INFORMATION DYNAMICS VIEW OF BRAIN PROCESSING FUNCTION

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Abstract- **We present a methodology for the analysis of electromagnetic (EM) brain signals. In a dynamical systems framework we assume that the measured electroencephalogram (EEG) and the magnetoencephalogram (MEG) are generated by the non-linear interaction of a few degrees of freedom. Within this framework, we then construct an embedding matrix, which consists of a series of consecutive delay vectors. The embedding matrix describes a trajectory on the Euclidean manifold recreating the unobservable system manifold, which is assumed to be generating the measured data. The embedding matrix can be used to quantify system complexity, which changes with the changes in brain-'state'. To this end, we use measures of entropy and Fisher's information measure to track changes in complexity of the system over time. It is also possible to perform Independent Component Analysis on the embedding matrix to decompose the single channel recording into a set of underlying independent components. The independent components are treated as a convenient expansion basis and subjective methods are used to identify components of interest relevant to the application at hand. The method is applied to just single channels of both EEG and MEG recordings and is shown to give intuitive and meaningful results in a neurophysiological setting.**
***Keywords* – EEG, MEG, dynamical systems, complexity, ICA, single channel analysis**

I. INTRODUCTION

We describe a methodology whereby it is possible to analyse the electromagnetic (EM) fields of the brain as they vary with time. Both electroencephalographic (EEG) and magnetoencephalographic (MEG) recordings of brain function allow the opportunity to view brain function at the millisecond level. Neurophysiological interpretation of the EM brain signal recordings is usually restricted to the observation of the absence/presence of 'rhythms' of particular frequencies, or of specific wave morphologies. As the brain-'state' is ever changing (e.g., awake and alert as opposed to asleep) then the observation of the above signals is never a straightforward operation. Further compounding the issue is the presence of artifacts, of both a physiological origin or otherwise. Artifacts tend to obscure or mimic brain function of interest as this is usually contributing only a fraction of the percentage of the overall power of the measured signal.

The viewpoint we hold makes the assumption that underlying sufficiently short segments of the measured EM brain signals is a system of a few degrees of freedom which are nonlinearly mixed. These sources would then describe the brain-'state' over the short period of time in question (usually around the order of 1s). We then endeavor to extract information about this underlying system which we relate to a neurophysiological model.

II. THE DYNAMICAL SYSTEMS VIEW

EM brain signals in the form of EEG and MEG are usually recorded with very good temporal resolution and, in the latter case, with very good spatial resolution. A dynamical systems approach allows the viewpoint outlined in the previous section and is particularly applicable to analysis of the temporal dynamics of EM brain signals, although not necessarily restricted to the temporal case. Given a sampled time series, within a dynamical systems viewpoint we attempt to uncover as much information as possible about the underlying generators based only on the measured data [1], this is done through a technique known as dynamical embedding (DE). The assumption that the measured signal is due to the nonlinear interaction of just a few degrees of freedom, with additive noise, suggests the existence of an unobservable deterministic generator of the observed data. If the number of degrees of freedom of the underlying system is given by D, then D can be used as a coarse measure of the system complexity. Takens' [2] theorem allows the reconstruction of the unknown dynamical system that generated the measured time series by reconstructing a new state space based on successive observations of the time series.

A DE matrix is constructed from a series of delay vectors taken from the observed data $x(t)$, say, where the state of the unobservable system at time t, $X(t)$, is given by

$$X(t) = \{x(t-\tau), x(t-2\tau), \ldots, x(t-(m-1)\tau)\} \in \Re, \quad (1)$$

where τ is the lag and m is the number of lags or the embedding dimension. This delay vector describes observations of the underlying system states, assuming that the data, $x(t)$, $t=1,2,\ldots,N$, are generated by a finite dimensional, nonlinear system of the form

$$x(t) = f[X(t-1), X(t-2), \ldots, X(t-D)] + e_t, \quad (2)$$

where $x(t)$ is real valued, and e_t is independently and identically distributed, and zero mean with unit variance.

