which the wavelet-based energy is used. Refer to Zheng and Washington (*33*) for more details. However, we did not limit the range of scales since it is difficult to be automated, and thus is difficult to be implemented at a large scale, a feature important to this study.

[1]A function that conveys information about a phenomenon is called as a signal. For instance, a function $S(t)$, representing the time series of speeds of a follower, is a signal that imparts the acceleration/deceleration behaviour of the follower.

$$E_b = \frac{1}{max(a)} \int_0^\infty |T(a,b)|^2 \tag{2}$$

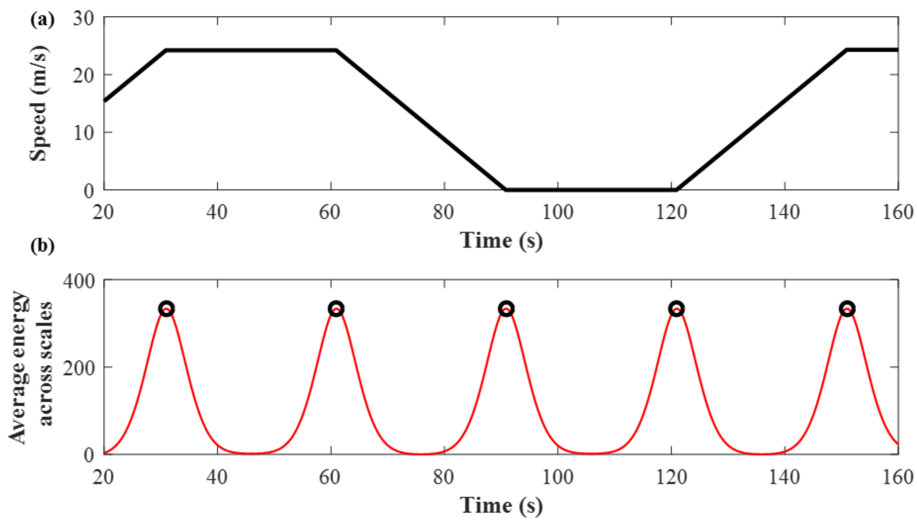

FIGURE 3 Illustration of change point detection using wavelet-based energy. (a) Time series of speed; (b) WED across scales with change points identified.

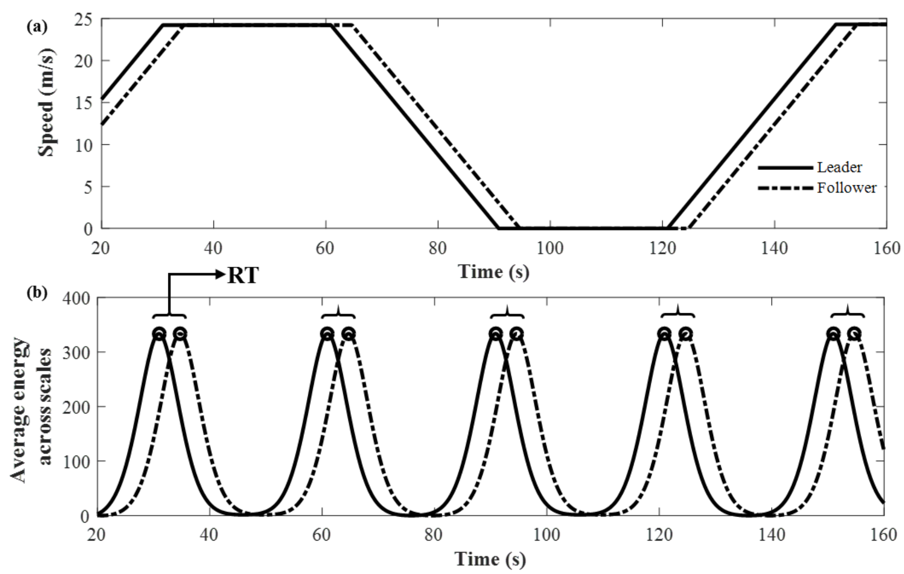

Figure 4 RT estimation in TE. (a) Speed profile of the leader and the follower; (b) WED for the leader and the follower with peaks identified.

