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Prediction of Emergency Braking Intention Using Machine Learning Models

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Abstract

Since 2000, road accidents are on the rise, being a leading cause of death worldwide. Approximately 94% of all traffic crashes are due to human mistakes. These mistakes include speeding, reckless driving, or driving under the influence. A significant proportion of automobile accidents could be avoided with emergency braking support. Driver's status monitoring and human mistake detection are some of the most successful applications of electroencephalogram (EEG) signals. This paper proposes a prediction model for predicting the intention of the driver to use emergency braking using the driver's electroencephalogram (EEG) signals coupled with electromyography (EMG) data from leg muscles. The dataset utilized in this investigation was obtained from eighteen subjects while driving a simulated car by using an electrode cap with 64 scalp sites. The electroencephalogram (EEG) data signals are segmented to a 150 ms window and applied to five different machine learning classifiers (*k*-Nearest Neighbor, Support Vector Machine, Random Forest, Logistic Regression, and Naïve Bayes) for prediction. The proposed model can successfully predict the driver's emergency braking intention 150 ms before the moment of the brake with an accuracy of 99.6%; that is, at 100 km/h driving speed, our model can anticipate emergency braking intention 4.22 m earlier. Furthermore, the model increased the driver's prediction of emergency brake intention by 15.2% compared to other models.

Keywords: Electroencephalogram; Emergency braking; Machine learning; Prediction

1. Introduction

Since the 20th century, cars have been the primary means of transportation. Cars indicate freedom, movement, and autonomy. However, all these benefits have been significantly expensive. The World Health Organization (WHO) states that there are 1.3 million people killed in vehicle accidents each year [1]. This means 3,424 losses per day or almost two per minute. Further, 20–50 million more people are harmed or incapacitated. WHO places road accidents as the leading cause of mortality for adolescents between the ages of 15 and 24 and the world's second-largest cause of death among children aged 5 to 14 years. Shockingly, accidents cause 2.2% of all deaths worldwide [1].

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Vehicle accidents can be traumatizing. Brain and head trauma injuries are common in car crashes, for example, injuries to the neck, trauma to the brain, and spine injuries, such as fractures, strains, sprains, or disk injuries, not to mention the psychological or emotional distress as a long-term result of these incidents. Furthermore, the economy bears a massive burden as a result of car accidents. It is anticipated that the globe would suffer around $1.8 trillion from 2015 to 2030, with low- and middle-income nations suffering nearly $834 billion [2].

Driving assistance systems have been presented as a possible solution to this problem to assist and enhance human-based car control to minimize potential accidents. These systems are equipped with internal sensors (e.g., speed meters, accelerometers, and pedals) and external sensors (e.g., lidar, sonar, and visual cameras) to collect and analyze information from the car and its surroundings (e.g., the presence and condition of other cars or pedestrians) [3]. If there is an action on the brake pedal, it is perceived as the driver's affirmation of the situation's seriousness. This gives the system permission to begin an emergency braking operation once the driver touches the brake pedal, saving time [4]. Nonetheless, the brake pedal is merely the final action in a series of behavioral reactions initiated throughout an emergency braking situation. As a result, attempts have been made to recover the driver's braking intent ahead of time by taking into account additional behavioral cues, such as steering angle, foot position, head motions, and gas pedal release [4]. The purpose of this study is to provide a model that can anticipate a driver's desire to brake in an emergency braking condition using electroencephalogram (EEG) data of the driver's brain combined with the electromyography (EMG) signals from leg muscles on the brake pedal.

The remainder of the article is structured as follows: Sections 2 and 3 explain the associated work and the used methodology, respectively, section 4 demonstrates the discussion and results of this work, section 5 concludes the article, and the references are in section 6.

