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Brain Source Localization Based on Fast Fully Adaptive Approach

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Abstract—**In the electroencephalogram (EEG) or magnetoencephalogram (MEG) context, brain source localization (beamforming) methods often fail when the number of observations is small. This is particularly true when measuring evoked potentials, especially when the number of electrodes is large. Due to the nonstationarity of the EEG/MEG, an adaptive capability is desirable. Previous work has addressed these issues by reducing the adaptive degrees of freedom (DoFs). This paper develops and tests a new multistage adaptive processing for brain source localization that has been previously used for radar statistical signal processing application with uniform linear antenna array. This processing, referred to as the fast fully adaptive (FFA) approach, could significantly reduce the required sample support and computational complexity, while still processing all available DoFs. The performance improvement offered by the FFA approach in comparison to the fully adaptive minimum variance beamforming (MVB) with limited data is demonstrated by bootstrapping simulated data to evaluate the variability of the source location.**

Keywords-component; Brain source localization; fast fully adaptive processing; EEG signal

I. INTRODUCTION

Estimating the locations of sources of electrical activity in the brain is an important problem in electro- and magneto-encephalography (EEG and MEG). A large variety of algorithms have been developed for solving the EEG/MEG source localization problem, including multiple signal classification (MUSIC) [1], [2], minimum variance beamforming (MVB) method [3], sLORETA [4], and dipole fitting [5]. The EEG/MEG source localization problem is particularly difficult because the signal-to-noise ratio (SNR) is typically very low, the noise is spatially colored and often temporally nonstationary, and the number of data samples containing the activity of interest is often very limited. Scenarios involving both low SNR and a small number of observations are common, e.g., in the important case of measuring evoked potentials.

Localization methods that rely on estimating the second order statistics of the measured data or related quantities (such as signal/noise subspaces) such as MUSIC [1], MVB [3], and maximum likelihood dipole fitting (MLDF) [5] can provide excellent performance given a sufficient number of observations. However, in limited data scenarios the estimated second order statistics or subspaces possess considerable variance and localization performance deteriorates. The data requirements for such algorithms generally increase as the number of spatial channels (or electrodes) increase. For example, obtaining an accurate estimate of the sample covariance matrix to estimate the spatial covariance matrix of the data for MVB with N channels (N DoFs) to achieve statistically stable source location estimates requires at least $2N$ statistically independent data [3]. Consequently, the potential advantages of having large numbers of spatial channels are offset by the requirements for increased data.

To address these issues, researchers have developed techniques with lower complexity and fewer adaptive DoFs. One of these approaches is partial adaptivity, e.g., [6], in which the number of adaptive DoFs is reduced to meet the constraints on available data. A closely related approach is beamspace processing, e.g., [7], in which the sensor space data is mapped into a lower dimensional space using a linear transformation before applying the desired statistical signal processing algorithm. Reducing the adaptive DoFs yields corresponding reductions in the required sample support and computational load, at the expense of performance and reduced source discrimination.

An alternative approach is the Fast Fully Adaptive (FFA) method that exploits all available degrees of freedom while simultaneously reducing computational complexity and required sample support. This method has previously been used in the radar context for detecting targets buried in clutter using measured high frequency surface wave radar data with uniform linear antenna arrays [8], [9]. This multistage adaptive processing technique draws its inspiration from the butterfly structure of the Fast Fourier Transform (FFT). Essentially, the FFA approach sub-divides the N channels into several sub-channels of smaller dimensions, and then uses the fully adaptive approach within each such sub-channel to compute an intermediate statistic. The key idea underlying the FFA approach is that the *outputs* from each stage form the data matrix of the subsequent stage. This process of partitioning the newly formed data matrix, followed by adaptively processing each resulting partition, is repeated until the original $N \times 1$ dimensional (channel) data matrix be compared against a chosen threshold to determine if there is any activity at the location and time under test. Hence, as with the FFT algorithm, the FFA achieves lower complexity via a divide-and-conquer approach. A distinct advantage the FFA approach has over other conventional low-complexity beamforming methods, such as the beamspace approach, is that all the adaptive DoFs are used at every stage.

