This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/TCDS.2019.2963476, IEEE Transactions on Cognitive and Developmental Systems

Detecting Fatigue Status of Pilots Based on Deep Learning Network Using EEG Signals

Edmond Q. Wu, Ping-Yu Deng, Xu-Yi Qu, Zhiri Tang, Wen-Ming Zhang, Li-Min Zhu, He Ren, Gui-Rong Zhou and Richard S. F. Sheng

Abstract**—**This work presents a solution for fatigue recognition through a new deep learning model that has a characteristic input of the power spectrum of an electroencephalogram (EEG) signal. Firstly, four rhythms are obtained through the designed FIR filters, and the curve areas of their power spectrum density are coupled into four fatigue indicators. Secondly, a deep sparse contractive autoencoder network is proposed to learn more local fatigue characteristics, and the recognition results of pilots mental fatigue status are given. Compared with the state-of-the-art models, the results show that our model has good learning performance in extracting local features and fatigue status detection.

Index Terms**—**pilots fatigue; EEG signals; deep network; fatigue characteristics.

I. INTRODUCTION

A. Motivation

With the continuous attention to aviation safety and the continuous progress of aircraft automation design technology, aircraft has made great progress in reliability and safety. The proportion of accidents caused by aircraft mechanical failure has dropped from 80% to 20%, safety performance has been greatly improved, and the proportion of accidents caused by human error has gradually increased. Human factors cause more than 76% of current flight accidents [1-4]. **For pilots, factors such as scheduling, lack of sleep, circadian rhythm disturbances, and prolonged working hours can cause fatigue. Pilot fatigue is a potential hazard to flight safety and an important issue for aviation operations. Therefore, detecting mental status of pilots is of great significance for improving aviation safety** [5, 6, 7, 8].

B. Related work

In general, EEG (Electroencephalogram) signals are closely related to brain fatigue [10]. Human behavioral consciousness is the result of controlling the movement of a large number of neurons through the nerve center of the brain. When a large number of neural cell groups are synchronized. Changes in postsynaptic potentials can be recorded and used for analysis and research, Obviously, feature extraction is very important in EEG signals classification. The main feature extraction methods include entropy feature, fast Fourier transform (FFT) and wavelet analysis [12]. Many achievements indicate that changes in the four rhythms are related to one's mental status [21, 25]. There are two types of judgement rule for fatigue. In the first category, the state of fatigue can be judged by the change of four rhythms in the time domain. The established rule is that during fatigue, δ and θ activities increase, while β one decreases [21, 22, 23]. Jap *et al.* [24] conclude that the decrease in rhythm α is smaller than that in rhythm β. The Opposite finding is that when the driver feels fatigue, the θ and β rhythms increase sharply [9]. In the second category, different rhythmic power ratios are used to determine fatigue [25, 26]. Obviously, power spectrum indicators show more fatigue information than time-domain features. These achievements indicate that pilot indicators can be used to determine pilot fatigue.

How to identify these characteristics is a very important issue to identify the fatigue state. Traditionally, researchers have used some raw EEG signals directly as input of the classifier, and they also get some desired results. Obviously, this approach has some disadvantages. Raw EEG signals are difficult to provide information on latent fatigue. Different experts summarize different characteristics. They have limitations due to different human experience. Therefore, it is necessary to further develop these initial functions. Through some advanced time-frequency analysis, we can extract richer mental state information How to further learn these primitive features is very important for identifying mental state. To solve this problem, we can call for deep learning methodology.

Deep learning methods can learn more feature representations [13,14,15,16, 40]. The wise unsupervised pre-training of greedy layer is its key idea. Deep learning methods can use an unsupervised method to learn new feature representation [17]. Deep learning methods such as recurrent neural networks (RNN) [40], autoencoders (AE) [41], and convolutional neural network (CNN) [42] have been reported for features learning and classification of EEG signals. Hubert *et al.* [28] proposed a four-layer CNN to learn the features from the Fourier transform of the embedded EEG signals with a recognition accuracy of 97%. Zheng *et al.* [29] use deep belief network (DBN) to build an EEG-based emotion model to identify three emotions, with an average recognition accuracies of 86.08%, which is better than support vector machine (SVM), logistic regression (LR), and k-Nearest Neighbor (KNN). Bash Ivan *et al.* [30] propose a deep recurrent convolutional network for feature learning of multi-channel EEG signals. Compared with the prior art, the model has significantly improved classification accuracy. Autoencoder network is also an important tool for

Edmond Q. Wu is with the Key Laboratory of System Control and Information Processing, Ministry of Education, Shanghai Jiao Tong University, China. He is also with Science and Technology on Avionics Integration Laboratory, China National Aeronautical Radio Electronics Research Institute, Shanghai, China. Email: deng_pingyu@careri.com, edmondqwu@163.com, Qiu_xuyi@careri.com, wenmingz@sjtu.edu.cn
Ping-Yu Deng and Xu-Yi Qu are with Science and Technology on Avionics Integration Laboratory, China National Aeronautical Radio Electronics Research Institute, Shanghai, China.
Zhiri Tang is with Department of Computer Science, City University of Hong Kong, China. E-mail: Gerin.Tang@my.cityu.edu.hk
Wen-Ming Zhang and Li-Min Zhu are with State Key Laboratory of Mechanical System and Vibration, School of Mechanical Engineering, Shanghai Jiao Tong University, Shanghai 200240, China.
He Ren, Gui-Rong Zhou and Richard S. F. Sheng are with COMAC Shanghai Aircraft Design and Research Institute (SADRI). Email: 781688397@qq.com.

feature extraction of EEG signals. Li *et al.* [31] use a denoising autoencoder to learn some potential characteristics of incomplete EEG signals. Their results show that it can successfully decode incomplete EEG to good feature representations. Lin *et al.* [32] propose a stacked sparse autoencoder network to learn more sparse feature representations. Many deep models have played important role in feature learning and classification of EEG signals. However, these sparse or denoising autoencoders also have some disadvantages. For example, a sparse auto-encoder means that only a small percentage of neurons is active at any one time. This causes it to be difficult to capture local information on the input points. The denoising autoencoder emphasizes the robustness of this function. They are difficulty learning local interference information from all directions around the input points.

C. Our model

To solve this problem, we propose a stacked contractive sparse autoencoder (CSAE) network to improve the robustness of conventional autoencoders to the local features of input data, which combines the L_1 regularization with Jacobian penalty to form a novel cost function. CSAE learns valid representations of observation inputs. It is able to capture the local manifold structure around each data point by the singular vectors of the Jacobian ranks of the transformation from input to representation. The corresponding singular value specifies a reasonable amount of local variation in the direction.

In summary, the main contribution of this study can be summarized as follows:

1) Two experiments are designed to verify the pilots' fatigue airworthiness. In our work, Four fatigue indicators are defined by the rhythmic power spectral density curve area. The relationship between the increase or decrease of the energy of rhythms and the state of fatigue is summarized and generalized;

2) When the conventional autoencoder network is used to learn more representations, functional redundancy is easy to occur. Its hidden layer unit is no sensitive to input interference. Therefore, we can add two penalty items to its cost function, such as a structured sparse item and a Jacobian constraint. Sparse constraints cause most neurons to be in a suppressed state and enhance the network's ability to discover features. Jacobian constraint can effectively learn small changes in all directions around the input points, strengthen the extraction of local features, and improve the stability of the model and the effectiveness of feature extraction. Finally, a novel contractive and sparse autoencoder is proposed to learn more abstract feature of the fatigue status. Through some stacks of CSAE, we obtain a novel deep CSAE network (DCSAEN) that can detect pilots fatigue.

