FULLY DATA-DRIVEN CONVOLUTIONAL FILTERS WITH DEEP LEARNING MODELS FOR EPILEPTIC SPIKE DETECTION

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ABSTRACT

Epilepsy is a chronic disorder that causes unprovoked, recurrent-seizures. Characteristic spikes are often observed in the electroencephalogram (EEG) of epileptic patients in order to diagnose the disorder. Several methods have been investigated to automatically detect such spikes. The most common methods employ sub-band decomposition with discrete wavelet transform (DWT) or other filters to preprocess the EEG data before feeding it into a machine learning model. This paper introduces a fully data-driven method that automatically determines EEG frequency bands of interest. The raw signal is fed into a convolutional layer to detect suitable frequency bands, followed by a feedforward convolutional neural network (CNN) model or recurrent neural network (RNN) models for epileptic spike and non-spike classification. Fitting data of six patients, annotated by an epilepsy specialist, resulted in a convolutional layer with a frequency characteristic similar to bandpass filters. This result strongly justifies limiting the bandwidth of a signal, as done in previous studies. Moreover, results of the cross-subject validation indicate that a classical support vector machine with fixed preprocessing achieves comparable performance in the classification with fully data-driven models.

***Index Terms*—** epilepsy, spike detection, data-driven preprocessing, deep neural networks, electroencephalogram (EEG)

1. INTRODUCTION

Epilepsy is a complex neurological disorder that is common in early childhood, and can lead to an adverse impact on an individual's cognitive functions. Although a single cause of epilepsy has not yet been discovered, an early diagnosis can help patients to access appropriate support and significantly improve their quality of life. To diagnose epilepsy, a patient's seizure symptoms are important; however, it is often difficult to determine such symptoms. In addition, diagnosis of the type of epilepsy syndrome is critical for medical treatment.

Measuring and analyzing electroencephalogram (EEG) are essential steps to diagnose epilepsy. Paroxysmal spikes are frequently recorded in the EEG of epileptic patients who do not have seizures [1]. These spikes are important bio-markers in diagnosing epilepsy. However, due to the lack of highly skilled professionals and long-time EEG recordings, manual spike detection is often time-consuming and insufficient. Hence, autonomous detection has become powerful and relevant in solving those problems. Recently, machine learning methods—such as support vector machine (SVM), random forest (RF), and convolutional neural network (CNN)—for automatic spike detection have gradually gained in popularity and usage [2–5].

To exploit machine learning-based methods, preprocessing and feature extraction are rather crucial. A majority of the methods decompose EEG signals into the standard clinical bands of interest: gamma, beta, alpha, theta, and delta [6]. Methods using discrete wavelet transform (DWT) or a bank of filters belong to this category. The subband or narrowband signals are then fed into machine learning. However, with different methods or different goals of detection, the selection of frequency bands of interest varies. For example, while many neurologists prefer the frequency range of 1 to 30 Hz [7] for detection of paroxysmal spikes, some machine learning methods use the frequency range of 0.4 to 60 Hz [6], and some select the range of 1 to 70 Hz for feature extraction before training [8]. Choosing a wide frequency range may deteriorate detectability, or require better models for spike classification. Otherwise, an excessively narrow frequency band of interest may lead to lack of information for training data. Therefore, extracting appropriate bands of interest during preprocessing is vital, as it can help the machine learning model to train more easily without the need for more signal processing or feature selection.

In this study, we hypothesize that such frequency bands of interest can be estimated through annotated data using machine learning techniques. To this end, we propose a fully data-driven method, where the raw signal is fed into a convolutional layer to extract the band of interest without preprocessing, followed by a feedforward CNN model or RNN model for epileptic spike and non-spike classification. The result is compared to that of the machine learning method using DWT for EEG subbands.

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2. RELATED WORK

Recently, many researches that study EEG epilepsy have applied DWT decomposition methods [9–11]. Other, types of filter methods (such as time-frequency domain) [12,13], or other wavelet transform methods [11, 14] in a preprocessing stage. However, the parameter selection for the range of filters is empirically given.

In [8], in order to detect the epilepsy spike, the researchers use a bandpass filter of 1–70 Hz as a preprocessing method. Then, they employ peak detection by a numerical classification technique as a feature extraction to put into the classifier. In [15], the method also applies a band-pass filter in the range of 0.5–70 Hz for filter and then implements the energy of the wavelet transform and wavelet packet methods for classifying an epileptic spike. Another work [6] uses DWT decomposition to select the frequency range from the delta band to the gamma band (0.4–60 Hz).

