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Spectrum Analysis of EEG Signals Using CNN to Model Patient's Consciousness Level Based on Anesthesiologists' Experience

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ABSTRACT One of the most challenging predictive data analysis efforts is an accurate prediction of depth of anesthesia (DOA) indicators which has attracted growing attention since it provides patients a safe surgical environment in case of secondary damage caused by intraoperative awareness or brain injury. However, many researchers put heavily handcraft feature extraction or carefully tailored feature engineering to each patient to achieve very high sensitivity and low false prediction rate for a particular dataset. This limits the benefit of the proposed approaches if a different dataset is used. Recently, representations learned using the deep convolutional neural network (CNN) for object recognition are becoming a widely used model of the processing hierarchy in the human visual system. The correspondence between models and brain signals that holds the acquired activity at high temporal resolution has been explored less exhaustively. In this paper, deep learning CNN with a range of different architectures is designed for identifying related activities from raw electroencephalography (EEG). Specifically, an improved short-time Fourier transform is used to stand for the time-frequency information after extracting the spectral images of the original EEG as input to CNN. Then CNN models are designed and trained to predict the DOA levels from EEG spectrum without handcrafted features, which presents an intuitive mapping process with high efficiency and reliability. As a result, the best trained CNN model achieved an accuracy of 93.50%, interpreted as CNN's deep learning to approximate the DOA by senior anesthesiologists, which highlights the potential of deep CNN combined with advanced visualization techniques for EEG-based brain mapping.

INDEX TERMS Depth of anesthesia, convolutional neural network, electroencephalography, short-time Fourier transform.

I. INTRODUCTION

Anesthesia is a crucial procedure for doctors in the surgical environment, which enables doctors to perform surgery on patients with unconsciousness and painlessness [1], [2]. The earliest depth of anesthesia (DOA) monitoring methods are mainly estimated by the experienced anesthesiologists through patient's physiological response, and these evaluation methods lack clear quantitative indicators and ability to avoid external interference. The results will lead to inaccurate anesthesia, which brings clinical safety hazards to patients during surgery [3]. Thus, scientists have been looking for parameters that characterize the DOA from medical signals, so that anesthetic drugs can be used more accurately for achieving anesthesia. However, from which the study of electroencephalogram (EEG) parameters is the most effective [4]–[6], it is still non-standard and no any best solution so far.

Recently, EEG-based DOA assessment method has been rapidly developed. With the reason that general anesthesia makes the brain's conscious activity disappear mainly

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through the inhibition of the central nervous system and EEG is the main physiological signal that reflects the activity of brain consciousness. Even then, there is no effective way that is approved by clinical anesthesiologists to define DOA.

Since the 1960s, some emerging EEG-based DOA monitoring technologies (including spectral peak frequency, median frequency, marginal frequency, etc.) [7]–[10] were based on the evaluation of EEG nonlinearity under anesthesia within a specific medical dataset, which helps to explore the potential dynamics of EEG signals in DOA according to the non-linear and random nature of EEG signals [11]. Zhang *et al.* [4] used Lempel–Ziv complexity analysis to quantify the relationship between the brain activity patterns and DOA, which achieved 93% accuracy on discriminating awake and asleep states. Lalitha and Eswaran [12] adopted correlation dimension (CD), Lyapunov exponent (LE) and Hurst exponent (HE) to extract DOA features and two neural network models, i.e., multi-layer perceptron network (feed forward model) and Elman network (feedback model) for classification. Which finally producing an overall accuracy of 99% at the anesthesia levels (Low, Medium, and High). Moreover, Peker *et al.* [13] divided the anesthesia levels into six categories and achieves 99.05% classification accuracy by using effective feature extraction and classification algorithms in high-performance GPU computing systems. In general, these complex analysis methods on EEG-based DOA monitoring promote the progress of precision anesthesia within the local dataset. However, these research on EEG in anesthesia is within a small sample size or specific dataset, resulting in the inability to resolve patients' individual differences due to the large sample size of patients in the actual application process. Besides, excellent feature extraction methods are time-consuming, computing-intensive and difficult to be promoted when used for commercial purpose. Therefore, considering a DOA monitoring technique based on large sample data or a small amount of work for feature extraction is of great significance for accurate anesthesia to various patients in clinical surgery.

As a result of rapid development of machine vision and the graphics cards, deep learning, i.e., convolutional neural network (CNN) has gradually evolved into the mainstream in EEG. Some studies [15] have shown that deep learning technology is expected to surpass traditional machine-based classification and feature extraction algorithms. Of which the use of CNN model has made a good development in the state of brain falling asleep, but it has still not broken through the theory of "a fixed state" [16], [17]. Moreover, CNN has been further developed in the medical field including seizure, brain coma, imagination, etc. [18]–[20]. However, the application of deep learning is seldom studied on anesthesia. This is because it is not easy for researchers to have the patient's total anesthetic state, apart from the extremely strict requirements of CNN on the operating environment. There are only few research teams that can meet the above conditions. However, our research team has had decades of experience in DOA research with published achievements [21]–[24] and our lab also satisfies the hardware conditions for CNN operation. Hence, if a breakthrough can be made on the DOA, it will be a great attempt at success.

As for CNN, one of its attractive property is to learn from large sample data without any priori feature selection, which happened to hit our conjecture. However, raw EEG is not suitable for deep learning training directly in anesthesia since the EEG time domain data has no intuitive anesthesia information. The reason is that when the DOA changes from shallow to moderate, the main changes including β-wave (13–30 Hz) and α-wave (8–13 Hz) are all manifested in the frequency domain characteristics [14]. In addition, the EEG signal has a relatively low signal-to-noise ratio, that is to say sources without task-related information typically reflect EEG signals more strongly than task-related sources. These characteristics may make the input-to-output learning function more difficult for EEG signals than for images. Therefore, looking at the existing CNN architecture from the field of computer vision, the form of the EEG input requires being changed to its spectrogram. EEG research applying to the medical field in the time-frequency domain has constantly brought surprises to people [25]. The simplest time-frequency domain analysis method, short-time Fourier transforms (STFT) [26] can be used to explain the time-varying law of EEG signal spectrum in different states. Särkelä et al. [27] used the STFT method for spectral analysis to effectively detect the burst suppression caused by different anesthetics. Yuan and Cao [19] and Truong *et al.* [28] adopted the STFT analysis method to perform spectrogram conversion on the EEG signal and obtained good disease prediction results after training. This indicates that it is an effective measure to applying STFT to EEG analysis, which also well explain the real-time changes of anesthetic features in the frequency domain. Therefore, in this study, application of STFT to DOA is being attempted which result in the classification accuracy requiring more rigorous evaluation than traditional feature extraction methods. For this reason, a clear classification criterion is crucial. As a medical DOA indicator, BIS has been widely used to detect patients' conscious awareness although it is still not perfect [29], [30]. In this study, the average value of "the state of anesthetic depth" called expert assessment of conscious level (EACL) which is decided by five senior anesthesiologists based on detailed records during surgery is used as the classification standard to train CNN [21].

