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Clustering strategies for optimal trial selection in multisensor environments. An eigenvector based approach

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HIGHLIGHTS

- In this paper we have considered real, clinical scenarios in magnetoencephalography.
- We improve the performance of methods such as LCMV by using clustering techniques.
- The basis for these clustering techniques is the covariance matrix diagonalization.
- The eigenspace/eigenvector corresponding to the highest eigenvalue must be used.
- The projection of this eigenspace across trials provides the dissimilarity matrix.

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ABSTRACT

Background: Quite often, magnetoencephalography (MEG) measurements are contaminated by a series of artifacts that degrade the quality of the various source localization methods applied to them. In particular, eye blinking, minor head movement and related activities are a constant source of measurement contamination. In order to solve this problem, trial selection and rejection is applied, a task that is usually performed manually.
New method: The present work shows an automatic trial selection and rejection algorithm based on clustering techniques. These techniques employ a measurement of the dissimilarity of the items belonging to a set. This measure, based on the projection of the eigenvector corresponding to the largest eigenvalue of the covariance matrix, is provided and its rationale is explained. Subsequently, covariance matrices belonging to the selected cluster are averaged and used in the well-known Linearly Constrained Minimum Variance (LCMV) Beamformer.
Results: The results show a marked improvement of the specificity of the localization algorithm compared to the application of the LCMV without clustering.
Comparison with existing method(s): The method shows a marked reduction in computational cost compared with other data cleaning procedure widely used: Independent Component Analysis (ICA).
Conclusions: Thus, we propose clustering techniques to be used in brain localization activity algorithms.

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1. Introduction

Adaptive source localization techniques, such as LCMV, require prior knowledge or estimation of the covariance matrix for all the sensors for a specified time window. However, typical phenomena that arise during the measurements, such as minor head movements or eye blinking, can alter dramatically the underlying measures, and its corresponding covariance matrices. This, in turn, alters the estimation of the source position, a very important issue for further applications of the technique as a diagnosis tool Mäkelä et al. (2007).

The basis of the high resolution techniques considered in this paper is to relate the electromagnetic activity from groups of neurons (the emitter element) and the external recording of the magnetic field using appropriate sensors disposed around the head forming an array, such as shown in Fender (1987), Kavanagh et al. (1987), Salu et al. (1990) and Mosher et al. (1992). Especially relevant is the review of Ilmoniemi et al. (1985) in which several theoretical and practical aspects of biomagnetism are treated in depth.

The forward problem, i.e., the calculation of the value in any point of the space of the magnetic field produced by charge or current dipoles located in a defined position in the brain, has been thoroughly addressed. The solution depends on the geometry of the anatomical model and the electromagnetic properties of the different tissues, as Fender (1987), Kavanagh et al. (1987), Salu et al. (1990), Vrba and Robinson (1987) and Sarvas (1987) demonstrated. The forward problem, in essence, involves the calculation of the leadfield, that is, the measure obtained in the sensors when the unit elementary current is placed in a given place.

However, the main interest for the experimental and clinical problem is in the opposite problem, denoted as the inverse problem, i.e., to estimate the location of the underlying current dipoles from the measurements taken by an array of sensors which sample the magnetic field.

We shall focus on spatial filtering techniques, originated from the field of array signal processing (Haykin, 1985), (Pillai, 1989), that constitute a set of techniques well suited to provide a solution for the inverse problem.

From a mathematical point of view, spatial filters are designed as a constrained minimization problem. The specific formulation of the mathematical constrained minimization problem determines the type of the solution of the inverse problem.

For instance, the objective of the LCMV method Van Veen et al. (1997) is to design the spatial filters that pass the signal coming from specific locations, while attenuating signals from other locations. Specifically, the method designs the spatial filter which minimizes the output variance with the constraint of unit gain in the desired location.

In this paper we focus on a practical case related to the study of the auditory system. A MEG registry is realized to several subjects with previous informed consent. Acoustic stimuli could produce activity in different brain regions including the frontal or even the parietal lobe, depending on the subject expectancy and previous experience. However, it is expected that the main activity or at least the most stable activity should lie in the superior or mid temporal lobe where the primary auditory cortex is located. This localization of the activity was used in this study as a guide to evaluate the efficiency of the different source reconstruction methods as explained in the Section 3. Nevertheless the characteristic of the neural activity, namely its distribution over different spread areas, must be taken into account when evaluating the results obtained by different techniques.

We will use the LCMV implementation of Van Veen et al. (1997) without leadfield normalization. We think that this implementation provides an adequate basis for the generalization of the results here presented.

If there is an underlying phenomenon in a set of trials, given the measurements are subject to additive zero-mean noise, one possible way to treat this noise is via averaging the covariance matrices corresponding to each trial, as described in (Van Veen et al., 1997). If the noise is at least theoretically zero-mean, the averaging process should cancel or at least attenuate it. However, this averaging does not provide any protection against a possible bimodality or multimodality of the quantities under measurement. For instance, a subject under study could adequately receive a particular stimulus in a specific trial, while missing it altogether in another trial. Thus, a technique is needed to cope with these and similar problems that may arise in the measurement process. In this paper we propose the use of clustering techniques for this purpose.

The clustering techniques Pérez (2007) are multivariate techniques whose main goal is to create a number of approximately homogeneous groups among a given population. Another technique is the discriminant analysis Fisher (1936), which will not be discussed here. The most widely clustering methods used have the following features (Pérez, 2007):

- *Hierarchical*: it consists in a sequence of $g+1$ clusters $G_0, \ldots, G_g$, in which G_0 is the disjoint partition of all elements/individuals and G_g is the partition set.
- *Sequential*: the same algorithm is applied to each group in a recursive manner.
- *Agglomerative*: both individuals and groups are considered and successively the two most similar groups fuse until a classification is reached.
- *Exclusive*: no element/individual can belong to two distinct groups in the same stage.

All clustering techniques are based on the possibility of measuring, somehow, how similar or different are the members of a set. It must be noticed that in the general case, this dissimilarity may or may not be a distance, let alone a Euclidean distance. Sokal and Sneath (1963) classify the dissimilarities according to for great groups, namely, distances, association coefficients, angular coefficients and probabilistic similarity coefficients.

To realize the clustering, we propose the measure of the dissimilarity of the subspaces spanned by the eigenvectors corresponding to the largest eigenvalues of the covariance matrix of the trials. At this point, it should be taken into account that the dissimilarity measurement proposed should consider the fact that the same vector subspace is spanned by the vectors $\mathbf{u}_1$ and $-\mathbf{u}_1$. Therefore, the dissimilarity measurement should be almost zero when we compare an eigenvector $\mathbf{u}_1$ with an eigenvector $\mathbf{u}_2$, which is very near to $\mathbf{u}_1$ and should also be almost zero when we compare the eigenvector $\mathbf{u}_1$ with an eigenvector $\mathbf{u}_2$, which is very near to $-\mathbf{u}_1$.

The rationale for this approach is based on the following fact: if there is a main underlying phenomena (in our case the auditory stimulus) that causes the activation of determined channel sensors, it should be apparent from the low-rank approximation using the largest eigenvalues and its corresponding eigenvectors.

Finally, we present a set of tables and figures that illustrate the better performance when the clustering techniques are used against the case of using the whole set of covariance matrices that correspond to the full set of available trials, and also against the widely used Independent Component Analysis (ICA) method (Makeig, 1993; Comon, 1994; Makeig et al., 1997; Hyvärinen and Oja, 2000; Makeig et al., 2004). Additionally, it should be