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# Driver Distraction Detection Using Bidirectional Long Short-term Network Based on Multi-scale Entropy of EEG

Xin Zuo, Chi Zhang, Fengyu Cong, Jian Zhao, and Timo Hämäläinen

***Abstract*—Driver distraction diverting drivers' attention to unrelated tasks and decreasing the ability to control vehicles, has aroused widespread concern about driving safety. Previous studies have found that driving performance decreases after distraction and have used vehicle behavioral features to detect distraction. But how brain activity changes while distraction remains unknown. Electroencephalography (EEG), a reliable indicator of brain activities has been widely employed in many fields. However, challenges still exist in mining the distraction information of EEG in realistic driving scenarios with uncertain information. In this paper, we propose a novel framework based on Multi-scale entropy (MSE) in a sliding window and Bidirectional Long Short-term Memory Network (BiLSTM) to explore the distraction information of EEG to detect driver distraction based on multi-modality signals in real traffic. Firstly, MSE with sliding window is implemented to extract the EEG features to determine the distraction position. Statistical analysis of vehicle behavioral data is then performed to validate driving performance indeed changes around distraction position. Finally, we use BiLSTM to detect driver distraction with MSE and other traditional features. Our results show that MSE notably decreases after distraction. Consistent with the result of MSE, driving performance significantly deviates from the normal state after distraction. Besides, BiLSTM performance of MSE outperforms other entropy-based methods and is better than behavioral features. Additionally, the accuracy is improved again after adding MSE feature to behavioral features with a 3% increasement. The proposed framework is useful for mining brain activity information and driver distraction detection applications in realistic driving scenarios.**

***Index Terms*—Driver distraction, EEG, driving performance, MSE, BiLSTM**

## I. Introduction

NOWADAYS, the traffic system is highly developed with the increasing number of cars on road. Unfortunately, traffic accidents have become frequent. The World Health Organization reported that over 1.35 million people were killed and about 50 million were injured due to traffic accidents all over the world in 2018 [1]. According to the National Highway Traffic Safety Administration (NHTSA), one of the major contributory factors of traffic accidents is driver distraction [2].

Driver distraction is a diversion of attention away from activities critical for safe driving (i.e., the task of driving) toward a competing activity (e.g., using a cell phone) [3]. In a survey released by Ford Motor Company and Tsinghua University in 2017, almost 39% of respondents caused or nearly caused an accident because of distraction [4]. Due to the use of cell phones and advanced infotainment systems in cars, drivers' attention is often taken away from roads while driving, thus reducing their abilities to control the vehicles and to aware of the surroundings causing more accidents [5]-[7]. What's more, it can also increase the reaction time to the upcoming obstacles [8]. Using cell phones even topped the list for distracted driving reported in 2017 [4].

The existing research about driver distraction mechanism usually could be divided into four different types: manual distraction, audio distraction, visual distraction, and cognitive distraction [9]-[12]. In the previous studies, the subjects were usually asked to perform a specific secondary task while driving for a certain type of distraction to obtain distracted data and then to analyze driver distraction. For instance, "operate devices" tasks are usually used to get the manual distraction signals. Wollmer *et al.* [13] chose eight tasks (e.g., adjust radio sound settings, switch the TV mode and so on) as manual distraction conditions to get the vehicle behavioral signals. They found that tasks with different levels of difficulty would cause different degrees of distraction. As for cognitive distractions, Anh Son *et al.* [14] set an n-back task of digit recall in a simulated situation as well as in a naturalistic situation to impose cognitive workload. The result showed that tasks accompanied by high

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cognitive demand had effects on the drivers' eye involuntary movement and would cause a high level of distraction. Although these experiment designs of different kinds of distraction tasks mainly lead to a specific type of distraction to some degree and contribute to the research of distraction mechanism, it usually involves more than one type of distraction in realistic driving situations. For example, when drivers are asked to adjust the radio sound settings for collecting the manual distraction signals in a distraction experiment, they firstly should find where the button is and then turn it to the required place. This process involves not only the manual distraction but also the visual distraction. As driver distraction is a product of the driver-vehicle-environment interaction, its forms are not fixed and usually a combination of different types of distraction in real scenarios. Thus, there is still challenge in the detection of driver distraction in real driving scenarios.

In fact, previous studies have explored many kinds of sensing technologies to detect driver distraction. A commonly used technology is video camera capturing drivers' facial and body behaviors (e.g., gaze movement and head pose) [15]. This kind of method can easily collect the visual data and conveniently detect distraction. However, the results are sensitive to the illumination, facial occlusion, and drivers' behavioral habits. The Controller Area Network-Bus (CAN-Bus) data providing the vehicle behavioral information is also widely utilized in the field. It mainly includes the speed, lateral position, and steering wheel angle, etc. [16]-[19]. The facilities of this kind of method are easy to obtain and quite low cost, but the signals are subject-dependent and influenced by the weather and traffic conditions easily [20]. There is also some work that has been done by using the microphone to collect the acoustic signals for driver distraction detection [21], [22]. The performance of this approach is acceptable, but it just works for audio distraction. Moreover, wearable sensors have also been employed to get the human's physiological signals such as electroencephalography (EEG), electrocardiogram (ECG), and electrooculography (EOG) [23]-[25]. EEG is the predominant and most used signal among all physiological signals. Although physiological signals provide more reliable results for representing drivers' real internal state, the data collecting process is intrusive and may to some degree affect drivers' behaviors.

In recent years, with the development of portable and less intrusive equipment as well as the multi-sensor collection techniques, more and more researchers tend to use hybrid signals to study driver distraction, for it is widely agreed that no single signal alone could provide sufficient information about driver distraction [26],. Li *et al.* [27] collected data from video cameras, microphone arrays and CAN-Bus to model drivers' behavior while executing secondary tasks. Zhang *et al.* [28] utilized vehicle behavioral signal, EMG, acoustic signal as well as visual signal for detecting driver distraction. Lechner *et al.* [29] designed a lightweight framework involving signals of driver movement and GPS position to recognize driver inattentiveness. In addition, Almahasneh *et al.* [30] conducted a simulated driving experiment to study how EEG and driving performance changes because of cognitive secondary tasks. They found that the effects of driver distraction can be clearly seen in the lane keeping ability and accidents occurrence level. As EEG provides reliable information of brain activities, and vehicle behavioral signals reflect the changes of driving performance, it is obvious that the system performance would be improved if EEG and vehicle behavioral signals are employed at the same time to develop driver distraction detection system. In this context, we propose a multi-modality driver distraction detection framework in real driving scenarios based on EEG and vehicle behavioral signals.

The paper is organized as follows. Section II lists the related works about the literature review. Section III introduces the accomplished experiment details and the captured signals used in our research. The adopted methodologies are described in Section IV. Results of the study are presented in Section V and discussed in Section VI. Finally, Section VII concludes the paper.