The rest of this paper is arranged as follows: Section II presents feature extract method of EEG signals. Section III proposes the DCSAEN-SoftMax model. Section IV arranges two experiments. The application of pilot fatigue detection indicate that our model has better recognition ability. The conclusion can be obtained in Section V.

II. Feature extraction

Due to the complexity of human physiological signals, EEG signals are often affected by other physiological signals such as EOG signals and EMG signals. EEG signal acquisition equipment has more mature technology that can filter out interference from other signals, but due to the complexity of the driving environment, it will still be interfered by other electromagnetic waves (usually higher frequency signals). Common methods for high-frequency signal noise filtering of include wavelet transform, empirical mode decomposition, and digital filter design. The EEG signals related to human fatigue are mainly concentrated in the four rhythms of δ, θ, α, and β waves, and their frequency bands are: 0-4 Hz, 4-7 Hz, 8-13 Hz and 14-30 Hz.

A. Rhythm extraction

The four frequency bands (such as δ, θ, α, and β) are in the lower frequency range. Four different frequency bands are obtained by an FIR filter with Chebyshev approximation. We can recombine the waveforms of four frequency bands to form a "pure" EEG signal. Figure 1 shows the original EEG signal and its spectrogram, the "pure" signal and its spectrogram, four rhythms and their spectrogram. The original EEG signal has some components above 30Hz, and the filtered signal will remove the higher frequency components and retain the lower frequency components that are more related to the fatigue state.

B. Fatigue indicators

Different fatigue states show different rhythmic changes. In this work, we use the power spectral density of these rhythms to form fatigue-related indicators, and introduce the trends of these indicators under fatigue. The curve area of power spectral density can reflect the energy of the signal. We use welch method to obtain the power spectral density shown in Fig. 1. The input is a 24s EEG signal with a sampling frequency of 160 Hz. A hamming window is used, and the number of coincidence points of adjacent window segments is 20. In Fig. 1, the power density of the original signal is distributed over a large frequency range, and the filtered power of the four rhythms are concentrated on the corresponding frequency. The power of the filtered "pure" EEG signal is in the low frequency range. The power of each rhythm can be expressed by the sum of the power density, that is, the area within the frequency band corresponds to the power density curve.

TABLE I

EEG FREQUENCY AND CORRESPONDING DESCRIPTIONS

Wave	Frequency	Activity description
δ wave	1~4Hz	Excessive fatigue and deep sleep
θ wave	4~8Hz	Suffer a setback or a mental depression
α wave	8~13Hz	In quiet status and in a status of concentration
β wave	13~30Hz	Nervous, emotional or excited status

During fatigue, slow wave increases while fast wave decreases accordingly. At the same time, the power of δ and θ increases, while the powers of α and β decrease. In fatigue evaluation, power ratio index is more effective than time-domain features [22]. δ reflects drowsiness. It provides more status information of sleepiness. Table I describes more rhythm properties. Therefore, we can form a new indicator, namely $(\delta+\theta)/(\alpha+\beta)$. The corresponding fatigue indicators are

This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/TCDS.2019.2963476, IEEE Transactions on Cognitive and Developmental Systems

$$\begin{cases} (\alpha+\theta)/\beta \\ \alpha/\beta \\ (\delta+\theta)/(\alpha+\beta) \\ \theta/\beta \end{cases} \quad \text{with} \quad \begin{cases} \delta = \int_{0.1}^{4} PS(f) \\ \theta = \int_{4}^{7} PS(f) \\ \alpha = \int_{8}^{13} PS(f) \\ \beta = \int_{14}^{30} PS(f) \end{cases} \tag{1}$$

where $PS(f)$ is a function of the power spectrum density.

$(\alpha + \theta) / \beta$ represents the power ratio of the two rhythms. When a person feels tired, θ increases and β decreases. $(\alpha + \theta) / \beta$, θ/β, α/β and $(\delta+\theta)/(\alpha+\beta)$ have an increasing tendency. We can use the window function to calculate its effective power [22]. Figure 2 shows four indicators. Compared with the window function methods, traditional FFT-based power spectrum method has more errors. In this work, we provide three different types of window functions for the power spectrum.

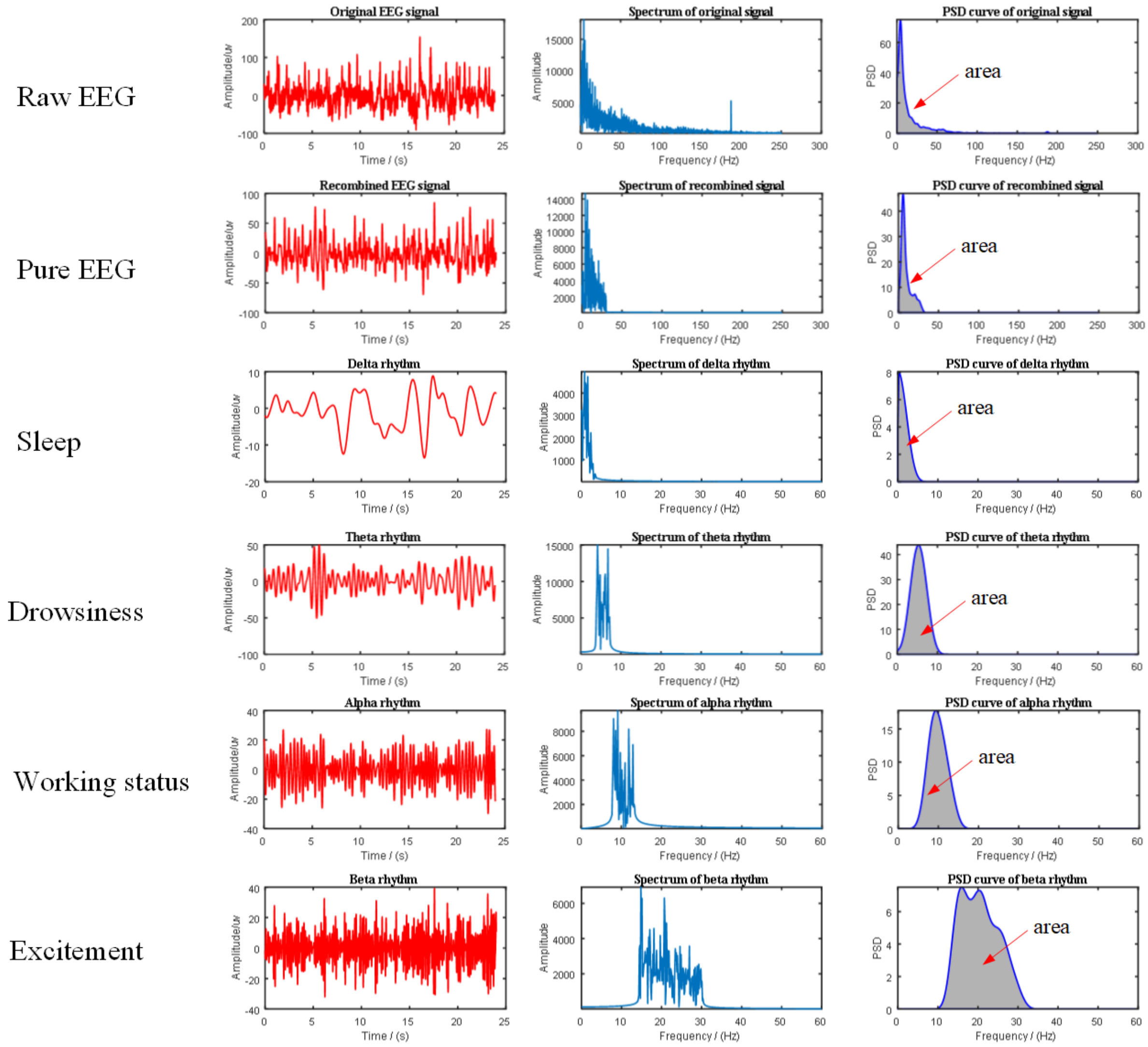


Fig. 1 Rhythm signals and their spectrum, curve area of power spectral density

This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/TCDS.2019.2963476, IEEE Transactions on Cognitive and Developmental Systems

