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A Complex Network-Based Broad Learning System for Detecting Driver Fatigue From EEG Signals

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***Abstract*—Driver fatigue detection is of great significance for guaranteeing traffic safety and further reducing economic as well as societal loss. In this article, a novel complex network (CN) based broad learning system (CNBLS) is proposed to realize an electroencephalogram (EEG)-based fatigue detection. First, a simulated driving experiment was conducted to obtain EEG recordings in alert and fatigue state. Then, the CN theory is applied to facilitate the broad learning system (BLS) for realizing an EEG-based fatigue detection. The results demonstrate that the proposed CNBLS can accurately differentiate the fatigue state from an alert state with high stability. In addition, the performances of the four existing methods are compared with the results of the proposed method. The results indicate that the proposed method outperforms these existing methods. In comparison to directly using EEG signals as the input of BLS, CNBLS can sharply improve the detection results. These results demonstrate that it is feasible to apply BLS in classifying EEG signals by means of CN theory. Also, the proposed method enriches the EEG analysis methods.**

***Index Terms*—Broad learning system (BLS), complex network (CN) analysis, driver fatigue detection, electroencephalogram (EEG) signals.**

I. Introduction

A MENTAL fatigue state is a psychobiological state which results from a prolonged intensive cognitive work [1]. Mental fatigue may lead to the absence of concentration, the decline of work efficiency and sometimes impairs the physical performance in humans to some extent [2]. As a kind of cognitive activities, the driving process demands for the high concentration of our brains. Drivers under the fatigue state are prone to lose fast and accurate emergency response capacity and good judgment, which is a huge threat for the road safety. Many vehicle crashes and traffic injuries were reported in association with driver fatigue [3]. Therefore, in order to lessen the economic and societal loss, it is an extreme necessity to develop a driver fatigue detection method.

Until now, various indicators of humans have been used to monitor mental fatigue, including facial expressions [4], [5], and several physiological variables like heart rate variability [6], electroencephalogram (EEG) [7]–[9], electromyogram (EMG), and electrocardiogram (ECG) [10], [11]. Among them, EEG brain signals are widely used because they are closely linked to physical and mental activities [12]. Besides, the rising of varied portable and low-cost acquisition apparatuses for EEG signals makes the EEG-based driver fatigue detection accessible. So in this article, we put our concern on the EEG-based driver fatigue recognition task. In this area, numerous works have been accomplished to detect the fatigue state. The work of [13] proposed an EEG-based drowsiness-estimation system where independent component analysis (ICA), power spectrum analysis, correlation evaluation, and linear regression model were applied collectively. In [14], four frequency features were used to train the support vector machine (SVM) to automatically analyze EEG signals during car driving. The study of [15] extracted wavelet entropy (WE) from EEG signals to be fed into SVM for classifying the fatigue state and normal state.

In recent years, deep learning (DL) techniques experience a soaring development and have been applied in varied image analysis areas, including human pose recovery [16], single image super-resolution [17], and brain tumor segmentation [18], to name a few. Except for the image processing field, diverse physiological signals analysis works have also been benefited a lot from the development of DL. In [19], a time-frequency convolutional neural network (CNN) was designed for emotion recognition task from EEG signals. The work of [20] put forward a deep CNN-based method for identifying patients with paroxysmal atrial fibrillation (PAF) from ECG signals. In [21], a deep belief network (DBN) was proposed to classify emotion states from EEG recordings. In the EEG-based driver fatigue detection field, DL techniques have also received widespread attention, like channel-wise CNN [22] and EEG-based spatio–temporal CNN [23].

The stacking of multilayer nonlinear units makes an access for DL to automatically learn representative features from input data [24], [25]. However, many DL structures frequently suffer from time-consuming training process because vast hyper-parameters and complicated structures are involved.

Manuscript received January 25, 2019; revised May 17, 2019 and July 31, 2019; accepted November 23, 2019. This work was supported by the National Natural Science Foundation of China under Grant 61922062 and Grant 61873181. The work of J. Kurths was supported by RSF under Project 17-15-01263. This article was recommended by Associate Editor E. Chen. *(Corresponding author: Zhongke Gao.)*

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Digital Object Identifier 10.1109/TSMC.2019.2956022

Recently, a novel broad learning system (BLS) was provided from the work of [26], which is an alternative pattern of learning in deep structure and can avoid the above problems of the DL model. This system is derived from a random vector functional link neural network (RVFLNN) [27], [28] which has no requirement to a long training process and enables to dynamically update the output weights. Basic BLS is composed of three steps. First, the input data is mapped as mapped features and stored in feature nodes; second, the feature nodes are transferred into enhancement nodes for broad expansion; finally, all the feature nodes and enhancement nodes are connected to the output and the connection weights are calculated by ridge regression of the pseudoinverse. The broadness of BLS is realized by the expansion of both feature nodes and enhancement nodes. The network weights computation in BLS is solved by ridge regression meaning fewer iterations are required to train BLS. Moreover, BLS needs fewer training samples, which benefits from fewer network parameters in BLS [29]. Nowadays, BLS is still in infancy. Most of the existing works of BLS are still concentrating on the image research area [30], [31]. Whether it can be used to the signal classification area is an appealing subject.

