Critical Power Two Wheeler Driving Patterns at the Emergence of an Incident

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ABSTRACT

The paper proposes a methodology based on Bayesian Networks for identifying the Power Two Wheeler (PTW) driving patterns that arise at the emergence of a critical incident based on high resolution driving data (100Hz) from a naturalistic PTW driving experiment. The proposed methodology aims at identifying the prevailing PTW drivers' actions at the beginning and during critical incidents and associating the critical incidents to specific PTW driving patterns. Results using data from one PTW driver reveal three prevailing driving actions for describing the onset of an incident and an equal number of actions that a PTW driver executes during the course of an incident to avoid a crash. Furthermore, the proposed methodology efficiently relates the observed sets of actions with different types of incidents occurring during overtaking or due to the interactions of the rider with moving or stationary obstacles and the opposing traffic. The observed interrelations define several driving patterns that are characterized by different initial actions, as well as by different likelihood of sequential actions during the incident. The proposed modelling may have significant implications to the efficient and less time consuming analysis of the naturalist data, as well as to the development of custom made PTW driver assistance systems.

Keywords: naturalistic driving, road incidents, driving patterns, power two wheelers, cluster analysis, Bayesian networks

INTRODUCTION

Risky Power Two Wheeler (PTW) driving has been for long a critical consideration in traffic safety. The majority of research efforts focus on demystifying the PTW driving behavior in critical situations (incidents) in order to extract useful knowledge on the manner PTW users react to internal of external stimuli and develop efficient countermeasures for PTW safety; attempts range from macroscopic and in-depth analyses of PTW accident datasets based on police reports or in-depth investigation (Mannering and Grodsky 1995, Jonah et al. 2001, Horswill and Helman 2003, Harrison and Christie 2005, Yannis et. al., 2005, Chen 2009, Chen and Chen 2011) to advanced riding simulator experiments that target the continuous monitoring of the PTW microscopic traffic characteristics (Cossalter and Lot 2002, Nehaoua et al. 2007, Hima et al. 2007, Liu et al. 2009). The limitation of police reports and queries is that riders/drivers involved in accidents usually – intentionally or unintentionally – provide police with misleading information, as well as little accurate information on the pre-crash conditions (Jovanis et al. 2011). As for simulators, although they provide a setting for studying in detail the reaction of riders during extreme situations, they can hardly claim similarities to reality, especially with regards to the dynamics of PTWs that are very difficult to replicate (Hima et al. 2007).

Recently, PTW driving studies have been supported by significant technological advances that enable the efficient, least intrusive and continuous monitoring and recording of data on the manner a rider behave on its own physical environment, the road. Such experiments, known as naturalistic driving experiments, integrate high resolution video recorders, sensors and data storage units that may efficiently monitor and record all rider's activities, such as brake activation, steering, speed, acceleration, yaw and so on. Although some naturalistic experiments have been conducted in Europe, the US and Australia to understand driver behavior (NHTSA 2006, Csepinszky and Benmimoun 2010, SHRP2 2011), so far no quantitative results are publicly available concerning PTW driver's behavior, especially concerning the prevailing driving patterns observed at the occurrence of an incident (NHTSA 2006, Regan et al. 2006, FESTA (2008). This information may be considered as critical in order to reveal the manner a driver reacts to internal or external stimuli.

In all methodological approaches documented so far, some shortcomings regarding the detection and identification of PTW drivers' reactions can be identified. All studies implement typical fixed driving parameters' thresholds to reveal risky driving situations, regardless of the type of driver (male or female, experienced or novice driver and so on) and the type of area or other roadway of rider characteristics- (2BESAFE 2009, Jovanis et al. 2011). This technique lacks consistency with the fact that each PTW driver may have its own personal stock of values, ideas, beliefs and practices, reflecting rigorously on its driving style or behavior on the road, such as the braking, overtaking and so on, that may not converge to a "typical" driver's behavior. In this framework, every driver may have different perception on the notion of incident or react differently to the emergence of a critical situation during driving.

Furthermore, the use of fixed thresholds to identify critical incidents severely biases the driving behavior that may be associated to the occurrence of a specific incident. Recently, a statistical approach to detect critical incidents from a multivariate set of driving parameters that define the characteristics of a specific PTW driver has been proposed (Vlahogianni et al. 2011); incidents are defined as those situations that the PTW driver's actions deviate from its mean driving behavior. The mean behavior and its deviation are defined in relation to changes of the braking, wheel speed, steering and throttle. Although relationships between the different driving parameters and the probability of having an incident could not be established, this methodology is a first attempt to automatically detect irregularities and critical incidents from a vast amount of complex and high resolution naturalistic PTW driving data.

