SOURCE LOCALIZATION OF BRAIN ELECTRICAL ACTIVITY VIA TIME-FREQUENCY LINEARLY CONSTRAINED MINIMUM VARIANCE METHOD

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ABSTRACT

The locations of active brain areas can be estimated from the surface recordings. We describe the localization of the sources of the brain electrical activity via spatial filtering. This method incorporates the time-frequency characteristics of the neural sources for its location. The estimation of the location of active brain area is done in non-parametric fashion. The spatial filters are implemented as weighted sum of data recorded at different sites. The weights are chosen to minimize the output of the filter subject to linear constraint. The function of the linear constraint is to pass the brain electrical signal from a specific location, while attenuating the overall variance at the output of the filter. The method exploits space-time-frequency covariance matrix of the data. The proposed algorithm is suited to localizing sources of time-varying and nonstationary signals. For this reason, this paper focuses on the class of frequency modulated (FM) signals, e.g., chirp signals.

1. INTRODUCTION

Functional brain imaging is a relatively new and multidisciplinary research field that encompasses techniques devoted to better understanding of human brain through noninvasive imaging of the electrophysiological, hemodynamic, metabolic and neurochemical processes that underlie normal and pathological brain function. Neural activity in the brain is often recorded from a scalp electrodes. Magnetoencephalography (MEG) and electroencephalography (EEG) localize neural electrical activity using noninvasive measurements of external electromagnetic signals. In this paper, we propose a novel method that incorporates source time-frequency characteristics into the source location estimation. In our approach, the evaluation of quadratic time-frequency distributions of the data snapshots across the sensors yields spatial time frequency distributions (STFD). These distributions are most appropriate to handle non-stationary sources. STFD localize the signal energy while spreading the noise in the entire time-frequency plane and thus enhance SNR. Our method (time-frequency Linearly Constrained Minimum Variance (LCMV) method) is shown to have superior performance than conventional LCMV proposed in [1]. This superior performance is attributed to the following reasons: 1) Increase in SNR 2) the localization of signals in time-frequency domain permits to select fewer signals than those incident on the array and hence the space time frequency distribution matrices can be constructed by taking into account fewer signals which can be used in place of data covariance matrix in LCMV method.

The paper is organized as follows: In section 2, the data model is presented and conventional LCMV method is discussed. Section 3 is devoted to spatial time frequency distributions and the LCMV method based on these distributions. Section 4 and section 5 discusses simulations and conclusions respectively.

2. DATA MODEL

If the extent of the source area is small as compared to the distances to the sensors, the measured magnetic field resembles that generated by a current dipole. Multiple spatially separated sources can be modeled by several dipoles. For the sake of simplicity we assume that we have knowledge of dipole orientation. The relationship between dipoles models and the surface recordings is obtained in the following way.

Let \( \mathbf{z} \) be an \( M \times 1 \) vector composed of the potentials measured at the \( M \) electrodes sites at a given instant of time associated with the \( p \) dipoles sources. Let \( a(q_i) \) be the gain vector associated with the dipole at location \( q_i \). The source
magnitude vector is defined as
\[ s(t) = [s_1(t)s_2(t)\ldots s_p(t)]^T \] 
(1)
The measured signal can be expressed mathematically as
\[ x = \sum_{i=1}^{p} a(q_i)s_i(t) + n(t) \] 
(2)
where \( n(t) \) is the measurement noise. The electrical activity of an individual neuron is assumed to be a random process influenced by external inputs to the neuron. Electrical data is collected as a potential measured with respect to a reference electrode.

2.1. Linearly constrained minimum variance localization (LCMV)
The LCMV approach or Capon method is based on the concept of spatial filtering. Spatial filtering refers to the discrimination of the signals on the basis of their spatial location. LCMV method originated in radar and sonar signal processing but has since found applications in diverse fields ranging from astronomy to biomedical signal processing. Let us consider a LCMV method that monitors signal from dipole at location \( q_o \), while blocking contribution from all other active brain locations. Let \( a(q_o) \) be the gain vector associated with the dipole at location \( q_o \). Having multiple observations at different time intervals, we now design a single spatial filter \( w(q_o) \) to minimize the output variance subject to unity gain constraint on the response to the dipole of interest. In other words the LCMV problem can be written as
\[ \min_w \{w(q_o)^TC_{xx}w(q_o)\} \] 
subject to
\[ w(q_o)^Ta(q_o) = 1 \] 
(3)
(4)
where \( C_{xx} = E[xx^T] \), where \( E \) is expectation operator. Solving the above constrained minimization problem using the method of Lagrange multipliers yields
\[ w(q_o) = \frac{C_{xx}^{-1}a(q_o)}{a(q_o)^TC_{xx}^{-1}a(q_o)} \] 
(5)
The estimation of the location of the dipole is given by the minimum of the following equation
\[ \operatorname{var}(q_o) = \frac{1}{a(q_o)^TC_{xx}^{-1}a(q_o)} \] 
(6)
Similarly we can produce estimate of neural activity at any other location. Unfortunately, often correlated nature of the neural activation in the different parts of the brain will often limit the performance of the LCMV method. This is because the correlation between different sources will result in partial signal cancellation. In the case of perfectly correlated sources the LCMV method completely fails. Better results will be obtained by using time-frequency LCMV method as described below.