RT estimation methodology for TE (RTEM-TE)

In CF, a follower notices a change in the leader's driving behaviour (stimulus) and responds accordingly after a certain time delay (response). In Figure 4(a), change points in the leader's speed profile and time-delayed change points in the follower's speed profile can be observed, which represent stimulus-response points. These change points can be easily detected using WED as demonstrated in Figure 4(b). Therefore, RT to the leader's action, RT_{lead}, is given by

Equation (3):

$$RT_{lead} = T_{folpeak} - T_{leadpeak} \quad (3)$$

where $T_{leadpeak}$ and $T_{folpeak}$ are abscissas (time coordinates) of neighbouring peaks (encircled in Figure 4(b)) on WED curves of the leader's and the follower's speed profiles.

RT estimation methodology for CE (RTEM-CE)

In CE, both the leader's change in driving behaviour and the information assistance provided will serve as a stimulus to the follower. Unquestionably, a stimulus-response relationship will also exist between the information provided and the follower (assuming that driver complies with the information). Contrary to TE, a leader's speed profile in CE will lack signatures of information stimulus i.e., the time when information is delivered to the driver, thus, RTEM-TE is unsuitable for estimating driver's RT to the information provided. Nonetheless, it is reasonable to assume that data collected from connected vehicles will have observations of time whenever the information is delivered to the driver. Figure 5(a) displays a portion of the speed profile of a participant from the simulator experiment data. Moreover, we can observe the participant's deceleration response to the message ('leader braking hard'). Note that this message is an advanced event-triggered information, hence, it is expected that the participant responds only to the message, which leads to the fact that the follower starts decelerating prior to the deceleration of the leader.

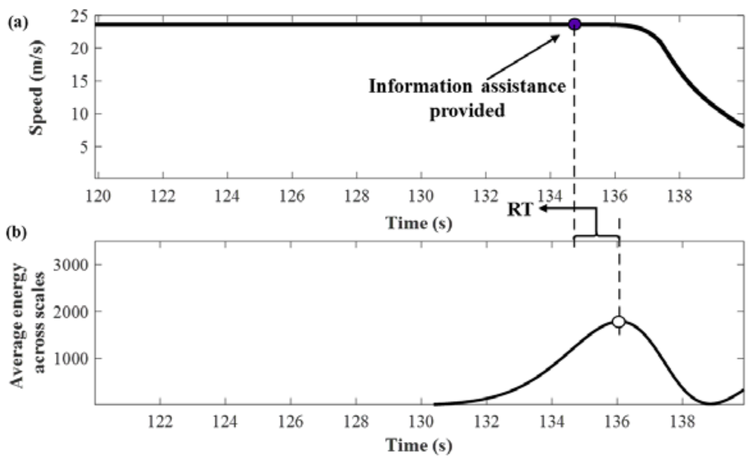

Figure 5 RT estimation in CE. (a) Speed profile of the follower and the time when the advanced message is delivered; (b) WED for the follower with peak identified.

The change in the speed profile, due to the participant's response to the message, is also captured in the WED curve presented in Figure 5(b). Hence, RT to any information, RT_{info}, is calculated as shown in Equation (4):

$$RT_{info} = T_{firstpeak} - T_{info} \quad (4)$$

where T_{info} is the time when an information is delivered to a driver, and $T_{firstpeak}$ is the time when the first peak appears after T_{info} on the WED curve of the speed profile.

ANALYSIS

RTEM-TE and RTEM-CE are assessed at three stages using synthetic and driving simulator data. The primary advantage with synthetic data is the availability of the ground truth, in this case true RT, thereby allowing objectively testing the performance of developed methodologies before applying them for estimation purposes. Other advantages include flexibility to design complex scenarios, and generated data are noise free. A description of the three stages is provided below:

- Numerical experiment I: Noise free synthetic trajectory data are employed to assess the capability of both the methodologies;
- Numerical experiment II: Noisy synthetic trajectory data are utilised to examine the efficacy of RTEM-TE and RTEM-CE;
- Driving simulator experiment: RTs estimated using RTEM-TE and RTEM-CE are compared to RTs calculated using the physical response of participants obtained from the simulator experiment to underscore the reliability of the developed methodologies.

