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Synchronization Measures of Neuro-Statistical Based Selected EEG features

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Abstract: ***Electroencephalographic (EEG) signals are the recordings of brain's spontaneous electrical activity along the scalp. It may be low or high dimensional data according to the numbers of electrode placed on the scalp. High dimensional EEG data take longer time to analyze. So features are searched with reduced dimension using neural canonical correlation analysis (NCCA) for minimizing computational cost. The NCCA takes the advantages of neural network with CCA where data are fed sequentially without at once. In this paper, we measure capability of NCCA network for finding salient features by using various synchronization measures, namely cross correlation, coherence function, standard deviation and interdependencies. All of these measures give a useful quantification. These measures are done for selected feature sets and original dataset, which shows almost identical result. So we may claim that NCCA is a better network for feature selection (FS) of EEG signals.***

Keywords: Neural canonical correlation analysis (NCCA), electroencephalogram (EEG), features selection (FS), synchronization**.**

1. Introduction

The electroencephalogram (EEG) is one kind of electrical signal of brain which is related to body functions. These signals are measured noninvasively with electrodes placed on the scalp. The EEG signals are collected with a sufficient time. These signals may low or high dimensional. When various subjects are focuses for different trials on the repetitive flicker of visual stimulation [1], it forms high dimensional set. FS is an appropriate process for analyzing such high dimensional data. In these sense, we want to search reduced size of dataset which carry almost same information as original dataset.

In this paper for finding reduced set of EEG data, we execute canonical correlation analysis (CCA) using neural network (NN), since NN is well known for their powerful capacity [2]. The NCCA method is advantageous because of i) capacity of machine is not needed to be high enough, ii) exhibits better correlation than standard statistical methods, iii) instead of complete data is fed at once, entered sequentially in the network. For that reason, we want to search salient features of EEG data using NCCA.

Due to very large features in high-dimensional datasets, it causes learning to be more difficult and also degrade the generalization performance of the learned models. So, FS process is used for various purposes. Ordinarily, spurious features are deleted from the original dataset using FS without sacrificing generalization performance. FS is very essential in real-world problems due to (i) noise contamination, (b) fake information, and (iii) unrelated and redundant features in the original feature set [3]. In this way, FS is used hopefully for pattern recognition; data mining, text categorization, image mining and many others field [4].

Feature subsets can be generated using different search process. The sequential forward search (SFS) [5] process adds features successfully in an empty set where sequential backward search (SBS) [6] option start with a full set and features are successfully removed. When search processes are started from both ends with features addition and removal occurs simultaneously that is called bidirectional selection [7]. There have another search process approach [8], which is started with a randomly selected subset using bidirectional or sequential strategy.

Three types of FS processes such as wrapper, filter and hybrid [9] approaches are generally used. Where features are selected justifying the learning performance from predetermined learning is called wrapper approach. On the other hand filter approach use statistical analysis of the feature set without utilizing any leaning model. In the hybrid approach, Complementary strengths of the wrapper and filter approaches are utilized.

A large number of features are usually measured in many pattern recognition applications, but all of them are not equally important for a particular task. In different case study, CCA framework with a minimum mean-square-error criterion [10] is evaluated for selecting feature subspaces. On the other hand NN is suitable for feature selection due to the ability to solve a task with a smaller number of features [11]. We take the advantages of statistical CCA with NN for extracting informative features from original EEG signals on the basis of maximizing correlation. This process works as a

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filter approach with SBS strategy. The attributes are deleted from expected features according to correlation minimization and subset of EEG data is obtained for maximum correlation.

As the measures of synchronization from both original and subset of data give equivalent result, then the performance of network is well. Data synchronization is the process of establishing consistency among the continuous harmonization of the data over time [12]. The observation of identical [13] and non identical [14] synchronization of chaotic systems are analyzed for different purposes. The concept of generalized synchronization to real data is observed for non identical systems. To establish the communication between different regions of the brain [15], synchronization phenomena have been increasingly recognized as a key feature for EEG signals as well as pathological synchronization as a main mechanism responsible for an epileptic seizer [16].