Furthermore, regardless of the definition and identification of PTW incidents, literature has also underlined the huge gap of knowledge on the manner a PTW driver reacts to the emergence of a critical incident. More specifically, there is no knowledge coming from microscopic data on the interrelations between braking, speeding and maneuvering under different driving or roadway conditions. The present paper proposes a methodology based on Bayesian Networks for identifying the patterns that arise at the emergence of a critical incident based on high resolution driving data (100Hz) from a naturalistic PTW driving experiment. Patterns will refer to PTW driver's actions both at the beginning and during the incident with regards to interactions between driving variables, such as wheel speed, braking steering etc. These patterns will be further associated to different types of incidents.

METHODOLOGY

A fundamental research question related to identifying criticalities in PTW driving behavior is whether there is a way to relate critical driving actions to specific critical situations (incidents). Uncertainty in PTW driver reactions to external or internal stimuli may increase the complexity in the driving tasks, especially in extreme driving situations. A method previously applied to transportation problems, such as traffic flow analysis (Vlahogianni et al. 2007, Castillo et al. 2008), freeway accident analysis (Vlahogianni et al. 2010) and young drivers' overtaking behavior modeling (Vlahogianni and Golias 2012), that may well tackle the uncertainty in large multivariate datasets is the Bayesian Networks (BNs). BNs are powerful in handling incomplete data and uncertain phenomena (Charniak 1991). Moreover, due to their probabilistic nature, they can easily integrate both qualitative information and quantitative information in modeling (Jensen 2001).

In this paper, the problem of identifying criticalities in PTW driving behavior is treated in two steps. First, it is assumed that, at the emergence of an incident, the PTW driver performs a far from typical (mean) driving action that is followed by a set of sequential actions during the incident in order to avoid a near-miss or crash. For this step, a clustering approach is undertaken in order to reveal the critical driver's actions at the beginning and during the occurrence of an incident. In the second step, the revealed actions are further associated to specific incident types, for example overtaking, avoiding stationary obstacle and so on taking into consideration the uncertainties arisen from the manner the PTW driver will react to each situation.

Both methodological steps are modeled using BNs. A $BN = \langle K, L, \mathbf{\Theta} \rangle$ is a directed acyclic graph $\langle K, L \rangle$ of $k \in K$ nodes that represent the x_i random variables of the network (Cheng and Greiner 2001). Nodes are connected by links $l \in L$ that describe the probabilistic relationship between interconnected nodes; this relationship is quantified using a conditional probability distribution $\theta_i \in \mathbf{\Theta}$ for each node k_i (Friedman et al. 1997): $\theta_{x_i|\Pi_{x_i}} = P_B(x_i|\Pi_{x_i})$, where $\Pi_{x_i} \in \Pi_{X_i}$, where Π_{X_i} stands for the set of parents of X_i in the network. Independency between variables is denoted by the lack of a link. A BN defines a unique joint probability distribution over *X* given by (Friedman et al. 1997):

$$P_B(x_1, ..., x_n) = \prod_{i=1}^{n} P_B\left(x_i \middle| \Pi_{x_i}\right) = \prod_{i=1}^{n} \theta_{i|\Pi_i}\left(x_i \middle| \Pi_{x_i}\right) \tag{1}$$

The BN can act as a classifier; given the characteristics $x_i \in \mathbf{X}$ as inputs (for example the PTW driving parameters) and a set of classes *Z* (for example the PTW driving situations), a new unclassified observation *S* can be assigned to a class by the rule (Friedman et al. 1997):

$$\mathit{classify}(x_1, ..., x_n) = \arg\max_n p(z) \prod_{i=1}^{n} p\left(x_i | z\right) \tag{2}$$

A BN can be also used as a clustering model. Clustering is a task to partition the objects in the dataset *D* into clusters of similar objects. By using a BN, each object with attributes x may be classified to its most probable cluster (class) $k*$, based on the estimated parameters θ_i, by using a membership probability as a score (unsupervised classification):

$$k* = \underset{1 \le k \le K}{\arg\max}\, p\left(k \middle| \mathbf{x}, \hat{\boldsymbol{\theta}}\right) = \underset{1 \le k \le K}{\arg\max}\, p\left(k, \mathbf{x} \middle| \hat{\boldsymbol{\theta}}\right) \tag{3}$$

