NeuroTRIP: a framework for bridging between open source software.

Application to training a Brain Machine Interface

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Abstract— **Within the field of Brain Computer Interface, the sub-field of Neurofeedback that consists in training subjects to control specific brain rhythms is gaining momentum. Spatial filtering of brain source activities using Independent Component Analysis (ICA) may help subjects to specifically train specific brain regions. Here we propose an integrated platform built on top of two Open Source software namely BCI2000 and EEGLAB, to design and run source-based ICA Neurofeedback experiments. Our public software NeuroTRIP (Neurofeedback TRaining Ica Program) automates the sequence of procedure necessary to train a computer program to recognize brain sources and apply this training to isolate these sources in real time and provide feedback to subjects. In addition to provide an innovative technique for EEG Brain Machine Interface protocols, it will offer a flexible open source tool to conduct controlled experiments on neurotherapy methodology and results.**

Keywords-BCI; neurofeedback; OSS; ICA

I. INTRODUCTION

With the recent development of software and dedicated hardware for real time acquisition and processing of electrical brain signals such as electro-encephalogram (EEG), new perspectives in the domain of Brain Computer Interfaces (BCI) have arisen. Even within the framework of controlling electrophysiological signal attributed to cerebral sources, different applications are possible. The main BCI application is to use the electrical signal generated by the brain to control an input communication software or mechanical device. The control signal may be used for instance to control a Virtual Reality setup or video games. Another possible BCI application, Neurofeedback, aims at training subjects over several weeks to up-regulate or down-regulate the activity of specific electrical brain signal. More specifically, Neurofeeedback consists in having subjects train to modify brain waves at specific frequencies in order to suppress abnormal oscillatory activity usually linked to a psycho-pathological state such as ADHD [1-3], drug addiction [4,5], depression [6], or even neuro-pathological states such as epilepsy [7-12]. Neurofeedback has also been used to improve a specific aspect of cognition [13] such as concentration, stress management, or even musical performances [14].

Historically, the Neuroscientific community has long discredited Neurofeedback. Despite the fact it has been used extensively by therapists in the past 30 years, there have not been serious scientific studies to back up Neurofeedback-based therapeutic interventions. Moreover, most of these interventions were based on the intuition of the therapist or on observation in isolated patients or subjects. The few controlled-group studies achieved so far, suffer from the small sample size and the absence of control for patient and therapist characteristics that could influence their outcome. Although it is clear that significant, beneficial effects have constantly been reported in patients who volunteered to receive this type of treatment, additional controlled, group studies are needed in order to promote a clearer understanding of this alternative to chemical therapies.

Neurofeedback training is usually performed using one or two scalp electrodes. One of the main drawbacks of using single channel Neurofeedback is that it requires many sessions until the subject or patient starts gaining control over his EEG signal. One way to speed up learning could be to compensate the poor spatial resolution of EEG using efficient spatial filtering and source reconstruction, as this could potentially increase the functional specificity of the training. Because of volume conduction in the brain, the single-channel signal used in Neurofeedback is the sum of the projection of the activity originating from several cortical sources. Therefore, it makes it difficult to infer what brain region activity subjects are training to regulate and the neural mechanisms involved in Neurofeedback training are still largely unknown.

Using a large number of electrodes allows to isolate the different sources of EEG activity and to use the activity of these sources as feedback for the subject. Source separation may be achieved using signal processing and statistical techniques such as Independent Component Analysis (ICA) [15-18], and some studies suggest that this processing could help improve the learning process [19,20].

This paper presents a piece of software called NeuroTRIP that would allow to easily design and run experimental Neurofeedback protocols. NeuroTRIP uses different open source solutions already widely used in BCI, namely BCI2000 [21] for acquiring the data and providing feedback to the subject or patient, and EEGLAB for EEG analysis [22]. We will start by describing standard single-electrode Neurofeedback protocols. We will then introduce

ICA and explain how it can extract brain sources to allow subjects to directly control the activity of specific brain areas. We will then present the BCI2000 software, the EEGLAB software and the sequence of processing required to perform Neurofeedback on ICA components. The last part of this report describes how we implemented this stream of processing in our software, NeuroTRIP. As illustrated in Fig. 1, NeuroTRIP allows smoothly designing and monitoring a complete experimental neurofeedback paradigm and helps integrate for the first time ICA in Neurofeedback research applications.