In general, the aim of this research is to form a set of CNN-based DOA assessment index theories and methods as clinical application demonstration for anesthesia patients via applying CNN model to EEG-based DOA monitoring. Therefore, this article started from the EEG signal acquisition and proposed corresponding pre-processing methods for various artifacts [31]–[33] in raw EEG signal. Then, a series of different CNN models were created and adjusted to an optimal and specific CNN structure for DOA assessment system, so as to assist the anesthesiologist in fully understanding the patient's physiological state at different stages of surgery and giving the patient better care.

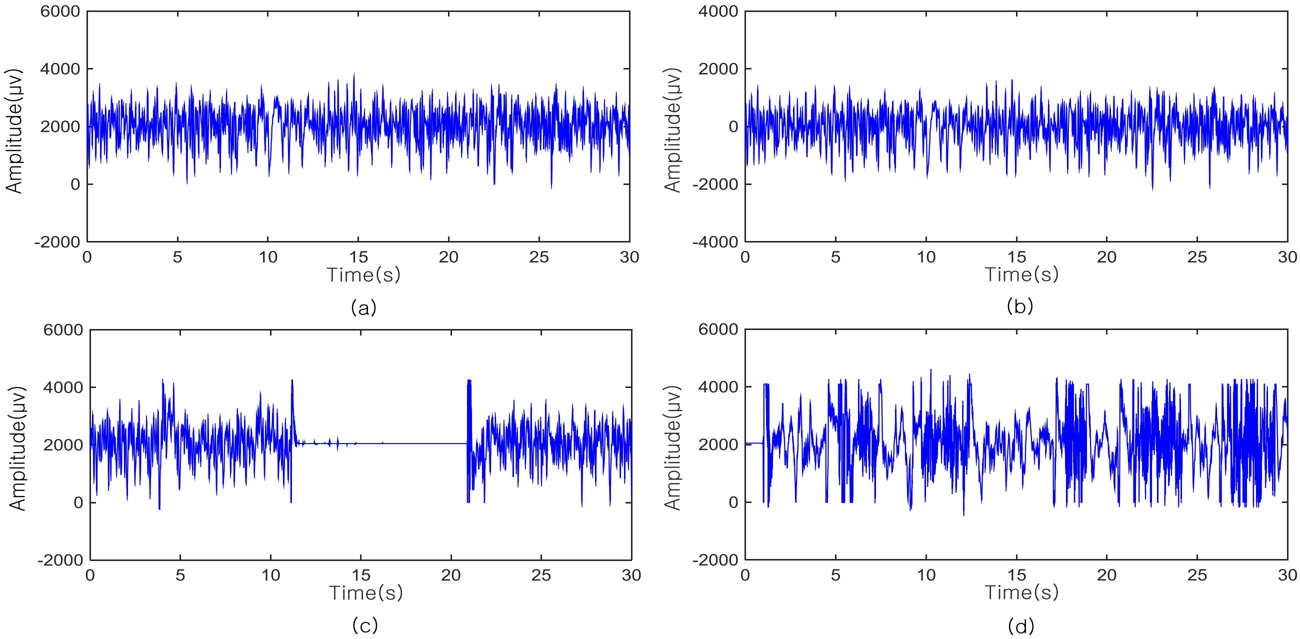

FIGURE 1. Data preprocessing. (a) Raw EEG; (b) 0.5-30 Hz filter of (a); (c) Signals that have been lost due to fragment loss in the signal; (d) Signals caused by interference from environmental factors.

II. EXPERIMENTAL SECTION

A. THE ANESTHETIC DATASET

This work collects two types of data sets: one is the dataset for the complete surgery of general anesthesia raw EEG signals and anesthesia record sheets collected from the National Taiwan University Hospital (NTUH) anesthesiology department; the other is the DOA dataset of the patient's surgical procedure drawn by experienced senior anesthesiologists, which is called expert assessment of conscious level (EACL) dataset. These datasets contain 50 patient data (their ages range from 23 to 72 years old who received ENT surgery at NTUH) as a database for this study [22]. In these data, the average EEG signal collected from each patient is about 2.5 hours. The data is processed every 30s (i.e., window size). Thus, it gives an approximately 14100 sample data, contributing enough data for this study.

TABLE 1. Range of average EACL value for different levels of DOA.

Consciousness Level	Data structure	Range
Anesthetic Light (AL)	2187 (19%)	average EACL (60-100)
Anesthetic OK (AO)	4940 (43%)	average EACL (40-60)
Anesthetic Deep (AD)	1394 (12%)	average EACL (0-40)
Signal Polluted (SP)	2991 (26%)	--

Since medical datasets are often "biased", in that the number of conventional samples is much larger than the number of unconventional instances, or that the numbers of images per class are uneven. Thus, the structure of anesthesia sample from each patient differs in different DOA levels with the same contribution, which is shown in Table 1 [12]. Similarly, the average EACL value between 40 and 60 is defined as anesthetic OK (AO) named "suitable for surgery", a value below 40 is anesthetic deep (AD) indicating that the DOA value is low, and a value between 60 and 100 is anesthetic light (AL) indicating that the DOA value is light and may only be suitable for certain types of surgery. Of course, some external interference may exist in the EEG signals collected from a complex environment (i.e., patch off, external frequency interference, etc.), which called signal polluted (SP).

