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Techniques for identifying the occurrence of stop-&-go waves in traffic: A literature review

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Abstract

Stop-&-go (S&G) waves usually occur in congested traffic and are characterised by cyclic patterns of deceleration followed by acceleration. Due to its frequent and annoying nature, drivers tend to avoid travelling on routes with more occurrences of stop-&-go waves. Existing transportation models need to be modified to incorporate the impact of S&G waves on route choice. This raises the question about how to quantify the number of S&Gs waves experienced by vehicles. The question has been extensively studied in two independent fields, namely traffic engineering and control theory. This paper aims to conduct a review of S&G quantification techniques in both fields of study and propose a unifying approach. The study proposes to determine the surrogate measures around the locations of vehicles undergoing S&G using signal processing techniques. The integrated approach would help in understanding the complex and latent nature of S&G waves by expressing its formation in terms of kinematic measures.

Keywords: Stop-&-go waves; route choice; wavelet transformation; adaptive cruise control; surrogate measures

1. Introduction

A stop-&-go (S&G) wave, also called traffic oscillation or phantom jam, is a traffic phenomenon that often exists in urban road networks during congestion. Under S&G traffic, vehicles are forced to decelerate and travel at a lower speed, or even come to a halt before resuming their original speeds (Shott, 2011). Li et al. (2010) found a cyclic occurrence of S&G waves which alternates between slow (stop) and fast (go) movements. These waves can be triggered due to multiple reasons which include: asymmetric driving behaviour (Edie and Baverez, 1965; Laval and Leclercq, 2010), lane change manoeuvers (Ahn and Cassidy, 2007; Laval, 2007), any kind of moving bottleneck in a traffic stream (Koshi et al., 1992; Laval, 2007), a drop in the roadway capacity (Bertini and Leal, 2005; Cassidy and Bertini, 1999a,b), and due to different roadway geometric features like curves and uphill segments (Jin and Zhang, 2005). These oscillations not only cause an increase in fuel emissions (Helbing, 1997), but also lead to safety risks. Moreover, numerous studies in the health domain have found that traffic oscillations have a detrimental effect on driver physiology, particularly the cardiovascular measurements like blood pressure and heart rate (Apparies et al. 1998; Yang et al. 2013). As drivers need to be more focussed while driving in S&G traffic, it results in heightened discomfort and frustration levels among drivers (Levinson et al. 2004). These factors tend to influence drivers to avoid travelling on routes where S&G conditions are frequent. It can thus be hypothesised that an increase in the number of S&Gs on a route increases its disutility for a driver. A recent study by Saxena et al. (2015) showed the validity of this research hypothesis. However, a limitation of the study was that it asked participants to recollect the number of S&Gs experienced by them in their most recent travel. Unlike travel time and cost, the number of S&G is not perceived well by participants due to its subjective (latent) nature. This might introduce a measurement bias in the collected data, which can lead to an incorrect estimation of the WTP measures. Thus, it becomes important to come up with techniques which can quantify the evolution of S&G waves in a way that is systematic and easy to comprehend across practitioners and policy makers.

A rich literature exists in the field of traffic engineering on techniques that are able to study the evolution characteristics of stop-&-go (S&G) waves. Different time series and signal processing methods have been used to determine the location of S&G waves in space and time from the observed traffic or vehicle specific data (Li et al., 2010; Zheng et al., 2011a,b; Zheng and Washington, 2012) . These techniques provide a reasonable measure of when a stop-&-go wave is initiated, but do not provide any information about the kinematic characteristics (speed, acceleration (deceleration), etc.) around the vehicle undergoing S&G. Understanding these features around a vehicle in S&G traffic can further enhance our knowledge about the initiation of these waves from traffic kinematics perspective.

Alternately, the phenomenon of S&G waves is also studied and applied extensively in the domain of control theory, which relates to the design of adaptive cruise control (ACC) systems in modern luxury cars. Unlike the cruise control (CC) function, ACC is an automated feature which adapts to the relative speed and distance between the host and leader vehicle by controlling both the brake and throttle system of the vehicle. As a latest extension, the stop-&-go ACC (S&G-ACC) mechanism facilitates smooth vehicle movement under S&G traffic. This not only eases the mental burden on drivers from the reduction of acceleration and deceleration cycles, but also leads to an increased throughput and reduced fuel emissions (Benz et al., 2003). The control algorithms are designed and rigorously tested using simulation experiments to imitate driver behaviour. Different surrogate safety measures, like peak acceleration/deceleration value, time headway and jerk value (rate of change in acceleration/deceleration), are used as criteria for the performance evaluation of the designed system. These measures can be useful to quantify the occurrence of S&G waves in an empirical context.

