Detecting Powered-Two-Wheeler Incidents from High Resolution Naturalistic Data

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ABSTRACT

During risky conditions, Powered-Two-Wheeler (PTW) drivers often alter their behavior from a regular driving pattern to an irregular chain of driving actions by braking, changing the throttle pressure, maneuvering and so on, or combinations of the above. However, both the actual and perceived thresholds of regular and irregular driving behavior differ among PTW drivers. A simple and flexible methodology is proposed in order to define PTW driving profiles by distinguishing between regular and irregular PTW driving behaviors using high resolution naturalistic data. "Irregularities" in driving behavior are consistently expressed as outlying values in the dataset of driving parameters. The detected irregularities are those that diverge from the centroid of the jointly considered driving parameters. These irregularities may be considered to define critical driving situations (incidents) that are further associated to typical driving events. Results indicate that the joint consideration of variables which are directly connected to the mechanical characteristics of PTW, such as front and rear brake activation, wheel speed, throttle and steering, are adequate to distinguish the regular from irregular PTW driving behavior.

Keywords: Powered Two Wheelers, driving behavior, naturalistic experiments, microscopic incident analysis, outlier detection.

1. INTRODUCTION

Understanding Powered-Two-Wheelers (PTWs) driving behavior and interactions with the rest of the traffic is critical to the design of efficient accident countermeasures and is, hence, essential (Yannis et al., 2005). An efficient manner to understand PTW driving behavior - given the improvements and innovations of modern technology - is through constant monitoring and analysis of PTW driver's actions during driving. Until recently, PTW accident risk has been largely studied through macroscopic and in-depth data analyses (Thomas et al. 2005, Dupont et al. 2009, Yannis et al. 2010), as well as through behavior analyses such as questionnaire based surveys, guided discussions, video-based methods or simulators (Engstrom et al. 2005, Savolainen and Mannering 2007, Haque et al. 2010, Huang and Abdel-Aty 2010). These analyses are inherently destined to qualitatively assess on the factors that increase accident risk mainly from a social point of view, without being able to extract accurate and detailed information on the manner PTW drivers behave on the road and especially before, during and after critical driving situations (incidents).

A new and efficient way to understand PTW driving behavior is by creating a least intrusive - restrictive (naturalistic) - environment to monitor and record drivers' actions on the road by employing advanced sensor technologies. Recently, a number of such attempts have been conducted in Europe, the US and Australia to understand driver's behavior. Some prevailing efforts are described in large scale projects such as the 100-Car study (NHTSA 2006), SHRP 2 Naturalistic Driving Study (SHRP2 2011) and Euro-FOT (Csepinszky and Benmimoun 2010). Several findings on commercial vehicle driver's behavior and inattention are summarized in Olson et al. (2009) and Klauer et al. (2010). However, so far no results are publicly available concerning PTW driver's behavior (Reagan et al. 2006, NHTSA 2006, FESTA 2008, Baldanzini et al. 2009).

A key problem in naturalistic PTW driving studies is to define which driving situation may be considered as critical or risky. Interestingly, in all relevant approaches documented so far, such as the 100-Car study (NHTSA 2006) and SEMiFOT project (SEMiFOT 2010), typical driving parameters' (speed, acceleration etc) thresholds (triggers) are empirically established uniquely for each driving parameter; based on those values, criticalities are extracted and further analyzed (a review of such approaches may be found in Baldanzini et al. 2009). This technique is univariate, since it detects incidents from changes in a single driving parameter. But maneuvering on roads may be reflected on changes to more than one parameter.

Moreover, the specific technique addresses all drivers as being similar in their driving behavior. This lacks consistency with the fact that each driver has its personal stock of values, ideas, beliefs and practices, reflecting rigorously on its behavior on the road, such as the braking, overtaking and so on, that may not resemble to the behavior of other drivers on the road (Vlahogianni et al. 2013). Evidently, the driving conditions which are considered as critical are not the same for all drivers, but should be defined on the basis of driving parameters' values that may vary among drivers. Moreover, a critical event may be reflected on changes to a single driving parameter (e.g. braking), but also to more than one driving parameter (e.g. steering and decelerating). In this context, the question that emerges is how the high resolution naturalistic driving data which is, by nature, multivariate and noisy, can be used to define a self-contained multivariate personalized PTW driver's profile.

The objective of this paper is to propose a methodology for identifying PTW driver's profile based exclusively on high resolution naturalistic driving data without the need to observe the videos for identifying situations where the behavior of the driver may be considered as beyond normal. The data exploited concern information on wheel speed, acceleration, throttle, steering, brake activation and so on. A comprehensive methodological shell is proposed in order to distinguish between regular and irregular driving behavior. "Irregularities" in the driving behavior are consistently expressed as outlying values in a multivariate consideration of the available driving parameters. The detected irregularities are those values that diverge from the centroid of the jointly considered driving parameters and define critical driving situations that may further be associated to typical driving events.

