Multimodal Fusion of Muscle and Brain Signals for a Hybrid-BCI

Robert Leeb, Hesam Sagha, Ricardo Chavarriaga and José del. R. Millán

Abstract—Practical Brain-Computer Interfaces (BCIs) for disabled people should allow them to use all their remaining functionalities as control possibilities. Sometimes these people have residual activity of their muscles, most likely in the morning when they are not exhausted. In this work we fuse electromyographic (EMG) with electroencephalographic (EEG) activity in the framework of a so called “Hybrid-BCI” (hBCI) approach. Thereby, subjects could achieve a good control of their hBCI independently of their level of muscular fatigue. Furthermore, although EMG alone yields good performance, it is outperformed by the hybrid fusing of EEG and EMG. Two different fusion techniques are explored showing graceful performance degradation in the case of signal attenuation. Such a system allows a very reliable control and a smooth handover if the subjects get exhausted or fatigued during the day.

Index Terms—BCI, EEG, EMG, fusion, hybrid BCI.

I. INTRODUCTION

The development of practical brain-computer interfaces (BCIs [13]) for disabled people should allow them to use all their remaining functionalities as control possibilities and to use the currently best available ones. The physical and mental condition of a patient changes over the day and sometimes muscular activity would be available (most likely in the morning when they are not exhausted), whereas at other times maybe only brain signals can be voluntarily controlled. Although BCI technology has shown an impressive progress in the last years [1] its performance and interaction speed is still not on a level to be compared to non-BCI control channels. We propose here to use other signals from the patients in parallel to the BCI for the control of assistive technologies (AT), if such signals are available. This hybrid BCI (hBCI) would combine different signals including at least one BCI channel [8]. Thus, it could be a combination of two BCI channels but, more importantly, also a combination with other biosignals (such as muscular activities, etc.) or special AT input devices (e.g., joysticks, switches, etc.). The control channels can operate different parts of the assistive device or all of them could be combined to allow users to smoothly switch from one control channel to the other depending on their preference and performance. An example of the former case is a neuroprosthesis that uses residual movements for reaching objects and a BCI for grasping. In the latter case, a muscular dystrophy patient may prefer to use speech in the morning and switch to BCI in the afternoon when fatigue prevents him from speaking intelligibly. This combination of different signals may improve the quality of life of a patient.

Already a few examples of hybrid BCIs exist in literature. Some are based on multiple brain signals, like the combination of motor imagery (MI)-based BCI with error potential (ErrP) detection and correction of false mental commands [4]. Others combined steady-state visual evoked potentials (SSVEP) and MI [2], [3]. Furthermore hBCI could also combine brain and other biosignals: for instance, the combination of a standard SSVEP BCI with an on/off switch controlled by heart rate variation [12].

In this hBCI framework we want to explore the parallel usage of muscle and brain activity, depending on their availability and reliability. Here we are reporting on the combination of electromyographic (EMG) with electroencephalographic (EEG) activity on the same hand control task. The control abilities of both channels will be fused and thereby a smooth transition between the muscular to the brain channel will allow the subject to continuously perform his task even when muscular activity is too weak to do so (e.g. because of the subsequent fatigue).

II. METHODS

A. Experimental paradigm

The participants were instructed to execute left or right hand movements depending on a cue presented on the screen in front of them. The exact timing of this synchronous BCI recording was that every trial started with a fixation cross over 3 seconds until the cue was displayed as an arrow to the left or right. Afterwards the subjects had to perform repetitive movements with their left or right hand depending on this cue, i.e. clutching the hand in a fist. During this period of 5 seconds a liquid cursor feedback was simulated based on a fake feedback (64 decisions/samples per trial). Afterwards a random pause of up 2.5 seconds was given.

In total four runs (5 min each) with 15 trials for right and 15 trials left motor execution were recorded per subject, resulting in 60 trials per class. The EEG and EMG data were recorded with two g.USBamps (gtec medical engineering, Schiedelberg, Austria) using a sampling rate of 512 Hz and
a band pass filter between 0.1 to 100 Hz with activated notch filter (see Figure 1).