This paper aims to present a review of literature in traffic engineering and control theory to identify the techniques and parameters used in the quantification of S&G waves, discussing about their accuracy, merits and disadvantages. A thorough review will enable the selection of a suitable technique and a set of measures to identify the occurrence of S&G waves from the observed data. This study proposes a unifying approach to determine the surrogate measures around the locations of S&G which can be found using signal processing techniques from the traffic engineering literature. This study adds to the existing knowledge on the formation of S&G waves by proposing an alternative way to define the occurrence of S&G waves in terms of vehicle kinematics. Vehicle kinematic variables are easy to measure and perceive, and thus can help in reducing the subjectivity associated with the way formation of S&G waves is defined. To the best of our knowledge, no other paper the past has looked at integrating the knowledge in traffic engineering and control theory to understand and model the formation of stop-&-go waves.

The remainder of this paper is organised as follows. Section 2 presents a detailed review of literature on the techniques used to identify the occurrences of S&G waves from observed data. The section initially reviews different time series and other widely used stationary signal processing techniques currently in practice. The second half of the section discusses a more recent technique, called the wavelet transformation, its applications and superiority over previously existing methods. Section-3 presents a review from the literature of control theory and lists out the surrogate measures that are generally used while designing adaptive cruise control algorithms. Section-4 presents an example where surrogate measures are evaluated around traffic oscillations using a detailed vehicle trajectory dataset. Finally, Section-5 discusses the findings from this study and its implications, followed by future research works in this direction.

2. Identifying stop-&-go waves through observed data

Stop-&-go (S&G) waves were first observed inside the Lincoln tunnel in the US by Edie (1961). The study observed significant speed fluctuations on a one lane traffic stream caused due to small perturbations. Since then, numerous studies have been carried out to understand the intricacies associated with the nature and life cycle of S&G waves (Laval and Leclercq, 2010a). These studies can be broadly classified into empirical and theoretical. The empirical studies used different signal processing techniques to determine the amplitude and number of traffic oscillations from the time series of observed traffic data. For example, empirical studies found that S&G waves generally repeat in intervals of 2-15 minutes, last for up to 30 seconds and propagate backwards at a wave speed between 10 to 20 km/h (Ahn et al., 2004; Laval et al., 2009; Laval and Leclercq, 2010; Li et al., 2010; Mauch and Cassidy, 2004). On the other hand, theoretical studies focussed more on modelling the dynamics of S&G waves by encompassing asymmetric driving behaviour (Yeo and Skabardonis, 2009) and driver heterogeneity (Laval et al., 2009; Laval, 2011) into the simplified car following model proposed by Newell (2002). For the scope of this paper, we restrict our discussion to empirical studies that were conducted to quantify the occurrences of S&G waves.

Empirical techniques can further be classified into stationary and non-stationary signal processing. An input signal is considered as stationary, if its frequency or periodicity remains constant with time. In other words, an analyst is only interested in knowing the underlying frequency component, while working on a stationary input signal. A pure sinusoidal function is a perfect example of a stationary wave, which has got a uniform frequency of $1/2\pi$ cycles/radian. Non-stationary wave analysis techniques, on the other hand, are capable of reporting both frequency and time information of any fluctuation embedded in the signal.

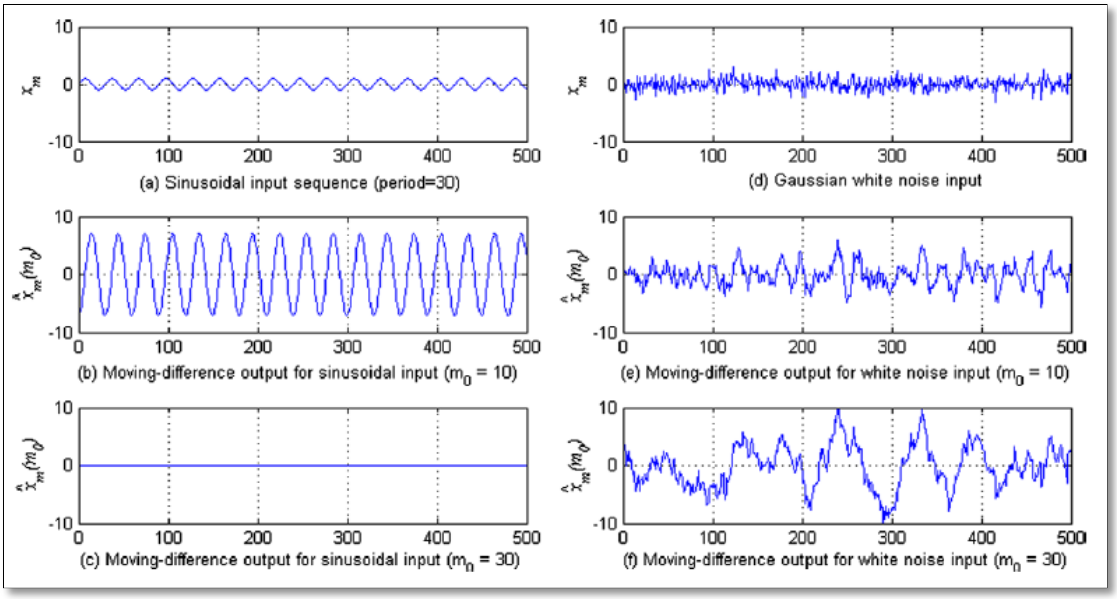
2.1 Stationary wave processing techniques

