Feature Selection Based on Variance Distribution of Power Spectral Density for Driving Behavior Recognition

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***Abstract*— Abnormal driving detection and recognition is a crucial area of research towards achieving safety in intelligent transportation systems (ITS). In this study, we propose a feature extraction approach and use the extracted features to train a deep learning model that is used for abnormal driving behavior recognition. The proposed approach derives the features based on variances calculated from each frequency bin containing the power spectrum data that is generated using the short time fourier transform. A subset of features is further selected based on variance similarity of the power spectral data. Similarity is realized by finding intersecting variance data of different variance samples obtained from defined data segments of a given driving behavior class. The driving behaviors considered are weaving, sudden braking and normal driving. Experiments were performed using an artificial neural network to test the efficiency of the proposed feature extraction approach. Results show that an accuracy of 91.0% can be achieved with accelerometer data. The accuracy is further improved to 96.1% by combining accelerometer with gyroscope data.**

Keywords—Abnormal driving, deep learning, spectrogram, variance

I. Introduction

Road accidents are one of the leading causes of death in the world predicted to rank 7th by 2030 by the World Health Organization [1]. This prevailing catastrophe can be prevented with effective interventions such as driving behavior monitoring and evaluation. Given the advancement in technology, deep learning techniques have been acclaimed to produce remarkable results in behavioral recognition [2], [3]. For example in Google's self-driving car, Apples' Siri voice assistant, earthquake prediction systems [4] to mention but a few.However, a deep learning model heavily relies on a set of inputs that have to be supplied to progressively improve its ability . The supplied inputs can slow down the model or cause unrealistic results if it is not optimally selected. With the start-of-the-art results achieved by use of spectrogram features in signal processing [5], [6]. This study sets out to use variances of the power spectral density (PSD) generated from the short time fourier transform (STFT) for each collected data sample. Intersecting values are considered as the set of similar points among the samples and used to narrow down on the region of interest. A subset of 25 values of the PSD is identified as features to be used as inputs for a neural network model. Patternet, a pattern recognition neural network in particular was used to train the features and obtain a classifier model for recognizing driving behavior. In this paper, we leverage on smart phone sensors [7] to obtain accelerometer and gyroscope readings from a moving vehicle. For safety purposes, normal driving, weaving and sudden braking are executed and recorded by the smartphone sensors. The rest of this paper is organized as follows, review of related work, detailed description of proposed algorithm, experiments, results and conclusion.

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II. Related Work

In this section we review existing work on driving behavior detection, and work on the use of spectrogram features.

In [8], a state graph-based behavioral model was used. Data was split into segments and compared with the state graphs of normal data to determine how much it deviates from the normal. The results suggest that the model performs well in recognizing various driving anomalies without using labelled training data.

In [9], a support vector machine (SVM) was trained using features based on the maximum, minimum, value range, mean and standard deviation of the time, acceleration and orientation sensors values to attain fine grained identification of driving behaviours.

Unlike the aforementioned approaches, this study sets out to use spectral data for abnormal driving detection and recognition. The use of spectral data has produced remarkable results where it has been applied.

In an epileptic seizure prediction [10], power spectral density was used to obtain spectral power of well-known frequency bands of a raw electroencephalogram recording to form a feature vector. A subset of candidate features was selected based on maximum difference of amplitude distribution histograms. The subset was fed to support vector machines in order to classify the data. The performance was superior to that of analytical random predictor.

In an evaluation of convolutional neural networks (CNN) for music classification [11], features were extracted from images of signal spectrograms. The good performance of the CNN was attributed to the robust representation that was capable to learn from the data.

In [12], a spectrogram based feature extraction approach was proposed for learning human activity recognition. A set of least and greatest values from the spectrogram was selected to represent the feature vector that was used to train the deep learning model. Varying the size of the feature vector showed to achieve state-of-the-art recognition performance with fewer features.

