Real-time EEG Source-mapping Toolbox (REST): Online ICA and Source Localization

Luca Pion-Tonachini, *Student Member, IEEE,* Sheng-Hsiou Hsu, *Student Member, IEEE,* Scott Makeig, Tzyy-Ping Jung, *Fellow, IEEE,* and Gert Cauwenberghs, *Fellow, IEEE*

***Abstract*— The Electroencephalogram (EEG) is a noninvasive functional brain activity recording method that shows promise for becoming a 3-D cortical imaging modality with high temporal resolution. Currently, most of the tools developed for EEG analysis focus mainly on offline processing. This study introduces and demonstrates the Real-time EEG Source-mapping Toolbox (REST), an extension to the widely distributed EEGLAB environment. REST allows blind source separation of EEG data in real-time using Online Recursive Independent Component Analysis (ORICA), plus near real-time localization of separated sources. Two source localization methods are available to fit equivalent current dipoles or estimate spatial source distributions of selected sources. Selected measures of raw EEG data or component activations (e.g. time series of the data, spectral changes over time, equivalent current dipoles, etc.) can be visualized in near real-time. Finally, this study demonstrates the accuracy and functionality of REST with data from two experiments and discusses some relevant applications.**

I. Introduction

Electroencephalogram (EEG) source analysis combining Independent Component Analysis (ICA) and source localization has generally been solved offline because of its computational cost. With faster processors and algorithmic advances, near real-time online applications are becoming even more viable. Bringing these analysis methods to the domain of real-time processing would allow for the use of more specific neurophysiological information in closed-loop brain-computer interfaces (BCI) and neurofeedback paradigms, and could also provide experimenters online feedback useful for data quality control.

Analyzing EEG data at the level of cortical source dynamics is a complicated problem, but allows for much more biologically plausible, physiologically meaningful, and functionally significant results than treating scalp data channels as if they indexed single brain sources. A source-resolved imaging approach models the collected EEG as the sum of electric fields produced by many small patches of cortex whose local field activities are fully or partially synchronous, each such patch thus functioning as an effective EEG source with a scalp projection identical to that of a single equivalent current dipole (ECD). Source localization requires solutions to both the forward and inverse imaging problems: the forward problem (FP) determining the scalp projection patterns of the possible brain sources based on accurate modeling of head tissue geometries and conductivities, and the inverse problem (IP) estimating the locations and orientations or cortical surface distributions of one or more source projection patterns.

Many existing EEG processing toolboxes attempt to solve these problems, including core EEGLAB [1], BCILAB [2], LORETA-KEY [3], and Fieldtrip [4]. They all operate offline or attempt to solve the IP by directly operating on, e.g., response-averaged EEG channel data. Approaching the IP directly from the EEG channel data complicates the problem by requiring determination of the number of sources to localize [4], a problem whose computational cost and number of false local minima increase dramatically with the number of sources being estimated. Other approaches simply attempt a low-resolution joint spatial estimate of all the active sources [3]. Blind source separation can be used as an initial unmixing step to simplify an inverse problem by separating it into much simpler problems of finding the locations of the individual effective sources [5][6][7].

ICA has been shown to work exceedingly well when applied to EEG [8] as EEG data and ICA share many important assumptions. ICA assumes that input data are the result of a linear mixing of spatially stationary independent time series or independent components (ICs). Here, we present the Real-time EEG Source-mapping Toolbox (REST), a collection of automated EEG analysis methods accessible through a graphic user interface (GUI). By applying Online Recursive ICA (ORICA) [9], we can estimate a solution to the source separation problem in near real-time, allowing low-latency access to source information, making possible innovations in experimental designs including a wide variety of clinical and non-clinical BCI paradigms. REST also allows the user to estimate the brain locations of the estimated sources using either LORETA [3][10] or minimum-variance ECD fitting [4].

REST provides estimates of source activations and their current power spectra, plus source scalp maps (source scalp projection patterns) and cortical source locations. Below, we show the layout of the REST GUI and detail the measures used in its analysis pipeline. We then test its accuracy and

L. Pion-Tonachini and S.-H. Hsu made equal contributions to this work.

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L. Pion-Tonachini (lpionton@ucsd.edu) is with Dept. of Electrical and Computer Engineering and Swartz Center for Computational Neuroscience (SCCN) of University of California, San Diego (UCSD).

S.-H. Hsu (shh078@ucsd.edu) is with Dept. of Bioengineering (BIOE), SCCN, and Institute for Neural Computation (INC) of UCSD.

S. Makeig (smakeig@ucsd.edu) is with SCCN and INC of UCSD.

T.-P. Jung (tpjung@ucsd.edu) is with BIOE, SCCN and INC of UCSD.

