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Analysis of the Driving Behaviour at Weaving Section Using Multiple Traffic Surveillance Data

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Abstract

Weaving sections are formed when a merge area is closely followed by a diverging area, or when an entry slip road is closely followed by an exit slip road and the two are joined by an auxiliary lane. Driving in the weaving section involves complex car-following and lane-changing interactions. This paper presents two empirical data collection and data extraction processes based on traffic surveillance camera and loop detector measurements. It examines the quality of the extracted data, and highlights the possible sources of measurement errors considering that the speed and acceleration are varied significantly. This paper proposes locally weighted regression method for data cleaning and presents example results to demonstrate the method by combining the two data sources. The study succeeds in identifying some key driving characteristics of vehicles in the weaving section. We found that 30% of the weaving movements took place in the first 50 meters from the point of merge. Around 30% of the total traffic involved in one lane-changing movement. Meanwhile, the transit time for the driver with more than one lane-changing is 4.09 sec in average. The appearance of auxiliary lane in the weaving section provides further opportunity to delay the lane-changing, which affects the traffic performance.

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1. Introduction

Driving behaviour, which describes the drivers' intentions behind the maneuvers from the current position towards a target position, significantly affects the traffic performance. These effects are more pronounced in multilane facilities where each driver has a preference to maintain his/her current lane or shift to the target lane (Bonsall et al., 2005).

Driving movements are typically motivated by expectations of one/more gains or advantages from the ambient traffic i.e. increasing speed, avoiding delay, and overtaking the lead vehicle. Moreover, the movement can be mandatory in order to comply with a traffic regulation, avoiding an incident in the current lane, or to take an exit or make a turn to follow the path-plan (Laval and Daganzo, 2006).

Weaving is defined as the crossing of two or more traffic streams traveling in the same direction along a significant length of the highway without the aid of traffic control devices. Eventually, in a motorway weaving section, the lane-changing appears in high number especially closer to the end of the merging and diverging points where the drivers expect to merge or diverge from the main traffic. Thus, the lane-changing drivers have to critically observe and evaluate the traffic condition both in the current and the target lane. They pursue continuously for a safest condition to precede the lane-changing movement. The movement in motorway section is critical since the distance between the merging and diverging area are relatively short (2,000-3,000 metres according to the Design Manual for Roads and Bridges (DMRB) (2006)).

This paper analyses the characteristics of driving behaviour in a motorway weaving section two sources of traffic surveillance data: an extraction from a direct video recording and the Management Incident Data Analysis (MIDAS) loop detector data. Individual vehicles trajectories are extracted from a 5min video recording, using the Semi-Automatic Video Analysis (SAVA) software (Archer, 2003). MIDAS provides traffic flow, speed and headway data (averaged over 1 minute) from loop detectors. The observation is taken at the M1 motorway network between Junctions 41 and 43, which is near Leeds, United Kingdom.

2. Background

Vehicle interactions, in terms of their car-following and lane-changing behaviour, have a significant impact on motorway traffic performance. These interactions are contributing to traffic flow breakdown and capacity drop in the main carriageway and the entry slip road (Cassidy & Rudjanakanoknad, 2005; Wang, Liu, & Montgomery, 2005a, 2005b). The traffic interaction on a motorway weaving section is even more complex because the lane-changing and weaving interactions have to occur at a relative short distance between an entry and exit split roads.

Number of factors affects the driving behaviours; road geometric, available gap and traffic condition both in the current and the target lane. Those factors are significant input for the microscopic modelling. Moreover, in this regards, the drivers may seek for a condition which gives them the highest utility. Depending on the particular situation, a driver has his/her own preference to evaluate and decide either to stay in the current lane or make a lane-change to left/right (Ahmed, Ben-Akiva, Koutsopoulos, & Mishalani, 1996; Choudurry, 2007; Toledo, Choudhury, & Ben-Akiva, 2005).

Therefore, to capture the driving behaviour in weaving sections in microscopic level, this paper proposes the traffic surveillance camera and the loop detector data as the main source. The aim of the traffic surveillance technique is to trace the vehicle location and the traffic condition around the observed vehicle at the specific time (t) sec. Combining the traffic surveillance camera and loop detector data sources thus allows us to use the strengths of both data sets.

