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Inferring Cognitive State of Pilot's Brain Under Different Maneuvers During Flight

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***Abstract*— This work designs an adversarial Bayesian deep network to solve the cognitive detection of pilot fatigue. Batch normalization and data enhancement are adopted in the posterior inference of the proposed model parameters to effectively improve the generalization of neural networks. The generator is used to enhance the brain power map generated from three cognitive indicators and improve the accuracy of fatigue state recognition. This work also adds adversarial noise in the vicinity of each brain electrode to form an adversarial image, which further reveals the correlation between the cognitive state of brain and the location of brain regions. Compared with other deep models and parameter optimization methods, our model achieves better detection accuracy.**

***Index Terms*— Cognitive detection, adversarial Bayesian deep network, adversarial noise, brain power map.**

I. Introduction

A PILOT'S perception and cognitive state are greatly significant to improve the ergonomics of the airborne environment and ensure the safety and efficiency of mission execution. The human-in-the-loop flight control system forms an organism with the pilot and the aircraft. The pilot determines the control measures through the changes in the external environment and then controls the aircraft; the aircraft converts the operation input into the dynamic output. The pilot obtains the dynamic state information of the aircraft through the instrument panel to form a feedback of cognition and manipulation action, which is a basic human–machine–environment interaction system. Dealing with difficult flight situations causes changes in pilots' multiple physiological modes, which also lead to changes in their cognitive levels and affect their flight control capabilities. Especially, pilots performing flight tasks are more easily affected by the complexity of the external environment and the impact of massive visual information in a short period, which increases cognitive load and decreases task performance. Therefore, studying the evolution law of pilots' brain cognitive state under different maneuvers has great application value for flight safety [1], [2], [34]–[36].

Currently, brain cognitive state recognition mainly uses the time-frequency distribution and entropy-based features of EEG signals, which are inputted to the deep network for learning and recognition of cognitive states. Showing the ability of convolutional neural network (CNN) to learn these one-dimensional features is difficult in this case. On the basis of this idea, this work compresses the EEG signals during flight, generates brain cognitive indicators, and fuses them into 2D images so that the deep network model can more easily deal with the inference problem of the pilot's brain fatigue state.

Owing to the high flight cost, the amount of data collected by a pilot's EEG signal is small, so the general deep convolutional network model is prone to overfitting when learning the pilot's EEG signal. To solve this difficulty, this work puts forward two solutions: 1) Generative adversarial network (GAN) is proposed to enhance data and improve the accuracy of cognitive state detection. 2) Adversarial noise at each brain electrode position is proposed to reveal the mechanism of the influence of rhythm signals in different brain regions on the fatigue state of pilots.

The rest of this paper is organized as follows. Section II presents related work. Section III defines adversarial Bayesian deep network. Section IV shows experimental results. Section V concludes this work.

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II. Related Work

A. Adversarial Generative Network

Adversarial learning method has gradually emerged in recent years. It mainly solves the problem of insufficient data. Through the mutual checks and balances of the generator and discriminator, this method generates enough fake samples. In specific applications, it can performance improvements for semi-supervised learning.

Prabhat *et al.* [3] explored the effects of various GANs on handwritten data sets. Mudavathu *et al.* [4] used the conditional GAN for expanding handwritten data to better restore the detailed information of an image. Wang *et al.* [5] developed an unsupervised GAN to expand the number of lung nodule samples and then used CNNs for classification and recognition, achieving good accuracy rate. Li *et al.* [6] used GANs to suppress irrelevant noise signals, enabling the learning model to pay increased attention to the main information and achieve more accurate classification. Obviously, the GAN has the effect of not only data enhancement but also interference suppression. Interference suppression is to remove irrelevant information and retain the most useful information, which plays a role in feature screening.

B. Deep Model

Artificial intelligence models have been applied to intelligent vehicles [7]–[9] and target task learning [32] and detection [10]–[13], [33]. Shalash *et al.* [14] adopted an Alexnet network to process a single channel of EEG signals to determine whether a driver is fatigued. This method only considers the impact of a single channel and loses most of the channel information. Gao *et al.* [15] used a spatio-temporal convolutional neural network to process multi-channel EEG signals to obtain the fatigue state of the subjects. This method achieves high classification accuracy. However, their experiment is based on the simulation software on an office PC. The experiment is not carried out on the simulator, so the environmental factors are almost unchanged and have almost no influence on the experimental subjects. Therefore, their approach is difficult to extend fatigue detection of pilots who perform complex operations.

Panwar *et al.* [16] developed a semi-supervised GAN to solve the issue of insufficient labeled data, which is often encountered in fatigue detection problems. However, the performance improvement from this data enhancement is often due to excessive noise signals in the original image. When the original data are noisy in the experiment and the network cannot learn general knowledge, the synthetic samples obtained by the GAN can help the network learn fatigue characteristics and improve classification accuracy. Wang *et al.* [17] used a CNN model to pre-train the EEG emotion recognition data set. They use some pre-trained weights to train the detection model of EEG fatigue. Their work provides new ideas for solving the fatigue detection problem with insufficient data. However, the EEG data contain a large amount of redundant information, which leads to insufficient model learning. Common CNN networks are able to learn more latent features, but their network structures are poorly interpretable. Gan *et al.* [18] combined the restricted Boltzmann machine and CNN to extract the relevant features of the EEG signals of ten electrodes in the occipital region of the brain to achieve fatigue classification. They designed a visual fatigue experiment, in which the subjects watched the checkerboard squares on the screen to generate EEG signals. They then used a multi-channel restricted Boltzmann machine algorithm and CNN to extract the EEG features of the subjects and identify their fatigue state, respectively. The experimental results show that the accuracy of fatigue classification based on Gan *et al.*'s model is 10% higher than that of the traditional method. This outcome illustrates the advantages of the deep model in automatically extracting EEG fatigue-related features. However, the model lacks a fatigue state assessment of the whole brain, and most of the useful EEG signals are lost. The interpretability of the deep model structure is weak, and it is difficult to promote in new scenarios. Li *et al.* [19] presented a novel driving distraction detection method that is based on a new deep network. Unlike traditional methods, the proposed method uses spatio-temporal information of EEG signals as model inputs. Convolutional techniques and gated recurrent units are adopted to map the relationship between drivers' distraction status and EEG signals in the time domain. Wang *et al.* [20] proposed a novel method that can automatically capture the nonstationary dynamics of EEG signals for diverse classification tasks. The method consists of two components. The first component uses an autoregressive-deep variational autoencoder model for automatic feature extraction, and the second component uses a Gaussian mixture-hidden Markov model for EEG classification with the extracted features. Zuo *et al.* [21] proposed a novel framework based on multi-scale entropy in a sliding window and bidirectional long short-term memory network for exploring the distraction information of EEG to detect driver distraction based on multi-modality signals in real traffic. The proposed framework is useful for brain activity information mining and driver distraction detection applications in realistic driving scenarios.