Recently, the complex network (CN) theory has received extensive attentions, due to its capacity of characterizing the topologies of complex systems [32]–[35]. A classical CN is composed of numerous nodes and edges which is decided by the interrelationships between nodes. In this way, a complex system with numbers of interconnected units is then mapped into a network and a corresponding network matrix can be received. As the brain is also an acknowledged complex system [36], CN theory has also received an extensive concern in brain research, like Alzheimers disease [37], biometric system research [38], and sleep deprivation research [39]. Among these existing CNs, the recurrence network is a method which could detect the recurrence properties of a complex system [40], and recurrence network-based methods have been employed to study real-world systems like the cardiorespiratory system [41], climate [42], and multiphase flow systems [43]. In addition, for EEG-based fatigue research, multivariate weighted recurrence networks (MWRNs) were developed aiming at characterizing the difference of the brain cognitive process between mental fatigue and normal states [44]. In MWRN, each channel represents one node and the interchannel relationship is characterized by an index which enables to detect the phase and generalized synchronization even in nonstationary time series [45]. Thus, EEG signals can be mapped into a network and the elements in the network matrix are carrying the information of raw signals. The network matrix resembles an image, which is the traditional input of BLS. Therefore, we propose a CN-based BLS (CNBLS) for providing a solution for the application of BLS to the EEG-based driver fatigue detection task.

This article is organized as follows. In Section II, a driver fatigue experiment is introduced and EEG signals both in alert state and fatigue state are collected and preprocessed for the following analysis. In Section III, we offer a detailed description of the construction of MWRN, the principle of BLS, and the overall framework of CNBLS. In Section IV, the test results are provided and four existing methods are compared with our CNBLS. Finally, the conclusions and an outlook for future applications of the novel model in other EEG recognition studies are given in Section V.

Fig. 1. Simulating experimental setup for obtaining EEG signals under alert and fatigue driving states.

II. Experiments

A. Subjects and Experiment Procedure

The EEG acquisition experiments were conducted in the Laboratory of CNs and Intelligent Systems at Tianjin University, China. The experimental process was approved by the ethics committee of General Hospital Affiliated to Tianjin Medical University in China.

In this article, 11 right-handed, healthy and without psychiatric-related disorders students (seven males and four females, mean age 23.5 ± 1.7 years), recruited from Tianjin University, participated in the experiment. For the subjects, the intake of anti-fatigue drinks and drowsiness-causing pills was not allowed and enough rest with over 7 h was required two days before the experiment. In addition, the experiment was conducted in an indoor driving simulator, but the subjects had no experience in them. Therefore, all the subjects were required to have some practices until they were skilled. Besides, before the experiment, all the subjects were given written consent where information like the design and purpose of the experiment were given.

The adopted driving simulator was equipped with a steering wheel, a clutch, a brake pedal, and an accelerator. The driving scene was set at a flat highway with few bends and views, and the day was selected on a sunny day. Furthermore, a webcam 360D618 was added for monitoring the facial state of the subjects and a projector as well as a stereo cabinet were applied for better visual perception. The experimental scene is shown in Fig. 1.

