

Evaluation of Noise robustness of Sparse Representation based Classification method for BCI systems

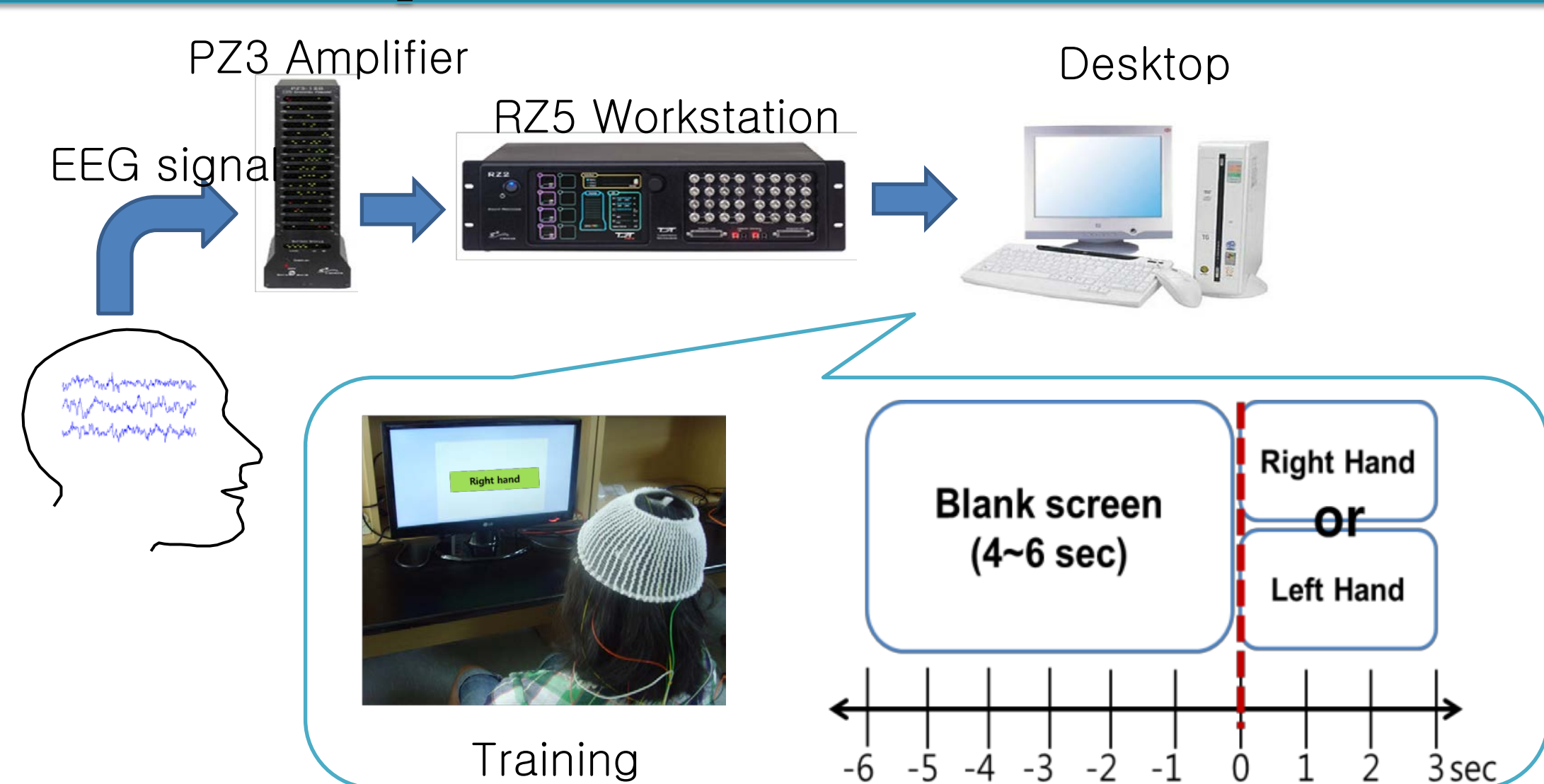
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Abstract

➤ Brain-computer interface system (BCIs) is very helpful to people who are suffering from severe motor diseases. Electroencephalogram (EEG) signals are widely used for measuring brain signals in BCIs. However, scalp-recorded EEG signals have inherent non-stationary properties. Therefore, in real-time BCI classification, EEG test signal is polluted by noise. This is one of major obstacles for EEG signal processing. In this study, we aim to evaluate sparse representation based classification (SRC) method as the EEG signal classifier. We mimic the real-time BCI classification situation with the addition of random Gaussian noise and scalp recorded background EEG signal into the original test signal, then we assess the noise robustness of the SRC. We compare classification performance of SRC with that of SVM which has been known as the state of the art classifier in many studies