Traffic surveillance is a method in capturing the driving behaviour at the observation location. The video data provides observed driving behaviour in high level of details (Al-Jameel, 2011; Choudhury & Ben-Akiva, 2008; Koutsopoulos & Farah, 2012; Kusuma & Koutsopoulos, 2011; Toledo et al., 2005). In fact, the video observation produces number measurement error due to imaging processing and obstruction. Therefore, the locally regression method is introduced to increase the data accuracy level (Punzo, Borzacchiello, & Ciuffo, 2011; Toledo, Koutsopoulos, & Ahmed, 2007). More details of the locally regression will be discussed in the section **Error! Reference source not found.**.

In the UK, the Highways authority records and stores the loop detectors data into a system which is known as MIDAS. It records and stores the loop detectors data at the specific location. It records the basic traffic data such as traffic volume, time speed, level of occupancy, and headway for each lane. MIDAS data has been used in a wide range in order to capture the traffic characteristic and driving behaviour on a specific motorway network

Wang (2006) used both the traffic surveillance and MIDAS data to investigate the driving behaviour in the merging motorway section. The video observation showed that most of the lane-changing occurs at the first available gap. In the other words, the lane-changing occurs at the upstream traffic where the main traffic and entry-slip road traffic meet at the end of the taper marking. The length of the auxiliary lanes in merging area length affects the merging behaviour. In fact, a longer auxiliary lane leads the lane-changing drivers to become conservative in order to seek for larger gap rather than accept the first gap. The average speed between the lanes, where most of the lane changing occurs, is relatively similar.

Al-Jameel (2011) observed the effect of lane-changing in a motorway weaving section. To do so, the study applied a simulation the traffic surveillance and MIDAS loop detector. It showed that the average speed of the lane-changing drivers, when it starts the lane-changing movement, is lower compare to the lead vehicle at the target lane. Then, the lane-changing vehicle speed increased slightly during the lane-changing. This study found that the lane-changing drivers prefer to precede the lane-changing at the end of the taper at the merging area.

The current research extends the usage of traffic surveillance method and MIDAS to capture the lane-changing characteristics at the weaving section. This research proposes the traffic surveillance camera to extract the vehicle trajectory and the movement characteristic of each vehicle (i.e. acceleration, lane-changing location). The study realise that the video observation there is a significant error in the video extraction process. Moreover, the error is clearly represented in speed and acceleration analysis. The study adopts the locally weighted regression method to relax the error which this approach has not been used in the two previous researches.

MIDAS provides the ambient traffic condition at the observation location at macroscopic level. It provides the base line dataset for the validation process. In fact, this paper validates the observed speed of the traffic surveillance extraction result with MIDAS. More details regarding the data extraction and validation process will be discussed in the next section.

3. Methodology

3.1. Traffic video recording

This research applies the SAVA software to extract the driving behaviour and vehicle trajectory data from the traffic surveillance camera. All the extraction process in SAVA has to be done semi-manually. The software provides only playbacks interface and several measurement features such as the virtual measurement line for recording the passage time, transport mode and distance measurement. The application records the traffic movement for every 40 millisecond. Each record of the traffic movement contains the transport mode and the passage time at the specific location. It classifies the transport mode into the Car, Multi-Purpose Vehicle (MPV), Van, Light Goods Vehicle (LGV), Heavy Goods Vehicle (HGV), and Bus.

It, firstly, is important to validate the pixel in the video footage with a specific object in the observed location. The validation stage is critical where the measurement error must be minimised. A good aerial map helps to increase the level of accuracy in distance measurement. The spatial measurement features has been used in this regard. It also gives flexibility for the user to point or mark at the interested point. Once the calibration process is completed, the next phase is to draw the virtual lines on the specific locations. This research records and stores the position of each vehicle at every 1sec interval.

Using the vehicle trajectory information, we calculate the speed and acceleration of each vehicle at the time(t). The speed and the acceleration can be written;

$$v(t) = \frac{d(t) - d(t - \Delta t)}{(t) - (t - \Delta t)} \tag{1}$$

and,

$$a(t) = \frac{v(t) - v(t - \Delta t)}{(t) - (t - \Delta t)} \tag{2}$$

where; $v(t)$ is the vehicle speed at the observation time (m/sec or km/h), $v(t - \Delta t)$ is the vehicle speed at the previous observation time (m/sec or km/h), $d(t)$ is the vehicle location at the observation time (m), $d(t - \Delta t)$ is the vehicle location at the previous observation time (m), $a(t)$ is the vehicle acceleration at the observation time (m/sec^2), (t) is the observation time (sec) and $(t - \Delta t)$ is the previous observation time (sec) . The Δt is presumed as 1 sec.