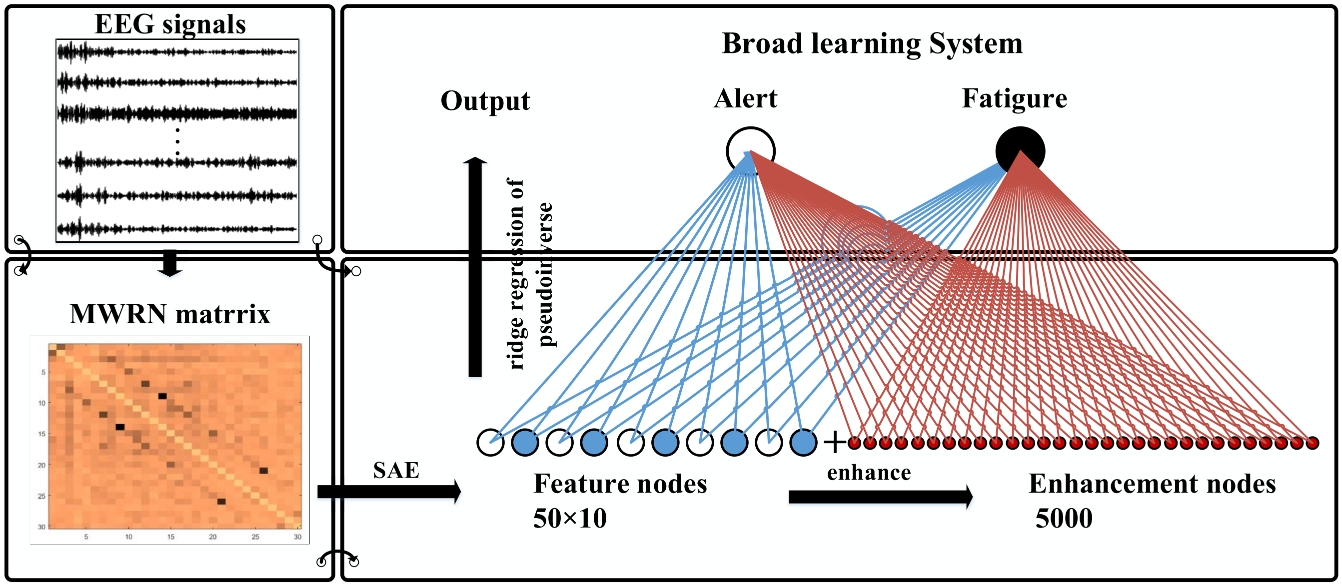

Fig. 2. Flow chart of the proposed CNBLS.

Each experiment begun at 14:00 and lasted about 90 min because, at this period, subjects were shown to be easier to fall into the fatigue state. In addition, subjects were suggested to stop the experiment at any time if any discomfort appeared or they were too sleepy. All subjects were suggested to avoid unnecessary body movement during data collection. During driving, they were advised to drive at a constant speed and avoid traffic collision as far as possible.

The 9-point Karolinska sleepiness scale (KSS) [46], which gives an evaluation from 1 (extremely alert) to 9 (very sleepy), was applied for subjective assessment of fatigue level. According to KSS, drivers state was classified into three parts, namely, alert, mild fatigue, and fatigue state. All subjects began their data acquisition after a KSS survey for ensuring their alertness. Then they kept driving until reporting their mild fatigue, which commonly lasted about 30 min as an alert state. Next, after a 10-min driving for transition, they went into another 30-min driving which was considered as fatigue state. After finishing the whole driving task, they were asked to do a post-experiment survey.

As the experiment procedure was a little boring and repetitive, the drivers' fatigue level was supposed to increase over time. Actual facial state, an essential physiological measurements of fatigue states, combined with subjective assessment, demonstrated the gradually increased fatigue.

B. Data Acquisition and Preprocessing

The EEG signals were collected by a 40-channel recording cap (Neuroscan, America) where the electrodes were arranged according to the standard international 10/20 system. The left and right mastoids were set as reference electrodes. Four electrodes, horizontally and vertically placed around eyes, were electrooculogram (EOG) monitor. The sampling rate was 1000 Hz in this experiment.

The acquired data were preprocessed by EEGLAB software where the raw signals were filtered into 1–50 Hz by a band-pass FIR filter. As there are artifacts in collected EEG signals, some blind source separation (BSS) methods have been developed to remove these artifacts [47]. In this article, the widely used ICA was applied to remove artifacts. Then the signals were downsampled into 200-Hz for decreasing the computation burden. After this preprocessing procedure, we obtain clean 30-channel signals for each subject.

We removed the data from the mild fatigue state for each subject and labeled the first 20 min of the driving process as an alert category and the last 20 min as fatigue category. The data from the two categories are divided into a series of 1 s samples without overlapping. Then for each subject, there are totally 2400 samples and each category has 1200 samples.

III. Methods

CNBLS starts from the construction of MWRN namely the transform of EEG signals and then the obtained network matrix is fed into the BLS for driver fatigue detection. The flow chart of the proposed technique is shown in Fig. 2.

A. Construction of MWRN

The driver fatigue detection system starts from the construction of MWRN, by transforming the EEG data to a network matrix like an image representation. The basic idea of MWRN is the calculation of the synchronization index which describes the generalized synchronization between two systems [45]. Thereafter, we consider each channel of the EEG signals as a node and regard the synchronization index as the weight between two channels to construct the MWRN.

