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IDENTIFYING RIDING PROFILES PARAMETERS FROM HIGH RESOLUTION NATURALISTIC RIDING DATA

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The question

- Is there a way to automatically detect riding situations (incidents) using solely data and without seeing the video?
→ *Automatic Riding Incident Detection*
- Assumption
 - Each driver has a distinct behavior when reacting to internal/external stimuli that...
 - is reflected to the riding parameters (abrupt changes or deviation from the mean “typical” values)
 - may impose different riding profiles among riders
- Riding profiles define different boundaries of risky behavior.



The Scope

- Identify incidents based exclusively on high resolution naturalistic riding data without observing the videos.
 - distinguish between regular and irregular riding behavior.
 - artificial intelligence techniques to construct a regressor and uncover the influence of riding profile parameters.



The Methodology

Raw time-series of riding parameters



Outlier detection



Riding incident detection

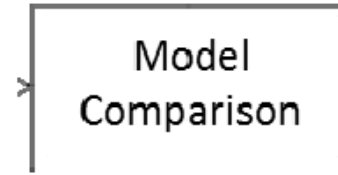


Neural Network Classifier



Influential parameters of changes in riding style

Model Comparison



Methodology

- Identify Incidents
 - High-resolution data (multivariate or not) often contain outliers
 1. Jointly consider 100Hz riding parameters time series
 2. detect the deviations from the mean behavior (Outliers)
 3. nominate the occurrence of a deviation as the beginning of an incident.



Methodology

- an outlier is defined as an observation for a specific time interval that the rider for some reason drastically alters its riding behavior due to and external or internal stimulus.
- Mahalanobis distance: $d_i = \sqrt{(x_i - \hat{\mu})S^{-1}(x_i - \hat{\mu})}$, $\hat{\mu}$ and S^{-1} are the sample mean and covariance matrix respectively
- At a significance level α , a determination as to whether a new observation can be considered as outlier or not can be made based on the following formula:

$$d_i \leq \left[p(n-l)(n+l) / n(n-p) \right] F_{p,n-p}$$

Methodology

- Neural Networks Classifier

- a generalization of a single-layer Perceptron because it encompasses a hidden layer consisting of a set of processing units
- each layer consists of a set of processing units (neurons) that receive inputs and transfer them to the next layer through a set of connections (synapses).
- Each connection possesses certain strength, the synaptic weight.
- There are no connections between the units of the same layer.
- In the input layer no kind of processing is performed.

- The output:
$$y_k = f_k \left(a_k + \sum_{jk} w_{jk} f_i \left(a_k + \sum_{ij} w_{ij} x_i \right) \right)$$



Naturalistic riding study

- Instrumented motorbike
 - BMW F650 Funduro
 - 12 important signals
 - Video installation was used to capture the frontal environment (required a minimum 90° field of view) and the rider's face.
 - 100Hz signals' data resolution, 10Hz video resolution and GPS position which can be sampled at 1Hz



Naturalistic riding study

- The route
 - rural two-way roads
 - 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
 - several zones where passing is permitted
 - daylight with good visibility and fine weather conditions



Naturalistic riding study

- The final dataset:
 - 56 trips of 20 minutes duration, meaning a set of time series of riding parameters with $6.72 \cdot 10^6$ data.

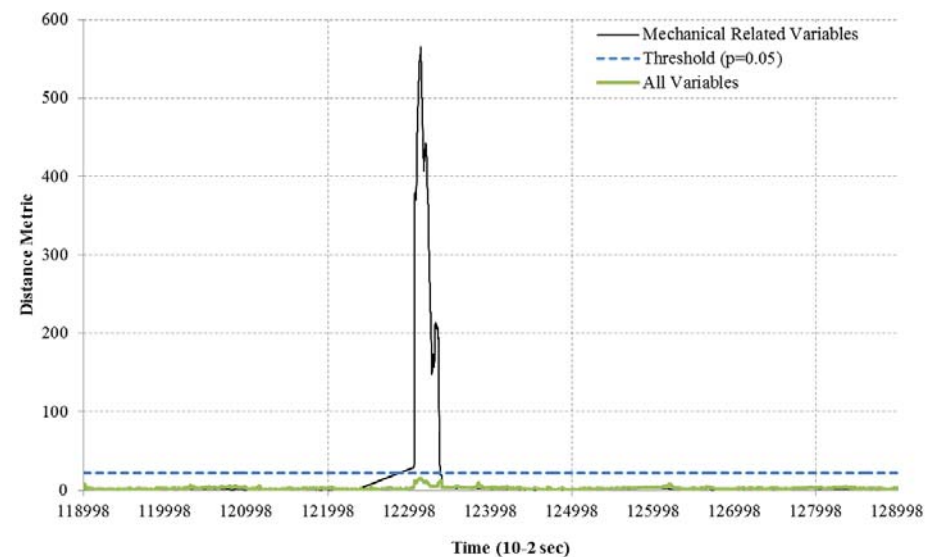
Monitored Basic Variables	Description
Longitudinal acceleration [g]	linear acceleration
Lateral acceleration [g]	
Vertical acceleration [g]	
speed [kph]	longitudinal speed
yaw rate [deg/s]	roll, yaw and pitch rates
pitch rate [deg/s]	
roll rate [deg/s]	
Throttle [%]	throttle position
Brake Rear [%]	brake 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



