NONLINEAR TECHNIQUES AND NEURAL ACTIVITY: EMERGENT TRENDS IN MEG DATA

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ABSTRACT

Nonlinear spatio-temporal analysis was performed on neural activity recorded with 148-channel whole-head Magnetoencephalography (MEG). The analysis consists of two phases: artifact removal and nonlinear feature evaluation. Known artifacts, produced by cardiac and eye movement, and unknown artifacts have been isolated from neural activity by using two adaptive filters in a cascade configuration. Secondly, phase space reconstruction of multivariate MEG measurements were performed using both temporal and spatial embedding. Indices of nonlinear dynamics are defined and evaluated showing invariant features both in time and space.

1. INTRODUCTION

The spatio-temporal activities of neurons disposed in cortical columns performing collective tasks are known to exhibit with unique neural patterns [1]. MEG measures a fundamental macroscopic quantity that corresponds to a sum of neural dendrite currents that are the receptive input of a large number of neurons [2].

The purpose of the present work is to outline a spatio-temporal approach for the nonlinear analysis of neural activity recorded by MEG. The data are from a subject performing a specific yogic breathing exercise and recorded with a 148-channel whole-head Magnes 2500 Biomagnetometer (4-D Neuroimaging, San Diego, California) located at The Scripps Research Institute (La Jolla, CA). Spatio-temporal nonlinear analysis was performed in two phases: artifact removal and nonlinear feature evaluation. The first phase was undertaken prior to analysis and eliminates the known and unknown artifacts from neural activity [3]; heart electrical activity and eye muscle activity interfere with MEG recording and are irrelevant here. In the second phase, nonlinear features of multi-channel MEG data are investigated and the appropriate indices are evaluated. Phase space dynamics have been reconstructed both in time and in space.

Temporal embedding has been performed using the single time series of each channel. Spatial embedding has been performed by constructing the trajectory of the system by using the values of each channel as coordinates in a time sample [4]. Each state variable corresponds to a channel.

2. MEG DATA CHARACTERIZATION

MEG signals were recorded by using 148 SQUIDS from one subject highly trained with yogic breathing meditation techniques. The timing of the protocol, shown in Table 1, consists of three phases: rest, exercise, and post-exercise rest. The exercise consists of selective left nostril breathing (using a plug for the right nostril) with a rate of one breath per minute for 31 consecutive minutes. The breath pattern has four phases - a 15 sec inspiration, 15 sec breath retention, 15 sec expiration, and 15 sec breath hold out phase [5]. During the protocol the subject was monitored continuously for heart rate activity with an electrocardiogram (ECG) and for eye movements with an electro-oculogram (EOG). Preprocessing of the data was performed to investigate the fundamental characteristics of the signals in both space and time. Correlations between each channel and its neighbors were evaluated to yield spatial information. Fourier spectra were analyzed for data frequency bands.

Table 1. Timing of the Yoga protocol.

<table>
<thead>
<tr>
<th>Rest Phase I</th>
<th>Stop Recording</th>
<th>Exercise Phase</th>
<th>Stop Recording</th>
<th>Rest Phase II</th>
</tr>
</thead>
<tbody>
<tr>
<td>10 min</td>
<td>1 min</td>
<td>31 min</td>
<td>1 min</td>
<td>10 min</td>
</tr>
</tbody>
</table>

The correlation function of each channel with its neighbors gives information for interdependence. The maximum value of the correlation between each pair of channels identifies spatial clusters in spatio-temporal data. Each channel is highly correlated with its neighbors and the influence decreases with distance. According to the results of this spatial analysis, the scalp has been separated into six influence zones and six channels were selected as representatives of the different areas of the
whole-head MEG system. The numbers indicating the selected channels and their position on the scalp are reported in Table 2.

The spectral artifacts must be removed to investigate the neural dynamics. It is well known that the spectrum of brain activity decreases linearly with log frequency (“1/f”) [2], and that MEG data spectra include high values of power in the low frequency band up to 10 Hz [6]. ECG and EOG spectra are mainly distributed in the low frequency bands quantifying the cardiac activity and the eye movement effects.

Table. 2. Selected Channels.

<table>
<thead>
<tr>
<th>Channel</th>
<th>1</th>
<th>83</th>
<th>95</th>
<th>99</th>
<th>108</th>
<th>112</th>
</tr>
</thead>
<tbody>
<tr>
<td>Position on the scalp</td>
<td>Central</td>
<td>Back</td>
<td>Front-Left</td>
<td>Left</td>
<td>Right</td>
<td>Front-Right</td>
</tr>
</tbody>
</table>

3. MEG ARTIFACT REMOVAL

MEG records include both neurally mediated and other physiological dynamics such as cardiac activity and eye movements, etc. In addition, unpredictable events can affect measurements with sudden spikes. The known artifacts can be detected by using specific tools. Unknown artifacts can be the result of undefined movements and unpredictable activities of the surrounding electromagnetic fields.

