StaR: An EEGLAB Framework for the Measure Projection Toolbox (MPT) Statistical Analyses to be Performed in *R*

Yannick Roy, Jean-Claude Piponnier and Jocelyn Faubert

Abstract EEGLAB, a widely used toolbox in MATLAB (The Mathworks, Inc.), uses Independent Component Analysis (ICA) to decompose the EEG signal into sub-signals, and localizes brain sources of those sub-signals prior to independent component (IC) clustering for group study. In 2013, the Measure Projection Toolbox (MPT) was introduced as a new data-driven IC clustering toolbox for EEGLAB. Despite the numerous features and advantages offered by EEGLAB and the MPT, they both have limitations for statistical analyses with more than two independent variables. In order to work around those limitations, this paper introduces StaR, an EEGLAB framework for the MPT statistical analyses to be performed in *R*. StaR initially exports the data from different clusters generated by the MPT for different measures of interest (e.g., Event-Related Potentials (ERPs) and Event-Related Spectral Perturbations (ERSPs)) and formats the data such that further statistical analyses can be performed in *R*. Once in *R*, StaR uses linear mixed models as its default method to better handle missing values and intra-subject variability. Finally, StaR brings the results back into MATLAB to plot the results with the well-known and easy to interpret EEGLAB graphics. To make the whole process easy, StaR also offers an intuitive user interface that integrates into EEGLAB's menu.

Keywords EEG · EEGLAB · Measure projection toolbox · Mixed models · *R*

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1 Introduction

EEGLAB [1] is an open-source toolbox running in MATLAB (The Mathworks, Inc.) made for EEG signal analysis and conceived to go beyond traditional mean peak analysis. One of its major preprocessing steps is the Independent Component Analysis (ICA) [2]. A dipole fitting plugin, DIPFIT [3], is then used to locate the corresponding potential brain sources (modeled as dipoles) in a brain template.

EEGLAB uses the Independent Component (IC) clustering approach for multi-subject analysis in the brain source domain. The number of adjustable parameters available in its GUI to cluster the ICs might, however, introduce subjectivity into the process. To address this issue, Bigdely-Shamlo, Mullen, Kreutz-Delgado, and Makeig (2013) developed a plugin for EEGLAB, called the Measure Projection Toolbox (MPT), which proposes a simpler and objective clustering procedure.

Even though EEGLAB and MPT offer performing algorithms intended for processing individual datasets and for IC clustering, they both have some important limitations when it comes to creating and running multi-subject studies with complex statistical designs such as longitudinal designs.

These limitations are (1) EEGLAB does not allow one to create a "studyset" (dataset gathering all the individual datasets) including different ICA decompositions for a given subject; (2) the STUDY feature in EEGLAB, which handles the statistical modules for multi-subject comparisons (i.e., "study design"), which does not support more than two independent variables; (3) the MPT statistical feature only supports two independent variables (*Group* and *Dynamic*); (4) in the MPT, once the domains (i.e., clusters) are computed, only two types of univariate analysis are available (*t*-test and permutation); and (5) in the MPT, in the case of comparison of two different groups for one condition, missing values are replaced with zeros (0) in order to keep the number of datasets equal in both groups, and in the case of comparison of two different conditions for both groups gathered together, the datasets with even a single missing value are completely removed from the statistical analysis, which can have a significant impact on the results.

Since its release in 2013, the MPT has been used in only a few published studies [4–8]. We believe that the limitations mentioned above are one of the reasons why few researchers have used it.

As a solution to these limitations, we developed a framework for EEGLAB called StaR (Statistics in *R*). StaR provides a complete pipeline extracting the data from EEGLAB, the MPT, and MATLAB altogether, in order to perform statistical analyses in *R* framework, and bringing the results back in MATLAB to easily plot them in various ways using the StaR UI that leverages the EEGLAB graphics [9–12].

2   Methodology

This section describes the StaR framework that we have developed. The code can be downloaded from https://github.com/FaubertLab/StaR. Questions can also be sent to yannick.roy@umontreal.ca. If we were to receive positive feedback and requests to provide a complete toolbox, we would happily seek funding to do so.