The process of calculating the synchronization index and constructing MWRN is as follows. First, for multichannel EEG signals $\{x_{k,l}\}_{l=1}^{L}, k = 1, 2, \ldots, p$ containing p subsignals of equal length L, a phase-space reconstruction is performed on each subsignal, respectively, to generate p trajectories $\vec{x}_k(t)$

$$\vec{x}_k(t) = \left(x_{k,t}, x_{k,t+\tau}, \ldots, x_{k,t+(m-1)\tau}\right)$$
$$t = 1, 2, \ldots, N, k = 1, \ldots, p \tag{1}$$

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where N is the number of vector points in each trajectory, m is the embedded dimension determined by the false nearest neighbors (FNNs) algorithm [48], and τ is the time delay decided by the C-C [49] method. Then, the single-channel recurrence plot (RP) is used to visualize the behavior of each trajectory in phase space

$$\mathrm{RP}_{i,j}^{\vec{x}_k}\left(\varepsilon^{\vec{x}_k}\right) = \Theta\left(\varepsilon^{\vec{x}_k} - \|\vec{x}_k(i) - \vec{x}_k(j)\|\right)$$
$$i = 1, \ldots, N \quad j = 1, \ldots, N \tag{2}$$

where $\varepsilon^{\vec{x}_k}$ is an adaptive threshold for controlling the density of recurrence points in the RP, namely, the recurrence rate (RR) to be 0.1, and i as well as j are the vector points of current trajectory. Thus, for each p subsignals, we obtain p RPs. In order to describe the pair-wise relationship between RPs, the joint RP (JRP) [50] is introduced. It characterizes the joint probability that recurrences of pair-wise subsignals happen simultaneously. JRP can be obtained by

$$\mathrm{JRP}_{i,j}^{\vec{x}_{k1},\vec{x}_{k2}}\left(\varepsilon^{\vec{x}_{k1}}, \varepsilon^{\vec{x}_{k2}}\right) = R_{i,j}^{\vec{x}_{k1}}\left(\varepsilon^{\vec{x}_{k1}}\right) R_{i,j}^{\vec{x}_{k2}}\left(\varepsilon^{\vec{x}_{k2}}\right). \tag{3}$$

On this JRP, the density of recurrence points is depicted by the following joint RR:

$$\mathrm{JRR}(\vec{x}_{k1}, \vec{x}_{k2}) = \frac{1}{N^2} \sum_{i,j=1}^{N} \mathrm{JRP}_{i,j}^{\vec{x}_{k1},\vec{x}_{k2}}. \tag{4}$$

Finally, we infer the synchronization index of pair-wise subsignals as follows:

$$S(\vec{x}_{k1}, \vec{x}_{k2}) = \frac{\mathrm{JRR}(\vec{x}_{k1}, \vec{x}_{k2})}{\mathrm{RR}}. \tag{5}$$

Thus, for a multichannel EEG signals containing p subsignals, a synchronization matrix with size $p \times p$ is acquired which is then mapped into an MWRN.

B. Driver Fatigue Detection With BLS

The algorithm of BLS starts from a feature mapping process. For an input dataset X with N samples and M dimensions, n feature mappings, each of them has k nodes, are conducted through the following equations:

$$Z_i = \phi(XW_{ei} + \beta_{ei}), \quad i = 1, \ldots, n \tag{6}$$

where W_{ei} and β_{ei} are randomly produced. Notably, sparse autoencoder is then used to fine-tune the random features for receiving better feature mappings. Thereafter, the n feature mappings' combination $Z^n \equiv [Z_1, \ldots, Z_n]$ is enhanced by

$$H_m \equiv \xi\left(Z^n W_{hm} + \beta_{hm}\right) \tag{7}$$

where m represents the mth group of the enhancement nodes. Thus, the output matrix Y can be expressed as

$$\begin{aligned} Y &= \left[Z_1, \ldots, Z_n | \xi\left(Z^n W_{h1} + \beta_{h1}\right)\right. \\ &\qquad \left. \ldots, \xi\left(Z^n W_{hm} + \beta_{hm}\right)\right] W^m \\ &= [Z_1, \ldots, Z_n | H_1, \ldots, H_m] W^m \\ &= \left[Z^n | H^m\right] W^m \end{aligned} \tag{8}$$

where W^m is the connecting weights from the feature and enhancement nodes to the output matrix. It can be determined through the problem

$$\underset{W^m}{\operatorname{argmin}} \left\| \left[Z^n | H^m\right] W^m - Y \right\|_2^2 + \lambda \left\| W^m \right\|_2^2 \tag{9}$$

where λ indicates further constraints on the sum of W^m. In order to solve the problem, the ridge regression is used and then W^m can be calculated by

$$W^m = \left(\lambda I + \left[Z^n | H^m\right]^T \left[Z^n | H^m\right]\right)^{-1} \left[Z^n | H^m\right]^T Y. \tag{10}$$