## II. RELATED WORK

There are two major parts in driver distraction detection including the feature extraction part and classification part. Various features are adopted to explore distraction information existing in different types of data. Many researchers analyzing driver distraction based on EEG in the literature, and they usually extract the frequency domain, or the time domain features of EEG to mine the distraction information. Fan *et al*. [31] calculated the energies of different EEG rhythms and their ratios as frequency domain features of EEG and used them for distraction detection. Yang *et al*. [32] extracted the power spectral density and log-transformed power of four EEG waves to evaluate the distraction detection performance. Barus *et al.* [33] used not only frequency domain features but also time domain features of EEG like kurtosis and Hurst Exponent to detect drivers' cognitive load. However, it still only achieved about 70% accuracy. As we all know, EEG signals are recorded directly on the scalp surface and the reflection of the driver's internal electrical activity originated by the brain [34]. But they are also quite complex containing a large amount of information [35]. The conventional features can surely represent the frequency or time domain features of EEG, but how to manifest the complexity of EEG still needs to be further studied. It can reflect the non-linear dynamic changes of the brain activities and manifest the complex distraction information by analyzing the EEG signals of the distracted drivers from the perspective of complexity. The complexity-based algorithm is currently widely utilized in many other areas (e.g., fatigue analysis, emotion classification and sleep staging) and has shown advantages. For example, Gao *et al.* [36] implemented the wavelet entropy to investigate the EEG-based fatigue driving and found that a significant difference exists between the alert and fatigue states. Zheng *et al.* [37] trained an advanced deep learning model with differential entropy. The results showed that differential entropy possesses accurate and stable information of EEG data for emotion classification. Tang [38] applied sample entropy and fuzzy entropy to represent the features of the sleeping EEG data. He demonstrated that the two kinds of features could effectively improve the accuracy of sleep staging. In these studies, the dynamic changes of EEG during fatigue and sleep are reflected through the complexity-based features.

In spite of the existing advantages, a significant challenge still remains in the distracted EEG analyzing procedure based on complexity features. Actually, no matter what kinds of preprocessing methods are adopted, the artifacts cannot be eliminated completely and will still exist to a certain extent [39]. In this case, the residual noise will be included in the complexity of EEG while calculating the complexity-based feature, and the robustness of the obtained result will be relatively poor. Multi-scale entropy (MSE) can reduce the influence of residual noise on the results by calculating complexity features in different time scales [40] and has been successfully used in many fields. Azami *et al.* [41] calculated the MSE feature as well as variate MSE features of the EEG signals to observe the dynamical complex properties in the EEG signals gathered from Alzheimer's disease (AD). They found that MSE could characterize the EEG changes in a detailed way. Luo *et al.* [42] proposed a method based on MSE to detect driver fatigue. The result showed that MSE can obviously present the fatigue features and effectively improve the accuracy of fatigue detection.

As for how to recognize driver distraction, there are many classification techniques utilized in the literature to detect whether a driver is distracted or not. Traditional methods like support vector machines (SVM) and multiple adaptive regression trees (MART) are widely employed in various research areas. Liao *et al.* [43] proposed a method to detect cognitive distraction based on the optimal features extracted by SVM and classify driver state based on SVM. It also compared the SVM performance between two different driving situations. Wu *et al.* [44] used SVM to recognize flight operating patterns based on physiological parameters and reached an average accuracy of 0.84. Torkkola *et al.* [45] described an approach based on MART to find the inattention duration while driving according to the vehicle data. It could detect about 80% of the driver inattention time segments. Besides, deep learning methods has been applied to recognize mental status in the literature. In the work of Wu *et al.* [46], they proposed a stacked contractive sparse antoencoders network to detect the mental status of pilots. What's more, they also designed a gamma deep belief network to study the cognitive status of pilots, which could learn the EEG features with simplest network structure [47]. However, traditional deep learning methods usually learn the information in a single time point and it has been revealed that the time dependencies are critical in predicting human's mental status [48]. Recurrent Neutral Network (RNN) is a typical deep learning method with memory that could keep the information from the contexts and then make decisions. However, the vanishing gradient problem occurs when the input data is too long (i.e., to keep long-term memory) [49]. As a variant of RNN, Long Short-term Memory Network (LSTM) has the property of capturing both short and long-term dependencies, which has been successfully applied to many time-series classification tasks such as driver identification, seizure detection and driver behavior classification [50]-[52]. It is realized by adding memory blocks in the hidden unit to mine for and store critical information for classification over long time periods [53]. Kouchak *et al.* [54] proposed a distraction recognition method based on LSTM and validated that it outperformed multilayer neural network (MLP) for considering dependency between input data. Wollmer *et al.* [13] used LSTM to model the long-term dependency in vehicle behavioral data for detecting driver distraction. They also made a comparison with SVM and found the classification accuracy of LSTM was obviously higher than that of SVM. Recently, the Bidirectional Long Short-term Memory Network (BiLSTM), an improvement of LSTM, has been proved to achieve better performance than traditional one directional LSTM in fields of sleep apnea detection and text classification [55], [56]. As BiLSTM learns long-term dependencies both from former time steps to later time steps and from later time steps to former time steps, it could learn and store more useful information thus improving the performance of the model [57].

In this paper, we propose a framework for driver distraction detection based on MSE with a sliding window and vehicle features. Our approach, using BiLSTM, is to model the bidirectional contextual information in EEG and vehicle behavioral data captured in real scenarios. To collect the distracted EEG and vehicle behavioral signals, a distracted driving experiment is firstly performed in realistic driving situations. The MSE in a sliding window is then implemented to extract the features of the captured EEG signals. Statistical analysis is performed on the vehicle behavioral data to find out whether significant differences appear in driving behaviors before and after distraction. After that, BiLSTM classifier is utilized to learn the time dependent relationships in the extracted MSE and vehicle statistical features and to detect driver states. Finally, the classification accuracy of BiLSTM is compared with four different types of traditional classifiers.


Fig. 1. The distraction experiment scene.

## III. EXPERIMENT DESIGN

In order to collect the data reflecting the physiological and vehicle behavioral changes of the distracted drivers, we conducted an experiment in realistic driving scenarios. This section is a description of the participants, the data collection system, and the procedure.

### A. Participants

This study was reviewed and approved by Ethics Committee, Dalian University of Technology. There were six right-handed subjects without mental illness or neurological diseases involved in the experiment. All subjects have normal or corrected to normal vision and normal auditory. A driving license and driving experience are required for each subject. All of the subjects owe smartphones and are experienced in using WeChat (an online chatting APP in China). What's more, they are banned from consuming coffee, tea, alcohol as well as smoking the day before the experiment. The qualification of each subject was verified and informed consent from each subject was obtained prior to the experiment.

### B. Data collection system

The experiment was conducted on a real straight road at Dalian University of Technology. The Mangold-10 Bluetooth enabled wireless multipurpose polygraph, a portable and non-intrusive data acquisition headband, was used to collect drivers' EEG signals. It transmitted the EEG data via wireless Bluetooth. As the headband is designed to have little effects on drivers' behaviors, and more importantly, previous studies have demonstrated that the occipital brain region is related to driver mental state [58], [59], we put the electrodes on O1 and O2 in accordance with the International 10-20 System. The sampling rate was kept at 256 Hz.

As the car signals could provide useful information about the vehicle's behavior, a car equipped with sensors was used as the experimental car. The vehicle behavioral data including speed and deceleration with a sampling frequency of 50 Hz was analyzed in our present study. Fig. 1 shows the experiment scene.

### C. Procedure

All subjects were given written and oral instructions on the driving experiment. To obtain the data of the distracted drivers, a "cellphone use" task was set as distracting factor. The distracting task could be described simply as: The drivers were asked to use WeChat for at least 3 seconds when they drove to half of the distance.

