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Learning Driver Braking Behavior using Smartphones, Neural Networks and the Sliding Correlation Coefficient: Road Anomaly Case Study

Stavros-Richard G. Christopoulos, Stratis Kanarachos, and Alexander Chronos

Abstract—The present study focuses on the automated learning of driver braking “signature” in the presence of road anomalies, using smartphones. Our motivation is to improve driver experience using preview information from navigation maps. Smartphones facilitate, due to their unprecedented market penetration, the large-scale deployment of Advanced Driver Assistance Systems (ADAS). On the other hand, it is challenging to exploit smartphone sensor data because of the fewer and lower quality signals, compared to the ones on board. Methods for detecting braking behavior using smartphones exist, however, most of them focus only on harsh events. Additionally, only a few studies correlate longitudinal driving behavior with the road condition. In this paper, a new method, based on deep neural networks and the sliding correlation coefficient, is proposed for the spatio-temporal correlation of road anomalies and driver behavior. A unique Deep Neural Network structure, that requires minimum tuning, is proposed. Extensive field trials were conducted and vehicle motion was recorded using smartphones and a data acquisition system, comprising an IMU and differential GPS. The proposed method was validated using the probabilistic Receiver Operating Characteristics method. The method proves to be a robust and flexible tool for self-learning driver behavior.

Index Terms—Advanced Driver Assistance Systems, Braking behavior, Neural Networks, Smartphones, Road condition.

I. INTRODUCTION

Over the last decade, mobile phones, transformed from simple cell devices for making calls, to powerful sensing, communication and computing devices [1]. First, smartphones have numerous sensors embedded, for example, GPS, accelerometers, gyroscope and magnetometer [2]. Second, the upcoming 5th generation of wireless systems (5G) will provide high quality and uninterrupted mobile services [3]. Third, it is estimated that by 2020, 70% of earth's population will be a smartphone user [4]. In this context, smartphones can facilitate the rapid and large-scale deployment of Intelligent Transportation Applications (ITS) [5].

Smartphones are increasingly exploited for monitoring driver behavior [6]. Some recent examples include Singht et al. who detected sudden braking and lateral maneuvers by analyzing vehicle motion using Dynamic Time Warping [7]. Predic and Stojanovic [8] classified driver behavior by correlating driving data to pre-recorded samples. Castignani et al. [9] assigned driving scores using smartphone data and fuzzy logic. Saiprasert et al. monitored over-speeding as a means to classify risky driving [10]. Insurance industry is responding to this trend by gradually introducing smartphone-based Pay-as-You-Drive schemes [11].

Although the usage of smartphones for ITS is desirable, there are standard challenges that need to be overcome. These are the free position of a smartphone in the vehicle, the low accuracy of GPS position/speed signals in urban areas and the high noise to signal ratio in the accelerometer/gyroscope signals. Regarding the first, some applications require mounting the smartphone at a fixed position or dynamically reorienting its axes by real-time computing the Euler angles. The Euler angles are computed using the magnetometer readings and the direction of gravity or by using the longitudinal, lateral and vertical acceleration along the smartphone’s axes [12]-[13]. Smartphone GPS signal accuracy was studied in [14]. In general, smartphone GPS measurements were consistent. However, in obscured environments the deviation from ground truth deteriorated by a factor of two. Crowdsensing and 5G technology will considerably improve positioning accuracy in urban areas [15]. With respect to the noisy accelerometer and gyroscope signals, these can heavily affect driving analytics. To this end, many methods depending on the end application have been proposed [16].

The present study focuses on driver comfort and particularly on modeling the driver braking behavior in the presence of

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discrete road anomalies. Most of the studies, found in the
literature, focus either on braking for safety or on road
anomalies detection without considering the human element.
We extend the usual scope of analysis by correlating driver
behavior and road condition. The aim is to learn driver
preferences so that an intelligent ADAS adapt and maximize
driver comfort, when preview map information is used [17].

To this end, a flexible method is required that can adapt to
human subject response and vehicle characteristics. We
propose a data-based method using a unique Deep Neural
Network structure, suitable for the analysis of multivariate time
series [18], [19]. Extensive field trials, using different vehicles
and drivers, demonstrated that the method performs robustly
and requires minimum tuning. Furthermore, it is the first time
that a new visualization scheme can reveal in one figure a
driver’s braking preferences for different types of road
anomalies and speeds. This method can be extended to other
scenarios like braking before turning.

