Applying CLDNN to Time-Frequency Image of EEG Signals to Predict Depth of Anesthesia

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Manuscript submitted June 11, 2020; accepted August 29, 2020.
doi: 10.17706/ijbbb.2020.10.4.154-160

Abstract: Convolutional neural network (CNN) have been widely used in various fields in recent years. However, the CNN method is rarely used in EEG studies to assess the depth of anesthesia (DOA) in patients. In this study, EEG signal is used as the input to the convolutional, long short-term memory, fully connected deep neural networks (CLDNN) to predict DOA using continuous wavelet transform (CWT). According to the bispectral (BIS) index and signal quality index (SQI) measured by medical equipment, the anesthesia state is divided into anesthesia light (AL), anesthesia OK (AO), anesthesia deep (AD). The computing window of CWT is 120s. Moreover, 75% overlapped computing window is set to enrich medical data. Through different models, the epoch, timestep and input size of the CWT image were changed to get the best experimental results: AL was 82%, AO was 89%, and AD was 87%. The overall accuracy of the model is 87.79%, and AL and AD can be fully predicted.

Key words: Electroencephalogram (EEG), continuous wavelet transform (CWT), fully connected deep neural networks (CLDNN), depth of anesthesia (DOA).

1. Introduction

Deep learning has been widely used in various fields in recent years, especially the longest development of convolutional neural networks (CNN) [1], such as AlexNet, VGG16, GoogLeNet and other models. In addition, recurrent neural networks (RNN) or long short-term memory (LSTM) models can deal with problems in terms of time and continuity. Combining CNN and RNN (or LSTM) multi-layer models, image features and sequence features can be extracted for training.

The depth of anesthesia (DOA) is a very important reference indicator for patients with general anesthesia during surgery. If the depth of anesthesia is too shallow, the patient may feel pain during the surgery. Long-term maintenance of deep anesthesia may lead to postoperative memory impairment [2]. However, in the research related to EEG in biomedical engineering, the depth of anesthesia has not been explored. Most of the methods using deep learning are sleep [3], epilepsy [4], emotion recognition [5], etc. In addition, although many products for DOA monitoring have been developed on the market, they are very expensive. We hope to use deep learning to analyze the depth of anesthesia and reduce costs.

In the past research, the authors have developed a technique for converting data from a continuous signal to an image. Using the original data of EEG via the continuous wavelet transform (CWT), time-frequency signal with time domain and frequency domain have been constructed. Of an activity through different frequencies can represent the physiological condition of the patient at the time. During anesthetics reduce high frequency beta and alpha band activity and reduce low band activity during deep anesthesia [6]. Thus, it can be observed that EEG shows changes in signal characteristics and activity intensity during induction of anesthesia, maintenance periods and recovery periods in time-frequency domain images.

Although the instantaneous frequency and intensity can be obtained from the time-frequency image of the EEG, the EEG signal does not have clear and highly reproducible graphical features. In past studies, we used CNN to classify EEG CWT signals. This study will use the mixed model of CNN, LSTM and DNN (CLDNN) as a classification task for anesthesia depth. The time-frequency image after converting the EEG to CWT is used as the input image of the CLDNN. The images were classified according to the BIS values given by the Philips patient monitor. The aim of the study was to improve the accuracy of assessing the depth of anesthesia by using more efficient models.