In this paper we design an FFA method for localizing brain sources from an EEG signal. The performance of this method is then evaluated by comparison with the MVB approach by applying the bootstrap [10] to the simulated EEG signal.

II. System Model and Fully Adaptive Approch

Here we design the FFA approach in the context of an EEG recording system with N electrodes. The N electrodes record the brain electrical activity over a short period of time T with the sampling frequency of f, so the number of time samples is $M = T \times f$. Hence the data can be organized as a $N \times M$ data matrix $\mathbf{x}$.

Let $\mathbf{x}(k)$ be an $N \times 1$ vector composed of the potentials measured by the electrodes at a given time instant k associated with a single dipole source. If this source has location represented by the 3×1 vector $\mathbf{q}$, then $\mathbf{x}(k) = \mathbf{H}(\mathbf{q})\mathbf{m}(\mathbf{q})$, where the elements of the 3×1 vector $\mathbf{m}(\mathbf{q})$ are the x, y and z components of the dipole moment at the time instant k that $\mathbf{x}$ is measured and the columns of the $N \times 3$ lead field matrix $\mathbf{H}(\mathbf{q})$ represent solutions to the forward problem. That is, the first column of $\mathbf{H}(\mathbf{q})$ is the potential at the electrodes due to a dipole source at location $\mathbf{q}$ having unity moment in the x direction and zero moment in y and z and directions. Similarly, the second and third columns represent the potential due to sources with unity moment in y and z directions, respectively.

The medium is linear so the potential at the scalp is the superposition of the potentials from many active neurons. Suppose $\mathbf{x}(k)$ is composed of the potentials due to active dipole sources at locations $\mathbf{q}_i, i = 1, 2, ..., L$ and noise. Then

$$\mathbf{x}(k) = \sum_{i=1}^{L} \mathbf{H}(\mathbf{q}_i)\mathbf{m}(\mathbf{q}_i) + \mathbf{n} \quad , \tag{1}$$

where $\mathbf{n}$ is the measurement noise. Note that $\mathbf{x}(k)$ does not contain any temporal information since it is obtained by sampling all electrodes at a single time instant k. It represents the spatial distribution of the measured potential at a sampling time. A linear processor uses a spatial $N \times 3$ weight (filter) matrix $\mathbf{W}(\mathbf{q}_0)$ to form a filtered output at location $\mathbf{q}_0$, i.e.,

$$\mathbf{y}(k) = \mathbf{W}^{\mathrm{T}}(\mathbf{q}_0)\mathbf{x}(k). \tag{2}$$

is reduced to a single final statistic whose magnitude can The optimal weight matrix, in the minimum output variance sense under the constraint $\mathbf{W}^{\mathrm{T}}(\mathbf{q}_0)\mathbf{H}(\mathbf{q}_0) = \mathbf{I}$ is given by $\mathbf{W}(\mathbf{q}_0) = \mathbf{R}^{-1}\mathbf{H}(\mathbf{q}_0)(\mathbf{H}^{\mathrm{T}}(\mathbf{q}_0)\mathbf{R}^{-1}\mathbf{H}(\mathbf{q}_0))^{-1}$ [3], where $\mathbf{R}$ is the covariance matrix of the noise, $\mathbf{R} = \mathrm{E}(\mathbf{n}\mathbf{n}^{\mathrm{T}})$, and T denotes the transpose of a matrix. In practice, the noise covariance matrix is unknown and must be estimated using training data as

$$\hat{\mathbf{R}} = \frac{1}{M}\sum_{k=1}^{M} \mathbf{x}(k)\mathbf{x}(k)^{\mathrm{T}} \quad . \tag{3}$$

However, as mentioned earlier, when the number of electrodes is large, an adequate number of time samples may not be available to estimate **R** accurately. This makes the estimation impractical.