The rest of the paper is structured as follows: in section 2
studies on smartphone-based road condition monitoring are
reviewed. Section 3 describes the experimental part. Section 4
describes the Anomaly Detection Filter (ADF), while in section
5 the sliding correlation coefficient is applied and numerical
results are discussed. Finally, in section 6, we set out the
conclusions obtained and discuss future steps.

II. RELATED WORK: ROAD CONDITION MONITORING

One of the first contributions in the field of smartphone-
based road condition monitoring was Nericell [20]. Nericell
utilized a GPS receiver, GSM for cellular localization and a 3-
axis accelerometer sensor. The acceleration signal was sampled
at 310 Hz, a rate which is high even with today’s standards. To
detect braking incidences, the mean of longitudinal acceleration
\( a_x \) was calculated over a sliding window. When the mean value
exceeded a predefined threshold, a braking event was declared.
The ground truth was established using the GPS signal, despite
that GPS signal is not always accurate. For bump detection, two
different criteria were employed, depending on the speed of the
vehicle. At speeds, greater than 7 m/s the surge in vertical
acceleration \( a_z \) was used. When the spike along the vertical
acceleration signal \( a_z \) was greater than a predefined threshold
\( T_z \), a bump was declared. At speeds, lower than 7 m/s the
algorithm searched for a sustained dip in \( a_z \), reaching below a
threshold \( T_3 \) and lasting at least 20 ms. The detection of road
anomalies at low speeds was less successful, as stated in [12].

Perttunen et al. detected road anomalies by recording the
acceleration signal at 38Hz and GPS position at 1 Hz [21]. The
raw signals were filtered by applying a Kalman filter.
Subsequently, features were extracted using sliding windows.
The standard deviation, mean value, variance, peak-to-peak
value, signal magnitude area, 3\textsuperscript{rd} order autoregressive
coefficients, tilt angles and root mean square for each
dimension of the acceleration signal and the correlation
between the signals in all dimensions were calculated.
Additional features were used by extracting the Fast Fourier
Transformation energy from 17 frequency bands in each
acceleration direction. A linear transformation was applied to
make the features speed independent. Support Vector Machines
(SVMs) were applied to perform the classification. Support
Vector Machines is a supervised machine learning method,
requiring labeling of all road anomalies. Ground truth was
produced using two independent labelers. The best performance
achieved 82% sensitivity and 18% false negatives rate.

Douangphachanh and Oneyama presented a method for
estimating the International Roughness Index (IRI) of road
segments using smartphones [22]. Four different cars were used
in the experiments and two smartphones at different positions
in the vehicle. The sampling rate was 100 Hz. At this rate, the
smartphone’s processing power is almost exclusively used for
the measurement purpose. The raw data were pre-processed
using a high pass filter. It was assumed that road anomalies
cause only high frequency accelerations. A linear relationship
between IRI and the magnitude of acceleration signal at specific
frequency bands was derived. Correlation ranged between 0.6
and 0.78. A road survey vehicle was used to generate the ground
truth. IRI was estimated for 100 m long road sections, which is
rather too long for discovering discrete road anomalies.

Vittorio et al. proposed a threshold-based method [12]. The
accelerometer and GPS data were transferred at 1 Hz frequency
to a central server. First, the data were filtered to remove the
low frequency components. Then the minimum, average and
maximum acceleration values of every batch of measurements
was calculated. The high-energy events were identified by
observing the vertical acceleration impulse and comparing it to,
heuristically derived, thresholds. The algorithm’s best
performance achieved more than 80% correct positive road
anomalies classifications and 20% percentage of false positives.

MAARGHA, developed by Rajamohan et al., is different to
the aforementioned approaches because it employed image
processing [23]. Images using the smartphone camera were
captured at a frequency 0.5 Hz. The focus was 1 – 2 m ahead of
the vehicle. The GPS location and speed were sampled at 1 Hz.
The accelerometer was sampled at 15 Hz. Features were
extracted in sliding windows, 2s long. A high pass filter was
employed to to the raw signal. Classification was performed
using the K-Nearest Neighbor (K-NN) algorithm. Under clear
sky the classification was 100% accurate, while in segments
where the road was laden with shadows of buildings the
accuracy degraded to roughly 50%.

