An Effort to Detect Vehicle Driver's Drowsy State Based on the Speed Analysis

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Abstract—**Detection of the driver's drowsy state is still an actual task since it is a reason for a significant number of traffic accidents. The carried out literature review showed that a significant number of approaches rely on special equipment for driver state identification. At the same time, efficient operation of computer vision-based techniques heavily depends on the lighting conditions, which are usually not good in a moving car. The paper presents a research effort aiming at using speed recordings to identify the driver's state. For this purpose, the speed recordings are analyzed as a time series, and its characteristics are used as features for the classification task. The results show that the suggested approach is viable and promising.**

I. INTRODUCTION

Though self-driving vehicles are currently developing fast, the human factor is still the main reason for vehicle accidents (e.g., [1], [2]). Fatigue and drowsiness are not often reported as the main reasons for road accidents on their own, however, they often (20-30%) are accompanying reasons, thus being an indirect reason [3]. Hence, driver's state detection in terms of fatigue and drowsiness is an important research topic.

The importance of this topic is also confirmed by multiple research efforts. However, most of them are based on either computer vision technologies or additionally apply rather complex medical equipment for driver's state recognition. Unfortunately, in real driving conditions usage of the medical equipment is nearly impossible. The computer vision techniques seem to be a better option since the required quality of the video can be achieved even using a smartphone camera [4]–[6].

However, previous experience of using computer vision technologies for driver state recognition revealed that they are significantly affected by lighting conditions (e.g., [7]), and the cabin of a moving car is subject to continuously varying lighting due to the reflected or direct sun flares (when a car turns), lights of oncoming vehicles and road lights.

In order to avoid all the above drawbacks, a different source of information that would enable driver state analysis and could be implemented in a smartphone without interfering with car equipment was searched for. The found source was the speed of the vehicle that could be easily captured by a smartphone with a certain degree of precision.

The goal of this paper is to check the hypothesis that the vehicle speed could be effectively used for the driver's state identification (in particular, the fatigue state), select models that can be applied for this purpose, and evaluate the level of precision that can be achieved.

The paper is structured as follows. The next section presents the state-of-the-art review. It is followed by the description of the source data used. Section IV presents the research results, that are discussed in Section V. Some concluding remarks and future work direction are presented in the Conclusion.

II. RELATED WORK

The carried out literature review has indicated that there are two major groups of the approaches. The first group of approaches is based on the usage of data acquired through special sensors supplying physiological parameters of the driver. One of the most popular metrics is EEG (electroencephalogram) signal. The authors of [8] achieved 92.4% accuracy using only the EEG signal. Other metrics include respiration rate, heart rate, EMG (electromyogram), ECG (electrocardiography), EOG (electrooculogram), and many others. Combinations of metrics make it possible to achieve even better results (e.g. up to 96% accuracy in [9]). However, mass usage of the required equipment is nearly impossible. The authors of [10] conclude that though this field is continuously improving "driver monitoring system using physiological signals does not exhibit any significant success in routine use".

Another group of approaches is based on computer vision techniques. The popularity of such approaches is significantly boosted today by the exploding development of machine learning models. Different video streams can be analyzed to solve the task set. For example, these could be applied to analyze the image or video of the driver to measure blink rates, yawning, etc. The authors of [11] achieved the precision for normal and fatigue states of 85.02% and 95.18%, respectively based on the analysis of the PERCLOS metric (percentage of eyelid closure). The model taking into account changes of various face features over time (facial actions) results in 93.82% accuracy [12]. Some features including head movement and yawning are considered in [13].

Computer vision can also be applied outside of the vehicle in order to monitor its movement. For example, Morris et al. [14] propose to identify drowsy drivers via an analysis of the vehicle's trajectory within the lane. Though, they do not report results on actual driver's state identification but claim that this is a promising direction.

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There exist approaches based on the less popular features such as hand movement on the steering wheel [15], as well as approaches combining some of the above techniques [16].