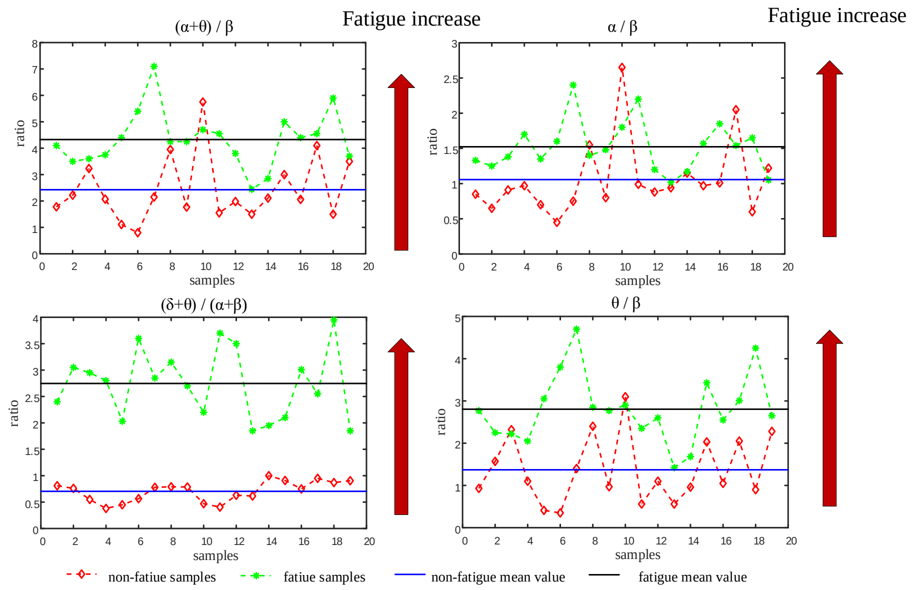


Fig. 2 Fatigue indicators under different mental statuses

III. DCSAEN-SOFTMAX

Due to input interference, the hidden layer units of conventional AE are easily offset. We can add structural sparse and Jacobian constraints to its objective function to form a new deep contractive sparse auto-encoder network. Sparse constraint keeps most neurons in a state of inhibition and enhances the ability of the network to discover features. Jacobian constraint captures weak changes around the input points. It strengthens the representation of local features and improve the stability of the model and the effectiveness of feature extraction.

A. Contractive auto-encoder

A contractive mapping is defined as $O: f \to f$ on the complete metric space (f, d). For any x and y in this space, we have

$$d(Ox, Oy) \leq \lambda \cdot d(x, y),\ 0 \leq \lambda < 1 \tag{2}$$

More clearly, contraction is a function of the output distance between two points being less than the input distance. For example, for two points x and y, their distance is d_1 as the input of the contractive function. After this map, the output distance is d_2, then $d_2 < d_1$. Further, we have the following inequality

$$\|f(x) - f(y)\| \leq \lambda \cdot \|x - y\| \tag{3}$$

When y is replaced with $x + dx$, we have

$$\frac{\|f(x) - f(x+dx)\|}{\|dx\|} \leq \lambda \tag{4}$$

Obviously, when $dx \to 0$, we have the following inequality.

$$\left|\frac{df(x)}{dx}\right| \leq 1 \tag{5}$$

For a CAE with hidden units $h_i(x) = f_i(x)$, a tangent plane is defined at the input x along the direction of the larger singular value of the Jacobian matrix so that a local variation xˆ of x can be obtained. It has larger movement in the Jacobian direction with larger singular values [34], [35].

$$\hat{x} = x + \sum_i^D \epsilon_i \frac{\partial f_i(x)}{\partial x} \tag{6}$$

where ϵ_i is a Gaussian perturbation with small variance σ^2 in *h-space*, and the vector ϵ is isotropic with $\epsilon \sim N(0, \sigma^2 I_k)$.

In addition, we have the hidden units representation related to the perturbed sample $\hat{x}$:

$$f_j(\hat{x}) = f_j\left(x + \sum_i^D \epsilon_i \frac{\partial f_i(x)}{\partial x}\right) \tag{7}$$

Through the first-order Taylor expansion, we obtain a movement of h space as follow:

$$f_j\left(x + \sum_i^D \epsilon_i \frac{\partial f_i(x)}{\partial x}\right) \approx f_j(x) + \sum_i^D \epsilon_i \frac{\partial f_i(x)}{\partial x}^T \frac{\partial f_j(x)}{\partial x} \tag{8}$$

Therefore, in the first-order operation, when x interferes in the direction of the maximum singular value of its Jacobian matrix, an offset from $h = f(x)$ to $h + JJ^T\epsilon$ is generated for the hidden layer unit, and ϵ is a small isotropic perturbation.

B. Contractive Sparse Auto-encoder

Adding Jacobi constraint on the cost function of SAE can suppress interference in all directions. This can lead to an enhancement of the local feature learning capabilities of SAE. The new cost function can be defined as follows:

$$J_{CASE_{cost}}(\theta) = J_{MSE}(\theta) + J_{Jacobian}(\theta) + J_{Sparse}(\theta)$$
$$= \frac{1}{m}\sum_{i=1}^{m} \frac{1}{2}\left(\frac{1}{2}|y_i - x_i|^2 + \frac{\lambda}{2}\left|J_f(x)\right|_F^2\right) + \beta \sum_{i=1}^{2} KL(\rho|\rho_j) \tag{9}$$

where $J_f(x) = \frac{\partial h_j(x)}{\partial x_i}$ is Jacobian matrix, and $\left|J_f(x)\right|_F^2 = \sum_i j\left(\frac{\partial h_j(x)}{\partial x_i}\right)$.

C. Softmax classifier

The logistic classifier can only solve two classification problem, and the Softmax classifier can provide more choices for the classes. Softmax classifier is a supervised learning algorithm. It is used to solve many types of problems in pilot fatigue. Given a training set $\{(x^{(1)}, y^{(1)}), (x^{(2)}, y^{(2)}), \cdots, (x^{(m)}, y^{(m)})\}$, where $y^{(i)} \in \{1,2,\cdots,r\}$, and then the probability is $p(y^{(n)} = k|x^{(n)})$. And then, the corresponding probability vector $h_\lambda(x^{(n)})$ has the following expression as

This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/TCDS.2019.2963476, IEEE Transactions on Cognitive and Developmental Systems

$$h_\lambda(x^{(n)}) = \begin{bmatrix} p(y^{(i)} = 1|x^{(i)}); \lambda \\ p(y^{(i)} = 2|x^{(i)}); \lambda \\ \vdots \\ p(y^{(i)} = r|x^{(i)}); \lambda \end{bmatrix} = (\sum_{k=1}^{r} e^{\lambda_k^T x^{(i)}})^{-1} \begin{bmatrix} e^{\lambda_1^T x^{(i)}} \\ e^{\lambda_2^T x^{(i)}} \\ \vdots \\ e^{\lambda_r^T x^{(i)}} \end{bmatrix} \quad (10)$$

where $\lambda_1, \lambda_2, \ldots, \lambda_k \in R^{n+1}$ are the parameters of the Softmax classifier model and $\frac{1}{\sum_{k=1}^{r} e^{\lambda_k^T x^{(i)}}}$ normalizes the distribution so that it sums to one. The probability that $x^{(i)}$ belongs to the kth class is

$$p(y^{(i)} = k|x^{(i)}) = e^{\lambda_k^T x^{(i)}} / \sum_{k=1}^{r} e^{\lambda_k^T x^{(i)}} \quad (11)$$

We select the maximum of $p(y^{(i)} = k|x^{(i)}; \lambda), k = 1,2,\cdots,r$ as the class of sample $x^{(i)}$.