C. Model Parameter Optimization

Bayesian optimization is a new parameter optimization method of deep network. It can provide constraints on a parameter fluctuation range of a network, which leads to a more robust model generation. Charles *et al.* [22] proposed a Bayesian parameter methods. Its global parameters need more precise settings, which limits its wider application. Zhang *et al.* [23] developed a variational-inference-based posterior parameter estimation method. Their network uses deep learning techniques such as data augmentation and batch normalization. However, the results show that their optimization method was unstable after the batch normalization layer. Mohammad *et al.* [24] proposed an approximate Gauss–Newton online inference method to solve the problem of unstable network parameter convergence and further improve Bayesian network parameter optimization theory.

III. Adversarial Bayesian Deep Network

EEG signal often contains a lot of noise. GAN can increase the amount of data and expand the corresponding feature data

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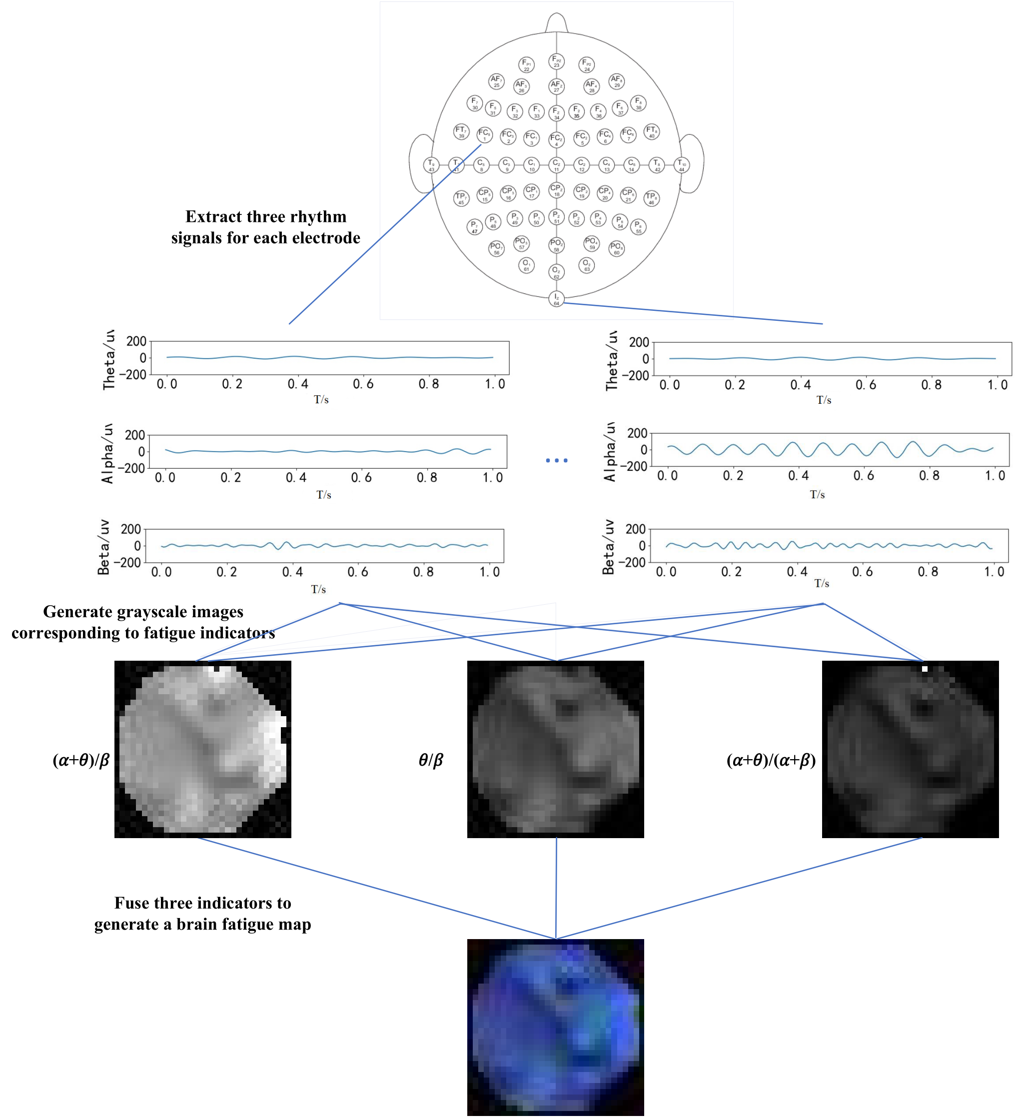

Fig. 1. Generation of a brain map.

set [25]. The design of the network structure not only hopes to find the best cognitive state detection model, but also tends to find the relationship between each electrode and the cognitive state of the brain. GAN can present a certain counterattack to the electrode signal, which can reveal the relationship between the changes in the signal of each electrode and the overall cognitive state.