Parameters are learnt via an Expectation-Maximization algorithm (Dempster et al. (1977). After learning, each link encompasses a strength that is quantified using mutual information, an information theoretic criterion that quantifies the amount of information flow between two nodes x_i and x_j. The mutual information $I\left(x_i, x_j\right)$ between variables x_i and x_j measures the expected information gained about x_j, after observing the value of the variable x_i (Friedman et al. 1997):

$$I\left(x_i, x_j\right) = \sum_{x_i \in X, x_j \in X} P\left(x_i, x_j\right) \log \frac{P\left(x_i, x_j\right)}{P\left(x_i\right) P\left(x_j\right)} \tag{4}$$

The mutual information between two nodes can quantify the relationship between two variable e.g. if the two variables are dependent and if so, how close their relationship is. The information flow with respect to the set of "evidence" variables (condition-set), in this case the Class membership Z $I\left(x_i, x_j | z\right)$ is given by conditional mutual information (Friedman et al. 1997):

$$I\left(x_i, x_j | z\right) = \sum_{x_i \in X, x_j \in X, z \in Z} P\left(x_i, x_j, z\right) \log \frac{P\left(x_i, x_j | z\right)}{P\left(x_i | z\right) P\left(x_j | z\right)} \tag{5}$$

THE EXPERIMENT

The application of the proposed methodology refers to a large scale naturalistic PTW driving experiment conducted in the city and at the suburbs of Volos, a medium scale Greek city, during the period November 2010 - April 2011. The specific experiment was conducted using an instrumented BMW F650 Funduro. During the period of the experiment, three PTW drivers of age ranging from 24 to 38 years old, with at least 5 years of actual driving experience on a motorcycle resembling the experiment's motorcycle and on road environments similar to the experiment, for a period of 6 weeks each were recruited. The available signals that were being stored are summarized in Table 1. Moreover, video installation was available and calibrated to capture the frontal environment (a minimum of 90° field of view) and the rider's face. The data acquisition of all signals was set to be recorded at an accuracy of 100Hz except for video signals which are sampled at 10Hz and GPS position which can be sampled at 1Hz (values indicate minimal requirements). Details on the specific experiment can be found in 2BESAFE (2010).

<Table 1>

PRELIMINARY DATA ANALYSIS

Data selected for further study encompass trips of 20 minutes duration made during a period of three months by one rider in rural two-way roads. 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 riders in terms of 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 minutes duration, meaning a set of time series of driving parameters with $6.72 \cdot 10^6$ data.

In order to identify the critical actions a PTW driver undertake at the emergence and during an incident, the critical driving situations in the available data should be detected. Based on a similar dataset, previous research has provided a methodology to detect critical incidents using a robust outlier detection methodology based on the Mahalanobis distance d_i (Vlahogianni et al. 2011); the Mahalanobis distance is defined as $d_i = \sqrt{(x_i - \hat{\mu}) S^{-1} (x_i - \hat{\mu})}$, where, $X_i = (x_{i1},...,x_{ip}),\ i = 1,...,n$ be the multivariate space of p driving variables that independently come from a multivariate normal distribution $X = N(\mu, \sigma^2)$, where μ is the mean and σ is the covariance matrix, $\hat{\mu}$ and S^{-1} are the sample mean and covariance matrix respectively (Barnett and Lewis 1994). The Mahalanobis distance can be approximated by an F-distribution $\left[p(n-l)(n+l)/n(n-p)\right]F_{p,n-p}$; at a significance level *α*, a determination as to whether a new observation X_i can be considered as outlier - critical incident - or not can be made based on the following formula: $d_i \leq \left[p(n-l)(n+l)/n(n-p)\right]F_{p,n-p}$. For a given PTW driver, the above algorithm may distinguish between typical – mean – driving patterns and irregular - far from the mean - driving behavior. This approach may be implemented using various other distance measures.

Based on the above methodology, Vlahogianni et al. (2011) found that steering, throttle, brake activation and wheel speed are the optimum set of parameters in order to effectively detect the critical incidents, meaning situations with increased probability of leading to an accident; the traffic related variables have been found less influential in detecting incidents and, thus, are not considered in the analyses to follow. An example of the incident detection methodology is seen in Figure 1 where the temporal evolution of the distance metric d_i is depicted. As can be observed, a large deviation from the mean signifies the onset of a critical incident; the larger the deviation the greater the change of the PTW driver's style. Moreover, by this method, the duration of the event may be also measured as the time difference between the first deviation of distance metric from the mean value and the return to the mean driving pattern.