Mean absolute percentage error (MAPE) (Equation (5)) between the ground truth of RT and estimated RT for each leader-follower pair is calculated to showcase the performance of RTEM-TE and RTEM-CE.

$$MAPE = 100 \times \frac{1}{N} \sum_{i=1}^{N} \left| \frac{RT_{GTi} - RT_{Ei}}{RT_{GTi}} \right| \tag{5}$$

where the ground truth of RT for i^{th} stimulus is RT_{GTi}, estimated RT is RT_{Ei}, and the total number of stimuli is N. Note that MAPE is an excellent relative accuracy measure but it gets penalised for small numbers, e.g., if the ground truth of RT is 1 s and the estimated RT is 2 s, then MAPE will be 100 % while the absolute difference is only 1 s. Therefore, absolute differences between the ground truth of RTs and the estimated RTs are also calculated and checked.

Assessment of RTEM-TE

In general, when generating synthetic data, leaders' trajectories are selected from real data and followers' trajectories are generated using a CF model. Since the ground truth of stimulus points will assist in rigorously assessing RTEM-TE, synthetic leader trajectories are also generated. In addition to RTEM-TE, we apply the DTW based method (*29*) on synthetic data to estimate RT, and compare RTEM-TE's performance against DTW's.

Numerical Experiment I

This experiment generates 50 leader-follower pairs travelling on a single lane road in the urban environment. Below we describe how a leader is generated, and similarly, the rest of the 49 leaders are generated. The maximum speed of leaders is sampled from the range [15, 40] m/s using Latin Hypercube Design (LHD). Refer Park and Qi (*34*) for a discussion on LHD.

At $t = 1$ s, the leader is 5000 m ahead of the reference point (the leader's position $x_{n-1}(1) = 5000$ m, speed $v_{n-1}(1) = 0 \text{ m/s}$, and acceleration $a_{n-1}(1) = 0 \text{ m/s}^2$). At $t = 1.1$ s the leader starts to accelerate with the acceleration a_{n-1} of 0.81 m/s^2. The leader attains a speed v_{n-1} of 24.21 m/s at $t = 30.9$ s and maintain it until $t = 60.8$ s. A traffic signal is positioned 250 m ahead of this point. From $t = 60.9$ s, the leader starts to decelerate and stops at $\mathrm{t} = 90.9$ s. The leader starts accelerating at $\mathrm{t} = 121$ s, attains a speed $\mathrm{v_{n-1}}$ of $24.3\ \mathrm{m/s}$ at $\mathrm{t} = 150.9$ s, and maintain until the end of the experiment, i.e., $\mathrm{t} = 180$ s.

Newell's CF model (*35*) (Equation (6)) is used to generate 50 followers' trajectories and its mathematical formulation is provided in Equation (6). Newell's CF model is adopted in this study for two main reasons: (a) Newell's CF model is simple and consistent with the RT phenomenon; and (b) using Newell's model to generate synthetic data can guarantee that the trajectory data reflects ground truth of RTs. This feature is critical since it gives us a powerful and reliable way to assess the developed methodologies' performance by calculating the error between the ground truth of RTs and RTs estimated from trajectories using the developed methodologies.

Error! Bookmark not defined. $$x_n(t+\tau_n) = \min\{\underbrace{x_n(t) + V_0 \times \tau_n}_{free-flow}, \underbrace{x_{n-1}(t) - d_n}_{congestion}\} \quad (6)$$

where $x_n(t)$ and $x_{n-1}(t)$ represent the positions of the follower n and the leader $n-1$ at time t, respectively. In addition, τ_n is the time gap, d_n is the distance gap, and V_0 is the desired speed. The starting positions of followers are close to leaders to ensure 100% CF. Moreover, for each follower, τ_n is sampled from the range [1, 5] s and d_n is sampled from the range [5, 15] m using LHD, thereby incorporating inter-driver heterogeneity. For 50 pairs, the ground truth of RT is equal to the corresponding τ_n values.

Numerical Experiment II

As already established in the traffic flow theory literature, measurement errors (or noise) are the plague of data. They falsify vehicle dynamics (*36*), reduces the reliability of calibration results (*37*), and harm the estimation results of data analysis techniques (*29*). Thus, it is imperative to test the efficacy of RTEM-TE using noisy data. We add noise at different signal-to-noise ratio (SNR)[2] levels to the error-free synthetic data generated in the previous experiment (as SNR increases, noise in data decreases). Note that the purpose of adding white noise in our analysis is not to reproduce real trajectories from synthetic ones, but for testing the robustness of the proposed methodologies.

