

LETTER

Applying K-SVD Dictionary Learning for EEG Compressed Sensing Framework with Outlier Detection and Independent Component Analysis

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SUMMARY This letter reports on the effectiveness of applying the K-singular value decomposition (SVD) dictionary learning to the electroencephalogram (EEG) compressed sensing framework with outlier detection and independent component analysis. Using the K-SVD dictionary matrix with our design parameter optimization, for example, at compression ratio of four, we improved the normalized mean square error value by 31.4% compared with that of the discrete cosine transform dictionary for CHB-MIT Scalp EEG Database.

key words: EEG, compressed sensing, independent component analysis, outlier detection, K-SVD dictionary learning

1. Introduction

Electroencephalograms (EEGs) are widely used to detect the presence and extent of various brain pathologies, such as epilepsy [1] and Alzheimer's disease [2]. These diagnoses may be performed continuously over a long period of time [3]. Therefore, a wireless EEG measuring device smaller and lighter than current designs is required. The size of the battery installed in the device is an essential factor for downsizing the wireless EEG measuring device. Therefore, in this study, we focused on applying compressed sensing (CS) [4] technique for EEG measurement devices to reduce power dissipation.

In this regard, the reconstruction accuracy is an essential aspect to improve. Especially, it is a critical problem that reconstruction accuracy of signals achieved by CS reconstructed algorithm become worse by impulse-like disturbance called eye-blink artifacts [5]. Thus, remove eye-blink artifacts before reconstruction is desirable [6], [7]. Recently, a framework was proposed to efficiently remove the eye-blink artifacts before reconstruction by applying outlier detection and independent component analysis (OD-ICA) [8] to compressed EEG signals [9]. However, increasing the reconstruction accuracy is still a critical aspect because further improvements in reconstruction accuracy will allow CS

to be used in also several other applications. Therefore, in this study, we focus on dictionary matrix to realize high accuracy reconstruction.

For example, researchers have applied the K-singular value decomposition (SVD) [10] to the dictionary matrix for EEG CS measurement [11]. The dictionary matrix capturing the characteristics of EEG signals can be developed using the K-SVD dictionary learning, which enables a higher sparse representation and improves the reconstruction accuracy. However, no previous studies have discussed on designing a framework for artifact-infested environments where the K-SVD is applied. When applying K-SVD dictionary matrix with K-SVD learning algorithm to a CS framework removing artifacts, it is an important research topic to find out how it can be designed and how much improvement can be achieved. In this letter, we present how the K-SVD dictionary can be designed and how much improvement is possible to obtain when applied to a CS framework that removes artifacts.

2. K-SVD Dictionary Learning

Figure 1 shows the CS framework using the OD-ICA. EEGs pass through the analog circuit. Subsequently, the signal is digitalized using a random undersampling analog-to-digital converter to perform compression. Compressed signals are transmitted to the processing unit, and reconstructed there. Generally, CS reconstruction is performed using known and fixed dictionaries, such as the discrete cosine transform (DCT) matrix and wavelet matrix. In this study, we develop a dictionary matrix suitable for the EEG CS framework by using the K-SVD dictionary learning and confirm the effectiveness of the proposed framework.

The K-SVD algorithm [10] is an algorithm for dictionary learning that developed by generalizing the k-means clustering process. The object of the algorithm is to determine the suitable dictionary matrix to provide a sparse representation to a large number of training signals. Figure 2 shows the conceptual diagram of the K-SVD dictionary learning. Each variable is explained below. $X \in \mathbb{R}^{N \times P}$ represents the training set containing P training signals $\{\mathbf{x}_i\}_{i=1}^P$ for columns, $D \in \mathbb{R}^{N \times L}$ is the dictionary matrix containing L prototype signals-atoms $\{\mathbf{d}_j\}_{j=1}^L$ for columns, $S \in \mathbb{R}^{L \times P}$ is the sparse matrix containing P sparse signals $\{\mathbf{s}_i\}_{i=1}^P$ corre-

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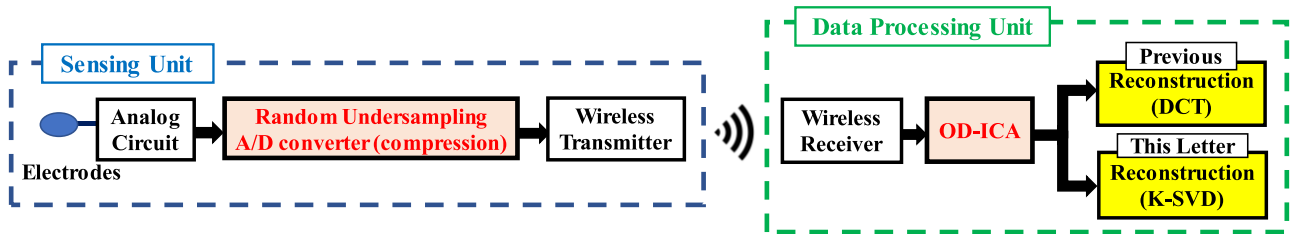


Fig. 1 EEG measurement frameworks.