2. EXTRACTING POWERED-TWO WHEELER IRREGULAR DRIVING PATTERNS

2.1 The Concept

In general, driving is a complex - often cyclic - task; at a specific instance, the driver will have to scan and recognize stimuli from the road environment and decide which action(s) to take mainly described by braking, accelerating/decelerating or steering. The above actions lead to a change of the status of the vehicle (e.g. velocity or yaw, pitch or roll rate). During the course of a trip, the driver will be forced to repeat these actions for forthcoming driving instances. Evidently, this cyclic task is strongly dependent on factors such as the level of actual knowledge and skill, the amount of experience, the individual level of development and maturity, the social situation and lifestyle (Gregersen and Berg 1994, Boyce and Geller 2002, Møller 2004); thus, each vehicle's driver may act or react to stimuli in a unique manner.

Given the ability to monitor the exact actions of a PTW driver, literature has for long supported the uniqueness of driver behavior in automobiles and the possibility to use it for personal identification to achieve safer driving (Igarashi et al. 2004, Wahab et al. 2009). This uniqueness may be reflected to the variability of driving signals e.g. braking, accelerating and so on; such driving characteristics, in particular, the amount of pressure a driver applies on the accelerator pedal and/or the brake pedal have been utilized in personal identification and define personal driving profiles (Wahab et al. 2009). Although such argument may readily extend to the case of PTWs, PTW research lacks focus on defining PTW driver individual profiles. Nevertheless, the ability to define a driver- specific profile is important and may hav significant implications to various Intelligent Transportation Systems (ITS) applications. A system that may recognize each driver's individual style and manner to react to different driving situations may improve the safety and mitigate the risk during driving. By implementing necessary actions, a system can control the vehicle every time a driver may deviate from its individual driving norm and engage in irregular driving.

The challenge of the proposed approach in introducing a manner to distinguish between normal and irregular driving patterns lies in two issues: first, deviation from the average "normal" PTW driving may not be uniquely defined based on one driving signal. Second, a mathematical manner to define the PTW driving vector and the emergence of irregularity should be introduced. In the present paper, a distance based metric is implemented to define the vector of driving and the concept of outlier data is used to distinguish between normal and irregular driving. Outliers form an important concept of multivariate time series. According to Barnett and Lewis (1994), an outlier is an observation (or subset of observations) which appears to be inconsistent with the remainder of that set of data. In the specific study, an outlier is defined as an observation for a specific time interval, during which the PTW driver for some reason drastically alters its driving behavior due to an external or internal stimulus. Outliers may be caused by measurement error or equipment failure (faulty values) or may depict a critical pattern in the observed data much more rich in information about the systems than the rest of the data e.g. congested patterns in traffic flow (Chen et al. 2009).

2.2 The Method

Although, intuitively, naturalistic data can be used to analyze transportation safety and driving behavior in various ways, their spatial and temporal characteristics is a multiplier of the complexity of any analyses, in both concept and computational intensity. PTW driving data collected in extremely high resolutions (e.g. 100Hz) may be considered to contain outliers. Outliers defined as any abnormal data may contain information on the shift of a driver's profile to extreme driving style due to a non-recurrent unexpected event. The detection of those values may be a cumbersome task – if conducted manually - especially in cases where rich data exist in terms of resolution and driving parameters monitored. The goal of the proposed methodology is to provide a manner to automatically detect those outliers using as inputs only the most relevant driving parameters.

Outlier detection is a critical step in data mining aiming at describing the abnormal data behavior as reflected in the data that deviates from the natural data variability (Hodge and

Austin 2004). There exist both univariate and multivariate approaches to outlier detection. In complex and highly volatile phenomena such as the evolution of the driving variables, the multivariate consideration is imperative, as, for a specific time interval, although one or more variables may be considered as outliers, the entire driving behavior defined by the joint consideration of all variables may not be a multivariate outlier. In the present paper, the proposed algorithm is a multistep approach known as BACON (Blocked Adaptive Computationally Efficient Outlier Nominators) that produces a set of observations nominated as outliers along with the discrepancies based on the Mahalanobis distance relative to a basic subset of the data. Let $X_i = (x_{i1},...,x_{ip}),\ i = 1,...,n$ be the multivariate space of p driving parameters of n observations. The Mahalanobis distance d_i is defined as:

$$d_i\left(\hat{\mu}, S\right) = \sqrt{\left(x_i - \hat{\mu}\right) S^{-1} \left(x_i - \hat{\mu}\right)}, \qquad i = 1,...,n \quad , \tag{1}$$

Where $\hat{\mu}$ and S^{-1} are the sample mean and covariance matrix respectively. In contrast to the Euclidean distance, the Mahalanobis distance takes into account the correlation structure of the data as well as the individual scales (Barnett and Lewis 1994).

The selection of the initial subset is based on Mahalanobis distances; the $m = cp$ observations with the smallest values of $d_i\left(\hat{\mu}, S\right)$ are identified and nominated as a potential basic subset. The term c is a constant that is selected by the researcher; setting c equal to 4 or 5 in a good typical choice (Hadi 1994). Although this approach for selecting the initial subset is not robust, it does not depend on the location, or scale of the data - especially for small percentages of outliers – and computationally less intensive than previous methods (Billor et al. 2000).

