A New Method for Classification of Hazardous Driver States Based on Vehicle Kinematics and Physiological Signals

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Abstract. Hazardous driver states are the cause of many traffic accidents, and there is a great need for detection method of such states. This study thus proposes a new classification method that is evaluated on a previously collected driving dataset, which includes combinations of four causes of hazardous driver states: drowsiness, high traffic density, adverse weather, and cell phone usage. The previous study was consisted of four sessions and eight scenarios within each session. Four physiological signals (e.g. electrocardiogram) and twenty vehicle kinematics signals (e.g. throttle, road offset) were recorded during each scenario. In both previous and present studies, the presence or absence of the different causes of hazardous driver states was classified. In this study, a new classifier based on principal component analysis and artificial neural networks is proposed. The obtained results show improvement across all classification accuracies especially when only vehicle kinematics data are used (mean of 12.7%).

Keywords: Hazardous driving state · artificial intelligence · driving performance · physiological measurements · affective computing

1 Introduction

Hazardous mental or physical states are the cause of many traffic accidents. For instance, fatigued driving resulted in an estimated 800 deaths and 41,000 injuries in the United States in 2015. Distracted driving, on the other hand, caused 1.25 million deaths worldwide in 2015, with an estimated 3,477 deaths in the United States alone [1].

A system with the ability to detect hazardous driving states (HDS) and intervene in dangerous situations can mitigate the number of deaths and injuries, thus increasing driving safety. Although several such systems have been proposed (e.g. [2]), there is room for improvement. One important issue with such automated intervention systems is that they usually monitor a specific gesture or posture of the driver (e.g., hands-on/off the wheels) and do not identify the cause of HDS (e.g., stress). This study therefore aims to develop an automated system that not only detects HDS, but can also identify specific causes of HDS based on a combination of vehicle kinematics and driver physiology. The obtained results can be used to tailor the response of an intervention system to each cause of HDS.

Many physical/physiological (e.g., fatigue) or cognitive/affective (e.g., anger) conditions may cause HDS, and most causes of HDS therefore have both physical and mental components. In this paper, we discuss four causes of HDS: distractions, fatigue, demanding driving conditions, and the driver's characteristics. Distracted driving is perhaps the most infamous HDS, and can lead to catastrophic situations. Performing secondary tasks in addition to driving (e.g., using a cell phone) results in both visual distractions [3] and cognitive distractions [4]. Drivers need 7-12 seconds to regain situational awareness after each distraction [5], increasing the likelihood of accidents. Fatigue and drowsiness make driving even harder and affect both driver physiology [6] and vehicle kinematics [7]. Even if a driver is alert, difficult driving conditions like blizzards introduce a high level of mental demand. During such conditions, drivers may devote all their mental resources and still not be able to drive effectively [3].

Regardless of their causes, HDS can be assessed using three methods: physiological measurements, vehicle kinematics, and self-report questionnaires. Physiological signals can be unobtrusively recorded during driving and are correlated with many psychological states (e.g. workload). A few examples of such signals in driving studies are the electrocardiogram (ECG) [8], which records heart rate [9], galvanic skin response (GSR), which records the activity of the skin's sweat glands [10], respiration rate (RR) [11], and skin temperature (ST) [12]. Vehicle kinematics, on the other hand, include signals such as longitudinal speed [13], rotation of the steering wheel [14], and the lateral lane position (distance from the lane center) [15].

In our previous study [10], we exposed drivers to four different causes of HDS (mild sleep deprivation, adverse weather, cell phone use, and high traffic density), and collected three different types of information: vehicle kinematics, physiological measurements (RR, ST, GSR, and ECG), and driver characteristics (personality, mood, and stress level). We then created different classifiers to automatically identify the presence or absence of each of the four causes of HDS. The contribution of this study is to propose a new classification method that does not need to extract features from raw data and increases the classification accuracies. Of the three types of data from the previous study, vehicle kinematics and physiological measurements are used in this study.