In order to isolate neural activities, two adaptive algorithms were employed to remove known and unknown artifacts, respectively [3]. Each MEG signal has been processed in a cascade scheme by using both algorithms sequentially.

1) Known Artifacts: Known artifact removal was performed by using an adaptive filtering algorithm based on a Normalized Stochastic Least Mean Square (NSLMS) evaluation. The ideal signal without artifacts \( s(n) \) is defined as the difference between the recorded signal \( r(n) \) and \( \hat{a}(n) \), where \( \hat{a}(n) \) is obtained by linearly filtering the recorded artifact \( a(n) \) at each sample \( n \):

\[
\hat{a}(n) = r(n) - \hat{s}(n). \tag{1}
\]

Both \( a(n) \) and \( r(n) \) are zero mean. Considering a \( N \)-th order filter, the algorithm output value is a signal \( \hat{s}(n) \) given by:

\[
\hat{s}(n) = r(n) - \hat{W}^T(n) \hat{a}(n) = s(n) + \bar{a}(n) - \hat{W}^T(n) \hat{a}(n) \tag{2}
\]

\[
\hat{a}(n) = [a(n), a(n-1), a(n-2), \ldots, a(n-N+1)]
\]

where \( \hat{W}^T(n) \) is the linear filter vector of weights that is updated at each sample by using the following equation:

\[
\hat{W}(n+1) = \hat{W}(n) + \mu \hat{s}(n) \frac{\bar{a}(n)}{\|\hat{a}(n)\|^2} \tag{3}
\]

where \( \mu \) is the adaptive gain. The choice of \( N \) depends on the recording sample time: the higher the sample frequency, the higher the correct value of \( N \).

The error between \( \hat{s}(n) \) and \( s(n) \) tends to zero as the number of processed samples in the adaptive algorithm increases

\[
\hat{a}(n) - \hat{W}^T(n) \hat{a}(n) \approx 0 \implies \hat{s}(n) \equiv s(n). \tag{4}
\]

2) Unknown Artifacts: The signal \( \hat{s}(n) \) obtained removing unknown artifacts is expressed by the following equation:

\[
\hat{s}(n) = r(n) - \Theta \left( \hat{W}_1^T(n) \hat{r}(n-1) \right) \hat{W}_2^T(n) \hat{r}(n-1) - \hat{r}(n-1) = [r(n-1), \ldots, r(n-N)]
\]

where \( \hat{r}(n) \) is the recorded signal with unknown artifacts, \( \left[ w_1(n), \ldots, w_M(n) \right] \) where \( r(n) \) is the recorded signal with unknown artifacts, \( \left[ w_1(n), \ldots, w_M(n) \right] \)

\[
\hat{W}_1^T(n) = \left[ w_1(n), \ldots, w_M(n) \right]; \hat{W}_2^T(n) = \left[ w_2(n), \ldots, w_M(n) \right]
\]

where \( \Theta \left( \hat{W}_1^T(n) \hat{r}(n-1) \right) \hat{W}_2^T(n) \hat{r}(n-1) \) is the predicted artifact and \( N \) the filter order.

The function \( \Theta \epsilon \left( \hat{W}_1^T(n) \right) \) individuates the artifact position and is defined as follows:

\[
\Theta\epsilon = \begin{cases} 
1 & \text{if } |x| > \epsilon \\
0 & \text{if } |x| < \epsilon 
\end{cases}
\]

\[
\epsilon^2 = \frac{1}{10L} \sum_{k=0}^{L-1} r^2(k) \tag{6}
\]

with \( L \) the total number of samples. Two vectors \( \hat{W}_1^T \) and \( \hat{W}_2^T \) are the weight vectors of the filter and are updated by using the recursive equations defined below:

\[
\hat{W}_1(n+1) = (1 - \gamma_1) \hat{W}_1(n) + \mu_1 \hat{s}_1(n) \frac{\hat{r}(n-1)}{\|\hat{r}(n-1)\|^2}
\]

\[
\hat{W}_2(n+1) = (1 - \gamma_2) \hat{W}_2(n) + \mu_2 \hat{s}_2(n) \frac{\hat{r}(n-1)}{\|\hat{r}(n-1)\|^2}
\]

where \( \mu_1 \) and \( \mu_2 \) are adaptive gains, \( \gamma_1 \) and \( \gamma_2 \) forgiveness coefficients.