G. Cauwenberghs (gert@ucsd.edu) is with BIOE and INC of UCSD.

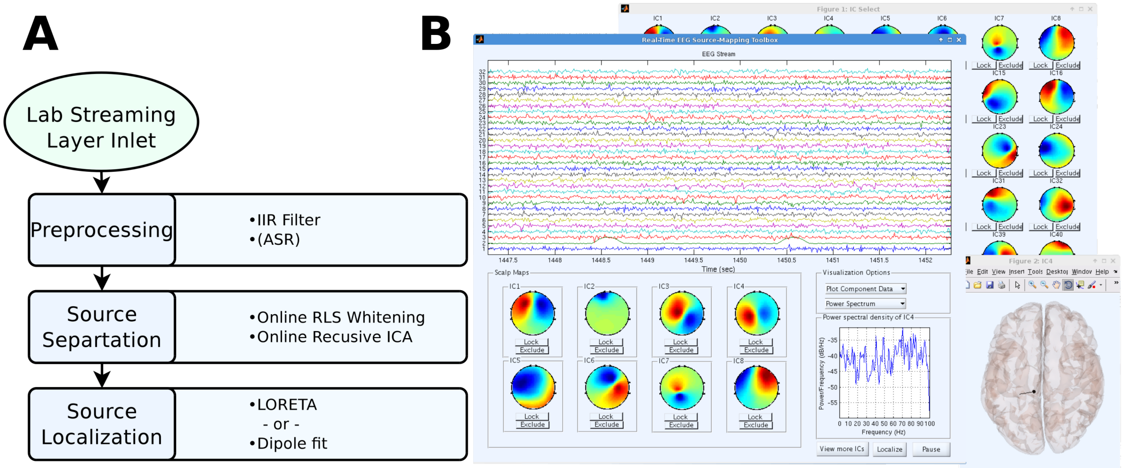

Fig. 1. A. The pipeline used in the Real-time EEG Source-mapping Toolbox (REST). B. The toolbox GUI. The main window (left) shows the scrolling EEG channel or independent component (IC) activation data plus 8 (constantly updated) IC scalp maps. A source location estimate for IC4 is shown (lower right). Behind this (upper right), another REST window shows all the estimated IC scalp maps.

efficacy by applying it to simulated EEG data with known source locations and activations. Finally, we demonstrate the real-world utility of REST and its ease of use by applying it in a common BCI paradigm recording session.

II. Methods

REST is coded in MATLAB [11] using the EEGLAB environment. It uses a processing pipeline, shown in Fig. 1A, designed to run from beginning to end with minimal user input. Preprocessing and source separation are implemented as a BCILAB pipeline followed by source localization implemented in part using routines in MoBILAB [10].

A. Preprocessing

The toolbox pulls EEG data from a data stream received through the Lab Streaming Layer framework [12]. The data are first preprocessed by IIR high-pass filtering. Artifact Subspace Reconstruction (ASR) [13] may be introduced as an additional preprocessing step to remove large movement-based artifacts.

B. Source Separation

Next, the EEG data are whitened using an online RLS whitening algorithm (to improve convergence) and then linearly unmixed using ORICA. ORICA is a centerpiece of this toolbox. It is, so far as we know, the only ICA implementation that is real-time capable with acceptable convergence rates for relatively large numbers of channels [14]. The output of ORICA is a set of linear IC filters that are used to separate the IC activation time courses and scalp maps from the EEG channel data. When the data sources are spatially and statistically stationary, the ICs that ORICA provide asymptotically approach those that (offline) Infomax ICA [15] returns. Unlike Infomax ICA (though compare AMICA [16]), ORICA can also adapt to source non-stationarities.

C. Source Localization

Estimated IC source locations are calculated using one of two cortically-constrained source models (either distributed or ECD). Distributed source location model estimates are calculated using cortically-constrained LORETA with Bayesian hyper-parameter estimation [17] from MoBILAB, while the ECD model estimates are computed using minimum residual variance fitting. Both the ECD and distributed source methods require a MoBILAB head model object to be created in advance, which can be computed easily using the included helper function. The head model uses spatial meshes representing the geometry of the cortex, scalp and one or more intervening head tissue types (e.g., skull, CSF, white matter). A lead field matrix (LFM) is calculated (automatically) using OpenMEEG [18], as well as a surface Laplacian operator for the cortical mesh. By default, the included helper function creates a 3-layer (scalp, skull, cortex) boundary element method (BEM) head model based on the MNI Colin 27 brain. The primary input to the source localization methods is an estimated ICA scalp map for the source being localized.

III. Materials

A. Toolbox

The REST main window, on the left of Fig. 1B, displays either raw EEG or estimated IC activations. It also shows scalp maps and power spectra for the estimated ICs, as well as convergence statistics. All the visualized information updates in near real-time. The (partially occluded) window in the top rights of Fig. 1B provides an easy way to select which ICs are displayed on the main window. On the bottom right of Fig. 1B is the source localization window which shows the current estimated source location for an IC as either an ECD or a distributed source.