The outlier detection algorithm encompasses 4 steps. In the first step the selection of the initial basic subset of size *m* occurs. Second, the computations of the discrepancies of each multivariate observation with the basic subset are conducted using the following equation (Billor et al. 2000):

$$d_i\left(\hat{\mu}_b, S_b\right) = \sqrt{\left(x_i - \hat{\mu}_b\right) S_b^{-1}\left(x_i - \hat{\mu}_b\right)}, \qquad i = 1, \ldots, n \quad , \tag{2}$$

where $\hat{\mu}_b$ and S_b^{-1} are the sample mean and covariance matrix of the basic subset respectively. Third, the new basic subset to all points with discrepancy less than $c_{npr}\chi_{p,a/n}$, where $\chi^2_{p,a}$ is the $1-a$ percentile of the chi-square distribution with z degrees of freedom, $c_{npr} = c_{np} + c_{hr}$ is a correction factor with $c_{hr} = \max\left\{0, \left(h-r\right)/(h+r)\right\}$, $h = \left[\left(n+z+1\right)/2\right]$, r is the length of the subset and $c_{np} = 1 + \frac{z+1}{n-z} + \frac{1}{n-h-z}$. The smaller the choice of a parameter the stricter the criterion for selecting which driving multivariate observations are outliers. The second and third steps are iterated until the size of the basic subset no longer changes. With the convergence of the algorithm, a set of observations are tagged as outliers and are excluded from the final basic subset.

The algorithm has been found to substantially reduce the number of iterations (Billor et al. 2000); it usually takes 3–5 iterations to converge and tolerates up to 20% contamination level (Kondylis et al. 2006). Each of these iterations requires computing and inverting a covariance matrix, but the number of iterations does not grow with the sample size n. Moreover, Billor et al. (2000) show evidence that if the first subset of observations is not near enough to the center of the (non-outlying) data, the successive provisional basic subsets identified by the algorithm tend to drift toward the center. The specific algorithm for outlier detention has not been previously implemented to transportation data.

The proposed approach requires defining which input data should be considered in the process of incident detection. In this paper, different models with different input spaces will be considered and the optimum input space will be identified using as criterion to produce the least data intensive model that will be able to detect all *significant* shifts from regular to irregular driving patterns. The statistical difference between the different models will be judged on the basis of the conditional entropy between two different categorizations of data – outlying or regular patterns - produced by two different models. The conditional entropy is an information theoretic criterion that quantifies the uncertainty of a variable Y conditional on the variable X taking a certain value x provided by the following equation (Schreiber 1999):

$$H_r(\mathbf{Y}\,|\,\mathbf{X}) = -\frac{1}{\log C_X}\sum_{j=1}^{C_Y} p_j \sum_{i=1}^{C_X} p_{ij}\log(p_{i|j}), \qquad (3)$$

where i, j are the categories, C_X, C_Y the total number of categories in data categorizations ***X*** and ***Y*** equally and p is a probability.

3. IMPLEMENTATION AND FINDINGS

3.1 The experiment

The available data come from a naturalistic driving experiment that took place in and around the city of Volos, a medium size Greek city, as part of the large scale naturalistic PTW driving study conducted in the framework of the focused research collaborative project 2BESAFE. 'Naturalistic' refers to a method of observation that captures driver behavior in a way that is most representative of typical driving and not influenced by the artificial features of controlled studies (Baldanzini et al. 2009). This method allows researchers to study drivers in their own vehicle and environment. Such data may provide insight into factors that may influence safe driving. In the specific naturalistic driving study, an instrumented BMW F650 FUNDURO was utilized. Instrumentation focused on throttle position, 3-axis accelerometer, 3-axis gyroscope (roll, pitch and yaw), handle bar rotation, brake lever application, turn signal activations, synchronised video (forward & driver facing) and GPS. Details on the instrumentation specifications may be found in 2BESAFE (2010).

The experiment was conducted in three phases. The first phase involved a testing period in order to correct malfunctions in the instrumentation. During the second phase, a pilot study was conducted in order to test the motorcycle's instrumentation in "on road" naturalistic conditions for verification and data quality issues using one PTW drivers for a period of 4 weeks. The scope of the pilot runs was twofold: first to detect and correct any installation or sensors malfunctioning problems and, second, to evaluate whether the recorded data maintain certain levels of quality (missing values, proper values ranges and so on).