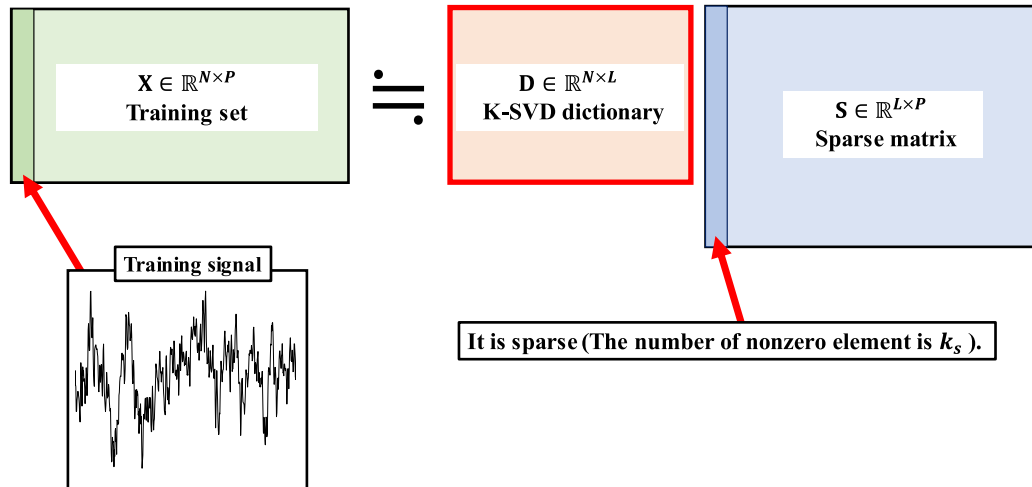


Fig. 2 K-SVD dictionary learning.

sponding to each training signal x_i for columns, and k_s is the number of non-zero elements of the sparse signal to be set. In the K-SVD algorithm, the goal is to find D to minimize Frobenius norm of the error matrix $X - DS$. Therefore, object function of the algorithm can be written as follows:

$$\min_{D,S} \|X - DS\|_F^2 \text{ s.t. } \|s_i\|_0 \leq k_s \forall i. \quad (1)$$

The algorithm consists of two steps, sparse coding and dictionary updating until the error falls within a specified range or the number of loops reaches the upper limit. Sparse coding of the K-SVD algorithm is performed by using some pursuit algorithms. In this study, the orthogonal matching pursuit (OMP) algorithm was used.

3. Evaluation

3.1 Dictionary Creation

All simulations for developing this letter were performed in MATLAB. We created a dictionary matrix using the K-SVD dictionary learning algorithm with EEG signals based on the CHB-MIT scalp EEG database [12]. The sampling rate of the EEG signals was changed from 256 Hz/sample to 200 Hz/sample to be the same as that used in [6], [7], [9]. The time corresponding to one epoch was 3 s.

The FP1-F7 EEG signals of 10 subjects, a total of $P = 10,000$ epochs, were used as training signals. The

EEG signals in the CHB-MIT database originally contained impulse-like artifacts; thus, the database was not suitable for training signals for the proposed framework directly. Therefore, to suppress the effect of eye-blink artifacts in the EEG signal, only those EEG signals in the database with amplitudes from -150 to $150 \mu\text{V}$ were selected and used as training signals. Moreover, natural eye-blink artifacts contained in selected EEG signals were removed using the OD-ICA method.

When using the K-SVD dictionary for a CS framework with OD-ICA, it is necessary to reveal the optimal sparse parameters during training and reconstruction, as well as the suitable number of the dictionary matrix size. Considering the relationship with the sparse parameter k_r when using the OMP algorithm in the reconstruction, we determined the optimal k_s parameter. In this study, the range of k_r and k_s was set from 10 to 100. L must be larger than the frame length 600 [10] and smaller than the number of training signals 10,000. Thus, the suitable value of L was selected from 600 to 9000.