In many cases, the speed and the acceleration of each vehicle varied among the observation time due to the traffic surveillance extraction error. This research, therefore, applies the locally regression method to fit the observed location.

3.2. Locally weighted regression

The locally weighted regression is common method to increase the observed vehicle trajectory level of fitness with global polynomial curve. In this paper, this method is applied to smooth the vehicle time-continuous trajectory from the observed vehicle locations. Moreover, it continuous to estimate the speed and the acceleration profile for the observed vehicles at the specific time(t).

Toledo et al. (2007) introduced the local regression method in smoothing the vehicle trajectory. This method consists of two phases which are (1) fitting the time-continuous trajectory function and (2) deriving the speed and acceleration estimation based on the fitted location. Assuming that the vehicle trajectory is a function of time(t);

$$d(t) = f(t, \beta) + \varepsilon(t) \tag{3}$$

where; $f(t, \beta)$ is the fitted location of the observed vehicle at the time (t) by the local regression, β the vector parameters of the estimated curve, and $\varepsilon(t)$a normally distributed error term.

The estimated function $f(t, \beta)$ is based on the weighted least-square estimation with the N observation of each vehicle in the window around time(t). The observed weighted values are calculated based on the time difference between the observation and the estimate fitted time. Moreover, the local regression objective function is to minimise the deviation between the observed vehicle trajectory and the global polynomial curve. The equation is written as;

$$\min_{\beta}[D - f(t,\beta)]^T W[D - f(t,\beta)] \tag{4}$$

where; D is a column vector of the N position observations used to estimate a trajectory function, $f(t,\beta)$ is the fitted values vector, and W is[NxN] matrix with elements corresponding to weight of observations used for local regression.

In terms of statistic, the difference between the observed and the fitted location can be evaluated by the Mean Absolute Error (MAE) and Root-Mean-Squared Error (RMSE) as follows:

$$MAE = \frac{\sum_{i=1}^{I} \left| d_i - \hat{d}_i \right|}{I} \tag{5}$$

and,

$$RMSE = \sqrt{\frac{\sum_{i=1}^{I} \left(d_i - \hat{d}_i \right)^2}{I}} \tag{6}$$

where; d_i is the observed vehicle location, $\hat{d}_i$ is the estimated vehicle location, i, I is the number of observation for each vehicle.

3.3. MIDAS

MIDAS system records traffic volume, spot speed, level of occupancy, and headway for each lane from all loop detectors in the UK motorway network, which can be accessed in www.midas-data.org.uk. In fact, each loop detectors has unique ID (xxxxy) which is identical with geographic position (xxxx) and the observed carriageway (y). The Highways Agency in England classifies the locations of the loop detectors based on the traffic approaches (northbound and southbound) and the location (main, entry slip road and exit slip road). The letter A, J and K represent the loop detector at the main, entry and exit slip road at the northbound traffic. Meanwhile, the letter B, L, and M, which observe the main, entry and exit slip road respectively, are located at the southbound traffic.

A moving mean method in this paper is proposed to capture the propagation of the traffic flow and the speed characteristic at the observed weaving section. This approach is used to describe the nature of the dataset which has series of average of different data subset. Meanwhile, this application expects as well to reduce the noise in the data set. The method can be written as;

$$EMM_l = \frac{x_l + x_{l-1} + x_{l-2} + ... + x_{l-L}}{L} \tag{7}$$

where; EMM_l is Estimated Moving Mean, l is the subset data ID, x_l is value of the subset l, and L is the length of moving average interval.

4. Observation

4.1. Site description

The study site covers two weaving sections located between Junctions 41and 43 on the M1 motorway in England. The site has to be located in a straight road section in order to capture clearly the traffic behaviour, especially the lane-changing behaviour. Moreover, there are fewer obstacles in the site such as, road works, road geometric, and clear sight distance for the traffic video recording.

The section is a major link road between two urban towns Wakefield and Leeds. Hence the traffic characteristic in this section is mixture traffic between long distance and commuting traffic. Moreover, J42 is an interchange that between M1 and the M62 motorway, whilst J43 (Northbound) links the M1 and M621 motorway.