2 Study Setup and Protocol

Study Setup: The dataset from the previous study includes data from 21 people (25.1 ± 8.7 years old, six females) who participated in four simulated driving sessions in the University of Wyoming driving simulator lab (WYOSIM). Of the four sessions, two were meant to mimic drowsy (mildly sleep-deprived) driving and were held in the early morning while it was still dark outside. In these two sessions, only night scenarios were used in WYOSIM, and the participants were told to have less than 6 hours of sleep the preceding night. The other two sessions were meant to mimic alert driving, and participants were instructed to have more than 7 hours of sleep the preceding night. These two sessions were held between 10 am and 5 pm, and only day scenarios were used in WYOSIM. The order of drowsy and alert driving sessions was random.

Each session consisted of 8 scenarios (4 min/scenario) that represented all possible combinations of traffic density (high/low), weather (sunny/snowy), and cell phone use (phone/no phone), in random order. For low traffic density, participants drove on a highway with few cars (density factor 0.3 in WYOSIM); for high traffic density, they drove in a town with dense traffic (density factor 1.5) (Fig.1). In snowy weather, visibility was lower than in sunny weather and the friction between the tires and the road was reduced to 60% of the sunny-weather value [16]. Furthermore, in the "cell phone" scenarios, participants used their cell phone to browse the Internet or send text messages [10].

Measured signals: In each scenario, the g.USBamp signal amplifier (g.tec Medical Engineering GmbH, Austria) was used to record 4 physiological signals: electrocardiogram, respiration, skin temperature, and galvanic skin response. Furthermore, 8 vehicle kinematics signals were recorded: throttle force, lane number, lateral lane position, road offset, longitudinal velocity, vertical velocity, and slip level of front and rear tires. In the previous study, three or more features were calculated from each raw signal (either physiology or vehicle kinematics), and the stepwise algorithm was used to select the best set of features. Then, three types of classifiers (support vector machine, decision tree, and logistic regression) were used to classify the presence or absence of each of the four causes of HDS (traffic density, weather, cell phone, drowsiness) [10]. In this study, the raw signals were directly used as inputs to the classifiers.

The contribution of this study: A classification method based on principal component analysis (PCA) and artificial neural networks (ANN) was implemented. Several binary ANN classifiers were used to classify the presence or absence of each cause of HDS. The computational advantage of the proposed method is that raw physiological and vehicle kinematics signals were used; therefore, there was no need for any preprocessing or feature extraction methods.

Let $\chi \in \mathbb{R}^{n_s \times n_e \times n_t \times n_p \times n_m}$ denotes the previously collected data, where n_s signifies the number of subjects, n_e is the number of sessions per subject, n_t is the number of scenarios within each session, n_p is the number of data samples, and nm denotes the number of raw signals. In our study, n_s=21, n_e=4, n_t=8, and five physiological signals with a sampling frequency of 512 Hz and eight vehicle kinematics signals with a sampling frequency of 60Hz were recorded. Therefore, if only physiological signals are used, n_m=4 signals and n_p=122,880 samples; if only vehicle kinematics signals are used, n_m= 8 signals, and n_p=14,400 samples. The number of samples is calculated based on the sampling frequency and the length of each scenario (4 minutes).

Fig.1. Town scenario (Left) and highway scenario (Right).

In the PCA-ANN method, we first need to generate a data matrix, D, by stacking the raw signals. The matrix, D, is of size $n_{pm} \times n_{set}$, where $n_{pm}=n_p \times n_m$ and $n_{set}=n_s \times n_e \times n_t$. Since n_{pm} is much larger than n_{set}, the original covariance matrix ($C' = D\, D^T$) is a large-scale square matrix that requires prohibitively extensive computations to calculate its eigenvectors. Instead, the covariance matrix with reduced dimensionality ($C = D^T\, D$) is used to allow easy calculation of eigenvectors. After calculating the eigenvectors of the covariance matrix with reduced dimensionality, the k best eigenvectors are selected (eigenvectors corresponding to the largest eigenvalues). The value of k is a hyperparameter that is selected by trial and error. In this study, $k = 20$ if only physiology or only vehicle kinematics are used while $k = 30$ if both physiology and vehicle kinematics are used. Let V_k denotes the matrix of k best eigenvectors. In the next step, the input data for the ANN classifiers was then generated using $W = D^T\, D\, V_k$, where W is the input data for the ANN [17]. Fig. 2 shows the structure of three-layer ANN classifiers with either 20 or 30 inputs and one output. For the first, second and third hidden layers, 25, 25 and 20 neurons are used, respectively. The hyperbolic tangent sigmoid function is chosen as the transfer function of all hidden layers as well as the output layer. For each cause of HDS, one ANN is developed using Levenberg-Marquardt backpropagation algorithm as the training method. To train and test the classifiers, 75% and 25% of the data are used, respectively. The 4-fold cross-validation method is used to validate the ANN classifiers, and the mean values of classification accuracies are reported.

