Restoration of dry electrode EEG using deep convolutional neural network

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***Abstract*—Electroencephalography(EEG) has been used widely in biomedical research and consumer products because of its reasonable size and cost. In order to reduce the electrical impedance between electrodes and skin of the scalp, we use conductive gel. However, it takes time to setup EEG. This problem is solved by dry electrodes, which do not require to use the conductive gel, however, the signal quality of dry electrodes is lower than that of wet electrodes.**

In this research, we propose a method to improve quality of the dry EEG signal. In order to design a restoration filter, we prepare wet and dry EEG signals recorded simultaneously. Then the filter is trained by both wet and dry EEG signals to restore wet EEG signal from dry EEG signal input. We used the fully connected deep neural network (DNN) and convolutional neural network (CNN). We conducted an experiment using the oddball paradigm to demonstrate the proposed method and compare with the classical Wiener filter.

I. Introduction

Electroencephalography(EEG) has been used widely in biomedical research and consumer products because of its reasonable size and cost. EEG signal is small potential on the scalp caused by action potential of neurons. Therefore, EEG contains large noise. The noise includes those derived from living bodies and those from the environment [1]. The body noise occurs from muscle activity, blinking, and myoelectricity. Independent component analysis (ICA) is used to remove these kinds of noise [2]. The environmental noise is caused by power supply, common mode, electromagnetic noise. It is removed by a band-pass filtering or an active amplifier which keeps an appropriate impedance.

EEG consists of the spontaneous potential and the event related potential (ERP). The event related potential (ERP) is caused by an internal or external stimulation. The visual evoked potential (VEP) or auditory evoked potential (AEP) is often used to evoke ERP method. In order to observe a waveform of ERP, the trial averaging is used. Since the noise and spontaneous potential are not synchronized to the event, their power is reduced in inverse proportion to the number of averaging. The brain computer interfaces (BCIs), which controls a computer or device by using only brain activity, are required to input command faster. Thus, it is necessary to extract ERP by using single or a few number of trials. Many methods to extract ERP using single or smaller number of trials have been proposed for BCI [3], [4], [5], [6], [7], [8].

These methods mainly focus on wet electrode EEG. Wet electrode EEG requires to use conductive gel to reduce the impedance between the electrodes and skin of a scalp to obtain higher signal-to-noise ratio (SNR) signal. However, the conductive gel has problems; has to be rinsed after the measurement; costs setup time; and dries during long-time measurement. In order to overcome these problems, a dry electrode has been developed. Although dry electrodes do not require to use conductive gel, its SNR is still much lower than SNR of wet EEG.

In this paper, we propose a method to improve quality of the dry electrode EEG signal. In order to design a restoration filter, we prepare wet and dry EEG signals recorded simultaneously. Then the filter is trained by both wet and dry EEG signals to restore wet EEG signal from dry EEG signal input. We used the fully connected deep neural network (DNN) and the convolutional neural network (CNN). We conducted an experiment using the oddball paradigm to demonstrate the proposed method and compared with the classical Wiener filter.

II. Experiment

A. Subject and task

The subject was three 21-23-year-old males, and the oddball task is conducted. In the oddball task, 1kHz and 2kHz tone bursts were generated in the ratio of 4:1. The subject counted in mind when 2kHz tone is presented. The stimulus lasts 0.2 seconds, and the stimulation interval was randomly determined from 0.8 to 1.3 seconds. One session consists of 250 stimulus presentations, and the subject took a break three minutes between the session. One session is about seven minutes. Four sessions were recorded for each subject.

B. EEG Recording

Dry and wet electrodes were attached to the subject. According to the international 10-20 method, the dry electrodes were placed at Cz, CPz and Pz. The wet electrodes were placed at C1, CP1 and P1. The sensors position is illustrated in Fig. 1. g.SAHARA system manufactured by g.Tec was used for dry electrodes, and g.GAMMA system was used for wet electrodes. The dry and wet EEG were amplified 2500 and 5000 times respectively. Then a band-pass filter of 0.5-100 Hz was applied and recorded at 16bit 512Hz A/D converted.

C. EEG Analysis

The recorded EEG was visually confirmed not to have large artifacts, and a band-stop filter of 45-55 Hz and a band-pass filter of 1-45 Hz were applied. EEG was standardized to have zero mean and variances one for each channel.

