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▶ **To cite this version:**

Joan Fruitet, Maureen Clerc, Théodore Papadopoulo. Preliminary study for an offline hybrid BCI using sensorimotor rhythms and beta rebound. International Journal of bioelectromagnetism, International Society for Bioelectromagnetism, 2011, 13 (2), pp.70-71. <hal-00727086>

**HAL Id: hal-00727086**

**https://hal.inria.fr/hal-00727086**

Submitted on 1 Sep 2012

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International Journal of Bioelectromagnetism
Vol. 13, No. 2, pp. 70 - 71, 2011 www.ijbem.org

# Preliminary study for an offline hybrid BCI using sensorimotor rhythms and beta rebound.

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***Abstract.*** *Our goal is to build a training free BCI based on beta rebound detection and discrimination during the first stage of use, while the learning of the conventional sensorimotor rhythms is done. We show in this preliminary study that it is possible to use the beta rebound to discriminate, real and imagined, right versus left hand movement with ether no or very little training.*

*Keywords: Brain computer interface, beta rebound, sensorimotor rhythms, classification, EEG*

## 1. Introduction

Scalp recorded electroencephalography activity (EEG) can be used for non-muscular communication and control systems, commonly called brain-computer interfaces (BCI). Some BCI systems [McFarland, 97] rely on the user's ability to control sensorimotor rhythms in the mu (813Hz) and/or beta (16-24Hz) frequency domain recorded over the sensorimotor cortex. These rhythms are naturally modulated during motor action or imagination. Unfortunately, to achieve a significant control level, users have to go through a series of training sessions.

In addition to the modulation of sensorimotor rhythms during the movement, a large increase of the beta power, called beta rebound, appears approximately one second after the end of the motor action or imagination. Some BCI paradigms use it only as a switch, usually triggered by feet movement imagination [Pfurtscheller, 09]. Such beta-rebound BCI does not require any training, but is intrinsically limited by the one-second delay of the beta rebound and by it one bit output.

Our goal is to build a hybrid BCI relying beta rebound during the early use of the interface, while learning the mu and beta sensorimotor rhythm modulation in the background, resulting in a training free BCI with the same long term performances as the sensorimotor rhythms BCI.

In this preliminary study, we investigate the possibility of using beta rebound to discriminate between right and left hand movement, and compare the result with the mu and beta rhythms during early stage of training.

## 2. Material and Methods

### 2.1. The EEG experiment

The user, a right-handed 26 year old male with no disabilities, was sitting at 1,5m of a 23' LCD screen. Scalp electrodes were recorded at a sampling rate of 512Hz, on 64 channels of a TMSI amplifier, using electrode AFZ as ground electrode, and Openvibe software [Renard, 10].

The signal is band-pass filtered and a spatial Laplacian is used to increase the signal to noise ratio [McFarland, 97].

The experiment was composed of 11 blocks of 20 trials and lasted one hour. Each trial started with the appearance of a fixation cross in the center of the screen. One second later, the cross was replaced during 2 seconds by a random image out of three. The images were : a resting symbol, a right or left arrow -indicating the user had to move (or imagine moving) his right or left hand. The user had to stay motionless during 2.5 seconds after the image disappeared in order to record the beta rebound. A 1.5-second break was observed before the next trial.

**2.4 Features extraction, features selection and classification**

For the *beta rebound*, a 2-second window, starting 0.5 second after the disappearance of the cue image, is used. The signal is band-pass filtered between 16 and 24Hz, a local average of the power is computed and the maximum over the whole 2-second window is used as feature of the rebound.

For the *sensorimotor rhythms*, a 1.4-second window starting 0.6 second after the appearance of the cue image is used to extract the power at different frequency bands in the mu and beta bands.

When training data is available, the most discriminant beta rebound and sensorimotor features extracted from all the electrodes over the sensorimotor cortex are selected by a recursive algorithm using student's T-test described in [Fruitet, 10]. When no training data is available, electrodes C3 and C4 are used for beta rebound.

Classification is done with a linear SVM and performance is evaluated by cross-validation.

## 3. Results

### 3.1. Right versus Left hand movement discrimination with the beta rebound

The presence of a beta rebound (due to right or left hand movement) can be detected with a 80% accuracy. Without training data, discrimination between right and left hand movements was achieved with a 84% accuracy and up to 89% when using a few minutes as training data (Figure 1A). When the subject just imagined the hand movement the discrimination was still possible with a 75% accuracy.

### 3.2. Evolution of the performances with beta rebound and Sensorimotor rhythms

Figure 1B shows the advantage of beta rebound, namely using only a small portion of the experimental data to adjust the parameters and train a good classifier, whereas the whole session is not sufficient when using sensorimotor rhythms. When very little data is available for training (Fig. 1B 10%) it is better to use electrodes C3 and C4 with standard beta (16-24Hz) than automatically selecting the features. When most of the data is used for training, few is left for the evaluation

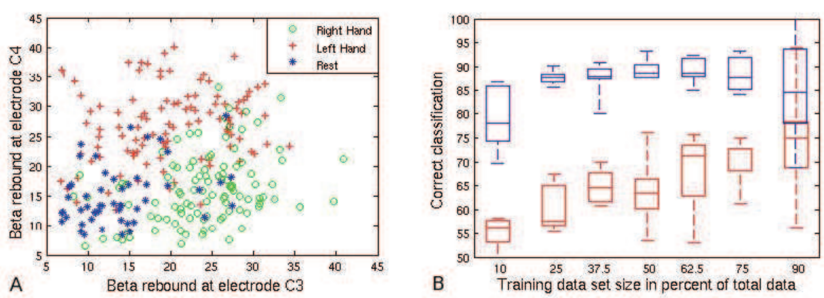


**Figure 1.** *A: Beta rebound amplitudes for right and left hand movement at electrodes C3 and C4. B: Evolution of the discrimination between right and left hand movement, with the beta rebound (blue, higher) and sensorimotor mu and beta rhythms (red, lower), in function of the percentage of data used for training in the cross-validation evaluation.*

## 4. Conclusion and Perspectives

The good performances of the beta rebound should make it possible to build training-free hybrid sensorimotors rhythms and beta rebound-based BCI. We will next investigate the evolution of the performances over multiple sessions, to see if the users are capable of learning to modulate their sensorimotor rhythms while initially using beta rebound to control this hybrid BCI.

We will try to use the beta rebound to classify online data in order to obtain unknown labels of new data to train and improve the classification of the sensorimotor rhythms algorithms.

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