Dictionary Update based Adaptive EEG Classification for Real Time Brain-Computer Interface Applications

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Outline of Presentation

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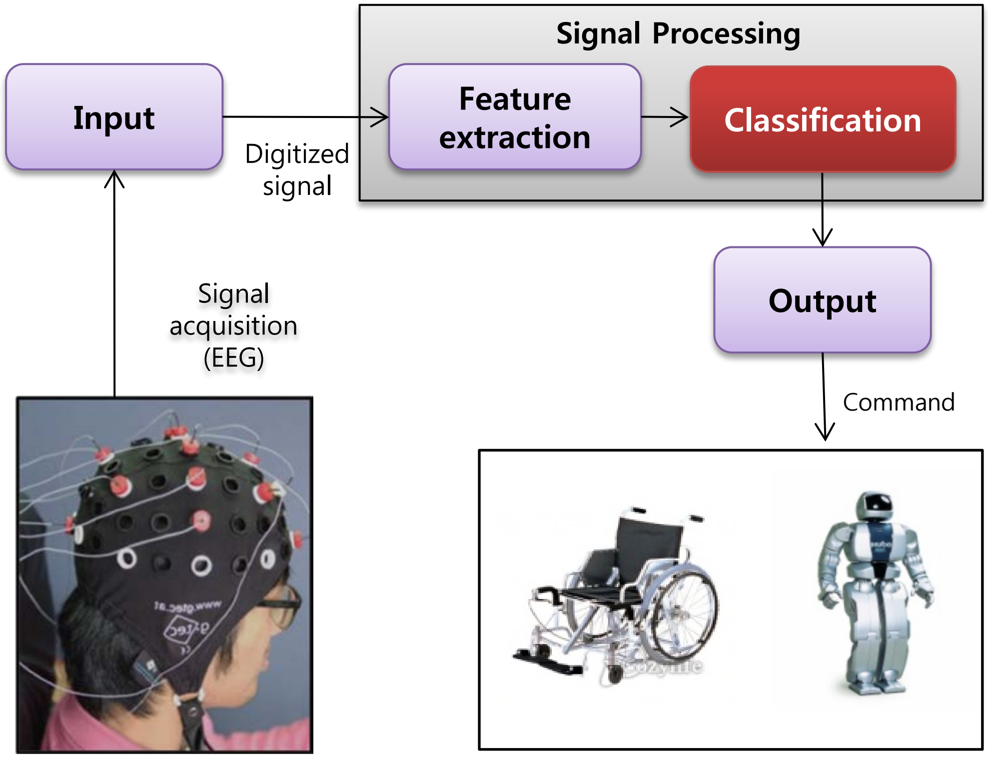
Brain Computer Interface

EEG based BCI systems

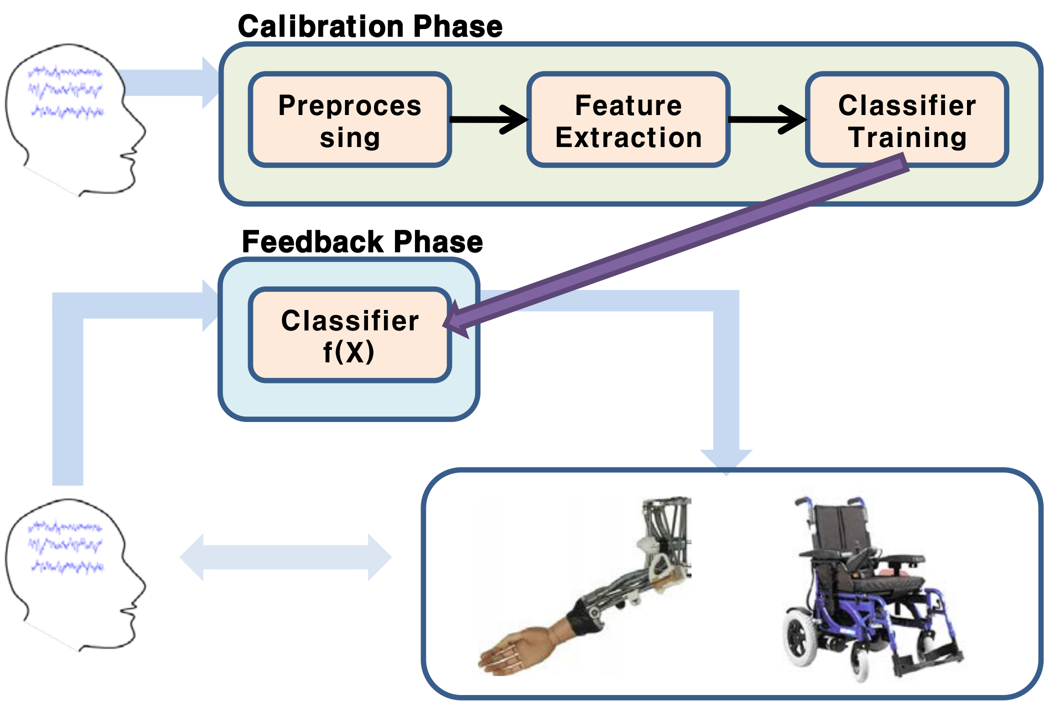
- Brain Computer Interface systems (BCIs)