Among the found approaches the goal of detecting driver's drowsiness by using minimal equipment without interfering with vehicle's equipment can only be achieved via the computer vision-based models running on a mobile phone. However, these approaches depend on the lighting conditions [7], [17], [18], which are far from perfect in a moving car. Besides, drowsiness detection is especially important at night, when lighting conditions are the worst (not only the light is low, but there are also significant lighting changes due to lights of oncoming vehicles and road lights). Infrared cameras can solve the problem of low light [19], [20] but not the problem of continuously changing lighting conditions.

Based on the above review, it can be concluded that an approach to driver's drowsiness detection not requiring special sensors or interfering with the car equipment and not depending on lighting conditions would be demanded. As it was already mentioned in the Introduction, speed has been chosen as a parameter to be analyzed since it can be easily captured by, for example, a smartphone or a navigation device. During the literature review, no approaches have been found that detect driver's drowsiness via the vehicle's speed analysis.

III. Source Data

Starting with the hypothesis that the driver's state can affect the speed characteristics of the vehicle movement, a search for available datasets with given driver's state and recorded vehicle speed was performed. We tried to concentrate on the real-world (not a simulator) data since the driver behavior (micro impacts to the acceleration pedal and specifics of movements) can significantly differ in the real world and in a simulator. This observation has also been confirmed in several works (e.g., [21]). Unfortunately, the search has not returned desirable results. A possible reason for that is that driving in a drowsy state is dangerous (and in some states illegal [22]), and one cannot ask people to do this even for conducting an experiment.

As a result, to get the required data, a search has been carried out for speed recordings with confirmed by the drivers drowsy and awake conditions among personally known by the author users of the DriveSafely system [23] by interviewing.

Performed data collection resulted in a dataset describing 6 rides of one driver (3 for driving in a drowsy state and 3 for driving in an awake state) with a total duration of 393 minutes (135 for definitely awake state and 258 for definitely drowsy state). The rides were recorded while driving different cars (equipped with both manual and automatic transmissions) in a city, in a countryside, and on a highway (without using a cruise control system) with different external conditions. The speed measurements were recorded using the DriveSafely system sunning on an Android-based smartphone 5 times per second.

It is quite obvious, that comparing speeds does not make any sense, since they can differ significantly when driving, for example, in a city or on a highway (an example of an absolute speed value is shown in Fig. 1). Thus, the acceleration (the derivative of the speed, Fig. 2) and the jerk (the derivative of the acceleration, Fig. 3) were used for the analysis along with their absolute values, resulting in time series of 4 parameters.

Based on these recordings, 581 time series of acceleration and jerk values, as well as absolute values of acceleration and jerk for 2000 successive measurements (duration of each row - 400 seconds) have been formed, of which 390 were related to driving in a drowsy state, and 191 – to driving in an awake state. The duration of the time series was selected experimentally, taking into account that the series should be long enough to reveal the features of the vehicle's movement, but not too long so that, with short trips, several series for the analysis could be formed. In the future, it is planned to analyze different durations of the time series to select the most suitable one.

IV. Research Results

To analyze the time series, the following 6 generally used features have been calculated for each set of parameters resulting in total 44 characteristics:

Mean value: $Mean = \frac{\sum_{i=1}^{N} x_i}{N}$.

Standard deviation: $StdDev = \sqrt{\frac{\sum_{i=1}^{N}(x_i - Mean)^2}{N-1}}$.

Variance: $Variance = StdDev^2$.

The ratio of the standard deviation to the mean value: $StdDev\_Mean = \frac{StdDev}{Mean}$.

