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Estimation of the Position of Electrocortical Generators via Subspace Techniques

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Abstract:

There are a number of approaches to the application of subspace techniques for solving spectral estimation problems. These approaches are derived from the covariance matrix which is constructed from incoming data. The covariance matrix can be broken down through the use of appropriate matrix properties and eigen-decomposition techniques into two subspaces. The performance of three traditional algorithms which incorporate subspace techniques in the direction of the arrival are evaluatedunder white and 1/f noise conditions. 1/f noise is chosen because it is typical of the EEG signals. Simulation resultssuggest that the Johnson and DeGraaf direction finding algorithm performs best under both noise environments.

Estimation of the Position of Electrocortical Generators via Subspace Techniques.

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ABSTRACT

There are a number of approaches to the application of subspace techniques for solving spectral estimation problems. These approaches are derived from the covariance matrix which is constructed from incoming data. The covariance matrix can be broken down through the use of appropriate matrix properties and eigen-decomposition techniques into two subspaces. The performance of three traditonal algorithms which incorporate subspace techniques in direction of arrival are evaluated under both white and 1/f noise conditions. 1/f noise is chosen becasuse it is typical of the EEG signals. Simulation results suggest that the Johnson and DeGraaf direction finding algorithm performs best under both noise environments.

A typical sample of EEG data was used to evaluate the performance of the three algorithms. The Johnson and DeGraaf algorithm gives estimates for the direction of the signal which approximately agree with the anatomical locations of possible electrocortical generators.

INTRODUCTION

There are a number of approaches to the application of subspace techniques for solving spectral estimation problems. These approaches are derived from the covariance matrix which is constructed from incoming signal data. The covariance matrix can be broken down through the use of appropriate matrix properties and eigen-decomposition techniques into two subspaces, the signal subspace and a noise subspace [1]-[5].

The work described here applies subspace techniques to the processing of electroencephalogram (EEG) signals, microvolt potentials generated by sources within the brain and measured at the surface of the scalp. The aim is the estimation of the position of electrocortical generators in the brain.

This paper consists of five sections. Section one reviews some of the current and past work in the area of subspace techniques for solving spectral estimation problems. Section two describes the area of application to both EEG and driven EEG. Section three describes the results of simulations with the subspace algorithms and a discussion of the limitations of these algorithms under the conditions outlined. In this section the algorithms are compared under white Gaussian noise and coloured noise conditions. Section four discusses the results of the application of subspace techniques to the EEG context.The final section offers conclusions and comments on possible further work in this area.

1. SIGNAL SUBSPACE METHODS

This section will briefly review signal subspace methods. The following analysis assumes a system model in which M far-field sources are viewed by N sensors ($N \geq M$). The sensors may exist in any configuration, for example a linear or circular array. This paper will be based on a linear phased array. Consider the system

$$\mathbf{x} = \mathbf{V}\mathbf{s} + \mathbf{n}, \tag{1}$$

where $\mathbf{x}^T = [x(1), x(2),..., x(n)..., x(N)]$,

represents the instantaneous signals at the N sensors;

$$\mathbf{s}^T = [s(1),s(2),...,s(m),...,s(M)],$$

represents the plane wavefronts from the M sources;

and $\mathbf{n}^T = [n(1), n(2),....,n(n),...,n(N)]$

represents the instantaneous receiver noise contributions to the signals at the N sensors, and the (N x M) matrix **V** represents the response of the N sensors in the M signal directions. The matrix V cannot be specified until the directions to the sources are known, thus eqn. (1) cannot be solved directly.

The subspace methods require the use of the covariance matrix of the system model which is defined as:

$$\mathbf{C} = E\{\mathbf{x}\mathbf{x}^H\}=E\{(\mathbf{V}\mathbf{s} + \mathbf{n})(\mathbf{V}\mathbf{s} + \mathbf{n})\}^H \tag{2}$$

where E is the expectation operator and H is the hermitian operator. If the sources are uncorrelated with the receiver noise then $E\{\mathbf{n}\mathbf{s}^H\} = E\{\mathbf{s}\mathbf{n}^H\} = 0$ (3)

and if the noise is white Gaussian with variance σ^2

$$\mathbf{C} = \mathbf{V}\mathbf{C}_s\mathbf{V}^H + \mathbf{C}_n = \mathbf{V}\mathbf{C}_s\mathbf{V}^H + \sigma^2\mathbf{I}, \tag{4}$$

