**REMOV: EEG artifacts removal methods during Lokomat lower-limb rehabilitation**

Fiorenzo Artoni, Carmelo Chisari, Danilo Menicucci, Chiara Fanciullacci, and Silvestro Micera

**Abstract**—Post-stroke rehabilitation is one of the major health-care challenges. Robotic-aided therapy, if coupled with adequate monitoring techniques, is able to provide task-specific highly-intensive repetitive treatments that may facilitate patients’ motor recovery. The EEG is the best non-invasive brain imaging modality in terms of sensors lightness, noninvasiveness, and temporal resolution, however artifact contamination has always made it difficult for scientists to use it in combination with lower limb robotic-aided rehabilitation. In this work we present for the first time REMOV, a method that combines various routines for the removal of EEG artifacts during Hocoma-Lokomat lower-limb rehabilitation. REMOV includes various preprocessing, abnormal data removal, channels rejection, ocular artifacts rejection and fine-tuning steps. This study, although at its preliminar state, may help scientists to use the EEG as brain imaging technique during Lokomat rehabilitation, and will hopefully pave the way to further advancements on EEG artifacts removal.

I. INTRODUCTION

Rehabilitation after stroke is nowadays one of the major health-care challenges, both from the clinical and economic points of view (it is one of the most frequent causes of disability, especially in the developed world, and it accounts for considerable health and social-services costs) [14]. Robotic-aided therapy, by providing highly-intensive, repetitive and task-specific treatments, facilitates patients’ motor-recovery monitoring but also helps regulating the intensity of the treatment, the self-initiative and the task specificity which synergically represent the key factors to a successful rehabilitative treatment [14], [21]. Indeed robots may potentially conjugate the effectiveness of neuro-rehabilitative treatments and cost reduction, particularly if coupled with home-based therapy [23], [12], [11], [14]. Although consensus has not been reached yet on this score [18], [17], determining the clinical outcome of robotic-rehabilitated post-stroke patients with respect to the one elicited by traditional therapies is a matter worth investigating. Consequently much effort is being devoted to robotic-assisted therapy [15], [22], [18], [9]. Though upper-limb rehabilitation is relatively easy, lower-limb rehabilitation constitutes more of a challenge. This is mainly due to the therapists’ required effort to set the paretic limbs and to control the weight shift [2] but also to the difficulty in monitoring (especially in real time) the outcomes of the rehabilitation treatment. One of the main assistive devices for lower extremity robotic rehabilitation is the Lokomat (Hocoma), which aids the therapist by providing weight relief, motor guidance and support and is nowadays widely used in post-stroke recovery [9].

Electroencephalography (EEG) is the only non-invasive brain imaging modality which uses sensors that are light enough to wear during ambulation [16]. Gwin et al. [8] also showed that its high temporal resolution provides timely information on the natural phenomena subserving gait thus making it as ideal an imaging technique as many other invasive ones, both in brain computer interfaces for neurological rehabilitation [3] and in therapy-outcomes monitoring [20].

Artifacts constitute the major issue that prevents the EEG technique to be used effectively during gait rehabilitation. Other EEG-recording experimental settings do not require particularly efficient methods in identifying artifacts as, generally, the subject which undergoes the experiment is asked to stay still and to move the eyes as little as possible. As such, bad portions of data can be detected manually as they are very rare. They can also be detected on the...
basis of whole-signal statistic computations (i.e. kurtosis and probability methods [4]) and discarded if out-of-bounds. It is also possible to use methods such as independent component analysis (ICA) to identify and remove ocular and muscular artifacts, as well as 50Hz and other line contaminations, under the stationarity hypothesis [5].

These remarks suggest that using the EEG in synergy with gait rehabilitation (i.e. Hocoma-Lokomat) constitutes a three-fold challenge from the technical, experimental setting and scientific points of view. Gwin et al. [8] demonstrated that it is indeed possible to couple electrocortical activity with gait cycle during treadmill walking and proposed a method to remove strongly-gait-related repetitive movement artifacts [7]. However studying a EEG signal recorded during lower-limb rehabilitation is fraught with complications: it could be masked by unpredictable head and cable movements, electrodes loss and displacement or impedance increase due to the draining of the conducting fluid, ocular movements, line noise (i.e. 50Hz) and EMG. Such artifacts are usually dealt with by performing statistics on the continuous or epoched signal (i.e. kurtosis and probability EEGlab methods [4], [5]) coupled with threshold-based rejection. These methods are in principle not guaranteed to succeed in case clean epochs are outnumbered by the artifacted ones. Statistics are known to be biased by prolonged artifacts and impaired in their effectiveness at detecting outliers. Also the efficacy of moving-window methods are inevitably dependent on the window length, which must be comparable to the length of the artifact that needs to be removed. Such length, whenever not tuned correctly, can generally single out only a part of the whole artifact. In most cases, due to their unpredictable nature, movement artifacts are dealt with by manual visual inspection. However, in gait rehabilitation, the high occurrence frequency of artifacts makes it impractical to detect them in such a way. In this work we present for the first time a method, which we called REMOV, that combines various approaches and routines to EEG artifacts detection and may aid scientists interested in monitoring rehabilitation improvements with the EEG to overcome the aforementioned issues. REMOV, by detecting most unpredictable artifacts, allows to manually check the results and fine-tune as need be. Further contamination may then removed safely with ICA or similar methods. Some routines are developed by customizing EEGLAB and BCILAB functions [13], [6] in the EEGLAB framework. All routines are tested on the EEG recordings taken from a healthy subject during gait training on the Hocoma-Lokomat robotic platform. Results shown here will pave the way to further developments, comparisons with other methods and eventual release of a dedicated toolbox.