In this paper, we measure synchronization as a cross correlation, coherency, standard deviation as well as interdependencies of EEG signals. These show significance result from both selected and non selected features. When analyze with selected features than computation cost is also reduced. The features are extracted using NCCA on the basis of correlation maximization. We have done this work for both low and high dimensional dataset, for showing capabilities of NCCA network to select salient features. From synchronization measures, it may claim that NCCA is a compatible network for selecting reduced size feature set.

The rests of paper are organized as follows. Section 2 describes about characteristics of collected EEG signals into two sections. We explore neuro-statistical method, NCCA on section 3. Different synchronization measure techniques are explained in section 4 into four subsections as cross-correlation, coherence function, standard deviation and interdependencies. Results and discussions are analyzed in section 5. Finally we conclude the work on section 6.

2. Characteristics of Collected Data

2.1 Low Dimensional EEG Signals

These EEG data **[17]** were recorded with two channels at the left and right frontal cortex of male adult WAG/Rij rats. There had three examples, each of them with 5 sec recording. Where example A corresponds to normal EEG but B and C contains spike-wave discharges. These signals were referenced to an electrode placed at the cerebellum with filtering between 1-100 Hz and digitized at 200 Hz. Each example has 1000 attributes of 2 samples.

2.2 High Dimensional EEG Signals

These EEG data are collected from Steady State Visual Evoked Potential (SSVEP) database where brain signal acquisition was performed at a sampling rate of 2048Hz using 128 active electrodes [18]. In this study, four healthy subjects were participated those having no any neurological disorders. At the time of data collection, subjects were seated 0.9m from a 21inch CRT computer display operated at a high vertical refresh rate. Before each experiment they were briefly tested for photo sensitive epilepsy. There were used small reversing black and white checkerboards with dimensions of $1.8^o \times 1.8^o$ arc and 6×6 checks for SSVEP stimulation. Three stimulus frequencies (8, 14 and 28Hz) were used sequentially for stimulus a single small checkerboard [19]. There were 5 trials of each subject for each stimulus frequency. Therefore, a total of 60 trials of four subjects were found in the database. There were 128 samples with more than 6000 attributes for a trial. When every trail of a subject is added together it shows more than 31500 attributes. So, feature selection may reduce the computational cost for further analysis.

3. Neuro- Statistical Method

Correlation of two datasets can be found based on CCA **[20]** that is an optimal multivariable statistical method but avoids nonlinear relationship between datasets. NN implementation with standard CCA can overcome nonlinearity problem of statistical CCA [2]. It is also searching correlations among two or more datasets. For simplification, a brief description of neuro-statistical CCA (NCCA) is presented here. Consider three different subsections of an EEG signal as $\mathbf{x_1}$, $\mathbf{x_2}$ and $\mathbf{x_3}$. In this regard, we attempt to find the maximum correlation between the linear combinations of the subsections as described in Fig. 1. Let

$$\mathbf{y_1} = \mathbf{w_1 x_1} = \sum_j w_{1j} x_{1j} \ldots\ldots\ldots\ldots (1)$$

$$\mathbf{y_2} = \mathbf{w_2 x_2} = \sum_j w_{2j} x_{2j} \ldots\ldots\ldots\ldots (2)$$

$$\mathbf{y_3} = \mathbf{w_3 x_3} = \sum_j w_{3j} x_{3j} \ldots\ldots\ldots\ldots (3)$$

Where, j is the number of attributes for every sample. Now we wish to find the values of correlation vectors $\mathbf{w_1}$, $\mathbf{w_2}$ and $\mathbf{w_3}$ that maximize the correlation between $\mathbf{y_1}$ and $\mathbf{y_2}$, $\mathbf{y_2}$ and $\mathbf{y_3}$ & $\mathbf{y_3}$ and $\mathbf{y_1}$ respectively. Input data comprises three matrixes as $\mathbf{x_1}$, $\mathbf{x_2}$ and $\mathbf{x_3}$ for three subsections. All attributes (rows) of a complete sample (column) for a particular subject is entered at a time in the CCA network as input. In this way, every sample is entered sequentially in the network. Due to respective weights of $\mathbf{w_1}$, $\mathbf{w_2}$ and $\mathbf{w_3}$ activation is fed forward from each input to the corresponding output. Different joint learning rules are used for linear correlation whose are given as follows.