B. Experiments

To show the utility of REST, we designed two experiments. One, using simulated source-resolved EEG data, for which we know the ground truth, tested the integrity of the REST pipeline. The other used actual EEG collected during a steady-state visually evoked potential (SSVEP) BCI paradigm to test the utility of the toolbox in interactive paradigms.

1) Simulated EEG Data: For the simulation, we used the default head model with ECD sources constrained to be normal to the cortical surface. We simulated 10 minutes of 64 channel EEG using SIFT [19] by placing ECDs at various vertices of the cortical mesh and generated source activation time-series for each. Two sources were handcrafted to imitate eye-blinks and occipital alpha activities while the rest were vector autoregressive processes driven by super-Gaussian noise. These are then mixed together using the LFM associated with the head model. As this was a test for accuracy rather than speed of convergence, we evaluated the accuracy of the ORICA decompositions and resulting source location estimates at the end of the simulated data collection. For information on the convergence properties of ORICA, see [14].

2) Actual EEG Data: To collect the actual human EEG we used a low-cost 14 channel Emotiv headset. This setup wirelessly streams data to a computer via Bluetooth. The streaming data were transferred to an LSL stream for REST. During the experiment, 2 minutes of eyes-closed resting allowed ORICA to identify relevant ICs. This was followed by 2 trials in which the subject looked at flashing phone-pad style digits on a tablet. The subject first focused on the symbol "1" and then afterwards at the symbol "#" which were flashing at 9 Hz and 11.75 Hz respectively. This tested the adaptivity of the pipeline, as going from eyes-closed rest to viewing flashing stimuli could be expected to produce a noticeable change in brain sources and source activities.

IV. Results

A. Simulated 64-Channel Stationary EEG

As shown in Fig. 2 and 3, ORICA and both source localization techniques perform as intended. Fig. 2 visualizes the full REST pipeline applied to 3 of the 64 simulated sources. In the first estimation step, ORICA successfully decomposes the sources, providing accurate scalp map estimates and source activations. In the second estimation step, the ECD estimates were very close to the ground truth (shown in the green simulation box) in both location and orientation. The distributed source estimates, despite not theoretically matching the model used during simulation, provided patches of active cortex that were well situated about the simulated dipole location.

Fig. 3 illustrates the accuracy of all 64 estimated dipole positions and orientations, which were generally correct within 3 cm and 20 degrees respectively. The majority of the errors in dipole position were related to the depth of the dipole as the true source positions tended to be closer to the scalp than their estimates. Disk sizes in Fig. 3, which represent scalp map error, showed a clear correlation between localization error and scalp map error and provides a means of judging whether localization error is due to poor results

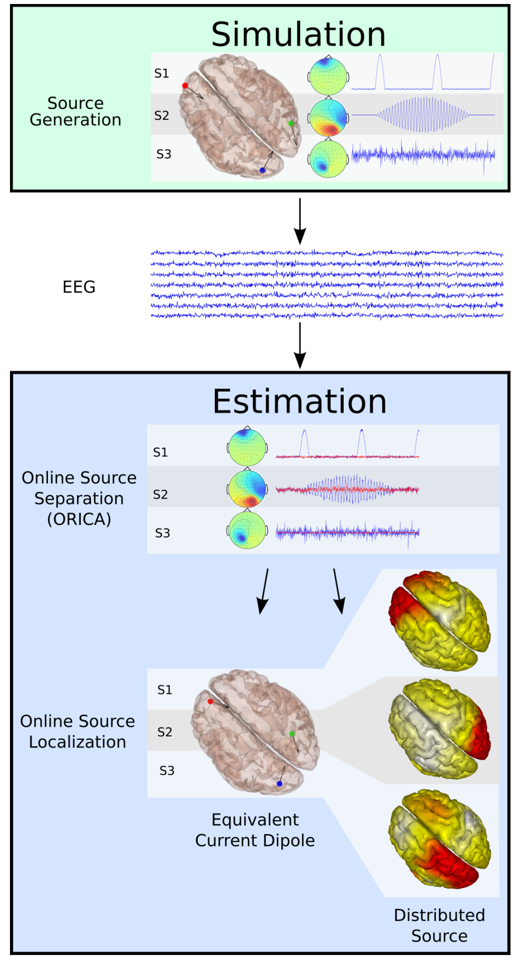

Fig. 2. The simulated data experiment: data simulation to source estimation. (Green box) The simulated data source activations are mixed. (Blue box) The simulated EEG data are first decomposed within REST into estimated independent components (ICs) using ORICA. Then the source location of each IC is estimated as either an equivalent current dipole (ECD, left) or as a low-resolution cortical distribution (right).