D. DCSAEN-Softmax Model

The pilots' fatigue status can be identified by a DCSAEN-Softmax. First, layer-by-layer learning of unsupervised DCSAEN is used to obtain the best initial weights of the entire network. Second, the Softmax classifier at the top layer of the network is used to adjust the parameters of the whole network. Finally, we use the network to learn the new features. The structure of DCSAEN–Softmax is shown in Fig. 3.

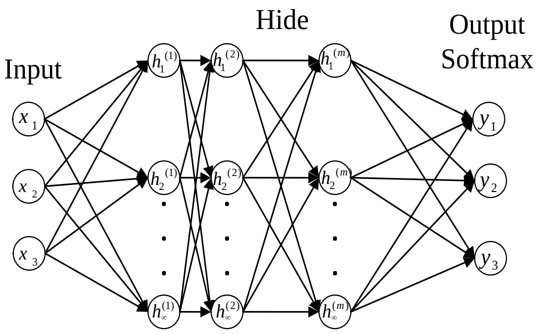


Fig. 3. Framework of DCSAEN –Softmax

IV. RECOGNITION OF PILOTS' FATIGUE STATUS

In order to collect the pilots' physiological signals during the flight simulation, experiments were performed in a 6-degree-of-freedom full flight simulator (Figs. 4 and 5), which provides a virtual environment for real-time flight simulation with motion cockpit, high-frame-rate vision, animated audio, and haptic controls of high fidelity and good immersion. In this work, we use flight dynamic models such as C919 and Military simulators. During the simulations, physiological data was recorded by a set of apparatus, including a multi-parameter telemetry and logging system (BioHarness, Biopac Systems Canada Inc., Canada) and an eye tracking system (Tobii Glasses, Tobii AB., Sweden).

Fig. 4. The flight simulator and monitoring system

Fig. 5. Experimental facility

The BCI200 system recorded EEG signals in a simulation experiment. The system has 64 reference electrodes, and a sampling frequency of 160Hz. We select typical physiological areas associated with brain fatigue [19, 20] and measure corresponding EEG signals. The selected electrodes contain FP1, T7, T8, P1, P2, P3, P4, P5, P6, P7 and P8.

A. Fatigue recognition under clear test conditions

Case 1. The pilots simulate a round-trip flight from Xianyang International Airport to Guangzhou International Baiyun Airport when the weather was fine. The flight test was conducted from 10:00 to 14:00 and lasted for 4 hours. Pilots arrived at the experimental site and rested for about 30 minutes. They started a two-hour medium-pressure simulated flight test, which lets pilots in working condition. After one hour of flight, EEG signals of pilots were collected for half an hour. Next, a 2-hour mild pressure simulation flight experiment was performed to put pilots into flight operation. The pilot's EEG signals were collected for half an hour. Finally, the third phase of the flight simulation was performed. Flight experiments at moderate load pressures were performed to simulate flight conditions with slight airflow disturbances. An hour of EEG signals was collected. In the final stage, one hour of take-off flight test was simulated. Pilots worked under high load pressure and their EEG signals were collected for 20 minutes.

Four fatigue indicators can be computed by formula (1) and shown in Fig. 6 respectively. Compared with Hamming and Blackman windows, rectangular window function can show more prominent features. Figure 7 represents the corresponding results from DCSAEN, where 'Label' represents the prediction label, '1' represents non-fatigue, '2' represents normal-fatigue and '3' represents extreme-fatigue. As shown in Table II, we present the recognition accuracy under three different dimensional outputs. Obviously, the higher the output size, the higher the recognition accuracy. Compared with other models, our model has better recognition performance.

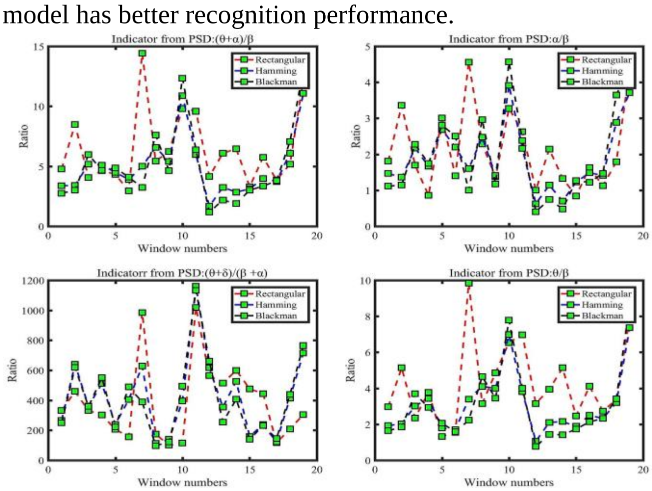


Fig. 6. Four fatigue indicators and their trend

TABLE II

Fatigue recognition accuracy under different input feature

This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/TCDS.2019.2963476, IEEE Transactions on Cognitive and Developmental Systems

dimensions

Method	Output dimension			
	39	20	9	3
PCA	28.14%	30.43%	21.73%	34.78%
DAEN	81.78%	82.60%	69.56%	56.52%
DCSAEN	**94.58%**	**91.30%**	**86.95%**	**73.91%**

We also verified the reusability of model parameters. The output of deep learning is not fixed, and the results of each program run are different. It needs to verify the repeatability of the model. We learned fatigue features using DCSAEN and DSAEN, respectively. The corresponding results are shown in Table III and Fig. 8.

TABLE III

Model learning accuracy rate of different experiments

Model	Trial 1	Trial 2	Trial 3
DCSAEN	**77%**	**74%**	**83%**
DSAEN	47%	49%	40%

The results show that our model is highly reliable for reusability. Each learning feature has subtle changes. The corresponding learning accuracy is also very stable. It also shows that our model is reusable and highly portable.

B. Fatigue recognition using unknown EEG signals

Case 2. In this case, we select a set of EEG data during the flight landing under different weather conditions. For example, the landing process of an airplane in rainy weather requires more manual operations, which encourages pilots to spend more brain workload and attention to deal with the harsh flight environment. In order to show that the brain workload of pilots in adverse weather is different from that in normal weather, we present the index of brain workload evaluation as mean instantaneous frequency $\mathrm{MIF} = \frac{\sum_{j=1}^{n} a_j^2 w_j}{\sum_{j=1}^{n} a_j^2}$, where w_j is instantaneous frequency of the jth piont of EEG signal, and a_j is its amplitude. Clearly, MIF consists of the instantaneous frequency and energy of EEG signals.