B. PRE-PROCESSING

Since two-dimensional CNN will be applied to our work, it is necessary to convert raw EEG signal into a matrix (i.e., image-like format) and its corresponding DOA level (i.e., tag data). After understanding the purpose of preprocessing, the first work is to divide the sample data into four categories including AL, AO, AD, and SP. Secondly, the first three categories (AL, AO, AD) of data are filtered: the raw EEG signal collected by each patient contains all message, as shown in Figure 1 (a). Then it is channel filtered from 0.5 to 30 Hz, with the reason that most of the EEG features occur at these frequencies during anesthesia [34]. Figure 1 (b) is the EEG signal filtered by 0.5 to 30 Hz of Figure 1 (a). For SP data, it is contaminated signal fragments through the manual selection. Figure 1 (c) is a form of SP data, which shows that the signal is lost during the collection phase. It can be due to many reasons, such as the loss of wires and poor contact of connectors. Figure 1 (d) is another form of SP data, which demonstrates that the signal is interfered by environmental noise other than physiological interference, such as equipment and instrument frequency interference, machine self-interference and so on. Accordingly, EEG data during pre-operation and operation stages are filtered and picked up as mentioned above. All 50 patients' data are used to obtain a new DOA index reflecting four consciousness level (including AL, AO, AD and SP) through CNN method.

Generally speaking, wavelet transforms and Fourier transforms are often used to convert time series EEG signals into image formats. Considering the integrity of the original information, the conversion of EEG should be purely reflected in the time-frequency domain. Thus, STFT is the best way to preserve the most complete anesthetic feature of the EEG signal. However, it has the problem of blindness selection in window type and window length, which will seriously distort the time-frequency spectrum due to the frequency aliasing caused by the strong time-variable signal [35]. Therefore, time-variable window based STFT method is designed for the characteristics of EEG signals in anesthesia. As shown in Figure 2, for the original EEG signal, by setting a varying window function $R(t)$, multiplying the EEG signal in the window and then performing Fourier Transforms with the sliding window along the time axis. The improved STFT was implemented in the following steps:

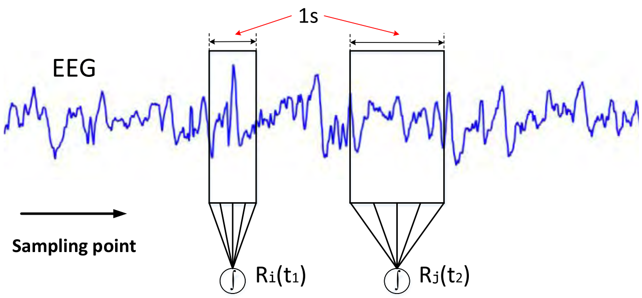

FIGURE 2. **Design of time-varying window function in short-time Fourier transform, where *Ri*(*t*) represents the time-varying window function.**

Step 1) The raw EEG sequence can be treated as a collection of sequence segments at 5s intervals. Which can be defined as

$$x(t) = [X_1, X_2, \ldots, X_p], \tag{1}$$

where p represents the number of the 5s EEG envelope.

Step 2) In order to solve inconsistent EEG length in every envelope due to burst suppression in anesthesia, a cubic spline interpolation method is applied for its re-sampling advantage. The windowed Fourier transform of improved STFT is calculated as

$$R'(t) = r(t) \times \exp(jS(t)), \tag{2}$$

where $S(t)$ is the cubic spline interpolation function. In addition, the size of window function is 1s EEG envelope as shown in Figure 2.

Step 3) The improved STFT is computed by

$$STFT = \int_{-\infty}^{\infty} X_{k1-km}(\tau) \times R'(t-\tau) \times e^{-j2\pi f \tau} d\tau, \tag{3}$$

where $k1$ -km represents the interval of consecutive 5s EEG envelope, that is, m consecutive envelopes.

Eventually, a series of Fourier Transforms results are arranged into a two-dimensional matrix, whose horizontal quantity represents the time sample point and its vertical quantity represents the frequency of the corresponding sample point of the segment signal. Furthermore, it is important to note that the size of the computing window (i.e., m value) really influences the STFT transform, which will cause interleaving effects between signals when it is too large or cause the EEG frequency to be more dispersed when it is too small. Therefore, the best setting for m is 24 (per m is 5s EEG envelope) through multiple trials, that is to say, the computing window of STFT is 120s. Moreover, 75% overlapped computing window is set to enrich medical data [19]. Thus, a well anesthetic spectrum is generated. As shown in Figure 3, four categories of anesthesia spectrogram are generated by modified STFT. These results are from the corresponding classification samples in Table 1. Furthermore, it is worth noting in this study, that the anesthetic map (i.e., EACL) drawn by clinical experienced senior anesthesiologists was digitized, averaged and used to train the neural networks as training targets, with the reason that it was used as a gold standard for determining DOA.

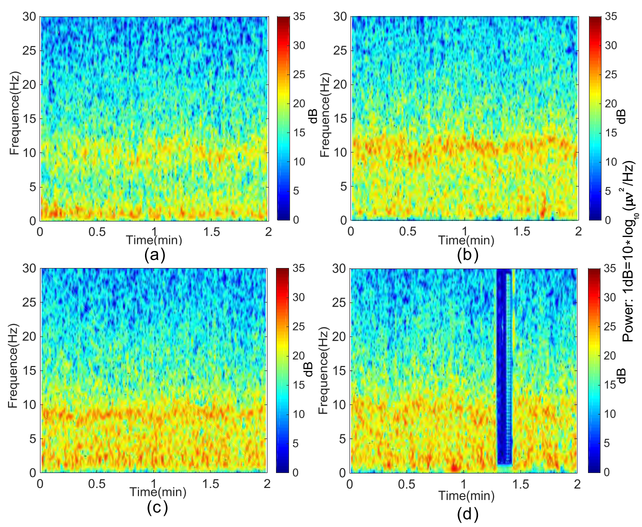

FIGURE 3. **Anesthesia spectrogram from: (a) Anesthetic Light patients' EEG; (b) Anesthetic OK patients' EEG; (c) Anesthetic Deep patients' EEG; (d) Signal Polluted patients' EEG. The level of DOA power decreases with signal-to-noise ratio from 35 to 0 decibel (dB) with step −1 dB. Moreover, the distribution of spectrogram from STFT processing of EEG signal is shown with uniform standards in the four figures.**

C. CONVOLUTIONAL NEURAL NETWORK MODEL

Since the target is anesthesia spectrum classification, a generic CNN model framework has been designed to recognize the DOA levels in the EEG spectrogram. However, the work of selecting the right model is not as simple as the classification of cats and dogs diagram, which needs to be continuously improved from the results of multiple training.