Each subject participated in two sessions amounted to six trials of the experiment. The first driving session was one normal driving trial (i.e., driving without distracting task) which lasted for at least 6 seconds. The second session included five distracted driving trials (i.e., performing the "cellphone use" task while driving), each trial lasted for around 20 seconds and the task began at about 12 seconds. There was a short break after each trial.

During the experiment, one experimenter was in the car together with the subject and gave hints for the start and end of the task. In the normal driving process, subjects were asked to drive down the road with full attention. However, they were supposed to drive normally at first in the distracted driving process, few seconds later the experimenter would send cellphone messages to them. After receiving messages, they had to check the messages for 3 seconds at least. In addition, another experimenter would throw a quadrate foam box to the road while each trial was going to end, and subjects were required to react to the obstacle as soon as possible. The EEG signal and the vehicle behavioral signals were recorded all the way from the car starting to stopping.

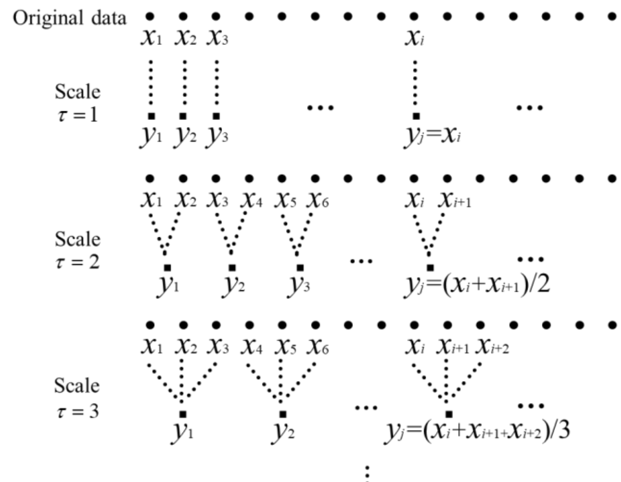


Fig. 2. Schematic illustration of the coarse graining process.

## IV. Methodology

### A. Analysis of EEG data

The process of EEG analysis contains three steps: preprocessing, artifacts removal and feature extraction.

#### 1) Preprocessing

We first extracted the EEG segments corresponding to the duration of each trial in our study. Then, the alpha frequency band was obtained applying wavelet decomposition, as previous studies have demonstrated that the alpha frequency band is highly correlated with distraction [30], [60].

Wavelet transform is a time-frequency analysis method, which can reflect the local features of signals both in the time and frequency domain. And with the property of multi-resolution, it is widely used to analyze non-stationary signals [61]. A mother wavelet $\psi(t)$, in order to decompose the signal, is utilized in this method. The signal can be decomposed and expressed in terms of scaled and shifted versions of $\psi(t)$ and a corresponding scaling function $\phi(t)$ in discrete domain [62]. The discrete mother wavelet is represented as

$$\psi_{j,k}(t) = 2^{\frac{j}{2}}\psi\left(2^{-j}t - k\right), \qquad k, j \in \mathrm{Z} \tag{1}$$

The signal $S(t)$ then can be expressed as

$$S(t) = \sum_k s_j(k)\phi_{j,k}(t) + \sum_k d_j(k)\psi_{j,k}(t) \tag{2}$$

where $s_j(k)$ and $d_j(k)$ are the approximate and detailed coefficients at level $j$.

In this paper, the EEG signal has been decomposed into 4 levels in which the detailed component at level 4 roughly represents the alpha band (8-13 Hz). Since db6 (Daubechies family) is similar to the EEG signal in our case as shown in Fig. 3, it is selected as the mother wavelet.

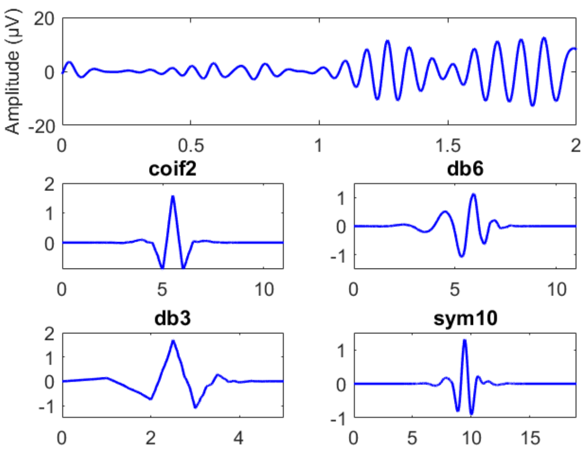


Fig. 3. Alpha wave and typical mother wavelets.

*2) Artifacts removal*

After preprocessing, the artifacts (e.g., the blinks) in the alpha band were then removed using a wavelet-based technique. The wavelet coefficients mentioned above represent the correlation between the signal and the selected mother wavelet. High amplitude coefficients will be generated at places where artifacts present. We can eliminate these kinds of coefficients utilizing a thresholding technique. It has been proven to be effective in the analysis of driver fatigue [63], [64]. The threshold can be defined as

$$T_j = mean(C_j) + 2 \times \text{std}(C_j) \tag{3}$$

where $C_j$ represents the wavelet coefficient at the $j$th level of wavelet decomposition. If the value of any coefficient is greater than the computed threshold, it is halved. Then the new set of wavelet coefficients are reconstructed to obtain the wavelet-corrected signal.

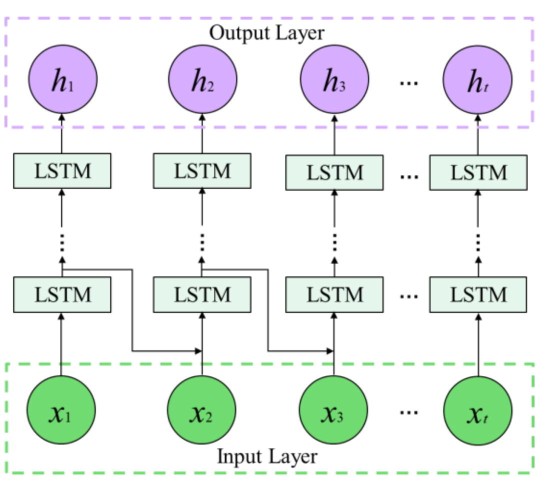


Fig. 4. The basic topological structure of LSTM.

*3) Feature extraction*

MSE extends the idea of Sample entropy (SE) to several time scales and is an effective method to quantify the complexity of a time series over different time scales. Time series with large fluctuation will produce a larger MSE value, which is considered to have high complexity. Similarly, a highly regular time series will generate lower entropy. This method was first proposed by Costa *et al.* in 2002 [65].

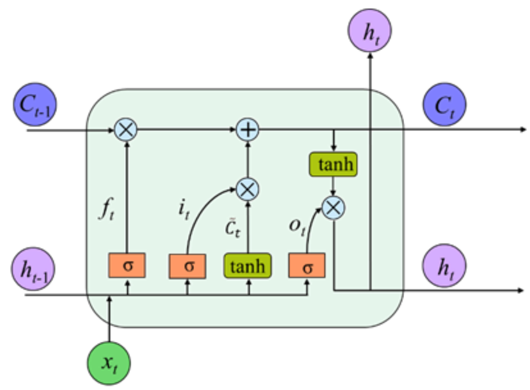


Fig. 5. The details of a LSTM cell.