The direction finding (DF) problem in this system is the identification of the direction vectors

$$\mathbf{v}_m^T=\{v(1,m),v(2,m),...,v(N,m)\}, \quad m = 1,...,M \tag{5}$$

Given that all the possible correlations between a pair of individual sensor signals exist in **C** it is possible through the use of eigen-decomposition techniques to decompose the complex space that **C** spans into two mutually orthogonal subspaces. These are the signal subspace and the noise subspace. It can be shown that either the signal or the noise subspace contain all the necessary information required to determine the number of sources and the direction of arrival[2].

Using the hermitian property of **C** we are able to transform it into a real diagonal matrix Λ using a unitary matrix **U** as shown below:

$$\mathbf{U}^H\mathbf{C}\mathbf{U} = \Lambda \text{ or } \mathbf{C} = \mathbf{U}\Lambda\mathbf{U}^H \qquad (6)$$

where the columns of $\mathbf{U}=[\mathbf{u}_1, \mathbf{u}_2,..., \mathbf{u}_N]$ are the eigenvectors of **C** and Λ holds the eigenvalues.

$$\Lambda = \mathrm{diag}[\lambda_1,\lambda_2,...\lambda_N] \text{ with } \lambda_1 \geq \lambda_2 \geq .. \geq \lambda_N \qquad (7)$$

The transformation can be written as:

$$\mathbf{C} = \sum_{n=1}^{N} \lambda_n \mathbf{u}_n \mathbf{u}_n^H \text{ and } \mathbf{C}^{-1} = \sum_{n=1}^{N} \lambda_n^{-1} \mathbf{u}_n \mathbf{u}_n^H \qquad (8)$$

and since $\mathbf{U}^H = \mathbf{U}^{-1}$ (a property of a unitary matrix), $\mathbf{u}_i^H\mathbf{u}_j$ constitute an orthonormal set.

Assuming that there are more sensors than unknown sources, i.e. $M \leq N$, [2] shows that there must be (N-M) eigenvalues λ_n equal to the noise variance σ^2. The corresponding (N-M) eigenvectors form the noise subspace. As a result the M largest eigenvectors of **C** are the M orthonormal vectors which form a subset of the entire complex vector space. This space is known as the signal subspace and it contains the signal vectors.

The subspace approach can be expressed concisely by:

$$\mathbf{C} = \begin{bmatrix} \mathbf{U}_s & \mathbf{U}_n \end{bmatrix} \begin{bmatrix} \Lambda_s & 0 \\ 0 & \Lambda_n \end{bmatrix} \begin{bmatrix} \mathbf{U}_s \\ \mathbf{U}_n \end{bmatrix} \qquad (9)$$

It can be shown [2][5] that $\mathbf{V}^H\mathbf{u}_n=0$ for $n=M+1,...,N$. By sweeping the direction vector $\mathbf{v}^T(\theta)$ through all possible values of θ and over all noise eigenvectors we can derive the MUSIC_n[2], Johnson and DeGraaf ($\mathrm{J\&D}_n$) [3] direction finding functions[5]. Whereas MLM_n[1] can be derived by sweeping $\mathbf{v}^T(\theta)$ over all eigenvectors.

$$\mathrm{MUSIC}_n(\theta) = 1 \Big/ \left(\sum_{n=M+1}^{N} \left| \mathbf{v}^H(\theta)\mathbf{u}_n \right|^2 \right) \qquad (10)$$

$$\mathrm{J\&D}_n(\theta) = 1 \Big/ \left(\sum_{n=M+1}^{N} \lambda_n^{-1} \left| \mathbf{v}^H(\theta)\mathbf{u}_n \right|^2 \right) \qquad (11)$$

$$\mathrm{MLM}_n(\theta) = 1 \Big/ \left(\mathbf{v}^H(\theta) \sum_{n=M+1}^{N} \lambda_n^{-1} \mathbf{u}_n \mathbf{u}_n^H \mathbf{v}(\theta) \right) \qquad (12)$$