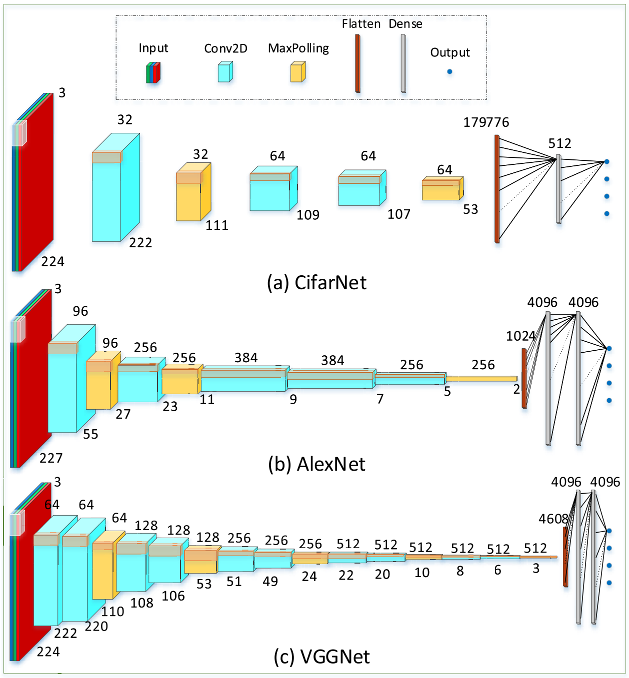

FIGURE 4. **Three different network layer structures. (a) CifarNet model; (b) AlexNet model; (c) VGGNet model. The number in the lower right corner of the box indicates the kernel size, the above number is filter size. The number on the sticks represents dense full connection weight parameter. The number of CNN layers in the paper is represented by the convolution layer and MaxPolling layer.**

In particular, judging from the ImageNet Large Scale Visual Recognition Competition (ILSVRC) in recent years, it seems that well performance mostly depends on the complexity of CNNs. However, it is not worth completing the identification of small sample characteristics at great cost, i.e., overall latency caused by insufficient memory capacity. In other words, based on the GPU capacity and small sample data in this paper, the most basic CNN model architectures need to be considered on DOA levels classification. As for identification of the earliest RGB image, CifarNet effectively promoted the advancement of machine vision with a simple structure [36], while LeNet is only excellent in the handwriting dataset [37] that is different from ours. As shown in Figure 4 (a), it has the characteristics of simple structure and low operating environment requirements. So, CifarNet-based model is preferred to promote our work. However, considering the versatility and reliability of the framework in this paper on the classification of DOA levels, a single CNN model framework is far from enough. AlexNet scaled the insights of LeNet into a much larger neural network that could be used to learn much more complex inputs and complicate problems like deciding the depth of anesthesia. Also, AlexNet has won by a large margin the difficult ImageNet competition in 2012 championship in ILSVRC [38]. Although the VGG networks won runner-up in ILSVRC competition in 2014 [38], this networks from Oxford were the first to use much smaller 3×3 filters in each convolutional layers and also combined them as a sequence of convolutions. It makes the improvement over AlexNet by replacing large kernel-sized filters with multiple 3×3 kernel-sized filters one after another. Because, multiple stacked smaller size kernel is better than the one with a larger size kernel. With a given smaller receptive field of the effective area size of input image where output depends, this multiple non-linear layers can increase the depth of the network which enables it to learn more complex features with a lower cost. Therefore, AlexNet-based model and VGGNet-based model, as shown in Figures 4 (b), (c), are also applied to this work for the comparison.

The number of convolution layers and MaxPolling layers of the three CNNs are from 5 deep CNN (CifarNet) to 8 layers deep CNN (AlexNet) and to 15 layers deep CNN (VGGNet), whose structures distribute from shallow to deep for training the EEG spectrograms. Also, a corresponding modifications have been made based on the existing CNN model instead of directly using the CNNs package in Theano which is a Python library that allows you to define, optimize, and evaluate mathematical expressions involving multi-dimensional arrays. Taking VGGNet for example, the input and output size were set to 224×224, delete the three-layer convolutional network layer, and change some function of active layer (i.e., Relu to tanh), etc. The purpose of our work on these CNNs is to testify the versatility, reliability and difference of their architectures on performance in DOA. Therefore, statistical comparison of their decoding accuracy in the same dataset is performed. On this basis, the same size of the input image is set to $224\times224\times3$, and output is four classes. In all cases, minimal preprocessing is used in order to perform fair CNN input-to-output comparisons.

III. RESULTS

A. PREDICTION PERFORMANCE

In this section, for purpose of verifying the performance of the modified STFT presented in Figure 2, 10 patients' data are randomly selected from Table 2. Obviously, each patient has

TABLE 2. **Classification on DOA result through using original STFT and modified STFT prior to CNN.**

Patient	Interval hours	Original STFT		Modified STFT	
		Acc (%)	SEN (%)	Acc (%)	SEN (%)
Pat A	2.53	84.13	82.43	91.76	88.95
Pat B	2.67	84.74	81.63	92.11	87.57
Pat C	1.65	83.17	80.88	92.02	87.70
Pat D	2.08	84.04	81.80	92.80	88.51
Pat E	3.80	83.61	81.48	92.28	87.98
Pat F	2.77	85.43	83.13	92.63	87.51
Pat G	2.70	84.48	81.45	92.28	87.98
Pat H	1.47	85.86	83.02	91.76	87.52
Pat I	1.48	84.91	81.83	91.93	86.98
Pat J	2.08	86.91	84.30	93.06	89.04
mean	2..32	84.73	82.20	**92.26**	**87.97**
std	0.72	1.11	1.02	0.44	0.67

different anesthesia interval time while the same contribution to sample categories (i.e., data structure in Table 1). Then a well-trained CNN (here is VGGNet, see Figure 4 (c)) is used to test the performance of modified STFT method compared with the original STFT with a fixed window function. As a result, Table 2 summarizes the performance of the classification on DOA for CNN with original and modified STFT analyses. By applying signal interruption noise removal and classifying the signal into one category, prediction accuracy is 84.73% ±0.011 and sensitivity is 82.20% ±0.010. When improving the STFT prior to CNN greatly improves prediction performance with accuracy increased to 92.26% ±0.004 and sensitivity increased to 87.97% ±0.007. It is worth noting that in this study, the proposed approach works without any de-noising processing except signal interruption noise removal.