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III. PROPOSED APPROACH

The contributions in this study are in the feature selection process. From 203 collected driving data samples, the PSD using STFT with a hamming window of 50% overlap between segments was generated for each Z-axis sample of the raw data. Z-axis signal data was used in this study because it stood out more compared to the X and Y axis data.Figs.1, 2 and 3 show the X, Y, Z axis of the raw accelerometer data signal. The PSD is generated as an $m \times n$ matrix. For each row m, variance is calculated to obtain an initial feature vector denoted by

$$f_i=(v_1,v_2,\ldots,v_m) \tag{1}$$

where f_i is the feature vector of the ith sample and v_m means the variance of the row of the PSD for that given sample. However not all of the features are necessary for abnormal driving identification and thus in order to narrow down to the region of interest, a threshold is determined by intersecting the feature vectors. The sets of intersecting values with their corresponding rows,m are then used to construct a histogram. The intervals with the highest count are considered to have the significant data and set the threshold for feature selection from the initial feature vector. We conclude that the first 25 values of f_i contain the significant features and are therefore used as input to train a neural network model. The summary of the algorithm is shown in Fig.4.

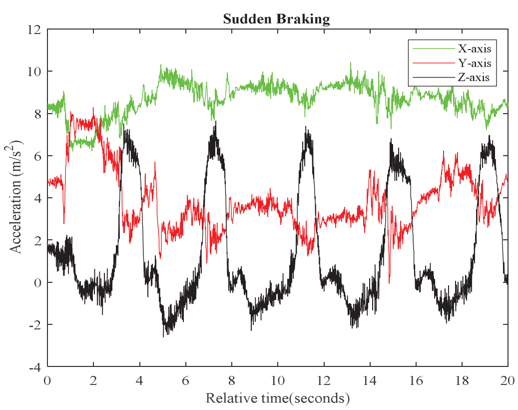

Fig. 1. Raw data signal for sudden braking

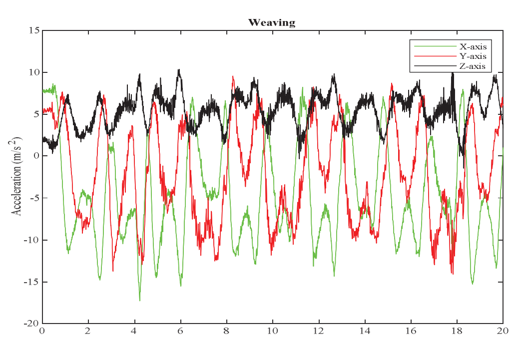

Fig. 2. Raw data signal for weaving

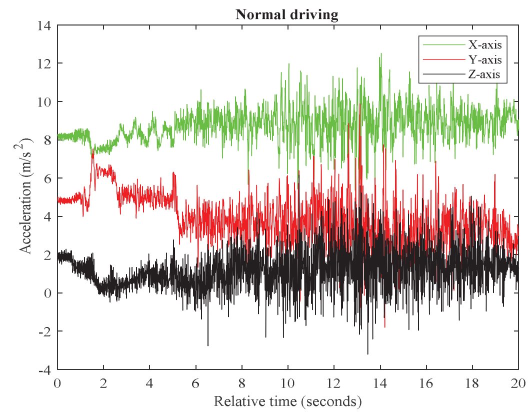

Fig. 3. Raw data signal for normal driving.