There are two steps in MSE analysis: coarse graining and SE calculation. Considering the EEG signal $\{x_1, \ldots, x_i, \ldots, x_N\}$, we should construct a consecutive coarse-grained time series $\{y^{(\tau)}\}$, corresponding to the time scale factor $\tau$: Firstly, the original EEG signal is divided into non-overlapping windows of length $\tau$, then the data points inside each window are averaged (see Fig. 2). Each coarse-grained time series can be defined as

$$y_j^{(\tau)} = \frac{1}{\tau} \sum_{i=(j-1)\tau+1}^{j\tau} x_i, \quad 1 \le j \le N/\tau \tag{4}$$

After the coarse graining procedure, SE is calculated for the obtained time series $\{y^{(\tau)}\}$. For a time series $\{y_1, \ldots, y_j, \ldots, y_n\}$, it can be made up into an $m$ dimension vector $Y^m(i) = [y(i), y(i+1), \ldots, y(i+m-1)],\ 1 \le i \le n-m$. And $d$, the distance between $Y^m(i)$ and $Y^m(j)$ is defined as

$$\begin{gathered} d = \max[|\, y(i+k) - y(j+k) \,|], \\ 0 \le k \le m-1, i \ne j, 1 \le j \le n-m \end{gathered} \tag{5}$$

Then count the number of $d < r$ for each $i$, and $B_i^m(r)$ can be expressed as

$$B_i^m(r) = \frac{\{\text{the number of } d < r, i \ne j\}}{(n-m-1)} \tag{6}$$

where $r$ is the given tolerable distance. The set of $B_i^m(r)$ are then averaged and the average value can be calculated by

$$B^m(r) = \frac{1}{n-m} \sum_{i=1}^{n-m} B_i^m(r) \tag{7}$$

Add the dimension by 1 to form an $m$+1 dimension vector and repeat the above process, then we can get $B^{m+1}(r)$. After all the procedures, the basic definition of SE is given by

$$\text{SE}(m, r) = \lim_{n \to \infty} \left[ -\ln \frac{B^{m+1}(r)}{B^m(r)} \right] \tag{8}$$

When $n$ is finite, it can be calculated by the following expression:

$$\mathrm{SE}\left(m,r,n\right)=-\ln\left[\frac{B^{m+1}\left(r\right)}{B^{m}\left(r\right)}\right] \tag{9}$$

In Narayan's study, it has been revealed that MSE changes with time scale and there will be a peak indicating the existence of maximum entropy at that time scale, which indicates high correlation exists in time scale and MSE value [66]. In this paper, the maximum MSE appears when time scale is five, then 5-scale MSE with a sliding window is calculated for the extracted alpha frequency band.

### B. *Statistical analysis of vehicle behavioral data*

The speed data and the deceleration data, corresponding to the duration of each trial, were further analyzed after the experiment. Statistical analysis was performed in MATLAB. To find out whether there were significant differences between the vehicle behavioral data before and after distraction, we firstly carried out significance tests on the vehicle behavioral data. Then the mean value and the standard deviation of the data were calculated to investigate the changes before and after distraction.

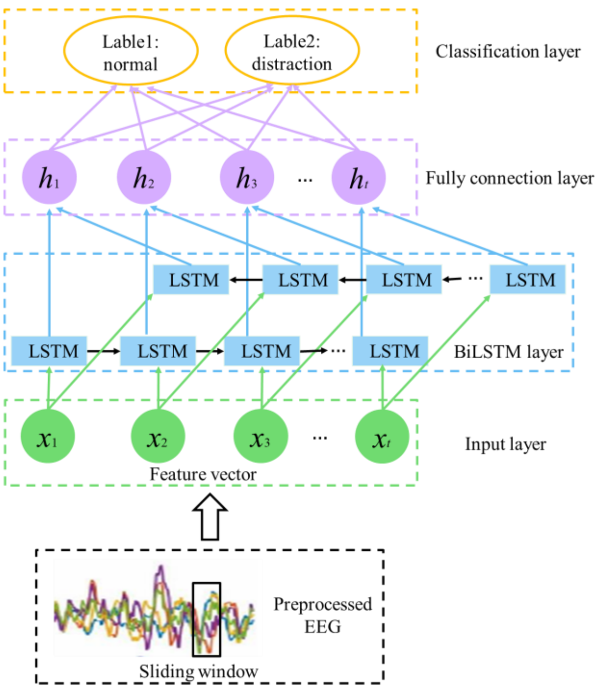


Fig. 6. Schematic illustration of the BiLSTM framework.

### C. *BiLSTM*

LSTM is a special kind of RNN, capable of addressing the vanishing gradient problem. It was firstly introduced by Hochreiter *et al.* [53] in 1997. LSTM has two major features compared with RNN [67]. One feature is that it can learn both short and long-term dependencies (i.e., keep both short and long-term memory). The other is that it cannot only add useful information but also remove irrelevant details during the learning process. Fig. 4 is the basic topological structure of LSTM. It consists of a chain of repeating modules of neural networks. The repeating module of LSTM has four neural network layers (see Fig. 5) unlike the standard RNN having one, and they interact in a specific way.

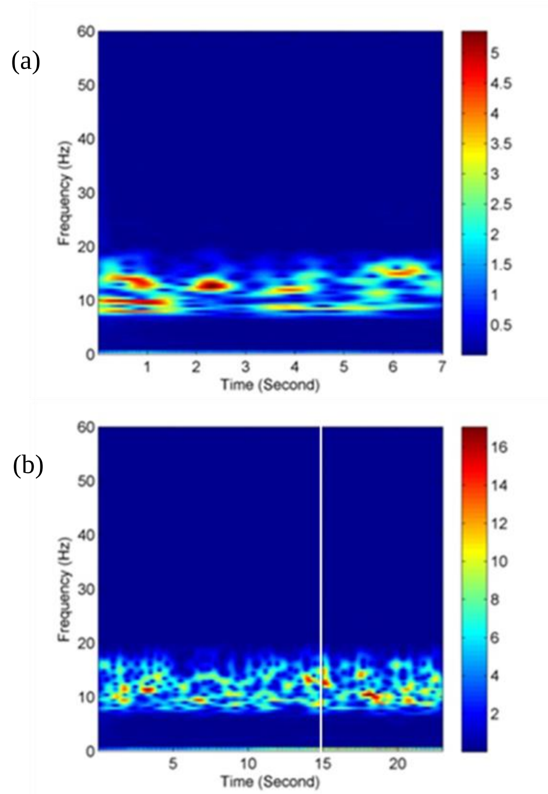


Fig. 7. The time-frequency results of alpha band. (a) Result of normal driving trial. (b) Result of distracted driving trial. The white solid line in (b) shows the onset of using cellphone.