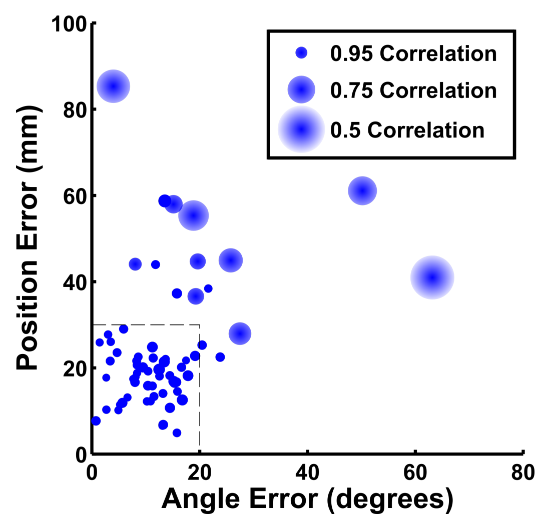

Fig. 3. Source localization accuracy in the simulated data experiment using an equivalent current dipole (ECD) model for each estimated independent component (IC). Each disk represents an IC. Disk size shows how well the recovered IC scalp map correlated with the simulated source scalp map. For 48 of the 64 recovered sources, map correlations were above 0.95 with ECD model errors less than 3 cm and 20 degrees (lower left).

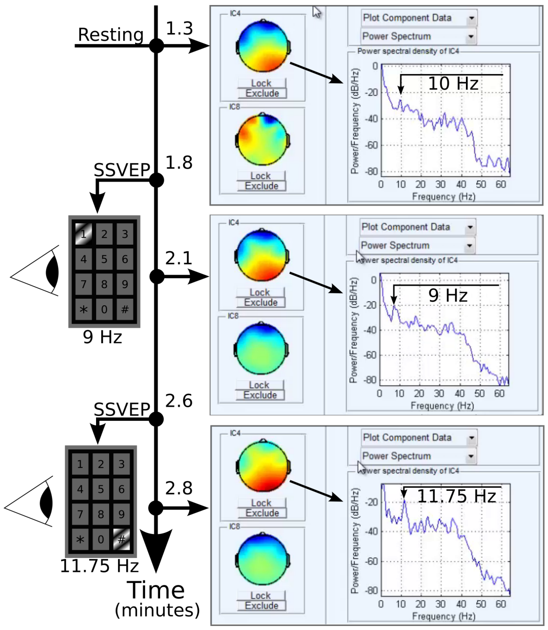

Fig. 4. Screen captures of the REST GUI during an actual EEG experiment. At 1.3 min (top panel) during eyes-closed rest, the baseline PSD for IC had a peak at 10 Hz (alpha). At 2.1 min (middle panel), the subject attended the symbol "1" flashing at 9 Hz (note change in the IC4 spectrum). At 2.8 min (bottom panel), the subject attended the symbol "#" flashing at 11.75 Hz (note IC4 spectral shift and possible scalp map change).

from ORICA or error from the underdetermined nature of the IP. Here we used the same simulated FP head model to solve the IP, something not possible in actual use where the true FP head model can only be estimated. Nevertheless, these results indicate that REST can generate accurate source locations and activations provided a minimum level of data quantity and quality and sufficient head model accuracy.

B. Actual 14-Channel EEG during SSVEP

The application of REST to data collected in an SSVEP paradigm showed that ORICA can converge to useful source solutions in real-life applications. Fig. 4 compares REST outputs during eyes-closed rest and attention to 9 Hz and 11.75 Hz flashing stimulii. Clearly, ORICA extracted an occipital IC, first during rest with a weak 10 Hz peak (top panel), and then during attention to 9-Hz (middle panel) and 11.75-Hz (lower panel) flashing stimuli. The ECD during the latter condition (not shown) changed in orientation as indicated by the change in its scalp map.

V. Conclusions

We have shown that REST can be accurate when applied to simulated data, and potentially usable in practice. There are many possible applications for real-time monitoring of sources of interest during an EEG experiment. The REST toolbox design allows possible extensions to implement near real-time computation, visualization, and application of other source-resolved EEG measures. REST could aid online data quality analysis, as when collecting EEG from particular sources if of specific importance. Additionally, the ORICA implementation in REST might be used to make a wide range of BCI paradigms more robust [20]. We plan to add more flexible and detailed data preprocessing, since ICA can be highly influenced by large amplitude artifacts, and also automated IC classification. In theory, the ORICA decomposition and, with some modifications, the source localization methods in the REST pipeline should be as applicable to MEG as to EEG data. Finally, this work follows in spirit, and some details, previous work [13] demonstrating a real-time application of the BCILAB [2] and SIFT [19] toolboxes, into which the source identification and localization methods in REST might easily be introduced.

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