As for the CNNs, limited to dependence on efficient computing environment, Nvidia Tesla k40 GPU from Lenovo Technology B.V. Taiwan Branch is used to our work, which reduces the process of CNN training to nearly its one-tenth (i.e., 36h to 3.4h). Under such conditions, three different depth CNN models mentioned in section II(C) are prepared to train EEG spectrogram image datasets which has been set to the same CNN input and output. These depth of CNNs have many convolutional layers and has large-scale input that can receive data from high-pixel images, with the advantage that universal feature can be obtained from big data through different CNN structures. Fortunately, this characteristic is just being used to reduce the differences between the datasets and the obtained universal feature is just called DOA feature.

At the beginning of the training step, small amount of data is selected to test the initial performance of these networks, and then the parameters need to be constantly changed according to the effects of multiple tests. These parameters include learning rate, batch size, epoch size, convolution kernel size, step size, sub-sampling layer size, step size, etc. The advantage of doing so is that it can improve the efficiency of CNN model building, which provides the possibility to adjust parameters of CNN model so as to achieve the optimal execution of the training model. As for the dataset, 70% of them was used as a training sample, 20% as a validation sample, and 10% as a test sample. The maximum epoch is based on the training of all images at least once (as determined by the model's training results eventually reaching steady state). Once the parameters of the model are adjusted, it will begin normal training. To clearly understand the changes in the performance of the CNN model during the training process, ModelCheckpoint instruction is used from the callback function. Its main task is to save the CNN model and all the weight values after each epoch, so that the model framework and weights can be saved when the model is in optimal performance.

After completing the training process of the CNN model, the testing stage of each model is started for the test dataset. The results are shown in Figure 5, which can be clearly seen that for the shallow to deep CNN model architecture, the classification effect for the DOA is better. In detail, CifarNet's best classification accuracy is approximately 87.50%, AlexNet's best accuracy is approximately 92.35%, and VGGNet's best accuracy is approximately 93.30%. In these three models (Figure 4), the result is getting better and better as the network gets deeper and deeper on the whole. Of course, special circumstances are not excluded, such as between 20–40 epochs and approximately 44 epochs, and so on. This performance also proves that CifarNet, AlexNet, and VGGNet are the benefits of the classic models of the era. Moreover, as the training process progresses, each CNN model presents a shift toward better performance, and the final model performance tends to be stable. Which explains that the model has achieved optimal performance at this stage and is consistent with CNN's own characteristics.

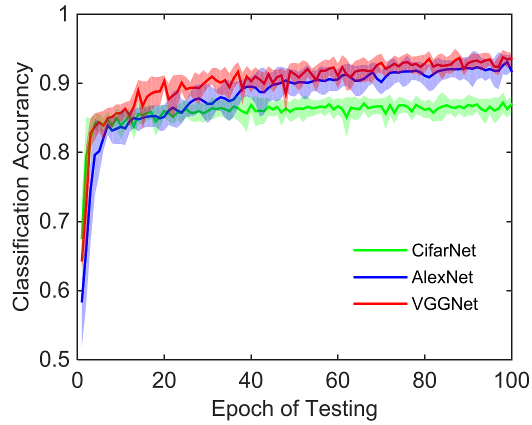

FIGURE 5. **Performance in Training of Three Model Structures.**

CNN training is implemented through the Tensorflow deep learning framework, using the NVidia K40 GPU utilizing the Ubuntu 14.04 Linux operating system. All models have undergone the training of the early stop criteria, with a high validation accuracy model for the final model. In addition to VGG-13, other batch-size sizes are set to 128, which is the maximum batch size of the NVidia K40 GPU with 12 GB of memory capacity. Table 3 shows the training time and memory requirements of the three CNN architectures for DOA classification based on the EEG spectrum images, normalized up to a maximum of 100 periods.

TABLE 3. **Training time and memory requirements of the three CNN architectures on DOA-based classification up to 100 epochs.**

	CifarNet	AlexNet	VGGNet
Time	4.47h	4.29h	7.84h
Memory	2.25 GB	3.45 GB	4.22 GB

This paper uses 10-fold cross-validation method [39] to evaluate the performance of the three trained CNN models. First, the time-frequency maps taken from each category of the EEG (AL, AO, AD, and SP) are individually and randomly divided into ten equal parts. Nine of these parts are

TABLE 4. Cross validation of three CNN framework.

Dataset	Testing Accuracy		
	CifarNet	AlexNet	VGGNet
S1	0.8613	0.9190	0.9267
S2	0.8778	0.9297	0.9311
S3	0.8746	0.9115	0.9224
S4	0.8798	0.9306	0.9421
S5	0.8679	0.9210	0.9356
S6	0.8753	0.9278	0.9361
S7	0.8834	0.9337	0.9427
S8	0.8823	0.9395	0.9478
S9	0.8745	0.9239	0.9326
S10	0.8756	0.9268	0.9324
mean	0.8753	0.9264	**0.9350**
std	0.0066	0.0079	0.0077

used to train the CNN while the remaining one part is used to test the performance of the system. After each training of the CNN model is completed, the model is evaluated using data not used to train the CNN model. This strategy is repeated ten times by disrupting and rearranging test and training data sets. The accuracy, sensitivity, and specificity values reported in this paper are averages obtained from these 10 assessments. Table 4 shows the accuracy of the cross-validation results for each experiment. From the results, the ten groups are almost all close to a constant, the std values are all below 0.0079, indicating that the experiment is successful and reliable. Therefore, it's reasonable to consider that the classification results obtained by the EEG spectrum after the CNN coding model can establish the degree of similarity with the DOA assessment.