A LSTM cell can add or remove information through structures called "gate". There are totally three types of gates in it: forget gate, input gate and output gate. They work as follows. At first, it is to decide what information should be removed from the cell state by forget gate (10). Then the input gate decides what new information is going to store in the cell state. This step can be divided into three parts. The first part is to use a sigmoid layer to find what is going to be updated using (11). Next is to create a new candidate cell state $\tilde{C}_t$ by a tanh layer (12). After that, the old cell state $C_{t-1}$ can be updated into the new cell state $Ct$ by (13). Finally, the output gate is activated to decide the output $h_t$ of the cell by using (14) and (15).

$$f_t=\sigma\left(W_f\cdot\left[h_{t-1},x_t\right]+b_f\right) \tag{10}$$

$$i_t=\sigma\left(W_i\cdot\left[h_{t-1},x_t\right]+b_i\right) \tag{11}$$

$$\tilde{C}_t=\tanh\left(W_C\cdot\left[h_{t-1},x_t\right]+b_C\right) \tag{12}$$

$$C_t=f_t*C_{t-1}+i_t*\tilde{C}_t \tag{13}$$

$$o_t=\sigma\left(W_o\cdot\left[h_{t-1},x_t\right]+b_o\right) \tag{14}$$

$$h_t=o_t*\tanh(C_t) \tag{15}$$

In these equations, $\sigma$ and tanh are the active functions in the cell, $W$, $h$, and $b$ represent the weight, hidden state, and bias separately. $x_t$ indicates the EEG feature of time $t$ in Figs. 4-6.

As the traditional the one directional LSTM usually learns the long-term information only from previous time steps to latter time steps, and research has found that the inputs of the latter time steps also contain some information about the inputs of the previous time steps [68]. BiLSTM, an update of LSTM, consists of two layers of LSTM. One layer processes the inputs in a forward direction, and the other learns information from the inputs in a backward direction. Additionally, it can also concatenate the two directions interpretations according to long-term dependency in the inputs. In this study, we use both LSTM and BiLSTM to learn the dependency among the extracted features and compare their performance for driver distraction recognition. The BiLSTM model structure diagram used here is shown in Fig. 6.

## V. RESULTS

### A. *Analysis of EEG data*

Time-frequency analysis of the extracted alpha frequency band was firstly performed. Fig. 7(a) shows the time-frequency graph of the normal driving trial and Fig. 7(b) is the result of a distracted driving trial. We also calculated the mean absolute amplitudes of alpha band, the results are shown in Fig. 8. During the normal driving process, the activity of alpha band showed a trend of decreasing, while it increased after using cellphone in the distracted driving process as shown in Fig. 7 and Fig. 8. Then the 5-scale MSE feature was calculated to extract the valuable information of the EEG signal. From the MSE result, we can see there is an obvious decrease after using cellphone. Fig. 9 gives the results of the MSE for both normal trial and distracted trial. Fig. 9(a) is the waveform of the normal driving trial, and the result of the distracted driving trial is shown in Fig. 9(b). It can be seen that the waveform in distracted trials fluctuated obviously. The MSE value began to decrease notably after the onset of distraction task and reached the minimum value a few seconds later after the task. Besides, the trough of MSE waveform was obviously lower than the average of MSE. However, there were small and gentle fluctuations in normal trials as shown in Fig. 9(a). The time that MSE reaches its minimum value is defined as the EEG most distraction position (DP) of the subject pointed out in Fig. 9(b). According to the MSE results, the EEG most distraction positions of all subjects could be obtained. The time difference between DP and the onset of using cellphone was then calculated and listed in Table I. Trial 1, which is the normal driving process, is excluded from the table.

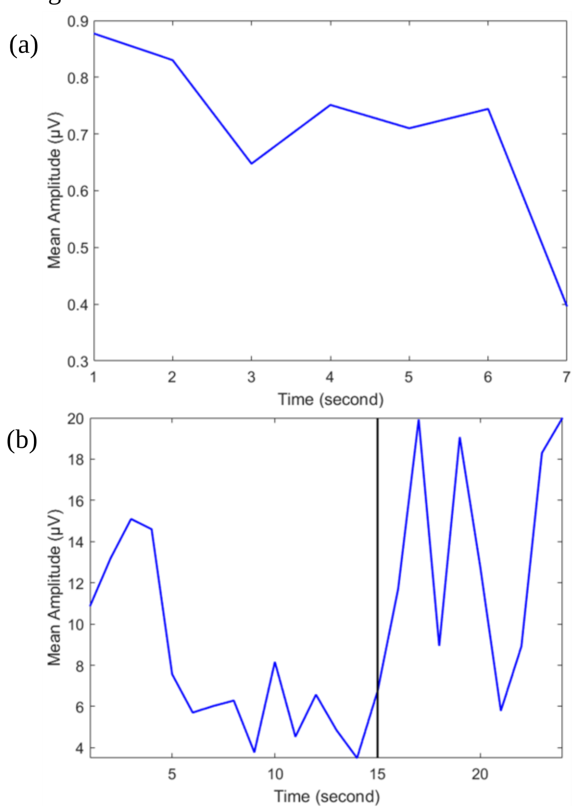


Fig. 8. The mean absolute amplitudes of alpha band. (a) Result of normal driving trial. (b) Result of distracted driving trial. The black solid line in (b) shows the onset of using cellphone.

### B. *Statistical analysis of vehicle behavioral data*

The statistical analysis of the obtained vehicle behavioral data (i.e., speed and deceleration data) was performed to validate abnormal changes also appear in driving performance before and after distraction. This section consists of two parts: the first part is to analyze data that before and after the subjects start to use cellphone, the other is before and after DP of the subjects.

#### 1) *Analysis of the vehicle data before and after using cellphone*

In this part, the speed and deceleration data before and after using cellphone was analyzed to investigate the impact of distraction task on the driving performance.

TABLE I
THE TIME DIFFERENCE BETWEEN DP AND THE ONSET OF USING CELLPHONE OF ALL SUBJECTS (S)

| Subject \ Trial | 2 | 3 | 4 | 5 | 6 |
|---|---|---|---|---|---|
| 1 | 1 | 0 | 0 | 1 | 2 |
| 2 | 4 | 4 | 1 | 5 | 8 |
| 3 | 1 | 2 | 4 | 8 | 0 |
| 4 | 1 | 5 | 5 | 7 | 1 |
| 5 | 5 | 5 | 7 | 5 | 5 |
| 6 | 2 | 0 | 3 | 7 | 2 |

At the beginning of the analysis, we performed unpaired $t$-test on the vehicle data in each trial to verify whether significant differences exist between the data before and after using cellphone. The significance level is set as 0.05. The $t$-test results are shown in Table II and Table III. Trial 2 to Trial 6 are distracted driving processes that drivers were asked to use cellphone while driving. $h$ indicates if there are significant differences between the vehicle data before and after distraction. $h$ = 1 means significant differences exist. $h$ = 0 means no significant differences. $p$ represents the probability that the data before and after distraction is distributed identically.

From the results of the speed data, we can see clearly that there are significant differences between the speed before and after using cellphone except for Trial 3. All trials show significant differences between the two conditions in deceleration data shown in Table III.