2. Related Work

Several studies used the driver's EEG signals to predict the intention of an emergency brake. Haufe et al. [4] conducted the first research on the link between EEG signals and emergency braking intention by utilizing event-related potential characteristics (ERP) during simulated driving. A combination of features (event-related desynchronization, event-related potential, and readiness potential) was used to distinguish between no braking, soft braking, and emergency braking intention [5]. An emergency braking intention detection model was proposed using the driver's EEG signals by applying spatial-frequency features with regularized linear discriminant analysis [6]. Three support vector machine-based classifiers were used to distinguish between 3 driving situations (no braking, soft braking, and emergency braking) using the driver's EEG signals [7]. The driver's EEG signals were integrated with surrounding data to better anticipate the driver's intention to brake [8]. A model was proposed for predicting emergency braking intention after exposing participants to fatigue, stress, and workload using a support vector machine and convolution neural networks [3]. A study was conducted on a couple of features, which were autoregressive based and EEG band power based, for detecting the driver's braking intention, but only the autoregressive-based features that were fed to an artificial neural network classifier yielded positive results [9]. A comprehensive model was developed for predicting emergency braking intention by employing convolution neural networks for feature extraction, and it proved to outperform the linear discriminant analysis [10].

3. Methodology

Figure 1 demonstrates an overview of our proposed model's architecture to predict the diver's intention to perform an emergency brake. The data for this investigation was obtained from Haufe et al.'s study [4]. The data was collected from 18 respondents, all of the same age (30.6 ± 5.4 years); four of them were females. Subjects were asked to drive a simulated car consisting of a monitor, gas/brake pedals, and steering wheel and tailed a computer-controlled vehicle. During their drive, they were exposed to a variety of scenarios where they had to do emergency braking. During each scenario, their EEG brain waves were recorded at a 1000 Hz sampling frequency from 64 scalp sites. Moreover, the EMG signals that were recorded using a bipolar montage from the right leg were used to pinpoint the moment that the subject performed an emergency brake and the corresponding EEG signal was recorded. EMG data were collected from the right leg at the moment the subject hit the brake pedal. The EEG and EMG signals were filtered and sampled at a 200 Hz sampling rate (for further details on the experiment and preprocessing, refer to reference [4]).

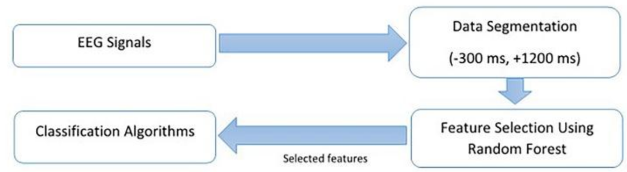

Figure 1: Proposed model architecture.

3.1. Preprocessing

The dataset contains two-time vectors, one for normal driving and one for emergency braking. Each vector contains a time record of the corresponding event's moments. To segment the EEG signals, we use the time vectors to locate each event in the original EEG data and extract a window of signals –300 ms and 1200 ms around the occurrence of each event. The average number of windows for the normal driving events was 209 windows, and an average of 219 windows for the subject's emergency brakes. Moreover, the average amplitude of the first 100 ms of the EEG data was subtracted to achieve a baseline correction segment-wise. For our prediction, we need to extract a smaller window from each segment by leaving a 150 ms gap before the moment of the brake and extracting 150 ms of EEG signals. This will be the EEG data used for classification to predict the driver's intention to perform an emergency brake, as indicated in Figure 2. All the preprocessing steps were conducted using MATLAB-Math Works R2020a.

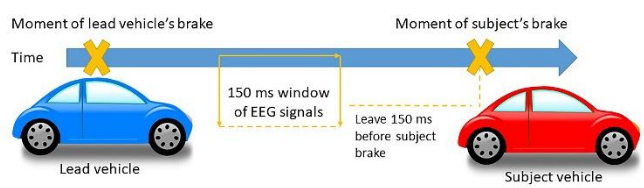

Figure 2: Extraction of various EEG signals' windows.

3.2. Classification Method

In this study, we employed five different supervised machine learning classification algorithms to classify between two classes (normal driving and emergency braking) to predict the driver's intention to perform an emergency brake. The data generated from the segmentation stage, consisting of 160,441 samples, was inputted into the Random Forest classifier for feature selection. Moreover, the selected features were split into 75% training cases and 25% test cases. The feature selection and classification algorithms were implemented on Anaconda-Jupyter Notebook using Python.

3.2.1. Random Forest Classifier

Random Forest classifier is a widely used algorithm for supervised machine learning. It is constructed from several decision trees, producing the classification prediction [11]. Not only does RF solve the overfitting problem that emerges with decision trees, but it also has less training time [12]. The hyperparameters used in this study were min_samples_leaf = 2, n_estimators = 200, n_jobs = 2, and random_state = 0.