2. Material and Methods

2.1. Anesthesia Dataset

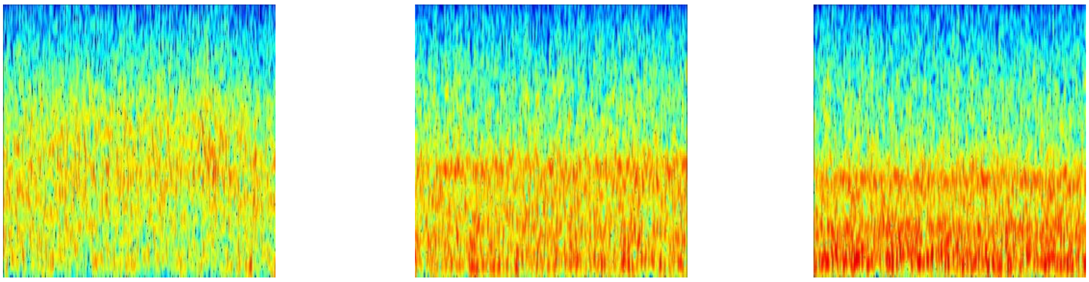
In this study, 55 patients were selected from the National Taiwan University Hospital (NTUH). Prior to the start of surgery, the patients were injected with propofol to place them in unconscious state. The patients were infused with sevoflurane anesthetic during the surgery for uterine and ovarian diseases. The EEG signal is recorded using the BIS™ Quatro Sensor of the MP60 at a sampling frequency of 128 Hz, and the BIS and Signal Quality Indicator (SQI) are recorded every 5 seconds. After, based on the obtained EEG data, CWT transformation using MATLAB is divided into the following three categories: Anesthesia Light (AL) (100 ≥ BI S≥ 60, SQI ≥ 50), Anesthesia OK (AO) (60 > BIS ≥ 40, SQI ≥ 50), Anesthesia Deep (AD) (40 ≥ BIS ≥ 0, SQI ≥ 50). Among them, SQI < 50 is judged as noise and is not listed as a training data set. After completing the CWT conversion, the data set is divided into three parts: training, verification and testing, which are 70%, 20%, and 10%, respectively as shown in Table 1. Good anesthesia has the most abundant data, with AO and AD accounting for 50.4% and 38.9%, respectively. The amount of data during light anesthesia was very small, accounting for Only 10.7%.

Table 1. Data Distribution for Each Category

55 patients				
Category	Training (70%)	Validation (20%)	Testing (10%)	Data distribution
Anesthetic Light (AL)	1151	328	164	10.7%
Anesthetic Ok (AO)	5406	1542	771	50.4%
Anesthetic Deep (AD)	4174	1192	596	38.9%
Total	10731	3062	1531	100%

2.2. Data Preprocessing

Since we apply CLDNN as our research model, the original EEG signal is converted to an image and presents the state of the DOA. The patient's data is converted to image by continuous wavelet transform (CWT) every two minutes (Fig. 1), and the data is updated every 30 seconds, so there is a 75% overlap between the front and back images.



(a) Anesthetic Light (b) Anesthetic OK (c) Anesthetic Deep

Fig. 1. Time-frequency image by CWT conversion.

2.3. Model and Operating Environment

Convolutional/long short-term memory/fully connected deep neural networks (CLDNN) (Fig. 2) is a deep learning algorithm proposed by Google Inc [7], which uses multi-layer convolution to extract image features and then uses the LSTM layer for sequence analysis. In this study, we used high-performance computer (HPC) equipment provided by Lenovo Taiwan Branch. The operating system and GPU devices use the Lenovo ThinkSystem SD530 and two Volta 100 GPUs, as shown in Fig. 3. First, the data is imported form the lab computer to Lenovo's HPC, then enter the CLDNN's convolution layer uses the 8-layer shallow Alexnet model that won the championship in ImageNet competition. Then the LSTM layer is added for analysis. Since it is a new model attempt, the number of epochs, input size and time_step value of CLDNN were tested for different settings in order to achieve the best results.

Even though there have been many EEG-related studies in recent years, the use of depth of anesthesia is still a minority. In addition, EEG is If patients use different anesthetics or perform different operations, their EEG will produce different forms. Because the amount of data is too small, a simplified deep learning models were used to implement the training.

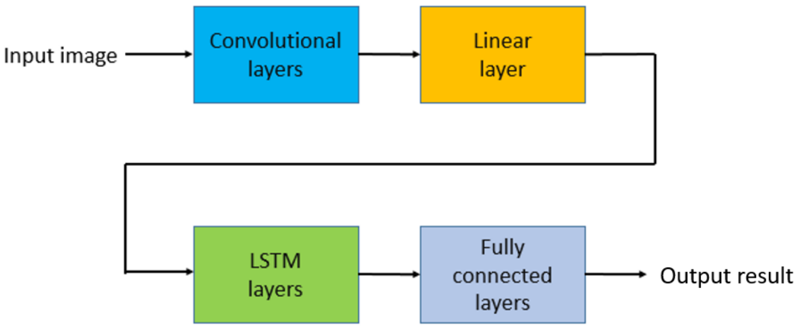


Fig. 2. CLDNN model.

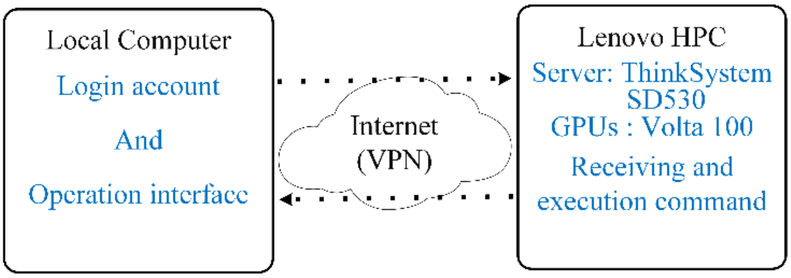


Fig. 3. Operating procedures and hardware devices.

