# Spatio-Temporal Clustering of Epileptic ECOG

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*Abstract*—**The spatio-temporal mechanisms underlying the generation of epileptic seizures is not yet clearly understood. In this study, we attempt to quantify the spatio-temporal interactions of an epileptic brain by using a previously proposed SOM-based Similarity Index (SI) measure. We further show that spectral clustering approach can be appropriately used to determine the average spatial mappings in the brain at different stages of a seizure, by interpreting the SOM-SI values as affinity matrices. Results involving two pairs of seizures of an epileptic patient suggest that there may not be a regular pattern associated with channels's spatio-temporal dynamics during the inter-ictal to pre-post ictal transition.**

## I. INTRODUCTION

It is becoming clear that epilepsy is a dynamical disease [1], i.e. the macroscopic spatio-temporal dynamics across different regions of the brain are consistent with rapid, sometimes gradual and often very subtle nonlinear dynamical interactions. In recent years, a major effort has been directed towards understanding the spatio-temporal interactions among various critical sites in the brain. One of the main difficulties is that the biological systems of interest have nonlinear complicated dynamics that can dictate overall changes in the system behavior. Synchronization between systems has been characterized in a number of different ways [2-6]. Many linear and nonlinear approaches have been developed and even though observations that EEG cannot be distinguished from linearly correlated noise [7] have been made, nonlinear approaches have still been able to extract coupling information in a manner that would not have been possible by spectral approaches.

Inspired by the similarity–index technique (SI) introduced by Arnhold *et al.* [6], we earlier proposed a SOM based computationally efficient measure, SOM-SI [8], to measure asymmetric dependencies between time-sequences. Conceptually, the SI and the SOM-SI methods rely on the assumption that if there is a functional dependency between two signals, the neighboring points in the state space of one signal maps to the corresponding neighborhoods of its counterpart. In other words, if the connection is assumed uni-directional, several states of the driver signal map onto a single state of the response signal. The SI [6] does not imply any causal relationship; however, it indicates that the driver signal has larger attractor dimension (more degrees of freedom) and hence is more active than the response signal. The SOM-SI method achieves to reduce the computational overhead of the SI by mapping the embedded data from signals onto a quantized output space through a SOM [10] specialized on these signals, and utilizing the activation of SOM neurons to infer about the influence directions between the signals. We showed in our previous work [9] that the SOM-SI was capable of determining the temporal evolution of dependencies between various cortical sites, at different stages of a temporal lobe epileptic seizure. In this study, we take a step ahead and qualitatively analyze the spatio-temporal groupings of channels. We propose a simple but effective spatio-temporal clustering model, comprising of spectral clustering and markov characterizations. Our approach essentially seeks to analyze the grouping of the channels at different stages of seizure, based on their average mutual interactions.

The paper is organized as follows: We first present a brief review of SOM-SI in section II. Section III discusses the spectral-clustering approach followed by markov chain characterizations in section IV. to determine spatial-temporal groupings of channels. In Section V, we present a simple simulation and make a subjective assessment of groupings in the epileptic ECOG data. Section VI. discusses about potential directions for future study.

## II. SIMILARITY INDEX (SI) MEASURE

### *A. Original SI measure*

Assume that $X$ and $Y$ are two time series generated by a system, which are embedded into two vector signals in time using delays. $N(X|Y)$ is defined as the average dependency of $X$ on $Y$ and it can be written as [6],

$$N(X \mid Y) = \frac{1}{N} \sum_{n=0}^{N-1} \frac{R^n(X) - R^n(X \mid Y)}{R^n(X)} \qquad (1)$$

where $Rn(X)$ is the average Euclidean distance between the state-vector of $Xn$ and the remaining state-vectors in $X$. $Y$-conditioned Euclidean distance $Rn(X|Y)$ measures the average Euclidean distance between $Xn$ and the vectors in $X$ whose corresponding time-partners are the $k$-nearest neighbors of $Yn$. This measure takes values in [0, 1], where 0 implies no coupling and 1 implies perfect synchronization [6]. Average dependence of $Y$ on $X$, $N(Y|X)$, is similarly computed.