II. MATERIALS AND METHODS

Participant to the experiment was a young healthy (age 27) right-handed male with unimpaired vision, nonsmoker, moderate caffeine and alcohol consumer and not on medication treatments. A semi-structured interview established the absence of relevant medical, traumatic or psychiatric history and he gave his informed consent to the experimental protocol. The participant performed a standard rehabilitative protocol on the Hokoma-Lokomat robotic platform. He walked continuously at constant speed while the body weight was increasingly relieved as time passed. The session length was 30 minutes. During the presentations, the (EEG) was recorded using a 64-channel DC-coupled monopolar amplifier (Micromed SD MRI, System Plus acquisition software). After careful scalp preparation EEG signals were acquired at a sampling rate of 500Hz by electrodes having contact impedance below 20kΩ and referenced to the FCz potential. Figure 1 shows the REMOV process flow which includes preprocessing, abnormal data removal, channels rejection, ocular artifacts rejection and optional fine tuning.

A. Preprocessing

REMOV must be applied on detrended and referenced signals, therefore offline re-referencing to the average potential of the two earlobes (A1 and A2) was done in order to obtain monopolar recordings with a balanced distribution of contact impedances over the scalp. A highpass Chebyshev type-2 filter (1 Hz passband, 0.1 Hz stopband, 80db attenuation) was used in order to remove the signal trend. Line noise and other stationary artifacts can be filtered out for instance by using a notch filter or blind source separation techniques (like ICA) [10].
Artifacts removal job flow

- EEG recording
- Preprocessing
  - Highpass
  - Notch
  - Lowpass
- Abnormal data removal
  - Moving windows
  - Local Range
- Channels rejection
  - Kurtosis
  - Probability
- Ocular artifacts
- Fine tuning

**B. Abnormal data removal**

As a first step, abnormal data with extreme magnitude (which include mean deviations, jumps and large oscillations) from the continuous dataset are removed by using a customized version of the routine flt_clean_windows (BCIlab) [6] to compute a moving windowed signal power. EEG windowed segments are removed if their power exceeds a pre-set distribution quantile. The parameters that yielded the best results on our dataset (by visually inspecting the resulting signal) were 90% (quantile threshold) and 1s (window length).

Secondly synchronous sudden increases in signal amplitude are detected by computing the difference between the superior and inferior envelopes (shape-preserving piecewise cubic interpolation [1]) and EEG portions producing values greater than 2 standard deviations (in amplitude distribution) are removed. Figure 2 shows how this step is performed.

Finally as a third step further artifacts are removed by iterative moving-window signal-power computing, as described above, with 90% as quantile threshold and increasingly lower window length (1s, 0.8s, 0.3s, 0.1s) thus rejecting smaller parts of data in each run. By iterating the method, each time different parts of the signal time-points are recognized as artifact-periods; that is results are not affected by artifact latency. The number of time points removed on our dataset each time decreased exponentially and the iterative movement cleaning stopped when the time-points removed in one iteration were below 0.01%.

**C. Channels rejection**

Major movements cleaning paves the way to channels rejection, by using both custom-made and EEGLab functions. Bad channel indexes are determined by computing prob-
ability and Kurtosis statistics of the entire signal using a threshold of 90% [5], [4]. Further indices are computed by customizing the function flt_clean_channels (BCIlab) [6]. A value of 0.6 was considered to be the minimum correlation between a channel and any other channel in a specified time window for the channel to be considered as not artifected. Sorted correlation values exceeding the 90% quantile are ignored. The window length for which the correlation is computed (which has to be short enough to reasonably capture global artifacts periods but no shorter so as to decrease the computational workload) is set to 1s. Also the 20% of the total data is ignored (it can contain arbitrary data without affecting the outcome) in order to limit outliers influence.

The choice of performing channel rejection after the movement cleaning is not arbitrary. Channel rejection doesn’t work properly if particularly bad portions of data are not removed first, as their amplitude can alter the characteristics of all the channels with strong correlation thus impairing the discriminant capabilities of the method.

