International Journal of Bioelectromagnetism
Vol. 13, No. 3, pp. 131 - 132, 2011

www.ijbem.org

Evidence Accumulation in asynchronous BCI

Serafeim Perdikis, Hamidreza Bayati, Robert Leeb, José del R. Millán

Defitech Foundation Chair in Non-Invasive Brain-Machine Interface, Ecole Polytechnique Fédérale de Lausanne, Lausanne, Switzerland

Correspondence: Serafeim Perdikis, CNBI, EPFL, Station 11, CH-1015 Lausanne, Switzerland.
E-mail: serafeim.perdikis@epfl.ch, phone +41216936914

Abstract. The non-invasive Brain-Computer Interface (BCI) developed in our lab targets asynchronous operation of devices by monitoring electroencephalographic (EEG) activity and identifying oscillatory patterns that the user can voluntary modulate through the execution of motor imagery (MI) tasks. Successful self-paced interaction under this framework requires the incorporation of an evidence accumulation module to eliminate the uncertainty of single-sample classification and to drive an efficient feedback visualization. In this work, we motivate the need for this additional module, describe its role in a closed-loop MI BCI and present a comparative study of two different frameworks for evidence accumulation.

Keywords: Asynchronous BCI; Motor Imagery; Evidence Accumulation; Exponential Smoothing; Naive Bayesian Integration

1. Introduction

The exploitation of Event-Related De-synchronization/Synchronization phenomena (ERD/ERS) related to imagination of movements [Neuper, 2006] has been proved to provide the means for achieving self-paced, user-driven brain-computer interaction, where the user voluntary modulates his brain activity compromising the need for external stimuli. The asynchronous MI-based BCI developed in our lab has been reported to successfully operate various devices [Millán, 2004;Galán, 2008] by continuously monitoring sensorimotor rhythms (SMRs) and deriving the subject's intentions through the identification of sustained SMR patterns.

Several reasons motivate the existence of an evidence accumulation framework under this perspective: Single sample classification tends to be quite uncertain with regard to the strict requirements imposed by the final goal of controlling devices. Furthermore, abrupt and intense oscillations of the feedback directly driven by the classifier output can hinder user-training. Finally, continuous classification of the user's brain activity for achieving asynchronous interaction can cause random false positives during periods when the user is not executing any MI task.

The proposed evidence accumulation module addresses the above issues by smoothing the highly oscillating classifier output to provide informative yet fast feedback, increasing the confidence of single sample inference and significantly eliminating random false positives during non-control periods.

2. Material and Methods

Our Gaussian statistical classifier implements a discriminative function for classification of EEG samples, that emits at 16 Hz a discrete posterior probability distribution over the mental task classes $\mathbf{p}_t = P(\mathbf{c}_t | \mathbf{x}_t)$ given the feature vector $\mathbf{x}_t$ extracted from the EEG signal at time t [Millán, 2008]. The goal of the evidence accumulation framework is to output a new series of probability distributions $\mathbf{P}_t$, which fulfills the requirements of smoothness and robustness.

Our current approach for evidence accumulation involves a leaky integrator model that implements exponential smoothing (ES) on the classifier output, as described by Eq. 1. The probability integration achieved by this model and its low-pass filter properties assist into achieving the aforementioned goals.

$$P_t = \alpha P_{t-1} + (1-\alpha) p_t, \textit{where } \alpha \textit{ smoothing parameter} \tag{1}$$

However, the above scheme cannot alleviate biasing effects. Therefore, we introduce here a novel approach based on Naive Bayesian Integration (NBI). In this case, the classifier's bias is explicitly modeled based on an additional training dataset, fitting either Beta distributions to the classifier's output $\mathbf{p}_t$ or discrete distributions in the form of a confusion matrix, by discretizing $\mathbf{p}_t$ (Eq. 2).