The third phase involved the actual experiments; 3 PTW drivers for a period of 6 weeks each were recruited. Previous literature has indicated that male PTW drivers are over-represented in accidents and in the PTW driving population (Vlahogianni et al. 2012). Moreover, experience is an important factor of PTW driver risk and it is positively related to age and low accident risk. Consequently, it was decided to select experienced participants (at least 5 years of actual driving on a motorcycle resembling the experiment's motorcycle) of age ranging from 24 to 38 years old that are less prone to risky behaviours, to reduce the likelihood of participants being involved in accidents (Vlahogianni et al. 2012). In terms of driving environment, PTWs in Greece are mainly used for commuting to avoid delays due to congestion rather than for leisure purposes; therefore, most of the time spent on PTW is within the urban and suburban road network. As such, the selected participants were chosen to be familiar with urban road environments and use PTWs for trips inside urban and suburban areas.

The specific experiment may be characterized as one of the largest naturalistic PTW driving experiment is a national level across EU. Although, the sample of the drivers may not claim to be representative of the entire population of young PTW drivers in Greece limiting, thus, the ability to extract generalized information on the PTW driving patterns, the small number of drivers may not be considered as a limitation for the applicability of the proposed approach; the proposed methodology for detecting critical driving patterns is focused on each driver individually and not on averaging the drivers' behaviors for extracting generalized thresholds of driving parameters.

3.2 Data Description and Preliminary Analysis

Data for all signals was recorded at a rate of 100Hz except for video signals which are sampled at 10Hz and GPS position which can be sampled at 1Hz (values indicate minimal requirements). GPS signals were not included in the analyses to follow because of their reduced reliability due to frequent signal disruptions. The selection of the specific signals will ensure that the PTW drivers' evasive maneuvers (necessity for: accelerations, speed, brake activation, throttle position and steering angle), as well as the interaction of PTW drivers with the environment will be continuously monitored. Moreover, video installation was used to capture the frontal environment (required a minimum 90° field of view) and the driver's face. The most important signals (driving parameters) monitored are given in Table 1.

<Table 1>

A look at Table 1 reveals two groups of available variables. The first is related to the mechanical characteristics and includes braking (front/rear brake activation and rear brake pressure), yaw rate, pitch rate and roll rate, throttle, steering and wheel speed. The second group refers to the traffic related variables such as linear acceleration components and speed. This distinction is made in order to differentiate those parameters that are directly related to driver's reactions from those that may be considered as outcome of others, such as acceleration.

Data selected for further study encompass approximately 20-30 minutes long trips made during a period of six weeks by one PTW driver in suburban two-way roads. Although the use of data from a single driver may not claim to produce generalizable results, it is adequate to test the usefulness and efficiency of the proposed methodology. The specific route has shoulder width less than 1.2m, rolling terrain and high curvatures, mixed traffic conditions, not equally distributed traffic across the two directions, a significant number of uncontrolled access points and several zones where passing is permitted; this setting seems to be challenging for PTW drivers in terms of driving patterns' complexity and difficulty in maneuvering. All trips were made in daylight with good visibility and fine weather conditions. The final dataset consists of 56 trips of 20 to 30 minutes duration, meaning a set of time series of driving parameters with $6.72 \cdot 10^6$ data. To eliminate any noise in the dataset a smoothing technique was implemented; data were averaged every 0.02 sec, meaning using 1 measurement before and one after a specific time interval. Figures 1 to 3 depict the time series of the most important driving parameters for a typical trip of approximately 30 minutes. As can be observed all driving parameters exhibit a highly oscillating behavior over rime.

3.3 Models for Detecting Irregular Behavior

The proposed outlier detection methodology is applied to the available PTW driving variables in order to detect the outliers and distinguish between regular driving behavior and changes to irregular driving style. The first step of the analysis is to assess the number of variables that should be taken into consideration. Three distinct outlier detection models are further evaluated:

- Model A: steering, throttle, brake activation and wheel speed.
- Model B: linear acceleration and speed.
- Model C: All available driving parameters.

For each model, the distance metric is calculated (Equation 1) and, based on the Bacon algorithm, observations are tagged either as outliers or normal driving patterns; consequently, a series of data categorization to mean “normal” driving pattern or irregular driving pattern is produced.

In order to evaluate the differences between the three models, comparisons are established on the basis of the distance metric and the produced categorization using the Wilcoxon signed rank test (Washington et al. 2010); this test may reveal differences in the temporal evolution of paired samples of data produced by the three different models. The null hypothesis is that the pairs of data computed using the three models come from the same population. As seen in Table 2 that depicts the results of the test, the difference between Model A and the other two Models with respect to the evolution of the driving patterns is significant. Moreover, the distance metric produced by Model B significantly differs from the one produced by Model C. Results also demonstrate that the nominated outliers produced by the three models are significantly different.

<Table 2>

Figure 4 shows the distance metric time series produced by Models A and C for a 5 minute time period. The dotted line represents the threshold values of the distance metric for 5% level of significance; values of the distance metric above that threshold may be nominated as outliers. As can be observed, the proposed methodology not only distinguishes between irregular and regular driving behavior, but it may reveal the specific time interval where a shift to irregular behavior may occur, as well as the actual duration of the irregularity. The larger the metric distance the more extreme the driving behavior is.

