Identifying Critical Power Two Wheeler Riding Behaviors at the Emergence of an Incident

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Abstract

High resolution riding data from a large-scale Power Two Wheeler's (PTW) naturalistic driving experiment are exploited in order to identify critical riding patterns emerging at the beginning and during an incident. A two-step analysis is adopted: first, a clustering approach is undertaken in order to reveal the critical rider's actions at the beginning and during an incident. Second, the revealed actions are associated to specific riding situations in order to identify the critical riding patterns. Both methodological steps are modeled using Bayesian Networks. Results reveal three different prevailing riding actions for describing the onset of an incident and an equal number of actions that a rider executes during the course of an incident to avoid a crash. Furthermore, the proposed methodology efficiently relates the observed sets of actions with the different riding incidents and produce riding patterns (moving or stationary obstacle, overtaking and opposing traffic) that are characterized by different initial actions, as well as by different rider's action likelihood during the incident.

Motivation and Objectives

Points of interest

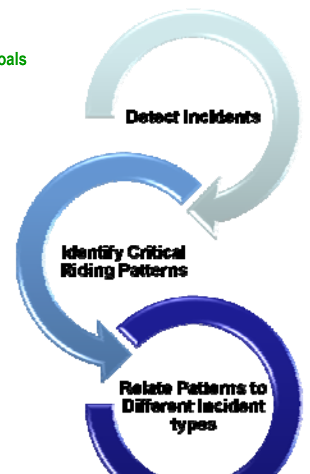
- All relevant approaches documented so far implement typical fixed driving/riding parameters' thresholds – regardless of the type of rider and the type of area or other roadway of rider characteristics- and, based on those values, the incidents are extracted and further analyzed.
  - ✓ This technique lacks consistency with the fact that each driver/rider 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 converge to a "typical rider's behavior".
  - ✓ The use of fixed thresholds to identify critical incidents severely biases the riding behavior that may be associated to the occurrence of a specific incident.
- Moreover, until now little is known on the manner a rider reacts to the emergence of a critical incident.
  - ✓ There is no knowledge coming from data collected on the interrelations between braking, speeding and maneuvering under different riding or roadway conditions.

The aim

- Detect critical incidents from a multivariate set of riding parameters that define the riding characteristics of a specific using statistical approaches
- Identify the riding behaviors that arise at the emergence of a critical incident based on high resolution monitored riding data (100Hz) from a naturalistic driving experiment.

Methodological Framework

Conceptual goals



Models and Methods

Automatic Incident Detection

Whoever knows the ways of Nature will more easily notice her deviations; and, whoever knows her deviations will more accurately describe her ways.

F. Bacon (1620)

•Concept:

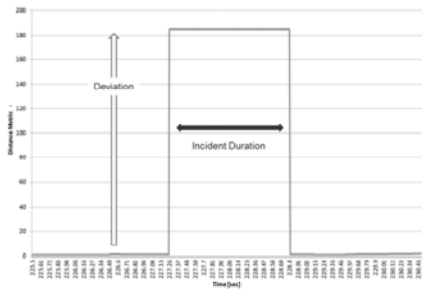
- Jointly consider 100Hz riding parameters time series
- detect the deviations from the mean behavior
- nominate the occurrence of a deviation as the beginning of an incident.

•The method

- from a clean subset of the multivariate data that can safely be presumed to be free of outliers, we test the "outlyingness" of the remaining points relative to the clean subset.
- Use a distance metric d to calculate the deviation from the mean riding behavior every t.

$$d_i = \sqrt{(x_i - \hat{\mu}) S^{-1} (x_i - \hat{\mu})}$$

where, $X_i = (x_{i1}, \ldots, x_{ip})$, $i = 1, \ldots, n$ be the multivariate space of p riding parameters 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



An example of a detected incident using the Mahalanobis distance metric.