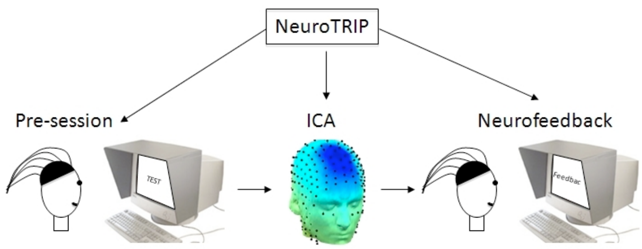

Figure 1. Overview of NeuroTRIP. ICA is run on pre-session data which is then used for Neurofeedback.

II. WHAT IS NEUROFEEDBACK

Neurofeedback is a technique used mainly in behavioral medicine and is often used in conjunction with psychotherapy. Surface electrical signals at a particular scalp location are amplified and processed in real time using dedicated hardware and software. Traditionally, Neurofeedback is done in clinical settings using only a few electrodes, such as CZ, C3 or C4 in the 10-20 system [13,23-26]. These electrodes are most often referenced to the nose or on one of the earlobes. Specific features of the EEG signal are extracted and converted to visual and/or auditory feedback. The visual or auditory feedback is performed in real time, so it reflects the brain activity with a minimum constant time delay, a delay which is usually kept under 1 second. Fig. 2 illustrates the structure and the consecutive steps of a neurofeedback loop.

A specific feedback element, for instance the speed of a virtual spaceship shown on screen, may represent the brain waves the subject is trying to control. Often, subjects have to reach specific thresholds in order to unlock a reward phase. In the spaceship example, once subjects reach a specific threshold, the spaceship will start moving at supersonic speed. The Neurofeedback process consists in having subjects or patients acquire an enhanced awareness of mental states they must enter to gain a volitional control over the visual or auditory feedback. One hypothesis is that Neurofeedback training can lead to brain plasticity and to long-lasting modification of the global pattern of brain electrical activity. This newly learned activity counteracts, suppresses, or replaces the pre-existent abnormal pathological electrophysiological rhythms.

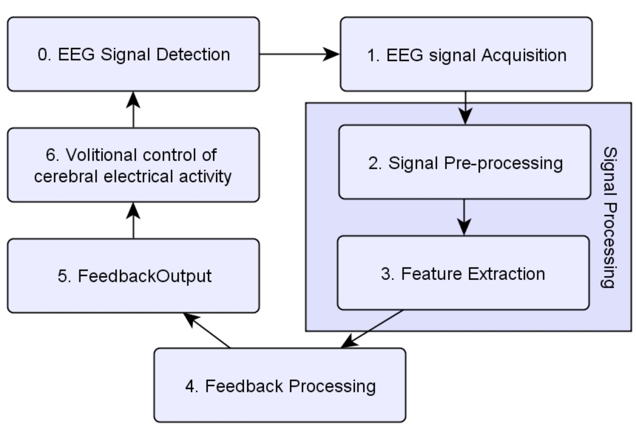

Figure 2. Classical neurofeedback loop.

Typical Neurofeedback trainings consists at least 20 30-minute sessions and up to 40 sessions depending on the subject's responsiveness to the treatment or experiment. Sessions are performed every two or three days. Original research on Neurofeedback started with experiments involving alpha rhythm training (8-13 Hz frequency band), a well-known cortical rhythm dominating the occipital region of the brain [23,24]. Kamiya [23] found that if participants were made aware of alpha frequency bursts recorded from electrodes located in occipital scalp regions, they eventually could gain a definite level of awareness of this rhythm even without feedback. Subjects also seemed to be able to increase voluntarily the incidence of their alpha rhythm and reported subjective experiences of being in a relaxed and peaceful state. For this reason and since alpha rhythms are idling brain rhythms, Neurofeedback protocols aiming at up-regulating alpha rhythms started to be commonly used as relaxation protocols. Since then, several Neurofeedback protocols have been developed for the treatment of different pathologies such as attention deficit disorder [1-3,25,27,28], affective disorder [29], epilepsy [7-12], chronic pain [30], and substance addictions [4,5,31]. A typical Neurofeedback training protocol consist for instance in training ADHD patients to up-regulate their Sensori Motor Rhythm (SMR) (frequency band of 12 to 20 Hz with a spectral peak in the area of 12 to 14Hz) and down regulate theta (4-8 Hz) power [25,32-34]. The visual feedback usually varies as a function of ratio of these two power estimates.