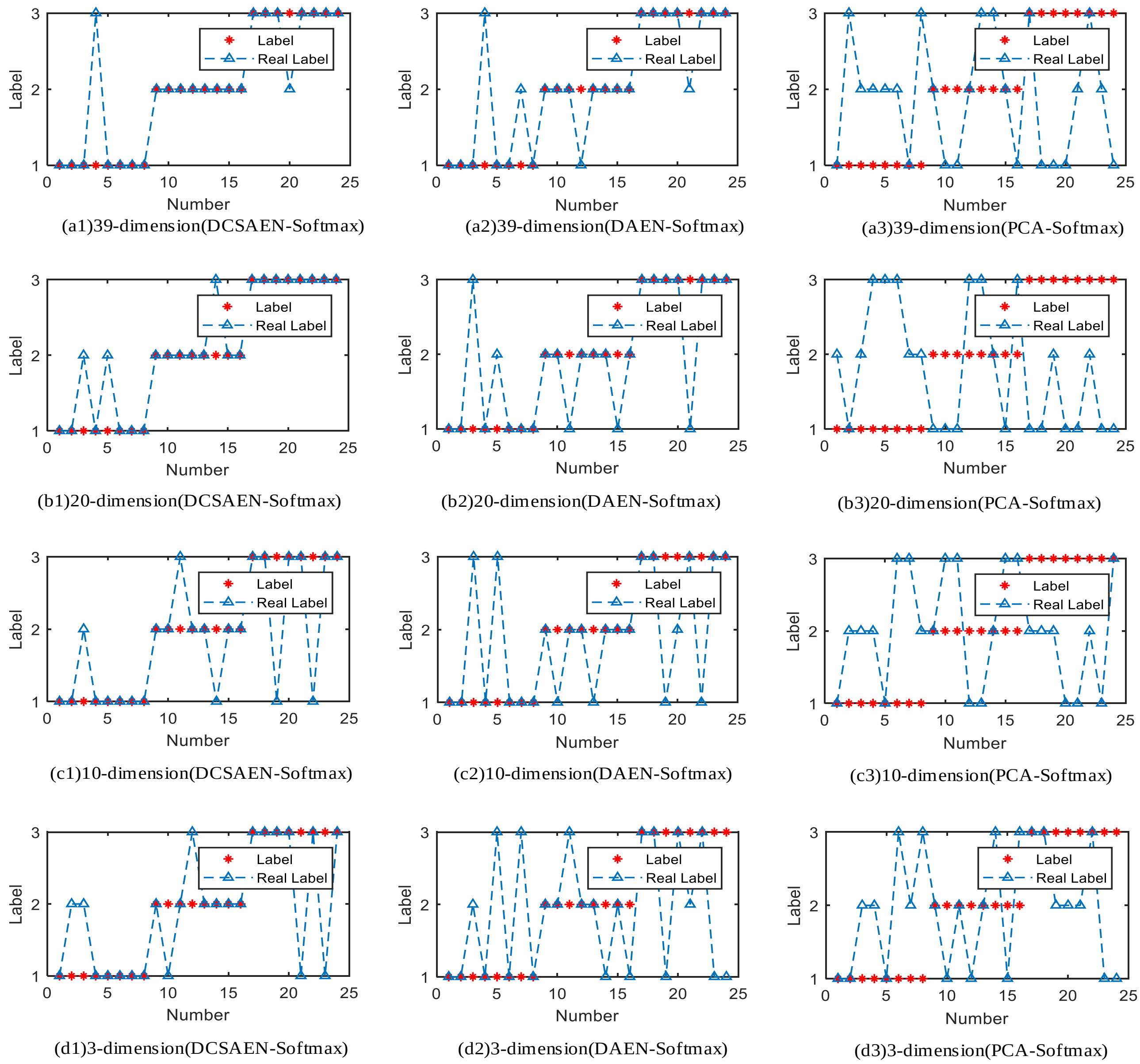
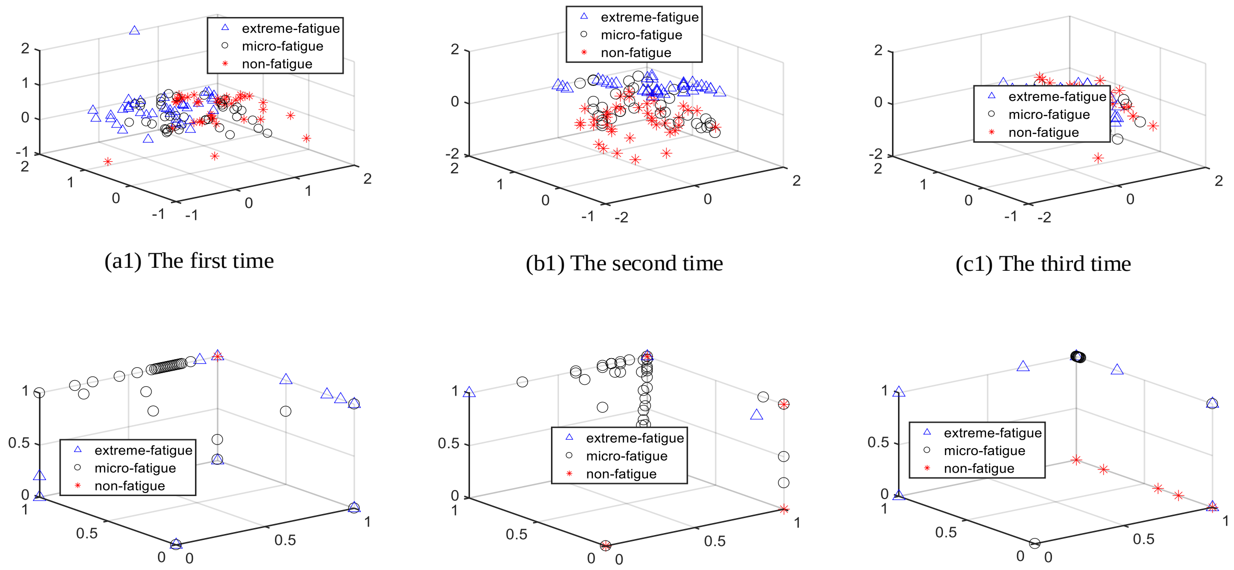


Fig.7 Classification results of DSAEN and PCA

This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/TCDS.2019.2963476, IEEE Transactions on Cognitive and Developmental Systems



(a1) The first time (b1) The second time (c1) The third time

(a2) The first time (b2) The second time (c2) The third time

Fig. 8. The features extracted by DCSAEN and DSAEN

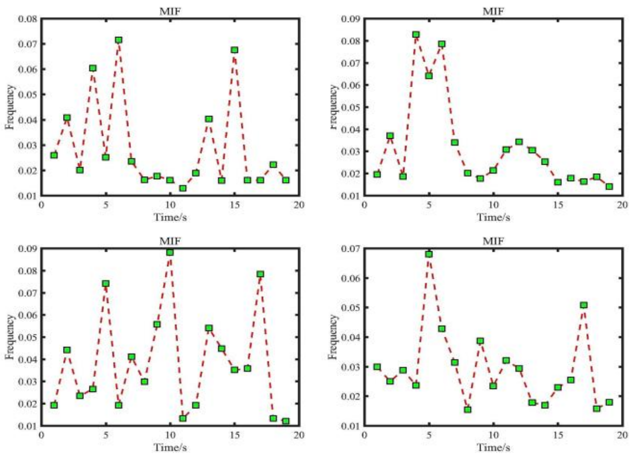


Fig. 9. Mean instantaneous frequency of four pilots

It can reflect the brain consumption by the changes of weighted instantaneous frequency of EEG signals. Obviously, for more complex flight operations, the pilots' brain power will often change with concentration of attention to cope with flight situations that occur at any time. Figure 9 shows the MIF under four different flight conditions, which are significantly different. It can be seen that different pilots face different brain workload changes when facing the same scene. This may be related to their work experience and the level of training expertise. We use a hidden Markov model to identify the hidden state of these EEG signals and implement attribute labels of EEG data. We only present trends of four fatigue indicators from the two pilots shown in Figs. 10 and 11.

The indicator $(\delta + \theta) / (\alpha + \beta)$ in Fig. 11 is significantly higher than that in Fig. 10, which indicates that the brain workload of the corresponding pilot consumes more energy. Obviously, $\delta + \theta$ is able to represent more brain fatigue information, as shown in Figs. 10 and 11, the average amplitudes of θ/β between the two pilots are very different. We can conclude that θ has more impact on drowsiness. The average amplitude of α/β between the two pilots is the same. This is because both α and β are full of energy. The average amplitude of $(\alpha + \theta) / \beta$ in Fig. 11 is also higher than that in Fig. 10. This is because θ has some effect on drowsiness.