The methodology is consistent to the complexity or rider's behavior as it does not limit is generalization power to typical threshold values of riding parameters, but produces custom-made riding profiles and irregular riding patterns allowing the thresholds of extreme riding behavior to vary among riders based on their personal stock of values, ideas, beliefs and practices.

Bayesian Networks

•Computational intelligence models for reasoning under uncertainty by combining probability and graph theory

- probabilities act as a connector between simple parts that based on the graph theory form a complex modular system

•Based on the idea of conditional dependence between variables and the updating of knowledge based on Bayes's theorem.

•The probability distributions are generally expressed in discrete form and are solved analytically

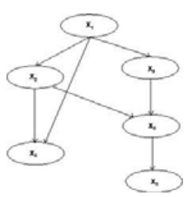
•Their probabilistic nature may explicitly account for uncertainties frequently met in dynamical systems.

•They can integrate qualitative and quantitative information, and/or erroneous or missing data in the modeling.

A Bayesian network $BN = \langle K, L, \mathbf{\Theta} \rangle$ is a directed acyclic graph $\langle K, L \rangle$ of $k \in K$ nodes that represent the x_i random variables of the network. 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: $\theta_{x_i|\Pi_{x_i}} = P_B(x_i|\Pi_{x_i})$, 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.

unique joint probability distribution over X

$$P_B(x_1, \ldots, x_n) = \prod_{i=1}^{n} P_B(x_i|\Pi_{x_i}) = \prod_{i=1}^{n} \theta_{i|\Pi_i}(x_i|\Pi_{x_i})$$



For classification

$$classify(x_1, \ldots, x_n) = \arg\max_n p(z) \prod_{i=1}^{n} p(x_i|z)$$

For clustering

$$k^* = \underset{1 \le k \le K}{\arg\max}\, p(k|\mathbf{x}, \hat{\boldsymbol{\theta}}) = \underset{1 \le k \le K}{\arg\max}\, p(k, \mathbf{x}|\hat{\boldsymbol{\theta}})$$

Mutual Information

•To quantify for the conditional dependences

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

The Experiment

Naturalistic Riding Experiment

•Conducted in the city and at the suburbs of Volos, a medium scale Greek city,
•Period: November 2010 - April 2011.
•BMW F650 Funduro

BMW F650 Funduro (University of Thessaly)

Instrumentation

•The available signals that are being stored are summarized in the Table.

•video installation is 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 is 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).

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

Recruiting

•3 riders for a period of 6 weeks each

•Characteristics of participants:

- Male riders
- riding experience of at least 5 years.
- The age ranged from 24-38 years old.
- should ride a bike resembling that of the study vehicle, which was a BMW 650cc bike
- they should all be frequent PTW users
- familiar with urban road environments and use PTWs for trips inside urban areas.

Other data acquisition

•travel diary; the questions and completion technique were described to them.
•weekly debriefing interviews

Data for Analysis

•Trips of 20 minutes duration made during a period of three months by one rider in rural two-way roads.

•Route Specifications:

- 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

• 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 riding parameters with $6.72 \cdot 10^6$ data.

Results

Incident Detection (Algorithmic calibration)

•Three different models with respect to the different input space are further evaluated:

Model 1: steering, throttle, brake activation and wheel speed.

Model 2: linear acceleration and speed.

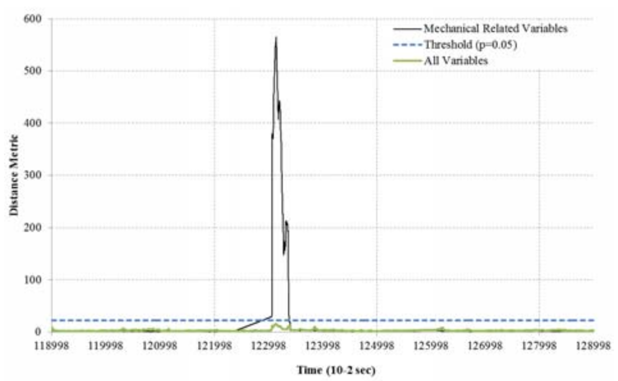
Model 3: All available variables.