Evidently, although the proposed models may classify the available PTW driving data to regular and irregular (outlying) patterns, it seems that the three models may diverge in terms of the produced categorization. Figure 4 shows that using all driving parameters for defining the regular and irregular driving may not necessarily be beneficial regarding the ability to define extreme driving patterns; the three incidents picked up by the Model A that uses as input variables the steering, throttle, brake activation and wheel speed are not detected by Model C that uses all the driving parameters available. The differences between each model will be further evaluated in the following section.

3.4 Comparing models for critical driving situations detection

A comparative study is undertaken in order to identify the least data intensive and most efficient model for the detection of critical PTW driving situations. First, considering the resulting categorization of patterns produced by each model, the conditional entropy is estimated in order to quantify the relation between two different data categorizations produced by two different models. The conditional entropy for Model B and Model C categorization knowing Model A categorization - $H_r(c_{\text{Model B}} \mid c_{\text{Model A}})$ and

$H_r(c_{\text{Model B}} | c_{\text{Model A}})$ respectively - equals to 0.009 and 0.025 respectively. These small values of conditional entropy indicate that the knowledge for the type of driving pattern coming from Model B and C when the classification from Model A is known does not provide any further information.

The above results underline that the larger the number of variables considered in the input space of the algorithm, the lesser the ability of the methodology to discern irregular from regular driving behavior and detect critical incidents degrades with the increase of the input space. This is probably due to the fact that certain variables are correlated (e.g. rear brake activation and brake pressure, acceleration and throttle position). Moreover, it seems that correlations between variables mask (smooth out) the dynamics of driving behavior. This is clearly observed in Figure 4 where the distance metric of the time series of all available variables is depicted (Model C); a critical incident is canceled out when using the entire set of driving variables instead of the ones that are directly connected to the PTW mechanical characteristics.

The variables which are related only to the PTW mechanical-related characteristics are more influential to the process of detection than using all the available variables including speed and acceleration, because the latter may be considered as the direct outcome of changes in throttle and brake activation. Furthermore, speeding or accelerating/decelerating may be the effect of more than one combination of the mechanical-related characteristics, such as steering, throttle and/or braking.

To assess the effectiveness of the detection methodology in relation to the different parameterizations three measures are implemented the Detection Rate (DR), the False Detection Rate (FDR) and the Precision of detection (P):

$$DR = \frac{\text{Nr. of Outliers Correctly Detected}}{\text{Total Nr. of True Outliers}} \cdot 100 \ \ (\%)$$

$$FDR = \frac{\text{Nr. of Outliers Falsely Detected}}{\text{Total Nr.of Data without Outliers}} \cdot 100 \ \ (\%) \qquad (4)$$

$$P = \frac{\text{Nr. of Outliers Correctly Detected}}{\text{Total Nr. of Outliers Detected}} \cdot 100 \ \ (\%)$$

DR is a measure of model's sensitivity that relates to its ability to identify outliers. *FDR* measures of the model's "false alarm" frequency. Finally, *P* is the ratio of the detected outliers that are true outliers to the sum of the detected outliers. To estimate these measures, test videos were used to detect outliers and, then, the same videos were thoroughly observed to manually detect any critical riding situations. From the application of the proposed approach to the test videos, all outliers picked up point to a change – regardless of being smooth or abrupt - in the driving style. Among the situations detected are braking and moving on the right to avoid opposing vehicle, braking due to pedestrians in high grade, waiting at an intersection to enter main traffic, moving on the left to avoid fixed object, entering sharp turn when interacting with opposite lane's traffic, braking and moving on the right after having overtaken vehicles (vehicles are in front of the PTW as well), overtaking more than one vehicle and PTW moving to the left to avoid stationary object. These situations may be considered as incidents where a driver is engaged to an unusual - far from the mean - driving behavior and, thus, may be candidate "critical" driving situations with high accident risk. The detected set of incidents may vary with regard to the accident risk they encompass.

Table 3 demonstrates the results with respect to the Detection Rate (DR), the False Detection Rate (FDR) and the Precision of detection (P) from comparing the detected critical PTW driving situations to those that were manually chosen as critical from direct video observations. Model C has a significantly decreased ability to detect outliers.

<Table 3>

The use of mechanical related driving parameters seems to be adequate in terms of detection rate and false detection rate (Model A). The errors that are observed may be attributed to the difficulty in detecting those situations where the PTW driver does change its driving characteristics but from the video it is evident that they may be considered as critical driving situations. A very frequent example in the on the fly overtaking that is associated with high opposing traffic.

4. DISCUSSION AND CONCLUSIONS

PTW drivers are a critical group of road users frequently engaged to high risk driving situations. During risky conditions, PTW drivers often alter their behavior from a regular driving pattern to an irregular chain of actions by braking and maneuvering, or combinations of the above. However, both the actual and perceived thresholds of regular and irregular driving behavior differ among drivers. To address this issue, the present paper presents a methodology to provide custom-made driving profiles by automatically detecting from collected driving parameters deviations from the individual regular driving behavior. By using high resolution naturalistic PTW driving data, the proposed methodology ensures that no artificial common thresholds of regular driving behavior are established and no subjective judgments of what is regular driving is required, while looking at videos. The detected irregularities are those that diverge from the centroid of the jointly considered driving parameters and define critical driving situations that may further be associated to typical driving events.