In conclusion, none of the above studies attempted to
correlate longitudinal driving behavior and the road condition.
However, drivers have different responses depending on the
road anomalies, driving style and vehicle. This study, attempts
to fill this gap, using a flexible method based on a widely
available tool, the smartphone.

III. EXPERIMENTAL PART

A. Smartphone-based data acquisition

Three different smartphones were used in the field trials. All
smartphones were equipped with GPS receivers. They also
comprised a tri-axial accelerometer and tri-axial electronic
compass. The smartphone was positioned on the box behind the
gearbox handle, see Fig. 1. A Gecko pad was used to minimize any relative movement between the smartphone and the vehicle. The sampling rate for the accelerometer, gyro and compass sensors was 10 Hz. The sampling frequency of GPS position and velocity was 1 Hz. The vehicle speed in urban areas ranged between 2.7-11.1 m/s. The maximum vehicle speed was 16.6 m/s. At higher speeds anomaly detection becomes rather straightforward due to the intensity of the event.

B. Instrumented vehicle data acquisition system

The test vehicle is a Ford Fiesta equipped with a motion data acquisition system, VBOX 3i data logger with dual antenna. The data logger uses a GPS/GLONASS receiver, logging data 100 times a second. An inertial measurement unit (IMU) is integrated into VBOX and a Kalman Filter is implemented to improve all parameters measured in real-time. Velocity and heading data were calculated from the Doppler Shift effect in the GPS carrier signal. The following CAN-bus signals were also logged: engine speed, steering angle, gear position, throttle pedal position, brake pedal position, brake pedal (on/off), clutch pedal, handbrake, wheel speeds, vehicle longitudinal acceleration and vehicle lateral acceleration. Video recording took place during the field trials. The signals obtained from VBOX in combination with the video footages were used to generate the ground truth.

C. Test Routes

Three experiments were conducted. The first experiment was carried out on a route at the center of Coventry City (Fig. 2). The driver drove the same route from point A to point B five times, following five different braking behaviors (a) no braking, (b) braking over and just after, (c) just before, (d) “normally before” and, (e) “quite before” the road “anomalies”. The second experiment was carried out with additional drivers at a different location, the campus of the National and Technical University of Athens, Greece. The campus contains several speed bumps, at known positions. The location was chosen because it was easier for the driver to follow different average speeds and the route also has significant road slope that may potentially mislead the classifier. The third experiment was conducted to monitor the naturalistic behavior of drivers. It was held at various locations including Coventry City entry routes, U.K. and Zografo-Iliissia, Greece.

D. Data collection - Ground truth

During the experiments, the X and Z-axis acceleration from VBOX and the position of the pedal brake from the OBDII port were extracted. Simultaneously, we recorded the X and Z-axis acceleration data using the smartphone sensors. Thus, for each route, we constructed files with the following columns: Time, X-axis acceleration that extracted from VBOX, Z-axis acceleration that extracted from VBOX, braking pedal position that extracted from VBOX, X-axis acceleration that extracted from smartphone sensor and Z-axis acceleration that extracted from smartphone sensor. As ground truth, we used the data extracted from VBOX and OBDII port. Additionally, video recordings of the road segment ahead of the vehicle supplemented with audio comments were collected.

IV. ANOMALY DETECTION FILTER

The Anomaly Detection Filter (ADF) is based on the Deep Neural Networks (DNNs) paradigm. DNNs have not been extensively applied in time series modeling, but recent applications in other areas demonstrated their potential [24]. In [19] DNNs were applied for the first time in the detection of road anomalies. The architecture of the DNN is presented in Fig. 3. The ADF comprises 5 steps. In the first step the signal is de-noised. In the second step, a subset of the time series is used to train the DNN. The subset corresponds to data generated in a smooth ride. In the third step, the error between the de-noised time series and the one generated by DNNs is calculated. In the fourth step the Hilbert transform of the error signal is computed. In the fifth step the ADF outcome is derived.

This study further develops [19] by detecting also braking events and correlating them to the vertical vehicle response.