3. Result and Discussion

3.1. Comparison between CNN Model and CLDNN Model

It can be found that the accuracy of the CNN model in AL, AO and AD is 59%, 75% and 85%, respectively, and the overall accuracy of the model is 77.27% (Table 2). After switching to the CLDNN model with added LSTM layer (time step=2), the accuracy obtained is much better than the CNN model, with AL, AO and AD being 64%, 82% and 86%, respectively. The overall accuracy rate is 83.74%. It is worth mentioning that the accuracy of AL is the lowest of the three, and it is easy to be mistakenly judged as AO.

Table 2. Model Testing Results

CNN model						CLDNN image model					
		Predict result			Individual			Predict result			Individual
		AL	AO	AD				AL	AO	AD	
True data	AL	97	64	3	59%	True data	AL	117	46	1	71%
	AO	21	582	168	75%		AO	21	632	118	82%
	AD	0	92	504	85%		AD	6	57	533	89%
Overall accuracy is 77.27%						Overall accuracy is 83.74%					

3.2. CLDNN Model by Changing the Epoch

In this comparison, an attempt was made to change the period (50, 100, 150) and found that when the period was increased to 150, the accuracy was 85.89%, which is the highest accuracy among the four control groups as shown in Table 3. This means that when the period is increased, the best value will be achieved. However, in the case of keeping increasing numbers, overfitting will occur so the accuracy will not increase.

Table 3. CLDNN Image Model by Changing Epoch

Epoch		50	100	150	300
Input size		227×227	227×227	227×227	227×227
Time-step		2	2	2	2
Time spent		99 min	197 min	315 min	589 min
Accuracy	AL	71%	69%	70%	79%
	AO	82%	91%	91%	89%
	AD	89%	80%	84%	84%
	Overall	83.74%	84.19%	85.89%	85.83%

3.3. CLDNN Model by Changing Time-Step

This phase attempts to increase the time-step from 2 to 3. As shown in Table 3, when the time-step is increased to 3, the accuracy is increased to 86.02% as shown in Table 4.

Table 4. CLDNN Image Mode by Changing Time-Step

Epoch		50	50	150
Input size		227×227	227×227	227×227
Time-step		2	3	3
Time spent		99 min	102 min	312 min
Accuracy	AL	71%	59%	80%
	AO	82%	89%	91%
	AD	89%	85%	81%
	Overall	83.74%	84.06%	86.02%

3.4. CLDNN Model-Change the Input Size

Since the original Alexnet setting has an input size of 227×227 and the CWT converted image size is 600×600. Hence the model is directly with the original size. The time step is kept at 3. At 150 epochs, the highest accuracy of 87.79% is achieved as shown in Table 5. When AL is predicted, no image is predicted to be AD, and when AD is predicted, no image is predicted to be AL as shown in Table 6, indicating that the model has high overall accuracy.

Table 5. CLDNN Image Mode-Change Input Size

Epoch		150	300
Input size		600×600	600×600
Time-step		3	3
Time spent		60 hr	118 hr
Accuracy	AL	82%	80%
	AO	89%	85%
	AD	87%	90%
	Overall	87.79%	86.22%

Table 6. CLDNN Image Model

		Predict result			Individual accuracy
		AL	AO	AD	
True data	AL	135	29	0	82%
	AO	24	689	58	89%
	AD	0	76	520	87%
Overall accuracy is 87.79%					

4. Conclusion

In this experiment, we can find the best accuracy of CLDNN model is 87.79%. In addition, the accuracy of AL is also increased to 82%, and the model can clearly distinguish between AL and AD. In the future work, we can change the CNN layer from Alexnet to VGG or GoogLeNet. Considering the change of time in EEG signal, the input model can be arranged in order of time, and it is hoped that the accuracy can be effectively improved. Also, due to lacking of huge patients' data, it would be better to apply the transfer learning into this prediction of anesthetic states in the near future.

Conflict of Interest

The authors declare no conflict of interest.

Author Contributions

YLC developed the algorithms and wrote the paper; SZF pre-processed the raw dataset; MFA and JSS evaluated and supervised the study.

Acknowledgment

This research is financially supported by the Ministry of science and technology (MOST) of Taiwan (MOST 107-2221-E-155-009-MY2).

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