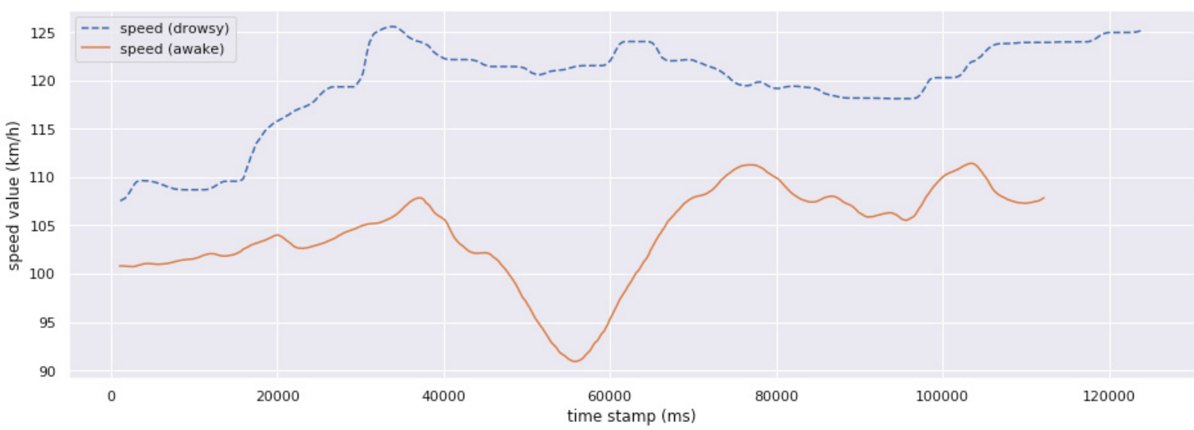

Fig. 1. An example of the absolute value of the vehicle speed (vertical axis) in time (horizontal axis) controlled by a driver in a drowsy state (dashed line) and in a awake state (solid line)

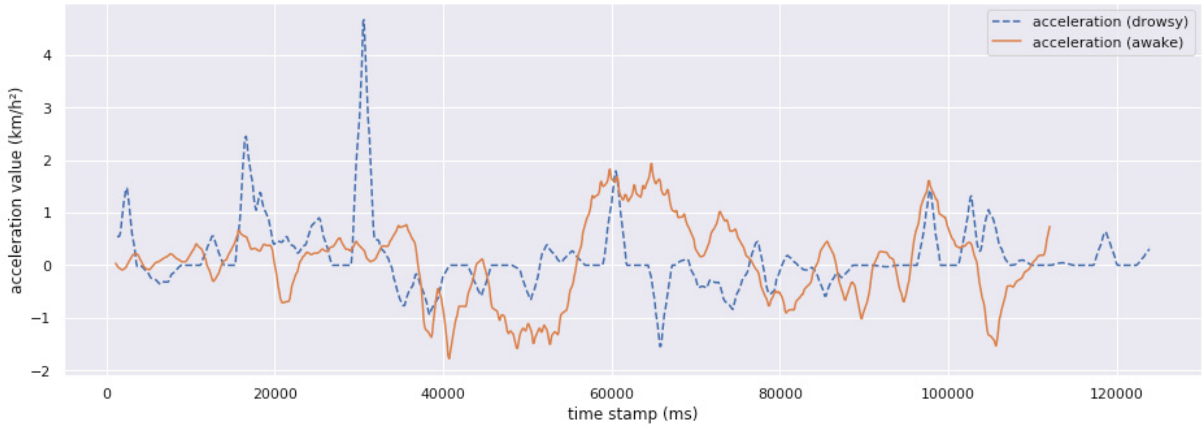

Fig. 2. An example of the absolute value of the vehicle acceleration (vertical axis) in time (horizontal axis) controlled by a driver in a drowsy state (dashed line) and in a awake state (solid line)