## III. SPECTRAL CLUSTERING

The SOM-SI on epileptic ECOG data revealed only temporal changes in dependency patterns, across different stages of seizures [9]. For illustration, we show in Fig. 1, the maximum average driving ability of 6 channels, computed for one of the patients, P092. We immediately observe that there are no obvious spatial patterns, obtained from SOM-SI. As pointed out earlier, it is important to characterize the evolving changes in spatial patterns of interactions, as well, to get an overall sense of how the synchronized systems are spatio-temporally clustered. To this extent, we propose a 3-fold approach

consisting of spatial-discretization of the data using spectral-clustering technique [5], Markov-chain characterization on discretized data followed by K-means clustering (Fig. 2).

Spectral clustering is one of the many clustering methods that use subspace decomposition on higher dimensional features derived from the data to achieve data-clustering. Using kernel methods, the data samples are projected onto a higher dimensional space where the discriminant analysis is much easier. Spectral clustering is inspired by the normalized cut theory in computer science where the distance between the nodes is interpreted as an affinity matrix on which subspace decomposition yield membership labels of the nodes. Although spectral-clustering techniques predominantly use euclidean distance measures to form affinity matrices, any metric that quantifies the affinity/closeness between two spatial structures can also be used for the same. The SOM-SI values, by their nature, very clearly represent the degree of affinity between two interacting structures. Also, the fact that the SOM-SI use Euclidean distance to find similarities supports their candidature for being construed as affinity matrices. A number of spectral clustering algorithms exist, however, in this study, we use the standard spectral clustering method by Ng *et al*. [11] to spatially cluster the similarity-indices obtained by the SOM-SI technique

The output from computing pair-wise SOM-SI on all the possible combinations of the multivariate ECOG sources leads to a $\kappa$ matrix of size ($k$ x $T$), where $k$ = *2*(CN2)* indicates the # of SOM-SI pair-wise entries ε[0, 1], computed at time-instance $t$ ε [*t1, t2,…,T*].

$$\kappa = \begin{bmatrix} 0.9 & 0.35 & 0.49 & \cdots & 0.05 & 0.09 \\ 0.1 & 0.4 & 0.47 & \cdots & 0.10 & 0.02 \\ . & . & . & \cdots & . & . \\ . & . & . & \cdots & . & . \\ .0.53 & 0.6 & 0.4 & \cdots & 0.01 & 0.84 \end{bmatrix} \quad (2)$$

Each column in $\kappa$ can be regarded as a square matrix of size $N$ x $N$, where $N$ is the # of channels. Note that the diagonal elements representing the affinity of a channel with itself are coded as 1. As we can imagine, the asymmetry property of SOM-SI will result in an asymmetric affinity matrix. However, eigen-decomposition step [11] requires that the affinity matrix be square and symmetric in nature. This is because the eigen-decomposition yields orthogonal column vectors (also called eigenvectors) only if the projection matrix is square-symmetric. One of the ways of doing this transformation is by adding the matrix to its transpose and dividing by 2. Mathematically, the transformation can be be represented as $\delta = \frac{(\chi + \chi^T)}{2}$.

The transformed affinity matrix $\delta$ represents the average information exchanged between all pairs of channels. This implies that we will not have the luxury of using the asymmetric nature of the dependencies to create a membership grouping among channels. The averaging of the dependency information is nevertheless not going to affect in large because

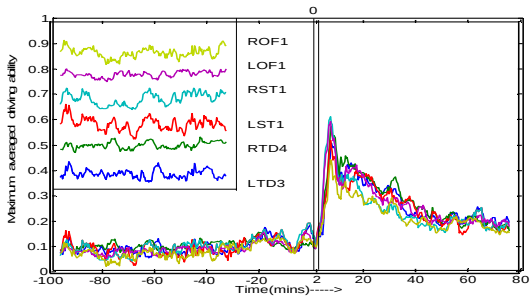


Figure 1. Maximum average driving ability of each of the six (6) channels, nearly 100 minutes before and 70 minutes after Seizure-1 in patient P092. (*The thin vertical bar corresponds to the time when seizure occurred (0 to 2 on the x-axis). For clarity, the box inside the figure shows a small portion of the maximum average driving ability of each of the 6 channels, baseline-offset by different scales.*) Drop in synchronization followed by an abrupt increase in phase synchronization at the onset of seizure is evident. Synchronization across channels during seizure is also clearly seen.