In this equation, if there is no constraint, namely $\lambda = 0$, then the above equation can be simplified into the least square problem. If the constraint is infinite with $\lambda \to \infty$, then the solution tends to 0. Thus, we set $\lambda \to 0$ here. Adding an approximation to the Moore–Penrose generalized inverse of $[Z^n | H^m]$ [51], then W^m can be received by

$$W^m = \left[Z^n | H^m\right]^+ Y \tag{11}$$

where

$$\left[Z^n | H^m\right]^+ = \lim_{\lambda \to 0} \left(\lambda I + \left[Z^n | H^m\right]^T \left[Z^n | H^m\right]\right)^{-1} \left[Z^n | H^m\right]^T. \tag{12}$$

In this article, the number of feature mappings n, the number of nodes in feature mapping k, and the number of enhancement nodes m are set as 10, 50, and 5000, respectively. The back propagation (BP) is used to fine-tune the enhancement nodes and connecting weights. Notably, in order to overcome individual differences of subjects, some previous works applied model transfer strategy to construct models for each subject [52], [53]. However, in this article, we construct the CNBLS model and adjust the parameters of the model on one subject. Then the adjusted model is generalized to the data of other subjects. The following results can indicate that our model has a strong generalization capability on each subject.

IV. Results and Discussion

The effectiveness of the proposed method is verified on the experimental datasets described in the previous experiment part. In addition, the results are compared with the results obtained from four existing methods. Furthermore, whether the signals can be directly fed into BLS is discussed and different incremental learning strategies are compared in this section.

A. Results

In this part, a rigorous validation way is performed on each subject's dataset. Specifically, for each subject, we select out the first 300 samples out from all 1200 samples of each category to train the CNBLS model. Then, the last 300 samples of each category are considered as the testing samples to verify the effectiveness of the proposed model. Thus, there is a 10-min interval between training and testing samples which can effectively avoid the influences resulted from the continuity of time series. Finally, we have 600 samples for training the model and 600 samples for the test.

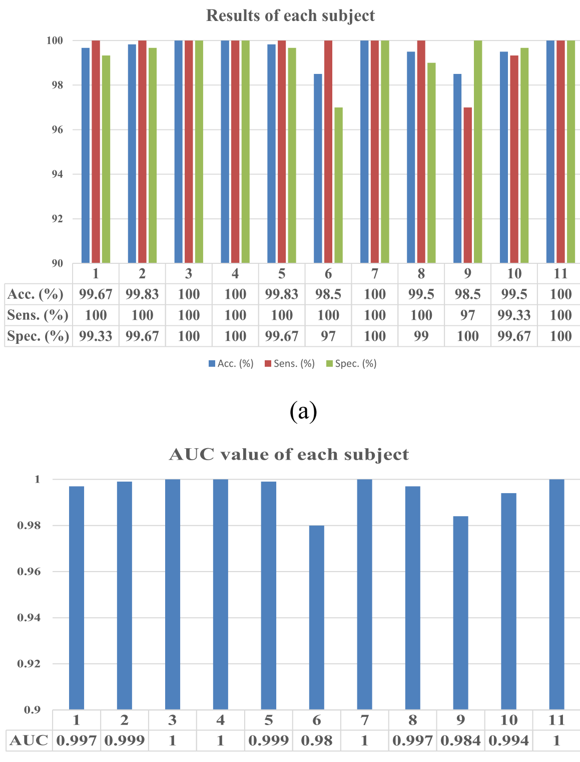

Fig. 3. Accuracy (Acc.), sensitivity (Sens.), specificity (Spec.), and AUC value of each subject.