III. Fast Fully Adaptive Approach

In this section we focus on the development of the FFA approach. The FFA scheme is of relatively low complexity, with the distinct advantage that the entire data is adaptively processed at every stage. The stages of FFA approach are illustrated in Fig. 1. In the first stage we adopt a divide and conquer strategy that partitions the N channel data vector $\mathbf{x}$ at each time instant k (k is removed for simplicity) into N_s smaller vectors of dimensions N' where $N' = N / N_s$ is chosen corresponding to the available training data. Importantly, $N' << N$. We then apply the fully adaptive approach algorithm on each of these partitions which results in a new $N_s \times 3$ matrix $\mathbf{y}$ whose entries are composed of the complex output statistics, using (2), of the corresponding fully adaptive processes. The resulting $N_s \times 3$ data-matrix $\mathbf{y}$ is again repartitioned (not necessarily in the same way as the original data vector) and each partition is processed by the fully adaptive approach yielding the next stage of outputs. This procedure is repeated until a final statistic is obtained. Note that in each stage the noise will be suppressed in each partition by the fully adaptive approach yielding an attenuated residual noise in the forthcoming processing stage.

Here we formalize the approach. At each time instant k the $N \times 1$ data vector $\mathbf{x}$ and the $N \times 3$ lead field matrix $\mathbf{H}$ for the location under test, $\mathbf{q}$ ($\mathbf{q}$ is removed for simplicity) are partitioned into N_s submatrices of size $N' \times 1$ and $N' \times 3$, respectively. Denote the n^{th} partition of the data and lead field matrix as $\mathbf{x}_n^0$ and $\mathbf{H}_n^0$, $n = 1, 2, ..., N_s$. The superscript ^{0} specifies that we are currently processing the starting (zeroth) stage in the tree-like structure. The fully adaptive approach is used within each partition. Consider the n^{th} partition, with data matrix $\mathbf{x}_n^0$ of size $N' \times 1$. The sample support required to estimate the relevant covariance matrix, $\mathbf{R}_n^0$, is reduced from $2N$ to approximately $2N'$, with corresponding reductions in the computational load to solve the resulting matrix

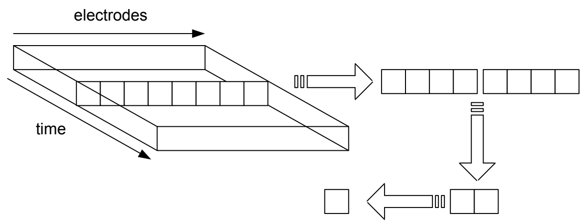

Fig. 1. The multistage representation of the FFA method.

equation. The weight matrix for the n^{th} partition is given by $N' \times 3$ weight vector $\mathbf{W}_n^0 = (\hat{\mathbf{R}}_n^0)^{-1}\mathbf{H}_n^0$. The intermediate statistic (the 3×1 vector $\mathbf{y}_n^1$, for the next stage, corresponding to this n^{th} partition is given by

$$\mathbf{y}_n^1 = (\mathbf{W}_n^0)^T \mathbf{x}_n^0 = (\mathbf{W}_n^0)^T \mathbf{n}_n^0 + (\mathbf{W}_n^0)^T \mathbf{H}_n^0 \mathbf{m} = \mathbf{n}_n^1 + \mathbf{H}_n^1 \mathbf{m}, \quad (4)$$

where $\mathbf{n}_n^0$ is the noise component in the n^{th} partition which reduces to $\mathbf{n}_n^1$ in the next stage, $\mathbf{H}_n^1$ is 3×3 and $\mathbf{m}$ is the dipole moment at location $\mathbf{q}$.