In terms of road geometry, the J41-J42 section is three lanes dual carriageway with two lanes both in the exit and entry slip roads. Moreover, there is ramp metering operated in the entry slip road at J41. Further North, the J42-J43 section is a five lanes dual carriageway (three lanes for the through traffic and two auxiliary lanes) with two lanes in entry slip road and three lanes in the exit slip road. Additionally, the length of those two sections is 1,250 m and 1,265 m considering that DMRB (2006) definition for weaving sections, which specifies that the length of weaving section is normally between 2,000 m to 3,000 m. That is to say, those two sections are departures from the DMRB standard.

Furthermore, to manage the traffic, the Highways Agency has installed a number of loop detectors between J41-J43. The loop detector captures the traffic characteristic at the observed location. More details of the observation location can be seen in Fig. 1 illustrating the J41-J42 road alignment together with the locations of loop detectors and traffic video recording.

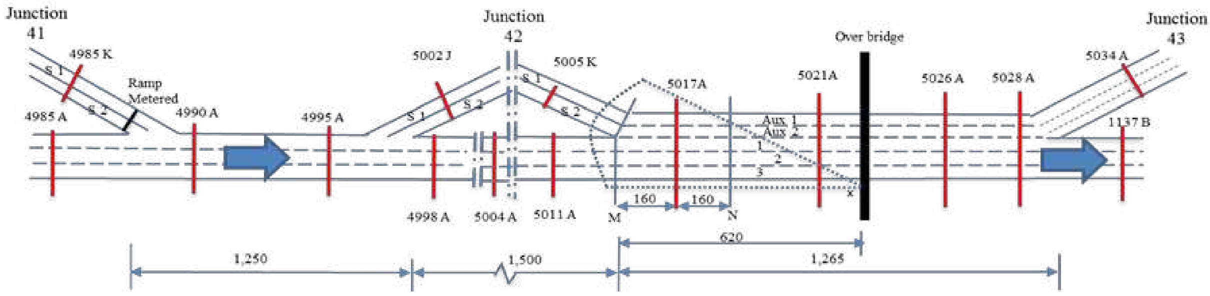

Fig. 1 The Observation Area (unit:metres)

Fig. 1 illustrates the locations and the ID of the MIDAS detectors, the location of the over bridge from where the video recording took place. The three lanes on the main carriageway are marked as lanes number 1, 2 and 3, whilst the two auxiliary lanes between J 42 and J43 are marked Aux1 and Aux 2 respectively. The distance between the over bridge and the start of the entry from J42 is 620m. Point M marks the entry from J42, and N 320m from the entry. The video data extractions were carried out vehicles travelling between M and N.

4.2. Data collection

The video recording was taken on Wednesday, 15th May 2013 during the afternoon peak period between 16:30-18.30. The study focuses only on the evening peak in order to capture the lane-changing when the vehicle moves in relatively at a free-flow condition. Due to the site and recording equipment tools, the study focuses only on the first 320 m of the weaving section between J42-J43. Moreover, the camera recorded the traffic from the Over bridge which is located around 620 m from the merging location.

The MIDAS loop detectors data were collected during the video observation period. The data is useful as validate instrument during the video extraction process. There are 15 loop detectors located around the study site (see. Fig. 1), meanwhile the loop detector 5017A is located inside the observation area.

5. Results

The MIDAS data shows that the total traffic flow reaches the peak between 16:45-17:45, with the highest flows of 4982 vehicles/hour detected from detector 4990 A between J41 – J42, and 5833 vehicles/hour from detector 5017A between J42-J43. The data includes all existing lanes at those sections where there are 3 lanes in J41-J42 and 5 lanes (3 main traffic lanes and 2 auxiliary lanes) in J42-J43.

As it is mentioned in the section **Error! Reference source not found.**, the lane-changing shall affect the traffic performance both in the main traffic and slip-road. This paper expects to capture the lane-changing affect at the main traffic at the observation site. We, therefore, propose the EMM (Equation.

(7) and present it in a traffic flow and the speed propagation map, which can be seen in Fig. 2.

Fig. 2 shows the total traffic flow and averaged speed for every 1 hour period. Moreover, it illustrates that around 60% of the traffic at J41-J42 moves continuously to the J42-J43, while the rest traffic exits to the M62 network.

Due to the lane-changing behaviour around the merging and diverging area, the speed propagation in the Fig. 2 indicates that there is a delay in the weaving section (J41-J42 and J42-J43). The average speed at the observation sites is around 80-90 km/h at the J41-J42 (4985A – 4998A), and 90-100 km/h at J41-J42 (5011A-5028A). Meanwhile, the average speed between the exit and the entry at J42 is increased, into around 120 km/h which is the speed limit in the UK.