  - EEG based BCI systems provide an alternative communication and control channel between human brain and external devices without any normal muscle movements.
  - In the BCIs, classification is needed to transform the extracted feature of a user’s intention into a computer command to control the external device.

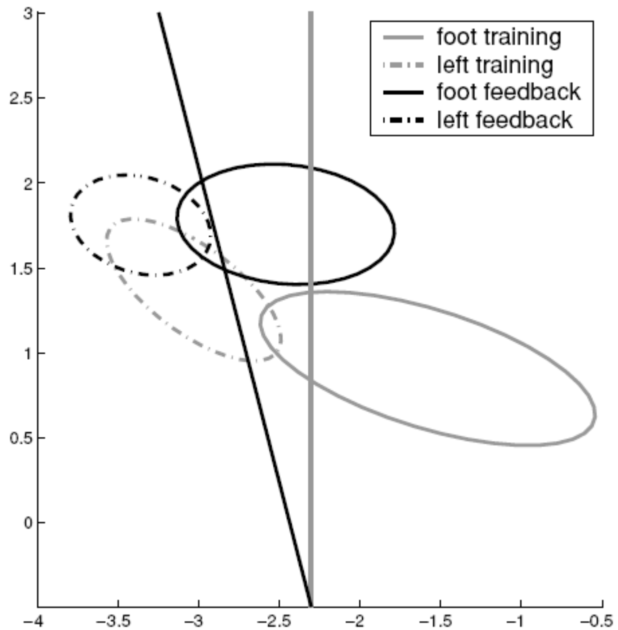
On-line BCI system

- BCI system consists of training (off-line calibration) session and testing (on-line feedback) session.
- In calibration session, classification rule is designed using training data.
- In on-line session, new test data are classified by the classification rule.



Non-stationarity of EEG

- EEG signals have inherent non-stationary characteristics and there exist significant day-to-day and even session-to-session variability.
- Therefore, features of experimental EEG signals are changed from the offline training sessions to online testing sessions.
- For reliable performance of BCI systems, classifier should be powerful for on-line data.



[Shenoy 2006]