A consideration in adapting the FFA method from the radar case to the BSL case is that the outputs $\mathbf{y}$ are 3×1 vectors instead of scalars. We address this issue as follows. From (4), the second stage comprises a $N_s \times 3$ data matrix $\mathbf{x}^1 = (\mathbf{y}_1^1, \mathbf{y}_2^1, \ldots, \mathbf{y}_{N_s}^1)$ containing the brain activity at location $\mathbf{q}$ but with new lead field matrix $\mathbf{H}^1 = (\mathbf{H}_1^1, \mathbf{H}_2^1, \ldots, \mathbf{H}_{N_s}^1)$ of dimension $N_s \times 3 \times 3$. In the second stage, first the lead field matrix $\mathbf{H}^1$ is reshaped to a $3N_s \times 3$ matrix $\mathbf{H}'^1$ by concatenating the N_s matrices of dimension 3×3. Similarly, the data matrix $\mathbf{x}^1$ is reshaped to a $3N_s$ vector $\mathbf{x}'^1$. Therefore the sample support required to estimate the relevant covariance matrix is three times of the first stage. The algorithm iterates the partitioning and processing in a similar fashion to the second stage until a single final statistic is obtained. Then the output of the final stage "P" is calculated by $\mathbf{y}^P = (\mathbf{W}^P)^T \mathbf{x}^P$.

The expected advantages of the FFA are clear: the use of the divide-and-conquer approach allows for all DoFs to be used while significantly reducing both the sample support requirements and computation load. However, it is important to note that the FFA scheme does not lead to an equivalent model of the optimal fully-adaptive method which solves for all N DoFs simultaneously. As a result, if adequate sample support were available, some performance degradation is expected. However, for the case where the number of channels is large and so the sample support is limited, the optimal fully adaptive approach is not implementable and the FFA becomes a strong practical alternative. The method is readily made adaptive by computing **R**, **W**, and **y** in a time-recursive fashion.

IV. Performance Evaluation

In this section we conducted a simulation for EEG measurements in the 4-layer spherical head model [11] in order to illustrate the performance of our methods for practical systems. The nominal radii and conductivities of the 4 layers corresponding to the brain, CSF, skull, and scalp, were chosen to be $[7.1, 7.2, 7.9, 8.5]$ cm and $[0.33, 1, 0.0042, 0.33]$ S/m, respectively [12]. To simulate our source, we chose a current dipole located at $[x, y, z] = [-3, 5, -2]$ cm. The x, y, and z components of the dipole moment in time are defined as:

$$\begin{aligned} m_x(t) &= 0.3e^{-(t/50-3)^2} - 0.13e^{-(t/50-4)^2} \\ m_y(t) &= 0 \\ m_z(t) &= 0.15e^{-(t/50-4)^2} - 0.5e^{-(t/50-3)^2} \end{aligned} \quad . \qquad (5)$$

In (5), t is continuous with a duration of 400 ms. We sampled these signals at a frequency of 200 Hz, thus obtaining $M = 80$ time samples for the computer simulations. We use a standard 10–10 EEG configuration of $N = 81$ channels for the lead field matrix. The lead field matrices $\mathbf{H}(\mathbf{q})$ are calculated for horizontally located cross-sections at 1 cm intervals. In each of the sections, lead field matrices are determined on a uniform grid with 1 cm spacing in each direction. The vertical location of each cross section is represented by a position on a z-axis, with increasing height corresponding to increasing values. Within each cross section the x -axis is front–back with front positive and the y-axis is right–left with left positive. In order to evaluate the performance of our method we added uncorrelated (in time and space) normally distributed random noise with SNR of 5dB. The result of the simulations using both FFA and MVB approaches are shown in Fig. 2. As is clear from Fig. 2(a), the MVB approach leads to a broad spatial spread in brain activity. This comes from the fact that the number of data needed to calculate the covariance matrix accurately for this case is $2N = 160$, while the available time samples are 80. This lack of data leads to an inaccurate estimation of covariance matrix and so the output. Figure 2(b) shows the same result using the FFA approach with the partitioning sequence of $[N'^1, N'^2, N'^3, N'^4]$=[3,3,3,3], where N'^i shows the length of the partitions in the i^{th} stage. The number of time samples needed for calculating the covariance matrix in this case is $2\times3\times\max(N'^i) = 2\times3\times3 = 18$, which is about one fourth of the number of available time samples $M = 80$. Therefore, the covariance matrix can be calculated accurately and so the FFA method shows just one peak at the source location with the amplitude of about 100 times larger than MVB method.