•Variables directly connected to the mechanical characteristics were found adequate:

- Steering
- Braking (front/rear activation and pressure)
- Throttle
- Wheel speed

•Refinement strategy to eliminate noise

•The traffic related parameters (acceleration, speed) were not influential to the detection of incidents.



A single riding situation as detected by the distance metric time series using as multivariate input space the time –series of the mechanical related variables and all available variables. Any distance metric value above the 5% threshold value signifies an irregular behaviour.

Results

Riding dynamics at the emergence of an incident

3 critical types of actions describing the onset of an incident

Node	Binary mutual information (%)	Binary relative significance	Modal Value[1]	
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 (1/4)	81%
Steering (%)	15.81%	0.29	<=0.42 (3/4)	81%
Wheel Speed (kph)	4.35%	0.08	<=49.743 (2/4)	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 (1/4)	57%
Throttle (%)	18.31%	0.25	<=2.47 (1/4)	100%
Rear Brake Activation (0/100)	7.61%	0.10	0	57%
Steering (%)	4.64%	0.07	<=0.42 (3/4)	57%
S_3 (18.66%)				
Throttle (%)	79.25%	1.00	<=16.69 (3/4)	50%
Rear Brake Activation (0/100)	27.39%	0.34	0	83%
Steering (%)	14.78%	0.19	<=0.42 (3/4)	50%
Wheel Speed (kph)	11.45%	0.14	>65.91 (4/4)	50%
Front Brake Activation (0/100)	0.78%	0.01	0	67%

[1] *Values in the parentheses are the ranges of variable discretization the modal value belongs to.*

Riding dynamics during an incident

Node	Binary mutual information (%)	Binary relative significance	Modal Value[1]	
C_1 (43.65%)				
Steering (%)	24.32%	1.00	<=1.84 (3/4)	86%
Rear Brake Activation (0/100)	21.53%	0.89	100	96%
Throttle (%)	15.13%	0.62	<=5.56 (1/2)	99%
Wheel Speed (kph)	11.45%	0.47	<=55.61 (3/4)	47%
Front Brake Activation (0/100)	0.60%	0.03	100	71%
C_2 (36.98%)				
Steering (%)	73.21%	1.00	<=-0.94 (2/4)	52%
Wheel Speed (kph)	54.71%	0.75	<=19.12 (1/4)	53%
Front Brake Activation (0/100)	19.69%	0.27	100	95%
Throttle (%)	13.24%	0.18	<=5.56 (1/2)	100%
Rear Brake Activation (0/100)	0.94%	0.01	100	77%
C_3 (19.37%)				
Throttle (%)	78.40%	1.00	>5.56 (2/2)	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 (3/4)	91%
Steering (%)	22.76%	0.29	<=1.84 (3/4)	98%

[1] *Values in the parentheses are the ranges of variable discretization the modal value belongs to.*

3 critical types of actions during an incident

Detected Incidents Classification

Independent	Dependent
Start (S_1, S_2, S_3)	Incident Category
Nr of actions ($1, 2, \ldots$)	• Stationary obstacle,
Action C_1 (0 if no, 1 if yes)	• Moving obstacle,
Action C_2 (0 if no, 1 if yes)	• Overtake,
Action C_3 (0 if no, 1 if yes)	• Opposing Traffic.

Results from associating the type of the incident with specific riding 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%

Conclusions

The questions addressed:

1. When an incident occur and how long it lasts
2. What are the prevailing rider's actions and their characteristics at the beginning and during an incident
3. According to how it starts and how it evolves, what type of incident it is

- The Automatic Detection Method is a simple and flexible methodology to detect incidents from massive datasets without taking the time to examine video.
- The Bayesian Analysis framework enables to identify the type of incident according to how it starts and how it evolves.
- The findings correspond to specific riders but the methodology is transferable.
- Actual risk was not identified as it was not observed.