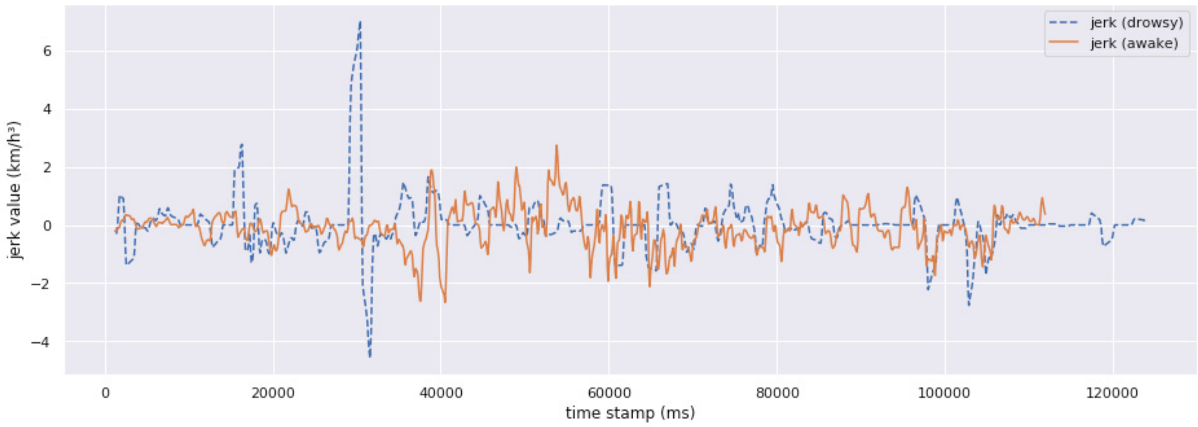

Fig. 3. An example of the absolute value of the vehicle jerk (vertical axis) in time (horizontal axis) controlled by a driver in a drowsy state (dashed line) and in a awake state (solid line)

Skewness: $Skew = \frac{\sum_{i=1}^{N}(x_i - Mean)^3}{(N-1)StdDev^3}$.

Kurtosis: $Kurtosis = \frac{\sum_{i=1}^{N}(x_i - Mean)^4}{(N-1)StdDev^4}$.

Besides, features specific to time series [24], [25] have also been calculated:

Difference between the peak values: $PeakToPeak = max_{i=1}^{N}(x) - min_{i=1}^{N}(x)$.

The ratio between the peak value difference and standard deviation: $PeakToPeak\_StdDev = \frac{PeakToPeak}{StdDev}$.

Crest factor: $Crest = \frac{max_{i=1}^{N}(x)}{StdDev}$.

Impulse factor: $Impulse = \frac{max_{i=1}^{N}(x)}{Mean}$.

Energy factor: $Energy = \left(\frac{\sum_{i=1}^{N}\sqrt{|X_i|}}{N}\right)^2$.

In the above formulas, the following notations are used:

N – is the number of samples in a time series;

x_i – is the value of the i-th sample in the time series.

The initial analysis was based on 5-fold cross-validation carried out using a decision tree with a depth limit of 10. The k-fold cross-validation procedure (in this particular case, $k = 5$) assumes that the dataset is divided into k subsets of approximately equal size, and k experiments are carried out so that each of the k subsets is used once as the test set and the other k-1 subsets are put together to form the train set. The following indices were used for the evaluation of the model adequacy: precision, recall, F1-measure, accuracy, and area under the error curve (ROC-AUC). The results are summarized in Table I. These results indicate that it is possible to fairly successfully classify the driver's state based on speed data using a decision tree.

Then, the feature importance analysis has been carried out. Based on its results (see Fig. 4) it was concluded that the most important features for the driver's state identification are:

- the variance of the acceleration (*acc_Variance*),
- the variance of the jerk (*jrk_Variance*),
- the energy factor of the jerk (*jrk_Energy*),
- the energy factor of the absolute acceleration value (*acc_abs_Energy*),
- the variance of the absolute jerk value (*jrk_abs_Variance*),