2.1   StaR Framework Steps

Steps #1 and #2 consist of preprocessing the data and creating a studyset in EEGLAB, then performing the clustering in the MPT (see EEGLAB (sccn.ucsd.edu/wiki/EEGLAB) and MPT wiki pages (sccn.ucsd.edu/wiki/MPT).

Step #3 consists of exporting the data from the MPT to *R*. StaR tags missing values with a NaN (Not a Number) value when exporting them from the MPT.

Step #4 consists of creating the complex data frame in *R*.

Step #5 consists of carefully placing the MPT values in the long data structure previously created. The dimensionality of the data will automatically be switched around by StaR to facilitate its usability by the user and developer while also optimizing for parallel computing. In order to study the EEG signal in greater detail, the different measures of interest (e.g., ERP, ERSP, etc.) are analyzed in a point-by-point fashion (i.e., considering each data point constituting a given graphical representation of the measure for each subject). Thus, for each subject, the data frame may hold tens of thousands of values, and hence there is the necessity for parallel computing.

Step #6 and #7 consist of the actual statistical analysis and post hoc tests. We opted for the linear mixed model procedure (*lme4* package) to capture the within-subjects variability and to use as much of the data as possible, instead of removing subjects having missing values [13, 14]. Nevertheless, other tests can be used in *R* with small modifications in the code. Options of correction methods for multiple comparisons are also offered such as False Discovery Rate (FDR) [15] or Bonferroni.

Step #8 consists of bringing the results back into MATLAB to use EEGLAB graphics that are easy to recognize and interpret [10, 16]. One of the challenges here was the poor protocol of exchange between *R* and MATLAB. The data had to be linearized by carefully reshaping the matrices.

Step #9 consists of plotting the results. Handling more than two independent variables is not possible in EEGLAB and the MPT, therefore, even if the graphics are generated with EEGLAB functions, having the ability to plot this kind of graphics from a combination of three or four independent variables is new. The illustrations presented here come from a subset of datasets used in a longitudinal study initially comprising of four factors (*Group*, *Session*, and two condition-related crossed factors such as *Dynamic and Modulation*). In order to better handle the missing values, we have included a cluster-related factor (*Domain*).
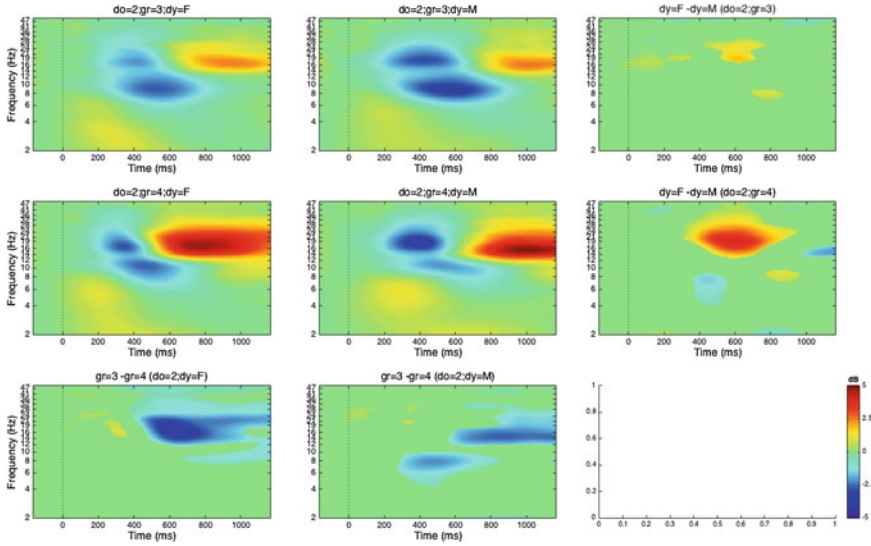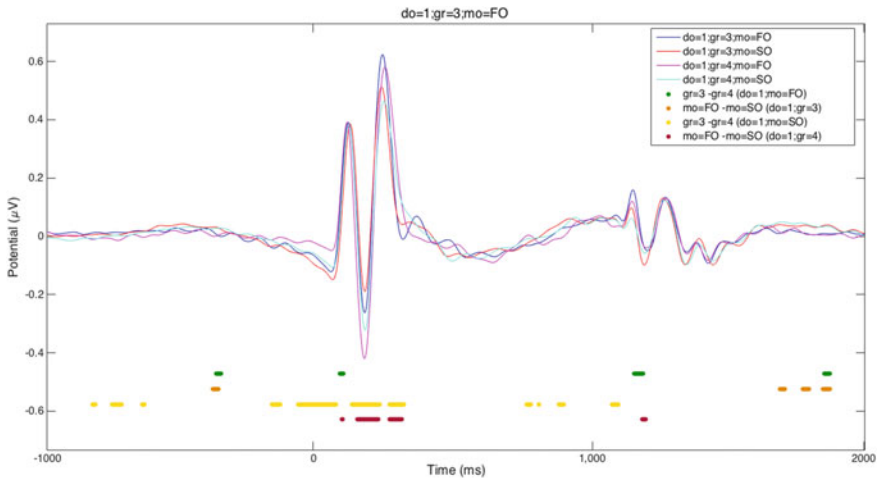
Fig. 1 ERSP 2 × 2. In this figure, the two factors are *Group* (2 levels: 3 and 4) and *Dynamic* (2 levels: M and F, where M stands for motion and F for flicker) for *Domain 2*. The effect of the factor *Dynamic within* a specific group is figured in the first two rows and the effect of the factor *Group* within a specific condition is figured in the first two columns. In the outer graphs, the green regions mean that it is not significant and the values are set to 0