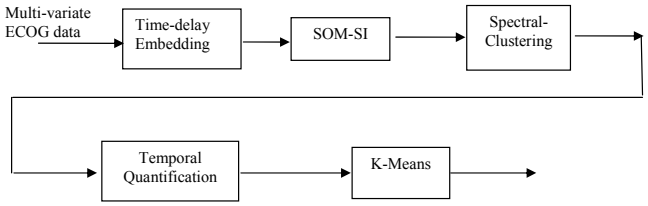


Figure 2. Block diagram to extract spatio-temporal dependency information in multivariate ECOG structures

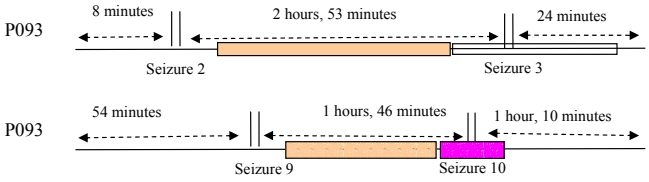


Figure 3. Graphical illustration of the data analysis on patient P093 (figures not drawn up to scale). Inter-ictal region (shaded): 20 minutes after seizure 2 (correspondingly seizure 9 ) upto 20 minutes before seizure 3 (correspondingly seizure 10). Pre-Post Ictal region (shaded): 20 minutes before seizure 3 (or seizure 10) and 20 minutes after seizure 3 (or seizure 10).

of the earlier observation [9] that there is no major difference in the driving and receiving information of the channel.

On the transformed affinity matrix $\delta$, the sub-space decomposition yields a set of labeled clusters (set to 3 based on significant eigen values) representing the membership of the channels. Repeating this procedure on every column in the $\kappa$ matrix (2) will yield a discrete-valued cluster matrix $\kappa_{spect}$.

$$\kappa_{spect} = \begin{bmatrix} 3 & 2 & 2 & \cdots & 3 & 1 \\ 1 & 2 & 2 & \cdots & 3 & 2 \\ . & . & . & \cdots & . & . \\ . & . & . & \cdots & . & . \\ 3 & 1 & 2 & \cdots & 1 & 2 \end{bmatrix} \quad (3)$$

## IV. MARKOV-CHAIN MODELING

Spectral-clustering is a powerful technique to achieve spatial-quantization on continuous SOM-SI data. However, the task is to be able to detect the channels that on an average, exhibit a similar behavior over a specified time-interval. In other words, we would like to find out rows of the $\kappa_{spect}$ matrix that are similar with each other over a time interval *T*. We propose a Markov-chain approach as a metric to quantify the rows in the $\kappa_{spect}$ matrix.

As we can observe from the $\kappa_{spect}$ matrix, the entries across the columns indicate the temporal-transition of a channel's interaction between clusters. When there are only 3 states or clusters, one of the 9 state-transitions are possible; namely; (1-1), (1-2), (1-3), (2-1), (2-2), (2-3), (3-1), (3-2), and (3-3). The transitions can be characterized by associating a probabilistic structure that takes into consideration the likelihood of a channel to be in a particular state (marginal probability) and the likelihood of making a transition from one state to another state (transitional probability). Mathematically, on each row of the $\kappa_{spect}$ matrix, we describe the following:

$$\pi^r = \begin{bmatrix} P_1 \\ P_2 \\ P_3 \end{bmatrix} \quad , \quad \mathbf{A^r} = \begin{bmatrix} P_{11} & P_{12} & P_{13} \\ P_{21} & P_{22} & P_{23} \\ P_{31} & P_{32} & P_{33} \end{bmatrix}$$

where '*r*' is a particular row in the matrix $\kappa_{spect}$ and *Pij* corresponds to probability of transition from cluster '*i*' to cluster '*j*' and *Pk* corresponds to marginal probability of cluster '*k*' .