$$P\left(p_t | c_t\right) \tag{2}$$

Given this model, one can formulate the evidence accumulation output $\mathbf{P}_t$ using geometric smoothing, as normalized posteriors (Eq. 3):

$$P_t = P\left(c_t \mid p_1, p_2, \dots p_t\right) \propto P_{t-1}^{c} P\left(c_t \mid p_t\right)^{1-c}, \; where\; P\left(c_t \mid p_t\right) \propto P\left(p_t \mid c_t\right), c\; smoothing\; parameter \quad (3)$$

3. Results

In an offline experiment, 3 experienced subjects have performed a pair of MI tasks for 4 runs without feedback. Each run contains 30 trials, 4 seconds long (15 per MI class). Table 1 reports the accuracy improvement achieved by means of the two evidence accumulation frameworks and Figure 1 demonstrates their smoothing effects. Another 2 subjects (one BCI naive) have performed 8 runs with real-time feedback driven by the evidence accumulation output, 4 using the ES integration and 4 using NBI. Trials end when posterior P_t^i for class *i* reaches a predefined decision threshold. All the parameters have been fixed in the beginning of the experiment. Table 1 also presents the online

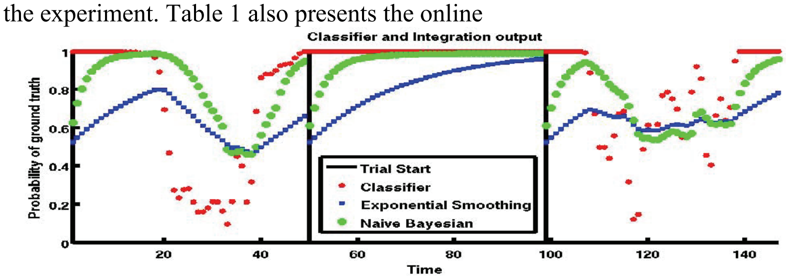

Figure 1. *Comparison of classifier to evidence accumulation output: Evidence accumulation smooths the raw output , eliminates false positives and achieves gradual and consistent convergence to the true user intentions.*

Table1. *Robustness improvement through evidence accumulation and online command delivery performances.*

Offline experiment				Online experiment				
Single-sample accuracy [%]				Trial-based accuracy [%]			Mean Delivery Time [s]	
Subject	*Classifier*	*ES*	*NBI*	*Subject*	*ES*	*NBI*	*ES*	*NBI*
1	70.68	75.85	80.27	1	100	98.3	2.54	3.24
2	92.24	94.15	100	4	88.1	86.7	4.94	2.76
3	83.88	85.85	89.66					

4. Discussion

The offline experiment (Table 1) demonstrates robustness improvement with both methods. In this aspect, NBI is superior to ES, as expected due to bias elimination. In the online experiment, both subjects achieve accurate and fast operation, similar for both methods, with slight differences depending on the subject's familiarity with each method and the chosen parametrization. Finally, Fig. 1 illustrates the smoothing effect of both methods leading to a more consistent, yet, quickly updated at 16 Hz feedback visualization and avoidance of false positives that are apparent in the classifier output. NBI provides faster convergence at the cost of more intense feedback oscillations.

Future work entails online adaptation of the model in Eq. 2 for addressing the bias introduced by the non-stationary EEG signal, as well as further evaluation with more subjects in online experiments.

Acknowledgements
This work is supported by the European ICT Programme Projects FP7-224631 and 225938.

References

Galán F, Nuttin M, Lew E, Ferrez PW, Vanacker G, Philips J, Millán JdR, A brain-actuated wheelchair: Asynchronous and non-invasive brain-computer interfaces for continuous control of robots. *Clin Neurophysiol.* 2008, 119:2159–69 Millán JdR, Renkens F, Mouriño J, Gerstner W. Brain-actuated interaction, *Artif Intell.* 2004, 159: 241–59

Millán JdR, Ferrez PW, Galán F, Lew E, Chavarriaga R. Non-invasive brain-machine interaction, *Int J Pattern Recogn.* 2008, 22:959–72 Neuper C, Wortz M, Pfurtscheller G. ERD/ERS patterns reflecting sensorimotor activation and deactivation, *Prog Brain Res.* Elsevier, Amsterdam, 2006, 159: 211–22