Meanwhile, other studies prefer shorter bandpass filter ranges for preprocessing. In [16], a bandpass filter range of 0.53–40 Hz is applied, and then the discrete Fourier transform is used to extract features for the decision tree classifier. Similarly, [17] also used this range of filter, but with the DWT decomposition method. The method given by Srinivasan et al. [18] applies the filter range of 0.15–36 Hz before classifying the epileptic and non-epileptic data segments. Similarly, in [19, 20], their methods implement DWT decomposition with Daubechies 4 (DB4) to extract the EEG frequency bands from 4–32 Hz.

In addition, both [21] and [22] use DWT decomposition corresponding with a range of 3 and 25 Hz. In [22], they make feature selections from the raw signal of frequency bands of delta (0.5–4 Hz), theta (4–8 Hz), alpha (8–12 Hz), and beta (12–25 Hz); thereafter they employ the holdout technique and k-fold cross validation, passing into many different classifier models for distinguishing the seizure and non-seizure EEG records.

In these studies on the classification or detection of epilepsy, DWT decomposition and other filter methods are effective. However, the selections of filter range are set empirically in different studies. This motivates us to identify filter parameters from data.

3. METHOD

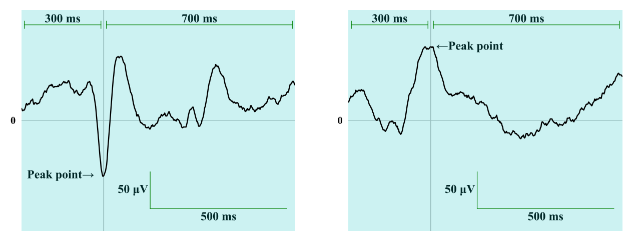
3.1. Dataset

We collected EEG records of six patients with Benign Epilepsy with Centro-Temporal Spikes (BECTS) [23]. The age at examination ranged from 5.7 to 10.6 years. They were two male and four female patients. The data was taken with conventional 10-20 methods using the Nihon Koden EEG-1200 system. The sampling frequency was 500 Hz for each channel. This dataset was recorded and analyzed under approval from the Juntendo University Hospital Ethics Committee and the Tokyo University of Agriculture and Technology Ethics Committee.

First, an epilepsy specialist (pediatrician) selected a focal channel that is associated with the origin of the epileptic discharge. Typically, one EEG dataset may contain multiple focal channels, and the specialist selected the most intense channel as the focal channel. Then, peaks of each channel's waveform from the recording signals were detected by PeakUtils [24]. Second, the specialist annotated each peak as either a paroximal discharge (spike or spike-and-wave) or an artifact. Fig. 1 illustrates an example of typical waveforms. Waveforms are normalized at every channel before all processing. Then, a 1-s epoch is extracted, including 300 ms before and 700 ms after every detected peak. It must be noted that each epoch represents one candidate spike. Table 1 represents the annotated data information.

Table 1. Labeled data information

Patient	Age of years	Sex	Number of paroxysmal discharges	Number of artifacts
1	7.0	Female	178	424
2	6.8	Male	629	263
3	5.7	Male	580	240
4	10.1	Female	461	236
5	10.6	Female	321	188
6	6.5	Female	728	939
Total			2897	2290



(a) A paroximal discharge (b) An artifact

Fig. 1. Typical waveforms of detected peaks in a 1-s epoch.

3.2. Preprocessing and subband decomopsition

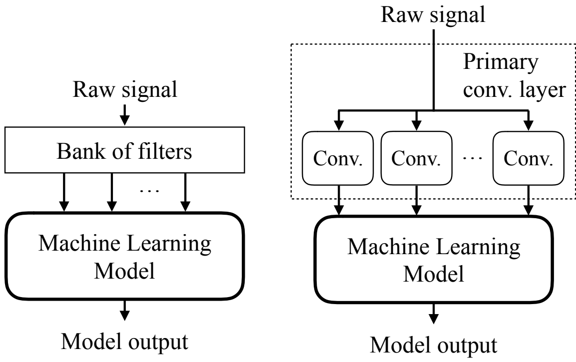
In this paper, we consider two models as shown in Fig. 2. The first model uses a predefined preprocessor, as shown in Fig. 2(a), which considers several previously employed methods. The second model is data-driven, where the parameters in the preprocessor are searched on the basis of the data.