Takens showed that the Euclidean embedding dimension $\hat{m}$ must be at least as large as D, but in practice must be such that,

$$\hat{m} > 2D + 1. \quad (3)$$

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Abstract

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When applied to real world data the delay vector size m actually used needs to be a lot larger than the Euclidean embedding dimension ($\hat{m}$) because of dependencies in the time series data and inherent noise in the system. m needs to be 'big enough' to capture the information content necessary and if the time series data is heavily correlated, then more time series samples are needed to make up the required information content of the delay vector. Once the optimal delay vector size is found, an embedding matrix is constructed out of a number of consecutive delay vectors. The number of delay vectors N, is determined by the length of the signal to be analysed but in practice must be at least as large as m. Hence the embedding matrix consists of a series of delay vectors such that

$$\mathbf{X} = \begin{bmatrix} x_t & x_{t+\tau} & \cdots & x_{t+N\tau} \\ x_{t+\tau} & x_{t+2\tau} & \cdots & x_{t+(N+1)\tau} \\ \vdots & \vdots & \ddots & \vdots \\ x_{t+(m-1)\tau} & x_{t+(m)\tau} & \cdots & x_{t+(m+N-1)\tau} \end{bmatrix}. \tag{4}$$

Provided the sampling rate of the acquired data is chosen sensibly, then the practical minimum size for m can be chosen based on the lowest frequency of interest and the lag τ can be set to 1, i.e.,

$$m \geq \frac{f_s}{f_L}, \ \tau = 1, \tag{5}$$

where f_s denotes an appropriate sampling frequency, and f_L the lowest frequency of interest in the measured signal. For the EM brain signals described here, we derived values for m and τ in this manner, and over a diverse set of neurophysiological test signals, the choice of $m = 90$ and $\tau = 1$ proved optimal. If the choice of lag term τ, delay vector size m and number of lag vectors N is adequate, the embedding matrix is now rich in information about the temporal structure of the measured data. If N is set such that the embedding matrix covers a quasi-stationary signal, it becomes possible to extract an estimate for the unobserved degrees of freedom D.

In effect, each column of the embedding matrix represents a point on the manifold of the Euclidean embedding and together all the columns of the embedding matrix trace a trajectory over this manifold. Fig.1. gives a diagrammatical representation of the embedding process and what it represents in terms of the EM brain signals.

A. Complexity Analysis

Once the embedding matrix is constructed it is possible to get an estimate of the system complexity. To do this we obtain a signal/noise subspace decomposition through the use of singular value decomposition. In this way,

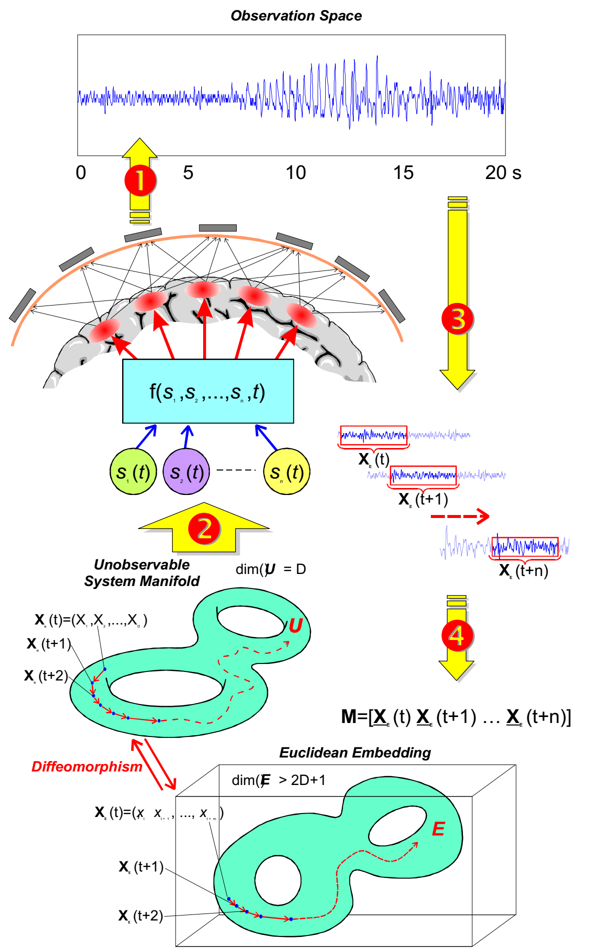

Fig. 1. The dynamical systems view of the genera tion of EM brain signals: (1). The recorded EM brain signals are assumed to be generated by a non-linear system with a few degrees of freedom. (2). Sources generate data that lies on an unobservable system manifold *U* of dimension *D*. (3). Data from a single measurement channel constitutes the measurement space from which consecutive delay vectors are extracted. (4). Delay vectors form an embedding matrix M that traces a trajectory on the manifold generated by the Euclidean embedding.

