 DOI:10.3217/978-3-85125-260-6-138

Muscular Activity Estimation From EEGs Using Principal Component Analysis for Brain Machine Interface

Y. Yoshikawa[1], C. Zhu[1], M. Yoshioka[1], K. Uemoto[1], Y. Yan[2], H. Yu[3], F. Duan[4]
[1]Maebashi Institute of Technology, Maebashi, Gunma, Japan; [2]Santa Clara University, CA, USA; [3]National University of Singapore, Singapore; [4]Nankai University, Tianjin, China

Correspondence: Chi Zhu, Maebashi Institute of Technology, Kamisadori 460-1, Maebashi, Gunma, 371-0816, Japan.
E-mail: zhu@maebashi-it.ac.jp

Abstract. In this paper, aiming to estimate the force/torque information from the brain activity to help and support the human's daily life, we estimate the human's muscular activity from EEGs by PCA (Principal Component Analysis). The concept of the proposed approach using PCA is explained, and then the proposed approach is verified by experiments. The results show that the estimation of EMG from EEG is possible and this implies a great potential to use EEGs for supporting human's activities.

Keywords: EEG, EMG, Muscular Activity Estimation, PCA, BMI

1. Introduction

Recently, a lot of BMIs (Brain-Machine Interfaces) are being developed to control external devices and robots. For example, an "EEG keyboard" is developed to input characters by gazing at the character shown on a display [Yamada, 1996]; electrical powered wheelchairs are controlled moving forward, turning left or right by motor imagery [Millán et al., 2004; Vanacker et al., 2007]. Such BMIs select the desired modes from the several predetermined patterns of the motion intention. On the other hand, in many situations to support human's daily life, the force/torque information in the motion is necessary as well as the motion intention. Recently, a study on muscle activity reconstruction is reported [Yoshimura et al., 2011] by estimating the signal source, in which, the signal source at the brain cortex from EEG is estimated and its spatial resolution is compensated with fMRI.

To further explore the potential applications of BMI, we consider whether it is possible to estimate the muscle activity directly from the EEG in motion. In this paper we propose an approach to achieve this purpose when a subject flexes his arm while holding a load. The experimental results show that the estimation of EMG from EEG is possible and this implies great potential to use EEG for supporting human's activities.

2. Material and Methods

2.1. Relationship between EEG and EMG

There are a lot of literatures on the relationship between EEG and EMG. The coherence in beta wave band between EEG and EMG during isometric motion is reported in [Halliday et al., 1998]. The fact that gradual potential fluctuations occur in EEG immediately before a human motion is revealed in [Kornhuber and Deecke, 1965]. From these, we believe that human motion, or saying, muscular activity, can be estimated from brain activity by exploring the relationship between EEG and EMG.

2.2. Acquisition and processing of EEG and EMG signals

In measurements, the subject (a healthy young man) is sitting in a chair and his 4 CH EEG signals over the sensorimotor area (C_4-A_2, F_4-A_2,C_3-A_1, F_3-A_1) and his 1 CH EMG signal of biceps brachii of his left arm are measured and recorded at the same time. In the measurement process, the subject closes his eyes in order to prevent noise caused by blink. Firstly, the subject holds a 3 kg dumbbell vertically downward. Then, the subject flexes his left arm (elbow joint) at arbitrary time moment to horizontal position in a few second while holding the dumbbell. The same measurement is performed 26 times.

The electrodes embedded in a head cap are positioned according to International 10–20 method. C_z is right at the top of his scalp and used as ground, and the right wrist is used as body earth. The sampling frequency is 1kHz. The EEG signals are amplified 200,000 times by an amplifier (UBIO-II, Unique Medical Co.Ltd., Tokyo, Japan) and a built-in filter with 1–100 Hz bandwidth. While the EMG signals are amplified 10,000 times by another amplifier (DELSYS

