Using the Spatio-Temporal Variogram for the Classification of Electroencephalographic (EEG) Assessment

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Abstract. *Electroencephalography (EEG) is an important tool in neuroscience used to study the electrical brain responses following traumatic brain injuries (TBI), with the goal of clinical diagnosis and assessment. It is widely recognized that EEG produces inherently spatio-temporal data; however, the use of analytical methods that explicitly account for auto-correlation in both space and time have been limited. The lack of appropriate statistical methods, coupled with increased prevalence of TBI in both athletic and military settings, necessitates the development of sophisticated techniques for analysis of EEG data. We propose a novel method of EEG classification based on the spatio-temporal variogram. Using data from subjects with and without a history of TBI symptoms, we first computed spatio-temporal variograms for each EEG assessment. Second, we produced group-median variograms for both the healthy and the TBI groups. Third, we developed a two-parameter measure of dissimilarity between variogram surfaces and applied this measure to subject-specific and group-median variograms. Results indicate that our proposed measure out-performs several established measures of dissimilarity for the classification of EEG assessments.*

Keywords. *Classification; Dissimilarity; EEG; Brain; Variogram*

1 Introduction

1.1 Motivation

Electroencephalography (EEG) is a neuroscience imaging tool that has become widely used for evaluation of pervasive impairments following a traumatic brain injury (TBI) with the potential for clinical identification of sustained injury (e.g. [4];[5]). In addition to its diagnostic utility, EEG has gained popularity due in part to being non-invasive and cost effective compared to other common brain imaging methods, e.g. Magnetic Resonance Imaging (MRI). Even though EEG data have been recognized as inherently spatio-temporal in nature (e.g. [1];[10]), appropriate statistical methods to model such data have yet to be established. Attempts to classify EEG data have relied primarily on variance-covariance decomposition through the use of techniques such as Principle Component Analysis (PCA) and Independent Component Analysis (ICA), among others (e.g. [8];[9];[3];[6]). Neither of these methods account for auto-correlation in space and time simultaneously and thus may misrepresent the underlying spatio-temporal process.

In this paper, we propose a novel method of EEG classification based on the spatio-temporal variogram. Using the variogram (instead of ICA or PCA) preserves the nature of spatio-temporal auto-correlation in data, while reducing its dimension. Our research objectives are as follows: (1) develop a two-parameter measure of dissimilarity for two variogram surfaces and suggest a method of finding parameter estimates; (2) classify EEG assessments of healthy subjects and subjects with TBI symptoms using only their spatio-temporal variogram surfaces; and (3) compare performance of the proposed measure to established methods of dissimilarity.

1.2 Spatio-temporal Variogram

Spatio-temporal variograms have long been used to describe the structure of spatio-temporal correlation in point-referenced data (e.g. [2]). Let $Y_{ij}(s,t)$ be the EEG response vector in millivolts of the i^{th} subject belonging to the j^{th} group, collected at location s and at time t. Formally, we define $Y(s,t)$ as a Gaussian, isotropic, second-order stationary spatio-temporal process on $\mathbb{R}^3 \times \mathbb{R}$, such that $s \in \mathbb{R}^3$ and $t \in \mathbb{R}$. Subject-specific spatio-temporal variogram surfaces were computed as:

$$2\widehat{\gamma}_{ij}(h,u) = \frac{1}{|N(h,u)|} \sum_{(s_k,s_l,t,t') \in N(h,u)} \left(Y_{ij}(s_k,t) - Y_{ij}(s_l,t')\right)^2$$

where $h = ||s_k - s_l||$ and $u = |t - t'|$. Group-median variogram surfaces represent median variogram values for the j^{th} group (e.g. group of subjects with TBI symptoms). Group-median variogram surfaces $\widetilde{\gamma}_j(h,u)$ were computed as: $\widetilde{\gamma}_j(h,u) = med_i\left\{\widehat{\gamma}_{ij}(h,u)\right\}$ for all h and u. The group-median variograms represent "typical" variogram values for the two groups across spatial and temporal distances.

In the case where there are two groups, and thus two group-median variogram surfaces $\widetilde{\gamma}_1(h,u)$ and $\widetilde{\gamma}_2(h,u)$, our proposed classification method works as follows. First, we determine the dissimilarity between subject-specific variogram $\widehat{\gamma}_{ij}(h,u)$ and each of group-median variograms $\widetilde{\gamma}_1(h,u)$ and $\widetilde{\gamma}_2(h,u)$. If $\widehat{\gamma}_{ij}(h,u)$ is more similar to $\widetilde{\gamma}_1(h,u)$ than to $\widetilde{\gamma}_2(h,u)$, we assign subject i to Group 1. If $\widehat{\gamma}_{ij}(h,u)$ is more similar to $\widetilde{\gamma}_2(h,u)$ than to $\widetilde{\gamma}_1(h,u)$, we assign subject i to Group 2. The dissimilarity between variogram surfaces is computed according to the proposed measure described in Section 2.