A. Signal decomposition

The first step in the proposed method is the decomposition of a time series $x(t)$ using wavelets. Wavelets can detect anomalies of short duration better than the Fourier transform [25]. Furthermore, they analyze a signal in multiple scales, a very useful property for distinguishing nonlinear signals. For example, Fig. 4 presents the spread of Holder exponents obtained when analyzing the acceleration signal for a smooth (red color) and an anomalous road segment (blue color). A
signal $x(t)$ is decomposed into different levels of detail, by convolving wavelet $\psi_{m,n}$ and signal $x(t)$:

$$\psi_{m,n}(t) = 2^{-m/2} \cdot \psi \cdot (2^{-m} \cdot t - n) \quad (1)$$

$$T_{m,n} = \int_{-\infty}^{\infty} x(t) \cdot \psi_{m,n}(t) \cdot dt \quad (2)$$

where $T_{m,n}$ are the discrete wavelet transform values given on a scale-location grid of index $m, n$. The integers $m, n$ control the wavelet dilation and translation respectively. The inverse discrete wavelet transform reconstructs signal $x(t)$ using coefficients $T_{m,n}$ and the wavelet basis $\psi_{m,n}$:

$$x(t) = \sum_{m=-\infty}^{\infty} \sum_{n=-\infty}^{\infty} T_{m,n} \cdot \psi_{m,n}(t) \quad (4)$$

To obtain a multi-resolution of signal $x(t)$, the use of a scaling function $\varphi(t)$ is necessary:

$$\varphi_{m,n}(t) = 2^{-m/2} \cdot \varphi \cdot (2^{-m} \cdot t - n) \quad (5)$$

$$\int_{-\infty}^{\infty} \varphi_{0,0}(t) \cdot dt = 1 \quad (6)$$

The scaling function is convolved with signal $x(t)$ to produce the approximation coefficients $S_{m,n}$:

$$S_{m,n} = \int_{-\infty}^{\infty} x(t) \cdot \varphi_{m,n}(t) \cdot dt \quad (7)$$

and obtain a continuous approximation of signal $x_m(t)$, at scale $m$:

$$x_m(t) = \sum_{n} S_{m,n} \cdot \varphi_{m,n}(t) \quad (8)$$

where $x_m(t)$ is the approximation of signal $x(t)$, at scale $m$. Combining Equations (4) & (8), signal $x(t)$ becomes:

$$x(t) = \sum_{m=\infty}^{m=\infty} \sum_{n} S_{m,n} \cdot \varphi_{m,n}(t)$$

If $d_m(t)$ is the signal detail, at scale $m$:

$$d_m(t) = \sum_{n} T_{m,n} \cdot \psi_{m,n}(t) \quad (10)$$

then (9) is rewritten as:

$$x(t) = x_{m,0}(t) + \sum_{m=-\infty}^{m=\infty} d_m(t) \quad (11)$$

$$x_{m-1}(t) = x_m(t) + d_m(t) \quad (12)$$

Equation (12) describes how to obtain the multiresolution analysis of the signal. The signal approximation $x_{m-1}(t)$ is obtained if the signal detail $d_m(t)$, at an arbitrary scale $m$, is added to the approximation $x_m(t)$ at that scale.

To remove noise from signal $x(t)$, a threshold $\lambda$ is defined and the detail coefficients $T_{m,n}$ are adjusted according to:
\[ T_{m,n} = \begin{cases} 0, & \text{if } |T_{m,n}| < \lambda \\ \{T_{m,n}, & \text{if } |T_{m,n}| \geq \lambda \end{cases} \] (13)

\[ x_d(t) = x_{m0}(t) + \sum_{m=0}^{m=\infty} d_{dm}(t) \] (14)

where \( d_{dm}(t) \) is the filtered signal detail, at scale \( m \).

Different wavelet bases were investigated and among \( db2, db3, db4, db5, db6, db7, db8, db9, \) and \( db10, db9 \) achieved the best performance. Fig. 5 shows the distance, obtained using Dynamic Time Warping, between the different wavelet bases and the sample signal utilized for training the DNN.

![Graph showing distance between wavelet bases](image)

Fig. 5: a) Distance, using dynamic time warping, between wavelet bases \( db2, db3, db4, db5, db6, db7, db8, db9, \) and \( db10 \) and the training signal.