The proposed modeling approach is applied to a number of naturalistic driving trips made during a period of three months by one PTW driver in suburban two-way roads. Results from the application of the proposed methodology indicate that the joint consideration of variables that are directly connected to the PTW mechanical characteristics, such as braking, wheel speed, throttle and steering, are adequate to distinguish regular from irregular driving behavior. The traffic related parameters (acceleration, speed, etc) were found to contribute only marginally to the detection of the critical driving situations when the mechanical related parameters were considered. This can be explained by the fact that traffic related characteristics may be considered as the outcome of the driver's actions. The information conveyed by these actions in the procedure for the definition of the "critical" conditions is obviously predominant and precedes any information conveyed by the outcome of these actions. This outcome may open a discussion on the required instrumentation of PTWs during naturalistic studies. However, the use of fewer sensors to detect incidents does not necessarily mean that the other driving parameters should not be measured, as they may still prove useful in providing additional information for categorizing critical situations.

By considering these deviations from the mean driving style no useful information on which of the observed situations is associated to more extreme/irregular driving behaviors may be identified. An additional limitation lies in the fact that there might still be few cases that may not be detected by the specific approach, as well as by any other approach that relies on signals only and not on videos. These include cases where a critical situation may arise (e.g. red light violation by the PTW driver) and go unnoticed by the PTW driver, or other critical situations where the PTW driver may cope with - efficiently or not - without significantly altering its driving characteristics, or those driving characteristics that are being measured. In such cases, integrating video analytics to the proposed approach will increase the detection power and decrease any subjective judgment coming from manually observing videos.

Moreover, further research is needed for uncovering the determinants of each driving behavior with respect to the manner a PTW driver conduct a maneuver in the beginning or during a critical driving situation. In any case, it should be noted that as the available dataset did not encompass any crashes, the deviations from the mean driving style may not characterize direct accident risk. The situations revealed may be considered as potential situations with increased probability of having an accident ("near-miss"). Moreover, the specific approach does not incorporate any information on the road, traffic and control conditions that may be valuable to explaining the causes of the emergence of irregular driving. Although the causalities involved during non-recurrent driving situations fall beyond the scope of this paper, the incorporation of information on the road, traffic and control conditions should be considered in future modeling approaches for enhancing the explanatory power of the models.

From a conceptual perspective, the proposed methodology is capable of defining custom-made driving profiles and detects critical driving incidents with regard to the risk they encompass only on the basis of the magnitude of the deviation from the average driving style of each PTW driver individually. However, the proposed approach as presented and applied encompasses certain limitations. It is evident from the restriction on the available PTW driver's sample size that no generalized results may be extracted; nevertheless, this limitation seems not to conceptually contradict the scope of the proposed approach. Moreover, at this point, this methodology cannot group irregular driving conditions by relating then to specific parameters associated to the road types, trip characteristics and so on. Furthermore, such conditions cannot be directly associated to specific types of real life driving incidents; further research therefore is needed towards uncovering the determinants of the individual driving reactions in the beginning or during a critical driving situation, in an effort to reveal the type of incident PTW drivers are involved in.

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Table 1: The list of monitored PTW driving variables and their description.

Variable	Description
Longitudinal acceleration [g] Lateral acceleration [g] Vertical acceleration [g]	linear acceleration
speed [kph]	longitudinal speed
yaw rate [deg/s] pitch rate [deg/s] roll rate [deg/s]	roll, yaw and pitch rates
Throttle [%]	throttle position
Brake Rear [%]	brake pressure rear
Steering [%]	steering angle
Brake activity Front [0/100]	brake activation front
Brake activity Rear [0/100]	brake activation rear
Wheel Speed [km/h]	Speed of the rear wheel

Table 2: Wilcoxon Signed Rank Test.

	Model B- Model A	**Model C-Model A**	**Model B-Model C**
		Distance Metric d	
z	-277.330	-106.776	361.249
Prob > |z|	<0.001*	<0.001*	<0.001*
		Detected Outlier	
z	86.022	96.500	-26.372
Prob > |z|	<0.001*	<0.001*	<0.001*

**1% level of significance*

Table 3: Incident detection results regarding the detection rate (DR), the false rate (FR) and the precision (P) with 5% level of significance.