A. Fatigue Indicator Distribution Map Construction

When the pilot feels fatigued, the energy of the four rhythms in Table I also changes accordingly. Normally, the energy of the slow-wave rhythm increases when fatigued, whereas that of the fast-wave decreases accordingly. The power of δ and θ increases, and the power of α and β decreases. Some studies demonstrate a definite relationship between rhythm power and the degree of human fatigue. They conclude that the relative power ratio can be used to judge a person's cognitive state change of fatigue [26], [27]. In the state of fatigue, the calculated values of the three indicators have an upward trend, which shows that these indicators are sensitive to the state of fatigue. This work takes $(\alpha+\theta)/\beta$, $(\alpha+\theta)/(\alpha+\beta)$, and θ/β as important criteria for pilot fatigue judgment.

TABLE I

EEG Frequency and Corresponding Descriptions

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

As shown in Fig. 1, the pixel values of the three fatigue indicators $(\alpha+\theta)/\beta$, $(\alpha+\theta)/(\alpha+\beta)$, and θ/β are fused to generate a brain power map. The specific generation process is as follows: 1) The 64 electrode positions are projected onto a 32×32 image by using the equidistant azimuth projection method. 2) Three cognitive indicators are calculated on each

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TABLE II
STRUCTURE PARAMETER OF FDMNET

Layer	Data dimensions	Network operation	Output dimension	Parameter Amount
1	32×32×3	6×Conv2D(1×1×3) ReLU	32×32×6	6×3=18
2	32×32×6	9×Conv2D(5×5×6) BN+ReLU +MaxPool (2)	14×14×9	9×5×5×6+18=1368
3	14×14×9	12×Conv2D(5×5×9) BN+ReLU +MaxPool (2)	300	12×5×5×9+24=2724
4	300	FC(300×96) ReLU	96	300×96+96=28896
5	96	FC(96×32) ReLU	32	96×32+32=3104
6	32	FC(32×4) Softmax	4	32×4+4=132
Total	-	-	-	36242

electrode: $(\alpha+\theta)/\beta$, $(\alpha+\theta)/(\alpha+\beta)$, and θ/β. 3) The average value of the three indicators is used as the value of the three colors of RGB. At that time, a 32 × 32 image is obtained, and the uncovered pixels in the image use bilinear interpolation to generate their pixel values. What is finally generated is a brain cognitive state indicator distribution map, that is, a brain power map.

B. Fatigue Indicator Distribution Map Network

The structure of the neural network usually must be adjusted according to the scale and complexity of the processing problem. The structure of the network has a high correlation with the inherent regularity of the problem as well as the scale and complexity of the problem. The handwritten digit recognition task generally uses a Lenet network, and the 10 image classification problems of the Cifaar10 data set commonly use an Alexnet network. The size of the brain cognitive picture generated in this study is 32 × 32. To facilitate the processing of the brain cognitive map sequence, this study designs a fatigue-indicator distribution map network (FDMNet) model to detect the cognitive state of the pilot's brain. Its structure is shown in Table II. The input of the FDMNet model is the generated sequence of brain cognitive maps. Table II also shows the composition of FDMNet and its parameter settings. Fig. 2 depicts the FDMNet structure. In this case, the loss function is defined as $\bar{\ell}(\boldsymbol{w})+\delta\boldsymbol{w}^T\boldsymbol{w}$, where $\bar{\ell}(\boldsymbol{w}) := \frac{1}{N}\sum_i \ell\left(\boldsymbol{y}_i, \boldsymbol{f}_w(\boldsymbol{x}_i)\right)$, $\boldsymbol{f}_w(\boldsymbol{x}_i) \in R^K$ represents the output results of DNN when the weight is $\boldsymbol{w}$. $\ell\left(\boldsymbol{y}_i, \boldsymbol{f}_w\right)$ represents the difference between the expected output $\boldsymbol{y}$ and the network output $\boldsymbol{f}$, and $\boldsymbol{w}^T\boldsymbol{w}$ represents L_2 regularization where $\delta > 0$.

The problem of pilot fatigue detection is a multi-category problem. These categories include non-fatigue state, mild fatigue state, moderate fatigue state, and extreme fatigue state. For multi-classification problems, the experiment generally uses one-hot encoding. However, the fatigue classification is not an ordinary image category classification, and the fatigue degree is similar to a regression problem. Therefore, one-hot encoding cannot well combine the correlations between different categories. A label enhancement problem is encountered. Unlike the method of data enhancement to increase the amount of data, label enhancement is to enhance the expression ability of the label. The smooth transition between labels is an important method whose purpose is to make full use of the fuzzy boundaries between adjacent tag categories.

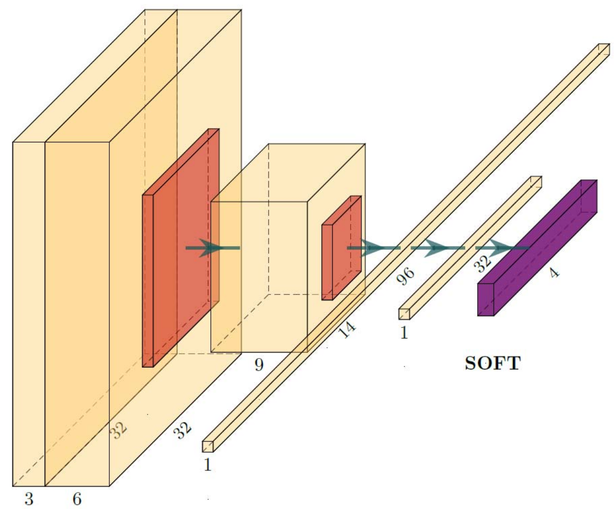

Fig. 2. Network structure of FDMNet.