Motivation

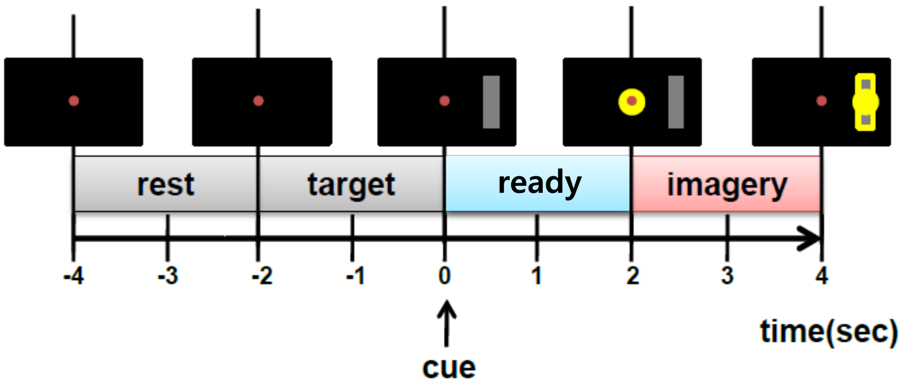
- Recently, we propose a sparse representation based classification (SRC) scheme for EEG based BCI applications [Younghak 2012].
- We also revealed that the SRC shows better classification accuracy and noise robustness than the well-known SVM method [Younghak 2015].
- However, no research has been studied for adaptive SRC scheme for online BCI applications.
- In this study, we propose a simple dictionary update rule based adaptive SRC method for real-time BCI systems.
- We consider supervised and unsupervised dictionary update methods.
- Using online motor imagery based BCI experimental datasets, we evaluate classification performance of the proposed adaptive method by comparing with the conventional methods.

Experiment

- We performed online motor imagery based BCI experiment.
- 10 subjects were participated.
- Right hand(R), left hand(L) and foot(F) motor imagery signals are collected
- Among R-F, L-F, L-R pairs, best pair is chosen for online classification.
- 64 EEG channels and 512 sampling rate were used.
- The same experimental paradigm was used for both calibration (training) and feedback (online) phases.
- In the one session experiment, total 60 training and 75 online testing trials per class were collected for each subject.

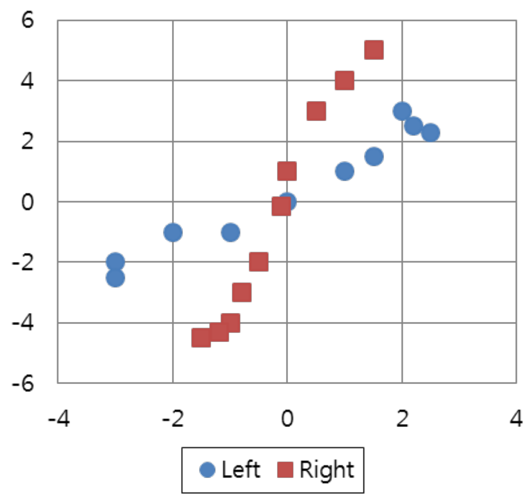
Experimental paradigm

- In each trial, the target bar was represented on 0sec at left, right or down side of monitor screen corresponding to the left, right or foot motor imagery.
- On 2sec after cue onset, subject was instructed to perform the motor imagery task.
- Then, subject imagined their left, right hand or foot movement such as grasping and releasing hand.
- In training session, we just collected training trials for each motor imagery signal.
- At that time, the classifier had not been designed. Therefore, the yellow ball (feedback) was set to move into the target direction automatically.
- In the online (feedback) session, the online feedback was provided in each trial.
- Thus, the yellow ball was controlled by the classified result which was analyzed from intention of each subject using the EEG data collected from 2 to 4sec.

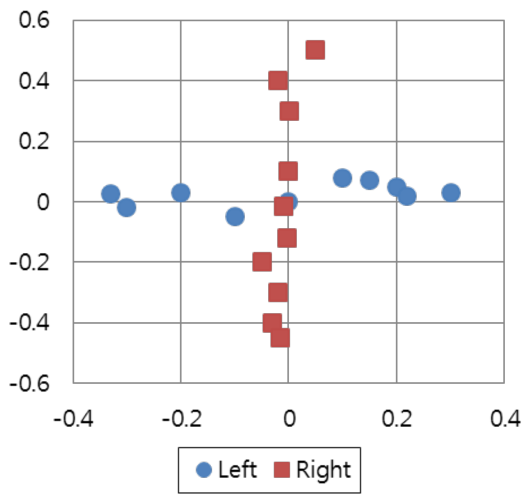


Feature extraction

- Time sequences from 2 to 4sec after cue onset are extracted.
- Band pass filtering with 5~30Hz is applied to EEG data.
- The well-known CSP (common spatial pattern) filtering is used for feature extraction.
- The CSP filters maximize the variance of the spatially filtered signal for one class data while minimizing it for the other class data [Shenoy 2006].
- After CSP filtering frequency power of 8~15Hz is computed to form final feature vector.