Unfortunately, there is currently insufficient evidence to support conclusively the effectiveness of Neurofeedback treatments, and this is due mainly to the lack of large-scale randomized controlled clinical studies. Studies to date have provided evidence for its potential for improving attentional abilities in healthy subjects and clinical groups [13,14,35,36], but much research remains to be done. A practical concern in Neurofeedback is how to optimize the nature and duration of the training. Details of session length, schedule length, reward contingencies, electrode placements will require controlled investigation.

Another reason for the lack of Neurofeedback research is the absence of proper research tools. Here NeuroTRIP provides a strong basis for performing Neurofeedback research using modern neuroimaging tools.

III. INDEPENDENT COMPONENT ANALYSIS

We are interested in testing the impact of an increased functional specificity of the signals used as a base for Neurofeedback training, and this could be achieved by using a specific component or set of components activity.

When recording brain electrical signals, because of volume conduction (the diffusion model of electrical potentials generated in the brain), surface electrodes do not record the sources situated directly under them. Instead they may record distant sources. When using the signal recorded at a single electrode sites, as this is done during Neurofeedback training, we can reasonably assume that this signal will be noisy and will not reflect the activity of a single underlying functional brain source but instead be contaminated by distant brain source activities as well as artifacts.

A promising approach in EEG data analysis is based on blind source separation techniques such as independent component analysis. ICA has been mostly used so far to remove artifacts, but it may also help isolate independent activities from compact patches of cortex [19,20].

It is generally assumed that brain electrical activity can be measured at the scalp level because of the synchronous activity of pyramidal cells in the cortex. The EEG signal results from the simultaneous fluctuation of post-synaptic potentials of pyramidal cells assemblies. Because of the ionic charge difference between upper and lower part of the cell, these neurons act as electromagnetic dipoles. These cells are organized in the same direction along macro columns, and coordinated activity in these columns result in an electrical field that may be modeled using a single equivalent dipole. The activity of these equivalent dipoles, if strong enough, may be detected at the scalp level. Since the local cortical connectivity is denser and stronger than the long-range connectivity, the activity of these cortical patches may be considered to be relatively independent. This is one reason why ICA may be able to recover and separate the activity from different patches of cortex.

In addition to background brain noise generated by the activity of numerous groups of pyramidal cells oriented in different directions, another problem with EEG is that several electrical artifactual sources are embedded in the recorded signal. These artifacts can have either a physiological origin (eye movements, eye blinks, face muscles contractions, etc...) or non-physiological (interferences due to other electrical devices, power lines, pour electrodes contact, etc...). All these artifactual electrical sources might contaminate the recorded signal and may interfere with Neurofeedback training. ICA helps separate brain signal from artifacts since the electrical activity of environmental artifacts is mostly independent of the brain activity.

Because of Maxwell's equations of volume conductions, we obtain at each electrode a linear combination of all the sources (cognitive and articfactual). ICA is a linear separation method to attempt to recover the original source signals by multiplying the multi-electrode recorded data vector at each timepoint by an unmixing matrix. It has first been implemented using neural network models [18], and several algorithms have been developed using different approaches such as, for instance, Information Maximization [37], Natural Gradient Learning [38], Joint Approximate Diagonalization of Eigenmatrices [39]. The "runica" function of EGGLAB [22], an open source matlab toolbox for Electrophysiological research, provides a way to calculate unmixing matrix from EEG data recordings. This matrix is used as a spatial filter in order to train a specific component of the cerebral activity. These techniques have been applied with success to EEG data [17] and could potentially be used to separate EEG sources and use their activity for Neurofeedback training. Using ICA in conjunction with Neurofeedback will help select functionally relevant brain sources and filter out the activity of non-relevant sources as well as electrical artifacts. We believe that, by increasing specificity, it could speed up the Neurofeedback training process.

IV. NEUROTRIP

BCI2000 is a general-purpose publicly available software for brain-computer interface research. It may be used for data acquisition, stimulus presentation, and brain monitoring applications. BCI2000 thus represents a flexible framework for designing BCI experiments. This software has already been used in several published studies on BCI [40-42] and is currently been used by about 300 laboratories worldwide. BCI2000 has however been less used for neurofeedback applications although it does embed the main required features. Fig. 3 and 4 show an example of BCI2000 Neurofeedback module we developed. The experimenter screen is shown in Fig. 3 and the subject screen is shown in Fig. 4.