B. EEG processing

The brain activity was acquired via 16 EEG channels over the motor cortex (Fz, FC3, FC1, FCz, FC2, FC4, C3, C1, Cz, C2, C4, CP3, CP1, CPz, CP2, CP4) with reference on the left and ground on the right mastoid. From the Laplacian filtered EEG the power spectral density (PSD) was estimated in the band 4–48 Hz with 2 Hz resolution over the last second. The PSD features were then estimated every 62.5 ms (i.e., 16 times per second) using the Welch method with 5 overlapped (25 %) Hanning windows of 500 ms.

Machine learning techniques based on canonical variate analysis (CVA) were used to select subject-specific spatio-frequency features that maximize the separability between the different mental tasks [6]. Only features which appear to be stable across the whole training set were used to train a Gaussian classifier [5], [9]. A rejection threshold was set on the probability distribution over the mental classes emitted by the classifier, thus filtering out decisions with low confidence. Furthermore temporary evidence about the executed task was accumulated using an exponential smoothing probability integration framework [10].

C. EMG processing

Four EMG channels were bipolarly recorded over the flexor and extensor of the left and right forearm (see Figure 1). The prehensile EMG activities were rectified and averaged over 0.3 s to get the envelopes. The resulting features were subject-specific thresholded per channel, normalized and classified based on maximum distance. For estimating the EMG thresholds the ongoing activity during the non-execution time was averaged. The thresholds were finally set to twice the mean plus standard deviation (SD) per channel. Therefore only activities larger than these thresholds were further used.

D. Fusion of EEG and EMG

Generally the fusion module receives probabilities from a set of processing modules, in our case from the two classifiers for EEG and EMG. The probabilities coming out of the fusion are used to control the BCI feedback (see Figure 2). The simplest fusion would be a simple switch between the input channels (with weights at 0 and 1) which we applied in our first tests [7]. In this implementation we used a hierarchical approach with static rules. Furthermore we could restrict the fusion to the same timing (both classifiers are running at 16 Hz) and resolution of the input space (both are producing probabilities).

Two fusion techniques have been used in this work. In the first approach the fusion weights were equally balanced between the two classifier and in the second one we used the Bayesian fusion approach [11]. Bayesian fusion uses the normalized confusion matrix for each source to represent the total reliability of the corresponding source (EEG and EMG) for each class (left or right hand). The fused output is computed as follows:

$$C_{out} = \arg \max_{c_i} \left( \prod_s P(C = c_i | O_s = o_s) \right)$$

where $O_s$ is the class label from a source (classifier) $s$. Computing the probabilities is straightforward via Bayes Rule:

$$P(C = c_i | O_s = o_s) \propto P(C) P(O_s = o_s | C = c_i)$$

We suppose that the prior of all classes $P(C)$ are the same. $P(O_s = o_s | C = c_i)$ is estimated using the training data.

E. Simulation of fatigue

The feedback can be controlled either by one modality alone (EEG or EMG) or by the fused activity of both. Furthermore, to simulate fatigue of exhausted muscles, the amplitudes of the EMG channel were degraded over the run time (attenuation from 10 % up to 100 %), so that the EEG activity became more and more important in the fusion. Nevertheless the same classifier for EEG and EMG and the same fusion rules (so the same weights, no updated ones) were used, similar as this fatigue would happen in the case of a patient in real life. Reported performance measures are calculated based on the number of correctly classified samples over the trial time (0–5 second).
Fig. 3. Mean ± SD of correctly classified samples during feedback time for the six conditions with simple fusion. On the far left the pure EMG performance, on the far right the pure EEG performance is given, while in the middle the fused activity with a more and more attenuated EMG component.

F. Subjects

Six healthy subjects (mean age 27.7 ± 4.2 years) participated in the recordings. Unfortunately one subject had very strong electrode movement artifacts in the EEG and had to be removed from further analysis. Furthermore another subject was excluded, because no EEG classifier with a performance better than the chance level could be identify.