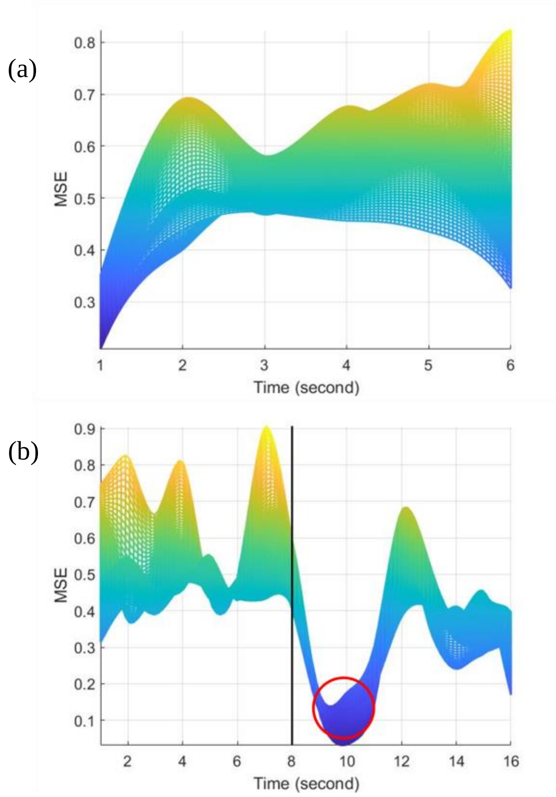


Fig. 9. The MSE results of alpha band. (a) Result of normal driving trial. (b) Result of distracted driving trial. The black solid line shows the onset of using cellphone and the red circle is the distraction position of this trial in (b).

TABLE II
THE *T*-TEST RESULTS OF THE SPEED DATA

| Trial | 2 | 3 | 4 | 5 | 6 |
|---|---|---|---|---|---|
| *h* | 1 | 0 | 1 | 1 | 1 |
| *p* | < 0.05 | 0.935 | < 0.05 | < 0.05 | < 0.05 |

TABLE III
THE *T*-TEST RESULTS OF THE DECELERATION DATA

| Trial | 2 | 3 | 4 | 5 | 6 |
|---|---|---|---|---|---|
| *h* | 1 | 1 | 1 | 1 | 1 |
| *p* | < 0.05 | < 0.05 | < 0.05 | < 0.05 | < 0.05 |

The statistical features (i.e., mean value and standard deviation) of speed and deceleration before and after using cellphone are calculated and listed in Table IV - Table VII separately. "Before" and "After" represent before and after distraction, respectively.

TABLE IV
THE MEAN VALUE OF SPEED (km/h)

| Trial | 2 | 3 | 4 | 5 | 6 |
|---|---|---|---|---|---|
| Before | 5.877 | 5.397 | 5.145 | 5.410 | 5.496 |
| After | 5.406 | 5.331 | 4.903 | 4.775 | 5.094 |

TABLE V
THE MEAN VALUE OF DECELERATION (m/s$^2$)

| Trial | 2 | 3 | 4 | 5 | 6 |
|---|---|---|---|---|---|
| Before | -0.131 | -0.121 | -0.126 | -0.134 | -0.114 |
| After | 0.234 | 0.246 | 0.277 | 0.229 | 0.232 |

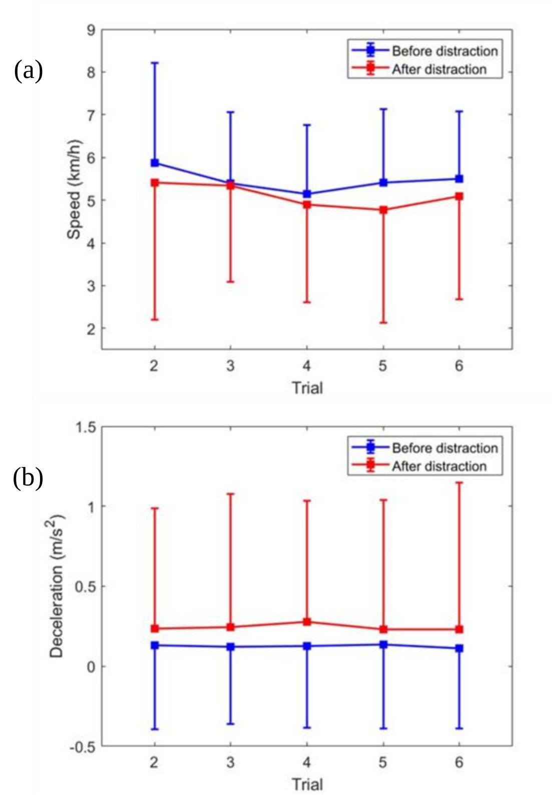


Fig. 10. Statistical results of the vehicle data. (a) The mean value of speed. (b) The absolute value of mean deceleration. Error bar shows the standard deviation.

All of the mean values of speed before using cellphone are greater than those after distraction in Table IV and Trial 3 has the smallest gap between the two conditions. Table V shows that the mean values of deceleration before using cellphone are all negative and that the mean values become positive after distraction. When comparing the absolute values of the deceleration mean values, it is obvious that the absolute values after using cellphone are greater than that of before distraction.

TABLE VI
THE STANDARD DEVIATION OF SPEED

| Trial | 2 | 3 | 4 | 5 | 6 |
|---|---|---|---|---|---|
| Before | 2.343 | 1.657 | 1.613 | 1.720 | 1.583 |
| After | 3.199 | 2.240 | 2.294 | 2.641 | 2.411 |

The standard deviations of the speed and deceleration data reflect the same trend that all of them becomes greater after using cellphone shown in Table VI and Table VII. The changing patterns of the speed and deceleration data could also be clearly shown in the following error bar figures (see Fig. 10) according to the statistical results.

TABLE VII
THE STANDARD DEVIATION OF DECELERATION

| Trial | 2 | 3 | 4 | 5 | 6 |
|---|---|---|---|---|---|
| Before | 0.523 | 0.484 | 0.508 | 0.523 | 0.502 |
| After | 0.752 | 0.832 | 0.760 | 0.810 | 0.915 |

### 2) *Analysis of the vehicle data before and after the most distraction position*

The vehicle behavioral data before and after the EEG most distraction position (DP) was also analyzed. The analyzing procedure in this part was similar to 1). To explore whether significant differences exist between the vehicle data before and after DP, unpaired *t*-test was firstly performed with the assumption that all subjects are considered as a whole.

The test results are shown in Table VIII and Table IX. It is clear that significant differences do exist in all trials for both speed and deceleration before and after DP.

TABLE VIII
THE *T*-TEST RESULTS OF THE SPEED DATA

| Trial | 2 | 3 | 4 | 5 | 6 |
|---|---|---|---|---|---|
| *h* | 1 | 1 | 1 | 1 | 1 |
| *p* | $< 0.05$ | $< 0.05$ | $< 0.05$ | $< 0.05$ | $< 0.05$ |

TABLE IX
THE *T*-TEST RESULTS OF THE DECELERATION DATA

| Trial | 2 | 3 | 4 | 5 | 6 |
|---|---|---|---|---|---|
| *h* | 1 | 1 | 1 | 1 | 1 |
| *p* | $< 0.05$ | $< 0.05$ | $< 0.05$ | $< 0.05$ | $< 0.05$ |

Then the mean value and the standard deviation of the data before and after DP were calculated separately. Table X to Table XIII give the results. We can see from Table X that all of the mean values of speed before DP are obviously greater than that of after DP. Table XI shows that the mean values of deceleration before DP are negative and that after distraction the mean values are positive. Besides, the absolute values of the mean deceleration after DP are greater than before DP. As for the standard deviation, it becomes greater after DP showed in Table XII and Table XIII.