Figure 1 shows an example of the data and statistical results for a given cluster (*domain 2*) from a combination of two factors (*Group* × *Dynamic*), both with two levels, while all other factors were kept combined. Any other pair of two variables could have been selected and would have produced a similar output. One could also fix the other variables to a specific value (e.g., *Session* = 1) instead of leaving them combined. It is also possible to select the option to only plot the significance mask showing only two colors (i.e., significant or not) instead of a color scale representing the difference between the two graphs.

Figure 2 shows an example of the data and statistical results for a given cluster (*domain 1*) from a combination of two factors (*Group* × *Modulation*), both with two levels, while all other factors were kept combined. Any other pair of two variables could have been selected and would have produced a similar output. One could also fix the other variables to a specific value (e.g., *Session* = 1) instead of leaving them combined.

2.2   StaR UI

Creating an intuitive user interface (UI) that makes it easy to plot different layouts of graphs based on the interaction of multiple independent variables, all with a dif-

Fig. 2 ERP 2×2. In this figure, the two factors are *Group* (2 levels: 3 and 4) and *Modulation* (2 levels: FO, SO). Colored dots or lines below the curves indicate where the differences are significant. The legend indicates the independent variables being compared. For example, "gr = 3–gr = 4 (do = 1; mo = SO)" means that datasets from group 3 for domain 1 and second-order modulation were compared to datasets from group 4 for the same domain and modulation levels, all other factors combined

ferent number of values (e.g. 2 x 2, 2 x 3), is a challenge. Actually, when supporting multiple independent variables the combinations and possibilities quickly become manually unmanageable. The simple and intuitive StaR UI simplifies all these possible combinations and options.

2.3 Exploratory

We added a feature called *specific Dipoles* (Fig. 3) allowing the visualization of the domains generated by the MPT with the contributing dipoles from different groups and sessions represented with different colors. This feature does not compute anything but simply plots the dipoles already identified and located (i.e., source localization) with EEGLAB plug-in such as DIPFIT using a brain template such as the Montreal Neurological Institute, one prior to using the MPT and therefore before using StaR.