The earlier empirical studies analysed traffic oscillation properties using the time series of raw traffic data. For example, Kuhne, (1987) fit sinusoidal waves on the speed profile from a loop detector to determine the characteristics (amplitude and frequency) of S&G waves. Paolo (1988) also conducted a similar study using the traffic count information from different loop detectors. The two studies aggregated information over a given time period to smoothen the raw data. However, aggregation dampens the effect of traffic oscillations by smoothing it out along with other unwanted components (Zheng and Washington, 2012). Thus, these techniques are not reliable in estimating traffic oscillations, as they might provide contradictory results from what is actually present in the original data. Neubert et al., (1999) conducted a cross-correlation analysis on traffic flow parameters (average speed, flow and density) which revealed that S&G waves were characterised by a strong correlation between flow and density ($\rho \sim 1$). The time period of oscillations was determined by measuring the separation between neighbouring peaks on a correlogram, which was found to be around 10 minutes. However, few limitations of this method, as highlighted by Li et al., (2010) were: 1. identification of distinct peaks becomes challenging in case of multiple comparable frequency components, and 2. amplitude of traffic oscillations cannot be determined from the correlogram plot, which is standardised between [-1,1]. Muñoz and Daganzo, (2003) used another signal data processing technique, called the oblique coordinate system, to plot cumulative traffic counts against time and reveal the underlying traffic oscillations. The data analysed comprised of aggregated loop detector counts, occupancy and average speeds over a 20 second interval. The oblique coordinate system amplifies the signal pattern by a technique that is similar to the second order difference of cumulative vehicle counts with a moving time window (Mauch and Cassidy, 2004). The advantages of considering a moving time window are: 1. it helps to reduce the local noise from traffic data, and 2. it provides frequency along with an approximate location of signal fluctuation in time. The smoothed data signal is given by Equation 1

$$\widehat{x_m}\,(m_0) = f_m - \frac{1}{2}\left(f_{m+m_0} + f_{m-m_0}\right) = \frac{1}{2}\left[\sum_{i=0}^{m_0-1} x_{m-i} - \sum_{i=1}^{m_0} x_{m+i}\right] \qquad (1)$$

Where $\widehat{x_m}$ represents the cumulative traffic counts at an instant m, and m_0 is the half window length on either side of m, which was taken as 7.5 minutes. Wiggles in the oblique plot represent the oscillation pattern in the data. The technique became popular, and was picked by other researchers due to its simple framework. However, later research works identified few limitations inherent in the model formulation. The oblique coordinate system method requires a careful selection of the time window, a failure to do so might lead to biased traffic oscillation information from the smoothed data. Figure 1 has been taken from Li et al., (2010), which gives a good illustration of the impact of time window length on the resulting oscillation patterns. Figure 1(a) shows a pure sinusoidal signal used as an input, and Figure 1 (b) and (c) show its resulting patterns using window lengths as 10 and 30 units respectively. While Figure 1(b) shows amplification of signal (meaning frequent traffic oscillation), Figure1(c) shows a considerable dampening of the same input signal (inferring negligible traffic oscillation). Another limitation of the method can be seen through Figures 1(d-f) wherein different lengths of time window might cause a noisy signal (Figure 1(d)) to depict periodic oscillations of different magnitudes (Figures 1(e and f)). Thus, an inappropriate window length might lead to under or over representation of underlying traffic oscillation patterns.

Figure 1: Effect of window length on the signal resolution [Source: Li et al. (2010)]



Li et al., (2010) conducted a frequency spectrum analysis, a popular technique in signal processing, to reveal traffic oscillation patterns from the aggregated traffic data. Frequency spectrum analysis comprises three steps: 1. De-trending the signal to remove traffic demand effects, 2. identifying stationary time intervals for analysis, and 3. detecting oscillations of interest in these time intervals. De-trending is generally carried out by fitting a low order polynomial function. A short time Fourier transformation (STFT) is then applied to identify the oscillation pattern within the de-trended, non-stationary time series data. STFT overcomes the limitation of Fourier transform by using multiple smaller sized windows to capture irregularities in the non-stationary data. STFT plots are helpful in dividing the signal into smaller, same sized time intervals within which an oscillation pattern remains invariant. The oscillation pattern within this time interval is analysed further to determine its amplitude and frequency, which represents the magnitude and period of oscillations. The authors also used a term called cycle abundance index (CAI) to quantify the number of oscillations caused during a given time interval.