In such a single-memory Markov-chain characterization of a channel's behavior, each channel has a distinct set of states and a distinct transition between states. Finding similarity between channel interactions is now reduced to finding similarity between their Markov models. We observe that the product of the transitional probability matrix with the corresponding marginal probability vector will result in a vector unique to each row and can thus be used to distinguish between two Markov characterizations. Mathematically,

$$\chi^r = \mathbf{A^r} . \pi^r \tag{9}$$

In this particular case, the product will result in a 3-dimensional vector for each row of the $\kappa_{spect}$ matrix. *K*-means clustering (or any other simple clustering procedure), on a pre-defined number of clusters, in the 3-dimensional space will eventually result in the rows corresponding to channel-interactions to be clustered. The clustering will enable us to know the groups of channels that, in an average sense, possess similar behavioral structure.

## V. RESULTS

*A. Roessler – Lorenz System*: In this subsection, we present a simple synthetic simulation to demonstrate the validity of the spectral-clustering technique to cluster a multivariate time series data based on their mutual interactions. Our example combines the 6 phase space components, taken together from Roessler and Lorenz dynamical systems. The dynamics of each system evolve as a result of interactions within their components. An 8x8 SOM is trained on each of the 6 components (adding some measurement noise as well) to recreate their dynamics in phase space. The SOM-SIs is then pair wise computed to get a 6x6 SOM-SI affinity matrix. Assuming that the number of clusters is apriori known (2 in this case), spectral clustering on the SOM-SI affinity matrix gives a clear discrimination between Roessler and Lorenz systems. The simulation, although is very simple, demonstrates the applicability of using SOM-SIs as affinity matrix in clustering approach.

*B. ECOG data* : The spatio-temporal techniques described in the previous sections were applied to the SOM-SI data (obtained pair wise from 24 channels), computed between two-pairs of seizures, in patient P093. The analysis was done in the inter-ictal region between two pairs of seizures and also on the pre-ictal and post-ictal regions surrounding these seizures. The time duration details of analysis are shown in fig. 3. In both instances, i.e, during spectral clustering and then during K-Means step, the number of clusters were empirically chosen to as 3.

**P093, Seizure 2&3, Inter-ictal activity:**
**$C_1$:** {LST1, LST2, LST3, LST4, RST1, LTD7, ROF4}
**$C_2$:** {RTD4, RTD6, RTD8, RTD10, LOF1, LOF2, LOF3, LOF4, ROF1, ROF2, LTD9}
**$C_3$:** {LTD3, LTD5, RST2, RST3, RST4, ROF3}

In cluster $C_1$, all the Left SubTemporal (LST) channels are grouped together, while it is easy to see from cluster $C_2$ that all the Right Temporal Dept (RTD) and the Left Orbito Frontal (LOF) channels exhibit similar dynamical behavior. Cluster $C_3$ encompasses the Righ Sub Temporal (RST) channels (except RST1).

**P093, Seizure 2&3, Pre-post ictal activity:**
**$C_1$: {**RST1, RST2, RST3, RST4, LTD7, LST2, LST3}
**$C_2$:** {LTD3, LTD5}
**$C_3$:** {RTD4, RTD6, RTD8, RTD10, ROF1, ROF2, ROF3, ROF4, LOF1, LOF2, LOF3, LOF4, LST1, LST4, LTD9}

