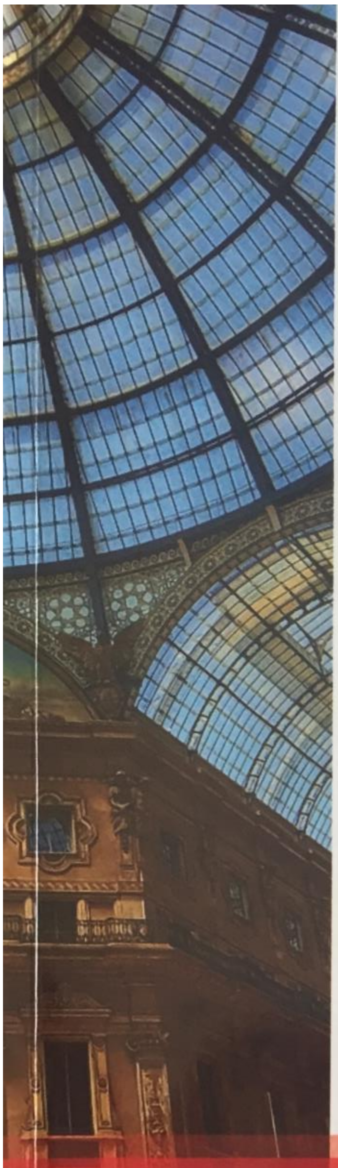

EMBC 2015 MILANO

August 25-29th 2015
Milano, Italy

Program Book

37th Annual International Conference of the
IEEE Engineering in Medicine and Biology Society
Biomedical Engineering : a Bridge to improve the Quality of Health Care and the Quality of Life

10:00-11:30 SaBPoT1.9

Noise-Robust Auditory Evoked Potential Extraction Algorithm

Ku, Yunseo *Seul National Univ., Samsung Advanced Institute of Technolo*; Byun, Wooseok *Chungnam National Univ.*; Kim, Ji-Hoon *Chungnam National Univ.*; Kim, Hee Chan* *Seoul National Univ.*

10:00-11:30 SaBPoT1.10

Feature Extraction in Accelerometer-Based Mechanomyography during Pediatric Gait

Plewa, Katherine* *Univ. of Toronto*; Chau, Tom *Univ. of Toronto*

10:00-11:30 SaBPoT1.11

Evaluation of Sparse Representation based Classification Method for Online Brain-Computer Interface Systems

Shin, Younghak *Gwangju Institute of Science and Technology*; Lee, Seungchan *Gwangju Institute of Science and Technology*; Lee, Heung-No* *Gwangju Institute of Science and Technology (GIST)*

10:00-11:30 SaBPoT1.12

Control of the One Dimensional Map Dynamics of the Cardiac Action Potential Duration

Kesmia, Mounira *Univ. de Constantine 1*; Boughaba, Soraya *Univ. de Constantine 1*; Jacquir, Sabir* *Laboratoire LE2I UMR CNRS 6306, Univ. de Bourgogne*

10:00-11:30 SaBPoT1.13

Assessment of Cardiorespiratory Interactions in West Syndrome using Phase Rectified Signal Averaging

Varon, Carolina* *Katholieke Univ. Leuven*; Jansen, Katrien *Dept. of Pediatrics, Univ. Hospital Gasthuisberg, Leuve*; Lagae, Lieven *Univ. Hospital of Leuven*; Van Huffel, Sabine *Katholieke Univ. Leuven*

10:00-11:30 SaBPoT1.14

Online EEG Artifact Rejection based on Automatic Dimensionality Reduction

Freitas, Lorena* *NeuroTechnology Group, Technische Univ. Berlin*; Blankertz, Benjamin *Technische Univ. Berlin*; Höhne, Johannes *Berlin Institute of Technology*

10:00-11:30 SaBPoT1.15

Interictal Networks in Temporal Lobe Epilepsy Revealed by Joint ICA

Hunyadi, Borbala* *KU Leuven*; Van Huffel, Sabine *Katholieke Univ. Leuven*

10:00-11:30 SaBPoT1.16

Detection of Change in Time-Course of Cortical Connectivity during Short-Term Memory Test

Kikuchi, Ryo* *Waseda Univ.*; Ono, Yumie *Meiji Univ.*; Yokosawa, Koichi *Hokkaido Univ.*; Ishiyama, Atsushi *Waseda Univ.*

10:00-11:30 SaBPoT1.17

Estimation of Knee Extensor Strength using Wearable Sensors

Sato, Yoshikuni* *Panasonic Corporation*; Nakada, Toru *Panasonic Corporation*; Kozuka, Kazuki *Panasonic Corporation*; Kiyono, Masaki *Panasonic Corporation*; Nonoyama, Tadayoshi *Univ. of Fukui Hospital*; Kubota, Masafumi *Univ. of Fukui Hospital*; Koie, Yusuke *Univ. of Fukui Hospital*; Yasutake, Masaki *Univ. of Fukui Hospital*; Yamamura, Osamu *Second Dept. of Internal Medicine Univ. of Fukui*