$$\mathbf{X} = \mathbf{USV}^{\mathrm{T}}, \tag{6}$$

where $\mathbf{U}$ and $\mathbf{V}$ are orthogonal and $\mathbf{S}$ is a diagonal matrix of singular values known as the singular spectrum (the eigenvalues of $\mathbf{XX}^{\mathrm{T}}$). The singular spectrum describes the signal and noise structure of the measured data. If the embedding is repeated over a number of consecutive windows of the data, then the change in structure of the singular spectrum can be observed – this is closely linked to the relative complexity of the underlying generators. Fig. 2. shows the singular spectra of embedding matrices derived from a single channel of seizure EEG data. There is a noticeable change in structure of the singular spectrum as the EEG becomes more rhythmic due to the onset of seizure activity. For a signal of low complexity the first few singular values will be large compared to the rest and for a signal of higher complexity more than a few of the singular values will have large values. It is required to quantify this change in structure and this can be done by calculating a measure of entropy for each consecutive singular spectrum [3]. For the singular spectrum **S** which is made up of components s_i, i=1,2,…,N, along the diagonal, the singular values are first normalized such that

$$\hat{s}_i = s_i \Big/ \sum_{j=1}^{m} s_j \,, \tag{7}$$

and the entropy is defined as,

$$H = -\sum_{i=1}^{m} \hat{s}_i \log \hat{s}_i \,. \tag{8}$$

In practice the measure of entropy is heavily influenced by, and closely reflects, the power of the signal under analysis. Entropy is also not influenced by the *shape* of the singular spectrum, and as it is apparent that the shape of the spectra characterizes the system we have obtained another measure for tracking the changes in singular spectrum complexity using Fisher's information measure [4]. This measure highlights the changes in gradient of the singular spectrum. Fisher's information measure is defined as the information about a point θ in a sample of n independent observations

$$I_n(\theta) = E\left[\left(\frac{\partial(\log P(\theta))}{\partial\theta}\right)^2\right], \tag{9}$$

where $P(\theta)$ is the likelihood of the sample. We can then derive the discrete version of the Fisher measure as

$$I_n(\theta) = \sum_{i=1}^{m} \frac{(P_i'(\theta))^2}{P_i(\theta)}, \tag{10}$$

where $P_i(\theta) = \hat{s}_i$.

B. Component Analysis

It is also possible to span the trajectory over the manifold in the Euclidean space (i.e., the embedding matrix) with an appropriate basis. This is done in an attempt to characterise the underlying sources in the embedding matrix. In our case we choose to use ICA, although it is in fact possible to span the embedding matrix with any basis, such as Principle Component Analysis for example. We have shown in previous work [5], however, that the use of such an orthogonal spanning set as a means of identifying underlying components in EM brain signal data is inferior to ICA. ICA performs a blind separation of statistically independent sources, assuming linear mixing of the sources at the sensors, generally using techniques involving higher-order statistics. Several different implementations of ICA can be found in the literature; [6],[7],[8],[9] and [10]. As this paper is not meant as an overview of the various ICA algorithms, we will restrict ourselves to the use of the Fast ICA algorithm, [9] and [12], mainly because of its ease of implementation and speed of operation. Further details about the other algorithms can be obtained from the given references.

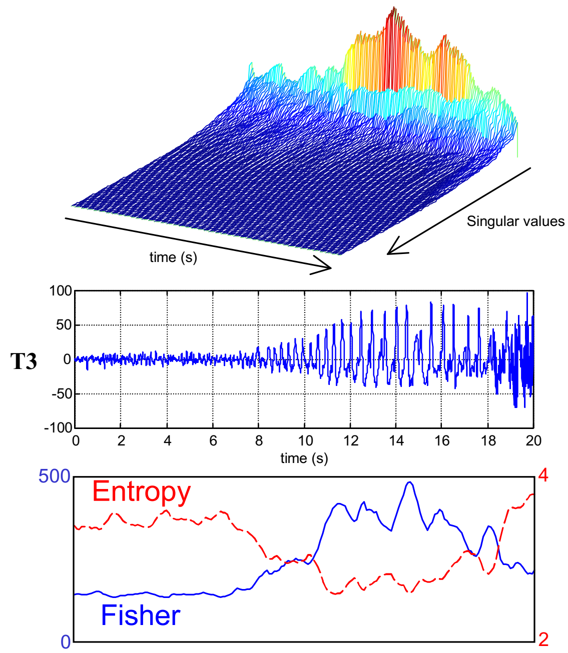

Fig. 2. Complexity analysis of EM brain signals in a dynamical systems framework. T3 represents a 20 s segment of seizure EEG over left temporal lobe. Consecutive singular spectra obtained from embedding matrices show change in structure coinciding with seizure onset. Both measures of entropy and Fisher information can be use to quantify the change in structure.