The RTD and the LOF channels, separately continue to be clustered in a same group even during the pre-post ictal states. In fact, we also observe that the ROF channels belong to the same group as the RTD and the LOF channels. As in the inter-ictal activity, the RST channels are closely cluttered within the same group. Unlike during the inter-ictal activity, the LST channels no longer exhibit a uniform spatio-temporal behavior (We consider an area of the brain such as RTD, LTD or LOF to be strongly belonging to a particular cluster if more than 2 channels out of the 4 channels in each area lie in the same cluster).
Comparing the cluster configuration between inter-ictal and the pre-post ictal stages, we see that the RST channels and

LTD channels were similar in terms of the amount of information they exchanged with other areas of the brain, over the inter-ictal period. However, during the pre-post ictal stage, the RST channels may have been closer to the LST channels. Overall, it appears that a few areas of the brain such as the LST and ROF channels underwent drastic changes in their spatio-temporal interactions during the inter-ictal to the pre-post ictal transition.

**P093, Seizure 9&10, Inter-ictal activity:**

**$C_1$:** {LST1, LST2, LST3, LST4, LOF1, LOF2, LOF3, LOF4, ROF1, LTD3, LTD9}
**$C_2$:** {RTD4, RTD8, RTD10, ROF2, ROF3, ROF4, LTD5 LTD7, RTD6}
**$C_3$:** {RST1, RST2, RST3, RST4}

Here, the left hemisphere channels, (particularly LST and the LOF channels) are closely connected within a cluster, $C_1$. The right hemisphere channels (namely RTD and the ROF channels) are also closely connected, in a different cluster $C_2$. $C_3$ consists of all the RST channels. Firstly, a clear separation between the left and right hemisphere channels is seen and secondly, we see that the RST channels behave differently from the RTD/ROF channels. When the number of clusters was set to 2, the RST channels merged with the other right-hemisphere channels. This implies that the RST channels have very subtle differences with the RTD and ROF channels while a clear difference exists between the RST and the left-hemisphere channels.

**P093, Seizure 9&10, Ictal activity:**

**$C_1$:** {LOF1, LOF2, LOF3, LOF4, LTD3, LTD5, LTD7, LTD9, LST1, LST2, LST3, LST4, RTD4, ROF1}
**$C_2$:** {RST1, RST2, RST3, RST4, ROF2}
**$C_3$:** {RTD6, RTD8, RTD10, ROF3, ROF4}

All the left hemisphere channels namely, the LOF, LST and the LTD channels form cluster $C_1$. Similar to the inter-ictal activity, the right-hemisphere channels and the left-hemisphere channels are clearly separated in terms of their overall spatio-temporal dynamics. Subtle differences exist between cluster configurations in the Inter-ictal and the Pre-post ictal activity though.
Overall comparison between inter-ictal and pre-post ictal behavior shows a very little difference in the cluster-configuration of the channels during seizure 10. This probably implies that the average spatial-distribution of the electrode sites did not have any major changes in the inter-ictal to pre-post ictal transition.

## VI. DISCUSSION

In this study, we applied the previously proposed SOM-SI measure [8] to detect functional dependencies among multivariate structures. A spectral-clustering approach was adopted to determine how channels are clustered in an interval of time, and how the clustering configuration changed with time. During inter-ictal to pre-post ictal transition, we observed drastic changes in the spatio-temporal configuration of a few channels in seizure 2 and 3, while on seizures 9 and 10, the analyses showed that the transitional changes were meager. This probably suggests that there may not be a regular pattern associated with channel's spatio-temporal dynamics during the inter-ictal to pre-post ictal transition. However, from the analysis on complex partial seizures (9 & 10), we find that the left hemisphere channels, for most part, may be polarized from the right hemisphere channels. A much larger observation is needed from analysis on more seizures and more patients. Statistical quantification of the changes in spatial-similarity of the ECOG recordings, could give us a better understanding of changes in sensory-cortical networks during inter-ictal and ictal periods. So far, the SOM-SI coupled with the spectral clustering approach seems to provide a reasonable description of the spatial connectivity of the brain at different stages of a clinical event. We believe that these results could be a value addition to the current efforts of understanding how the sensory areas are networked with each other, at different times and during different clinical events.

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