Results

- Detecting Incidents
 - Three models are evaluated using different data:
 - Model 1: steering, throttle, brake activation and wheel speed.
 - Model 2: linear acceleration and speed.
 - Model 3: All available variables.

*Distance metric time series of Model 1 and Model 3.
Any distance metric value above the 5% threshold value
signifies an irregular behavior (outlier).*



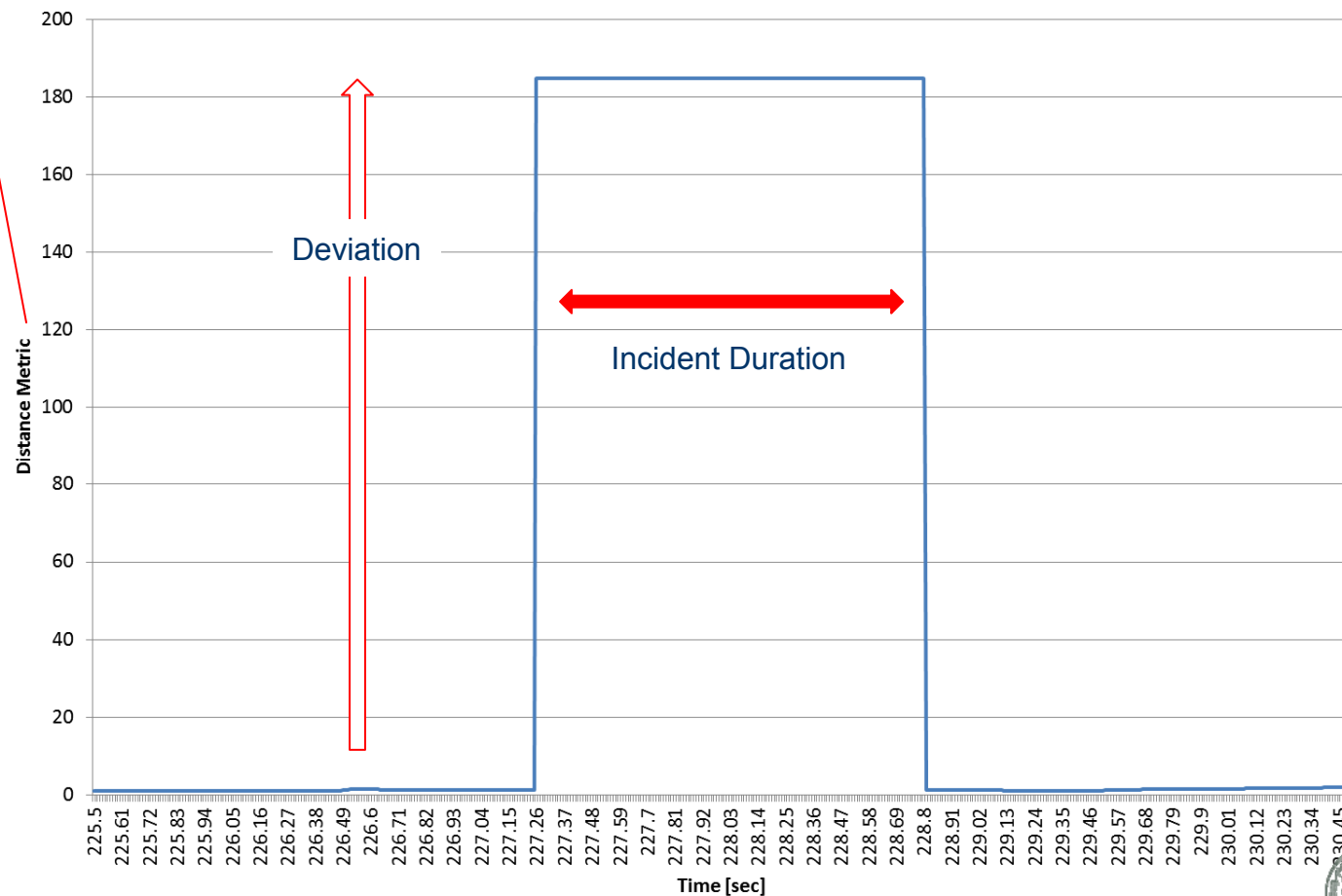
- Model 1 is the optimum
- Traffic related variables have been found less influential in detecting incidents.