For this reason, a cross-entropy loss function with smoothness constraints between labels is designed in (1) as the objective cost function of the developed CNN in this work.

$$\begin{aligned}\ell&\left(\boldsymbol{y}_i, \boldsymbol{f}_w(\boldsymbol{x}_i)\right)\\ &= -\sum_{c=1}^{2}\boldsymbol{y}_{ic}\log\left(\boldsymbol{f}_{wc}(\boldsymbol{x}_i)+\varepsilon\boldsymbol{f}_{w(c-1)}(\boldsymbol{x}_i)+\varepsilon\boldsymbol{f}_{w(c+1)}(\boldsymbol{x}_i)\right)\\ &\quad-\boldsymbol{y}_{i0}\log\left(\boldsymbol{f}_{w0}(\boldsymbol{x}_i)+\varepsilon\boldsymbol{f}_{w1}(\boldsymbol{x}_i)\right)\\ &\quad-\boldsymbol{y}_{i3}\log\left(\boldsymbol{f}_{w3}(\boldsymbol{x}_i)+\varepsilon\boldsymbol{f}_{w2}(\boldsymbol{x}_i)\right),\end{aligned} \tag{1}$$

where ε is the smoothness constraint parameter in the middle of different fatigue degrees, which can be understood as the tolerance for misjudgment of adjacent fatigue degrees. $\boldsymbol{y}_{i0}$ is the expected output of the initial state, and $\boldsymbol{y}_{it}$ is the expected output of the state t. $\log\left(\boldsymbol{f}_{w0}(\boldsymbol{x}_i)+\varepsilon\boldsymbol{f}_{w1}(\boldsymbol{x}_i)\right)$ represents the cross-entropy loss function of the initial state affected by state 1. $\log\left(\boldsymbol{f}_{w1}(\boldsymbol{x}_i)+\varepsilon\boldsymbol{f}_{w0}(\boldsymbol{x}_i)+\varepsilon\boldsymbol{f}_{w2}(\boldsymbol{x}_i)\right)$ represents the cross-entropy loss function of state 2 affected by the initial state and state 2. $\log\left(\boldsymbol{f}_{w2}(\boldsymbol{x}_i)+\varepsilon\boldsymbol{f}_{w1}(\boldsymbol{x}_i)+\varepsilon\boldsymbol{f}_{w3}(\boldsymbol{x}_i)\right)$ represents the cross-entropy loss function of state 2 affected by states 1 and 3. $\log\left(\boldsymbol{f}_{w3}(\boldsymbol{x}_i)+\varepsilon\boldsymbol{f}_{w2}(\boldsymbol{x}_i)\right)$ represents

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the cross-entropy loss function of state 3 affected by state 2.

The second-order Gaussian variational inference (SGVI) [24] is used in FDMNet network training. **Data augmentation** (DA) can increase the accuracy of fatigue state recognition when training the fatigue indicator distribution map. DA increases the diversity of training data, which can alleviate the difficulty of data collection and the impact of insufficient data. **Batch normalization** (BN) [28] is widely used in data processing neural networks. The BN layer is usually located in front of an activation function to ensure that the distribution of the activation function is in a stable range. In SGVI, the BN layer is usually inserted directly before the activation function. It uses conventional hyperparameter settings. However, not all activation functions require the BN layer. The extra BN layer even makes the network difficult to converge, which must be adjusted according to the network structure. In FDMNet, the BN operation is used to control the output data distribution after the convolution operation of the second and third layers so as to avoid the problem of network learning difficulties caused by gradient explosion or gradient disappearance. **Momentum and initialization** can also improve the learning speed and stability of the network [29]. Similar to Adam, a momentum term is used in SGVI. Its setting refers to the Adam method. The difference between these two algorithms is that SGVI method should set the variance parameter $\boldsymbol{\sigma}^2$, where $\boldsymbol{\sigma}_0^2 = \frac{\tau}{N(s_{\mathbf{0}})+\delta}$. **Learning rate** [30], [35] can improve the convergence speed of the network model and obtain a better fatigue detection accuracy on the test set. Generally, the learning rate decays by a factor after a certain number of iterations. In SGVI, the learning rate attenuation strategy is proposed to deal with the above situation.

C. Adversarial Network Learning

The GAN is an important method in network learning. Adversarial learning mainly includes two methods: adversarial data augmentation and network adversarial strike. Owing to the high cost of flight experiments and the preciousness of the special population of pilots, the number of pilots participating in the experiment is limited. The GAN uses the original data to generate more data of the same type and enhance the learning ability of the network. The adversarial counterattack can be applied to feature screening. By adding adversarial noise to a corresponding area of a certain electrode, this work explores the influence of the EEG cognitive indicator of each different electrode on fatigue detection. The generating network is G, and $L_G(z)$ is its loss function. The adversarial network is D, $L_D(x,z)$ is its loss function. The real data are represented by x, and the random sequence is z. The adversarial learning aims to make $D(x)$ close to 1, and $D(G(z))$ close to 0. The generation network intends to make $D(x)$ and $D(G(z))$ close enough. Their objective function can be expressed as

$$\min_G \max_D \mathbb{E}_{x\sim p_{data}(x)}\left[\log D(x)\right] + \mathbb{E}_{z\sim p_z(z)}\left[\log\left(1 - D\left(G(z)\right)\right)\right], \quad (2)$$

where $\mathbb{E}$ represents the calculation expectation. The input of the generating network is random Gaussian noise. The input of the confrontation network is the generated image and the original one. The network adopts batch learning, and the size of each batch is set to N. Its loss functions are as follows:

$$L_G(z) = -\frac{1}{N}\sum_{i=1}^{N}\log\left(D\left(G\left(z_i\right)\right)\right),$$
$$L_D(x,z) = -\frac{1}{N}\sum_{i=1}^{N}\left(\log D\left(x_i\right) + \log\left(1 - D\left(G\left(z_i\right)\right)\right)\right). \quad (3)$$