3.2.1. Fixed approach

The first approach is to adopt two steps of preprocessing for each epoch. First, a zero-phase Butterworth infinite impulse response filter (IIR filter) is applied. The signal is filtered by a bandpass filter with a frequency of 1–30 Hz. The high-pass filter of 1 Hz plays the role of eliminating all the low frequency components such as breath or eye movement, and the low-pass filter of 30 Hz helps to meet the goal of reducing noise in the EEG recording. Further, DWT is used for decomposition to extract the frequency subbands of an EEG. The mother wavelet in this study is the Daubechies wavelet of order 4 (DB4), which is said to be appropriate for analyzing EEG signals [25, 26]. The input filtered signal is decomposed to six detailed levels and one approximation levels. The coefficient level D6, D5, D4 are used for representing the frequency band of the theta band (4–8 Hz), the alpha band (8–16 Hz), the beta band (16–32 Hz), respectively [6]. The detailed coefficient of D1, D2, and D3 are eliminated because the frequency ranges of these bands are considered as noise.

3.2.2. Fully data-driven approach

Subband decomposition with DWT, described in Section 3.2.1 can be regarded as a filterbank comprising three finite impulse response filters. In this approach, we build a model that learns the coefficients



(a) The fixed approach (b) The data-driven approach

Fig. 2. The model diagrams.

of these filters. In other words, a simple convolution layer, called the *primary convolution layer*, is placed instead of the fixed subband filters, as illustrated in Fig. 2(b). The underlying idea behind the primary convolution layer is to estimate frequency bands of interest by learning data. The number of filters and the filter size of the convolution layer of the proposed method are set to 3 and 64, respectively. Therefore, the features size of each epoch would be 500×3.

The learning step is roughly divided into the following two parts:

1. Update only the coefficients of the primary convolutional layer.
2. Update all coefficients of the main layers of the "Machine Learning Model" in Fig. 2(b).

The first step assists the learning of the filter coefficients in the added convolutional layer to extract the effective frequency bands from the raw signal in a stable manner, without the influence of the learning of the following network. Then, in the next step, the main layers are tuned to extract the hidden features in the signal.

3.3. Machine learning models

In this paper, SVM, RF, Long Short-Term Memory (LSTM) [27], Gated Recurrent Unit (GRU) [28], and CNN are adopted as the machine learning models depicted in Fig. 2. SVM and RF are either combined with the traditional preprocessing or not combined in any preprocessing. Further, LSTM, GRU and CNN are combined with either the traditional preprocessing or the proposed method.

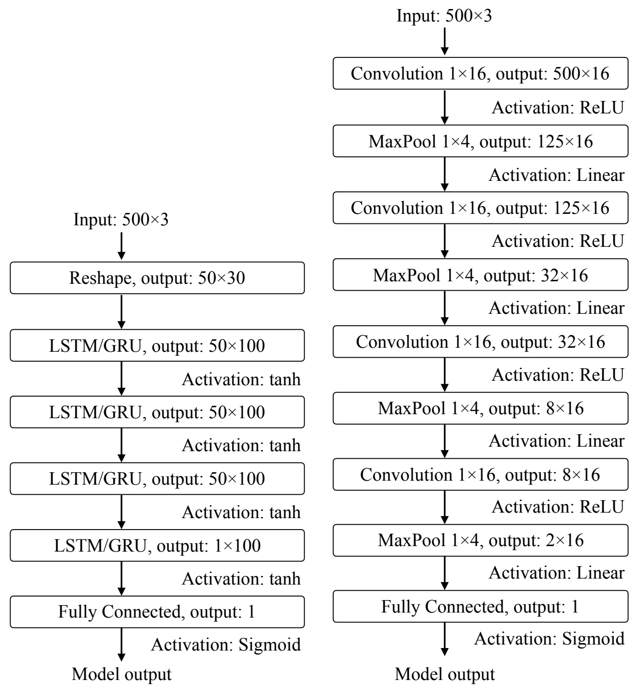
Each parameter of SVM and RF is tuned, as shown in Table 2, by grid search. For adjusting the grid search, the F1-score is used as the ranking score and the five-fold cross validation with two subsets is used. The model architectures of LSTM, GRU and CNN are depicted in Fig. 3. For the generation of initial weights of these models, the He initializer [29] is used for layers that employ the Rectified Linear Unit (ReLU) as the activation function, and the Xavier initializer [30] is used for other layers.