<Figure 1>

The specific detection methodology provides information in the form of joint consideration of steering, activation brake (front, rear), throttle and wheel speed for both the initial driving conditions at the occurrence of an incident, and the driving conditions during an incident. The initial conditions at the occurrence of an incident refer to a single action that is undertaken by the PTW driver as an instantaneous reaction to a stimulus, whereas the conditions during the evolution of an incident may encompass more than one action undertaken by the PTW driver in order to prevent an accident. In the latter case the sequence of PTW driver's actions may play an important role.

The available data are tested for multivariate normality and the above methodology for outlier detection is applied; overall, the process resulted to identifying 131 cases of critical driving situations; time series of the observed data regarding these cases will be further analyzed in the following sections. These cases are determined by the actions occurring at the emergence of a critical driving situations and a sequence of actions occurring during the situation and until the situation ends. Figure 2 depicts the distributions of all available data; as can be observed the distribution of the values of the available parameters may significantly vary between the beginning and during the observed incident.

<Figure 2>

CRITICAL DRIVING ACTIONS AT THE BEGINNING AND DURING AN INCIDENT

For each incident phase -beginning and during the incident - a BN clustering model is developed in order to reveal groups of critical PTW driving actions with respect to the steering, braking activation, throttle and wheel speed. By critical, we mean the different actions that the PTW driver engages in, both at the beginning and during a critical incident. The clustering quality s judged upon the purity defined as: $purity(C_j) = \frac{1}{|C_j|} \max_i \left(|C_j|_{class=i} \right)$,

where C_j is a cluster, $|C_j|$ is the size of the cluster and $|C_j|_{class=i}$ is the number of cases class *i* assigned to cluster *j*; the higher the purity the better the clustering. The trained BNs are able to produce clusters with 68% and 72% purity respectively; the relative high purity signifies that all clusters produced contain mainly cases from a sole class of actions and not from multiple classes of driving actions.

Results are summarized in Table 2 and Table 3 for the beginning and during an observed incident respectively. The profile of each cluster is established based on the binary relative significance, meaning the ratio between the mutual information brought by each variable and the greater mutual information; $\frac{\text{mutual information}_i}{\max\left\{\text{mutual information}_i\right\}}$, $i = 1, 2, ..., n$ where n is the number of variables describing PTW driving. Moreover, for each influencing variable, the modal value, meaning the most probable value with respect to the response variable and its observed state is provided; this modal value comes with its probability.

<Table 2>

<Table 3>

As seen in Table 2, the clustering reveals three distinct groups of driving actions associated with the prevailing conditions at the occurrence of an incident. Observing the binary relative significance values, it is found that, in each group of actions, the independent variables are ranked in a different manner, indicating that the variables' influence in the various groups of actions is different. More specifically, actions belonging to the group S_1 are the 59% of sample encompass actions where the PTW driver, at the beginning of an incident, activates the rear brake in medium speed, executing a minor maneuver. In this group, the most influential variables are the rear and front brake activation, followed by throttle and steering; wheel speed seems to be least influential. In the S_2 group (22% of sample), the rank order is different; front brake activation is the prevailing variable, followed by wheel speed, throttle and rear brake activation; in the second group of actions at the beginning of the incident, steering is the least influential variable. Actions belonging to the S_2 group show that the PTW driver most likely will use the front brake in low speed, again by executing a minor maneuver. Finally, there is a third group S_3 (19% of cases) where throttle ranks first in terms of influence to the target variable S_3, followed by rear brake activation, steering and wheel speed; the front brake activation is not significant. Actions belonging to the S_3 group are characterized by accelerations in high speed where the PTW driver executes a minor maneuver; brakes are not activated. A more thorough look at the results show that, although S_1 and S_2 cannot be easily intuitively assigned to specific situations, S_3 seems to refer to actions met in overtaking, as the PTW driver suddenly accelerates in high speed and executes a minor maneuver.