Artifact removal was performed in two steps by using the cascade of both adaptive algorithms illustrated above. Artifacts were estimated and removed from MEG data in all phases of the protocol. Known artifacts have been removed from the signals by applying the first procedure with parameters \( N = 2560 \) and \( \mu = 0.133 \). Then the signal, free from known artifacts, were filtered from unknown
reconstructed from a time series of a multi-channel system, a spatio-temporal embedding set performing a temporal embedding [7], and in the case particular, for a single time series, a phase space can be differences.

The state vector, reconstructed from a time series \( s \), is indicated with the following form:

\[
\mathbf{S}_n = \left[ s_{n-(m-1)d}, s_{n-(m-2)d}, \ldots, s_{n-d}, s_n \right]^T
\]  

(8)

where \( s_{n} \) is the generic value at the \( n \)th sample, \( m \) and \( d \) are dimension and the delay of embedding. Both values can be obtained by analyzing the time series: the dimension \( m \) is obtained looking for false neighbors; the delay \( d \) is the first minimum of the mutual information [7].

2) Spatio-Temporal Embedding: Phase space reconstruction for a multi-channel system is performed by considering the state vector dimension equal to the number of acquired channels \( K \). Considering the \( K \)-dimension time series \( s^k_n = s^k(n) \) where \( k = 1, 2, \ldots, K \) and \( n \) the generic sample the state vector is given as follows:

\[
\mathbf{S}_n = \left[ s^1_n, s^2_n, \ldots, s^K_n \right]^T
\]  

(9)

Nonlinear Analysis

The nonlinear properties of a system, both in temporal and spatio-temporal distributions, can be detected through appropriate indices by using the surrogate-based test. The surrogate method is based on the Null Hypothesis verification that hypothesizes linear data: if the time series verifies the Null Hypothesis then it is generated from a linear process. Rejecting the Null Hypothesis, the data are considered as characterized by nonlinear proprieties.

Sets of surrogates are generated through a Monte Carlo sampling of the original time series. Surrogates, compared with original data, have the same Fourier power spectrum and a random distribution of phases. They are linearly correlated with the original time series but lose the nonlinear proprieties that can be present. By considering the level of significance \( \alpha \) and a generic nonlinear statistic \( \zeta \), the Null Hypothesis can be rejected evaluating the index \( z \)-score given as:

\[
z = \frac{\xi - \langle \xi_{surr} \rangle}{\sigma} \geq 2
\]  

(10)

where \( \xi \) is the original data statistic, \( \langle \xi_{surr} \rangle \) is the mean value of surrogate statistics and \( \sigma \) is their standard deviation. The number of surrogates \( J_{surr} \) is related to the level of significance \( \alpha \) according to:

\[
J_{surr} = \frac{1}{\alpha} - 1
\]  

(11)

If \( \alpha \) is set at 5% the number of surrogates is 19.

The \( z \)-score index assumes the Gaussian distribution of the surrogate statistics \( \xi \). The Rank Based Test is then used to confirm the results of the previous analysis. It is performed by verifying that all the values of the surrogate statistics are bigger than the one from the original time series. If the test is positive the original data are considered different from the surrogates.

Nonlinear Measures

In order to quantify the nonlinear proprieties of the data, two statistics \( \xi_{surr} \) have been evaluated: high-order autocorrelation (HOA) and the maximum Lyapunov exponent (\( \lambda \)).

1) HOA: This parameter evaluates the temporal dissymmetry of a signal. Considering a time series \( s_n \) in the \( n \)th sample, the HOA is defined as follows:

\[
HA = \left| \frac{1}{n} \sum_{n=1}^{N} s_n^2 - s_{n+1}^2 \right|
\]  

(12)

2) Maximum Lyapunov exponent (\( \lambda \)): The measure \( \lambda \) quantifies the trajectories divergence over time from a different initial condition and is an invariant value of nonlinear systems.

5. RESULTS

The two embedding procedures help describe the intrinsic nonlinearity here in neural activity. In addition, the same value of the system dimension \( m \) has been suitable for both approaches.

MEG Temporal Embedding

The nonlinear characteristics have been investigated by considering the time evolution of the selected channels after the artifacts were removed. The phase space of the signals was reconstructed for each phase of the yoga protocol by using temporal embedding. The dimension \( m \), obtained from the false neighbors analysis is constant for all channels and is equal to six. The mutual information analysis gives a delay \( d=7 \). The \( z \)-score index and the Rank Based Test were evaluated by using two nonlinear statistics: HOA and \( \lambda \). The nonlinear characterization results obtained through the \( z \)-score and Rank Based Test are reported in Table 3 for \( \zeta = \lambda \). Light gray values are used for signals that verify the Null Hypothesis and are
similar to results of a Gaussian linear process. Eighty percent of the signals show nonlinear dynamical features and are characterized by the values of $\text{HOA}$ and $\lambda$. All data intervals are characterized by a positive value of $\lambda$ [$0.11 \div 0.229$] that is a fundamental feature of chaotic dynamics. Also, the Lyapunov exponent calculated can be considered almost invariant both in space and in different phases and it quantifies an intrinsic nonlinear dynamical feature of the neural activity.