The speed propagation illustrates that the existing of the auxiliary lane at J42-J43 weaving section is expected to reduce the delay. Moreover, it provides more opportunity for the driver to maintain their lane and proceed lane-changing later on downstream rather than forces the lane-changing at the beginning of the merging area.

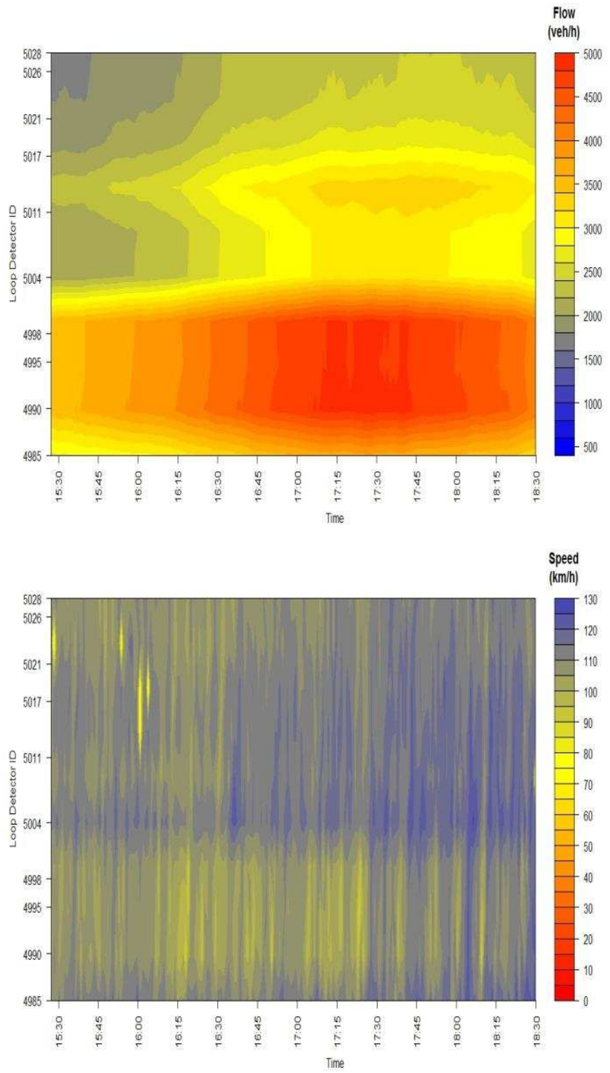

Fig. 2 Traffic flow and speed propagation at the main lanes traffic of the observation site

5.1. Traffic surveillance data

This process is only for the highest five minutes traffic between 17:15-17:20 considering that it is a massive undertaking to extract individual vehicle trajectories using a semi-automatic procedure. During this 5 minutes period, the video surveillance found 408 vehicles passing the observation area between J42-J43. In fact, the 5017A loop detector records 471 vehicles passing this area during the same time interval. That is to say, around 14% of the vehicle is missing due to the measurement error.

This study identified several issues, which may produce error, in the traffic surveillance method. In fact, video resolution, video time step and obstruction from the leading vehicle create the problem in the extraction process.

Due to those affecting factors, the analysis of the vehicle trajectory data shows that the speed and acceleration are varied significantly for each vehicle during the observation period. An application of locally weighted regression is adopted in this paper to globally fit the vehicle trajectory from the traffic surveillance method Equation. (2). It smooth and reduces the variation of the speed and acceleration. Moreover, the MAE and the RMSE are proposed to represent the fitness level of the traffic surveillance vehicle trajectory (observed data) with the trajectory function result (estimated data).