[before CSP filtering]



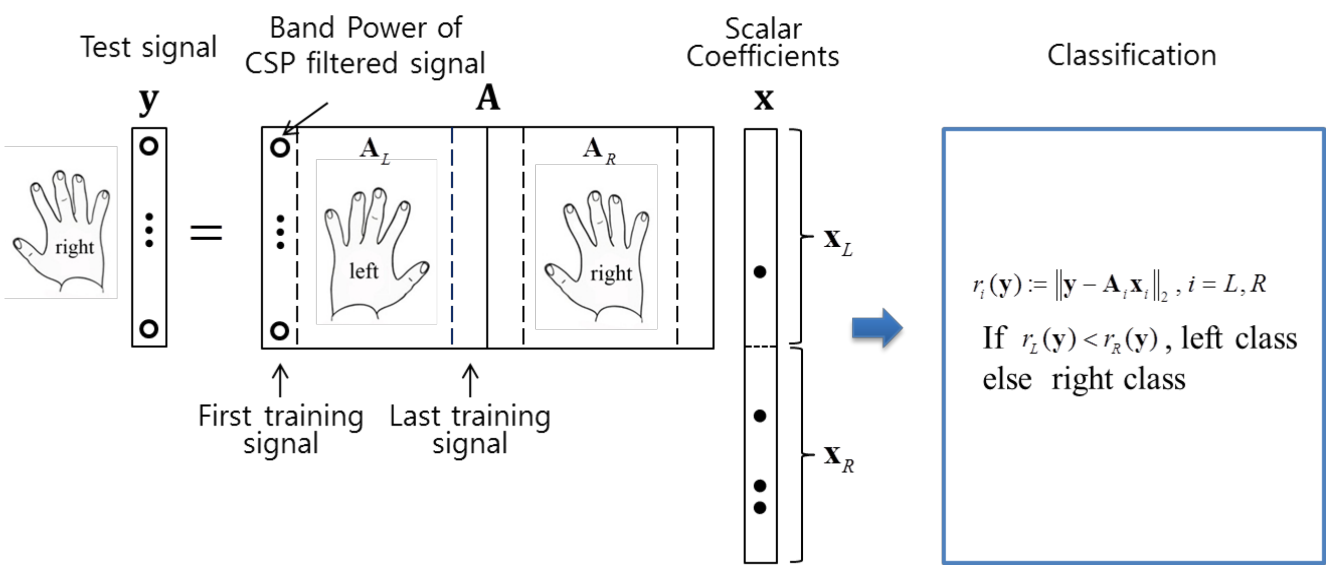
[after CSP filtering]

Sparse Representation based Classification

- The SRC method can be categorized as sparsification step and identification step.
- Sparsification step is formulated as **y = Ax**.
- Where, **y** and **A** indicate a test feature vector and a collection of training feature vectors (**A** is dictionary), **x** is an unknown coefficient vector.
- In the sparsification step, **x** can be recovered by solving following optimization problem via L1 norm minimization tool:

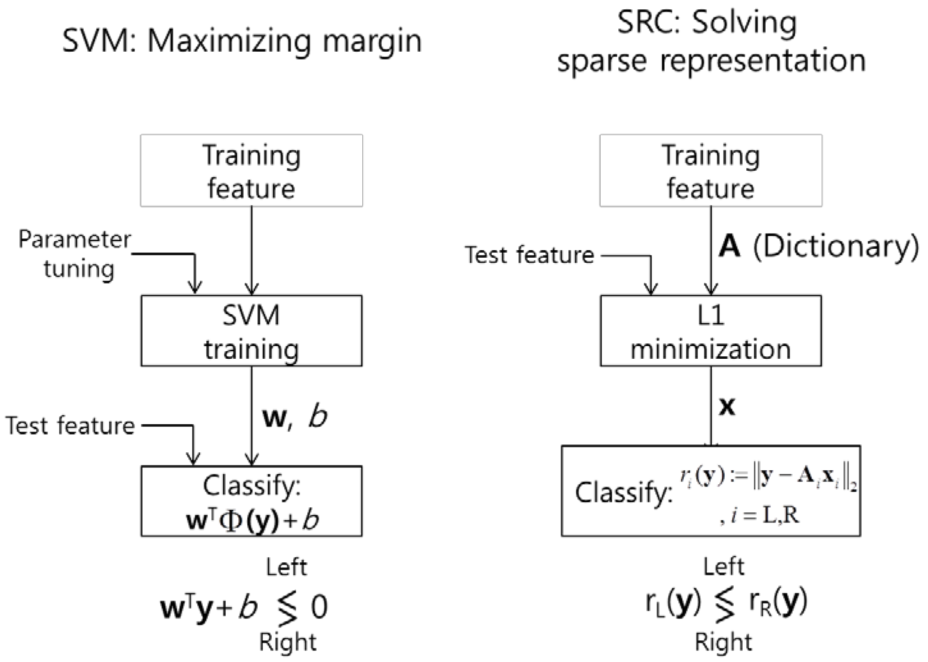
$$\min_{\mathbf{x}} \|\mathbf{x}\|_1 \text{ subject to } \mathbf{y} = \mathbf{A}\mathbf{x}$$

- Using the recovered **x**, class identification is performed as follows: $\text{class}(\mathbf{y}) = \min_i r_i(\mathbf{y})$



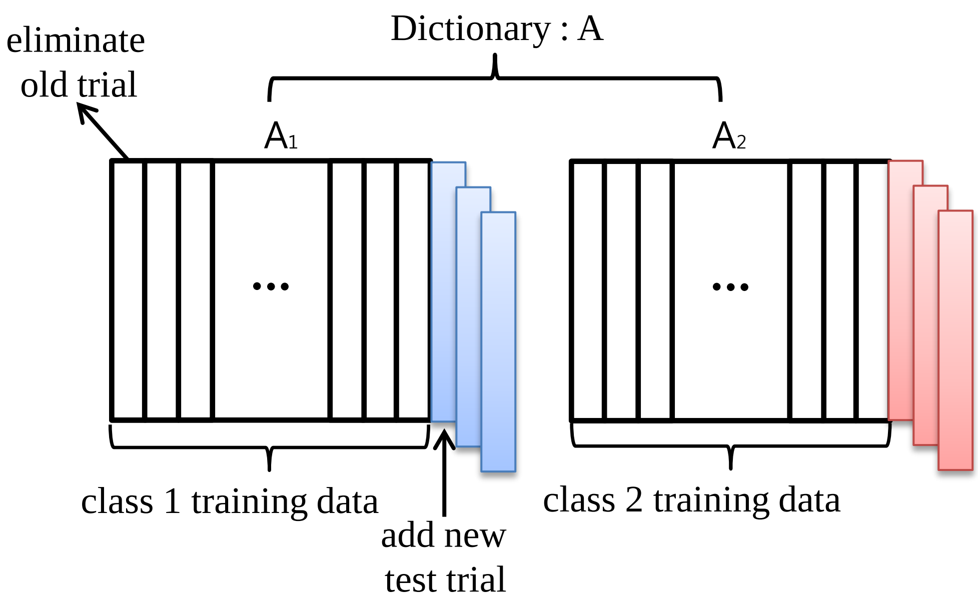
Comparison of classification mechanism

- In SVM (or LDA), a fixed decision boundary was obtained using all training signals. Then, for each test signal, the fixed decision rule was used for signal classification.
- However, in SRC, training(or parameter decision) of a classifier is not needed.
- Dictionary is simply formed by collecting the training features. Then, using the dictionary sparsification step is performed for each test data adaptively.
- Due to this unique classification mechanism, a simple intuitive method for adaptive SRC is dictionary update.