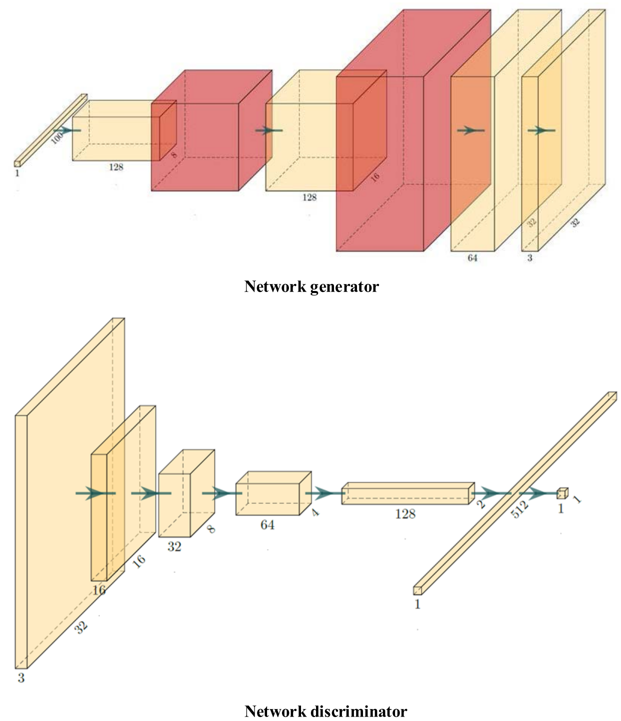

Fig. 3. Structure of the GAN.

An image is suitable for extracting features using convolution operations, so this work builds a GAN with a convolutional network module, and its structure is shown in Fig. 3. The GAN consists of two parts: one is the generative model, and the other is the discriminative model. A noise/sample is inputted to the generative model, which is then transformed into an imaginary sample, the output. A discriminative model is a binary classifier (similar to a 0-1 classifier) to judge whether an input sample is true or false.

GAN uses game methods to enhance data and improve the learning ability of the network. Adversarial learning can not only enhance data but also can be used for feature screening. Adversarial learning can be applied to explore the influence of each part of the image on the final brain cognitive state detection. In the experiment, the noise signal is used to replace the pixel value of the nearest neighbor area of a certain electrode area so as to realize adversarial attack learning. Supposing the nearest neighbor area of electrode i in an image is N_i, the original EEG image is I, the EEG image after the adversarial attack is I_D, and a certain pixel in an image is p.

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Fig. 4. Flight simulator and monitoring system.

The process can be described as follows:

$$I_D(p) = \begin{cases} n \sim \mathcal{N}(\mu, \sigma),\ p \in N_i \\ I(p),\ p \notin N_i \end{cases}, \tag{4}$$

where $\mathcal{N}(\mu, \sigma)$ is a Gaussian distribution, μ is its mean value, and σ is its variance. Through the adversarial attack of 64 electrodes, in turn, the influence of different electrode positions is reported, which is beneficial to reveal the mechanism of fatigue distribution in the brain.

IV. Experiments

The data for the experiments come from our previous work [31], where we define four cognitive indicators and then use a deep contraction autoencoder network to detect pilot fatigue state recognition accuracy. In the present work, we generate a brain cognitive map and establish a brain cognitive detection model on the basis of cognitive indicators. Owing to the high cost of flight experiments and the rarity of pilot subjects, the diversity of samples has become a bottleneck in the training and learning of brain cognitive models. For this reason, a GAN is proposed to generate diverse brain cognitive maps, which make up for the small number of experiments. We also study the effect of generative adversarial noise on the cognitive state detection accuracy of different brain electrode locations.

To collect the pilots' physiological signals during the flight simulation, experiments are performed in a 6-degree-of-freedom full flight simulator (Fig. 4), 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 are 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).

The BCI200 system recorded EEG signals in a simulation experiment. The system has 64 reference electrodes and a sampling frequency of 160 Hz.

Controlling an aircraft is a complex task that requires close coordination between the pilot's hands, feet, eyes, and brain. Given a mission, pilots need to make different operational responses within a very short period. These operations require pilots to have different levels of cognitive and operational abilities, corresponding to different degrees of workload. Pilot workload plays an important role in flight cockpit automation research. First, it implies the relationship between different levels of workload and flight automation, which facilitates the development of more efficient flight adaptive logic. Second, pilot workload can provide pilot-related information that can be integrated with aircraft flight performance assessments and pilot brain cognitive modeling to facilitate cockpit automation program adjustments. We collect the EEG signals of pilots under different operating actions and provide a method for detecting the cognitive state of their brains under less data.

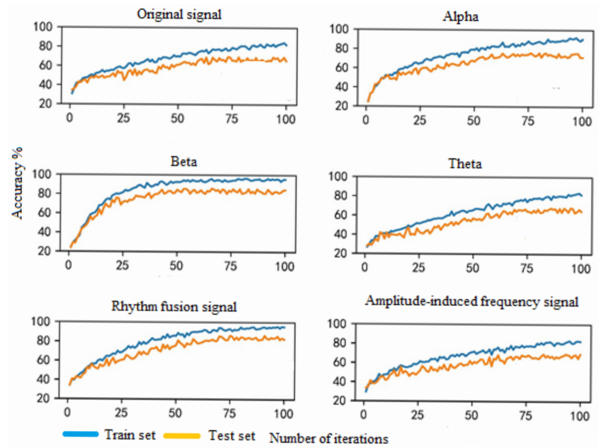

Fig. 5. Network performance of different feature representations.

Experiments performed address the following concerns: 1) An experiment provides a comparison of the fatigue detection accuracy of four cognitive feature representation methods. 2) Experiments use SGVI to infer model parameters of FDMNet and prove its generalization performance. 3) Experiments add adversarial generation data to FDMNet-SGVI network training to improve network learning capabilities. 4) Experiments apply adversarial learning methods for fatigue cognitive features filter. The results of online learning clarify the location of the brain areas related to fatigue in the brain and reveal the distribution of fatigue in the cerebral cortex.

A. Determination of Fatigue Feature

Our dataset has a brain map with four cognitive state types, which is a type of supervised learning, and our aim is to identify the overall accuracy. Like the famous handwritten digits 0 to 9 recognition, the purpose of its task is not to identify which specific number is but to identify the overall recognition accuracy of these numbers. Our experimental results are shown in Fig. 5.