3.2.2. Support Vector Machine Classifier

An SVM is a classifier that is driven by or composed of two ideas. The initial concept is to transform data into a high-dimensional space. This approach has the potential to reduce complicated issues (with complex decision surfaces) to more straightforward ones involving linear discriminant functions. The second principle of SVMs is driven by training and utilizing only inputs that are close to the decision surface since they give the utmost relevant details regarding classification [13].

3.2.3. *k*-Nearest Neighbor Classifier

The *k*-NN is a nonparametric, nonlinear classifier that is simple to use. It identifies a fresh sample by measuring its “distance” from a set of patterns stored in memory. The *k*-NN classifier chooses the class for this sample based on the pattern that most closely resembles it, which is the one with the shortest distance to it. Instead of choosing a single nearest neighbor sample, it is typically a majority vote among the *k*-nearest neighbors. The most often used distance function is the Euclidean distance [14]. In this study, we used $k = 10$.

3.2.4. Logistic Regression Classifier

The logistic regression, also known as binomial logistic regression, is easy to implement and efficient to train. The Logistic Regression algorithm offers a way of applying linear regression to classification issues. The classification outcome is a number between [0, 1], which is understood to represent the likelihood that the class of x is 1. Particularly, the logistic function, which is described as follows, is the sigmoid function [15].

$$f(z) = \frac{1}{1+e^{-z}} \quad \ldots, \tag{1}$$

where $z = \theta_0 + x_1\,\theta_1 + x_2\,\theta_2 + \ldots + x_n\,\theta_n$, n is the number of features (59 EEG channels), and x and θ represent the values of the EEG channels and weights, respectively.

3.2.5. Naïve Bayes Classifier

Based on Bayes’s theorem, the NB classifier gives a straightforward and probabilistic classification and claims that the retrieved attributes are independent. The NB model employs a maximum probability method to identify the class of earlier probabilities and the likelihood distribution of a feature from a training set to form the class of earlier probabilities. The results are then utilized to identify the exact class name for a brand-new test case using a maximized posterior decision tree [16].

4. Discussion and results

In this work, our aim was to predict the driver’s intention of emergency braking using EEG signals. The data utilized in this study originated from Haufe et al.’s study [4]. To forecast the driver’s intentions, we extracted a time window from the EEG data signals, leaving a 150 ms time gap before the emergency braking point. Additionally, a baseline correction was applied. For prediction, we tested five different classifiers (Random Forest, Support Vector Machine, *k*-NN, Logistic Regression, and Naïve Bayes). *k*-NN was capable of predicting the driver’s intention for emergency braking 150 ms before pressing the brake paddle with an accuracy of 99.6 percent, as shown in Table 1 and Table 2. Moreover, the model produces almost no false positives and no false negatives.

Additionally, the ROC (receiver operating characteristic) curve demonstrates the model’s excellent discrimination between normal driving and predicting emergency braking situations, which means at 100 km/h driving speed, our model was able to predict the intention of emergency braking 4.22 m earlier. Further, the SVM and the random forest classifier achieved similar results to the *k*-NN classifier with emergency braking prediction accuracy of 99% and 98.8%, respectively, as shown in Table 1 and Figure 3. However, the Naïve Bayes classifier did not perform as well as the other classifiers since it works better with categorical data.

Haufe et al. [4] used regularized linear discriminant analysis (RLDA) classifier, whereas, in our study, we used five different machine learning classifiers (*k*-NN, Support Vector Machine, Logistic Regression, Random Forest, and Naïve Bayes). Compared to [4], our model is able to distinguish between normal driving and emergency braking situations and to predict the driver’s intention to perform emergency braking 150 ms before the moment of the brake. In other words, our model is able to improve the prediction of the driver’s intention to perform an emergency brake by 15.20%.

Table 1: Performance accuracy of all classifiers.

	Random Forest	SVM	*k*-NN	Logistic Regression	Naïve Bayes

Accuracy	98.8%	99%	99.6%	80%	54%

Table 2: Classification report for all 5 classifiers.

