Smartphone Movement Detection Based on IMU Data as Basis for Driver Distraction Detection

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Driver distraction, as discussed frequently in literature, has a high influence on vehicle accidents all over the world [1], [2]. This high influence makes it a relevant research area, such as in the field of computer technologies. In this regard, a common first step to resolve this problem is to identify situations in which the driver is distracted. There are already many publications on how to identify such a distracted state of the driver. DarNet, for example, is a framework, which identifies such situations, using an inward facing camera and inertial measurement unit (IMU) data, e.g. acceleration and gyroscope data [3]. Also, other experimental settings, including even more input data sources (e.g. GPS position, microphones, distance sensors), are discussed [4], [5]. One drawback of these methods, however, is the need for elaborated sensor equipment, which hinders the application outside an experimental test setting. A more practical approach was introduced by Xie et al., by using only data available by an ordinary smartphone to infer the driver's distraction state [6]. In this setup, GPS and IMU data was used for different Machine Learning (ML) models to infer the binary distraction state. Based on this idea, we now propose an approach, using only easily accessible IMU gyroscope and acceleration data, to predict if the smartphone is moved, as a simple, first approximation of driver distraction through the smartphone, using a Neuronal Network (NN). This approach fits into a range of approaches getting more and more attention recently, focusing on the driver behavior detection [9], [10].

For this purpose, we developed a smartphone app, which was used in the experimental setting. The smartphone app is capable to recording IMU (gyroscope and acceleration) data with a frequency of 20 Hz. The corresponding state of the smartphone, rest- or action-state, was logged with a different device, using an ordinary app for recording points in time. During the test drives, two rest states (middle console and smartphone holder) and two action-states (phone call and app usage) were used. There were two test drives conducted, with two different cars and drivers, each for around 140 minutes, producing around 330 thousand measurement points in total.

The gathered data was used to train a NN based on a long short-term memory (LSTM) layer in TensorFlow [7]. The model takes six different input vectors of size five as input. This represents the six input quantities, three acceleration and three gyroscope measurements, of the last 5 measurement points within the last quarter second. These 30 values are feed into a LSTM layer with 32 neurons, followed by a dense layer with 16 neurons, ending in a two-neuron output layer. Using the adam optimizer [8] and the sparse-categorical-cross-entropy loss function, this 8626-parameter model was fitted to 70% of the data. The remaining 30% of the data were used for validation – in equal shares to evaluate the model performance during the fitting process (validation dataset) and to evaluate the model performance after the fitting process (test dataset).

The model was able to infer the correct state of the phone in around 94% of the cases. The accuracy, when applied to the training data, is 95%, applied to the validation data it is 94%. Fig. 1 shows a section of the visualization of the model's performance. One can see the six IMU quantities over time used as the model's input. The background represents the mobile phone's state, light grey for a rest state and dark grey for an action state, whereas the upper half shows the real states and the lower half shows the model's output.

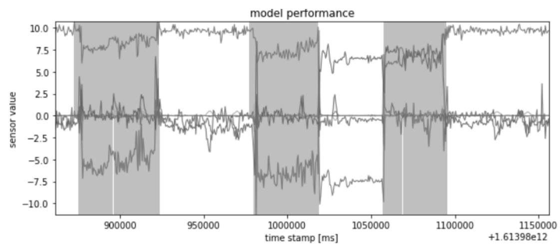

Fig. 1. Performance of the developed model in detecting phone movements.

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