In order to evaluate the accuracy and stability of the DCSAEN-Sofmax, the above basic models are also used to for identification. We extract different output of the size feature. The recognition results are shown in Table IV. Regardless of the output size of the learned features, the recognition accuracy of DCSAEN is higher than that of DAEN, DSAEN and PCA. With 39-dimensional feature, an average recognition accuracy of 81.5% can be achieved, which is significantly better than other models. In the 20-dimensional and 10-dimensional features, the average recognition accuracy of DCSAEN also exceeds 71%. Under the same network structure, the variance of the recognition accuracy of DCSEAN is smaller than that of DAEN. This is because the constraints of sparse and contraction terms are added to the cost function of the autoencoder, which increases the stability of the network and the reliability of feature extraction. Compared with the deep contractive autoencoder network, the deep sparse autoencoder network lacks the learning ability due to the weak change of the input feature points, so the accuracy is poor. Obviously, PCA loses some information of EEG signals, and the recognition accuracy is far worse than that of deep networks.

From the recognition rate trend of many experiments, the variance of DCSAEN is significantly smaller than that of DSAEN and PCA under 39 dimensions. The minimum variance from the DCSAEN model is 0.025. As the feature dimension decreases, the variance of the recognition accuracy increases, the fluctuation of the classification recognition accuracy increases, the stability and representativeness of the extracted features decrease, and the stability of the network model also decreases. The effect of different feature sizes on the accuracy of fatigue recognition shows that the node setting of each layer are of great significance to the stability of the entire network.

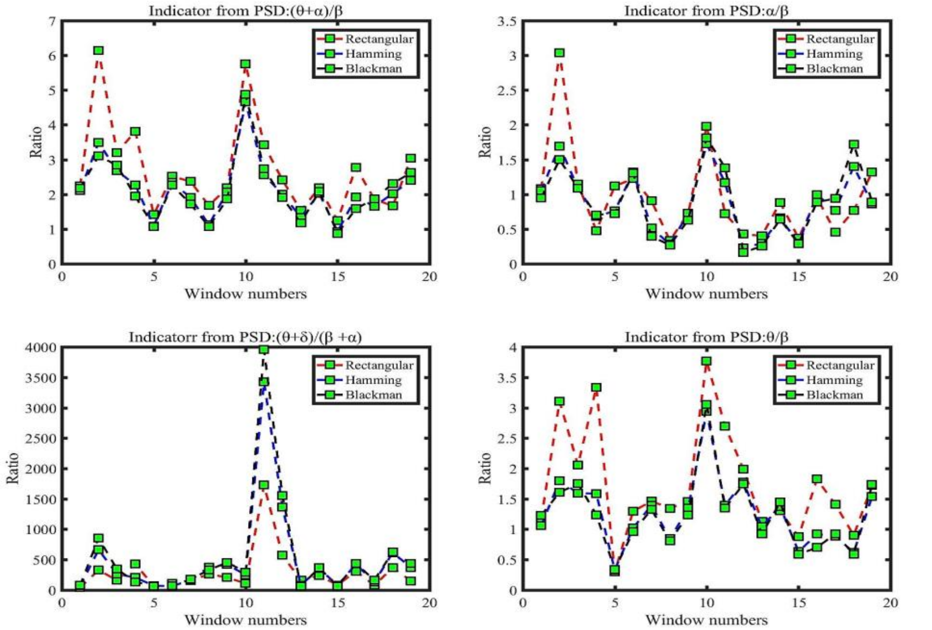


Fig. 10. Four fatigue indicators and their trend from one pilot

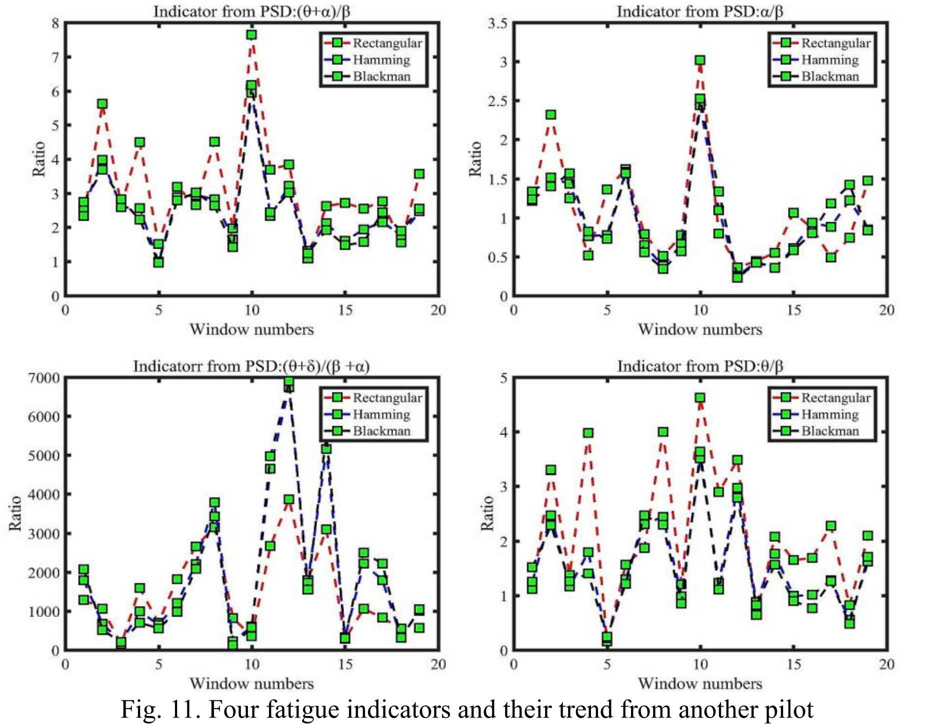


Fig. 11. Four fatigue indicators and their trend from another pilot

TABLE IV
The recognition accuracy from different models

Output Dimension	DCSAEN	DAEN	DSAEN	PCA
39	0.815 (**±0.025**)	0.734 (±0.031)	0.517 (±0.039)	0.427 (±0.083)
20	0.765 (**±0.051**)	0.678 (±0.063)	0.453 (±0.077)	0.286 (±0.126)
10	0.716 (**±0.075**)	0.652 (±0.079)	0.357 (±0.093)	0.258 (±0.136)
3	0.431 (**±0.089**)	0.401 (±0.097)	0.267 (±0.073)	0.244 (±0.182)

In most feature sizes, the variance of the recognition accuracy of DCSAEN is smaller than that of DAEN, DSAEN and PCA. Compared with the basic feature extraction method, DCSAEN has higher stability and repeatability. More stable feature learning results can be obtained. Obviously, the constraints of Jacobian matrix can suppress the perturbation in all directions, enhance the generalization of autoencoder, and maximize the discrimination between different features. It can learn subtle changes in all directions, enhance the influence of subtle changes on the output, and improve the classification accuracy.

IV. CONCLUSION

This work proposes a new autoencoder network to learn the features of pilots' EEG signals. Sparse learning mechanism of DCSAEN not only eliminates the redundancy of raw features, but also improves computational efficiency of model. The contractive loss function of DCSAEN significantly improves the identification of microfatigue. Compared with the-state-of-the-art methods, DCSAEN greatly improves the accuracy of fatigue recognition.