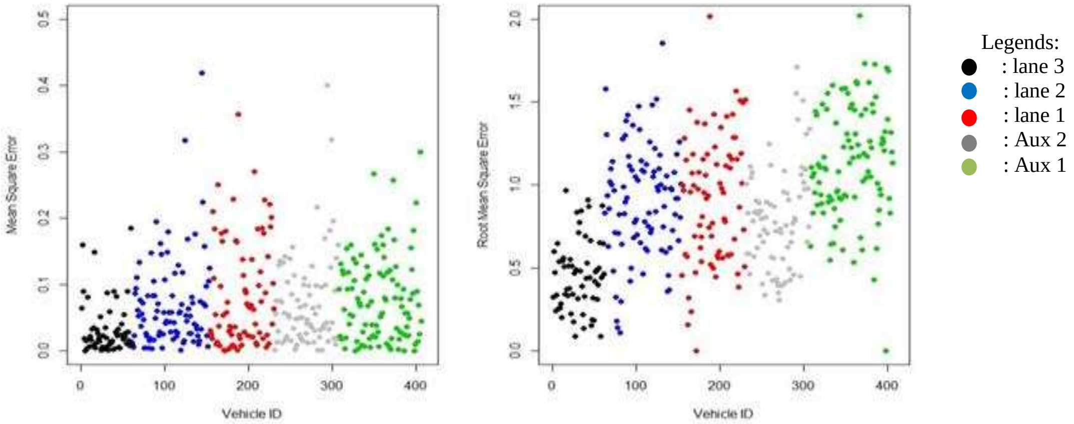

Fig. 3 Mean Absolute Error and Root Mean Square Error

Fig. 3 illustrates the MAE and RMSE of the traffic surveillance data. The data consist of the 408 vehicles. Most of the data showed that the MAE (which represents the variance of the estimator) is around 0.059, while RMSE is 0.782. Both of the analysis indicates that the traffic surveillance video data is relatively near the estimated value.

Table 1 MIDAS vs traffic surveillance video recording average speed between 17:15-17:20 (units: km/h)

Lane	MIDAS		Observation	
	mean	s.d	mean	s.d
Sample Size	471		408	
Overall	109.12	3.68	104.66	14.77
Auxiliary Lane 1	95.20	4.27	92.41	8.62
Auxiliary Lane 2	103.60	2.07	104.08	10.10
Lane 1	100.20	5.89	97.57	10.66
Lane 2	116.60	2.79	111.89	8.17
Lane 3	130.00	4.64	125.92	8.60

Furthermore, we validated the average speed of the fitted observation result to MIDAS average speed which is seen in Table 1.The analysis is aggregated for the whole 5 minutes and it classifies based on each lanes. It shows that the difference between the fitted traffic surveillance data and MIDAS is insignificant around 3%-5%.

5.2. Acceleration

Extending the fitted vehicle trajectory data, this paper observes the acceleration distribution during the 5 minutes period. There are 4238 events of acceleration which divides into acceleration ($\geq 0\ m/sec^2$) and deceleration ($\leq 0\ m/sec^2$). Additionally, there are 1908 events for the acceleration and 2378 events for the acceleration.

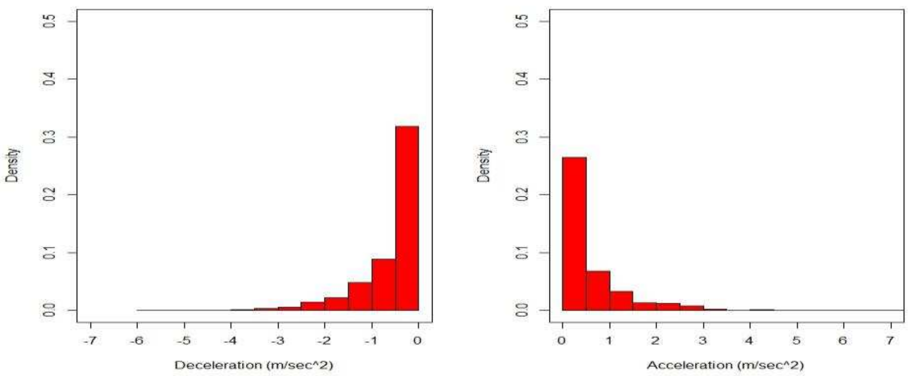

Fig. 4 Fitted acceleration distribution at the weaving section

Fig. 4 illustrates the density distribution of the fitted acceleration and deceleration. It can be seen that most of the fitted deceleration occurs between (0, -0.5] m/sec^2 the density 0.32. Then, the fitted accelerations are between (0, 0.5] m/sec^2 with a probability between 0.27. Both of the histogram distributions are skewed to zero value which fits with the log-normal distribution. This acceleration distribution is presented in the previous research findings (Koutsopoulos and Farah, 2012, and Toledo et al., 2009) is significant for the modelling section later on in this study.

5.3. Lane-changing characteristic

The traffic surveillance identifies around 148 vehicles (36.27% of total data) which involve in the lane-changing movement. We characterise the lane-changing based on the number of lane-changing moves and the type of lane-changing. From the observation, we define two types of lane changing: a direct and staggered lane-changing.