Following the approach reported in (*37*), first, noise is introduced in position values of the leader and the follower, and speeds for both are derived afterwards using the noisy position values. Moreover, eight noise levels are introduced i.e., no noise, SNR10 (i.e., SNR is 10 dB), SNR15, SNR20, SNR25, SNR30, SNR35 and SNR40, and a total of 63 scenarios (i.e., 8×8 – 1) with 50 leader-follower pairs in each scenario are designed. The scenario having noise free leader-follower pair is the same as the numerical experiment I, hence it is excluded to avoid repetitiveness.

Implementing RTEM-TE on synthetic data from numerical experiments I and II

MAPEs are calculated for 3200 trajectory pairs from numerical experiments I and II, and the median MAPE for no noise, SNR40, SNR30, SNR20, SNR10 are 1.6 %, 2.1 %, 3.5 %, 6.5 %, and 10.8 %, respectively. The performance of RTEM-TE declines as noise increases, though the maximum median MAPE is only 10.8 %. The mean RT of Australian drivers is 2-2.5 s (*38*). Thus, 10.8 % error conveys that RTEM-TE can estimate RT within ± 0.2 s of the true RT. Figure 6(a) displays distributions of MAPEs for the numerical experiment I and for those scenarios of the numerical experiment II in which leader-follower pairs have equal noise components. These

[2] SNR10 depicts that the signal-to-noise ratio per sample is 10 dB.

small MAPE values exhibit the excellent performance of RTEM-TE in estimating RT from noise free and noisy data. Moreover, low MAPEs are obtained for other scenarios as well. Furthermore, Figure 6(b) shows distributions of MAPE calculated from RTs estimated by applying DTW on synthetic leader-follower pairs. A comparison of Figures 6(a) and 6(b) illustrates the superiority of RTEM-TE over DTW, though the performance of DTW is also good for SNR levels 30 and above. Importantly, RTEM-TE is less sensitive to noise because wavelet transform filters the high noise components.

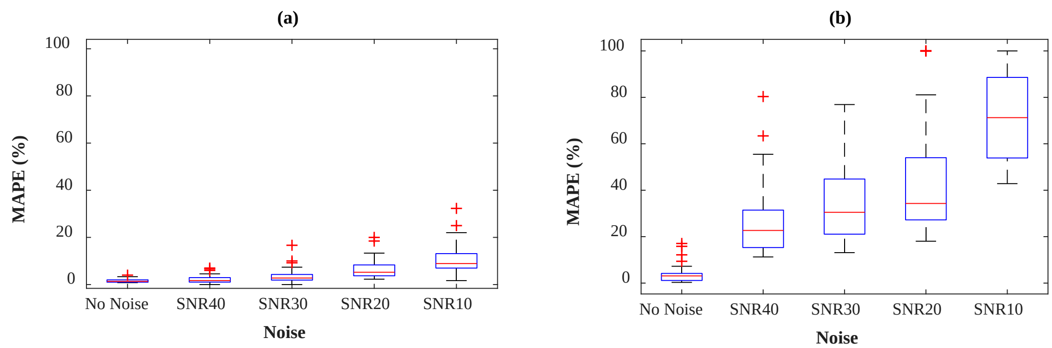

FIGURE 6 Comparison of MAPEs using Boxplots. (a) RTEM-TE; and (b) DTW-TE.

Assessment of RTEM-CE

We test RTEM-CE using the advanced event-triggered information to ensure that the driver's response is only to the message rather than the leader's action. Note that DTW is unfit for estimating RT in CE because DTW matches similar points on the two-time series, and as mentioned previously, leader's trajectory in CE is devoid of any signature of time when the information is delivered to the follower. Hence, it is unreasonable to compare DTW with RTEM-CE.

Numerical Experiment I

The trajectories of 50 leaders are randomly selected from the 78 leader-follower pairs in the connected scenario of the driving simulator experiment. Moreover, the time, when the advanced event-triggered information is delivered to the participants corresponding to these 50 leaders, is also obtained from the experiment.