Results

*An example of detected incident using the proposed methodology
(5 sec data, incident duration: ~ 1.5 sec)*

Joint consideration
of changes in
throttle, steering,
braking and wheel
speed



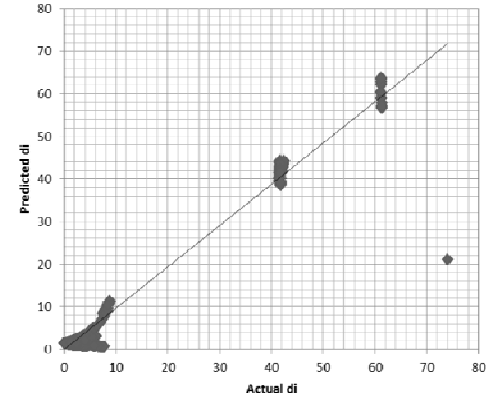
Results

- Examples the situations detected are:
 - Moped moving on the left to avoid fixed object,
 - Braking and moving on the right after having overtaken vehicles (vehicles are in front of the moped as well),
 - Overtaking more than one vehicle,
 - Moped moving to the left to avoid stationary object.
- These situations may be considered as incidents where a rider is engaged to an unusual - far from the mean - riding behavior and, thus, may be candidate riding situations with high accident risk.

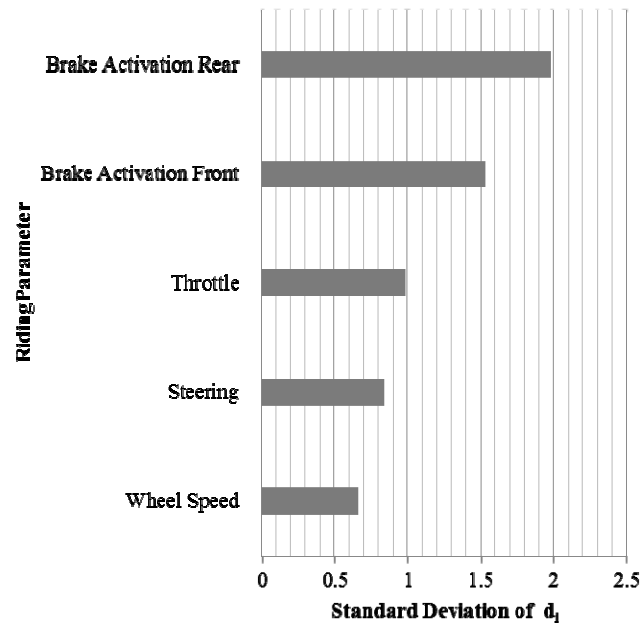


Results

Scatter plot of the actual versus the predicted Mahalanobis distance d_i



The mean standard deviation of the Mahalanobis distance d_i for each varied input



Results

- Braking is most influential factor
- Wheel speed is the less critical parameter
- Throttle seems to be more influential than steering
- Riding parameters' influence to the deviation from the mean riding behavior is closely related to the manner a rider reacts to specific stimuli



Conclusions

- A simple and flexible methodology to detect incidents from massive datasets
 - The method is validated in various trips
 - all outliers detected can be considered as incidents
 - Traffic related parameters were not influential to the detection of incidents
- Identify custom-made riding profiles
 - influence of each input parameter to the manner the rider reacts to external or internal stimuli



Conclusions

- Incidents may vary with regards to the accident risk they encompass.
- Results on the riding style may not claim transferability to either different riders, or different types of trips
- Further research
 - uncovering the determinants of each riding behavior with respect to the manner a rider conduct a maneuver in the beginning or during a critical riding situation.