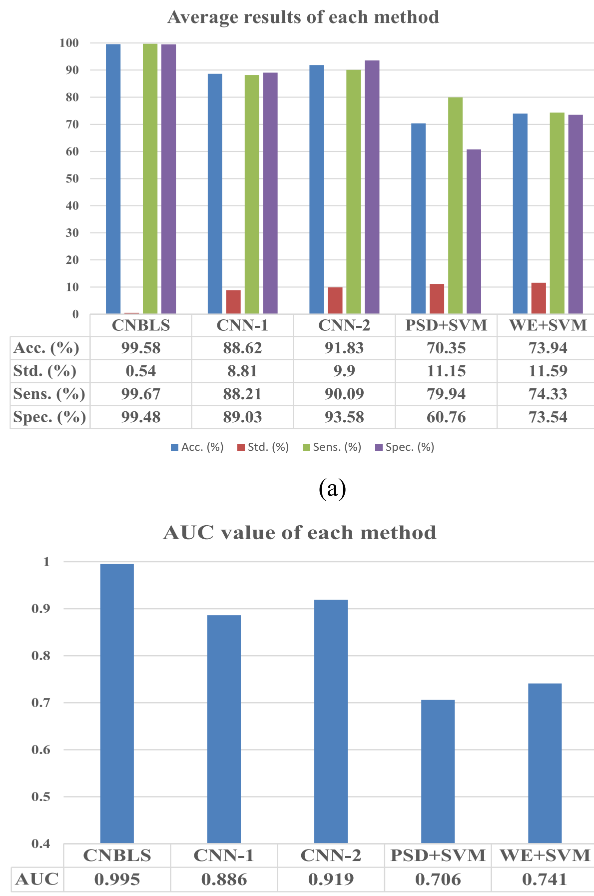

Fig. 4. Average accuracy (Acc.), standard deviation (Std.), average sensitivity (Sens.), specificity (Spec.), and AUC value of each method.

In Fig. 3, we provide the detailed accuracy of 11 subjects. Besides, we calculate the area under curve (AUC) value, sensitivity and specificity to evaluate the performance of the model from different perspectives. To be specific, AUC value can illustrate the classification ability of a binary classifier where the value range of AUC is 0.1∼1 and a higher AUC value represents a better classification effect. On the other side, sensitivity and specificity measure the proportion of the number of correctly classified positive/negative samples to the total number of positive/negative samples (equaling to 300), respectively. In this article, the fatigue state is defined as a positive class while the alert state is regarded as a negative class. From the results, we can clearly see that all the subjects reach an accuracy of over 98%, and, especially, 4 out of 11 subjects reach the peak accuracy of 100%. From the results of AUC value, we can find that four subjects can attain an AUC value of 1 while the AUC value of the rest seven subjects is all over 0.98. From the perspective of sensitivity and specificity, we can find that the fatigue samples of most subjects can all be predicted correctly. These results indicate that the proposed CNBLS model has a reasonably strong classification capacity.

In addition, the results are compared with some existing works in EEG classification. In detail, two conventional feature-based models and two CNNs models, which are commonly used in the detection of driver fatigue task and other EEG classification tasks, are included to the comparisons to validate the effectiveness of BLS in EEG classification. In particular, these models are reproduced following the description on their original literature, respectively. We provide a brief introduction of these models as follows.

PSD+SVM [54]: The power spectral density (PSD) characteristics of each channel are extracted in five certain frequency bands [delta (< 4 Hz), theta (4–7 Hz), alpha (8–12 Hz), beta (13–30 Hz) and gamma (31–50 Hz) frequency bands] to constitute the feature vectors. In addition, different ratios of these characteristics, (theta+alpha)/beta, alpha/beta, (theta+alpha)/(alpha+beta), and theta/beta, are also added to the feature vectors. An SVM is used as the classifier in this model. The kernel function of SVM is radial basis function and the other parameters are default values in LIBSVM toolbox [55].

WE+SVM [15]: Daubechies2 wavelet is chosen to obtain wavelet coefficients series at different resolutions for each channel of EEG signals and then, the corresponding WE is calculated for each channel. Feature vectors composed of WE are fed into an SVM to recognize driver fatigue condition and alert state.

CNN-1 [22]: A five-layer channel-wise CNN is proposed to detect drivers fatigue state from EEG recordings and preprocessed EEG signals are input into the channel-wise CNN directly. The CNN structure is composed of a convolution layer with kernel (1, 200), a max-pooling layer with size (1, 2), two fully connected layers with 500 and 100 nodes, and a classification layer.