Experimental data



- 20 subjects (11 male and 9 female)
- 64 EEG channels (Active two system made by Biosemi)
- 512 sampling rate and 100 trials per class

Methods

Sparse Representation based Classification

- SRC method can be summarized in the following two steps. The first step is to sparsely represent \mathbf{y} using \mathbf{A} via L1 norm minimization. This step is the sparsification step:

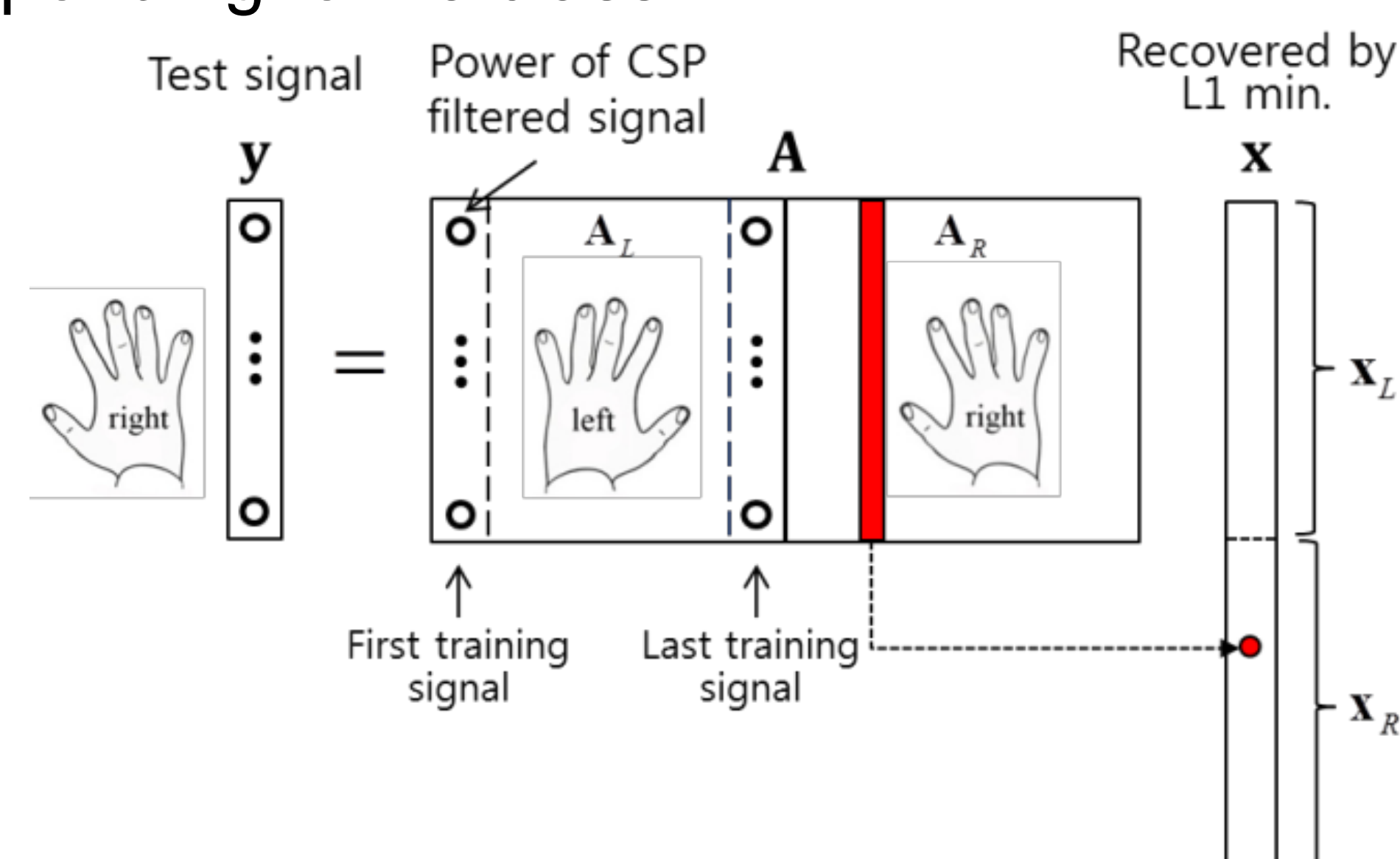
$$\min_{\mathbf{x}} \|\mathbf{x}\|_1 \text{ subject to } \mathbf{y} = \mathbf{A}\mathbf{x}$$

where, \mathbf{x} is a scalar coefficient vector and $\mathbf{A} \in \mathbb{R}^{m \times n}$ is the dictionary.