The study found the average oscillation periodicity between 8 to 12 minutes with an average CAI around 6 across different studied locations. However, a subjective judgement is required while selecting the oscillation-invariant time period, making it difficult to reproduce the same result across analysts (Zheng and Washington, 2012). The study also proposed a model to relate oscillations observed at loop detectors with the trajectory oscillations experienced by an individual driver. Equation 2 presents the proposed model which was developed using simplified vehicle trajectory and principles of traffic theory

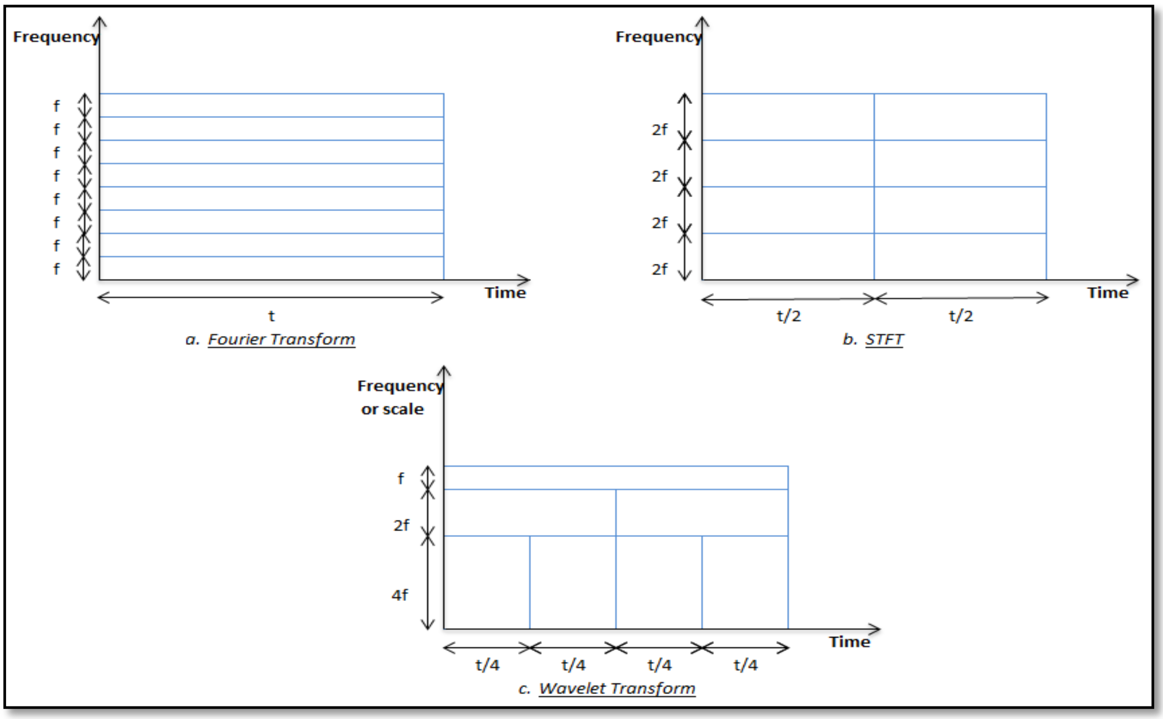
$$\frac{T_d}{T_t} = 1 + \frac{\bar{v}}{v_w} > 1 \qquad (2)$$

In this equation, T_d is the oscillation period observed from the detector data (using the frequency spectrum analysis), T_t is the period of oscillation faced by a driver, $\bar{v}$ the average speed of a vehicle and v_w the traffic wave speed (~ 15 km/h). The model is a useful find as it provides a reasonable and cost-effective means of determining traffic oscillations at an individual vehicle resolution from the easily available loop detector data. However, the model made few simplifying assumptions, which limit the application of the model in real world. First, the model assumed a steady traffic state which does not hold true as the traffic flow rate approaches or exceeds roadway capacity (Rouphail et al., 2005; Tanaka and Nakatsuji, 2011). Thus, a steady state assumption does not hold true in case of traffic oscillations, which are prevalent in congested traffic. Secondly, the model considered zigzag vehicle trajectories which does not reflect driver asymmetries (Laval and Leclercq, 2010; Laval, 2011; Yeo and Skabardonis, 2009).