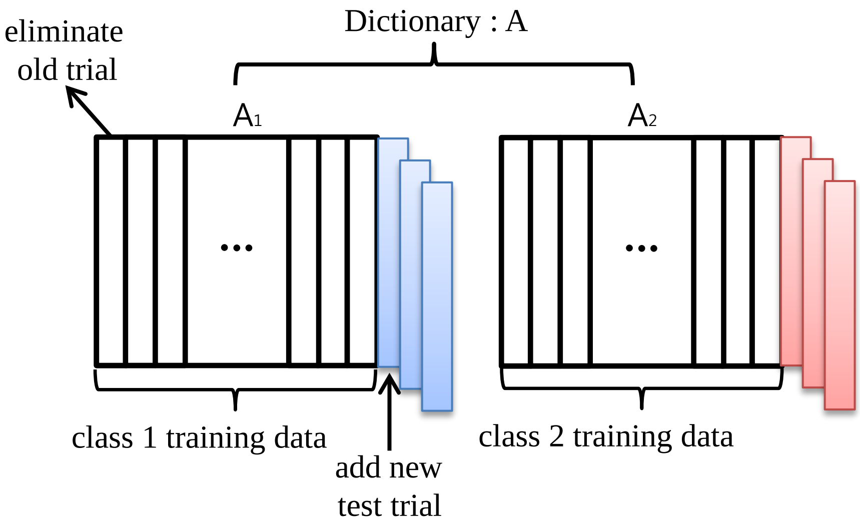
Dictionary update rules (1)

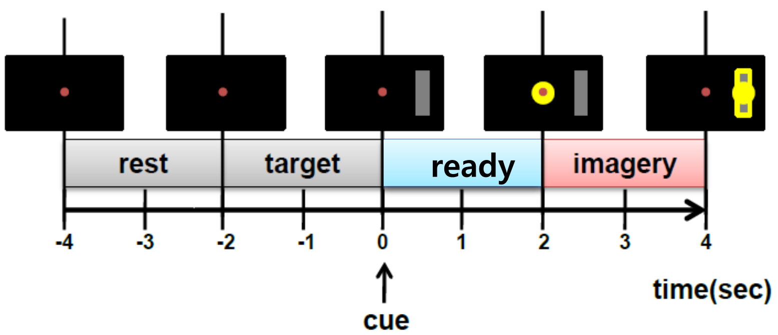
- For each test trial in the online testing phase, a feature vector of a new test trial **y** can be easily updated as a new column of the dictionary.
- At the same time the oldest training trial, i.e., the first training trial of the class-dictionary is eliminated.
- We consider two types of dictionary update rule, supervised and unsupervised update.



Dictionary update rules (2)

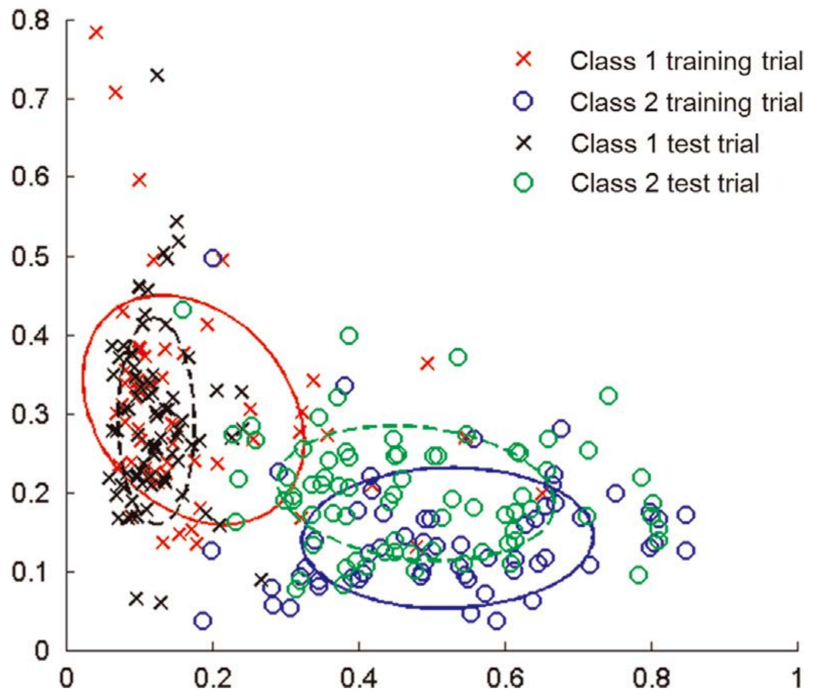
- In the supervised update rule, the target class label of test trials is used for updating the online test trials.
- In the unsupervised update rule, class label information of the test trial is not used. Thus, each test trial is updated into the corresponding class-dictionary based on the estimated result of the current classifier.