B. Deep Neural Network structure

The signals extracted using the wavelet analysis feed a DNN, that is trained to predict \( x_d \). The training data for the DNN are obtained while driving on smooth and slightly rough road segments. No intese braking events are included in the training data. Eventually, semi-supervised learning is employed; only training data relevant to smooth and slightly rough road conditions are included. Thus, it is not required to collect and record road anomalies for training the DNN, as is required in other methods e.g. SVMs. For the application deployment, a calibration phase is required during which the driver classifies the road condition or driving behavior as normal. In the calibration phase, the weighted acceleration according to ISO 2631-1:1997 is also calculated with the purpose to normalize driver’s subjective input.

DNN’s architecture is shown in Fig. 3(d). The first part is a set of stacked NNs that models the filtered time series \( x_d \) at different time scales. The second part is an autoregressive NN consisting of 10 hidden layers with nonlinear (log-sigmoid) activation functions and a three-layer buffer. Although the exact number of hidden layers and buffer size are problem-dependent it was found that relatively simple NNs (number of hidden layers less than five) cannot represent the temporal dynamics sufficiently. Numerical trials using buffers of different sizes have shown that a large buffer size decreases the detector’s performance. A buffer of size three achieved the best performance.

Among the different training algorithms examined – including the 1) Broyden–Fletcher–Goldfarb–Shanno (BFGS) Quasi-Newton algorithm, 2) Bayesian Regularization (BR), 3) Gradient descent with adaptive learning rate backpropagation (GDA), 4) Gradient descent with momentum backpropagation (GDM) and 5) Levenberg-Marquardt backpropagation (LM) - LM achieved the best performance. All training algorithms were repetitively applied (30 iterations). Fig. 6 shows the results of the Kruskal–Wallis test.

![Graph showing Kruskal-Wallis test results](image)

Fig. 6: Results of Kruskal–Wallis test for different NN training algorithms: Bayesian Regularization (2) and Levenberg-Marquardt (5) achieve the best performance.

C. Anomaly detection using Hilbert transform

The error signal \( e \) is defined as the difference of the filtered signal \( x_d(t) \) from DNN’s output \( y(t) \):

\[ e = x_d - y \] (19)

The features utilized for detecting the road anomaly and braking events are the envelope \( A \) and instantaneous frequency \( \dot{\theta}(t) \) of the error signal \( e(t) \). For this the Hilbert transform is utilized:

\[ e_H(t) = \lim_{\varepsilon \to 0} \left[ \frac{1}{\pi} \right] \int_{t-\varepsilon}^{t+\varepsilon} \frac{e(t)}{x-t} \cdot dt + \frac{1}{\pi} \int_{t-\varepsilon}^{t+\varepsilon} \frac{e(t)}{x-t} \cdot dt \] (20)

where \( e_H(t) \) is the Hilbert transform. Hilbert transform is the convolution of \( e(t) \) with a reciprocal function \( 1/x - t \), thus Hilbert transform emphasizes the local properties of \( e(t) \). If \( \dot{\theta}(\omega) \) represents the Fourier transform of \( e(t) \), then the Hilbert transform is:

\[ e_H(t) = \mathcal{F}^{-1}\{ -j \cdot \text{sgn}(\omega) \cdot \dot{\theta}(\omega) \} \] (21)

where \( \mathcal{F}^{-1} \) represents the inverse Fourier transform [26]. The instantaneous phase \( \theta(t) \), frequency \( \dot{\theta}(t) \), and amplitude \( A(t) \) of \( e(t) \) are defined:

\[ \theta(t) = \arctan \left( \frac{e_H(t)}{e(t)} \right) \] (22)
\[ \theta(t) = \frac{d\theta}{dt} \]

\[ A(t) = \sqrt{e(t)^2 + e_y(t)^2} \]  

(23)

Hilbert transform is useful for identifying instantaneous frequency changes in the higher frequency spectrum, in which wavelet transform is not performing well. When the instantaneous frequency is not informative the signal’s envelope is exploited instead.

V. DISCOVERING DRIVER BRAKING BEHAVIOR

Three different experiments were carried out for identifying and correlating the driver braking behavior to the road condition. The first experiment aims to verify five driver braking behaviors. The second experiment aims to identify the braking behavior for different drivers and driving styles (passive-normal-aggressive). The third experiment aims to identify the braking behavior when driving naturally.