III. RESULTS

Six different conditions were compared: two for the single modalities (EEG and EMG alone) and four for the fused activities with increasing muscular fatigue. The number of correctly classified samples over the feedback time is evaluated by a 4x4 cross validation. In the first fusion approach (equally weighted sources) the number of correctly classified samples over the trial time of all subjects in the case of EEG or EMG activity alone were 77% and 83%, respectively (see Figure 3). For the fused activity an increase to 91% could be achieved. Remarkably, thanks to the fusion of EEG and EMG, increasing muscular fatigue (from 10% to 50% to 90% attenuation) led to a moderate and graceful degradation of performance: 90%, 84% and 77% accuracy, respectively. The last fused condition with remaining 10% of EMG did not achieve a better performance than the EEG alone (Remember: the classifier and fusion weights were not updated but kept constant on the values from the setup).

The Bayesian fusion achieved similar results but with smaller SD (see Figure 4). Interestingly the Bayesian fusion performance is very stable over the first 3 fatigue conditions. Especially in the 50% EMG condition a tremendous increase could be achieved compared to the other fusion technique (from 83.9% to 88.8%). In contrast, in the last condition the Bayesian approach failed and had a result of 72.0%, which is worse then the EEG alone condition. This is because the confusion matrices of Bayesian fusion have been trained using a non-fatigued subject, therefore it still relies on the same sources, although we were imposing strong fatigue into data, causing the performance decrease in the condition with only 10% EMG contribution.

The improvement in both fusion cases of 8% from single EMG condition to the fused activity was not expected at all. Normally we would consider the muscular channel as the “perfect” control channel. A glance on the raw signals and the extracted classifier outputs is given in Figure 5. The EEG classifier had a smooth but stable improvement over the trial time compared to the fast and strong but fluctuating response of the EMG classifier together with a large variation over time. This is one of the reasons that the fused activity achieved a better performance, especially when the number of correctly classified samples over the whole trial time is used as performance measure.

IV. DISCUSSION

This experiment demonstrates multimodal fusion of muscular and brain activity for a Hybrid BCI. Thereby, subjects could achieve a good control of their hBCI independently of their level of muscular fatigue. Furthermore, although EMG alone yielded good performance, its combination with EEG improved it. Therefore such a system allows a very reliable control and a smooth handover if the subject gets exhausted during the day, because the increasing muscular fatigue led to a moderate and graceful degradation of performance.

The Bayesian fusion approach led to a very constant behavior over a wide range of muscular fatigue, compared to the steadily decreasing performance in the case of the simple fusion. The reason is that the Bayesian approach relied very strongly on the output of the EMG classifier, which
was reliable till a fatigue of 50%. Therefore the conditions in which the quality of the input signals drop below a certain threshold are critical. Otherwise the assumption of stable input patterns while setting up the Bayesian confusion matrices are violated and the performance drops.

Therefore we should adapt the way of weighting the contribution of the single modality, which reflects the reliability of the channel, or the confidence/certainty the system has on its output. In this work we used a static approach, but dynamically updated weights or different parallel streams would represent a more natural behavior. Generally these weights can be estimated from supervision signals such as cognitive mental states (e.g., fatigue, error potentials) and physiological parameters (e.g., muscular fatigue). Another source to derive the weights is to analyze the performance of the individual channels in achieving the task (e.g., stability over time, influence of noise . . .).

V. CONCLUSIONS AND FUTURE WORKS

Multimodal fusion techniques allow the combination of brain control with other residual motor control signals and thereby achieve better and more reliable performances. It is planned to develop hierarchical probabilistic approaches, where each channel is modeled independently and exploits appropriate priors. This hierarchical approach also incorporates the possibility to use a switch and to monitor mental states and other physiological parameters, which are a source of meta-control signals for weighting the contributions of the single modalities and/or switching between them.

Another advantage and possibility of an hBCI with dynamic fusion is in the case of progressive loss of muscular activity (as in muscular dystrophy, amyotrophic lateral sclerosis and spinal muscular atrophies). Early hBCI training while the user can still exploit her/his residual motor functions will increase long-term use of assistive products by smoothing the transition between the hybrid assistive device and pure BCI when muscular activity is too weak to operate them.

VI. ACKNOWLEDGMENTS

This work is supported by the European ICT Programme Project FP7-224631, TOBI: Tools for Brain-Computer Interaction and by the European STREP project ICT-2007-225938, OPPORTUNITY: Activity and Context Recognition with Opportunistic Sensor Configurations. This paper only reflects the authors’ views and funding agencies are not liable for any use that may be made of the information contained herein.

REFERENCES