$$\Delta w_{1j} = \eta x_{1j}(y_2 - \lambda_1 y_1) \ldots\ldots\ldots (4)$$

$$\Delta\lambda_1 = \eta_0(1 - y_1^2) \ldots\ldots\ldots\ldots (5)$$

$$\Delta w_{2j} = \eta x_{2j}(y_3 - \lambda_2 y_2) \ldots\ldots\ldots (6)$$

$$\Delta\lambda_2 = \eta_0(1 - y_2^2) \ldots\ldots\ldots\ldots (7)$$

$$\Delta w_{3j} = \eta x_{3j}(y_1 - \lambda_3 y_3) \ldots\ldots\ldots (8)$$

$$\Delta\lambda_3 = \eta_0(1 - y_3^2) \ldots\ldots\ldots\ldots (9)$$

Where λ_1, λ_2 and λ_3 are Lagrange multipliers, w_{1j} is the jth element of weight vector, w_1, etc. We choose $\eta_0 = 0.5$ & $\eta = 0.001$ and start at $\lambda_1 = 0.015$, $\lambda_2 = 0.20$ & $\lambda_3 = 0.025$ for representative result.

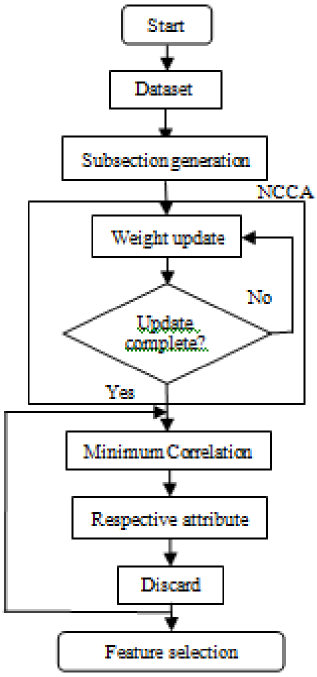

Figure 1: Feature selection using neuro-statistical method

4. Synchronization measures

Performance measurement of EEG signals with different synchronization techniques are used in **[21].** We mainly focus on four synchronization measurement techniques for test the capability of NCCA network. These measurements are done on non selected features and selected features using NCCA (neuro-statistical method).

4.1 Cross-Correlation

The cross-correlation is a measure of similarity between two waveforms with time-lag applied to one of them. Let, **x** and **y** be the two signals, then the cross-correlation C_{xy} between them is as follows.

$$C_{xy} = f(x) = \begin{cases} \sum_{n=0}^{N-l-1} x_{n+l} y_n^*, & l \geq 0 \\ C_{yx}^*(-l), & l < 0 \end{cases} \text{.....................} (10)$$

Where, N is the length of **x** and **y**. If the length **x** and **y** are not same, then shorter vector is zero-padded to the length of the longer vector. And y_n^* is the complex conjugate of y_n.

4.2 Coherence function

To examine the relation between two signals or data sets, coherence can be used. It is usually used to estimate the power transfer between input and output. If **x**(t) and **y**(t) are two real-valued signals then the coherence using Welch's averaged can be measured as follows.

$$\zeta_{xy}(f) = \frac{|G_{xy}(f)|\,|G_{xy}(f)|}{G_{xx}(f)G_{yy}(f)} \text{...........................} (11)$$

Where, G_{xy} is the cross power spectral density between **x** and **y**, and G_{xx} and G_{yy} the auto power spectral density of **x** and **y** respectively [22]. It is a function of frequency with values between 0 and 1 that indicates how well **x** corresponds to **y** at each frequency, where length of **x** and **y** must be same.