Such a tool gives the opportunity to quickly check if the data seem well-balanced in order to validate results. By selecting a specific domain with the groups and/or sessions of interest using different colors, one can see at a glance if (1) the groups seem to be equally represented and/or if (2) the sessions seem to be equally represented.
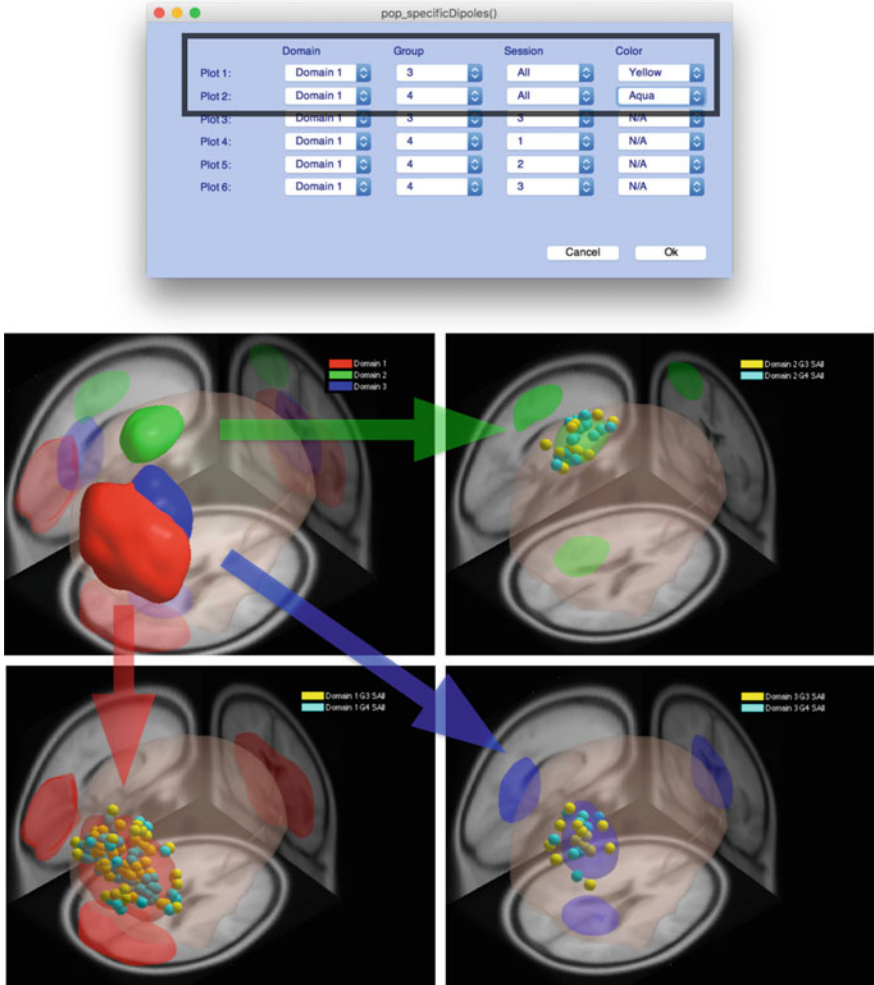
Fig. 3 *Specific Dipoles* UI and output. The UI (at the top) allows for the selection of a specific domain to show its contributing dipoles. The user can either select all groups for all sessions to see all the contributing dipoles of a specific domain, or can break down the analysis to a specific group and/or session

3 Discussion and Conclusion

StaR, the statistical framework introduced in this article is mainly targeting EEGLAB users, especially those interested in the use of the MPT as IC clustering tool. StaR creates a link between EEGLAB/MPT in MATLAB and *R*. It uses the "studyset" created in EEGLAB to perform statistical analyses of EEG signal characteristics of

interest (e.g., ERPs, ERSPs, power spectra, etc.) in *R*, and finally brings the results back into MATLAB in order to plot them using EEGLAB graphics.

The necessity for creating such a tool came from the limitations we encountered using EEGLAB and the MPT to create a longitudinal statistical study design with four factors (including two crossed condition-related factors).

The recent increase in computing power has made possible the use of more complex statistical designs like mixed-effect models, which are better at modeling within-subject variability and at dealing with missing values and unbalanced datasets than the classical ANOVA [17, 18]. Furthermore, contrary to the classical ANOVA, mixed-effect models do not violate underlying assumptions (e.g., linearity, sphericity, etc.) [19]. Else, mixed-effect models are well-suited for the analysis of longitudinal data containing missing values [20–22], and were thus particularly relevant in our case.

StaR was developed to be flexible and to easily support different statistical tests in *R* with minimum changes in the code while keeping all other steps untouched (e.g., exporting the data, plotting results with EEGLAB, etc.).

Finally, by making StaR freely accessible, we hope to encourage the research community to explore their EEG data beyond traditional ERP curves (peak amplitude and latency) obtained from the electrodes, especially by using the MPT as IC clustering tool.

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