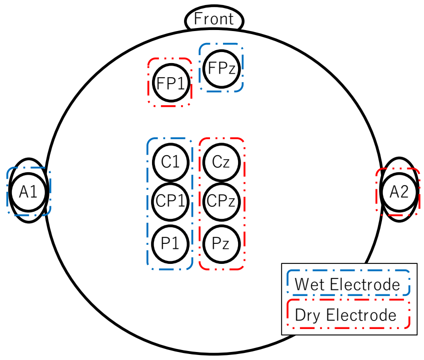

Fig. 1. Sensor position
Using 10-20 system. Red line: Dry electrodes, Blue line: Wet electrodes, FPz and FP1: Ground, A1 and A2: Reference

III. Signal Restoration Methods

A. Wiener Filter

The Wiener filter is an optimal linear filter in terms of minimizing the mean squared error. We minimize the mean squared error between the desired signal $y[n]$ and the filter output signal $\hat{y}[n]$ given by

$$\hat{y}[n] = \sum_{m=0}^{M-1} h[m]x[n-m], \tag{1}$$

where $h[m]$, $m = 0, \dots, M-1$ is the filter coefficients and $x[n]$, $n = 0, \dots, N-1$ is the input signal.

Let $e[n] = y[n] - \hat{y}[n]$ is the error, the mean squared error is

$$\min_{h[\cdot]} \epsilon = E\{e^2[n]\}, \tag{2}$$

where E denotes the expectation. The Wiener filter is $h[n]$ minimizing ϵ. The filter coefficients $h[n]$ is obtained by

$$\min_{\boldsymbol{h}} \|\boldsymbol{y} - \boldsymbol{X}\boldsymbol{h}\|^2, \tag{3}$$

where

$$\boldsymbol{X} = \begin{bmatrix} x[M-1] & x[M-2] & \cdots & x[0] \\ x[M] & x[M-1] & & \vdots \\ \vdots & & \ddots & \vdots \\ x[N-1] & \cdots & \cdots & x[N-M] \end{bmatrix} \tag{4}$$

$$\boldsymbol{y} = \begin{bmatrix} y[M-1] & y[M] & \cdots & y[N-1] \end{bmatrix}^T \tag{5}$$

$$\boldsymbol{h} = \begin{bmatrix} h[0] & h[1] & \cdots & h[M-1] \end{bmatrix}^T. \tag{6}$$

The optimal solution is given by

$$\boldsymbol{h} = (\boldsymbol{X}^T\boldsymbol{X})^{-1}\boldsymbol{X}^T\boldsymbol{y}. \tag{7}$$

If $(\boldsymbol{X}^T\boldsymbol{X})$ is singular or ill-posed, the l_2 regularization is used.

$$\boldsymbol{h} = (\boldsymbol{X}^T\boldsymbol{X} + \lambda\boldsymbol{I})^{-1}\boldsymbol{X}^T\boldsymbol{y}, \tag{8}$$

where λ is a regularization parameter.

We used a temporal Wiener filter designed for each channel, and spatial-temporal Wiener filter. The temporal filters were designed for three pairs, (Cz, C1), (CPz, CP1), and (Pz, P1). The dry EEG is used for the training input $\boldsymbol{X}$, and wet EEG is used for the desired signal $\boldsymbol{y}$. Then $\boldsymbol{h}$ is a restoration filter of dry EEG. The spatial-temporal Wiener filter is designed as follows. Let the input matrix and the filter factor be

$$\boldsymbol{X} = \begin{bmatrix} \boldsymbol{X}_1^T & \boldsymbol{X}_2^T & \cdots & \boldsymbol{X}_{S_{\mathrm{dry}}}^T \end{bmatrix}^T \tag{9}$$

$$\boldsymbol{y} = \begin{bmatrix} \boldsymbol{y}_1^T & \boldsymbol{y}_2^T & \cdots & \boldsymbol{y}_{S_{\mathrm{wet}}}^T \end{bmatrix}^T \tag{10}$$

$$\boldsymbol{h} = \begin{bmatrix} \boldsymbol{h}_1^T & \boldsymbol{h}_2^T & \cdots & \boldsymbol{h}_{S_{\mathrm{dry}}}^T \end{bmatrix}^T, \tag{11}$$

where $\boldsymbol{X}_i$ is $\boldsymbol{X}$ of channel i, $\boldsymbol{h}_i$ is $\boldsymbol{h}$ of channel i, S_{dry} and S_{wet} is the number of dry and wet electrodes respectively. A filter was created for combinations, (C1, Cz, CPz, Pz), (CP1, Cz, CPz, Pz), and (P1, Cz, CPz, Pz).