- Second step is to classify the testing signal via minimum residual. This step is the identification step:

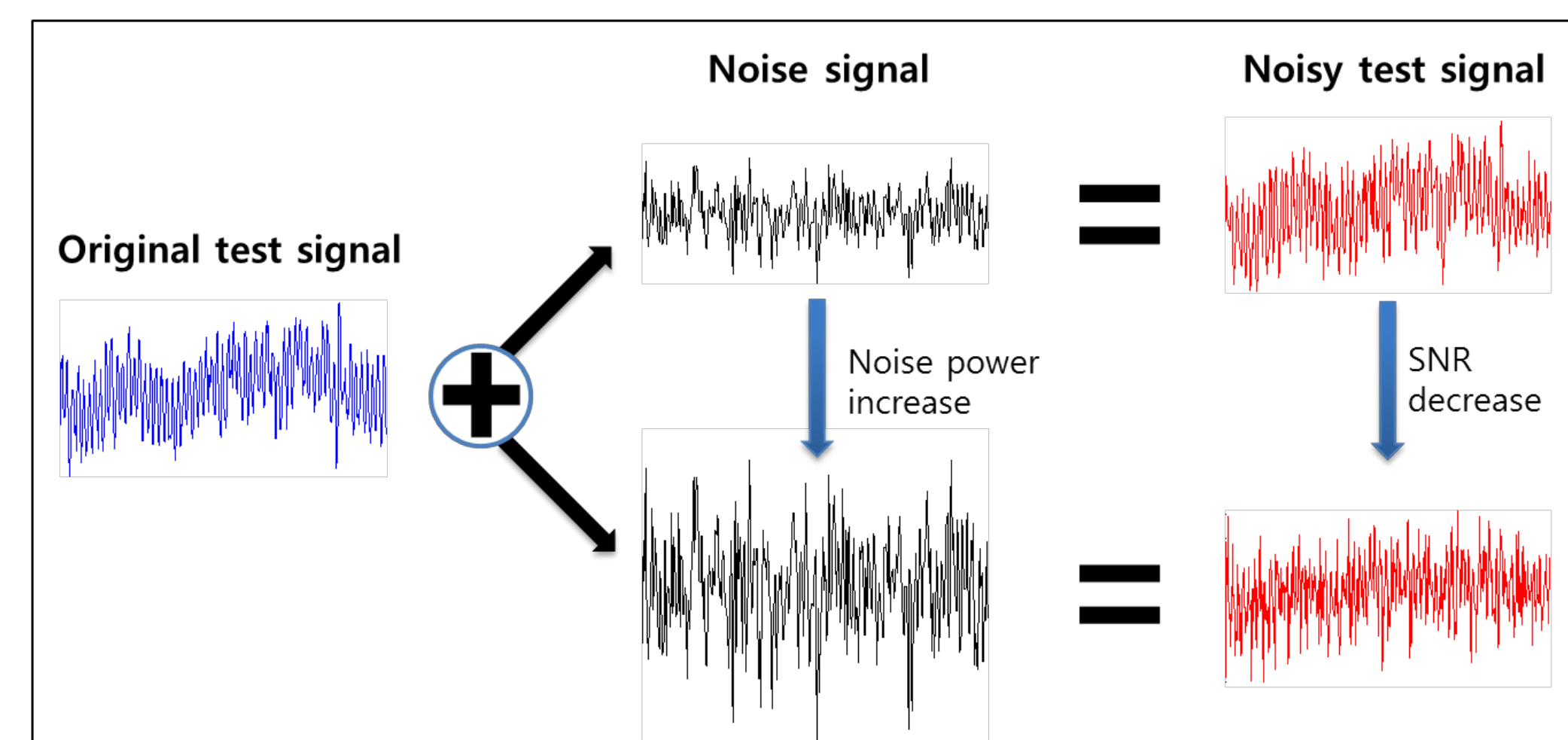
$$\text{class}(\mathbf{y}) = \min_i r_i(\mathbf{y})$$

where $r_i(\mathbf{y}) := \|\mathbf{y} - \mathbf{A}_i \mathbf{x}_i\|_2$, \mathbf{x}_i is the scalar coefficient vector corresponding to the class i .