4. EXPERIMET

In order to verify the effectiveness of the proposed method, an experiment is presented by using surface EEGs obtained from BECTS patients. A peak contained in the EEG is classified as a paroximal discharge or an artifact. In this experiment, SVM using RBF-kernel, RF (for the fixed approach), GRU, LSTM, and CNN (for both the fixed and data-driven approaches) are used as classification models.

Table 2. Parameters to be tuned by grid search

Model	Parameter	Range
SVM	Kernel precision γ	1E-4, 1E-3, 1E-2, 1E-1, 1E+0, 1E+1
	Trade-off parameter C	1E-4, 1E-3, 1E-2, 1E-1, 1E+0, 1E+1
RF	Number of trees N_{tree}	5, 10, 20, 30, 50, 100, 300



(a) Architecture for LSTM and GRU models (b) Architecture for CNN model

Fig. 3. The model architectures. The input is three signals decomposed by DWT or the primary convolutional layer.

As a comparison target, raw signals to which bandpass filters and DWT are applied are used as inputs to these models.

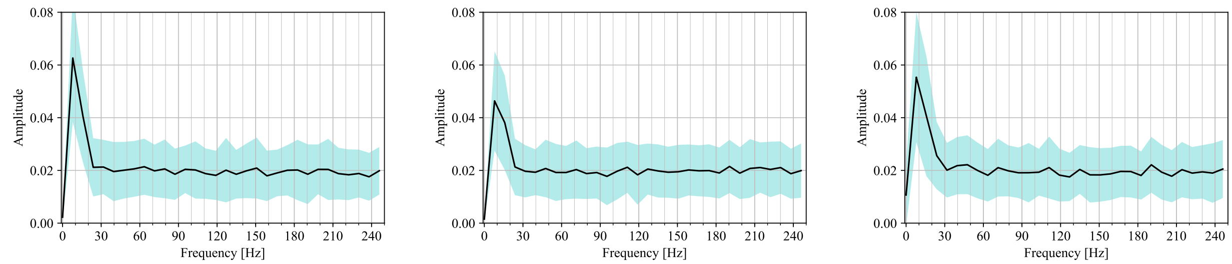
Inter-subject validation is conducted with five patients as a train-set and another one as a test-set in all combinations. To evaluate the model, the area under the curve (AUC) is used. AUC is the area of the curve drawn by the false positive rate (FPR) and the true positive rate (TPR) when the discrimination threshold is changed, and are calculated in the following manner:

$$\mathrm{FPR} = \frac{\mathrm{FP}}{\mathrm{FP} + \mathrm{TN}},$$
$$\mathrm{TPR} = \frac{\mathrm{TP}}{\mathrm{TP} + \mathrm{FN}},$$

where TP, FP, FN, and TN are the numbers of true positive, false positive, false negative, and true negative, respectively. In particular, for the evaluations of LSTM, GRU, and CNN, a mean AUC (by taking an average over 30 independent realizations) is adopted since the initial values affect the learning. In addition, the spectrum of the filter of the primary convolutional layer is analyzed after learning. The spectrum of each frequency is the mean of 30 independent runs and three filters.

Table 3. AUCs (mean ± STD of 30 independent runs at LSTM, GRU, and CNN) of each compared method.