Similarly, PTW driver's actions during an incident can be clustered into three groups (Table 3). The first group C_1 encompassing the highest percentage of cases (44%) is more influenced by steering, rear brake activation, throttle and wheel speed rather than the front brake activation. This means that C_1 encompasses actions during which the PTW driver executes a minor maneuver, while brakes are activated in medium speeds. In the second group C_2 (37% of cases), as in the case of C_1, steering is still critical, but wheel speed is more influential than braking. Moreover, front brake rather than real brake is influential. C_2 describes actions where the PTW driver executes a minor maneuver in very low speed when both brakes are activated. Finally, C_3 is strongly related to throttle and the non-activation of both brakes, whereas wheel speed and steering is less influential. This means that C_3 involves actions where the PTW driver accelerates in medium speed.

CRITICAL DRIVING PATTERNS AT THE EMERGENCE OF INCIDENTS

Interestingly, although S_i set of actions uniquely appear in each incident (each incident have one appearing S_i action), an incident may most likely involve more than one C_i actions during its evolution. The manner S_1 and C_i are related, as well as the manner a sequence of actions C_i during an incident may be formed with respect to the type of incident is of extreme importance.

A Bayesian classifier is developed in order to relate the identified PTW driving actions at the beginning and during an incident to specific incident categories. The aim is to identify prevailing PTW driving patterns encompassing sequences of actions that may be explicitly associated to critical incidents. As independent variables, apart from the action taken at the beginning of the incident (S_i), four other variables are considered. The first three are binary variables $\{0,1\}$ and refer to whether the action C_1, C_2 or C_3 has been observed during the incident. The fourth variable quantifies the number of actions a rider may conduct during a specific incident. As dependent variable a generalized incident categorization is proposed that distinguishes all detected incidents into four categories: those resulting from interactions with a moving obstacle, those resulting from a stationary obstacle, incident involving overtaking and, finally, incidents that are due to interactions with the opposing traffic. Table 4 shows the data specifications with respect to the dependent and independent variables.

<Table 4>

The Bayesian classifier developed can use the associated data (steering, throttle, front/rear brake activation and speed) for the prediction of incident type with relative high precision (function of the number of correct predictions of the target variable) of 82%. Results on the discovered associations are seen in Table 5 with respect to the binary relative significance and the modal value.

<Table 5>

As seen in Table 5, in incidents involving moving obstacles or interactions with opposing traffic, the rider, at the beginning of the incident, will most likely activate the rear brake in medium speed, executing a minor maneuver (S_1). The riders will then conduct - on average - 2 actions to avoid a near miss or crash, with the prevailing action being C_2, which is to activate both brakes and conduct a minor maneuver in very low speed. A low dependence on the different actions during an incident C_i may be observed that may be related to the increased speed of reactions observed in the case of incidents with a moving obstacle. In the case of incidents involving stationary objects, the most probable initial action is the front brake activation in low speed (S_2); the rider will most probably activate both brakes and conduct a minor maneuver in very low speed (C_2) during the course of the incident. Finally, overtakes are strongly related to the initial action S_3, that is accelerating at high speed, while conducting a minor maneuver. During the incident, there is a high probability of accelerating and executing 3 actions with the prevailing action being the acceleration (C_3).

CONCLUSIONS

Risk hindering in the behavior of PTW drivers is a common consideration in traffic safety. Until now, PTW drivers' behavior has been systematically studied through survey questionnaires, statistics based on police reports and in-depth investigation, methods that may be biased, lacking critical information or encompassing errors and inaccuracies due to estimations inherent to the data collection. Although current technological advances have foster the conducting of naturalistic experiments that may provide very detailed information on the manner a drive behave on the road, little is still known on the manner a PTW driver reacts to the emergence of a critical incident. The present paper proposes a methodology based on Bayesian Networks for identifying the different driving patterns at the emergence and during a critical incident using high resolution monitored driving data (100Hz) consisting of information on wheel speed, throttle, steering, brake activation.

Results reveal that the onset and duration of a critical incident is governed by a set of different driving actions that when considered as a sequence form complex PTW driving patterns. These patterns may be efficiently described by the interrelations between the PTW driving variables that are related to the mechanical characteristics of the PTW, such as the front and rear braking activation, the throttle position, the steering angle and the wheel speed. Furthermore, the proposed methodology relates the observed patterns with four rough incidents categories: interaction with moving or stationary obstacle, with opposing traffic and overtaking. Each incident category is characterized by different initial actions and by different likelihood of sequential PTW driving actions occurrence during the incident, providing thus a better insight on the real dynamics of the PTW incidents.