In all cases, using the ADF, we try to identify marked changes to the X and Z-axis acceleration.

In Figs 7 (a) and (b) the results of the ADF – for the first experiment – after the analysis of the smartphone acceleration data in the longitudinal x and vertical direction z are presented.

A. Evaluation of ADF filter

As a first step, we estimated the efficiency of the ADF. We employed, for this reason, the ROC diagram [27]. The value e of ADF can be used here as an estimator [28] and the M as an index which value is equal to one (M = 1) when there is an “anomaly” and zero (M = 0) when there is not. Thus, we examine if the value e of ADF lies over different values of threshold \( e_i \). The ROC graph depicts the True Positive rate (TPR) on Z-axis and the False Positive rate (FPR) on the X-axis. Therefore, there are four classifications (a) TP (True Positive) when \( e \geq e_i \) and \( M = 1 \), (b) FP (False Positive) when \( e \geq e_i \) and \( M = 0 \), (c) FN (False Negative) when \( e < e_i \) and \( M = 1 \) and, (d) TN (True Negative) when \( e < e_i \) and \( M = 0 \). Thus, the TPr represents the ratio \( TP/(TP+FN) \), and the FPr the ratio \( FP/(FP+TN) \). A schematic representation of ROC analysis is shown in Fig. 8. For a random estimator the curve is located close to the diagonal, where TPr and FPr are roughly equal. A popular measure is the area under the ROC curve (AUC)[39]. Additionally, we can use the recently proposed visualization scheme based on k-ellipses, for the examination of the statistical significance of the results [29]. With this technique, using the AUC of k-ellipses we can measure the \( p \)-value of the probability to obtain a ROC curve by chance for given values of the total of positives \( P=TP+FN \) and the total of negatives \( Q=FP+TN \), when ascribing \( e \geq e_i \) or \( e < e_i \) are random.

In Fig. 9 the very good efficiency of the “braking” detection using the above method is illustrated. The present ROC analysis was held taking as the threshold a value of the braking pedal position obtained from OBDII. The range of position values obtained was 0 to 60, thus the thresholds \( B_1 \) that we chose for the evaluation were equal to 20 and 30. Thus, when the value is greater or equal to the threshold then \( M = 1 \), otherwise \( M = 0 \). When \( B_1 \) is equal to 20 the value of AUC is 0.87 and when \( B_1 \) is equal to 20 the value of AUC is 0.97; the \( p \)-values of the corresponding k-ellipses in both cases are much smaller than \( 10^{-8} \). The fact that we obtain (Fig. 9) TPr=75% with FPr=16.3% when \( B_1 = 20 \) and TPr=91.5% with FPr=3.0% when \( B_1 = 30 \), allowed us to employ the ADF for detecting braking events.

Recently, the application of the ADF filter in the detection of road “anomalies” showed similar performance [19]. The \( p \)-values of the corresponding k-ellipse was much smaller than \( 10^{-8} \) and for TPr around 80.6% the FPr was 11.7%. Hence, these outcomes allowed us to use the ADF for detecting road anomalies.

B. Methodology

To discover the dependence of driving behavior on road
anomalies, we examined the correlation between the “anomalies” of ADF output on $X$ and $Z$ axes. Given the fact that the data is not Gaussian, we used the Spearman correlation coefficient $r_s$, which is a nonlinear statistical measure [30]:

$$r_s = \frac{\sum_i (x_i - \bar{x})(z_i - \bar{z})}{\sqrt{\sum_i (x_i - \bar{x})^2 \sum_i (z_i - \bar{z})^2}}$$  \hspace{1cm} (21)$$

$r_s$ ranges $r_s \in [-1,1]$. When $r_s$ is close to 1 the correlation is “strong”, while for positive values close to 0 it is “weak”. $r_s$ close to −1 indicates “strong” anti-correlation.