3.2 Reconstruction of Compressed EEGs

We simulated the reconstruction using the K-SVD and DCT dictionary in the framework shown as Fig. 1. Moreover, we verified the reconstruction performance.

A total of 400 epoch 16-channel raw EEG signals with amplitudes from -150 to $150 \mu\text{V}$ were prepared from four

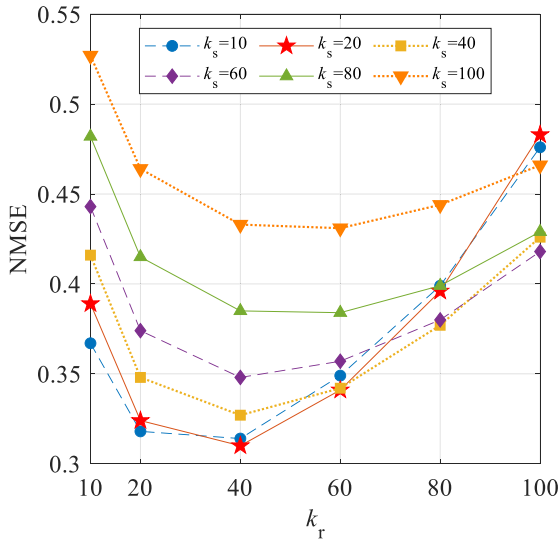


Fig. 3 NMSE vs k_s and k_r ($L = 600$, $CR = 4$).

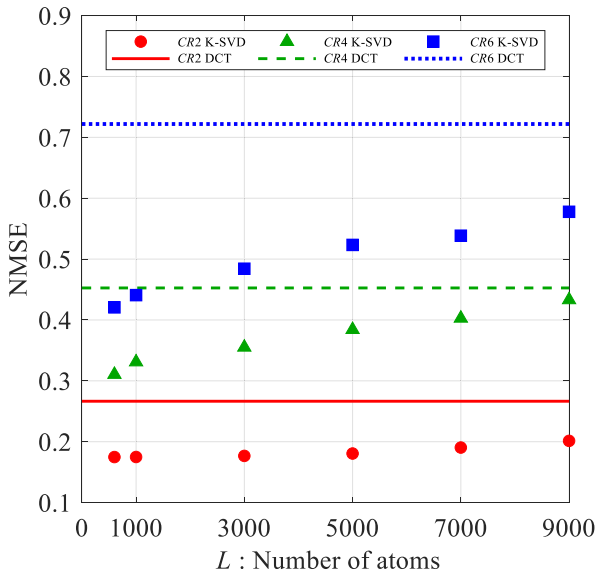


Fig. 4 NMSE vs Dictionary Size.

subjects different from those used to for training operation of the dictionary. These signals were passed through the OD-ICA and added the pseudo-eye-blink artifacts to generate the signals to be used in the evaluation of the proposed EEG CS framework. A pseudo-eye-blink artifact was set as a triangle wave with a time width of 150 ms. The amplitude of the pseudo-eye-blink artifact was set, considering that eye-blink artifacts have a larger amplitude at the electrode closed to the eye. Set to $300 \mu\text{V}$ in FP1-F7, F7-T7, FP1-F3, F3-C3, FP2-F4, F4-C4, FP2-F8, and F8-T8. Set to $30 \mu\text{V}$ in T7-P7, P7-O1, C3-P3, P3-O1, C4-P4, P4-O2, T8-P8, and P8-O2. The OMP algorithm was used for reconstructing CS. The compression ratio (CR) was set from 2 to 6. Until the pseudo-eye-blink artifact removal of the compressed EEG signal by OD-ICA, all 16-channel EEG

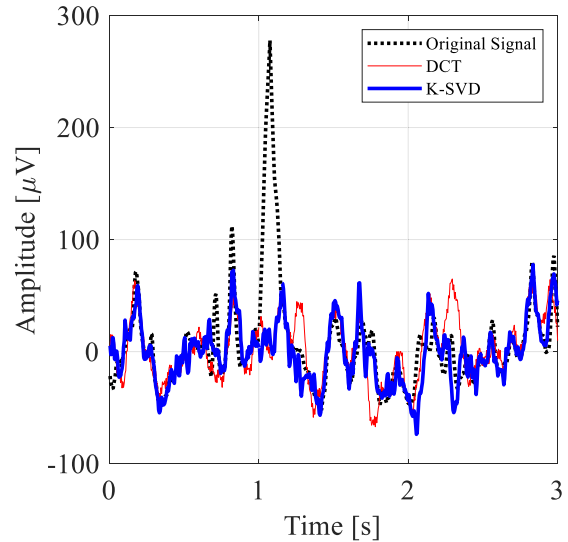


Fig. 5 Reconstructed waveform ($CR = 4$).