The success of connected vehicle technology will heavily rely on the driver compliance with the transmitted information (*12*). Connected vehicle driving strategy (CVDS) as detailed in Sharma et al. (*1*), incorporates driver compliance and thereby allows us to explicitly model driver response to on-time information and advanced information which is a significant advantage over previous connected vehicle CF models. In CVDS, the driver compliance is modelled using a celebrated decision making theory called as prospect theory (*39*). Moreover, CVDS is a general driving strategy that can be integrated with existing CF models. Furthermore, CVDS has two parts, the first part models the driver response to continuous information and the second part models the driver response to advanced information. This study integrates CVDS with the Intelligent Driver Model (IDM) (*40*). The mathematical formulations of CVDS-IDM part I are presented in Equations (7) and (8):

$$a_n(S_n, V_n, \Delta V_n) = a\left[1 - \left(\frac{V_n}{V_0}\right)^{\delta} - \left(\frac{s^*(V_n, \Delta V_n)}{S_n}\right)^2\right] \quad (7)$$

$$s^*(V_n, \Delta V_n) = s_0 + (1 + UT(h_{obs}))TV_n + \frac{V_n \Delta V_n}{2\sqrt{ab}} \quad (8)$$

where V_0, δ, T, s_0, a, and b are desired speed $(\mathrm{m/s})$, free acceleration exponent, desired time gap (s), standstill distance (m), maximum acceleration $(\mathrm{m/s^2})$, and desired deceleration $(\mathrm{m/s^2})$, respectively. Moreover, a_n represents IDM acceleration $(\mathrm{m/s^2})$, s^* represents the desired spacing (m), V_n is the speed$(\mathrm{m/s})$, ΔV_n is the relative speed (difference of the follower's speed V_n and the leader's speed (V_{n-1}))$(\mathrm{m/s})$, and S_n is the distance gap (m). To add the impact of driver's compliance with continuous and on-time event triggered information $(1 + UT(h_{obs}))$ is multiplied with T. In response to the warning message 'leader braking hard', the driver decelerates to achieve a desired headway (h_{des}) from his/her reference headway (h_{obs}). In addition, the driver responses in τ seconds after the advanced message is displayed. Here, τ represents the delay in the driver's response to the advanced message. CVDS-IDM Part II is presented in Equation (9) and (10):

$$d_n = -D \times \left(\frac{t_c}{T_c}\right)^3 \quad (9)$$

$$D = min\left\{ b_{max},\ (1 + UT(h_{obs})) \times \underbrace{b_{max} \times (1 - \frac{h_{obs}}{h_{des}})}_{required\ deceleration} \right\} \quad (10)$$

where t_c varies from 0 to T_c with $t_c = 0$ at the start of deceleration process and $t_c = T_c$ at the end of the deceleration process. T_c is called response period, i.e., the time taken by the driver to attain D. The maximum deceleration reached at $t_c = T_c$ is D, and b_{max} is the maximum allowable deceleration. The required deceleration is multiplied by a factor equal to $(1 + UT(h_{obs}))$ that incorporates the impact of the compliance on the deceleration. Finally, $UT(h_{obs})$ is the utility value calculated at h_{obs} using prospect theory shape parameters λ, α, and γ. For a detailed discussion on CVDS and how $UT(h_{obs})$ is evaluated, refer to Sharma et al. (*1*).

For 50 followers, the CVDS-IDM parameters are sampled using the LHD. The range for parameters is as follows, $V_0 \in [1, 40]$, $\delta \in [0.1, 5]$, $T \in [0.1, 4]$, $s_0 \in [1, 10]$, $a \in [0.1, 4]$, $b \in [0.1, 4.5]$, $\tau \in [0.1, 3]$, $\alpha \in [0.1, 0.5]$, $\lambda \in [0.5, 1]$, $\gamma \in [5, 10]$, $h_{des} \in [1, 10]$, and $T_c \in [1, 5]$. The parameter response delay τ serves as ground truth of RT in CE.

Numerical Experiment II

The efficacy of RTEM-CE is also tested using noisy data. The procedure to introduce noise and the eight noise levels remains the same as for RTEM-TE except that the noise is introduced only to the follower's positions as RTEM-CE employs only follower's speed profile to estimate RT.