Fig. 5 shows the detection accuracy under four types of feature input. They are the original EEG signal, the three rhythm signals, the rhythm fusion signal, and the amplitude-induced frequency signal. The original EEG signals can obtain an accuracy of more than 60%. Although its accuracy is not very high, the result shows that this method is effective. The results of the three rhythms show that the rhythm signal still can detect fatigue. The fatigue detection effect of the beta rhythm is better than that of other rhythms, and it is better than the original EEG signal. The fusion image of the four rhythms further improves the accuracy of fatigue detection on the test set. The frequency ranking method of rhythm signals converges slowly on the train set, and the accuracy on the test set is between 60% and 70%.

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TABLE III
PERFORMANCE COMPARISON OF DIFFERENT EEG INPUT MODELS

Feature	Accuracy		Time
	Train set/%	Test set/%	One iteration/s
Original signal	80.12	67.42	0.21
Alpha	83.21	73.46	0.21
Beta	**93.14**	83.88	0.21
Theta	78.52	64.23	0.21
Rhythm Fusion	92.56	**83.95**	0.25
Frequency signal	79.12	66.68	**0.18**

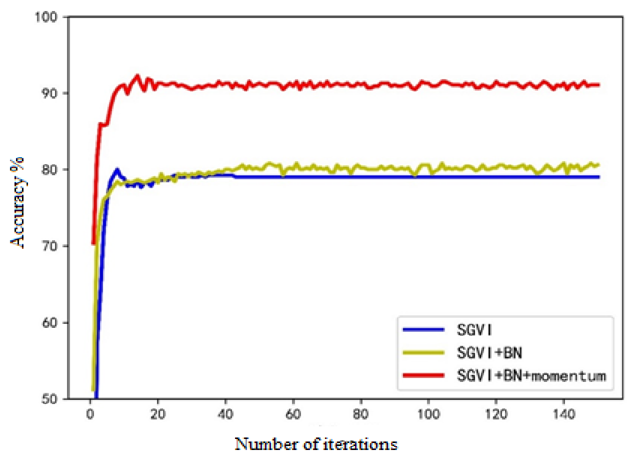

Fig. 6. Impact of parameter optimization.

Table III provides the detection results of the four types of cognitive features. All results are the average of the last 10 iterations. Fatigue detection through a brain image generated from the fusion of the four rhythm signals is clearly the best, and the amplitude-induced frequency feature provides the fastest learning efficiency. In this study, we divide fatigue into four levels, and a test accuracy of more than 83% is acceptable.

B. Performance of FDMNet

First, the following experiment presents the effect of SGVI on parameter optimization of FDMNet. Fig. 6 demonstrates that using SGVI to optimize the model parameters normally is feasible, and a stable result can be obtained. However, the accuracy of fatigue recognition is limited. Adding a batch normalization layer before the activation function can slightly improve the recognition accuracy, and then a momentum term adopted in the gradient descent significantly improves the recognition accuracy on the test set. Experiments show that BN and momentum technology can improve the recognition ability of FDMNet.

Fig. 7 shows the impact of smoothness tolerance on the detection accuracy. When a smaller smoothness tolerance constraint is presented, its accuracy can be improved, which also proves the effectiveness of the smoothness constraint. In this experiment, we choose $\varepsilon = 0.2$. Two commonly used image classification network architectures, Lenet and Alexnet, are chosen as baseline models. The network parameter optimization algorithm selects the commonly used Adam method and the SGVI method commonly used for Bayesian posterior inference. Fig. 7 shows the test results of three network architectures with two-parameter optimization methods. We adopt classic the Adam method as the peer of SGVI.

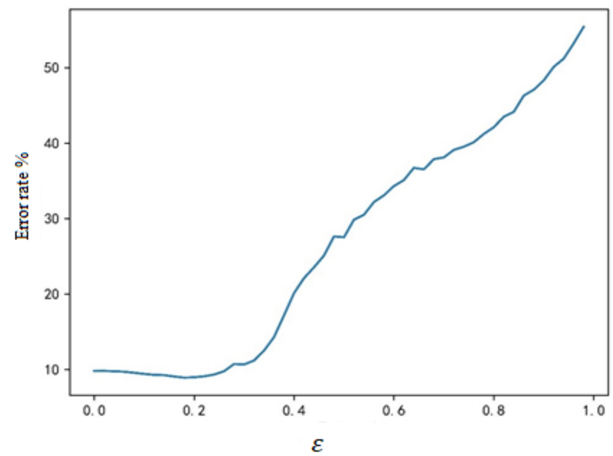

Fig. 7. Error rate under different tolerance ε.

In Fig. 8, the fatigue detection accuracy of a Lenet network is slightly lower than that of a Alexnet network. The reason is that the Lenet structure is a lightweight network compared with the Alexnet structure, with fewer network layers and lower complexity. In terms of the difference in detection accuracy between the train set and the test one, the Lenet network has a lower overfitting than the Alexnet network. This work constructs a FDMNet with medium complexity. When a conventional Adam method is used, the detection accuracy is close to the Alexnet network. When the SGVI is used, the test set has the highest fatigue recognition accuracy. Fig. 8 compares the two iterative optimization methods of parameters horizontally. The fatigue detection accuracy of the SGVI verification set is basically the same as that of the Adam method. Machine learning usually includes two situations, namely, underfitting and overfitting. The difference between them is that underfitting has poor performance on both the training and test sets, whereas overfitting tends to perfectly learn the properties of the training set data, with poor performance on the test set. The lower the accuracy of the model on the training set, the lower the risk of overfitting on the test set. When the model performance is satisfied, the model performance requirements on the training set can be lowered, and then a better model performance can be obtained in the test set. Therefore, lower fatigue identification accuracy is obtained on the training set, and higher model performance is obtained on the test set, which has a relatively low risk of overfitting.

In summary, by selecting an appropriate number of iterations, the SGVI can match or even be better than the Adam. The SGVI is also more robust and has a lower overfitting.