B. Deep Neural Network

A fully connected deep neural network (DNN) is used as a nonlinear regression method. We constructed a filter whose input is the dry EEG $\boldsymbol{x} = [x[0], \dots, x[N-1]]$, and teaching signal is wet EEG. LeakyReLU was used as the activation function of hidden layers,

$$\sigma(x) = \begin{cases} 0.3x & (x < 0) \\ x & (\mathrm{otherwise}). \end{cases} \tag{12}$$

The cost function is the squared error. The weight parameters were optimized by Adam algorithm. The hyper-parameters of the optimizer conformed to the proposed paper [9]. The number of hidden layers was two, and the number of kernels was set equal to the input dimension. Fig. 2 is an example of used DNN model. We trained DNN for combinations (C1, Cz), (CP1, CPz), and (P1, Pz). The input dimension N was chosen from 16, 32, 64, 128, 256 and 512. We used Python 3.5.4 and Keras 2.1.3 with TensorFlow 1.5.0 background to implement the neural network.

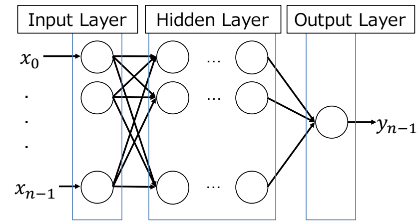

Fig. 2. Example of fully connected deep neural network
LeakyReLU is used for hidden layer's activation. Output layer's activation was linear.

C. Convolutional Neural Network

We used a convolutional neural network(CNN) for the spatial-temporal nonlinear filter. CNN deals with multi-dimensional structured data, on the other hand, fully connected

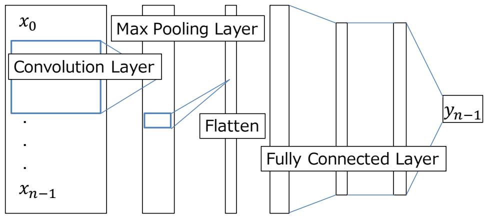

Fig. 3. Example of convolutional neural network
First layer was convolutional layer. Next layer was max pooling layer.

DNN is invariant for the structure and permutation of input dimension.

Multichannel EEG has a two dimensional structure which has time and channel. We applied two dimensional convolution for time and channel index. The filters were designed for combinations (C1, Cz, CPz, Pz), (CP1, Cz, CPz, Pz) and (P1, Cz, CPz, Pz). The network structure is illustrated in Fig. 3. The input dimension N was selected from with the result of DNN experiment. The number of units in hidden layers was set to the same as the input dimension. The number of hidden layer was two. The number of filters in the convolutional layer is ten. To aim channel cooperation, the kernel (filter) size of channel index was the number of input dry electrode channels, and time index was chosen from 4, 8, 16. The pooling method is the max pooling of the size 1×3. For the error function, the squared error function was used. The activation function was LeakyReLU, and Adam is used for optimization. All of these initial values were the same with those of DNN.

IV. Results

A. Deep Neural Network

DNN was designed for each pair of channels. One of the four sessions was used for training and remaining three sessions were used for test. We evaluated the performance by the mean squared difference between filter output and wet EEG. The error ratio E is calculated by

$$E = \frac{1}{4} \sum_{t=1}^{4} \frac{\|\hat{\boldsymbol{X}}_t - \boldsymbol{Y}_t\|_F^2}{\|\boldsymbol{X}_t - \boldsymbol{Y}_t\|_F^2}, \tag{13}$$

where $\boldsymbol{X}_t$ is dry EEG, $\hat{\boldsymbol{X}}_t$ is restored EEG, and $\boldsymbol{Y}_t$ is wet EEG of the tth session.

Fig. 4 shows the reconstruction error ratio of the temporal Wiener filter, the spatio-temporal Wiener filter and DNN. The error rates are averaged for four sessions, three pairs of electrodes and each subjects. The best of input size with the DNN was 32, and the temporal Wiener filter and spatio-temporal Wiener filter was 128.

B. Convolution Neural Network

From the result of DNN, CNN input dimension was set to be 32. CNN is evaluated in the same manner as DNN. Fig. 5 shows error rates of CNN. There was also no difference, temporal dimension 8 showed the lowest error rate. There is no significant difference between CNN and DNN in this result.