10:00-11:30 SaBPoT1.18

Influence of Soft Tissue Artifacts of Mid-Thigh Skin Marker during Treadmill Running in Different Speeds

Zeitoune, Gabriel *Federal Univ. of Rio de Janeiro*; Leporace, Gustavo* *Univ. Federal do Rio de Janeiro*; Metsavaht, Leonardo *Instituto Brasil de Tecnologias da Saúde*; Batista, Luiz Alberto *Univ. Estadual do Rio de Janeiro*; Nadal, Jurandir *Federal Univ. of Rio de Janeiro*

10:00-11:30 SaBPoT1.20

Assessment of Information Transfer between EEG and Near-Infrared Spectroscopy by Means of Transfer Entropy

Youssef Ali Amer, Ahmed* *KU Leuven*; Caicedo Dorado, Alexander *Katholieke Univ. Leuven*; Thewissen, Liesbeth *UZ Leuven*; Smits, Anne *UZ Leuven*; Elbarbary, Khairy *Suez Canal Univ.*; Allegaert, Karel *KU Leuven*; Naulaers, Gunnar *Univ. Hospitals Leuven*; Van Huffel, Sabine *Katholieke Univ. Leuven*

Evaluation of Sparse Representation based Classification method for Online Brain-Computer Interface Systems

Younghak Shin, Seungchan Lee and Heung-No Lee*

***Abstract*— Due to the inherent non-stationarity of electroencephalogram (EEG) signals, online brain-computer interface (BCI) classification is difficult task. In this work, we first evaluate sparse representation based classification (SRC) method for online motor imagery based BCI experimental datasets.**

I. Introduction

EEG based BCI systems are very helpful communication means to people who have severe motor disabilities. Due to the inherent non-stationary characteristics of EEG, signal features vary from the training to test sessions in the BCI experiment. This is one of the major obstacles in EEG signal classification. Therefore, classifier should be powerful for the online BCI scenario.

The SRC framework has shown robust classification performance in the EEG based BCI applications [1]. However, in [1], motor imagery signals collected in training session are only classified. In this study, we evaluate classification accuracy of the SRC for the online motor imagery based BCI datasets in which non-stationarity occurs from training to testing sessions.

II. Methods

The SRC scheme can be summarized in the following two steps. The first step is sparse coding step. In this step, each test trial $\mathbf{y}$ is sparsely represented using dictionary $\mathbf{A}$ via following L1 norm minimization:

$$\min_{\mathbf{x}} \|\mathbf{x}\|_1 \text{ subject to } \mathbf{y} = \mathbf{A}\mathbf{x} \qquad (1)$$

where $\mathbf{x}$ is a scalar coefficient vector and $\mathbf{A} = [\mathbf{A}_1 : \mathbf{A}_2] \in \mathbb{R}^{m \times n}$ is the over complete dictionary which consists of the training trials of class 1 and 2 as column vectors. The second step is to identify the test class via minimum residual. This step is the identification step:

$$\text{class}(\mathbf{y}) = \min_i r_i(\mathbf{y}) \qquad (2)$$

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=1 and 2. The detailed SRC algorithm for EEG classification can be found in [1].

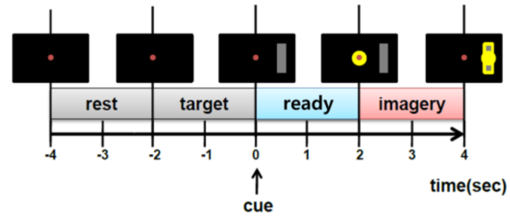

Figure 1. Procedure of online motor imagery experiment

In this study, we evaluate classification accuracy of the SRC using 12 online motor imagery experimental datasets. In the experiment, the training session and online test session were independently performed. Right (R) and Left (L) hand motor imagery were performed for each dataset. The sampling rate of these datasets was 512, and the number of EEG channels was 64. We collected 60 training trials and 75 online test trials for each class. In the training session, after cue onset, the subject was instructed to perform the motor imagery task and no feedback was provided. However, in the online testing session, the online feedback was provided in each trial as shown in Fig. 1. We use a common spatial pattern (CSP) filtering as a feature extraction method.

III. Results

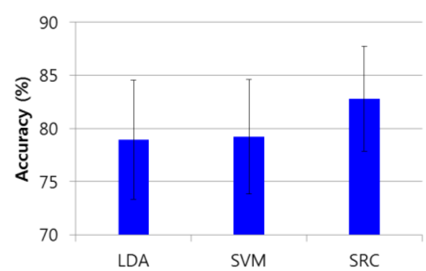

Figure 2. Average classification accuracy of LDA, SVM and SRC method

Fig. 2 shows the average classification accuracy (%) over 12 online datasets. We compare classification accuracy of the SRC with conventional linear discriminant analysis (LDA) and support vector machine (SVM) methods which are most widely used classifier in BCI field. From the results, the SRC shows superior classification accuracy for the online datasets.

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References

[1] Younghak, S., Seungchan, L., Junho, L., Heung-No, L., 2012. Sparse representation-based classification scheme for motor imagery-based brain-computer interface systems *J. Neural Eng.* 9, 056002.