The proposed methodology is purely probabilistic and compatible with the uncertainty hindering in the PTW driver's behavior. The revealed patterns may be explicitly distinguished. The latter associated with the fact that a broad categorization of observed incidents has been proposed, results to a flexible characterization of PTW driving behaviors at the emergence and during an incident through an automatic detection using solely data - without seeing the videos.

The findings of this research provide a solid framework for the analysis of critical incident situations of power two wheelers. Furthermore, they allow for the better understanding of the dynamics of a PTW incident based on measured driving variables that, when jointly considered with qualitative data, may improve the efficiency of in-depth studies. The identification of the PTW driver's reaction at the emergence and during a critical situation may also improve the effectiveness of intelligent crash avoidance systems.

Further research is needed on the variability of the observed behavioral patterns across different PTW drivers (male female etc) and different road settings (urban vs rural, signalized vs unsignalized networks etc). The inclusion of the characteristics of the driver and its behavior, as well as of the different road and traffic environments, may lead to naturalistic driving findings, which could be better generalized.

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TABLE 1: The list of monitored variables and their description.

Variable	Description
Longitudinal acceleration (g)	
Lateral acceleration (g)	Linear acceleration (three components)
Vertical acceleration (g)	
Speed (km/h)	Longitudinal speed
Yaw rate (deg/s)	
Pitch rate (deg/s)	Roll, yaw and pitch angles and rates
Roll rate (deg/s)	
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: Influence of PTW driving variables to the driving actions revealed at the occurrence of an incident.

Node	Binary mutual information (%)	Binary relative significance	Modal Value	
		S_1 (58.78%)		
Rear Brake Activation (0/100)	55.05%	1.00	100	100%
Front Brake Activation (0/100)	41.51%	0.75	0	100%
Throttle (%)	21.32%	0.39	≤2.47	81%
Steering (%)	15.81%	0.29	≤0.42	81%
Wheel Speed (kph)	4.35%	0.08	≤49.743	33%
		S_2 (21.56%)		
Front Brake Activation (0/100)	73.12%	1.00	100	100%
Wheel Speed (kph)	23.47%	0.32	≤33.45	57%
Throttle (%)	18.31%	0.25	≤2.47	100%
Rear Brake Activation (0/100)	7.61%	0.10	0	57%
Steering (%)	4.64%	0.07	≤0.42	57%
		S_3 (19.66%)		
Throttle (%)	79.25%	1.00	≤16.69	50%
Rear Brake Activation (0/100)	27.39%	0.34	0	83%
Steering (%)	14.78%	0.19	≤0.42	50%
Wheel Speed (kph)	11.45%	0.14	>65.91	50%
Front Brake Activation (0/100)	0.78%	0.01	0	67%

TABLE 3: Influence of PTW driving variables to the driving actions revealed during a detected incident.

Node	Binary mutual information (%)	Binary relative significance	Modal Value	
		C_1 (43.65%)		
Steering (%)	24.32%	1.00	≤1.84	86%
Rear Brake Activation (0/100)	21.53%	0.89	100	96%
Throttle (%)	15.13%	0.62	≤5.56	99%
Wheel Speed (kph)	11.45%	0.47	≤55.61	47%
Front Brake Activation (0/100)	0.60%	0.03	100	71%
		C_2 (36.98%)		
Steering (%)	73.21%	1.00	≤-0.94	52%
Wheel Speed (kph)	54.71%	0.75	≤19.12	53%
Front Brake Activation (0/100)	19.69%	0.27	100	95%
Throttle (%)	13.24%	0.18	≤5.56	100%
Rear Brake Activation (0/100)	0.94%	0.01	100	77%
		C_3 (19.37%)		
Throttle (%)	78.40%	1.00	>5.56	91%
Rear Brake Activation (0/100)	61.63%	0.79	0	100%
Front Brake Activation (0/100)	51.62%	0.66	0	99%
Wheel Speed (kph)	37.13%	0.47	≤55.61	91%
Steering (%)	22.76%	0.29	≤1.84	98%

TABLE 4: Data specification for the BN classifier.

Independent	Dependent
Start (S_1, S_2, S_3)	
Nr of actions (*1*, *2*,…)	Incident Category
C_1 (0 if no, 1 if yes)	(Stationary obstacle, Moving obstacle, Overtake, Opposing
C_2 (0 if no, 1 if yes)	Traffic)
C_3 (0 if no, 1 if yes)	

TABLE 5: Results from associating the type of the incident with specific driving actions at the occurrence and during the incident.