2. AREA OF INVESTIGATION

Since the discovery of the EEG 60 years ago, innumerable studies have investigated the relationships between neural phenomena, the performance of cognitive tasks, and associated changes in the EEG which are called Event Related Potentials [6]. The Swinburne Centre for Applied Neurosciences (SCAN) has developed a novel extension of traditional methodology, based on the technique of Steady-State Visually Evoked Potentials (SSVEP) in which the subject is exposed to a continuously flickering visual driving signal whilst performing cognitive tasks [7]. The signal processing significance of the visual driving signal is that in excess of 38% of all sensory input pathways to the brain's cortex are linked to the visual pathways [8], so that driving the visual pathways presents a substantial known input driving signal to the cortex. The system identification problems which are intrinsic to most EEG signal analysis work are therefore ameliorated to some extent.

The EEG is recorded with the subjects wearing a specially designed helmet with 64 sensors. The rigidity of the helmet guarantees the relative positioning of the electrodes, which are positioned according to the International 10-20 system for EEG recordings. Additional electrodes are placed at sites extrapolated between the 20 sites defined by the 10-20 standard. The resultant inter-electrode separation, with an average distance at the scalp of about 2.5 cm, is a significant improvement over that available with traditional 20 electrode arrays[7].

By measuring the spatial distribution of EEG activity under well-defined, stringent test conditions [7][9], estimation of the positions of the electrocortical generators in the brain is equivalent to the classical problem of estimating the location of multiple emitters. The estimation problem is complicated by the noise present in the system. This noise is not usually Gaussian but more likely in some, if not most, brain states of interest to be closer to 1/f noise. Where the noise is characterisable, it may be accounted for in the signal analysis, whilst errors in the characterisation of the noise component lead to consequential uncertainty in the parameter estimations.

3. SIMULATION RESULTS

This section describes the results of simulations with the subspace algorithms and a discussion of the limitations of these algorithms under the conditions outlined below:

-varying signal-to-noise ratio,

-varying numbers of signal snapshots, and therefore variations in the quality of the covariance matrix,

-varying numbers of sensors, thus variations in aperture.

Traditionally results have been presented in the literature which assume the noise to be white Gaussian. This last assumption is not true for the EEG environment, refer figure 3.1 where the noise is similar to 1/f noise. We reproduce the white and 1/f noise simulated conditions and compare the performance of each algorithm under the different noise environments.

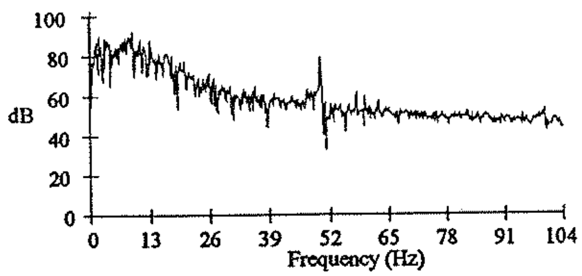

Figure 3.1 Typical EEG Spectrum

3.1 White Noise Results

The following simulation results apply to the MUSIC, J&D and MLM algorithms under the following conditions:

Linear array of NE sensors spaced at 0.5 l.

Two narrowband sources at +5 and -5 degrees.

Noise variance 1.0

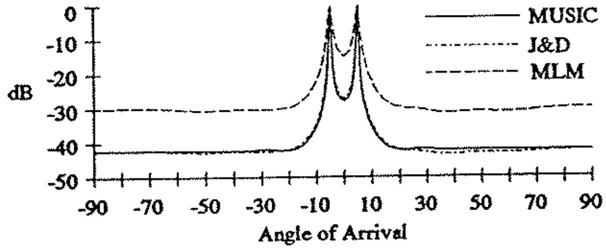

Figure 3.1.1 N=256 S/N=20dB NE=8

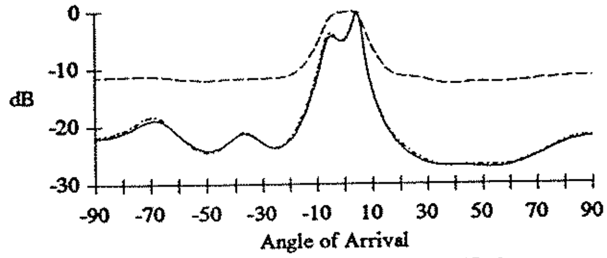

Figure 3.1.2 N=256 S/N=0dB NE=8

Figure 3.1.1 shows the results for a 20dB S/N ratio and 256 snapshots. As can be seen all three algorithms can successfully resolve the two sources. As the S/N ratio degrades the MLM cannot resolve the sources, while MUSIC and J&D offer better performance, see figure 3.1.2