### Table. 3. Z-score and Rank Based Test for MEG temporal embedding with nonlinear statistic $\lambda$

<table>
<thead>
<tr>
<th>$\lambda$</th>
<th>Rest Phase I (min. 3-4)</th>
<th>Exercise Phase (min.25-26)</th>
<th>Rest Phase II (min. 48-49)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Ch. 1</td>
<td>$z = 5.58$ R.B.T.=OK</td>
<td>$z = 2.05$ R.B.T.=OK</td>
<td>$z = 1.52$ R.B.T.=OK</td>
</tr>
<tr>
<td>Ch. 83</td>
<td>$z = 1.94$ R.B.T.=OK</td>
<td>$z = 0.5$ R.B.T.=NO</td>
<td>$z = 2.03$ R.B.T.=NO</td>
</tr>
<tr>
<td>Ch. 95</td>
<td>$z = 3.46$ R.B.T.=OK</td>
<td>$z = 4.16$ R.B.T.=OK</td>
<td>$z = 4.19$ R.B.T.=NO</td>
</tr>
<tr>
<td>Ch. 99</td>
<td>$z = 7.05$ R.B.T.=OK</td>
<td>$z = 8.9$ R.B.T.=OK</td>
<td>$z = 5.48$ R.B.T.=OK</td>
</tr>
<tr>
<td>Ch. 108</td>
<td>$z = 19.05$ R.B.T.=OK</td>
<td>$z = 4.3$ R.B.T.=OK</td>
<td>$z = 10.37$ R.B.T.=OK</td>
</tr>
<tr>
<td>Ch. 112</td>
<td>$z = 2.8$ R.B.T.=OK</td>
<td>$z = 7.2$ R.B.T.=OK</td>
<td>$z = 7.3$ R.B.T.=OK</td>
</tr>
</tbody>
</table>

#### MEG Spatio-Temporal Embedding

Phase space reconstruction was performed by considering the state vector dimension equal to six. In particular, each state variable corresponds to a selected channel in Table 1. Nonlinear characteristics have been checked making surrogate data sets and evaluating the z-score index and the Rank Based Test. In the three phases of the protocol the Null Hypothesis has been rejected. All phase space dynamics have been characterized as nonlinear by reconstructing spatio-temporal embedding. The results are reported in Table 4. The nonlinear measure $\lambda$ has been calculated for MEG spatial embedding and is reported in Table 5. The maximum Lyapunov exponent range of the global spatio-temporal system is comparable to single time series values of $\lambda$ and it is confirmed as an invariant measure of global neural activity.

### Table. 4. Z-score and Rank Based Test for MEG spatial embedding

<table>
<thead>
<tr>
<th>$\lambda$</th>
<th>Rest Phase I (min. 3-4)</th>
<th>Exercise Phase (min.25-26)</th>
<th>Rest Phase II (min. 48-49)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>$z = 4.45$ R.B.T.=OK</td>
<td>$z = 5.1$ R.B.T.=OK</td>
<td>$z = 5.32$ R.B.T.=OK</td>
</tr>
</tbody>
</table>

### Table. 5. Maximum Lyapunov exponent for MEG spatial embedding

<table>
<thead>
<tr>
<th></th>
<th>Rest Phase I (min. 3-4)</th>
<th>Exercise Phase (min.25-26)</th>
<th>Rest Phase II (min. 48-49)</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\lambda$</td>
<td>0.359</td>
<td>0.262</td>
<td>0.193</td>
</tr>
</tbody>
</table>

### 6. CONCLUSIONS

Nonlinear characteristics of neural activity have been investigated in MEG data. A spatio-temporal approach has been proposed consisting of two phases: artifact removal and nonlinear feature evaluation. The first phase removes known artifacts, cardiac and eye movement activity, and unknown artifacts, sudden spikes, by using two adaptive filters in a cascade scheme. In the second phase, nonlinear characteristics of MEG data were checked and quantified by performing both temporal and spatio-temporal embedding. The results obtained with both the temporal and spatio-temporal analysis highlight the intrinsic nonlinearity of these neural dynamics.

### REFERENCES