 DOI:10.3217/978-3-85125-260-6-138

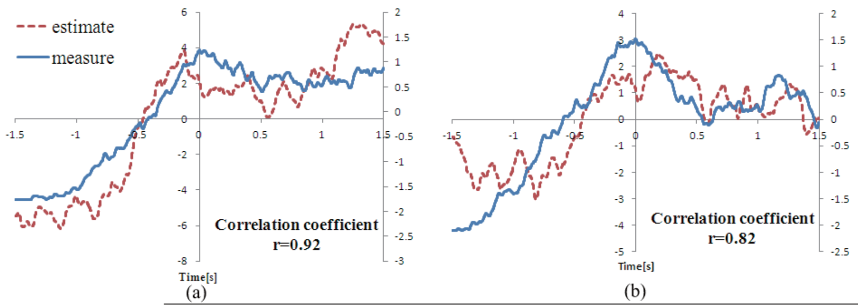

Figure 1: *EMG estimation results from EEGs.*

Inc., Boston, MA, USA), and a built-in filter with 20–450 Hz bandwidth. These signals are acquired through 12-bit A/D converters in a multi-functional interface board, and further processed with our proposed approach in computer. The measured signals are processed with moving average to remove the power supply noise of 50 Hz. Then the EMG is taken its absolute value. All of EEGs and EMG are further passed to a low-pass filter of 1 Hz to get smoothed signals. In this study, the maximum value of EMG is used as onset and the data of all EEGs and EMG signals between 1.5 s before and after the onset are extracted to be used as signal data. Further, these signal data are normalized and used as input data for estimation.

2.3. Proposed approach using PCA

Our proposed approach to estimate EMG from EEG is divided into two steps, Step 1 and Step 2. In Step 1, the eigenvectors l_i and principal components z are calculated with the above measured EEG and EMG signals by principal component analysis (PCA). Then these obtained principal components and eigenvectors are averaged as $\bar{x}$ and $\bar{l}$, and further used in Step 2. In Step 2, EMG is estimated from EEGs by the following equation,

$$\hat{y} = \frac{\bar{z} - (l_1 x_1 + l_2 x_2 + \cdots + l_M x_M)}{l_{EMG}} \tag{1}$$

where, x_i ($i = 1, 2, \ldots, M$) (here $M = 4$) are the measured EEGs, $\hat{y}$ is the estimated EMG, $\bar{z}$ is the average of principal component, and $\bar{l}_i$ is the average of eigenvector. In this study, $\bar{z}$ and $\bar{l}_i$ are considered as constants.

3. Results

Here, 10 sets of the measured and preprocessed EEGs and EMG signals are used to calculate the eigenvectors and principal components. Then the remained 16 sets of EEG signals are used for EMG estimation. The estimated EMGs are compared with the actually measured EMGs and the results are evaluated with correlation coefficient. Two results are shown in Fig. 1, in which, the solid curve represents the actually measured EMG and the dashed curve is the estimated EMG. The center vertical axis is the estimated value and the right vertical axis is the measured value. Fig. 1(a) shows the best result, in which the correlation coefficient is 0.92, while Fig. 1(b) shows the median result, in which the correlation coefficient is 0.82. This means that direct EMG estimation from EEGs is possible, and this implies a great potential to use EEG for supporting human's activities.

References

Halliday, D., Conway, B., Farmer, S., and Rosenberg, J. (1998). Using electroencephalography to study functional coupling between cortical activity and electromyograms during voluntary contractions in humans. *Neurosci Lett*, 241:5–8.

Kornhuber, H. and Deecke, L. (1965). Hirnpotentialänderungen bei Willkürbewegungen und passiven Bewegungen des Menschen: Bereitschaftspotential und reafferente Potentiale. *Pfluger's Archiv fur die gesamte Physiologie des Menschen und der Tiere*, 284:1–17.

Millán, J. d. R., Renkens, F., Mourino, J., and Gerstner, W. (2004). Noninvasive brain-actuated control of a mobile robot by human EEG. *IEEE Trans Biomed Eng*, 51(06):1026–1033.

Vanacker, G., Millán, J., and Lew, E. (2007). Context-Based Filtering for Assisted Brain-Actuated Wheelchair Driving. *Comput Intell Neurosci*, 2007:1–12.

Yamada, S. (1996). Improvement and Evaluation of an EEG Keyboard Input Speed. *Trans Inst Electron, Information Commun Eng*, J79-A(02):329–336.

Yoshimura, N., Sayo, D., Hanakawa, T., Sato, M., and Koike, Y. (2011). Muscle activities reconstruction using electroencephalography cortical currents. *IEICE technical report*, 111(06):35–40.