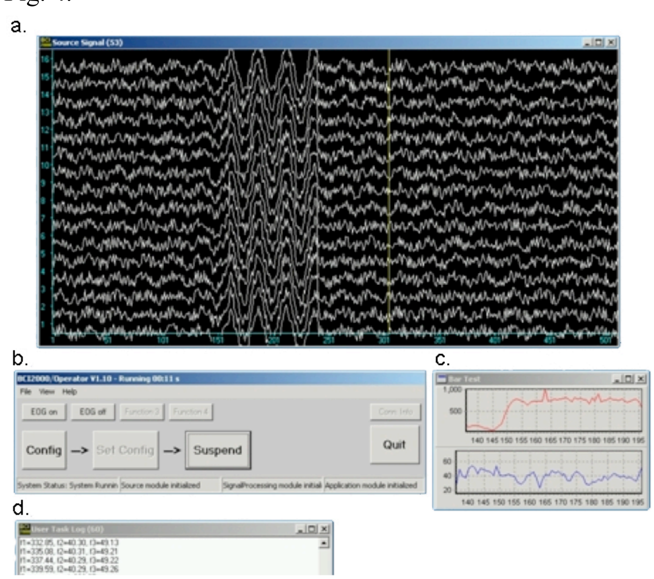

Figure 3. BCI2000 experimenter Screen during neurofeedback training: a. EEG signal; b. Operator window which allows to control configuration of the program and its execution; c. Window displaying control signals used for feedback, usually the power in a specific frequency band from a given independent component. d. Output console

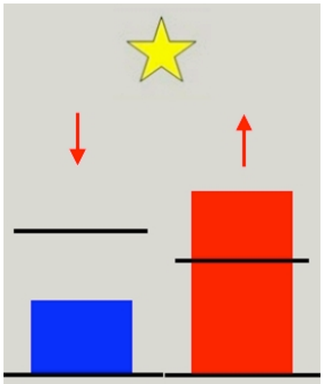

Figure 4. Neurofeedback application subject screen. Each colored bar represents the feedback for a control signal. The height of the bars covaries with the control signal value (for instance theta on the left and beta on the right). The red arrows are not shown to the subject but indicate the task, which is to lower the blue bar below the threshold represented by the horizontal black line, and increase the red bar above its threshold. When both conditions are met, a positive reinforcing feedback is given by displaying the star at the top.

BCI2000 allows to save parameters to files and to automatically load them through its Operator module. However, we encountered problems when we started using it with experimental paradigms that required to switch between parameter files, or executables modules, in order to perform a specific experimental sequence. The BCI2000 system does not allow implementing the sequence automatically and requires constant experimenter intervention, which could lead to errors. Moreover, if users want to use a different set of executables for each condition, it requires a restart of the software. Running ICA decomposition as explained in the previous section also proved very complex. We thus develop NeuroTRIP to supplement these lacks.

NeuroTRIP is a piece of software that comes on top of BCI2000 in order to allow definition of sequences of BCI2000 configurations and run them automatically. It automatically updates and saves BCI2000 parameter files that can embed complex configurations such as spatial filters derived from ICA decompositions. Figure 5 illustrates the sequence of actions that NeuroTRIP allows to perform automatically.

This involves acquiring pre-session data, running ICA on the pre-session data, visualizing selecting ICA components, and plug-in in the result into a BCI2000 parameter file for the actual Neurofeedback session.

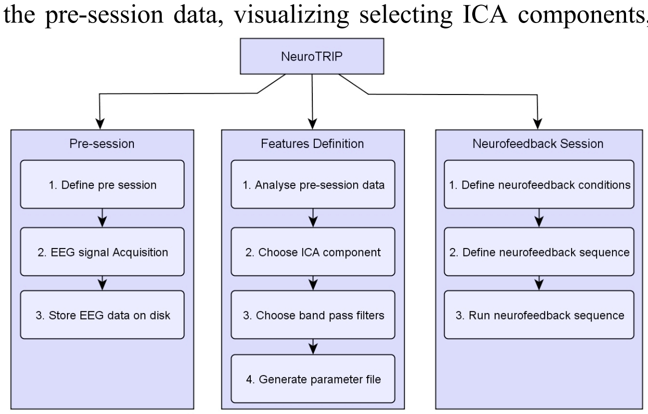

Figure 5. List of operations performed by NeuroTRIP for the pre-session, the feature extraction and the Neurofeedback session.