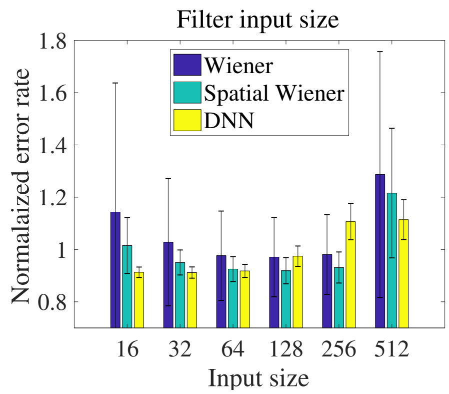

Fig. 4. Reconstruction error of temporal Wiener filter, spatio-temporal Wiener filter, and DNN

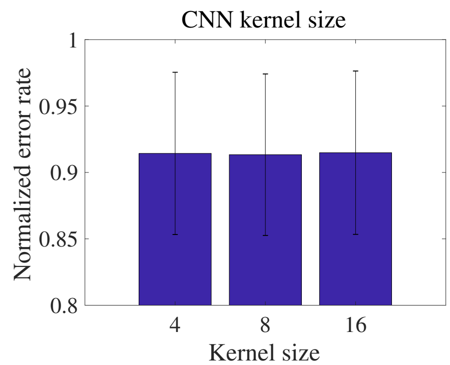

Fig. 5. Reconstruction error of CNN

C. Comparison of ERP waveform

We, next show quantitative comparison the reconstruction of ERP waveforms. As the ground-truth waveform, we obtained a grand averaging ERP waveform from wet electrodes. Then we compare correlation coefficients with the grand averaging and the reconstructed waveforms by the proposed methods.

One session is used for training and remaining three sessions are used for evaluation. We used CPz for dry electrode and CP1 for wet electrode. Fig. 7 shows forty times averaged ERP waveforms.

Fig. 6 and Tab. I show the relation between the correlation coefficients and the number of averaging. Fig. 6 shows correlation coefficients between forty times averaged wet electrode ERP waveforms and each times averaged ERP. Tab. I shows averaging times to leach correlation coefficient 0.8 in Fig. 6. Those shows CNN exhibited the best performance.

V. Conclusion

We have proposed a method to improve quality of dry electrode EEG. In order to design the restoration filter, we used simultaneously recorded dry and wet EEG. We compared four restoration models, temporal Wiener filter, spatio-

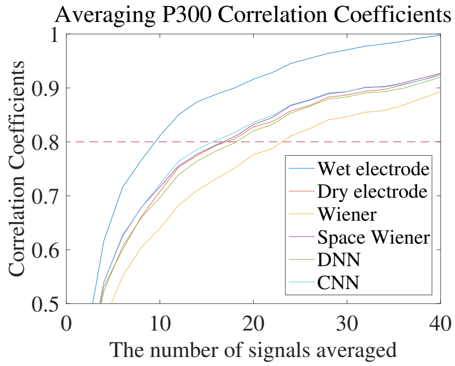

Fig. 6. Correlation coefficient and the number of averaging

TABLE I
CORRELATION COEFFICIENT AND AVERAGING TIMES TO LEACH 0.8

Methods	Averaging times
Wet electrode	9.5
CNN	15.6
Spatial Wiener filter	16.8
Dry electrode	17.0
DNN	18.2
Wiener filter	23.0

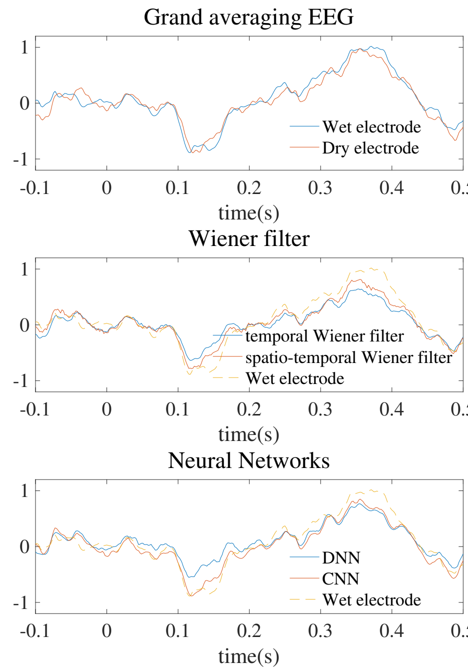

Fig. 7. averaged ERPs.

temporal Wiener filter, DNN, and CNN. Experimental results showed that spatial filtering which uses signal from neighbor electrodes exhibited better performance than single channel restoration filter, and nonlinear models, deep or convolutional neural networks, exhibited better performance than linear methods, Wiener filtering.

The proposed methods improve the quality of dry EEG, and solve the problems of wet electrodes. The proposed method is not only for extraction of ERP but also measurement of spontaneous EEG. Furthermore, the proposed methods will work with the other ERP enhancement filters such as common spatial potential (CSP) filter. Future works include investigation of inter-subject dependence, increase sensors and verify relationship, selection of hyper-parameter, and application of the other network structure.

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