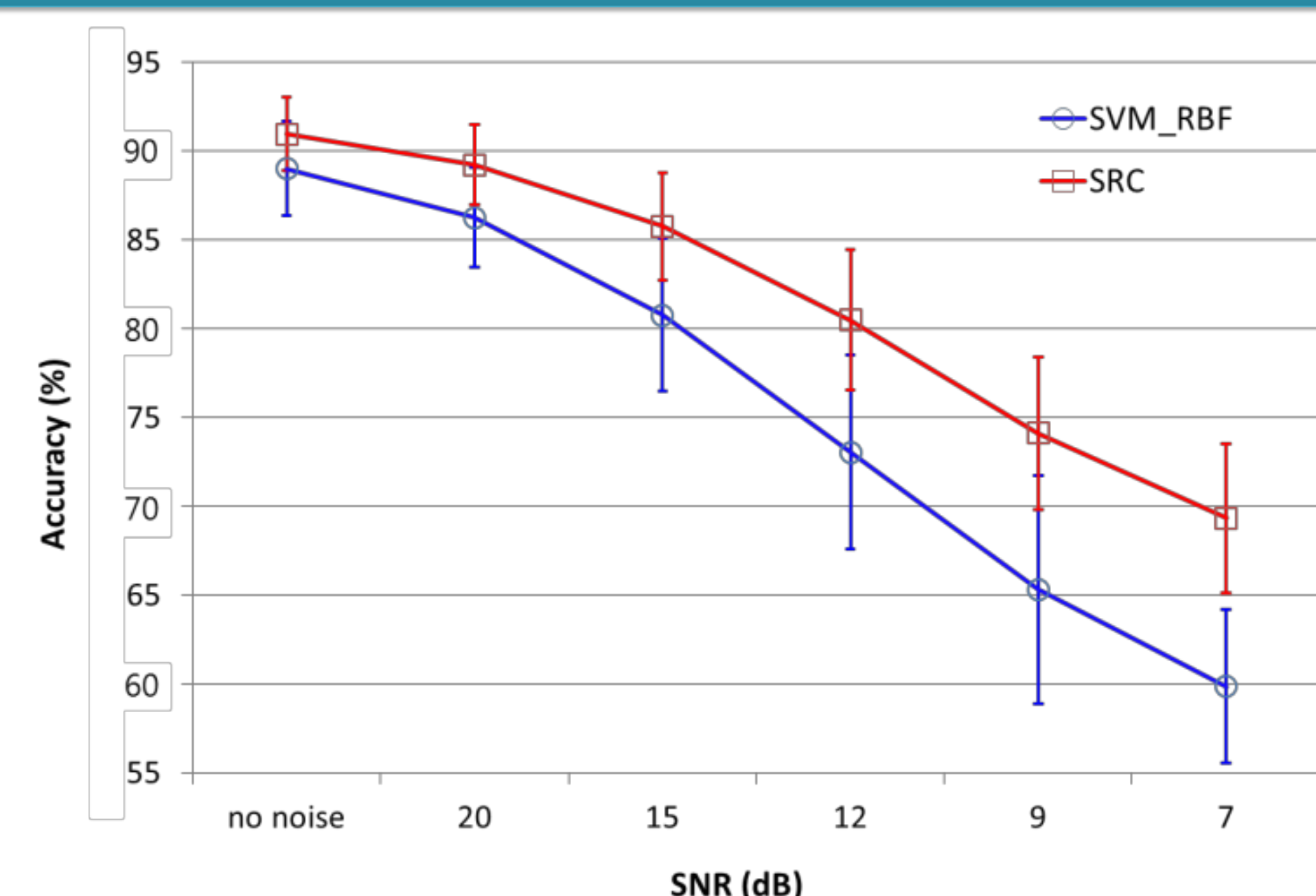
- This figure shows the formed dictionary \mathbf{A} and model of sparse representation for motor imagery based EEG signals.