To further investigate the performance of the FFA algorithm we evaluate the algorithm when a spike activity is injected at a particular location of a brain in a specific time sample. Bootstrapping is employed to assess the variability of the source location and time estimates when a spike source is placed in the same location but at different time instances, for data records of varying lengths. Figure 3 presents the percentages of the 100 resamples that are localized within 1 cm of the true location and within the true time sample, as a function of the number of observations for the MVB and FFA algorithms. This measures localization consistency for each method across the resamples. The results for MVB between 50-80 samples are not computed because the estimated covariance matrix is singular in this region (and thus is not invertible) and the performance of this method cannot be evaluated. As the figure shows, the consistency of the localization estimates is greatly improved by FFA processing with small numbers of time samples and is considerably less improved when more than 140 time samples are employed.

V. Conclusion

In this paper a fast fully adaptive approach is designed for brain source localization. This method uses a divide-and-conquer strategy to significantly reduce the computational complexity and sample support requirements of the fully-adaptive scheme. The performance of the FFA scheme is tested by applying the bootstrap to the simulated EEG data. The FFA brain localization showed a reduced variability in comparison to the fully adaptive MVB approach. The improved performance of the FFA schemes arises at the cost of increased computational complexity. This is because of the multiple, although smaller, fully adaptive processes that must be executed. One could envision a parallel implementation of these processes to reduce the computational time per brain location. However, it is important to note that the FFA scheme addresses the fundamental limiting factor in fully adaptive beamforming, which is the limited quantity of available training data.

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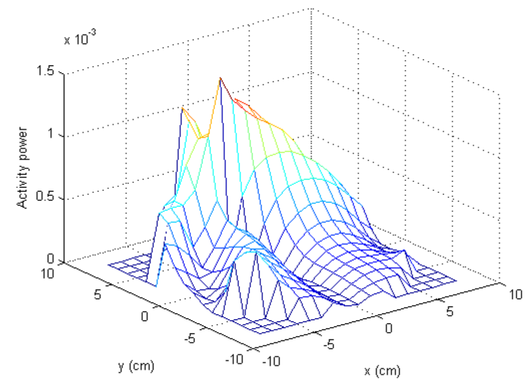
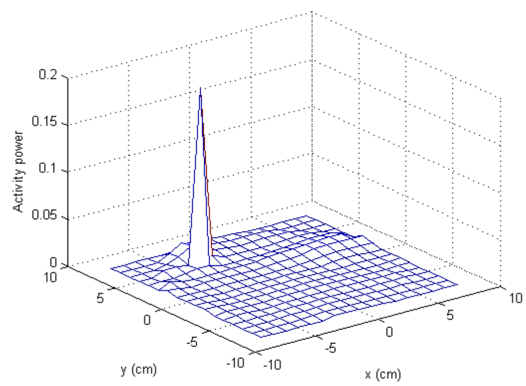


(a)



(b)

Fig. 2. The 2D plot of the brain activity at z=2 cm and t = 145 ms for (a) MVB and (b) FFA approaches.

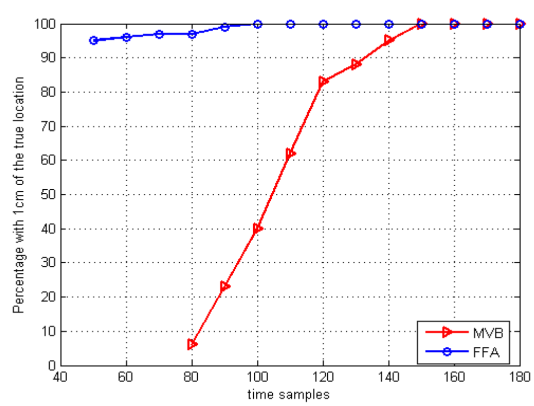


Fig. 3. Percentage of bootstrap resamples for which the source is localized within 1 cm of the true location for the MVB and FFA methods.