NeuroTRIP first starts a sequence of custom or native BCI2000 modules to acquire some pre-session data. Pre-session data is important, as ICA needs to be applied to separate brain sources specific to the current subject. During the pre-session, two or more conditions are defined where subjects are asked to generate specific mental states (relaxed, ready to move, mental mathematics, etc…). Pre-session data acquisition lasts less than 10 minutes. NeuroTRIP then runs a sequence of Matlab commands to preprocess the acquired data (the Matlab sequence of commands – including the ICA decomposition - may be conveniently entered in a dedicated NeuroTRIP text window). NeuroTRIP is written in C++ but Matlab instances may be started using the COM Matlab Interface. As shown in Fig. 6, a Matlab figure pops up showing the ICA components, their scalp map, power, and discrimination power to separate two or more given frequencies of interest (or a ratio of frequencies) for the condition tested during the pre-session data acquisition period. Note that this tool is not intended for analysis purpose. Detailed offline analysis may be performed under Matlab to select which component and frequency should be used for Neurofeedback training. The NeuroTRIP implementation aims at selecting these predefined features for the current subjects. Components with more discriminative power are placed first but if the Neurofeedback task consists in training the frontal midline theta rhythm, experimenters must systematically select this component in the interface even if they do not come in first position. Users enter the index of the component they wish to use for Neurofeedback in the native C++ NeuroTRIP graphic interface (several components – one per frequency band may also be used). Finally, NeuroTRIP writes all of ICA parameters into a BCI2000 parameter file. Pressing a button under NeuroTRIP finally starts a new sequence of BCI2000 modules that run the actual Neurofeedback session.

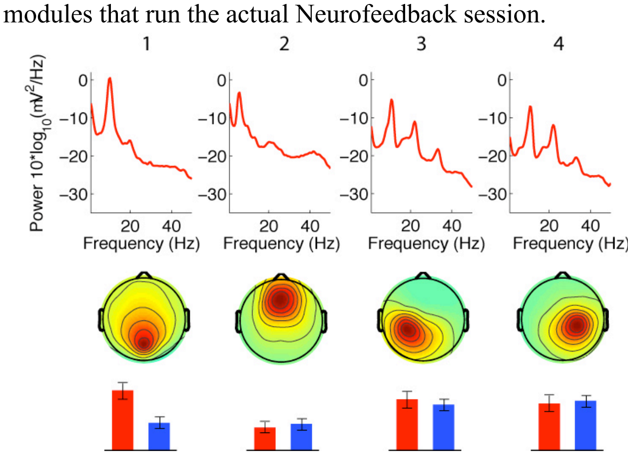

Figure 6. Figure poped up by NeuroTRIP. This figure is generated by Matlab called from NeuroTRIP. It indicates the component that discriminates best between two conditions. The two colored bars under each map define the power of the component in the two different conditions. In this idealized example, an alpha source is shown on the left and exhibit the strongest power difference between the two pre-session conditions. Next is a frontal midline theta source. Finally a left and right mu sources are represented. Users enter the index of the component he is interested in directly in NeuroTRIP.

Fig. 7 indicates the sequence of operation run by NeuroTRIP and how it interacts with BCI2000 and EEGLAB. Time goes from top to bottom. Fig. 8 shows the main NeuroTRIP interface that allows users to select sequence of BCI2000 modules. The upper part allows defining experimental conditions by associating the selection of native modules to be launched with specific parameter files. The lower part is used for the definition of the experimental sequence (pre-session, ICA extraction and Neurofeedback session).

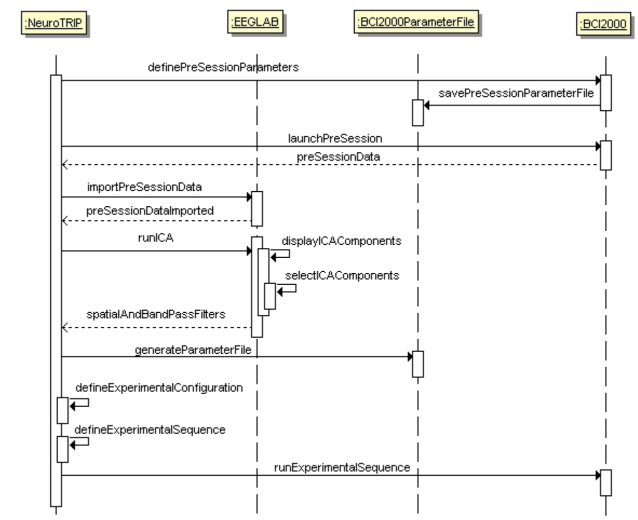

Figure 7. Sequence of operations run by NeuroTRIP and its interactions with different softwares.