A direct lane-changing is a lane-changing situation where a vehicle moves directly from the origin-lane to its target lane (which is adjacent to the origin lane). A staggered lane-changing describes a situation where a vehicle moves to transit lane(s) in between its origin lane and its target lane. Thus, the staggered lane-changing appears when the vehicles change the lane more than one-lane before reaching its target lane.

Furthermore, this paper defines a lane-changing prerequisite based on the time interval between each lane-changing movement; (i) the direct lane-changing; if the time interval between the consecutive lane-changing is ≤ 1 sec, (ii) the staggered lane-changing; if the time interval between the consecutive lane-changing is > 1 sec.

Table 2 shows the number and the proportion of the lane-changings from the total traffic by lane-changing types observed over the first 320m of the weaving section.

Table 2 Number of lane changing by types

No of Lanes-Changed	Type of Lane-Changing			
	Direct		Staggered	
0	260 (63.72%)			
1	119	(29.16%)	-	(0.00%)
2	14	(3.43%)	13	(3.19%)
3	1	(0.23%)	1	(0.23%)
Total	408(100%)			

We can see that 29.16% of the observed lane-changings are direct and involve only one lane. For those lane-changings involving more than one lane, the data shows that the proportions of the direct and the staggered lane-changing are similar, at lower than 10%. Moreover, the time interval between the lane-changing varies between [0.4-10.28] sec with a mean value 4.09 sec.

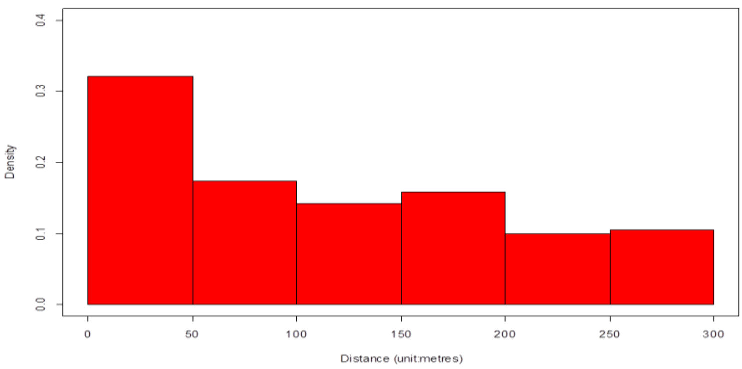

Fig. 5 Lane-changing location

Fig. 5 illustrates the proportion of the lane-changing location inside the observation area. It finds that around 30% of lane changing occurs in the first 50 metres. Meanwhile, the second preferable lane-changing locations are 50-100 metres and 150-200 metres. The data shows that they are in the same proportion, which is around

18%. Al-Jameel (2011) found that the lane-changing occurs in the first 70 metres and suggest enforcing the driver to delay the lane-changing towards the approximately 150 metres from the beginning weaving section.

6. Summary and Future Research

This paper discovers several issues that affect the traffic and driving characteristic such as, traffic flow, the road geometric, acceleration and lane-changing location. The existence of auxiliary lane in the weaving section gives opportunity for the planned lane-changing driver to relax instead of force to change their lane at the beginning of merging area. It is seen in Fig. 1, the speed at J42-J43 is slightly higher compare to the J41-J42.

Based on the fitted vehicle trajectory, 29.16% of the traffic precede one lane-changing and prefer to change the lane at the first 50 meter. A vehicle with more than one lane-changings can change the lane into the target lane either directly or staggered. The averaged transit time between the lane-changings is around 4.09 sec.

Identifying a traffic characteristic in microscopic level is a massive work while we have to track and record each observed vehicle. The traffic surveillance recording quality, site condition, playback time step and obstruction from the lead vehicle(s) affect significantly the data extraction process. The application of the local regression expects to reduce the measurement error and success to smooth the trajectory of the observed vehicles.

Most of the vehicle prefers to accelerate between 0 - 0.5 m/sec^2 and decelerate -0.5 - 0 m/sec^2. The distribution is skewed to zero values and it found to follow a log-normal distribution.

The results from the empirical observations and data processing will insight into the lane-changing and car-following behaviour of traffic at motorway weaving sections, and will inform the development of better traffic models. Future research will involve this result in structuring the car-following model and the lane-changing model

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