3. TIME-FREQUENCY LCMV METHOD
The time-frequency LCMV method is based on the construction of space time-frequency distribution (STFD) matrices. The STFDs based on quadratic (Cohens class) time-frequency distributions was introduced in [3]. We will discuss STFD method based on pseudo Wigner-Ville distribution. The discrete form of PWVD of a signal \( x(t) \), using rectangular window of length \( L \), is given by
\[ C_{xx}(t,f) = \sum_{\tau=-L}^{L} x(t+\tau)x^*(t-\tau)e^{-j2\pi f\tau} \] 
(7)
where \((\cdot)^H\) denotes the Hermitian transpose. Taking separately, i.e., for each sensor, PWVD of the received signal will give PWVD at each sensor. We consider time-varying signals, e.g., Frequency Modulated (FM) signals, these have clear (well separated) PWV representation. It is shown in [3] that if we select the time frequency points along the time-frequency signature of the signal of interest is given by
\[ C_{xx}(t_i,f_i) = \frac{1}{N-L+1} \sum_{i=1}^{N-L+1} C_{xx}(t_i,f_i) \] 
(8)
where \( f_i \) is the instantaneous frequency of the signal of interest at \( t_i \) time sample. In the above equation, we construct the space time frequency distribution matrix by taking into account the region of interest in the time-frequency plane i.e., signal of interest region plus noise in that region. Hence \( C_{xx} \) will almost be free of the interfering signals, i.e, neural activities other than neural activity of interest, (neglecting interference terms of the distribution). By replacing the covariance matrix in the LCMV method with the above space time frequency distribution matrix, we obtain time-frequency LCMV method. More precisely, we have
\[ w(q_o) = \frac{C_{xx}^{-1}a(q_o)}{a(q_o)^TC_{xx}^{-1}a(q_o)} \] 
(9)
and the output energy is

\[ E|x(t)|^2 = \frac{1}{\sigma(q_0)^T C_{xx}^{-1} \sigma(q_0)} \]  

(10)

The advantage of the time-frequency LCMV method over conventional LCMV method are follows:
1) Better source location estimates
2) Conventional LCMV method will completely fail if the two or more sources are correlated. On the other hand time-frequency LCMV method will resolve the source localization problem successfully by constructing space time frequency distribution matrix for each source separately.

4. SIMULATIONS

We assume that two areas of the brain are simultaneously active and model their signal as time varying (in our case as chirps). We also assume for simplicity that the active areas in brain and the sensors lie in the same plane. We consider a simple case of FM signals such that their time-frequency signatures do not overlap. The start and the end frequency of the first signal, \( s_1(t) \) are \( f_{1s} = 0.3 \) and \( f_{1e} = 0.5 \) respectively and those for the second signal \( s_2(t) \) are \( f_{2s} = 0 \) and \( f_{2e} = 0.4 \) respectively. The direction of arrivals (DOAs) of the two signals are \( \theta_1 = 5^\circ \) and \( \theta_2 = -5^\circ \) respectively. Both LCMV method and time-frequency LCMV method gives satisfactory results upto SNR of 5 dB. Figure 1 shows the mixture of two noiseless chirp signals. Figure 2 and figure 3 shows Wigner-Ville and Pseudo Wigner-Ville distribution of the two chirp signals respectively. In these figures we can see clearly the interference terms. Figure 4 shows Smoothed Pseudo Wigner-Ville distribution, it is clear from the figure the suppression of interference terms but this is achieved at the expense of signal resolution in the time-frequency plane. Now we fix SNR to be -5dB. The window length is chosen to be, \( L = 129 \) and the number of samples across the sensors, \( N = 256 \). For eight independent trials for DOA estimation (see figure 5 and figure 6), it is evident that the LCMV method based on space time frequency distribution matrix out performs conventional LCMV method.

5. CONCLUSIONS

In this paper, we presented nonparametric source localization estimation using time-frequency distributions. The results are compared with the LCMV method for source localization estimation. Better results are obtained because the covariance matrix in the LCMV method is replaced with the space time frequency distribution matrix. We considered the case of two chirp signals. These signals have clear time-frequency signatures. Using time-frequency distributions we enhance the SNR of signals and we can construct space
time frequency distribution matrices by selecting only region of interest, i.e., in order to calculate the DOA of source 1, we select source 1 region of interest in the time-frequency plane. In this manner we eliminate interference term which is due to the second source and the space time frequency distribution matrix can be constructed only from the signal of interest, the same procedure applies in estimating the DOA of the second source.

6. REFERENCES