TABLE X
THE MEAN VALUE OF SPEED (km/h)

| Trial | 2 | 3 | 4 | 5 | 6 |
|---|---|---|---|---|---|
| Before | 5.795 | 5.394 | 5.175 | 5.495 | 5.584 |
| After | 5.440 | 4.987 | 3.938 | 2.615 | 4.562 |

TABLE XI
THE MEAN VALUE OF DECELERATION ($m/s^2$)

| Trial | 2 | 3 | 4 | 5 | 6 |
|---|---|---|---|---|---|
| Before | -0.068 | -0.061 | -0.070 | -0.045 | -0.098 |
| After | 0.204 | 0.249 | 0.447 | 0.413 | 0.353 |

The error bar figures are drawn as Fig. 11 according to the statistical results. The changing rules mentioned above could be easily seen from the figures. Compared with Fig. 10, the statistical differences of the vehicle behavioral data between before distraction and after distraction increase in Fig. 11.

TABLE XII
THE STANDARD DEVIATION OF SPEED

| Trial | 2 | 3 | 4 | 5 | 6 |
|---|---|---|---|---|---|
| Before | 2.454 | 1.631 | 1.634 | 1.725 | 1.475 |
| After | 3.286 | 2.679 | 2.630 | 3.134 | 2.843 |

TABLE XIII
THE STANDARD DEVIATION OF DECELERATION

| Trial | 2 | 3 | 4 | 5 | 6 |
|---|---|---|---|---|---|
| Before | 0.615 | 0.591 | 0.534 | 0.596 | 0.493 |
| After | 0.671 | 0.780 | 0.912 | 1.009 | 1.067 |

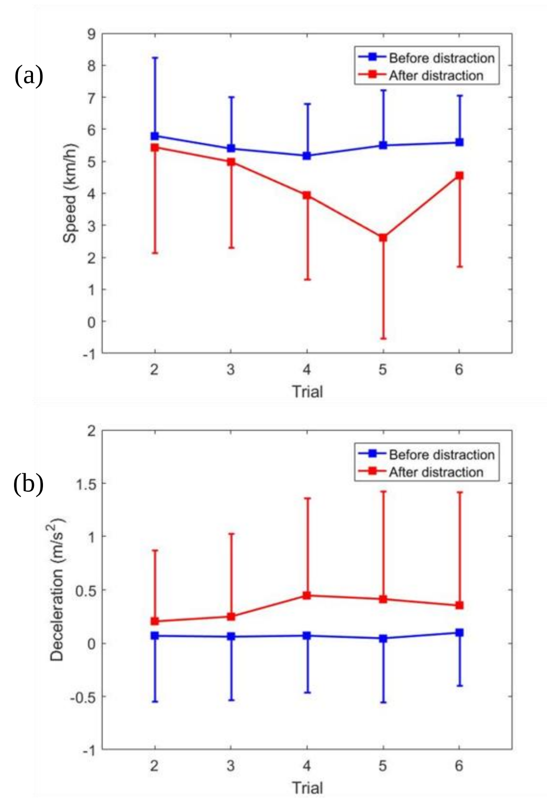


Fig. 11. The statistical results of the vehicle data. (a) The mean value of speed. (b) The absolute value of the deceleration mean value. Error bar shows the standard deviation.

## C. *The classification results of BiLSTM*

In this paper, we not only analyzed the dynamic brain activity changes of distracted driving based on MSE and the changes in driving performance but also detected whether a driver is distracted or not using BiLSTM. The detection results were compared with four different types of traditional classifiers, i.e., LSTM, SVM, convolutional neural network (CNN) and *k*-nearest neighbor (kNN). In addition, to be more reliable and convincing, the results were also compared with the results of traditional vehicle behavioral features and another four entropy-based algorithms i.e., Approximate entropy (AE), Differential entropy (DE), Fuzzy entropy (FE) and Sample entropy (SE) of

EEG.

We built and trained a BiLSTM model, which adopted the calculated feature matrixes as inputs and output the category vectors. There are 2 categories in the paper: distraction and non-distraction. The data of five subjects were used for training and that of the remained subject was utilized for testing. In the training process, different numbers of LSTM layers and training iterations were tried to find the best model in the BiLSTM classifier. The classification results of different features are shown in Table XIV. “VS” means statistical features (i.e., mean and standard deviation) of speed and deceleration.

TABLE XIV
THE MEAN ACCURACIES OF DIFFERENT CLASSIFIERS FOR DIFFERENT FEATURES (%)

| Feature | AE | DE | FE | SE | MSE | VS | VS+MSE |
|---|---|---|---|---|---|---|---|
| BiLSTM | 83.29 | 82.67 | 76.35 | 67.01 | 91.83 | 89.85 | 92.48 |
| LSTM | 82.24 | 81.31 | 71.03 | 63.55 | 89.72 | 88.79 | 91.59 |
| CNN | 62.62 | 73.63 | 62.01 | 60.32 | 73.90 | 67.29 | 78.5 |
| SVM | 52.94 | 54.6 | 54.27 | 56.75 | 66.72 | 74.85 | 77.76 |
| kNN | 69.45 | 71.93 | 67.12 | 59.05 | 65.34 | 76.84 | 77.07 |

Table XIV shows that the performance of BiLSTM and LSTM are much better than those of the other three common classifiers and that the BiLSTM model is slightly better than the conventional LSTM modal. As for the results of different features using BiLSTM and LSTM, the mean accuracy of the LSTM and BiLSTM using MSE of EEG reaches 89.72% and 91.83%, respectively, which is clearly higher than the results of using vehicle statistical features and other entropy-based methods. The SE feature of EEG leads to the lowest classification accuracy of 63.55% in LSTM and 67.01% in BiLSTM, and the accuracy of the other algorithms lies between the accuracy of SE and MSE. When inputting the features of EEG and vehicle data at the same time, the performance of BiLSTM increases, peaking at 92.48%. The accuracy of LSTM also improved under this condition. In sum, when we just use the EEG features to train the BiLSTM model, the best result is obtained by the MSE feature. Besides, MSE feature of EEG also performs better compared with the result of conventional vehicle behavioral features in BiLSTM, and the mean accuracy is about 3% higher than that of VS when we add MSE feature to the vehicle behavioral features.

## VI. DISCUSSION

The concern for driver distraction is growing in recent years with the development of advanced infotainment systems. There are many effects and characteristics of driver distraction [9]-[12]. The distraction information of the dynamic brain activity and the changing rules of vehicle behavioral data before and after distraction are here discussed. A driver distraction classification model using BiLSTM is proposed based on the MSE feature, and the results are compared with four kinds of traditional classifiers as well as other conventional feature extraction methods.