Implementing RTEM-CE on synthetic data from numerical experiments I and II

MAPEs are calculated for 400 trajectory pairs from numerical experiments I and II, and the median MAPE for no noise, SNR40, SNR30, SNR20, SNR10 are 14.5 %, 14.6 %, 17.9 %, 16.3 %, and 17.8 %, respectively. Similar to RTEM-TE results, when the noise level in the data increases, the performance of RTEM-CE deteriorates. Figure 7 depicts the box plots of MAPEs for numerical experiments I and II. The small MAPE values exhibit the excellent performance of RTEM-CE in estimating RT from noise free and noisy data. Similar to the RTEM-TE case, the maximum median MAPE i.e., 17.9 %, conveys that RTEM-CE can estimate RT within ± 0.4 s of the true RT.

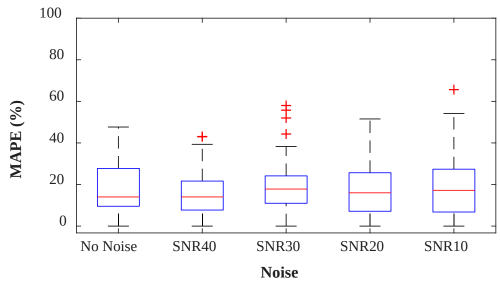

FIGURE 7 Comparison of MAPEs using Box plots for RTEM-CE.

Assessment of RTEM-CE and RTEM-TE using physical response of participants from simulator data

RTEM-TE and RTEM-CE are applied to trajectories collected from the simulator data, and RTs are calculated. These RTs are compared with RTs that are computed using the physical response of the participants. One of the advantages of using the data collected from the driving simulator experiment is the availability of the detailed driving behaviour data such as physical responses of participants, which makes such comparison possible. For demonstration purpose, trajectory data, corresponding to only low-speed emergency sections of TE and CE, are utilised.

In TE, the leader's hard braking behaviour is the stimulus, whereas in CE, the message 'leader braking hard' is the stimulus. Meanwhile, two types of physical responses of participants are noticed against these stimuli; releasing of the accelerator pedal and pressing of the brake pedal. RT from physical responses (RT_{phy}) is calculated using Equation (11):

$$RT_{phy} = T_{ar} + T_{bp} \tag{11}$$

where T_{ar} is the time difference between when the stimulus is presented (i.e., when the leader's hard deceleration starts in TE or when the message is delivered in CE) and when the accelerator pedal is released, and T_{bp} is the time difference between when the accelerator pedal is released and when the brake pedal is pressed. MAPE is calculated between RT_{phy} and RT_{lead} for TE data and RT_{phy} and RT_{info} for CE data.

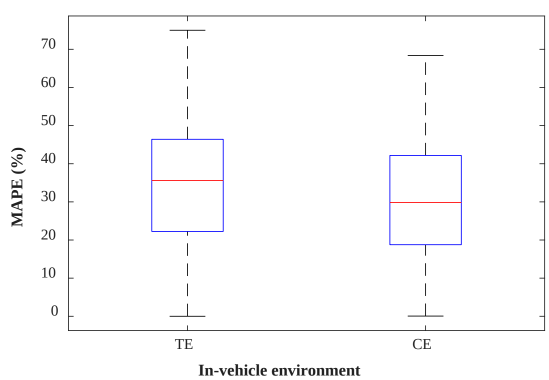

FIGURE 8 Distributions of MAPE between RTs estimated using physical response and using RTEM-TE (for TE) or RTEM-CE (for CE).

Figure 8 presents MAPE distributions for TE and CE. The median MAPEs are 35.3 % and 31.7 % in TE and CE, respectively. Moreover, the majority of the MAPEs are below 50 % in both the cases. The MAPEs are reasonable because the developed methodologies are applied to real trajectories rather than synthetic ones and it is widely accepted that real-world individual driving behavior is unpredictable and heterogeneous, hence difficult to model (*41*). Moreover, the median absolute difference between the physical response and the estimated RT is only 0.45 s and 0.74 s in TE and CE, respectively. Therefore, we conclude that RTEM-TE and RTEM-CE can provide reliable estimates of RT using trajectory data.

RESULTS AND DISCUSSIONS

RTEM-TE and RTEM-CE are applied to emergency sections of TE and CE, and the corresponding RT estimates are compared. Out of 78 trajectory pairs, 74 and 72 pairs are selected from high speed and low-speed emergencies, respectively. The rejected pairs are those in which participants showed no reaction to the stimulus because these participants were already decelerating when the stimulus was presented. Figures 9(a) and (b) show the distributions of RTs estimated. In TE, the mean and standard deviation of RTs in the high-speed emergency section are 2.07 s and 1.2 s, respectively, and in the low-speed emergency section are 1.56 s and 0.77 s, respectively. In CE, the mean and standard deviation of RTs in the high-speed emergency section are 2.43 s and 1.25 s, respectively, and in the low-speed emergency section are 2 s and 1.17 s, respectively.