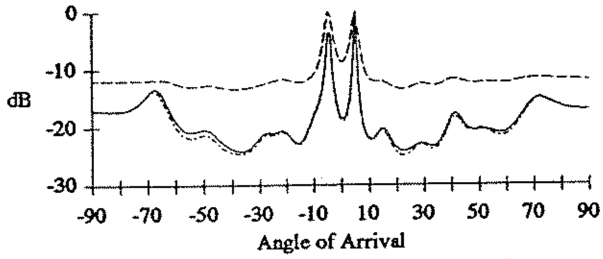

Figure 3.1.3 N=256 S/N=0dB NE=16

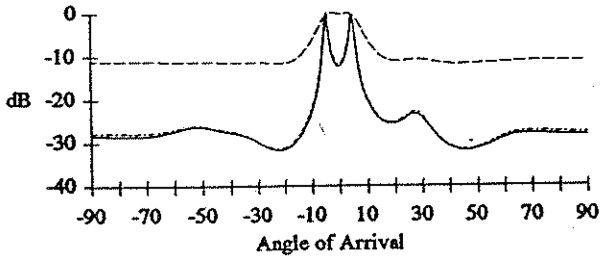

Figure 3.1.4 N=1024 S/N=0dB NE=8

Increasing the number of sensor elements improves the performance see figure 3.1.3 where all three algorithms successfully resolve the two sources. Extra peaks begin to appear at the lower S/N ratios. Increasing the number of snapshots also improves the performance for MUSIC and J&D, while MLM cannot resolve the two sources, refer to figure 3.1.4. Decreasing the number of snapshots or the number of sensors reduces the resolution capabilities of the three algorithms thereby broadening the peaks.

3.2 1/f Noise Results

The 1/f noise simulation results were conducted under similar conditions to the white noise case. The power of the 1/f noise was chosen so that the S/N ratios were directly comparable with the white noise case.

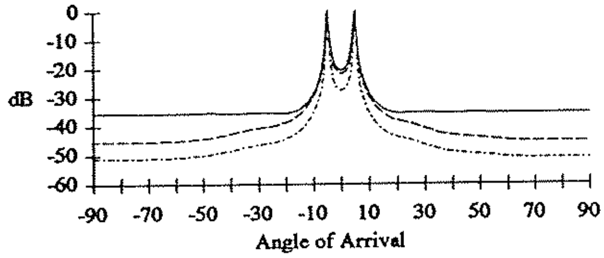

Figure 3.2.1 N=256 S/N=20dB NE=8

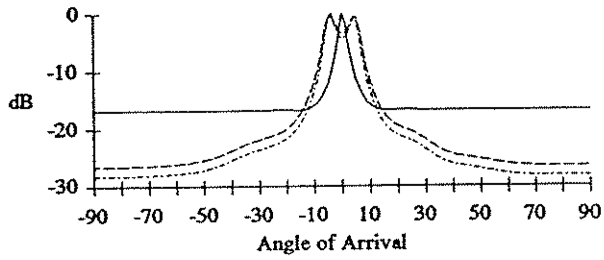

Figure 3.2.2 N=256 S/N=0dB NE=8

Figure 3.2.1 shows the results for a 20dB S/N ratio and 256 snapshots. Again all three algorithms can successfully resolve the two sources. As the S/N ratio degrades MUSIC cannot resolve the sources, while MLM and J&D offer better performance, refer to figure 3.2.2

