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Towards a General Architecture for a Co-learning of Brain Computer Interfaces

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Abstract— **In this article we propose a software architecture for asynchronous BCIs based on co-learning, where both the system and the user jointly learn by providing feedback to one another. We propose the use of recent filtering techniques such as Riemann Geometry and ICA followed by multiple classifications, by both incremental supervised classifiers and minimally supervised classifiers. The classifier outputs are then combined adaptively according to the feedback using recursive neural networks.**

I. Introduction

Nowadays, Brain Computer Interfaces (BCIs) are promising but are still mostly limited [15] to the traditional supervised setting. In a supervised setting, a user needs to go through a long and rigorous training phase before the system can be used online. Increasingly, researchers are attempting to shift away from this setting and strive for the co-adaptive training of BCIs. For example, one can use neurofeedback to help the users to modulate their brain signals [8, 11].

Even with the use of neurofeedback, training phases remain long and tedious. Efforts have mostly been focused on improving the signal processing aspects of BCIs (filtering, feature selection and classification paradigms) [14], however, they do not focus on making the system more pleasant and less tiring for end-users. In general there aren't enough efforts towards providing more interactive and shorter training phases.

The recent shift towards adaptive/incremental learning-based self-paced BCIs, is a good step towards a better experience [2, 9, 21]. However, while many research groups are working on the signal processing aspects, interfaces remain rudimentary and feedback is loosely integrated (e.g. a bar showing the *level* of the "feedback" [1]). With an asynchronous system (users chose when to perform an action rather than waiting for system instructions), the quality of the classification and of the interaction is even more closely related to the precise understanding the user has of his or her performance and of what to do at any given moment. This is true when the system is being calibrated or trained and when the user is learning to use the system subsequently.

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All the work on signal processing is paramount to obtaining usable BCI systems that are robust to noise and to inter-trial variability. However, the quality of the interaction and of the feedback impact two very important aspects of usability. First, they help users to get their mind into the best possible state so as to reduce noise and variability as much as possible and thus to improve the classification accuracy. Secondly, it optimizes the learning pace of the users and speeds up the operationalization of BCI interfaces.

Feedback strategies are one way to guide the user towards a state of mind compatible with a good BCI performance, as seamlessly and transparently as possible. We are of the opinion that two directions should be explored.

On the one hand, the system must provide feedback to the users on their performance, what they are doing right and what they are doing wrong, what to imagine, how to improve and so on. On the other hand, we do not want to require a separate training phase, but instead want to incrementally train the classifier by using continuous affirmative feedback from the user to the system.

This combination of mutual learning and training between the user and the system is what is often referred to as co-learning.

In this article we aim at proposing a general architecture that integrates all the aspects involved in the co-learning process that we just described. The training of the classifiers and all aspects of the system will adapt depending on this feedback and on the outcome of the classifications.

We will first present some related research, both in terms of BCIs and of feedback strategies in general so as to give an idea of the current state of the art. Then, we will describe in more details all the aspects pertaining to the architecture and provide some insights as to what led us to make those choices. Finally, we will conclude and present perspectives for the improvement of the architecture and then give an account of our ongoing experiments towards the validation of this model.

II. Related Work

There are mainly two directions in related works, one in terms of BCIs (Section II-A) and the other in terms of feedback (as in feedback used in education) and especially formative feedback (Section II-B).

A. Brain Computer Interfaces

As introduced previously, the use of feedback is limited. However, one of the requirements for developing effective

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feedback strategies in BCIs, namely asynchronous BCIs, in an incremental reinforcement learning setting [15] with single trial classification, is of active interest to researchers [11, 13, 14].

More recently, Barachant et al. [2] have proposed a method specifically aimed towards self-paced BCIs and that makes use of Riemann Geometry. This measure offers good performance on some datasets, even compared to other state of the art filtering techniques such as Common Spatial Pattern (CSP) filters (e.g. for the IV BCI Campaign, 71% vs. 64.8% for CSP).

As for feedback strategies, research is mostly confined to a few domains [8, 10]. Vidaurre et al. [20] have had good success in using a feedback strategy based on what is used in education. They introduce a bias in the nature of the feedback so as to boost the performance of novice users. Their work is presented as a potential cure for BCI Illiteracy, which is backed by interesting results. They showed through experiments, that people, who would normally be considered as BCI illiterate, could manage to attain usable BCI performance.

B. *Some insights from education: Formative feedback*

"I'm trying to free your mind, Neo. But I can only show you the door. You're the one who must walk through it" —The Matrix (1999) [18].

There is currently a lot of research on the topic of formative feedback, as it is a core issue in traditional education. There have been, thus far, many attempts at classifying feedback strategies so as to offer ways of easily determining which is the right feedback strategy for a given pedagogical objective and for a given student demographic.

However, it remains essential for the involvement of users that they retain the possibility to provide feedback to the system of their own initiative, that is, only when they deem the feedback will be beneficial for the system. This implies that users need to understand how the system utilises the feedback for training and to know about some of the internal mechanics of the classifier.