As shown in Fig. 7 and Fig. 8, the activity of the alpha frequency band is related to driver distraction, which increases after being distracted. However, it shows a trend of decreasing with the process of the normal driving trial. The results are consistent with previous studies that the activity of alpha rhythm increases in parietal-occipital brain regions if attentional lapses occur [69], [70]. The important changes in MSE feature of EEG after being distracted can be seen in Fig. 9. The EEG complexity is clearly illustrated by the fluctuation of MSE feature. The MSE value decreases sharply when drivers start to use cellphone (see Fig. 9(b)) compared with normal driving, which indicates that the complexity of the alpha frequency band decreases while distraction. Drivers have to keep high alertness to pay attention to the surroundings like the pedestrians and other cars so that they can drive safely in the normal driving process [71]. In this situation, the brain activity is usually active, and it embodies the relatively high complexity of the alpha frequency band. Contrary to normal driving, drivers’ perceptions of driving and the surroundings decrease while using cellphone and then the complexity also decreases, thus leading to the decreased MSE value while distraction. The time difference for each trial in Table I means that it usually takes drivers a few seconds to shift their attention to the task related work. Hence, DP occurs a few seconds later after drivers start to use cellphone.

Statistical analysis of the vehicle behavioral data before and after using cellphone is then performed considering all subjects as a whole. From the *t*-test results [Table II and Table III] of the speed and deceleration data, we confirm that the performance of drivers to control cars is highly affected by the “cellphone use” task, which has been validated in previous studies [72]-[74].

For the statistical analysis results, drivers tend to drive at a lower and much safer speed after beginning to use cellphone shown in Table IV and Fig. 10(a). Many studies have proved that drivers attempt to reduce their workload by decreasing speed while distracted [75], [76], which explained why the mean speed is lower after distraction than that before distraction. Besides, Trial 3 shows the smallest gap between before and after using cellphone. It is because that the changes between the two conditions in this trial are not obvious as listed in Table II. As shown in Table V, the mean deceleration is negative before using cellphone due to the stepwise accelerating stage in this process. However, it becomes positive after using cellphone. A possible reason for the phenomenon is that drivers tend to decrease speed for safety while distracted. What’s more, the absolute value of the mean deceleration before using cellphone is apparently lower than after using cellphone in Fig. 10(b), which indicates that distracted drivers often make emergency brakes when obstacles appear. When drivers begin to use cellphone, they are distracted by the task and their abilities to monitor the environment may be reduced, the decision to brake would then be consequently delayed. As a result, drivers will have to brake harder to avoid accidents. This explanation is in accordance with the results of Hancock *et al.* [77]. Their work reported that distracted drivers responded slowly to the traffic lights and had to take stronger braking actions to compensate for the delay in starting braking.

In line with previous driver distraction analysis, the variability of the speed and deceleration data increases after using cellphone in Table VI and Table VII. The change can also be seen from the error bar in Fig. 10. The previous study reported that variability in velocity increased while drivers performing auditory tasks as attention need to be shifted to the task processing streams from focusing on driving leading to the performance decrements [78]. In our study, drivers pay more attention to the task and the brake pedal controlling ability is then weakened. Hence, greater variability occurs in speed and deceleration, which explains why greater standard deviations appear.

In this paper, vehicle behavioral data analysis is discussed not only before and after using cellphone, but also before and after DP. Identical to the analyzing process before and after using cellphone, the speed and deceleration data are analyzed firstly considering all subjects as a whole. Results in Table VIII and Table IX imply that significant changes emerge in driving performance between conditions before and after DP as a consequence of distraction, which is also consistent with previous studies in [72]-[74]. Furthermore, the mean value and standard deviation of speed and deceleration are analyzed to find out how drivers are affected by the “cellphone use” task. As shown in Table X and Fig. 11(a), the mean speed in each trial after DP is visibly greater than that before DP. The results are agreed with the work of Reimer [75] and Mehler [76], pointing out that distracted drivers usually try to decrease speed to reduce workload and keep safe. As for the results of mean deceleration shown in Table XI, the same inference with Table V can be made. the mean deceleration is negative in the accelerating stage before DP, which becomes positive after DP when obstacles abruptly appear in the process. Moreover, compared to Table V, the difference value of the mean deceleration before and after distraction in Table XI is greater, which indicates the performance of controlling the brake pedal after DP is even weaker than after beginning to use cellphone. The absolute value of the mean deceleration is also compared in Fig. 11(b). Note that the ability to monitor the surroundings after DP may be reduced and then the decision on when to brake is delayed. Therefore, drivers have to make harder brake to avoid obstacles [77]. In addition, the variability of speed and deceleration also increases after DP in Table XII and Table XIII, which shows the same rules as the same as in Table VI and Table VII. Previous studies have validated that drivers will shift their attention to the task after distraction [78], thus the ability to handle the brake pedal is weakened. As a result, augmentation variability appears in speed and deceleration.

After mining the valuable information of driver distraction based on MSE feature of EEG and analyzing the changes in driving performance, we finally use BiLSTM to show that driver distraction can be detected with the MSE features. The classification results in Table XIV indicate that the classification accuracy of MSE using BiLSTM is better than traditional vehicle behavioral features and other entropy-based features since it can not only present the complex distraction information of EEG but also reduce the influence of the residual noise on the results [40]. The classification accuracy of MSE is comparable with the research of Li *et al.* [79], which used the temporal and spatial features of the 32-channel EEG signals and reached an accuracy of 92%. Besides, Xie *et al.* [80] also collected six kinds of vehicle signals and smartphone sensor signals to detect driver distraction. The accuracy of VS using BiLSTM in our work is 3% higher than their accuracy obtained from traditional classifiers. The performance of the trained BiLSTM model is further improved with an accuracy of 92.48% when adding MSE features to the statistical features of vehicle behavioral data, which suggests that MSE features could remedy the inadequacy of traditional vehicle behavioral features. It is consistent with the observation in the literature that hybrid signals can provide more sufficient information about driver distraction than one type of signal alone [28]. In addition, the performance of BiLSTM is compared to four conventional classifiers in the study. The results in Table XIV show that BiLSTM, which could learn the bidirectional long-term dependency among the extracted features, is slightly better than traditional one directional LSTM and significantly better than CNN, SVM and kNN. It corresponds to the results in [67] that BiLSTM can decrease the model’s train and test error and thus improve the classification accuracy. The reliable results of the study suggest the potential to mine the distraction information in realistic driving environment and to detect driver distraction using MSE and BiLSTM.

The limitation of the study is that only six persons participated in the experiment, so the dataset is a little bit small to some degree. It is difficult to collect the data with driver distraction in realistic driving scenarios. The sample size, while acceptable for distraction detection, had limited statistical power.

## VII. CONCLUSION

In this paper, we have applied the BiLSTM model to present a driver distraction detection framework based on the complexity-based MSE feature of EEG. It demonstrates that it is better to use MSE to explore the complex dynamic distraction information of EEG than other features used in the previous studies. Besides, compared to conventional vehicle behavioral features, the model performance is enhanced by adding features of EEG to features of vehicle data. It confirms that the MSE feature can provide complementary information about distracted drivers. For a driver, the MSE value of EEG decreases obviously in the distraction process and the ability to manipulate the vehicle is also greatly influenced, which is manifested in the decreased speed, harder brakes as well as the increased variability of speed and deceleration.

In the future work, an experiment will be designed in driving simulator involving more participants and more types of signals to study driver distraction applying the proposed method. The new dataset containing multi-modality signals provides better opportunities for further investigating the effectiveness of different kinds of signals in detecting driver distraction. What’s more, an improvement of the present algorithm will also be explored to detect driver distraction accurately. Another particular interest is to study the influence of the left- and right-handed in the detection performance in the future.

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