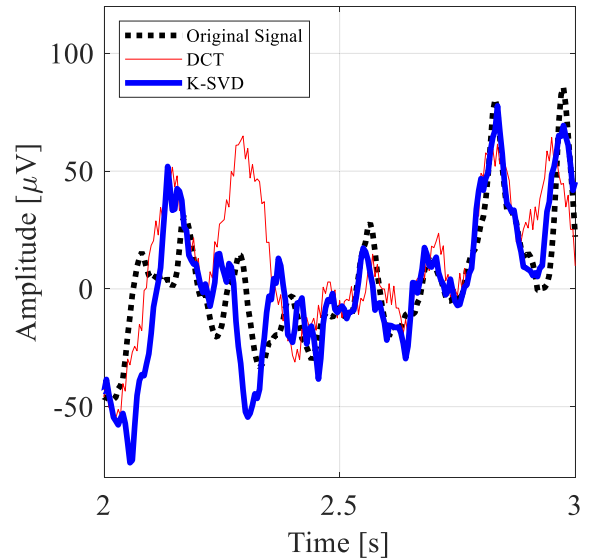


Fig. 6 Reconstructed waveform (zoomed-in view of Fig. 5).

signals were used. Moreover, the channel FP1-F7 used for dictionary learning was reconstructed, and the reconstruction accuracy was evaluated.

The simulation results are shown from Fig. 3 to Fig. 6. The reconstruction results are evaluated using the average of the NMSE values, where NMSE represents an index indicating the degree of error between the original signal \mathbf{x} and the reconstructed signal $\hat{\mathbf{x}}$ calculated using Eq. (2):

$$\text{NMSE} = \left(\frac{\|\hat{\mathbf{x}} - \mathbf{x}\|_2}{\|\mathbf{x}\|_2} \right)^2. \quad (2)$$

For comparison purposes, the region containing pseudo-eye-blink artifact was not considered when calculating the NMSE to realize same evaluation as [6], [7], and [9].

At first, suitable sparse parameters are evaluated. Figure 3 shows the reconstruction result when the parameter k_s

in the K-SVD algorithm and the parameter k_r in the OMP for reconstruction are changed from 10 to 100 in 6 steps in $L = 600$ and $CR = 4$. From this result, the optimum values of k_s and k_r for K-SVD dictionary were found to be 20, and 40, respectively. These optimum parameter values were used in the simulation shown below.

Subsequently, the optimized L value was obtained through MATLAB calculations. Figure 4 shows the NMSE of the reconstruction results for various L (points) and DCT (lines) when the compression ratio CR is 2, 4, and 6. As seen in the figure, the smaller the value of L is, the more the NMSE is improved for any CR . In particular, the K-SVD dictionary with $L = 600$, which showed the best reconstruction performance, improved the NMSE value by 34.4% at $CR = 2$, 32.1% at $CR = 3$, 31.4% at $CR = 4$, 40.5% at $CR = 5$, and 41.7% at $CR = 6$ compared with the DCT dictionary. Figures 5 and 6 show an example of the reconstructed waveform by the DCT dictionary (red line) and the K-SVD dictionary with $k_s = 20$ and $L = 600$ (blue line) when the compression ratio is $CR = 4$. With reference to these, it can be confirmed that the K-SVD dictionary matrix reconstructed the EEG signal more accurately than the DCT dictionary in terms of the actual waveform.

4. Conclusion

In this letter, the design and validation of a K-SVD dictionary learning algorithm that fits the CS EEG measurement framework with OD-ICA were reported. We improved the reconstruction accuracy by finding the optimum values of the sparse parameters in the OMP algorithm used for dictionary learning and reconstruction. The optimum values for the proposed framework of the K-SVD dictionary learning parameters, the number of non-zero elements per column of the sparse matrix k_s and the number of the K-SVD dictionary atoms L were found to be $k_s = 20$ and $L = 600$, respectively. In consequence, the K-SVD dictionary, using the optimal parameter, improved the NMSE value by 34.4% at $CR = 2$, 32.1% at $CR = 3$, 31.4% at $CR = 4$, 40.5% at $CR = 5$, and 41.7% at $CR = 6$ compared with the NMSE of the DCT dictionary.

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