In addition to the present work on a general architecture for co-learning, we are also actively exploring feedback strategies from education and more specifically formative feedback.

III. Architecture Overview

The idea behind the architecture (Figure 1) is to put the user in a more prominent position so as to achieve a co-learning setting, where both the system and the user learn. Co-learning, is actively related with the notions of active learning and reinforcement learning. Indeed, instead of having labelled training data, the system uses unlabelled data and subsequently queries the user to label the data online, following certain schemes that depend on the desired qualities [18] of the training labels.

Furthermore, co-learning should not be confused with co-training, where several classifiers are trained jointly for a better joint classification, even though we do exploit both co-learning and co-training aspects as will be described in the dedicated section.

Co-learning as we mean it here, corresponds to the training of the classifier by the user by providing labels and affirmative feedback (was it classified correctly?). It also corresponds to the training of users by the system, so they can learn to modulate their brain signals and use BCIs in general.

Our hypothesis is that users who are considered BCI illiterate, misunderstand how to modulate their signals in the appropriate way or simply have a slightly different modulation in their brains and thus cannot improve on their own without feedback. However, when guided they would be able to understand (even though subconsciously) how to modulate their signals properly and more importantly to devise a self-tailored strategy that works best for them.

In the architecture, in order of appearance, there are several steps in the closed classification loop. The first step is the acquisition of Electroencephalography (EEG) data and a preliminary signal processing step, where the signals are referenced and normalized in some way.

Then, in the training step, features are extracted from the filtered signals and are classified by a set of classifiers that are chosen so as to be as complementary as possible. The output of the classifiers is then combined through a classifier fusion operation (depending the feedback from the user during the operations of the system).

Subsequently, during the feedback adaptation step, the system incorporates the outcome of the classification, the outcome of the task at hand and provides an adapted form of feedback for that specific user. The feedback depends on the experience of the user, the nature of the task, the delivery timing of the feedback and other factors.

The last step of the process is when the user provides affirmative feedback to the system by indicating how the classification performed. Thus, a label is produced for the current feature vector. In turn it is used to individually train the classifiers, but also for the adaptation of the classifier fusion step.

A. *Signal Acquisition and Processing*

In the state of the art of Independent Component Analysis (ICA) for BCIs [20], it is apparent that systems based on ICA offer a very good performance and more readily enable single-trial classification and the implementation of adaptive online classifiers.

Another very promising technique results from the use of Riemann Geometry both as a spatial filter for extracting features and selecting electrodes [2]. This approach has mainly been applied in the context of single trial asynchronous BCI system for motor imagery.

B. *Classification and Classifier Fusion*

The main idea behind the multiple classifiers is to exploit the potentially complementary features in order to build a more robust classifier.

However, given that we also want to have classifiers that are fully incremental, without any explicit training phase, we cannot directly use supervised algorithms from the start, which is why we have also integrated minimally supervised classifiers.

Indeed, when a user first starts to use the system, we have no training on the supervised classifiers, which means that system would start off with a random classification performance and thus not be very useful for a while. This issue undermines the usefulness of incremental learning in the first place.

Thus, minimally supervised classifiers can have the effect of allowing a better classification at the start than we would have otherwise. In terms of such techniques, a very trivial approach is to record a reference signal of the resting phase (no action) and of action phases corresponding to each class and then to proceed on to using distance measures on the filtered signals to discriminate between the classes.

Possible measures include classical distance measures (Minkowski-based), correlation coefficients; the distance between n^{th} derivatives; distances based on differential geometry (Riemann, Kullbach-Leibner) [3] and so forth.

In terms of supervised classifiers, we are restricted to incremental learning algorithms, several of which have been proposed for BCIs. Those include: Recursive Partial Neural Networks [5]; Back propagation and Radial Basis Function Neural Networks (RBF-NN) [9]; Discriminative temporal Bayesian models such as Input Output HMMs (IOHMMs) or classifiers directly based on a modification of ICA (Generative ICA) [6]; Incremental Random Tree Forest [3].

For each classifier, the output of the algorithm is a vector the length of which is the number of classes. Each index of the vector corresponds to one class and contains the normalized likelihood value of the occurrence of that class.

Therefore a necessary condition for a classifier to be compatible with the proposed architecture is that it has the possibility of outputting a normalized likelihood distribution. An additional challenge when dealing with more than two classes (resting state and one action) is the case of binary classifiers, where an additional step to render them able to handle all the classes, would be required. This is the case for very classical algorithms, such as Linear Discriminant Analysis (LDA) or Support Vector Machine (SVM) but also our distance based minimally supervised algorithm.

Finally, for the fusion of the classifiers, we propose to use an incremental model based on RBF-NN and Evidence theory neural networks as described in [4]. Indeed, they correspond well to our incremental model and allow us to estimate adaptive weights for classifier fusion step. More specifically the input vector to the fusion neural network is the concatenation of the normalized output vectors from the individual classifiers. The output vector to the classifier fusion neural network is a vector identical to the output of the individual classifiers. The labels for the training of the fusion come from positive user feedback. A value of the one at the index corresponding to that class (zeroes elsewhere) represents a positively labelled problem instance for a given class.