	Classes	Precision	Recall	F_1-score
Random Forest Classifier	Normal driving	0.99	0.99	0.99
	Emergency braking	0.99	0.99	0.99
Support Vector Machine	Normal driving	0.98	1.00	0.99
	Emergency braking	1.00	0.98	0.99
***k*-NN**	Normal driving	0.99	1.00	0.99
	Emergency braking	1.00	0.99	0.99
Naïve Bayes	Normal driving	0.69	0.16	0.26
	Emergency braking	0.51	0.93	0.66
Logistic Regression	Normal driving	0.78	0.84	0.81
	Emergency braking	0.82	0.75	0.78

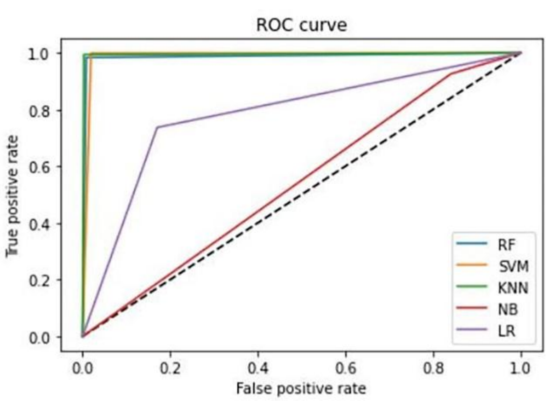

Figure 3: ROC curve for all classifiers.

5. Conclusion

This paper proposed a prediction model to predict the driver's intention to perform emergency braking using EEG data. The model predicted the driver's intention to emergency brake with a high accuracy of 99.6%. Moreover, our model improved the prediction performance by 15.2% compared to previous studies. As with the majority of studies, the design of the current study is subject to limitations, the EEG dataset used was recorded during a simulated driving experience in a car in perfect conditions. For more practical results, the EEG signals should be recorded during real-time driving, taking into consideration all the surrounding influences (e.g., driving time (day/night), rush hours, and highways) and the driver's state of mind. Additionally, it is preferable to consider more driving situations.

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التنبؤ بنيه الكبح في حالات الطوارئ باستخدام نموذج التعلم الآلي

الملخص العربي :

تزايدت حوادث الطرق منذ عام 2000 ، وهي سبب رئيسي للوفاة في جميع أنحاء العالم. ما يقرب من 94٪ من جميع حوادث المرور ناتجة عن أخطاء بشرية. تتنوع هذه الأخطاء من السرعة إلى القيادة المتهورة ، أو القيادة تحت تأثير الكحول. يمكن تجنب نسبة كبيرة من حوادث السيارات من خلال دعم الفرملة في حالات الطوارئ. تبين أن مراقبة حالة السائق واكتشاف الأخطاء البشرية من أكثر التطبيقات نجاحًا لإشارات مخطط كهربية الدماغ (EEG). تقترح هذه الورقة نموذج تنبؤ لتوقع نية السائق في إجراء الفرملة الطارئة باستخدام إشارات مخطط كهربية الدماغ للسائق (EEG) مقترنة ببيانات تخطيط كهربية العضل (EMG) من عضلات الساق. تم الحصول على مجموعة البيانات المستخدمة في هذا التحقيق من ثمانية عشر شخصًا أثناء قيادة سيارة محاكاة باستخدام غطاء قطب كهربائي مع 64 موقعًا لفروة الرأس. يتم تقسيم إشارات بيانات مخطط الدماغ الكهربائي (EEG) إلى نافذة 150 مللي ثانية ويتم تطبيقها على خمسة مصنفات مختلفة للتعلم الآلي (Random Forest ، آلة متجه الدعم ، K-Nearest Neighbor ، الانحدار اللوجستي ، و Naïve Bayes) للتنبؤ. يمكن للنموذج المقترح أن يتنبأ بنجاح نية الكبح الطارئة للسائق قبل 150 مللي ثانية قبل لحظة الفرامل بدقة 99.6٪ ، مما يعني أنه عند سرعة قيادة تبلغ 100 كم / ساعة ، يمكن لنموذجنا توقع نية الكبح في حالات الطوارئ قبل 4.22 مترًا. علاوة على ذلك ، زاد النموذج من توقع السائق لنية فرملة الطوارئ بنسبة 15.2 في المائة مقارنة بالطرازات الأخرى.