B. TESTING THE NETWORK ON THE REMAINING PATIENTS' RECORDS

The datasets in this paper are maintained similar distributions in the training and testing procedure to avoid over- and under-representation of classes due to dataset imbalance. Moreover, it is expected that our method will provide reliable reference for anesthetists in the classification of DOA levels. The errors in each prediction phase can be displayed by analyzing the confusion matrix, as shown in Figure 6. In general, there is an agreement among the proposed CNNs. All deeper CNNs perform better in different structures of CNN. Most of the errors are due to distinguishing AD / AO and AL / AO. The confusion matrix based on EEG spectrum images datasets for classification of DOA shows much variability in its category distribution, thus exhibiting a pattern that the sensitivity and precision of each category are less consistent, possibly because of the beauty of each CNN model, or its individualism.

In detail, the most striking finding from Figure 6 is that the samples with the highest classification error rate are AO and AD samples. For CifarNet (seen from Figure 6 (a)),

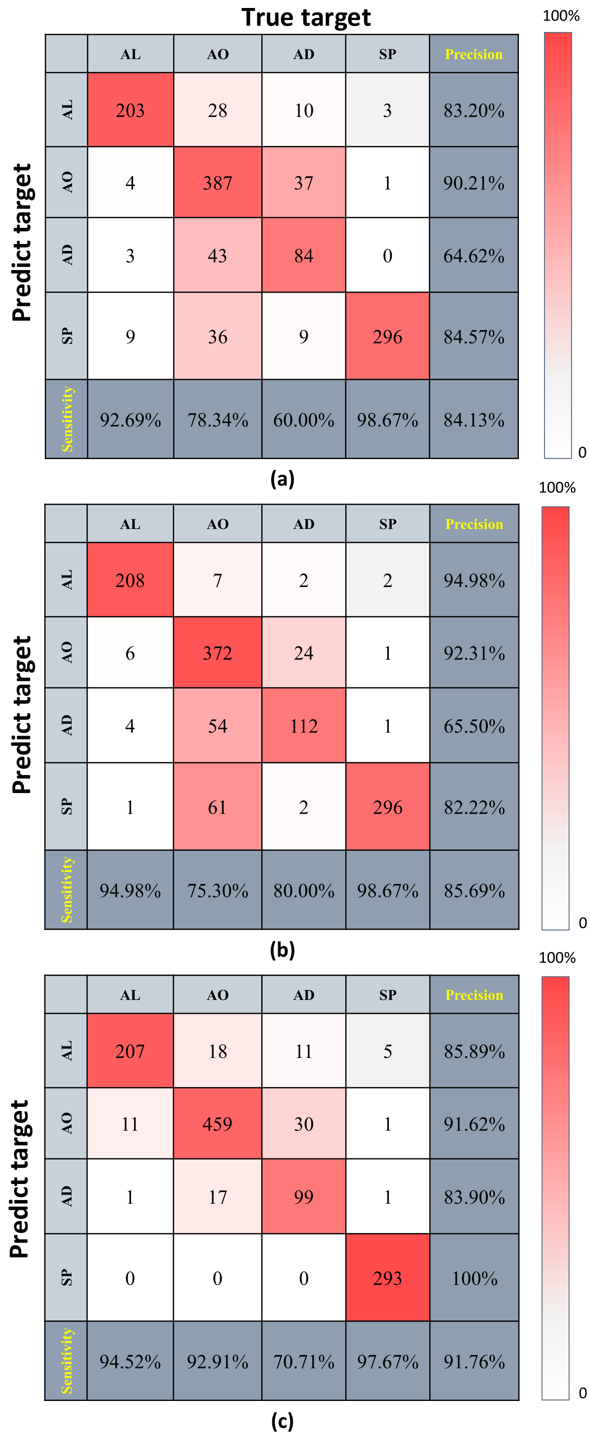

FIGURE 6. Confusion matrices for CNN-based decoding. (a) CifarNet; (b) AlexNet; (c) VGGNet. Results are shown for the high-accuracy dataset on DOA-based classification. Each entry of row r and column c for upper left 4×4-square: Number of trials of target r predicted as class c (also written in percent of all trials). Rightmost column corresponds to the accuracy of the prediction of the sample data. Bottom row indicates the accuracy of the predicted sample. The lower-right value corresponds to overall accuracy. The color depth of the right energy bar indicates the sample percentage (0–100%) in the overall sample.

21.66% of the model's AO samples were predicted to be AL, AD and SP class (with distributions of 5.67%, 8.70% and 7.29%), while 23.28% of AlexNet's AO samples (seen from Figure 6 (b)) were predicted to be AD and SP class (with distributions of 10.93% and 12.35%) and 7.09% of VGGNet's AO samples (i.e., Figure 6 (c)) were predicted to be AL and AD class (with distributions of 3.64% and 3.44%). This counter-intuitive error becomes more reasonable when viewing the corresponding EEG spectrum information. Thus, when the classification error of the AO sample was expanded, it was found that the DOA corresponding to the category predicted to be AD class was mostly AO, whose standard category values are 0–40 and 40–60, respectively. In other words, these categories are too close in the distribution of some certain values, which leads to a more ambiguous classification. Moreover, there is no absolute anesthetic boundary in medicine. In addition, anesthesiologists who personally assess the DOA will have different opinions in assessing the DOA, which also increase the rationality of this result. While most spectrum images corresponding to categories predicted to be SP class have noisy interferences (i.e., Figure 1 (c) and (d)), for the reason that 80% of patients' anesthesia time are in AO class during surgery, during this period, environmental factors are more or less recorded together with EEG signals. At this time, it is difficult to accomplish the goal of correct classification even if manual selection is joined for selection.