Once a spanning set is determined the independent components (ICs) of interest must be identified and this is by no means a trivial task. The nature of the square mixing matrix means that a great many more sources will be identified over the expected (smaller) number of sources underlying a measurement set. In the case of the embedding matrix of embedding dimension m ($m = 90$ in our case) there will be a total of m ICs – whereas it is generally assumed that the number of underlying sources *of interest* should number much less than that. For the moment we use subjective means of choosing relevant ICs based on our expectations of the underlying sources in terms of signal morphology and frequency rhythms of interest.

III. Discussion

In this section we introduce some typical results obtained on applying the methods to various EM brain signals acquired under different conditions from both EEG and MEG recording modalities.

Fig. 2. depicts a 20 s segment of EEG recorded from of the left temporal lobe (T3) of an epileptic patient. It depicts a seizure onset at roughly 7-8s which is characterized by the rhythmic activity. A series of embedding matrices were constructed using the parameters as described in this paper and the consecutive singular spectra were plotted. It can be seen that on and around the seizure onset there is a marked change in the structure of the singular spectra. This change in structure is captured by the two measures of complexity described within this paper.

Fig. 3. depicts ICA on an embedding matrix extracted from a 20 s segment of MEG data recorded from a healthy volunteer from channel MLT16 – over the left posterior side of the temporal lobe. A number of ICs are selected after ICA is performed on the embedding matrix. In particular, IC1 represents 50Hz contamination, IC2 ocular artifact and IC3 alpha activity. For each IC it is also possible to project the topography of the IC as a minimum norm solution given the entire multichannel MEG recordings.

Overall, the viewpoint we hold regarding the underlying sources generating measured signals is not unreasonable and dynamical systems analysis allows us to explore this very well. The use of DE has been shown to yield meaningful results when applied to various sets of recorded EM brain activity. The results obtained are intuitive, and although subjective (as in the case of IC identification), make sense in a neurophysiological framework.

IV. Conclusion

Although this is ongoing work, the results to date indicate a methodology that is both easy to implement and intuitive. The extraction of measures of complexity through dynamical embedding has many practical applications in neurophysiology that will be explored further. The technique of characterizing the embedding matrix with ICA has yielded very exciting results, extracting information that is not apparent in the strongly contaminated EM brain signal recordings. Finally, although the method yields significant results in just single channel analysis, which is desirable in many situations, it is not necessarily confined to single channel analysis and further work will be continued in the application of a dynamical embedding framework for multichannel analysis.

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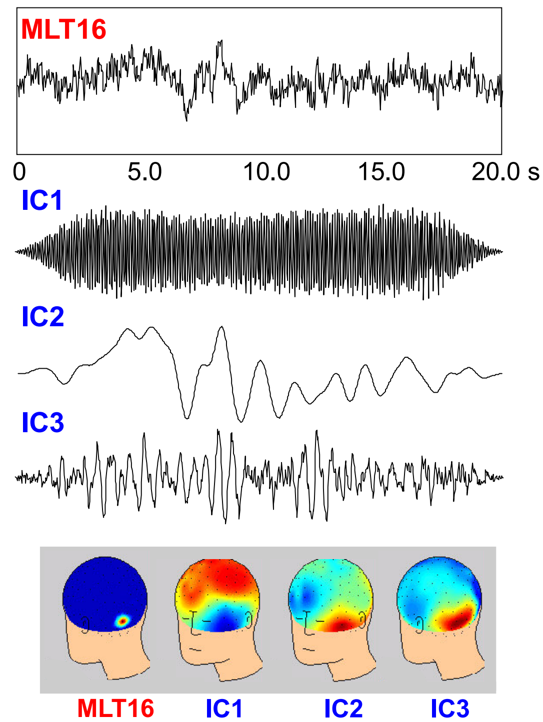

Fig. 3. Dynamical embedding is first performed on an 20 s segment of MEG data recorded from a healthy volunteer from channel MLT16 – over the left posterior side of the temporal lobe. After ICA is performed on the embedding matrix, a number of ICs are chosen; in particular, IC1 represents 50Hz contamination, IC2 ocular artif act and IC3 alpha activity. For each IC it is possible to project the topography of the IC given the entire multichannel MEG recordings.

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