The method is described as follows. First, we calculate the Spearman’s correlation coefficient between the segment of the time series of ADF on $Z$-axis and the corresponding $X$-axis segment slid backwards by $n$ positions (i.e. $\Delta t = n/10$ s). Subsequently, we slide forward this segment of $X$-axis by one, two, ..., $2n-1$ (in the following experiments $n = 50$) positions and calculate the correlation for each position. Finally, we repeat the same procedure for a range of thresholds $T_z$ of the ADF output on $Z$-axis corresponding to the different sizes of the road “anomalies”. The range of thresholds is from 0 to the maximum value of the outcome of ADF output on $Z$-axis, equally divided by 100. In more detail, for a given threshold $T_z$ we are taking the time series of the ADF output on $Z$-axis, which are greater than $T_z$ together with the corresponding time series on $X$-axis, see Fig. 10.

![Fig. 10: (color online) Schematic representation of the correlation coefficient calculation for a given threshold $T_Z$. The red line denotes the segments of the initial $Z$-axis time series that exceed the threshold $T_Z$ and the corresponding time series on the $X$-axis slid by 10 points (brown color).](image)

C. Experimental process

Experiment 1:

The aim of the first experiment is to examine if the proposed method can discover distinct driving patterns. In this experiment, the car followed the route indicated in Fig. 2. We performed the same route from point A to point B five times, following five distinct driving patterns (a) no braking, (b) braking over and just after, (c) just before, (d) “normally before” and, (e) “quite before” the road “anomalies”.

The application of the methodology, described in the previous section, led to a successful discovery of the distinct driving patterns. The results are shown in Figs 11 (a), (b), (c), (d) and (e), where yellow indicates the “strong” correlation coefficient and the black-purple, the “strong” anti-correlation coefficient, while, with red indicated the “weak” correlation and anti-correlation coefficient. At this point, it is appropriate to describe each route separately.

In the first route (A1), the driver (Driver A) applied the brakes immediately after passing the road “anomalies”. We observe in Fig. 11(a) that there is “strong” anti-correlation coefficient before and over the road “anomalies”, while, there is “strong” correlation coefficient after. Interestingly, we observe that for the small obstacles or potholes ($T_z \leq 0.2 \text{ m/s}$), the driver kept on driving without braking.

In the second route (A2), the driver attempted to brake while passing the road anomaly, but the human response time resulted in braking immediately after. As in the first route, the results in Fig. 11(b) are consistent with the reality. The driver was removing the foot from the accelerator pedal approximately, 1.1s before the obstacle or the pothole.

In the third route (A3), the driver was braking just before the “anomalies”. This behavior is clearly depicted in Fig. 11(c). Additionally, the results indicate that the driver was not braking for small “anomalies” and that the foot was removed from the accelerator pedal about 1.1 sec before the application of brakes.

Finally, in the fourth (A4) and fifth (A5) routes, the driver was braking “normally before” and “quite before” the road “anomalies”. The diagrams in Figs 11(d) and (e) confirm these patterns.

Experiment 2:

In the second experiment additional drivers were used and a wider range of average speeds was achieved. Two additional drivers, Driver B and Driver C, were asked to drive a route in Politechniopolis campus, Zografos, Greece. The campus features road bumps at known locations. Road slope within the campus varies significantly. Both drivers performed three trials (Driver B: routes B1, B2, B3 and Driver C: C1, C2, C3), each with a different driving style and average speed (i.e. low, medium and high).

At low and medium speeds, Driver B was usually braking at approximately 0.7s before the road “anomaly” and “just before” the obstacle (Figs. 12(a) and (b)). At higher speeds, Driver B was applying the brakes between 0.8 and 0.3s before the obstacle (Fig. 12(c)) and removing the foot off the brake pedal while passing over the “anomaly”. On the other hand, Driver C, at low and medium speeds, was braking 0.6-0.7s before the road “anomaly” (Figs. 12(d) and (e)) and again applying the brakes 0.9 sec after the road “anomaly”. Driver C was re-applying the brakes when the rear wheels of the vehicle hit the “anomaly”. At medium speeds (Fig. 12(e)) braking was occurring just before the road “anomaly”, while at higher speeds (Fig. 12(f)) braking was
Experiment 3:

The purpose of the third experiment was to evaluate the method’s performance using naturalistic driving studies. Two different drivers were asked to track Coventry City’s entry routes (drivers E1 with Driver E and F2, F3, F4 with Driver F). The results are presented in Fig. 13. We can see once again, that it was possible to discover the drivers’ braking patterns.