For both high-speed and low-speed emergencies, paired t-tests comparing means of RT estimates in TE and CE reveal significant differences between the mean values at 90% level of confidence (for high-speed: t-statistic = -1.849, p-value = 0.06; for low-speed: t-statistic = -2.863, p-value = 0.006). Moreover, in both the emergencies, the mean RT values in CE are greater than the mean RT in TE.

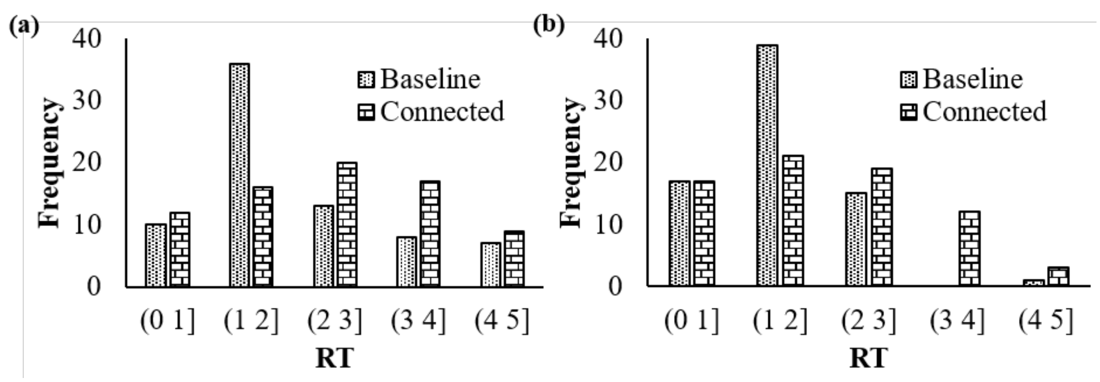

FIGURE 9 Distribution of RTs estimated using RTEM-TE and RTEM-CE in emergency sections. (a) High-speed emergency; (b) Low-speed emergency.

The mean RTs are within permissible limits, as most Australian drivers react in less than 2.5 s in an emergency (*38*). Aforementioned results also imply that when drivers are aware of surrounding traffic information they take more time to respond. This finding is consistent with the finding of Sharma et al. (*42*). They also report lower acceleration noise values in the emergency section of CE as compared to that of TE, and thereby conclude, drivers make better decisions by increasing their RT when advanced information is provided in CE. Another reason for the increased RTs in CE could be the increase in cognitive load on drivers due to the information assistance. To ascertain this possibility, a focussed study on cognitive load associated with CE, and how it influences RT is required. Such study can also assist car manufacturers in judiciously designing various elements of driving aids such as visual and audio quality, position, priority of some aids over others, and etc.

CONCLUSION AND FUTURE WORK

RT estimation methodologies for TE (RTME-TE) and for CE (RTME-CE) are developed by utilising the wavelet transform's power in detecting change points in time series. Both RTME-TE and RTME-CE are rigorously examined for their efficiency, accuracy, and reliability using noise free and noisy synthetic data, and driving simulator data. The analyses results demonstrate the excellent performance of both the methodologies. Thereafter, RTME-TE and RTME-CE are applied to emergency sections of TE and CE to estimate the corresponding set of RTs. A comparison between the two sets of RTs reveals that the mean RT in CE (in the case of advanced warning) is greater than the mean RT in TE. This implies that thanks to the connected environment drivers make better decisions in emergencies by increasing their response time.

This study also provides a general definition of RT. The definition is based on stimulus-response relationship and can explain the responses of drivers to different types of stimuli as discussed previously. In future, researchers can estimate RT for other categories of stimuli in any environment, TE or CE using the developed methodologies. Once RTs are estimated, RT statistical model similar to Haque and Washington (*43*) can be developed to comprehend the impact of other human factors such as age, gender, education, and etc., on RT in CE. Such work is ongoing.

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All the authors reviewed the results and approved the final version of the manuscript.

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