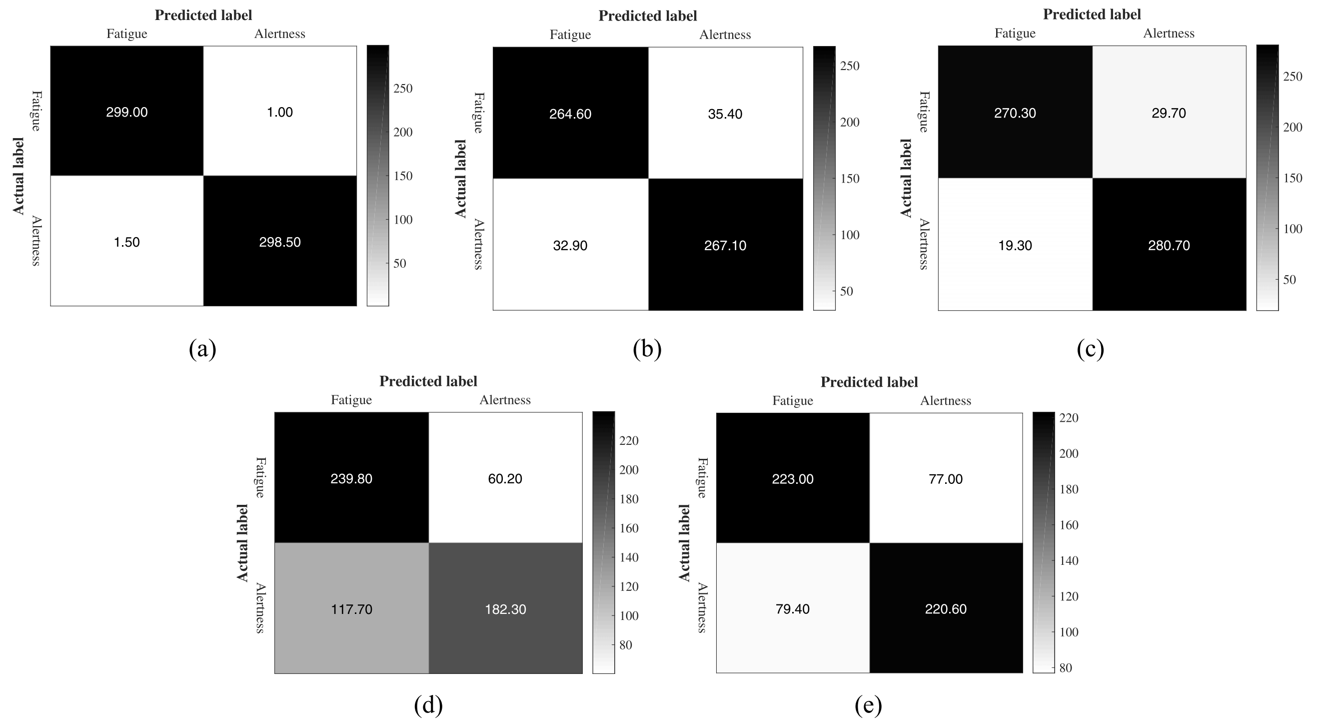

Fig. 5. Confusion matrix of each method. (a) CNBLS. (b) CNN-1. (c) CNN-2. (d) PSD+SVM. (e) WE+SVM.

CNN-2 [56]: A four-layer CNN is developed for motor imagery brain–computer interface system and preprocessed EEG signals are the input data. The CNN structure is composed of two convolution layers with kernals (1, 30) and (30, 1), an average pooling layer with kernel (1, 15), a fully connected layer with 80 nodes and a classification layer.

The average accuracy, standard deviation, average AUC value, sensitivity, and specificity of the four compared methods and the proposed method are shown in Fig. 4. In addition, the average number of successfully predicted samples of each type is shown in Fig. 5 in the form of confusion matrix. From the confusion matrix, we can distinctly uncover that the CNBLS method has almost the same classification ability to each type of state, which can also be reflected by nearly the same average sensitivity (99.67%) and specificity (99.48%). Moreover, it is obvious that CNBLS receives the highest accuracy among all five methods, followed by CNN-2 (91.83%) and CNN-1 (88.62%), respectively. In addition, the accuracies of two feature-based shallow models, which reach 70.35% and 73.94%, respectively, are far behind that of CNN models as well as BLS. From the perspective of standard deviation, the standard deviation of BLS (0.54%) is under 1%, which is quite less than that of CNN models and the feature-based SVM methods. The average AUC value of the proposed method approaches 1 which surpasses the other four methods by about 12%, 8%, 41%, and 34%, respectively.

These findings demonstrate that the proposed CNBLS not only possesses a fairly high recognition capability but also holds a satisfactory stability in driver fatigue detection task. Also, the CNBLS has nearly the same classification ability to each class.