The aviation industry urgently needs to solve the problem of pilots' fatigue detection. This work then proposes a way to address pilots fatigue. The main work of this paper can be summarized as follows:

1) This study designs pilot fatigue monitoring experiments. The FIR filter is used to extract four rhythms like δ, θ, α, and β waves. The study presents their relationship with the change of fatigue status. We present fatigue indicators related to the power change of rhythms as the basis for fatigue judgment. The results of the study show that the fatigue evaluation index has a high recognition rate for the fatigue state of the pilot.

2) Compared with a single contractive autoencoder, our model adds a sparse penalty term, which is able to learn significant features and greatly improve learning efficiency. Similarly, compared with a single sparse autoencoder, our model adds a Jacobian constraint term, which can better learn the perturbation characteristics in all directions around the input points, and greatly improve the efficiency of local feature learning.

REFERENCES

[1] J. A. Caldwell, M. M. Mallis, J. L. Caldwell, M. A. Paul, J. C. Miller, and D. F. Neri, "Fatigue countermeasures in aviation," *Aviation Space & Environmental Medicine*, vol.80, no.1, pp. 29-59, 2009.

[2] K. Avers, and W.B. Johnson, "A review of Federal Aviation Administration fatigue research: Transitioning scientific results to the aviation industry," *Aviation Psychology and Applied Human Factors*, 2011, vol.1, no.2, 87.

[3] L.J. Tian, T.T. Chen, and J.B. Wang, "Internal control, safety culture and aviation safety," *China Safety Science Journal*, vol. 26, no. 8, pp.1-6, 2016.

[4] P. Suraweera, G.I. Webb, I. Evans, and M. Wallace, "Learning crew scheduling constraints from historical schedules," *Transportation research part C: emerging technologies*, vol. 26, pp. 214-232, 2013.

[5] P.M. Bongers, C.T.J. Hulshof, L. Dljkstra, H. C. Boshuizen, H. J. M. Groenhout and E. Valken, "Back pain and exposure to whole body vibration in helicopter pilots," Ergonomics, vol.33, no.8, pp.1007-1026, 1990.

[6] C. Reis, C. Mestre, and H. Canhão, "Prevalence of fatigue in a group of airline pilots, Aviation," *space, and environmental medicine*, vol. 84, no.8, pp. 828-833, 2013.

[7] J.J. Liu, and L.J. Zhang, "Semantic network analysis of flight fatigue events," *China Safety Science Journal*, vol. 26, no.1, pp. 34-39, 2016.

[8] G. Borghini, L. Astolfi, G. Vecchiato, D. Mattia, and F. Babiloni, "Measuring neurophysiological signals in aircraft pilots and car drivers for the assessment of mental workload, fatigue and drowsiness," *Neuroscience & Biobehavioral Reviews*, vol. 44, pp.58-75, 2014.

[9] L.J. Trejo, K. Knuth, R. Prado, R. Rosipal , K. Kubitz , R. Kochavi , B. L. Matthews, and Y. Zhang, EEG-based estimation of mental fatigue: convergent evidence for a three-state model, in: *International Conference on Foundations of Augmented Cognition*, 2007, pp. 201-211.

[10] T. Akerstedt, L. Torsvall, and M. Gillberg, "Sleepiness in shiftwork. A review with emphasis on continuous monitoring of EEG and EOG," *Chronobiology international*, vol.4, no.2, pp.129-140, 1987.

[11] A. Ghaemi, E. Rashedi, A.M. Pourrahimi, M. Kamandar, and F. Rahdari , "Automatic channel selection in EEG signals for classification of left or right hand movement in Brain Computer Interfaces using improved binary gravitation search algorithm," *Biomedical Signal Processing and Control*, vol. 33, pp.109–118, 2017.

[12] Z. Iscan, Z. Dokur, and T. Demiralp, "Classification of electroencephalogram signals with combined time and frequency features," *Expert Systems with Applications*, vol.38, no.8, pp.10499-10505, 2011.

[13] J. Schmidhuber, "Deep learning in neural networks: an overview," Neural Networks, vol.61, pp.85-117, 2014.

[14] G. E. Hinton, and S. Osindero, "A fast learning algorithm for deep belief nets," *Neural computation*, vol.18, no.7, pp. 1527-1554, 2006.

[15] Y. Bengio, P. Lamblin, D. Popovici, H. Larochelle, and U. Montreal , "Greedy layer-wise training of deep networks," *Advances in neural information processing system*, pp. 153-160, 2007.

[16] C. Poultney, S. Chopra, and Y.L. Cun, "Efficient learning of sparse representations with an energy-based model," in: *Advances in neural information processing systems*, pp.1137-1144, 2007.

[17] Y. Bengio, A. Courville, and P. Vincent, "Representation learning: A review and new perspectives," *IEEE transactions on pattern analysis and machine intelligence*, vol.35, no.8, pp.1798-1828, 2013.

[18] C.V. Patriche, R. Pirnau, A. Grozavu, and B. Roşca, "A comparative analysis of binary logistic regression and analytical hierarchy process for landslide susceptibility assessment in the Dobrov River Basin, Romania," *Pedosphere*, vol.26, no.3, pp.335-350, 2016.

[19] P. Li, W. Jiang, and F. Su, "Single-channel EEG-based mental fatigue detection based on deep belief network," in: *the 38th Annual International Conference of Engineering in Medicine and Biology Society* (EMBC), 2016, pp. 367-370.

[20] Q. Ji, Z. Zhu, and P. Lan, "Real-time nonintrusive monitoring and prediction of driver fatigue," *IEEE Transactions on Vehicular Technology*, vol.53, no.4, pp.1052-1068, 2004.

This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/TCDS.2019.2963476, IEEE Transactions on Cognitive and Developmental Systems