4.3 Standard deviation

Standard deviation is the measure of variation or dispersion from the average or expected value. Let 's' be the measure of standard deviation for vector **x**. then 's' can be calculated as follows.

$$s = \sqrt{\left(\frac{1}{n}\sum_{i=1}^{n}(x_i - \bar{x})(x_i - \bar{x})\right)} \text{..............................} (12)$$

Where,

$$\bar{x} = \frac{1}{n}\sum_{i=1}^{n} x_i$$

And number of elements in the sample is 'n'.

4.4 Interdependencies measures

This is the measures of dependencies of subjects on the basis of correlation dimensions [23]. We try to calculate the interdependencies from both selected and original feature sets. Consider two feature sets as $\mathbf{x_4}$ and $\mathbf{x_5}$. Then maximum correlation can be found from the linear combination of the sets as shown in Fig. 2. Let

$$\mathbf{y_4} = \mathbf{w_4 x_4} = \sum_k w_{4k} x_{4k} \text{ .... } (13)$$

$$\mathbf{y_5} = \mathbf{w_5 x_5} = \sum_k w_{5k} x_{5k} \text{ .... } (14)$$

Where, k is the number of sampling points for each sample. Then we want to search for maximization between $\mathbf{y_4}$ and $\mathbf{y_5}$ those maximize weights $\mathbf{w_4}$ and $\mathbf{w_5}$ according to correlation.

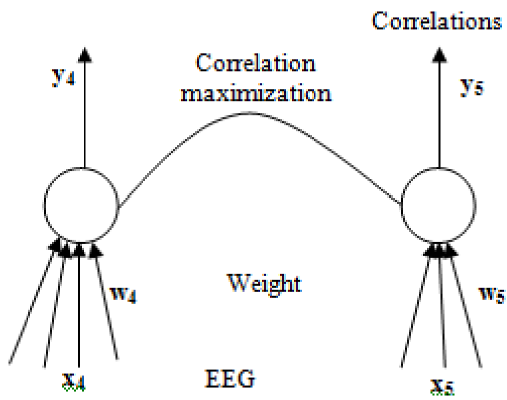

Figure 2: Measuring of correlation using NCCA network.

Here, activation is fed forward to output from each input for the respective weights $\mathbf{w_4}$ and $\mathbf{w_5}$. Different joint learning rules are utilized to find the dependencies between subjects [2] these are given as follows.

$$\Delta w_{4k} = \eta x_{4k}(y_5 - \lambda_4 y_4) \text{ .... } (15)$$

$$\Delta\lambda_4 = \eta_0(1 - y_4^2) \text{.................} (16)$$

$$\Delta w_{5k} = \eta x_{5k}(y_4 - \lambda_5 y_5) \text{ .... } (17)$$

$$\Delta\lambda_5 = \eta_0(1 - y_5^2) \text{ .... } (18)$$

Where λ_4 and λ_5 are Lagrange multipliers, $\mathbf{w}_{5k}$ is the k[th] element of weight vector, $\mathbf{w}_5$, etc. For representative result, we select $\eta_0 = 0.5$ and $\eta = .001$.

The correlation coefficient C_s between subjects is calculated as:

$$C_s = \sqrt{1 - \frac{||y_4 - y_5||^2}{||y_4 - E[y_5]||^2}} \text{ .... } (19)$$

Where, ||.|| denotes norm. Larger C_s implies more significant relationship between $\mathbf{y}_4$ and $\mathbf{y}_5$.

5. Results and Discussions

The NCCA is used to extracting features from existing datasets. Then synchronization is measured for different EEG feature sets. For that reason, we use two types EEG signals. According to dimensions they are low and high. We want to see the variations between original and selected features. The performed the work using matlab 7.5 on Pentium (R) Dual-core CPU E5700 @ 3.00GHz, with 2GB RAM and 64-bit operating system.

Firstly, we measure the cross correlation for low and features of low and high dimensional EEG signals. For that reason, second vector is shifted 4 bits and correlation is found between two signals. We take average cross correlation of datasets. For low dimensional datasets, there were three examples denote by A, B and C. For each example there was left and right cortex signal only. We take the 20, 30 and 60 features of these examples using NCCA and measure their cross-correlation as shown in table 1. We also calculate cross-correlation for selected features of high dimension SSVEP. For 15 features of SSVEP, cross-correlation is shown in table 1.