B. Discussion

In this article, EEG signals are transformed into a network matrix for the application of BLS in EEG classification. However, whether EEG signals can be directly classified by BLS, like CNNs, is a worth exploring question. Therefore, we have tested the performance of the method which uses EEG signals as the input of BLS. The parameters are set the same as CNBLS. The result attains 60.68% with the standard deviation 6.22%, showing that the way of directly using EEG signals as an input cannot receive a satisfactory fatigue detection result. On the other side, introducing the CN method significantly improves the detection result to nearly 100%. The results demonstrate that it is quite necessary to add the transform procedure for EEG signals to realize the application of BLS in fatigue detection task.

Except for the BP method used in this article, BLS has provided several incremental learning strategies for improving the detection performance [57]. We test the performances of three different strategies, namely, the increment of enhancement nodes, the increment of both enhancement and feature nodes, and the increment of input patterns [26]. The descriptions of these constructions are as follows.

CNBLS-1: This is the one-shot construction which has 50×10 feature nodes and 5000 enhancement nodes [26]. This is the basic construction.

CNBLS-2: The initial network is set as 50×10 feature nodes and 3000 enhancement nodes. Then, the number of enhancement nodes is dynamically increased by 500 until it reaches 5000. This method applies the way of increment of enhancement nodes.

CNBLS-3: The initial network is set as $50 \times 6 = 300$ feature nodes and 3000 enhancement nodes. Then, the number

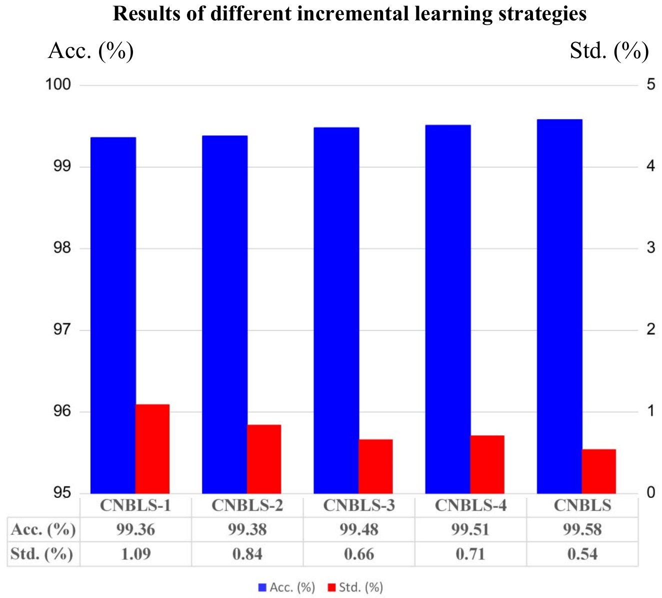

Fig. 6. Average accuracy (Acc.) and standard deviation (Std.) of each method.

of enhancement nodes is dynamically increased by (150+350) until it reaches 5000. At that same time, the number of feature nodes is dynamically increased by 50 until it reaches 500. This method applies the way of increment of both enhancement and feature nodes.

CNBLS-4: The initial network is trained under the first 400 samples and the incremental learning is used to dynamically add 50 input patterns each time until all the 600 training samples are fed. This method applies the way of the increment of input patterns.

As can be seen in Fig. 6, compared with one-shot construction, all incremental strategies can slightly improve the average accuracy. The results indicate that using incremental learning strategies to dynamically update the broad learning model could provide a compatible result which demonstrates the effectiveness of incremental learning algorithms. On the other hand, under our dataset, using the BP algorithm to fine-tune CNBLS model outperforms the other three incremental strategies. However, the overall performances of all CNBLS structures are better than the four existing methods listed in this article, demonstrating that the CNBLS method is quite effective for the driver fatigue detection task.

V. Conclusion

In this article, an MWRN has been extended to build a bridge between BLS and EEG-based driver fatigue detection. A strict test is conducted to verify the performance of the proposed method in differentiating fatigue state from alert state. The results have shown that the proposed method can reach an average accuracy of nearly 100% and an AUC value of approaching 1. The results have also been compared with two traditional methods and two existing CNN structures. We find that the proposed method highly improves the classification results obtained by four existing methods, including two CNN structures. In comparison to directly using EEG signals as the input of BLS, the proposed CNBLS provides excellent results demonstrating the necessity of the transform procedure based on CNs.

The proposed method provides a train of thought for the application of BLS in signal analysis. This successful application makes contribution to the enrichment and improvement of EEG-based signal analysis methods as BLS has plenty of merits. Moreover, we also expect the BLS-based model to get broader applications in other research fields. In the future work, we will increase the number of subjects to build a larger dataset for exploring the capability of the proposed model in online operation.

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