[21] A. Belyavin and N.A. Wright, “Changes in electrical activity of the brain with vigilance,” *Electroencephalography and Clinical Neurophysiology*, vol.66, no. 2, pp. 137-144, 1987.
[22] A. Subasi, “Automatic recognition of alertness level from EEG by using neural network and wavelet coefficients,” *Expert System with Applications*, vol. 28, no. 4, pp. 701-711, 2005.
[23] P. Rasmussen, H. Stie, L. Nybo and B. Nielsen, “Heat induced fatigue and changes of the EEG is not related to reduced perfusion of the brain during prolonged exercise in humans,” *Journal of Thermal Biology*, vol. 29, no.7–8, pp. 731–737, 2004.
[24] B.T. Jap, S. Lal and P. Fischer, “Using EEG spectral components to assess algorithms for detecting fatigue,” *Expert System with Applications*, vol. 36, no.2, pp. 2352-2359, 2009.
[25] H.J. Eoh, M.K. Chung and S.H. Kim, “Electroencephalographic study of drowsiness in simulated driving with sleep deprivation,” *International Journal of Industrial Ergonomics*, vol. 35, no. 4, pp. 307-320, 2005.
[26] W. Li, Q.C. He, X.M. Fan and Z.M. Fei, “Evaluation of driver fatigue on two channels of EEG data,” *Neuroscience Letters*, vol. 506, no.2, pp.235–239, 2012.
[27] N. Lu, T. Li, X. Ren and H. Miao, “A deep learning scheme for motor imagery classification based on restricted boltzmann machines,” *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, vol.25, no. 6, pp. 566 -576, 2017.
[28] H. Cecotti, and A. Graeser. “Convolutional neural network with embedded Fourier transform for EEG classification,” in: *19th International Conference on Pattern Recognition*, 2008, pp. 1-4.
[29] W. L. Zheng, and B. L. Lu, “Investigating critical frequency bands and channels for EEG-based emotion recognition with deep neural networks,” *IEEE Transactions on Autonomous Mental Development*, vol. 7, no.3, pp. 162-175, 2015.
[30] P. Bashivan, I. Rish, M. Yeasin, and N. Codella, “Learning representations from EEG with deep recurrent-convolutional neural networks,” *Computer Science*, 2015.
[31] J. Li, Z. Struzik, L. Zhang, and A. Cichocki, “Feature learning from incomplete EEG with denoising autoencoder,” *Neurocomputing*, vol. 165, pp. 23-31, 2015.
[32] Q. Lin, S. Ye, X. Huang, S. Y. Li, and M. Z. Zhang, “Classification of epileptic EEG signals with stacked sparse autoencoder based on deep learning,” in: *International Conference on Intelligent Computing*, 2016, pp. 802-810.
[33] B. B. Thompson, R. J. Marks, and M. A. El-Sharkawi, “On the contractive nature of autoencoders: Application to missing sensor restoration,” in: *Proceedings of the International Joint Conference on Neural Networks*, 2003, pp. 3011-3016.
[34] S. Rifai, Y. Bengio, Y. Dauphin Y, and P. Vincent, “A generative process for sampling contractive auto-encoders,” *in: Proceedings of the 29 th International Conference on Machine Learning, 2012*.
[35] Q. Wu, X. Chu, “Recognition of fatigue status of pilots based on deep contractive sparse auto-encoding network,” in: The 37th Chinese Control Conference, 2018, pp. 9220-9225.
[36] N. M. Nasrabadi, “DeepTarget: An Automatic Target Recognition using Deep Convolutional Neural Networks,” *IEEE Transactions on Aerospace and Electronic Systems*, (Early Access), 2019.
[37] O. E. Yetgin, B. Benligiray, and O. N. Gerek, “Power Line Recognition from Aerial Images with Deep Learning,” *IEEE Transactions on Aerospace and Electronic Systems*, (Early Access), 2018.
[38] B. Jokanović, and M. Amin, “Fall Detection Using Deep Learning in Range-Doppler Radars,” *IEEE Transactions on Aerospace and Electronic Systems*, vol. 54 , no.1, pp.180-189, 2018.
[39] C. Chen, W.Q. Tan, X.J. Qu, and H.X. Li, “A Fuzzy Human Pilot Model of Longitudinal Control for a Carrier Landing Task,”*IEEE Transactions on Aerospace and Electronic Systems*, vol. 54, no.1, pp. 453–466, 2018.
[40] Z. Ren, K. Qian, Z. X. Zhang, V. Pandit, A. Baird, and B. Schuller,“Deep scalogram representations for acoustic scene classification,” *IEEE/CAA J. of Autom. Sinica*, vol. 5, no. 3, pp. 662-669, 2018.
[41] E. Principi, D. Rossetti, S. Squartini, and F. Piazza, “Unsupervised electric motor fault detection by using deep autoencoders,” *IEEE/CAA J. Autom. Sinica*, vol. 6, no. 2, pp. 441-451, 2019.
[42] Y. F. Xia, H. Yu, and F. Y. Wang, “Accurate and robust eye center localization via fully convolutional networks,” *IEEE/CAA J. Autom. Sinica*, vol. 6, no. 5, pp. 1127–1138, Sept. 2019.

Edmond Q. Wu received the Ph.D. degree in Control theory and application from Southeast University, Nanjing, China, in 2009. He is an Associate Professor at the Key Laboratory of System Control and Information Processing, Ministry of Education, Shanghai Jiao Tong University, Shanghai, China. He is also with Science and Technology on Avionics Integration Laboratory, at China National Aeronautical Radio Electronics Research Institute, Shanghai, China. His research interests include deep learning, cognitive modelling and industrial information processing.

Ping-Yu Deng is now a professor with Science and Technology on Avionics Integration Laboratory, at China National Aeronautical Radio Electronics Research Institute, Shanghai, China. He is currently the deputy director of China National Aeronautical Radio Electronics Research Institute. He is the Chief Technology Officer of China National Aeronautical Radio Electronics Research Institute. His research interests include avionics system design, analysis and architecture.

Xu-Yi Qiu is now with Science and Technology on Avionics Integration Laboratory, at China National Aeronautical Radio Electronics Research Institute, Shanghai, China. He is currently working towards the Ph.D. Degree at Shanghai Jiao Tong University, Shanghai, China. His research interests include human-machine interaction and cognitive modelling.

Zhiri Tang received the Bachelor and Master Degree in Microelectronics from Wuhan University, Wuhan, China in 2017 and 2019, respectively. He is currently working towards the Ph.D. Degree at the Department of Computer Science, City University of Hong Kong. His research interests include machine learning and cognitive computing.

This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/TCDS.2019.2963476, IEEE Transactions on Cognitive and Developmental Systems

Wen-Ming Zhang (M'10) received the B.S. degree in mechanical engineering, the M.S. degree in mechanical design and theories from Southern Yangtze University, Wuxi, China, and the Ph.D. degree in mechanical engineering from Shanghai Jiao Tong University, Shanghai, China, in 2000, 2003, and 2006, respectively. He is currently a Distinguished Professor with the State Key Laboratory of Mechanical System and Vibration, School of Mechanical Engineering, Shanghai Jiao Tong University. He has been involved in the dynamics and control for micro/nanoelectromechanical systems (MEMS/NEMS). His current research interests include nonlinear vibration and control, smart materials and structures, rotor dynamics, vibration energy harvesting, dynamics of fluid-structure interaction, and soft robotics.

Li-Min Zhu (M'12) received the B.E. (Hons.) and Ph.D. degrees from Southeast University, Nanjing, China, in 1994 and 1999, respectively, both in mechanical engineering. He is currently the ``Cheung Kong" Chair Professor, Head of the Department of Mechanical Engineering, and Vice Director of the State Key Laboratory of Mechanical System and Vibration. His research interests include mechanical signature analysis for machine and manufacturing process monitoring, CNC machining and 3D measurement of complex shaped parts, and control, sensing, and instrumentation for micro/nano manufacturing. He has been an Associate Editor of the IEEE Transactions on Automation Science and Engineering. He is currently a Technical Editor of the IEEE/ASME Transactions on Mechatronics, and the Editorial Board Members of the Proceedings of the Institution of Mechanical Engineer, Part B: Journal of Engineering Manufacture, and the International Journal of Intelligent Robotics and Applications.

He Ren, Ph.D., is now a professor from National 1000 Talent Program in Shanghai Engineering Research Center of Civil Aircraft Health Monitoring, COMAC. His research interests are maintenance engineering analysis, diagnosis, prognosis and health management.

Gui-Rong Zhou is now a professor with COMAC Shanghai Aircraft Design and Research Institute as a deputy chief engineer on the C-919. He graduated from Northwest Polytechnic University in 1981. He was a deputy designer of the Institute of Helicopter Design of Aviation Industry. He participated in the research and development of several models, such as Zhi- 9 and Zhi-10, and enjoyed the special allowance of the Government of the State Council. In 2008, he was deputy designer of C919 large passenger aircraft model. His research interests are the design of avionics system, prognosis and health management.

Richard S. F. Sheng received two Doctoral degrees from the United States Pepperdine University and Northcentral University, degrees were in Institutional Management and Engineering and Technology Management. He has been selected for the 11th group for the National 1000 Talent Program and 4th group for Shanghai 1000 Talent Program. He has worked 23 years in the United States Boeing/McDonnell Douglas, in-depth participation in the Boeing B756, B767, B787 and C-17 aircraft development programs, and in the military missile technology development programs made many achievements, won the National Malcolm Baldrige Award, Boeing Company Technology Excellence Award, Cost savings, special achievement awards and many other honors. Since 2013 Dr. Sheng has been conducting research in COMAC Shanghai Aircraft Design and Research Institute （SADRI）as a Senior Technical Fellow on the C-919 and Wide Body CR-929 Programs.