D. Ocular artifacts rejection

Ocular artifacts are detected by computing a moving-window cross-correlation between the frontal EEG channels and the electrooculogram: high values of cross-correlations marked putative ocular artifacts. Cross correlation values are considered as high if greater than a threshold derived by computing the same moving-window cross correlation between phase-randomized surrogated [19] frontal EEG channels and the vertical electrooculogram. Furthermore, in order to detect just noteworthy artifacts, only those producing on frontal EEG channels fluctuations greater than 50µV and lasting at least 70ms are taken into account.

E. Optional fine-tuning

A fine-tuning optional step of REMOV comprises the removal of further events that have abnormally strong power by projecting them out of the data (BCILAB [6]). Finally single time-points (if they exist) with amplitude power greater than 300µV are removed (simple threshold).

III. RESULTS

In this work we present for the first time REMOV, a combination of various approaches and routines that may aid scientists using the EEG during lower limb rehabilitation. REMOV rejects most unpredictable artifacts, as visual inspection confirms and, coupled with manual fine-tuning or BSS methods, aids in studying strongly artifact-tuned EEG recorded in extreme conditions (i.e. during gait rehabilitation).

The EEG signals used in this work were thus collected from one healthy subject who was asked to keep the head as still as possible while performing a standard Hocoma-Lokomat rehabilitation exercise. Although this step ought to reduce artifacts, many unpredictable movements are unavoidable and strongly affect the EEG outcome. It is impossible to study the brain and the EEG dynamics without strong artifacts removal techniques. On this score REMOV combines different approaches and customized functions in the EEGlab, BCIlab [5], [6] environments to other original routines to address different aspects in artifacts detection.

Results were visually inspected before and after each REMOV cleaning step. The parameters described in the Materials and Methods section were accurately tuned to yield the best results in terms of removal aggressiveness, effectiveness and efficiency. Figure 3 shows a visual comparison between a representative EEG segment extracted both after and before the REMOV processing. Drifts, movement artifacts are clearly visible in figure 3B, while the signal in figure 3A looks much cleaner. Figure 4 shows the difference between the Power Spectral Density (Welch’s method) respectively before and after artifacts removal. The total power decreases but also the power amplitude span distribution is narrower after REMOV processing. Movement artifacts are in fact unpredictable and carry great power randomly across a vast frequency range. At the time being such results are to be considered as purely qualitative, the next steps will comprise a validation of the method presented here on simulated data, its comparison with other possible artifact removal techniques and its use on a larger dataset. It is important to point out however that visual inspection is likely the only reliable way to check for accuracy in artifact removal. Although working on simulated data may be as good a validation method as any, a very important drawback needs to be taken into account: the rules used to build the model are inherently limited by the actual knowledge of the process, while the very same knowledge is also used in the detecting algorithms themselves.
Fig. 3. Selected EEG segments before (B) and after (A) REMOV artifacts removal. Red lines in figure B show an example of unpredictable artifact. Drifts and electrodes displacements can be observed too. Visual inspection of figure A shows a representative 5s segment of cleaned EEG. Further analysis i.e. ICA decompositions can be performed safely after REMOV on the cleaned dataset for instance to remove further EMG contamination.

IV. DISCUSSION

Artifacts removal and detection nowadays remains one of the major issues to be addressed by specialists who wish to use noninvasive techniques like EEG to study brain activity. The small signal to noise ratio, coupled with strong artifacts, makes it almost impossible to extract meaningful information without well-developed and accurate artifact-rejection tools. Therefore many methods with the aim of increasing the signal to noise ratio have come to light, averaging being probably the most basilar one.

Due to their complex nature (variability of sources, patterns, frequency bands etc.) artifacts have mostly been removed manually but, as the dataset length increased and computational issues were partly overcome, an always increasing number of techniques to identify and remove them has been developed in the last decade. The principles used by each method are very different and based for instance on frequency constraints, correlation measures, statistics and many others. Among unsupervised or partially supervised techniques, ICA is probably the best as it is able to parse EEG signals into maximally independent components thus making it possible to identify (manually or with an automatic classifier dependent on select features) EMG, ocular artifacts, line noise contributes and project them out of the EEG signal. The drawback of ICA is the stationarity requirement and statistics-based methods rely on the absence of outliers in general. Using blind source separation methods on strongly artifacted signals does not yield any result if major unpredictable (hence out of statistical training capabilities) movement artifacts are not rejected first. REMOV should not be therefore considered as an alternative to such methods but more as a processing step that enables their use if needed.

On the whole artifacts removal in nonstationary conditions like gait rehabilitation (using the Lokomat for instance) requires a massive effort from the technical point of view. The
development of REMOV will hopefully benefit the scientific community to study the brain with as unharmful a imaging technique as the EEG in extreme (from the artifacts point of view) conditions. Heavier still artifact contamination is likely to occur when dealing with post-stroke impaired patients, hence the development of artifact-removal methods such as REMOV is a crucial step in EEG-monitored rehabilitation.

REFERENCES