Table I presents the characteristics of each route. The field trials were carried out in a wide range of average speeds and road slope variation. The results indicate that the proposed method is a robust tool for identifying the braking “signature” of drivers and identifying their braking preferences in the occurrence of different road anomalies.

<table>
<thead>
<tr>
<th>Experiment</th>
<th>Driving Analytics in Experiments 1, 2 and 3</th>
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<tbody>
<tr>
<td><strong>TABLE I</strong></td>
<td></td>
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<tr>
<td><strong>DRIVING ANALYTICS IN EXPERIMENTS 1, 2 AND 3</strong></td>
<td></td>
</tr>
<tr>
<td><strong>Experiment 1: Location Coventry, UK</strong></td>
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<tr>
<td>Route</td>
<td>AvS</td>
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<td>-------</td>
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</tr>
<tr>
<td>A1</td>
<td>6.90</td>
</tr>
<tr>
<td>A2</td>
<td>5.84</td>
</tr>
<tr>
<td>A3</td>
<td>5.39</td>
</tr>
<tr>
<td>A4</td>
<td>6.17</td>
</tr>
<tr>
<td>A5</td>
<td>6.50</td>
</tr>
<tr>
<td><strong>Experiment 2: Location Politechniopolis, Zografos, Greece</strong></td>
<td></td>
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<tr>
<td>Route</td>
<td>AvS</td>
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<td>-------</td>
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</tr>
<tr>
<td>B1</td>
<td>5.69</td>
</tr>
<tr>
<td>B2</td>
<td>7.96</td>
</tr>
<tr>
<td>B3</td>
<td>9.52</td>
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</tbody>
</table>
The proposed smartphones can facilitate the large
extension of driver behavior analysis for smartphone
sensing in context for informing and updating navigation maps. The overall aim is to improve driver experience when preview map information is utilized.

The determination of the marked changes of driver’s speed and the road anomalies was achieved using a novel Deep Neural Network architecture, suitable for the analysis and correlation of multivariate time series data. Extensive field trials were conducted to validate and test the method. The detection method was evaluated by employing the Receiver Operating Characteristics and the analysis proves its high level of efficiency. The true positive rate was 91.5% and the false positive rate 3%. Furthermore, for the first time, a new technique for discovering driver behavior by applying the sliding correlation coefficient is presented. The proposed visualization scheme reveals the driver’s reaction profile when approaching different types of road anomalies. The results using five different driving styles confirm that this new technique is a new formula for the estimation of driver behavior.

The method can be applied in other cases as well, for example in discovering the braking “signature” of drivers when approaching a turn. To further improve the method’s performance, we will explore neural network training methods considering also the ROC analysis outcome, not just the mean squared error. In the future, we intend to extend the present study by investigating the driver behavior predictive capability of the proposed Deep Neural Network.

**VI. CONCLUSIONS**

The widespread use of smartphones can facilitate the large-scale and rapid deployment of Intelligent Transportation Applications. However, the fewer and lower quality signals obtained using a smartphone, compared to the ones available on board, pose a challenge to their exploitation. Furthermore, the uncertainties involved in modeling – due to the variety of vehicles and smartphones – and difficulty in applying rigorous calibration methods, often found in scientific experiments, require the development of agile and adaptive methods. In this paper, a method for automatically learning, using smartphones, driver braking preferences for different types of road anomalies and speeds is presented. The proposed method can be potentially used in a crowd-sensing context for informing and updating navigation maps. The overall aim is to improve driver experience when preview map information is utilized.

The determination of the marked changes of driver’s speed and the road anomalies was achieved using a novel Deep Neural Network architecture, suitable for the analysis and correlation of multivariate time series data. Extensive field trials were conducted to validate and test the method. The detection method was evaluated by employing the Receiver Operating Characteristics and the analysis proves its high level of efficiency. The true positive rate was 91.5% and the false positive rate 3%. Furthermore, for the first time, a new technique for discovering driver behavior by applying the sliding correlation coefficient is presented. The proposed visualization scheme reveals the driver’s reaction profile when approaching different types of road anomalies. The results using five different driving styles confirm that this new technique is a new formula for the estimation of driver behavior.

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**REFERENCES**


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