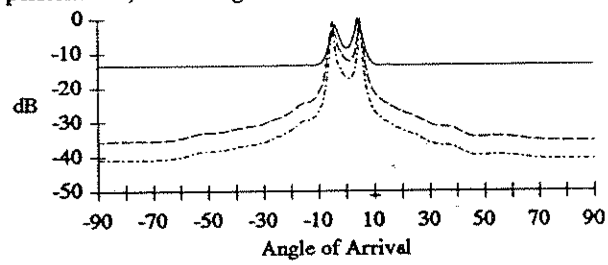

Figure 3.2.3 N=256 S/N=0dB NE=16

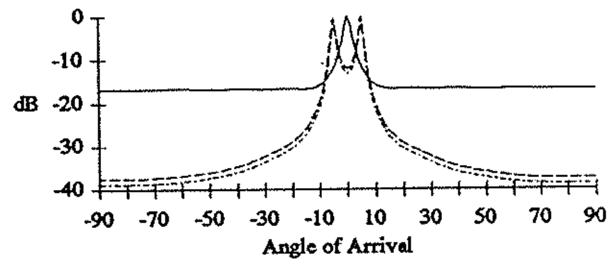

Figure 3.2.4 N=1024 S/N=0dB NE=8

Increasing the number of sensor elements improves performance, figure 3.2.3, however the improvement is not as good as for the white noise case. Increasing the number of snapshots also improves the performance for MLM and J&D, while MUSIC cannot resolve the two sources, refer to figure 3.2.4.

MLM and J&D provide better resolution performance in this 1/f noise environment, while MUSIC and J&D perform better than MLM in the white noise case. J&D performs best over both noise environments.

4. RESULTS OF EEG ANALYSIS

This work includes EEG data recorded in the presence of visually applied driving signals at a range of frequencies. The particular case under investigation is when the subject is exposed to a sinusoidal visual driving signal of 13 Hz. The algorithms require that the sensor array be a liner phased array. In this case, sensors on the helmet were chosen which approximated a linear array. The sensors chosen were spaced at approximately 35mm. Assuming an average wave velocity in the cortex of $7ms^{-1}$ the separation becomes approximately 0.065 wavelengths. The EEG signal was filtered to remove unwanted components, the correlation matrix formed and the DF plotted. Figures 4.1 and 4.2 show results of two perpendicular arrays located at the top centre of the scalp.

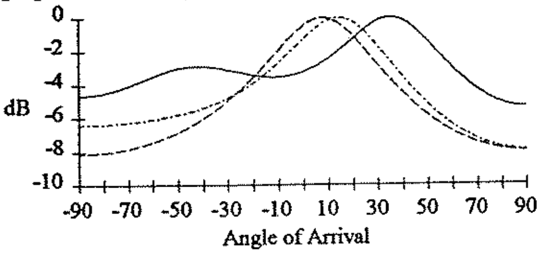

Figure 4.1 Driven at 13Hz NE=5 Array Normal

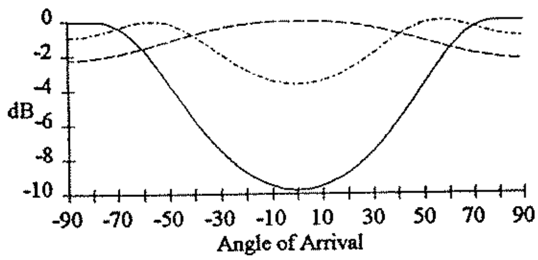

Figure 4.2 Driven at 13Hz NE=5 Array Perpendicular

From the simulation results we assume that J&D gives the best estimates for the direction of the signal the results approximately agree with the anatomical locations of possible electrocortical generators, one of which may be the visual cortex (+60,-60 +13 degrees). However, we must be careful in the interpretation of the results due to a number of factors. Firstly the S/N ratio in the EEG environment is low and the algorithms do not perform well in this case. The simulation results clearly show this. Secondly the sensors are assumed to be collinear and equispaced. This is not exactly true for the 10-20 system. Thirdly the algorithms are sensitive to the spacing of the sensors, since an average wave velocity was used this could introduce errors. Finally the decision making criteria which determines the number of sources was very simple and requires further work to establish more rigorous results.

CONCLUSION

The paper has presented a comparison of three DF algorithms in the presence of white and 1/f noise. From the simulation results Johnson and DeGraaf (J&D) outperforms MUSIC and MLM. The application of the subspace techniques to the EEG context are encouraging as a method for the location of electrocortical generators in the brain. J&D seems to be able to identify possible source locations in both the simulated 1/f noise environment and with the real EEG data. Whilst the results obtained are promising there is scope for further work, for example:

1) redesigning of the EEG measuring set-up to obtain the optimum sensor position and number of sensors,
2) investigating other subspace algorithms.
3) investigating non uniform sensor spacings to eliminate the possible correlation between sources.

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