C. Feedback, Training and Adaptation

The feedback from the system to the user takes various forms depending the skill of the user. We will include classical feedback techniques for BCIs, such as neurofeedback [10], as well as techniques adopted from the

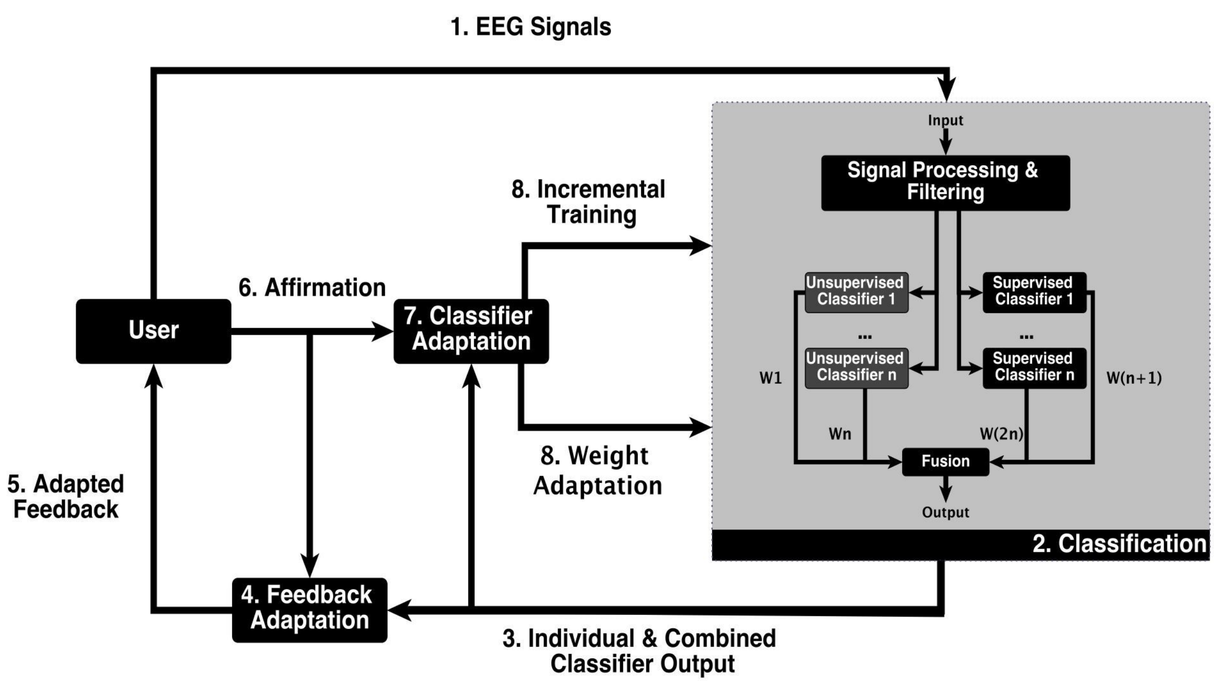

Figure 1. General overview of the proposed architecture

educational domain; especially, formative feedback in the context of computerized feedback [12].

For the training of the classifier, the user is enabled to voluntarily tell the system if the classification at a given time was successful or not, thus generating positive and negative labelled instances. However, a very important element is how the feedback is communicated to the system. While pressing a key is something we are using as a starting point, it is not suitable for a real usage. One of the directions for ongoing tests we envision is the use of facial Electromyography (EMG) electrodes on the user's brow and cheek to detect two actions (frown and smile) that would respectively correspond to negative and positive feedback. We have already performed some experiments involving EMG for feedback.

The adaptation for supervised algorithms corresponds to the incremental training of the algorithm, as feedback is fed into the system. The main issue to resolve, however, is that some classifiers may become over fitted if the training from the feedback is not constrained.

For the minimally supervised classifiers, the adaptation has to be implemented in an ad-hoc fashion for each specific method. For example, in the case of a simple distance based classifier, a positive example could be used as a new sample in the average used as a state reference to compute distances from.

IV. Conclusion

In this article we propose an architecture for asynchronous BCIs based on co-learning, where both the system and the user jointly learn by providing feedback to one another. We propose the use of recent filtering techniques, such as Riemann Geometry and ICA followed by multiple classifications with both incremental supervised classifiers as well as minimally supervised classifiers that are combined using a fusion based adaptive neural networks.

Along with our work on feedback strategies, we are currently performing the first preliminary experiments with 20 subjects towards the evaluation of the architecture with standard evaluation metrics for asynchronous BCIs. We already have a partial implementation of the architecture that includes the distance based minimally supervised classifier and a supervised neural network classifier. Furthermore, we have already attempted using EMG with two electrodes on the user's face as the feedback strategy.

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