Model	Bandpass Filter [Hz]	Feature extraction	Patients used as train-set					
			1, 2, 3, 4 and 5	1, 2, 3, 4 and 6	1, 2, 3, 5 and 6	1, 2, 4, 5 and 6	1, 3, 4, 5 and 6	2, 3, 4, 5 and 6
SVM	1–30	DWT	0.967	0.896	0.923	0.880	0.890	0.717
RF	1–30	DWT	0.964	0.914	0.925	0.940	0.887	0.833
SVM	None		0.857	0.866	0.594	0.203	0.582	0.620
RF	None		0.953	0.873	0.660	0.375	0.793	0.669
LSTM	1–30	DWT	0.942 ± 9.25E-03	0.889 ± 7.23E-03	0.841 ± 1.42E-02	0.842 ± 3.51E-02	0.792 ± 6.87E-02	0.768 ± 1.78E-02
GRU	1–30	DWT	0.948 ± 5.61E-03	0.891 ± 6.82E-03	0.846 ± 1.54E-02	0.866 ± 1.61E-02	0.873 ± 1.86E-02	0.492 ± 2.14E-02
CNN	1–30	DWT	0.942 ± 6.65E-03	0.894 ± 1.05E-02	0.885 ± 1.42E-02	0.869 ± 1.33E-02	0.905 ± 1.52E-02	0.785 ± 1.69E-02
LSTM	Primary conv. layer		0.945 ± 6.37E-03	0.844 ± 2.85E-02	0.866 ± 1.63E-02	0.672 ± 4.56E-02	0.893 ± 1.73E-02	0.779 ± 3.44E-02
GRU	Primary conv. layer		0.943 ± 6.27E-03	0.770 ± 8.50E-02	0.895 ± 1.23E-02	0.709 ± 3.44E-02	0.901 ± 9.75E-03	0.787 ± 2.55E-02
CNN	Primary conv. layer		0.961 ± 9.12E-03	0.896 ± 1.24E-02	0.771 ± 7.47E-02	0.554 ± 3.90E-02	0.847 ± 2.32E-02	0.751 ± 1.92E-02



(a) Mean spectrum (following model is LSTM) (b) Mean spectrum (following model is GRU) (c) Mean spectrum (following model is CNN)

Fig. 4. Mean spectrums of the filters in the primary convolutional layer

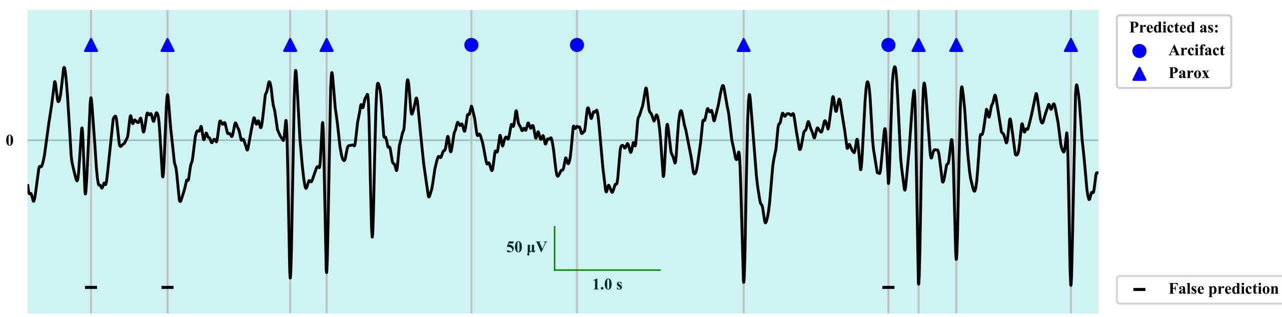


Fig. 5. An example of predictions by CNN with the proposed method. Vertical bars indicate the peaks detected by PeakUtils [24]. The top markers (circles and triangles) represent the results of the peak estimation by CNN. The bottom markers (horizontal short bars) represent the failures of the prediction.

5. RESULTS AND DISCUSSION

5.1. Results

Table 3 represents the results for each model and method. Fig. 4 illustrates the mean spectrums of the filters in the proposed method when learned by Patients 1, 2, 3, 4, and 5. These spectrums are the means of both the number of trials and the three filters. It is evident from Table 3 that the AUC of the proposed method achieves almost comparable AUC to that achieved in the traditional preprocessing. In addition, it is evident from Fig. 4 that the filters of the proposed method emphasize the lower frequency band (approximately 8–16 Hz). Therefore, the traditional method focused manually on the low frequency band, but it can be said that the proposed method automatically extracts this frequency band. Fig. 5 provides an example of predictions by CNN with the primary convolutional layer.

5.2. Discussion

This paper established a fully data-driven method which automatically determines EEG frequency bands of interest. As a result of machine learning with annotated data, the average amplitude spectra of the primary convolutional layers clearly showed a band-limited nature. This strongly supports bandpass filtering or subband decomposition, which have typically been done in lots of previous works. Moreover, the resulting narrowband is covered by bandwidths that are used in the literature and by epilepsy specialists. Further, the traditional classifiers (SVM and RF) with prefixed preprocessing (<30 Hz) achieved comparable scores in classification with those that were obtained with the fully data-driven approaches.

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