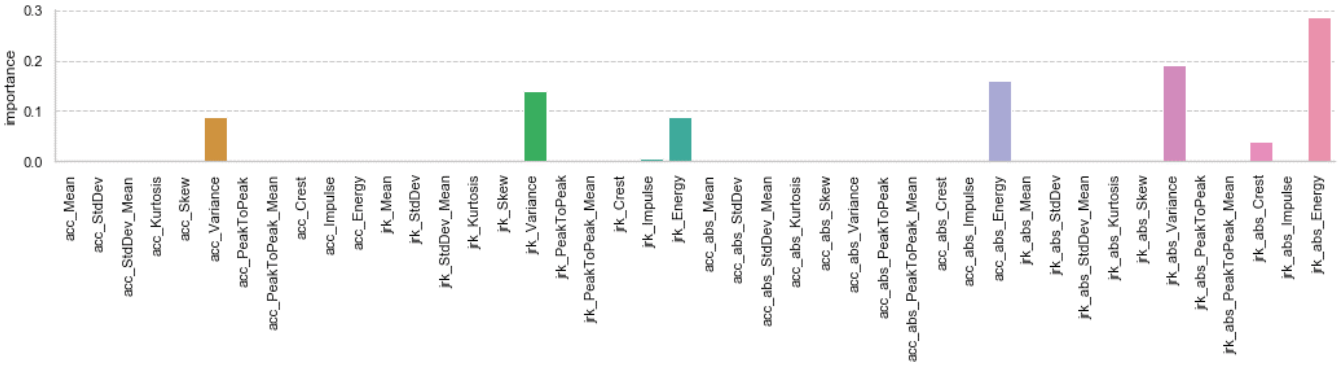

Fig. 4. An example of the absolute value of the vehicle jerk (vertical axis) in time (horizontal axis) controlled by a driver in a drowsy state (dashed line) and in a awake state (solid line)

TABLE I. 5-FOLD CROSS-VALIDATION RESULTS FOR DRIVER STATE CLASSIFICATION BY DECISION TREE BASED ON 44 FEATURES

Measure	Splits					Mean Value
	1	2	3	4	5	
Prec.	0.878	0.960	0.854	0.944	0.889	0.905
Recall	0.923	0.923	0.897	0.859	0.923	0.905
F1	0.900	0.941	0.875	0.899	0.906	0.904
Acc.	0.863	0.922	0.828	0.871	0.871	0.871
ROC-AUC	0.921	0,980	0.898	0.959	0.932	0.938

TABLE II. 5-FOLD CROSS-VALIDATION RESULTS FOR DRIVER STATE CLASSIFICATION BY DECISION TREE BASED ON 5 FEATURES

Measure	Splits					Mean Value
	1	2	3	4	5	
Prec.	0. 932	0.935	0.872	0.943	0.875	0.912
Recall	0.885	0.923	0.872	0.859	0.897	0.887
F1	0.908	0.929	0.872	0.899	0.886	0.899
Acc.	0.908	0.929	0.872	0.899	0.886	0.866
ROC-AUC	0.942	0.969	0.916	0.970	0.935	0.946

- the crest factor of the absolute jerk value (*jrk_abs_Crest*),
- the energy factor of the absolute jerk value (*jrk_abs_Energy*).

However, since the energy factor and the variance are always positive, additional analysis of their absolute values does not make sense, so *jrk_abs_Variance* and *jrk_abs_Energy* have also been removed resulting in 5 important features.

Fig. 5 visualizes the dependence between the driver's state and each pair of the selected features. One can see that some dependence exists indeed, though it is not linear.

After the reduction of the number of features, the cross-validation using the decision tree model has been performed once again. One can see that removing unimportant features that introduce some noise has not made the results worse but even improved these (Table II). Consequently, it was decided that these features are suitable for further analysis.

The further analysis was based on fitting other models besides the decision tree. The following additional models have been tested: logistic regression and Gaussian naive Bayes (implemented using Python machine learning library *scikit-learn* [26]), and gradient boosting on decision trees (implemented using Python library *CatBoost* [27]). The results fitting these models are shown in Tables II – V and summarized in Table VI.

One can see that the decision tree and gradient boosting on decision trees models provide the best results, whereas the logistic regression model is not successful what can be explained by the complexity of the considered dependency.