2 Dissimilarity Measure

The proposed measure of dissimilarity between subject-specific variogram surface $\widehat{\gamma}_{ij}(h,u)$ and group-median variogram surface $\widetilde{\gamma}_j(h,u)$ is computed as:

$$d_{ij}(h,u|\theta,p) = ln\left[\left|\frac{1}{2}\left(\frac{\widehat{\gamma}_{ij}(h,u)+\theta}{\widetilde{\gamma}_j(h,u)+\theta} + \frac{\widetilde{\gamma}_j(h,u)+\theta}{\widehat{\gamma}_{ij}(h,u)+\theta}\right)\right|\right]^p$$

$d_{ij}(h,u|\theta,p)$ is defined for all spatial lags h and all temporal lags u and thus represents a dissimilarity surface in itself. The proposed measure is valid as it is non-negative, symmetric, and reflexive. The measure depends on θ and p, which serve as a vertical tuning parameter and a penalty parameter, respectively. Both parameters accentuate differences between $\widehat{\gamma}_{ij}(h,u)$ and $\widetilde{\gamma}_j(h,u)$ when differences are present. The parameters allow the proposed measure to be adapted to the scale of each dataset, as well as the shape of variograms that each dataset produces. Optimal values of θ and p were found using a grid search with leave-one-out Cross Validation. The set of values over which grid search was performed was $[-2, 0.5]$ for θ, and $[0.25, 4]$ for p with a resolution of 0.25 for both parameters. Final parameter estimates were selected in order to maximize the sensitivity and accuracy of the left-out subjects' classification. These estimates represent median parameter values found using the leave-one-out Cross Validation procedure.

Total dissimilarity score for the entire dissimilarity surface of subject i vs. group median j is computed as $\sum_{h,u} d_{ij}(h,u|\widehat{\theta},\widehat{p})$. With two group medians, we define the threshold ratio R for subject i as: $R_i = \frac{\sum_{h,u} d_{i1}(h,u|\widehat{\theta},\widehat{p})}{\sum_{h,u} d_{i2}(h,u|\widehat{\theta},\widehat{p})}$. If $R_i < 1$, then the subject-specific variogram is more similar to group median 1, and vice-versa. Thus, if $R_i < 1$ we assign subject i to Group 1, and if $R_i > 1$ we assign subject i to Group 2. Note that the magnitude of R_i is easily interpretable in a clinical setting: confidence of correct classification increases as $R_i \to 0$ or $R_i \to \infty$.

3 Classification Results

3.1 EEG Data

The proposed method of EEG classification was applied to a dataset containing trial-averaged assessments of 34 college-aged athletes. EEG data were collected during a memory task aimed at detecting cognitive impairmets associated with TBI. Following [7], we used a self-report of persistent headaches as an indicator of TBI symptoms. Of the 34 athletes, 18 reported suffering persistent headaches. The main goal of classification was to correctly classify athletes as either having TBI symptoms, or not having TBI symptoms based on the variograms of their EEG assessments.

3.2 Results

Table 1 shows classification results for our proposed measure compared to several established measures of dissimilarity. All classification was performed using leave-one-out Cross Validation according to the procedure described in Section 2. The definition of the established measures was as follows: (1) Gaussian kernel $d_{ij}(h,u) = exp\left[-\frac{\left(\widehat{\gamma}_{ij}(h,u)-\widetilde{\gamma}_j(h,u)\right)^2}{2\sigma_j^2}\right]$; (2) L_1 Norm: $d_{ij}(h,u) = \left|\widehat{\gamma}_{ij}(h,u) - \widetilde{\gamma}_j(h,u)\right|$; and (3) L_2^2 Norm: $d_{ij}(h,u) = \left(\widehat{\gamma}_{ij}(h,u) - \widetilde{\gamma}_j(h,u)\right)^2$.

Dissimilarity Measure	Prediction	Headaches	No Headaches	Performance
Gaussian kernel	Headaches	12	9	Sensitivity: 0.67
	No Headaches	6	7	Accuracy: 0.56
L_1 norm	Headaches	8	8	Sensitivity: 0.44
	No Headaches	10	8	Accuracy: 0.47
L_2^2 norm	Headaches	8	7	Sensitivity: 0.44
	No Headaches	10	9	Accuracy: 0.50
Proposed measure	Headaches	16	8	Sensitivity: 0.89
$\widehat{\theta} = -1.50$; $\widehat{p} = 4.00$	No Headaches	2	8	Accuracy: 0.75

Table 1: EEG data classification results

4 Conclusion

Here we proposed a novel method of classifying subjects with TBI symptoms using the spatio-temporal variogram computed from their EEG. To aid in classification, we introduced a measure of dissimilarity between two variogram surfaces that depends on two parameters: a vertical tuning parameter and a penalty parameter. Estimates of the two parameters were computed using grid search with leave-one-out Cross Validation. Using median values of parameters obtained through the leave-one-out Cross Validation procedure, the performance of our proposed measure was compared to three established measures of dissimilarity. As shown in Table 1, our proposed measure has a sensitivity of 89% and an overall accuracy of 75%, which out-performs all three established methods of dissimilarity. The superior performance of our measure, in conjunction with a viable clinical interpretation of threshold value R_i, should improve the identification of sustained cognitive impairments following a TBI.

Acknowledgments. EEG data collection was supported by grants from NIH R01 HD073202, R01EB007684, HD062072, UNL Seed Grant, UNMC 36-0411-3001-001 to Dennis L. Molfese.

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