Since NeuroTRIP has been designed as a meta-launcher, it is not tightly linked to the underlying tools that are being used for BCI. It relies on the abstraction of a common process and aims to behave as a global controller which orchestrates and monitors both this information flow and the execution of various open source solutions related to BCI and neurofeedback domain. It may be extended to run a full sequence of BCI scripts under Matlab using Fieldtrip toolbox developed at the Donders Institute for Brain, Cognition and Behaviour, [43] or to interface the Openvibe platform, another OpenSource solution for BCI and neurofeedback applications [44]. NeuroTRIP (currently version 0.9) will be released as an Open Source software once it has been validated by a few laboratories. Perspectives for development involve automatic selection of ICA components based on pre-defined templates.

V. INTEGRATION IN OPEN SOURCE SOFTWARE DEVELOPMENT FRAMEWORK.

NeuroTRIP will be released as a “BCI2000 contribution”. “BCI2000 contributions” gather code that is contributed by users of BCI2000. Although the BCI2000 team tries to keep contributed code functional, they cannot apply the same standards of maintenance and testing than the one they use for the "core" BCI2000 distribution. In order to provide quality standard code that could be integrated in BCI2000 version control system, NeuroTRIP code should comply with some basic standard requirements.

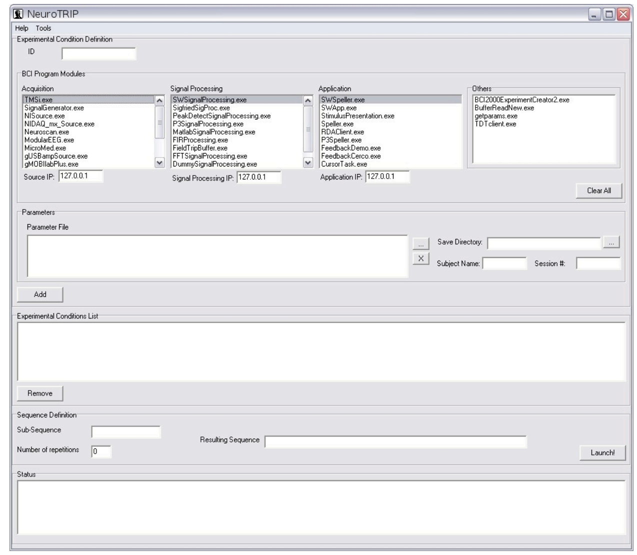

Figure 8. Screenshot of NeuroTRIP Graphical User Interface

First, BCI2000 developers maintain a set of guidelines and rules that is aimed at readability and maintenance efficiency. Rules include C++ coding style reference, and project settings regarding the pre-compiled headers (PCH).

The second part of the integration in BCI2000 development framework is to create a documentation page on BCI2000 Wiki. This page should give a short description of the code, i.e., an overview of its functionality, documentation of its parameters, and additional information that the user needs to know in order to use it. It should also be clear for which core BCI2000 version (source code revision) the code was developed, and which revisions have been used to test it.

Once NeuroTRIP code and documentation are integrated into the BCI2000 framework, a directory will be created by the BCI2000 Administrator in the SVN source code repository. NeuroTRIP will also be integrated into the BCI2000 project management software. The TRAC software has been deployed as the main solution for project management and bug/issue tracking system emphasizing ease of use and communication rather than formal document driven processes. It provides an integrated Wiki, an interface to version control systems, and a number of convenient ways to manage events and changes within a project.

The release of NeuroTRIP as an open source tool part of the BCI2000 framework will allow direct benefit to the OSS community. Moreover, it will allow direct contact to potential users and developers, which will hopefully lead to new requirements resulting in the implementation of new features. We hope that the release of the NeuroTRIP source code will help develop further research on neurofeedback.

VI. CONCLUSION

The field of Neurofeedback and BCI research is a new merging field in brain research that is advancing at a fast pace. Here we emphasized the potential use of ICA as a signal processing tools to separate electrical brain activity mixed at the level of scalp sensors. ICA would allow to have subjects train the activity of specific brain areas. We identified the need of improved open source technical tools to facilitate scientific studies on this promising technology. In this paper we present NeuroTRIP, a open source software tool aiming to automate sequences of procedures for neurofeedback and BCI experiments using ICA. We also describes how the NeuroTRIP solution can be readily integrated into existing open source management software.

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