TABLE III. 5-FOLD CROSS-VALIDATION RESULTS FOR DRIVER STATE CLASSIFICATION BY LOGISTIC REGRESSION BASED ON 5 FEATURES

Measure	Splits					Mean Value
	1	2	3	4	5	
Prec.	0.726	0.743	0.710	0.737	0.745	0.732
Recall	0.987	1.000	0.974	0.936	0.936	0.967
F1	0.837	0.852	0.822	0.825	0.830	0.833
Acc.	0.744	0.767	0.716	0.733	0.741	0.740
ROC-AUC	0.601	0.573	0.487	0.572	0.560	0.557

TABLE IV. 5-FOLD CROSS-VALIDATION RESULTS FOR DRIVER STATE CLASSIFICATION BY GAUSSIAN NAIVE BAYES BASED ON 5FEATURES

Measure	Splits					Mean Value
	1	2	3	4	5	
Prec.	0.772	0.773	0.742	0.767	0.756	0.762
Recall	0.910	0.962	0.923	0.885	0.872	0.910
F1	0.835	0.857	0.823	0.821	0.810	0.829
Acc.	0.761	0.784	0.733	0.741	0.724	0.749
ROC-AUC	0.782	0.800	0.642	0.774	0.735	0.747

TABLE V. 5-FOLD CROSS-VALIDATION RESULTS FOR DRIVER STATE CLASSIFICATION BY GRADIENT BOOSTING ON DECISION TREES BASED ON 5 FEATURES

Measure	Splits					Mean Value
	1	2	3	4	5	
Prec.	0.892	0.906	0.874	0.935	0.893	0.900
Recall	0.949	0.987	0.974	0.923	0.962	0.959
F1	0.919	0.945	0.921	0.929	0.926	0.928
Acc.	0.889	0.922	0.888	0.905	0.897	0.900
ROC-AUC	0.954	0.970	0.923	0.955	0.927	0.946

Fig. 5. Illustration of the distribution of the samples for awake (circles) and drowsy (crosses) driver depending on the energy factor of the absolute value of jerk (horizontal axis) and energy factor of the absolute acceleration value (vertical axis)

V. Discussion

The results obtained show that for the available data it is quite possible to identify the drowsy driver based on the vehicle speed analysis and it is reasonable to continue this research in terms of using more advanced classification models.

The limitation of the presented approach is its potentially lower quality of the classification. Though currently, the classification quality is high, we recognize that the source data is limited and the models can be overfitted, so an extension of the dataset can possibly lead to the degradation of the quality.

TABLE VI. Comparison of the Performance of Different Models for Driver State Classification Based on 5 Features

Measure	Model			
	Decision Tree	Logistic Regression	Naïve Bayes	CatBoost
Prec.	0.912	0.732	0.762	0.900
Recall	0.887	0.967	0.910	0.959
F1	0.899	0.833	0.829	0.928
Acc.	0.866	0.740	0.749	0.900
ROC-AUC	0.946	0.557	0.747	0.946

Thus, another direction of the future work is the dataset extension.

It is also worth to be mention that in real-life conditions it is not necessary to achieve 100% accuracy in detecting drowsiness. Usually, a human becomes drowsy not instantly, and the system will be able to accumulate and process several samples to classify the driver's state.

Analyzing vehicle movement has also been studied in [14], and the authors claim that this is a promising direction.

VI. Conclusion

The paper analyses the possibility to use the vehicle's speed as a source data for detecting the driver's drowsy state. For this purpose, speed recordings were used to calculate the acceleration and the jerk. These in turn were treated as time series to calculate various features. Feature importance analysis has shown that the variance of the acceleration, the variance of the jerk, the energy factor of the jerk, the energy factor of the absolute acceleration value, and the crest factor of the absolute jerk value were decisive for the classification.

The application of different classification models made it possible to achieve accuracy between 75% when using logistic regression and naive Bayes and 90% when using gradient boosting on decision trees.

Future work is aimed at the extension of the dataset, analysis of time series with different durations, as well as using more advanced classification models for classification.

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