2.2 Non-stationary wave processing techniques

For identifying transient locations in a non-stationary signal, wavelet transform (WT) has evolved as a widely used technique over time. WT is useful in discerning the location and frequency of a pulse in a signal, which is not visible to a naked eye, thus making it useful in analysing local events. The technique is quite popular in the field of image processing, geophysics, finance, engineering and medicine (Addison, 2002; Kumar and Foufoula-Georgiou, 1997). In the last one decade, WT has found numerous applications in traffic engineering relating to automatic detection of freeway incidents (Adeli and Samant, 2000; Ghosh-Dastidar and Adeli, 2003), traffic features around freeway work zones (Adeli and Ghosh-Dastidar, 2004; Ghosh-Dastidar and Adeli, 2006), traffic flow forecasting (Boto-Giralda et al., 2010; Jiang and Adeli, 2005), and traffic pattern recognition (Jiang and Adeli, 2004; Vlahogianni et al., 2008). Recent studies by Zheng et al. (2011a,b) and Zheng and Washington (2012) applied WT to distil origins of traffic oscillation characteristics from a transient non-stationary traffic data. Wavelet transform provides both time and frequency components of a signal fluctuation, which is more detailed than its stationary signal processing counterparts. For example, Zheng and Washington (2012) conducted a numerical simulation experiment to compare stationary wave processing techniques in time and frequency domain against WT. The experiment suggested the superiority of WT over popular techniques with regards to accuracy, robustness and consistency. Figure 2 explains the key differences in the degree of resolution among the Fourier, STFT and WT techniques, based on Heisenberg's uncertainty principle. Heisenberg's uncertainty principle states that the area of each rectangular box, as shown in Figure 2, must be equal (which is $f * t$ in this case). The thin, long rectangles in Figure 2(a) signify that Fourier transform gives a high frequency resolution, but compromises on the temporal detail. A short time Fourier transform (STFT) in Figure 2(b) improves the former technique by capturing some temporal detail through a smaller time window at an expense of losing some frequency resolution. However, the window length is decided subjectively by an analyst, and is fixed for the entire length of a signal. Wavelet transform (WT) in Figure 2(c) outperforms the other two techniques by using time and frequency windows of variable lengths to analyse transient points in a non-stationary signal. As a general rule, WT provides good frequency and temporal resolution by using long and short time windows for low and high frequency signals respectively. Studies show the superiority of WT over STFT and other techniques in consistently capturing accurate localised fluctuation details from a non-stationary signal (Addison, 2002; Zheng and Washington, 2012). As WT technique requires no subjective judgement in selecting the size and shape of a time window, the results can easily be replicated across analysts.

Figure 2: Frequency-time plots in accordance with Heisenberg's uncertainty principle for (a) Fourier, (b) STFT and (c) Wavelet transformations



Wavelet transformation identifies the location and frequency of a signal fluctuation by scaling (dilation and compression) and translating a suitable wavelet function over the time domain of a signal. A wavelet is represented by a complex mathematical function that should satisfy the conditions stated in Equation 3 and 4

$$E = \int_{-\infty}^{\infty} |\varphi(t)|^2 \, dt < \infty \tag{3}$$

$$\int_{-\infty}^{\infty} \varphi(t) \, dt = 0 \tag{4}$$

Equation 3, which is also called the admissibility condition, states that a wavelet must have a finite energy (E) at each point within a signal domain (Daubechies, 1992). This energy value is represented as brightness in the time-frequency plot shown in figure 2(c). The level of brightness increases as one nears a localised fluctuation. Equation 4 suggests that a wavelet should have a zero mean value, which implies that the total area under a given wavelet should be zero. This property also aids in recognising localised fluctuations.

Wavelet analysis can be broadly classified into continuous and discrete wavelet transformation. While discrete wavelet transform (DWT) provides an accurate location of fluctuation in space and time at lesser computational cost, continuous wavelet transform

(CWT) is considered ideal for detecting sharp changes in a signal (Kumar and Foufoula-Georgiou, 1997). A wide range of wavelets can be used to identify the traffic oscillation information from the given data. Zheng and Washington (2012) provide exhaustive guidelines for selecting an appropriate wavelet from a candidate set. According to the guideline, it is vital to know the mathematical properties of a given wavelet, which further paves the way for its application in a given context. The two important properties of a wavelet are: 1. vanishing moments and 2. compact support. A wavelet function $\varphi(t)$ is said to possess n vanishing moments if Equation 5 is satisfied.

$$\int_{-\infty}^{\infty} x^k \, \varphi(t) \, dt = 0 \qquad \forall \, k \in [1, (n-1)] \tag{5}$$

A wavelet with more vanishing moments is capable of analysing a more complex signal. For example, a wavelet with 2 vanishing moments can identify only a linear discontinuity (degree 1). Similarly, a wavelet with 3 vanishing moments can identify up to a quadratic fluctuation (degree 2). Compact support is defined as an interval within which a wavelet is defined (or is non-zero). The wavelet function is evaluated at each point in the support domain for CWT case and at discrete points in case of DWT. Some interesting points about vanishing moments and compact support are as follows:

- High frequency wavelets (at a smaller scale) have a compact support
- More vanishing moments denotes a complex wavelet, which ensures an accurate representation of an input signal. However, it leads to a sharp increase in the computation time
- Wavelets with more vanishing moments are high on regularity (more smooth wavelet function), but require a wider support domain
- Wavelets with a smaller support size are more efficient in detecting transient locations in a signal
- A good wavelet should preferably have fewer vanishing moments that are adequate enough for analysing the signal fluctuation of interest.