3 Result and Discussion

In this section, the classification accuracies obtained from the new PCA-ANN method are compared to the results of the previous study. Table 1 shows the accuracies for three input types: physiology only, vehicle kinematics only, and both physiology and vehicle kinematics. The PCA-ANN method exhibits higher accuracy for classification of drowsiness using any input type, demonstrating a strong potential advantage over the previous methods. Likewise, the proposed method outperforms the previous methods when using vehicle kinematics to classify all four HDS causes, especially high/low traffic density (nearly 100% accuracy). In contrast, when using physiological signals, the accuracy of the new PCA-ANN method varies significantly depending on the cause of HDS – from 16% worse to 23% better than the classification methods from the previous study. Overall, the obtained results show an improvement across all classification accuracies compared to the previous study: vehicle kinematics (mean improvement of 12.7%), physiological responses (mean improvement of 1.2%) and the combination of both (mean improvement of 2.7%). The high variation in differ

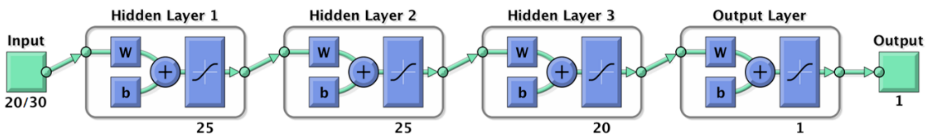

Fig.2. The proposed artificial neural network classifier. It uses 20 inputs for physiological or vehicle kinematics only, and 30 inputs for the combination of them.

Table 1. Classification accuracies obtained with different input data types using the classifiers from the previous study and using the proposed method (Physio: physiology, Vk: vehicle kinematics, Ps: previous study, PCA-ANN: current study).

	Cell phone	**Alert vs. drowsy**	**Highway vs. town**	**Snowy vs. clear**
Physio (Ps)	81.8%	55.2%	86.8%	56.8%
Physio (PCA-ANN)	69.9%	**78.9%**	70.5%	**66.1%**
Vk (Ps)	64.3%	53.1%	83.3%	71.2%
Vk (PCA-ANN)	**74.1%**	**69.6%**	**99.9%**	**79.5%**
Both (Ps)	82.3%	55.2%	91.4%	71.5%
Both (PCA-ANN)	75.9%	**82.7%**	81.5%	71.1%

ferent nature of the inputs (raw data for PCA-ANN vs. extracted features in previous study) or due to the difference in classifiers. The exact reasons for the differences between the new method and the previous methods could be further investigated in future studies.

The new PCA-ANN method does have a few negative aspects as well. For instance, since we do not know what properties of the raw data are being used for classification, it is more difficult to identify the specific effect of each cause of HDS on physiology and vehicle kinematics. Another drawback of the proposed method is the trial-and-error process of choosing the ANN topology.

4 Conclusion

This study uses a previously collected driving dataset to test the performance of a PCA-ANN classification method in categorizing the presence or absence of four causes of HDS. Two types of data (physiological and vehicle kinematics) and their combination are used, and the obtained accuracies are compared with the results of the previous study. The highest classification accuracies of the proposed method were 75.9% for cell phone use, 82.7% for alert vs. drowsy driving, 99.9% for low vs. high traffic density, and 79.5% for snowy vs. clear weather. Generally, the proposed method performed better than the method of the previous study when only vehicle kinematics data was used. In the case of physiological measurements only, however, the results vary significantly – the accuracy of the PCA-ANN method ranges from 16% worse to 23% better than the results of the previous study. This high variation in results indicates that different causes of HDS require different approaches to be classified accurately.

As the next step, the developed HDS detection systems should be combined with intervention systems that will take actions to increase driver safety based on the detected HDS. These intervention systems can then be tested in simulated and real driving to determine their effect on driver safety and satisfaction.

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