Results (1)

- To see the distribution change from training to test sessions, below figure shows scatter plots of training and test features of dataset 5 in two dimensional feature space.
- Each class training and test data element is fitted by a Gaussian distribution.
- When the distribution of the test data is changed from that of the training data, the previously designed dictionary based on the training data is not optimal for the classification of new test data.



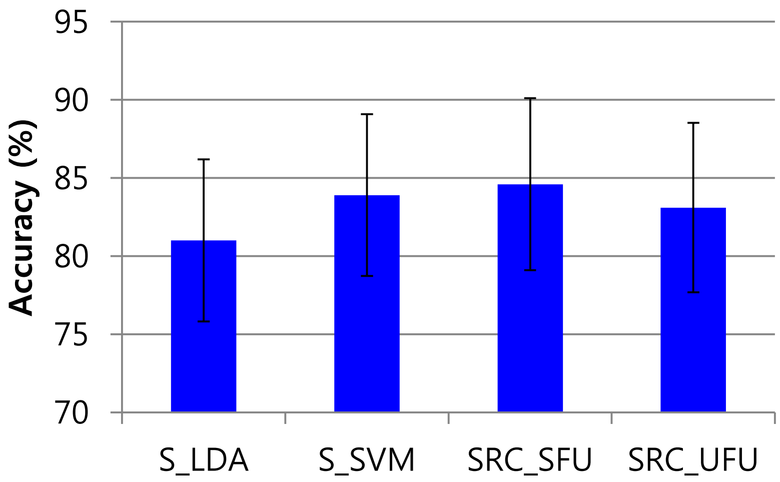
Results (2)

- We compare classification accuracy (%) of proposed methods with that of conventional SRC method.
- Total twelve session online experimental datasets from ten subjects are evaluated.
- Proposed dictionary update methods show improved mean classification accuracy than the conventional SRC method.
- Supervised SRC method shows better mean classification accuracy than the unsupervised SRC method. However, difference is very small.

Dataset	Classification methods		
	SRC	Supervised_SRC	Unsupervised_SRC
1	66	66	66
2	86	**88**	82.7
3	88.7	89.3	**90.7**
4	96.4	**97.1**	96.4
5	83.3	**96.0**	94.7
6	82.7	**84.0**	80.7
7	77.3	78.7	**79.3**
8	73.3	**89.3**	84.7
9	70.0	**73.3**	70.0
10	62.0	67.3	**68.0**
11	84.0	**88.7**	88.0
12	96.7	**97.3**	96.7
Mean	80.5	**84.6**	83.1
Std.	11.13	10.99	10.84

Results (3)

- Figure shows a comparison result of the proposed methods with conventional adaptive LDA and SVM methods.
- For the adaptive LDA and SVM methods, first, linear decision hyper-plane is determined by training data. Then in the testing session, the decision hyper-plane is re-trained for new test sample.
- We only consider supervised adaptation for the LDA and SVM methods.
- From the result, proposed adaptive SRC methods show competitive classification accuracy than the other adaptive LDA and SVM methods.
- Even though the mean classification accuracy of the unsupervised adaptive SRC method is a little bit lower than the adaptive SVM method, dictionary update is very simple process and re-training of classifier is not needed.



Conclusions

- Due to the inherent non-stationarity of EEG signals, performance degradation is an inevitable phenomenon in EEG based BCI systems.
- In particular, designed classifier by the training data does not guarantee satisfactory classification accuracy for new test data in the online feedback stage.
- We propose supervised and unsupervised dictionary update based adaptive SRC methods.
- Proposed adaptive SRC schemes show improved classification results compared to the conventional SRC and other adaptive LDA and SVM methods.
- With the unique classification mechanism of the SRC the test data are easily updated and utilized for the classification of other new test data without requiring any additional computation.

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Thank you