Noise Robustness Evaluation

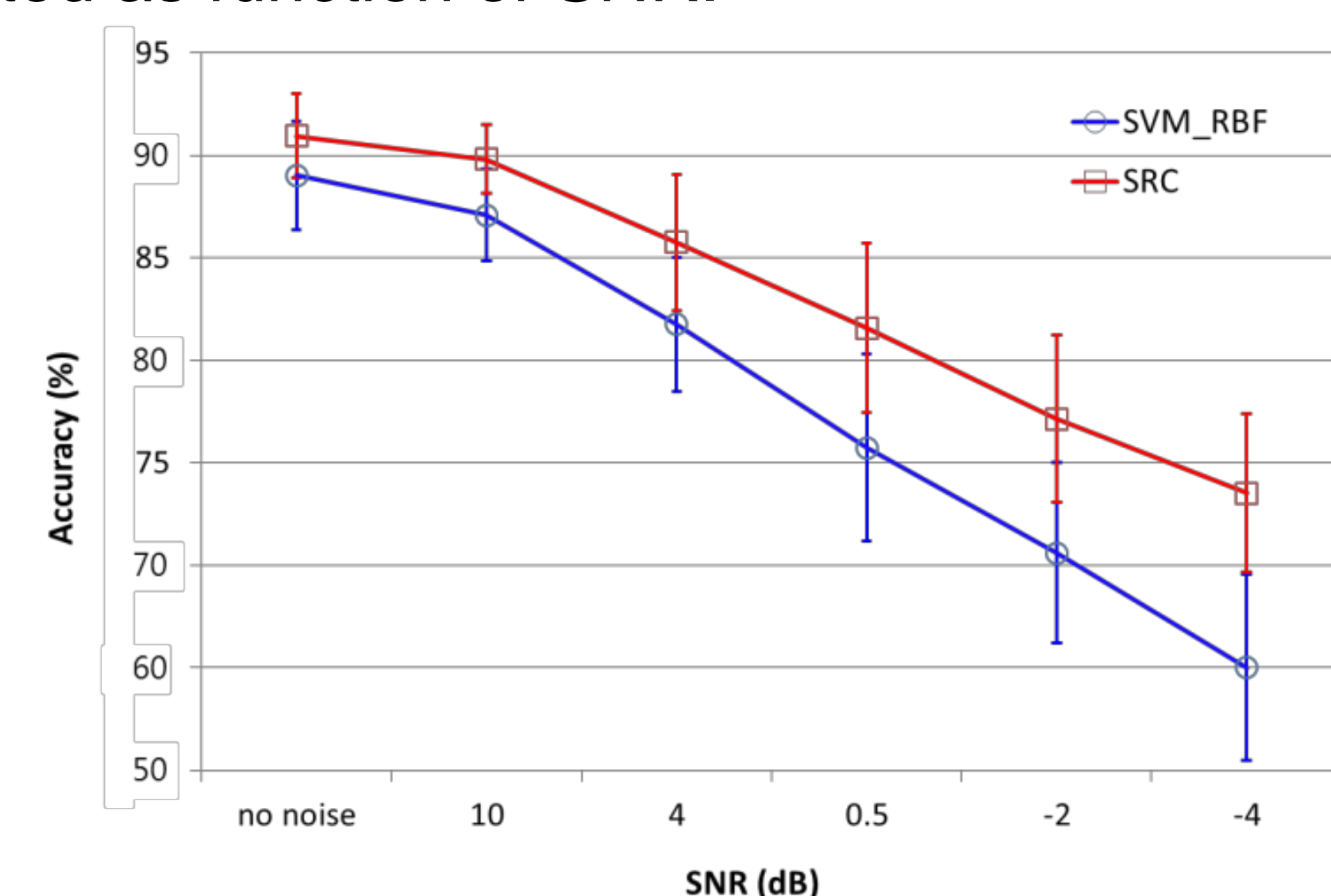


- We simulate the changed test data by introducing two different noise sources such as white Gaussian and background noise into the original test data.
- The figure shows the concept of generating polluted noisy test data using one noise source.

Results



- Average classification accuracy for Gaussian noise is represented as function of SNR.



- Average classification accuracy for background noise is represented as function of SNR.
- The classification accuracy of SRC is higher than that of RBF SVM for all SNR cases.

Conclusion

- We evaluate the sparse representation based classification (SRC) method for the motor imagery based BCI application.
- We make polluted EEG test signals using two noise sources such as random Gaussian noise and background noise.
- Then, we assess the classification performance of the SRC and SVM method when the noise power is varied.
- It is evident that the SRC shows superior noise robustness than the SVM for both Gaussian and background noise.

Acknowledgement

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