In this work, two common image classification network architectures, Lenet and Alexnet, are selected for the comparison model. Fig. 7 shows the comparison of the FDMNet network structure developed in this study and the structure of the two baseline models. Their parameter optimization methods adopt the Adam method and SGVI method. Table IV shows their results on the test set. The SGVI reduces the risk of model overfitting. In addition, the result illustrates the rationality of the FDMNet network structure. The SGVI+FDMNet achieves the best detection accuracy. The disadvantage of the Bayesian method lies in large calculation cost and time consumption.

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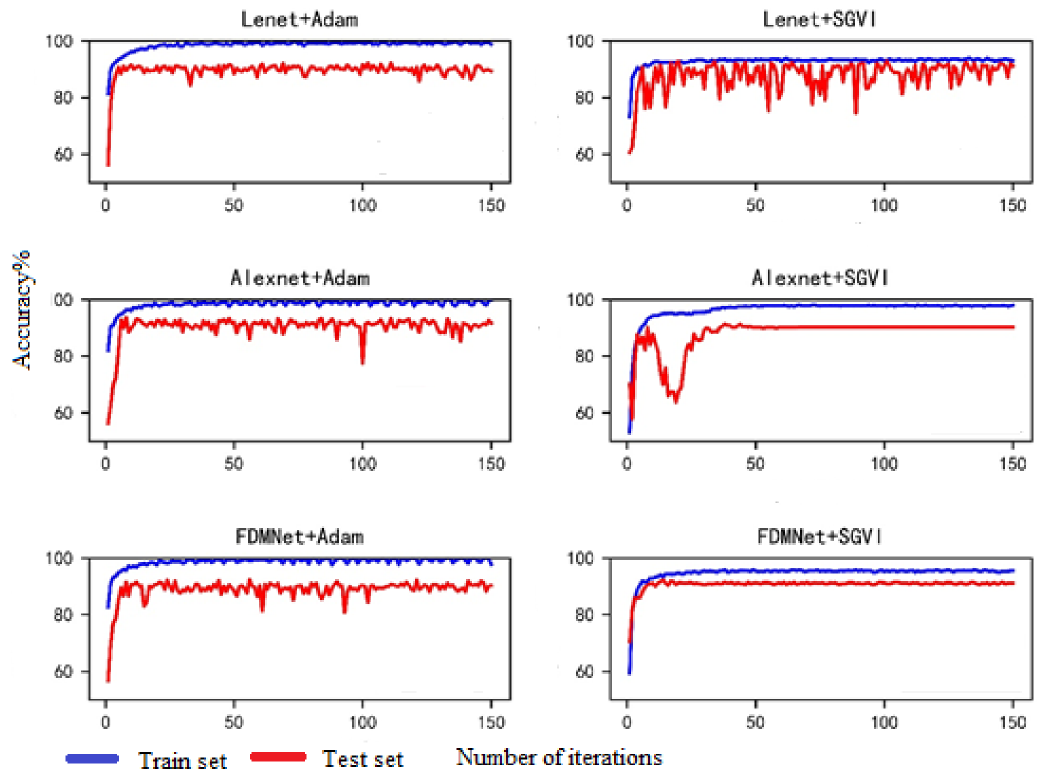

Fig. 8. Network performance.

TABLE IV
COMPARISON OF NETWORK PERFORMANCE

Network model	Number Iterations	Accuracy/% Train set	Accuracy/% Test set	Time /s One iteration
Lenet+Adam	150	**99.27**	89.46	**3.04**
Lenet+SGVI	150	93.31	90.72	27.13
Alexnet+Adam	150	99.05	91.01	9.68
Alaxnet+SGVI	150	97.82	90.31	231.57
FDMNet+Adam	150	99.21	90.56	4.08
FDMNet+SGVI	150	95.30	**91.06**	14.71

The time consumption of SGVI is three times more than that of Adam. However, in offline training, such consumption of computing resources is acceptable. As the training process does not affect the speed of online testing, pilot fatigue can still be detected quickly in the experiment. The FDMNet with SGVI can achieve a detection accuracy of 91%.

C. Adversarial Data Enhancement Performance

In the pilot fatigue detection experiment, as the limited number of pilots, the amount of data obtained are limited. The deep model experiences difficulties in playing its advantages without enough data. Many methods are available for data enhancement. The conventional methods include image flipping, random image rotation, and random changes in the chroma, brightness, and contrast of the image. The features contained in the pilot's cognitive map are not yet clear, and traditional data enhancement methods may destroy the fatigue-related features. GAN provides a feasible solution to this situation. This work calibrates the attributes of the three cognitive indicators through the student mixture model, obtains the level of these indicators, and then generates the corresponding brain cognitive fatigue map sequence, as shown in Fig. 9.

GAN generates fake and real pictures through a mutual game between the generator and discriminator. Fig. 8 shows an example of the brain cognitive map generated by the GAN. The original pictures in the four fatigue states are similar to the generated pictures of the GAN, as shown in Fig. 9. The generated picture is affected by random noise interference.

In the experiment, a GAN structure based on convolutional features is used. The corresponding enhanced pictures are generated for each category of the fatigue indicator map, and the corresponding data volume is doubled. The proposed network structure adopts FDMNet+SGVI. The result in Fig. 10 shows that using mixed data sets can improve the accuracy of fatigue detection to more than 92%.

D. Adversarial Feature Screening Results

The adversarial learning method can be used in feature selection. The fatigue indicator of each electrode position is closely related to the cognitive state of the whole brain. Deep network can obtain higher detection accuracy, but it is a black box for the mechanism of fatigue analysis. Although the FDMNet achieves a high detection accuracy, researchers want to obtain the main brain regions that affect brain cognitive state. In the experiment, we hope that the main brain areas that affect brain cognitive state can be identified. Adversarial learning provides an effective solution.