A Mexican hat wavelet is found to perform reasonably well in identifying stop-&-go waves from the vehicle trajectory data (Zheng et al., 2011a,b; Zheng and Washington, 2012). A Mexican hat wavelet represents the second derivative of the standard Gaussian function and its shape resembles a traffic oscillation pattern. Equation 6 gives a general equation for this wavelet where μ and σ represent the translation and scale parameter respectively. The value $\frac{2}{\pi^{1/4}\sqrt{3\sigma}}$ ensures that the wavelet function at different scales have the same energy. Properties of other wavelets like Haar, Gauss, Daubechies, Meyer, Morlet, etc. are thoroughly reviewed in Zheng and Washington (2012).

$$\varphi(\mu, \sigma, t) = \frac{2}{\pi^{1/4}\sqrt{3\sigma}} \left(\left(\frac{t-\mu}{\sigma} \right)^2 - 1 \right) \exp\left(- \left(\frac{t-\mu}{\sigma} \right)^2 \right) \tag{6}$$

$$T(\mu, \sigma) = \int_{-\infty}^{\infty} \varphi(t).\, v(t) \, dt \tag{7}$$

$$E_b = \frac{1}{\max(\sigma)} \int_{0}^{\infty} \left(T(\mu, \sigma) \right)^2 \, d\sigma \tag{8}$$

A wavelet is translated over the time domain of an input signal $v(t)$ and the correlation coefficient $T(\mu, \sigma)$ is determined at a given scale (refer to Equation 7). The wavelet is then dilated and is made to run over the entire signal again. Thus, we get a plot between the scale and translation parameter, where $T(\mu, \sigma)$ is represented by the level of brightness at that scale and translation. This plot is known as a scalogram. A brighter area on the scalogram signifies the spatio-temporal location of the point of singularity in an input signal. A scalogram plot requires a visual inspection to identify the transient points, which becomes a cumbersome task while analysing bigger datasets. Zheng et al. (2011a) proposed an automation procedure, by calculating average wavelet based energy (E_b) from the scalogram plot. Equation 8 gives an expression for evaluating this metric. An average wavelet based energy (E_b) at a given translation (μ) is defined as the average of squared correlation coefficients ($T(\mu, \sigma)$) across all scales (σ). A peak in the energy profile represents an approximate location of a transient point in data.

Zheng et al. (2011a) used speed time plots of individual vehicles (from NGSIM dataset) to locate traffic oscillations. The authors defined traffic oscillation as a cyclic pattern characterised by: 1. arrival of deceleration wave, 2. arrival of acceleration wave, and 3. arrival of another deceleration wave. A deceleration wave is identified by a sudden change in the speed of a vehicle which causes a sharp spike in the average wavelet based energy. Hence, one can precisely determine the occurrence of traffic oscillations experienced by individual vehicles using the wavelet transform.

As a recap to the discussion, stationary signal processing techniques are generally easy to implement, but suffer from the following limitations: 1. smoothing the low and higher frequency components of an original signal can cause disruption or complete loss of mid-frequency signals, which bear traffic oscillation information, and 2. some methods (e.g. STFT and oblique coordinate system) require subjective judgement, which does not ensure a unique solution across analysts and datasets. Moreover, working with aggregate traffic data cannot provide accurate traffic oscillation information experienced by an individual vehicle, which is required to test the proposed hypothesis. Given its advantages over other methods, we select the wavelet transform technique to quantify the number of traffic oscillations experienced by individual vehicles in this study.

3. Role of kinematic variables in the design of Adaptive Cruise Controls

A rich literature exists in the field of control theory on the adaptive cruise control (ACC) (also known as adaptive driver assistance systems, ADAS) feature that is available in vehicles today. Starting in the early 1990s within the luxury car segment, ACC systems are now available in vehicles across different car and truck segments. While a cruise control (CC) feature controls just the throttle of a vehicle, ACC is a semi-autonomous system that operates both the throttle and brake system of a car, by maintaining a pre-set value of time headway from the target (leading) vehicle in a traffic stream (Naus et al., 2008). As a more recent development, advanced systems come with a stop-&-go functionality that enables low speed adaptive cruise control in congested traffic. The feature is specifically designed for vehicles experiencing cycles of stop-&-go (S&G) waves in urban road networks. The advantages of stop-&-go ACC (S&G-ACC) are as follows: 1. it relieves the driver from an additional stress caused due to frequent cycles of deceleration followed by acceleration (Marsden et al., 2001; Venhovens et al., 2000), 2. it makes the vehicle accelerate and decelerate smoothly, which significantly helps in bringing down fuel emissions, and 3. it leads to an improved traffic efficiency, as vehicles cruise at a smaller and consistent time headway (than the ones maintained by drivers manually), thus increasing the throughput (Benz et al., 2003). A radar is mounted on the host vehicle, which tracks the relative speed and distance between itself and the target vehicle. A suitable time headway value is set upfront by the user, and the desirable relative distance is calculated using the selected time headway, host vehicle speed and separation between vehicles at standstill. The S&G feature is activated once the actual distance goes below the desirable value, which then decelerates the host vehicle by applying brakes.