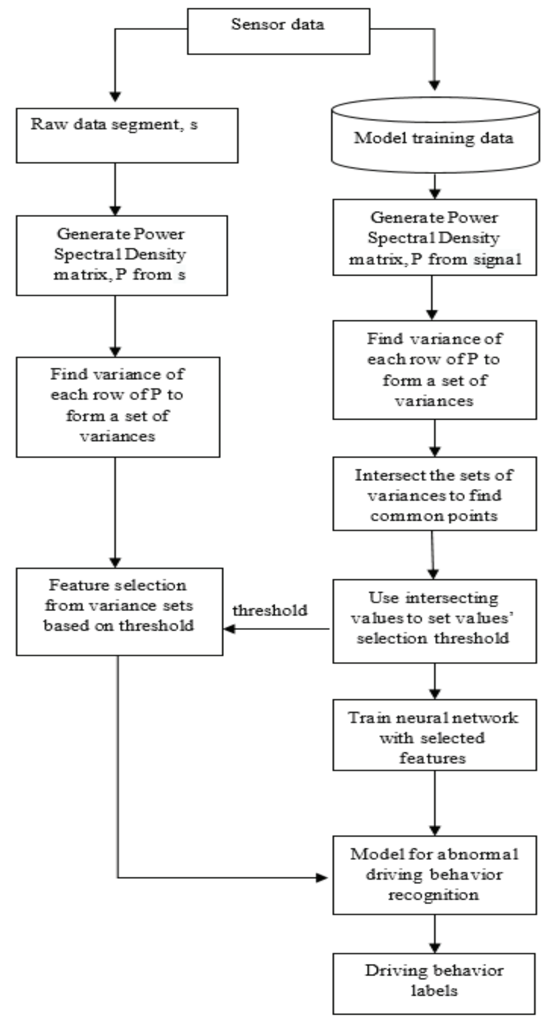

Fig. 4. Algorithm development

IV. EXPERIMENTS

A. Data Collection Setup

The accelerometer and gyroscope data was collected using a Samsung S5 smart phone .The phone was placed on the steering wheel of the vehicle as shown in Fig.8. Using MATLAB mobile phone application with the data transmission set to 100Hz, data of the vehicle acceleration was recorded while a male driver aged 32 executed the driving behaviors specifically; weaving, sudden braking and normal driving as described in [9].

Fig. 5.Smartphone placement on vehicle steering wheel.

B. *Neural Network Training Process*

The final feature set is then supplied as input to a pattern recognition network with hidden layer size of 25 and epochs set to 52 was used.70% of the data was used for training, 15% for testing and 15% for validation.

V. RESULTS

In this paper, we proposed using variances of power spectral density bins to form feature vectors for training a neural network. The variance feature vector is combined with zero crossing rate (ZCR), average peak width (APW) and peak prominence(PP). The performance of the classification model is shown by the confusion matrix in TABLE I. The classifier made a total of 203 predictions i.e. 203 samples of driving behavior were being classified. Out of the total number of samples, 51 were classified as sudden braking, 68 as weaving and 70 as normal driving. In reality, 59 samples belong to sudden braking, 73 to Weaving and 71 to normal driving. Accuracy is calculated by $\frac{TP+TN}{total} = \left(\frac{51+68+70}{203}\right) \times 100 = 93.1\%$ .The classifier is correct 93.1% of the time.

TABLE I. USING VARIANCE FEATURE WITH ZCR, APW AND PP.

True label	Sudden braking	**51**	5	1
	Weaving	6	**68**	0
	Normal driving	2	0	**70**
		Sudden braking	Weaving	Normal driving
		Predicted label		

The algorithm in Fig. 4 was then applied to the gyroscope Z axis data. 25 features from the accelerometer data are combined with 19 from the gyroscope data and the result is as shown in TABLE II. Combining the accelerometer and gyroscope features achieved an overall accuracy of 96.1%. Accuracy is calculated by $\frac{TP+TN}{total} = \left(\frac{55+70+70}{203}\right) \times 100 = 96.1\%$.

TABLE II. ACCELEROMETER AND GYROSCOPE FEATURE VECTOR

True label	Sudden braking	**55**	2	1
	Weaving	0	**70**	0
	Normal driving	4	1	**70**
		Sudden braking	Weaving	Normal driving
		Predicted label		

VI. CONCLUSION

In this study, the experiment results proved that the use of PSD variances as features for a neural network can achieve state-of-the-art performance in driving behavior recognition. For purposes of improving accuracy, accelerometer data was combined with gyroscope data that provided the best result. Further studies shall be done to compare the performance of the feature vector with other machine learning classification methods.

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