Similarly, 26.43%, 17.14% and 21.43% of AD samples in these CNNs were predicted to AO class. Obviously, this is a terrible error rate on a small test data. However, since AO data is much larger than AD data in anesthesia medicine, the data imbalance problem leads to the unconventional result. Furthermore, most of the misclassified samples also correspond to a DOA value of approximately 40 (i.e., the boundary between AD and AO), where it is difficult for the patient to reach anesthetic deep state during anesthesia according to the condition of the patient. In addition, during AD state, burst suppression in EEG is recognized as light anesthesia which is a serious problem in EEG based indicators when other methods are used such as median frequency and spectral edge frequency [40]. Therefore, the frequent confusion of the system is due to the fact that the EEG-based spectrum images is non-standardized (long span time, noisy existing). The AL category and the SP category had the best prediction effect (83.20% and 84.57% in CifarNet, 94.98% and 82.22% in AlexNet, 85.89% and 100.0% in VGGNet). In all the classifications, the AO sample is the most likely object to be predicted with 90.21%, 92.31% and 91.62% probability. Also, it has 78.34%, 75.30% and 92.91% sensitivity, which proves that AO class is frequently confused with other classes. This seems plausible because the AO state is located in the center of the DOA space, what makes the discrimination from other classes difficult. However, the SP class with shallower CNN (CifarNet and AlexNet), there is a higher false negative in the AO class reaching 10.29% and 16.94% respectively. When combined with the data structure in Table 1, the AO class and SP classes account for 43% and 26% of the total sample. Hence, it is reasonable to believe that a high percentage of data will always result in a slightly higher percentage of false negatives when it comes to the non-equilibrium medical data. Of course, it also shows that the performance of these two CNN models needs to be further strengthened.

Finally, each category in these CNNs show different classification accuracy and sensitivity, but they are still statistically significant. For the same input sample, the three CNN models perform different preferences in each category respectively. From Table 4, it can be seen that the prediction accuracy of CNN increases with the increase of its layers. And for the confusion matrices of three CNN models its performance is analogous as for overall accuracy. From the perspective of CNN structure, the reason for this type of result may be that the more complex the model structure, the more features it can store, and thus it is very attractive for regional-block classification of DOA. In general, almost all categories have reasonable errors and corresponding external factors and the overall classification accuracy can be considered as successful DOA prediction.

C. METHOD COMPARATIVE PERFORMANCE

In view of the creativity of the proposed method, its performance was compared with the recent DOA level assessment in the literature listed in Table 5 to highlight this article. It's difficult to judge which method is better with the reason that one method is usually adapted to one dataset that is limited in another dataset. In other words, one method can perform well with this dataset but probably poorly on other dataset. Therefore, the efficiency of the method is analyzed while ensuring high DOA level assessment accuracy. Thus, these methods listed in Table 5 are qualitatively analyzed for DOA assessment. Research reported in [4] has only used some traditional feature extraction projects and statistical methods to classify two DOA levels and achieved 93% accuracy, which got lower performance compared to the literatures [12], [13] and similar to our proposed methods. The authors in literatures [12], [13] were clever in corresponding feature extraction for patients. However, this leads to the need for sufficient expertise and time to run the feature extraction projects for new dataset. Finally, it gave a 99% accuracy rate via ANN or Forward Neural Network on three more DOA levels. Nevertheless, these methods are limited to feature acquisition or certain datasets. When applied to other datasets, they are not certain to perform well. Therefore, it's reasonable to believe that even if the accuracy performance of proposed method in this article not as good as the methods from literatures [12], [13], it cannot denies the progress of our method.

Furthermore, in this study, data reconstruction method was used instead of excellent feature extraction engineering, which greatly simplifies the complex process of manual features and mathematical calculation. It is believed that this study offers a motivational contribution to the anesthesia field, since it gave a 93. 50 % accuracy on three DOA levels. In terms of overall classification accuracy, the application of our method in anesthesiology is desirable and also provides some reference for the subsequent linear classification of

DOA. Moreover, there is no work being reported on successfully using similar methods on DOA assessment.

IV. DISCUSSION

From the performance of our work, it is creative to convert the time domain signal into a time-frequency signal in a DOA evaluation when the modified STFT is applied for this study. For the reason that it needn't complex manual feature design processes in promoting the performance of CNN in DOA assessment, the performance of our study was with the recent studies included in Table 5. This table shows that this paper uses data reconstruction method, which greatly simplifies the complex process of manual features and mathematical calculations, to achieve an accuracy of 93.50% when compared with the methods in [4], [12], [13], whose high accuracy is based on complex feature extraction. Furthermore, different layers of CNNs are used to explore the effectiveness of the proposed method. Considering the GPU environment for avoiding the overall delay caused by insufficient storage capacity and the non-specificity of a single CNN model, three infrastructures of CNNs are chosen to state the versatility and reliability of the DOA level classification rather than uniqueness. Of course, the purpose of this paper is not to design the CNN application, some modifications have been introduced based on the existing CNN model to adapt to the research in this paper. From the performance of CNNs in Figure 5 at DOA levels, as shown in Table 4, it is believed that CNN applied to our work provides novel ideas to the anesthesia field, since it gave a 93.50% accuracy rate on three DOA levels. In general, the advantage of our work is as follows: from the perspective of method complexity, the proposed method does not need complicated manual feature design process compared to the methods listed in Table 5.

In this paper, a modified STFT method is proposed combined with enhanced CNN model with satisfactory result, but there are still some challenges that should be solved. First, as an alternative to the conversion of EEG time domain to time-frequency domain, STFT is an optional but perhaps not the best information conversion method. In addition, the selection of the window function in the STFT may influence on the performance of the learning method [26]. Second, in the case of traditional CNN structure functions and simple design, it does not always produce good performance, especially when it comes to unbalanced datasets that are common problems in health informatics [41]. Finally, the EEG signal of patients on anesthesia changes significantly depending on the different anesthetic drugs, making it difficult to have a categorized quantitative standard. When infiltrated into the study in detail, for example, a well-trained CNN model does not perform well in the transition phase of DOA (i.e., from AL state to AO state or from AO state to AL state). The reason is that, in the transitional phase, the patient's consciousness state during the operation is manifesting as a conscious state to a coma or a coma to a conscious state, whose state transition becomes extremely unstable. Thus, the corresponding discrete spectrum images will lose certain characteristics and behave confusingly, leaving it more difficult to do classification. Therefore, the data in this part will show slightly higher misjudgment rate when tested, seen Section III (B) in detail.