Most ACC algorithms in practice are formulated as a linear (Naus et al., 2008; van Driel et al., 2007) or non-linear (Martinez and Canudas-de-Wit, 2007) programming problem. The main control objective is to maintain a desirable relative distance between the host and leader vehicle. The objective function is bounded by constraints or criteria for a better performance evaluation of an ACC system. These criteria can be divided into two main categories: 1. comfort and 2. driving behaviour characteristics. As S&G-ACC is a semi-autonomous system, it should resemble the non-linearity in driving behaviour to increase its user acceptability (Stanton et al., 2011). Time headway and time to collision (TTC) are generally used as proxies to analyse driving behaviour when following a preceding vehicle (Han and Yi, 2006; Yamamura et al., 2001). While the time headway is defined as the time difference between the fronts of leader and host vehicle, TTC denotes the time before two vehicles collide, if none of the vehicles takes an evasive action. We select the time headway over TTC, as it accounts for potential hazards, which is unlike TTC that is primarily used for evaluating safety (Vogel, 2003). The comfort criterion, on the other hand, can be expressed in terms of the longitudinal motion or fluctuation a driver experiences while travelling in stop-&-go traffic. Typically, peak acceleration (deceleration) and jerk (rate of change in acceleration or deceleration) values are taken as comfort metrics. Bounded values of the two metrics can ensure a certain degree of comfort in the longitudinal control of a vehicle (Martinez and Canudas-de-Wit, 2007; Naus et al., 2008; Yi and Moon, 2004). The algorithms undergo a rigorous testing and calibration exercise which involves simulation experiments. The experiments use wider bounds for comfort and driving behaviour constraints to accommodate heterogeneity in driving behaviour, which enhances the safety aspect of an ACC system. For example, Naus et al. (2008) used a peak deceleration value as high as $-9\ m/s^2$ to evaluate the ACC system being studied.

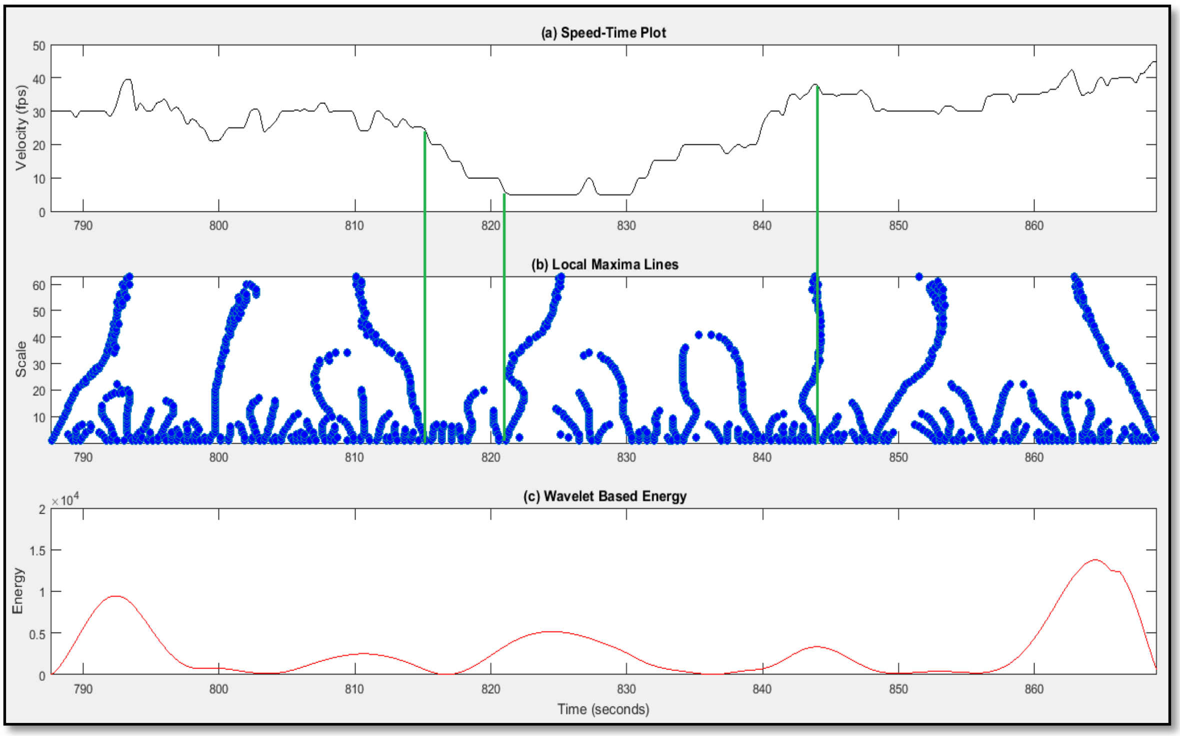
This section identified surrogate measures like the time headway, peak acceleration (deceleration) and jerk values that are widely used in the design of adaptive cruise control algorithms. These measures, which are part of an optimisation problem, help in evaluating when an adaptive cruise control switch gets activated in S&G traffic. The threshold values for these criteria used in simulation experiments are generally kept very high to make the ACC system robust against driver variability. Such high cut-off points cannot be used for quantifying occurrences of stop-&-go waves in a real world scenario as they focus more on avoiding S&G rather than accounting for it. Hence, this study evaluates the selected surrogate measures around locations of S&G waves obtained through the wavelet transformation on the NGSIM vehicle trajectory dataset. This is the first study to the best of our knowledge that attempts to empirically express the occurrence of S&G waves in terms of kinematic variables, which are used to measure the performance of ACC systems.