Node	Binary relative significance	Modal Value		Node	Binary relative significance	Modal Value	
Moving Obstacle (28.57%)				Opposing Traffic (28.57%)			
Start	1	S_1	90%	Start	1	S_1	90%
Actions	0.542	2	40%	C_1	0.843	0	100%
C_3	0.067	0	90%	Actions	0.768	1	70%
C_2	0.014	1	70%	C_2	0.180	1	80%
C_1	0.008	0	80%	C_3	0.074	0	90%
Stationary Obstacle (28.57%)				Overtake (14.29%)			
Start	1	S_2	60%	Start	1	S_3	80%
Actions	0.518	2	70%	C_3	0.591	1	80%
C_1	0.336	0	50%	Actions	0.326	3	60%
C_3	0.280	0	100%	C_2	0.078	0	60%
C_2	0.012	1	60%	C_1	0.001	0	80%

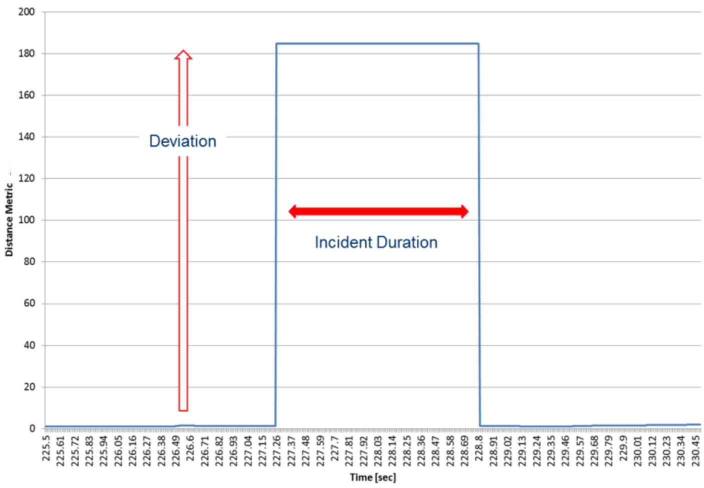

FIGURE 1: An example of a detected incident using the Mahalanobis distance metric encompassing joint information on throttle, steering, braking activation and wheel speed.

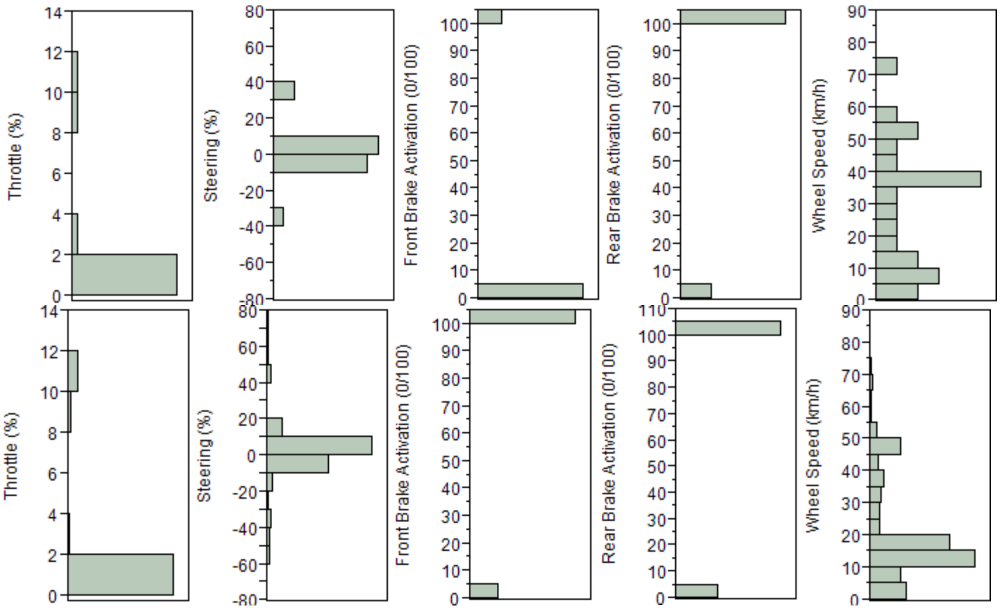

FIGURE 2: The distributions of throttle (%), steering (%), fron and real brake activation (0/100) and wheel speed (km/h) for modeling at the emergence (first row) and during a critical situation (second row).