	Model A	**Model B**	**Model C**
DR	80.0%	76.0%	8.0%
FR	3.5%	4.7%	0.0%
P	86.9%	82.6%	100.0%

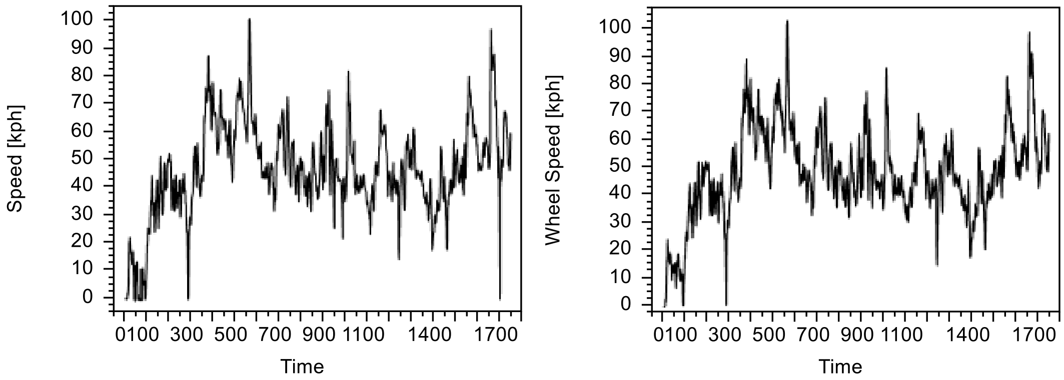

Figure 1: Time series of speed and wheel speed for a typical 30 minute trip form the naturalistic PTW driving study.

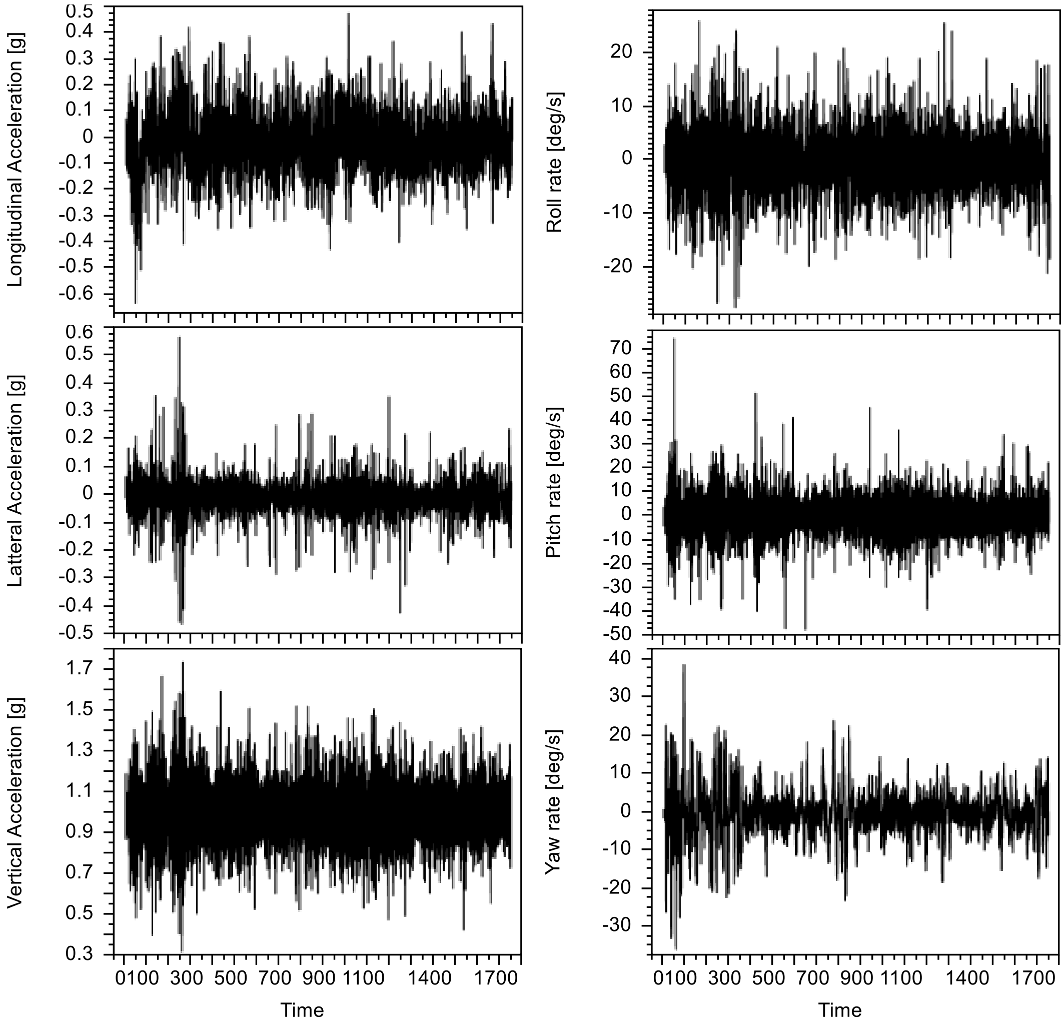

Figure 2: Time series of acceleration (longitudinal, vertical, lateral) and the roll, pitch and yaw rate for a typical 30 minute trip form the naturalistic PTW driving study.