In fact, the used datasets are from our research team [22], and it lacked certain standards. To some extent, it affects the accuracy of our method when comparing the recent research (see Table 5). Moreover, the traditional deep learning [42]–[44] is based on the specific objects in the image. For this paper, the characteristic of DOA level is uncertain, so it is difficult to design a specific CNN structure suitable for our work. As a result, three different CNN model structures are tested its performance in DOA. As described in [45], these architectures exhibit high-precision classical CNN models from existing image classifications, but it is unpredictable whether they exhibit high efficiency in the characteristic spectrum of physiological data. Therefore, the decoding performance of the three models was analyzed in the EEG spectrogram image set (see Section III (A) for details). In these cases, input-to-output comparisons of CNN was performed with minimal preprocessing. In addition to the whole CNN architecture, the designs were systematically evaluated of a series of important choices. Based on recent advances in learning and research on deep learning, the focused is on various network layer parameters, optimization algorithms, regularization strategies, batch normalization, and exponential linear unit activation parameters of the CNN training process to evaluate CNN's potential performance improvement in anesthesia assessments. From the training results in Table 4, it shows that the deep CNN can accurately identify the DOA features in the EEG signals of the entire anesthesia patient, and the wrong classification results are within acceptable error. It proves that the designed CNN framework can be used for the DOA classification, which may enrich commercial research on DOA.

In addition, the three architectural models all showed good performance with the accuracy above 85%, and the best accuracy is reaching 93% or more (Figure 5). This is an excellent phenomenon. It shows that deep CNN is used to perform DOA classification through EEG spectrum images and it is obvious that CNN displayed superior performance at the field of DOA. At the same time, once the CNN weight parameters are extracted and reshaped into CNN framework models by EEG data export equipment, patient's DOA state will be immediately displayed without complicated computational processes. Thus, the performance of CNN could achieve universal and highly-efficient levels when compared with other conventional feature extraction methods showed in Table 5, as well as in robustness. Moreover, there were three key factors being used and extensively evaluated in the process of no-regular coding of EEG to DOA: dataset characteristics, CNN's architecture, and CNN's parameters. As described in section II.C, three different depths of CNN frameworks were evaluated in training to identify the performance of the DOA features in the spectrum images from EEG, all of which were constantly updated CNN network parameters

TABLE 5. Comparison of the current study with the proposed methods.

Literatures	Anesthetic levels	Method	Accuracy rate
[4]	Awake, Asleep	Lempel-Ziv Complexity (LZC) Approximate Entropy (ApEN) Spectral Entropy (SE) Median Frequency (MF)	LZC: 93% ApEN: 89% SE: 76% MF: 64%
[12]	Low, Medium, High	Feature extraction: • Correlation dimension (CD) • Lyapunov Exponent (LE) Classification Algorithms: • Artificial neural network	CD+ANN: 97.8 % CD+LE+ANN: 97.5 % LE+ANN: 99 %
[13]	Deep anesthesia (0–25) Deep anesthesia (25–50) Moderate anesthesia (40–50) Moderate anesthesia (50–60) Light anesthesia (60–80) Awake (80–100)	Feature extraction: • time, non-linear, frequency-based and entropy based features Classification Algorithms: • Feed Forward Neural Network	99.05 %
Current study	Anesthetic Light (AL)(60-100) Anesthetic OK (AO) (40-60) Anesthetic Deep (AD) (0-40) Signal Polluted (SP)	Data reconstruction method: • Short-time Fourier transform Classification Algorithms: •Convolutional Neural Network	93.50 %

for achieving rapid and accurate patient's conscious status coding of anesthesia. The most exciting thing is that CNN can automatically complete the learning process of the target after the model learning parameters were adjusted. And filter weights in CNN are automatically adjusted during the training phase, making CNN like an automatic method of feature extraction. However, this paper still needs to further study CNN's performance features, such as experimental evaluation, CNN performance analysis, so that the classification process of CNNs on DOA can be explained in more detail, which perhaps enhance the accuracy and stability in DOA classification.

In the future work, high accuracy, more classification levels and efficient performance requires further research, i.e., the DOA level is divided into 6 units or more. The grouping of classes is critical to the CNN supporting scalability with multiple classes. In general, high-level organizations can be easily identified in the visualization of the hierarchy because their labels can be described more precisely. Therefore, in the next step, deeper CNN will be attempted (such as GoogleNet and ResetNet) to build and test a deep CNN for DOA assessment in a high-speed GPU environment. In addition, in the case of processing large amounts of data, a method of automatically classifying spectrum images should be proposed instead of manually selecting and classifying EEG spectrum images. Moreover, more kinds of patient samples should be tested using trained CNNs to improve the reliability of the method. Alternatively, the transfer learning approach can be considered for a pre-trained CNN to be fine-tuned with the pre-processed dataset in order to reduce the patient samples.

V. CONCLUSION

The ability to assess the DOA has been studied and improved in the past few years. From their development, it can be seen that a large number of them are extracted from the EEG using the manual feature extraction method, and a few are directly evaluated through the feature from the EEG time-frequency map. It rarely encountered that CNNs with very strong learning abilities were applying to assessment of DOA. Although only a qualitative analysis of DOA assessment is currently performed, that is, the three anesthesia levels classified as AL, AO, and AD have not yet reached the quantitative analysis requirements, but for the current CNN performance in DOA prediction. It is useful to provide physicians with reference information, which qualified with a senior anesthesiologist assessment. In this way, they can take some preparatory measures to prevent the influence brought by drug differences and individual patient differences to the dose of anesthetic drugs on the unique guidance from the anesthesia apparatus, in purpose to ensure the safety of the patient's surgery. This paper presents a new approach using CNN and minimal feature engineering. This proposal shows that it has a good relationship with the DOA characteristics in the EEG signals which opens up opportunities to have a safer intraoperative environment via building a simple DOA prediction device.

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