4. Analysis using the vehicle trajectory data: An example

In this section, we apply wavelet transformation on the vehicle trajectory data to identify locations of traffic oscillation, followed by evaluating surrogate measures around these spots. We present the analysis for a single vehicle undergoing S&G for illustration.

NGSIM data on the interstate US-101 is used for analysis in this study. The NGSIM dataset provides a rich information on the microscopic features of a vehicle like speed, location, acceleration, etc., collected at a fine temporal resolution of 10 Hertz (NGSIM, 2010). The data was collected during the morning peak traffic between 07:50am to 08:35am. The study site on US-101 is a 2100 feet long section in the southbound direction, Los Angeles, California, US. The section has 5 traffic lanes and also includes an on and off ramp. Lane-4, being in the vicinity of ramps, is selected because of a higher likelihood of witnessing S&G waves. Figure 3(a) shows the speed profile of the vehicle id 540 travelling on lane-4. The figure shows a major speed fluctuation between 810 and 845 seconds from the start of data collection.

Figure 3: Plots generated for vehicle id. 540 (a) speed-time, (b) Local maxima lines and (c) Average wavelet based energy



A wavelet transformation is conducted by selecting the Mexican hat mother wavelet with a scale range between 1 and 64 (Zheng and Washington, 2012). Figure 3(b) shows the local maxima lines obtained upon analysing the speed trajectory signal given in Figure 3(a). Like the scalogram, local maxima lines are another way of representing singularities in the input signal. A local maxima line is a locus of points across scales where the correlation coefficient is a local maximum. Only the lines that are formed over the entire scale spectrum are considered. Partial lines and scattered points are ignored as these are generated due to noise in the signal. The oscillation location can be accurately determined by tracing the location of a maxima line at the finest scale, which is 1 in this figure (Zheng and Washington, 2012). For example, the green lines show a mapping of oscillation points on the speed time plot. Figure 3(c) shows the plot of average wavelet based energy that was calculated using Equation 8. The figure shows the formation of three energy peaks, which jointly defines a traffic oscillation (Zheng et al., 2011a). Thus, it can be inferred that vehicle 540 experienced one cycle of stop-&-go (S&G). The unexpected peaks at the start and end of Figures 3(b) and 3(c) constitute the boundary effect (Addison, 2002), which are generally ignored. The analysis is done using the wavelet toolbox in Matlab.

Once the traffic oscillation location in time is determined from the plots, we then evaluate the surrogate measures around this location from the given data for vehicle id 540. The time headway, acceleration (deceleration) and experienced jerk value at an instant when the S&G wave is initiated are found as 1.90 seconds, -4.06 m/s^2 and -2.35 m/s^3 respectively. The negative value of jerk signifies that the driver hit hard on the brakes causing a sudden reduction in its speed. Not surprisingly, the observed deceleration value is much lower than what is used in the design of ACC systems. Thus, finding out these surrogate measures from the real-world data can provide us with alternate metrics of quantifying S&G waves.

5. Discussion

Driving in stop-&-go traffic (traffic oscillations) has got many negative effects such as, increased fuel emissions, safety risks and driver distress. The hypothesis that drivers experience increased disutility in route selection due to multiple occurrences of S&Gs was recently validated by Saxena et al. (2015). However, due to the subjective nature of the definition of an S&G wave, it becomes necessary to come up with a mechanism to quantify the occurrences of S&G experienced by individual vehicles. Studies in the fields of traffic engineering and control theory have looked into understanding the intricacies of S&G waves. While the objective in the former was to identify the formation of S&G waves, the latter focussed on controlling the parameters that jointly define the occurrence of these waves in the ACC systems of cars. In this paper, we review both sets of literature and propose a unifying approach of defining the formation of S&G waves. The approach suggests determining the surrogate measures (eg. time headway, acceleration (deceleration) and jerk) around the locations where a vehicle enters S&G wave, which can be found by using wavelet transformation on the vehicle trajectory data. Applying this approach to the observed trajectory datasets (like NGSIM) will provide empirical ranges of the surrogate measures which can be jointly used as thresholds in defining the occurrence of an S&G wave. Thus, the integrated approach expands the existing knowledge base by expressing the formation of S&G waves in terms of vehicle kinematics. The estimated occurrence of S&Gs thus obtained is expected to be close to the true value, which is generally unknown due to its latent nature. Moreover, the obtained empirical ranges can be coded in transportation models which increment the occurrence of S&Gs experienced whenever the threshold conditions are met. Hence, the proposed approach is also computationally efficient as it does not require quantification of S&G waves using wavelet transformation, which requires a large volume of trajectory data for all vehicles.

Future research endeavours will focus on expanding the current empirical analysis over other NGSIM datasets, including other sites, and compare if the results are statistically different across sites. Secondly, the authors will relate the estimated surrogate measures to the macroscopic variables like traffic density and flow. This inter-relationship would help quantify the formation of S&G waves and study their impacts on a larger area, which would provide wider insights to practitioners and decision makers.

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