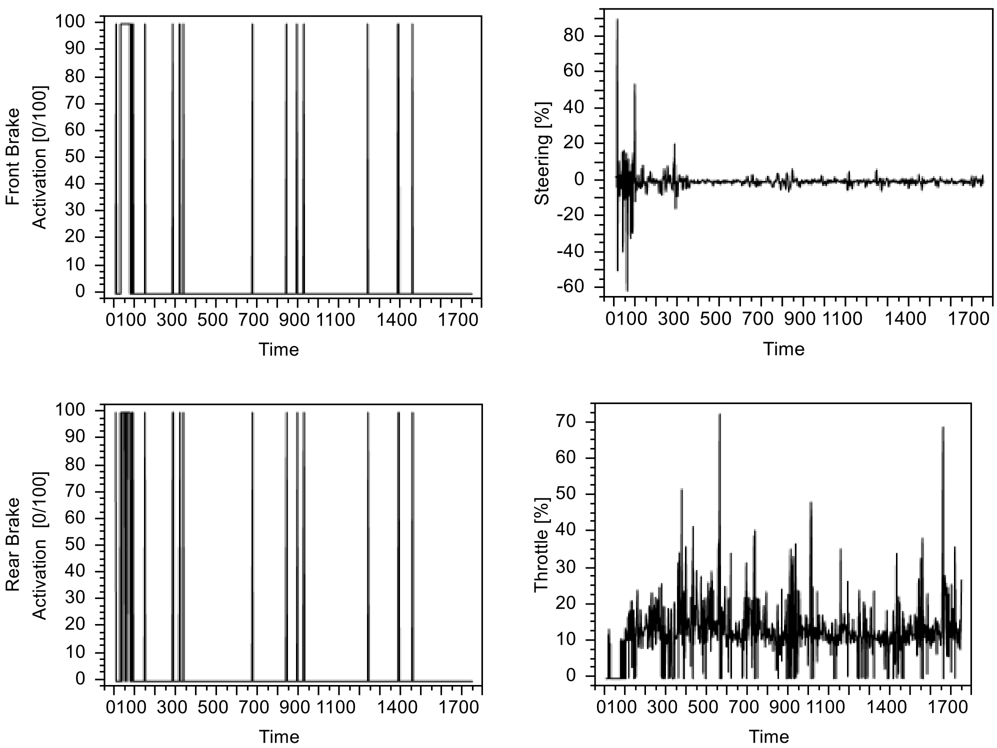

Figure 3: Time series of the brake activation (front and rear), the throttle and steering for a typical 30 minute trip form the naturalistic PTW driving study.

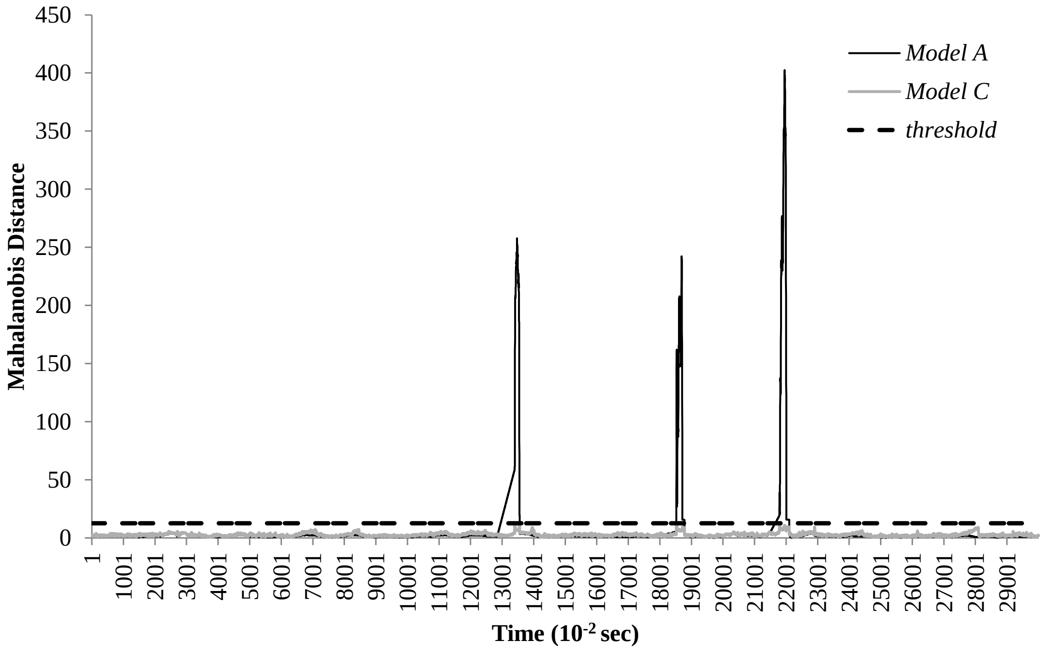

Figure 4: Time series of the Mahalanobis Distance computed for the Model A and C for a 5 minute time period. Any distance metric value above the 5% threshold value signifies an irregular behaviour.