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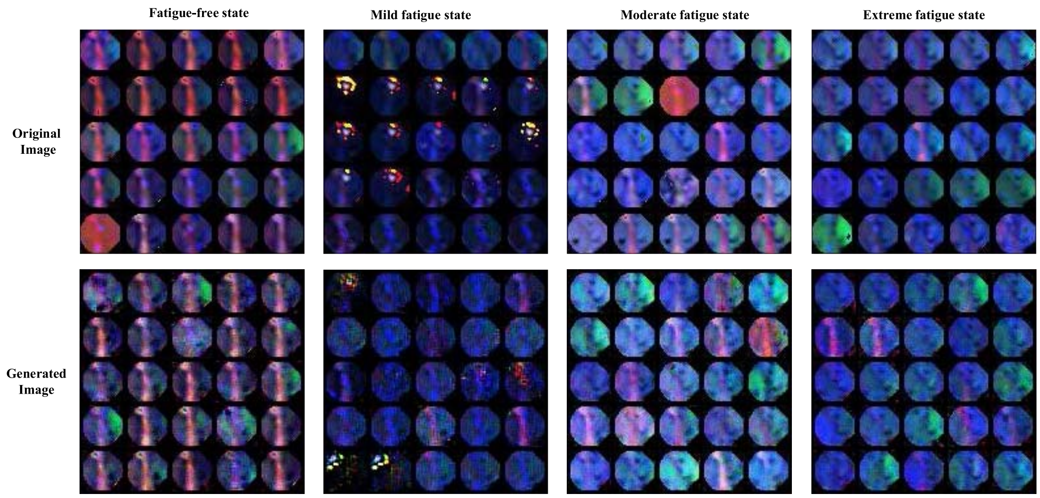

Fig. 9. Images generated from GAN.

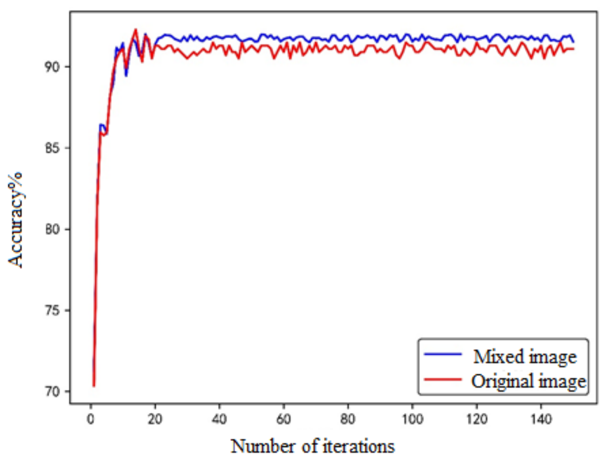

Fig. 10. Performance of data enhancement.

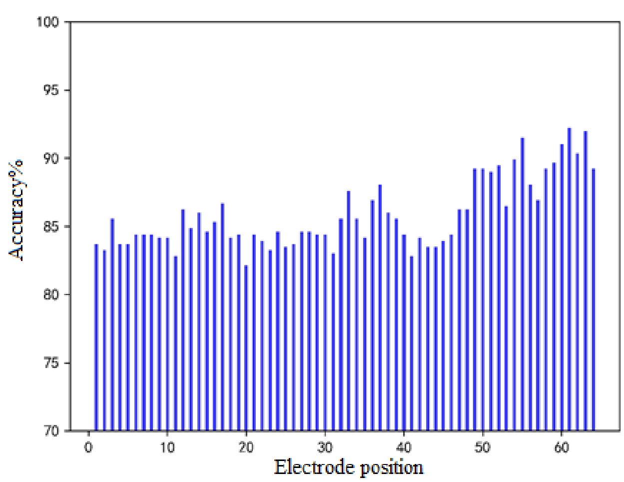

Fig. 11. Recognition accuracy from adversarial attack.

This work uses the adversarial learning method to add adversarial noise to the nearest neighbor area of each brain electrode in turn. This work aims to increase the anti-noise of each electrode, observe the fatigue recognition accuracy of the established network, and reveal the influence of adversarial noise on the cognitive state of the brain. This network adopts FDMNet+SGVI model, the ratio of generated data is 1:1, and the fatigue detection accuracy of each electrode is shown in Fig. 11 after increasing the adversarial noise. The importance of different electrode positions for fatigue detection varies. The addition of adversarial noise to the brain cognitive map at some electrode locations significantly reduces the accuracy of fatigue prediction. This result demonstrates that some regions of the brain respond more strongly when the pilot is fatigued, whereas some regions are hardly affected.

V. Conclusion

This study proposes an anti-Bayesian depth model method to detect the fatigue state of pilots. The specific work can be summarized as follows:

1) This work uses a deep filtering network to analyze the pilot rhythm timing chart and obtains a detection accuracy of more than 83%.

2) To further improve the accuracy of fatigue detection, the experiment extracts three kinds of fatigue cognition indicators and constructs its distribution map, that is, the brain cognition map.

3) While learning the brain atlas, Bayesian parameter optimization is introduced to optimize the neural network parameters to obtain higher generalization accuracy. The results show that the accuracy from the brain power map can reach 91%.

4) In response to the problem of limited sample data, this work establishes a generative confrontation network model and expands the pilot brain atlas data. The results show that the fatigue detection accuracy increases to 92% after data enhancement.

5) This work uses the adversarial learning method to explore the influence of each electrode position on the accuracy of the pilot's brain cognitive state reasoning. The ranking of the influence of each electrode on the final recognition accuracy

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is obtained, revealing the pilot fatigue mechanism during the flight mission.

Our future research will focus on both theory and application. The theoretical work to be carried out includes 1) exploring more representative EEG feature representation methods in the context of tasks, 2) building deep models and improving generalization capabilities in the case of insufficient data, and 3) exploring fatigue response mechanisms and representation in EEG signals. In terms of application, the work to be carried out mainly relies on the experimental conditions of the PLA Air Force Medical Center, collects pilot data on actual aircraft, and further explores the evolution of pilots' cognitive state in the context of the task.

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