Table 1: Cross-Correlation of EEG features

Example	*Original*	*Feature set*		
		20	*30*	*60*
A	0.7011	0.7618	0.609	0.751
B	0.8066	0.938	0.7178	0.8006
C	0.1168	0.2315	0.0356	0.0412
Between 1st and 2nd samples of 15 SSVEP features				
	S1	*S2*	*S3*	*S4*
8 Hz	0.694	0.6934	0.6529	0.6501
14 Hz	0.6939	0.69	0.6938	0.6923
28 Hz	0.6941	0.6925	0.6531	0.65
Between 14th and 15th samples of 15 SSVEP features				
	S1	*S2*	*S3*	*S4*
8 Hz	0.6945	0.6949	0.6712	0.6944
14 Hz	0.6942	0.6944	0.6939	0.6945
28 Hz	0.6938	0.6946	0.6722	0.6942

It is seen that from table 1, the correlation is maximum for every feature set of example B and correspondingly decreased from A and C. So, FS using NCCA can satisfy the conditions. For representative result, average correlated value is multiplied by 4.25. For SSVEP feature set, cross correlation is almost same between two signals. We test for different signals of various feature sets. Here S1, S2, S3 and S4 denote subjects 1 to subject 4 accordingly. And 8, 14 and 28 Hz denote stimulus frequency.

Then synchronization is tested according to coherence function. Table 2 shows the coherency for low dimensional EEG signals. It is also seen that better coherence is found for example B for selected and non selected features. And gradually decreased into A and C. Though selected features show the approximate results, then we may claim that NCCA is better network for FS.

Table 2: Coherency at 9Hz for EEG features

Example	*Original*	*Feature set*		
		20	*30*	*60*
A	0.8208	0.7819	0.6253	0.4937
B	0.8086	0.9634	0.642	0.6508
C	0.6905	0.4342	0.04336	0.07405

According to measuring standard deviations, we also test the capability of NCCA for extracting features. It is seen from table 3, standard deviation is quite enough for example B from other examples. It is applicable for both original and selected feature sets. So, FS can be done with NCCA.

Table 3: Standard deviations of EEG features

Example	*Original*	*Feature set*		
		20	*30*	*60*
A	0.0222	0.0604	0.0412	0.0088
B	0.1627	0.517	0.046	0.1205
C	0.0691	0.0259	0.0259	0.0666

Finally we apply test of inter subject dependencies for high dimensional SSVEP data sets. It is tested for both selected and original feature sets. We select 15, 30 and 60 features from higher dimensional datasets. These extracted features are test according to their linearity measurement. Firstly, we test for subset of 15 features and original signals. These show almost identical result. As an example, linearity measurement of subject 2 (S2) at 8 stimulus frequency with other subjects is explored in Fig. 3.

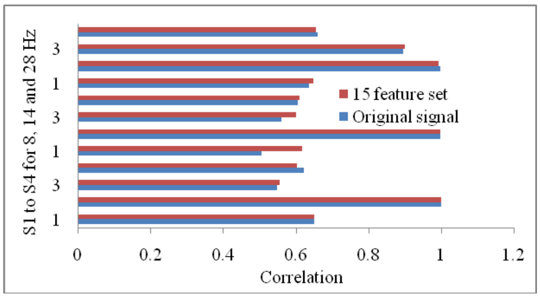

Figure 3: Correlation of S2 at 8Hz with other subjects

These measurements are done between original dataset and subset to subset. The linearly between same subject must be one. It is shown for both original and selected subsets. For other cases, this comment is applicable also. We may observe from Fig. 3 that there has only little variation for testing of interdependencies between original signals as well as between subsets.

The variations of linearity also tested for selected 30 features. These are tested for different subjects at three stimulus frequency. The testing result for S1 at 14 stimulus frequency is shown in Fig. 4.

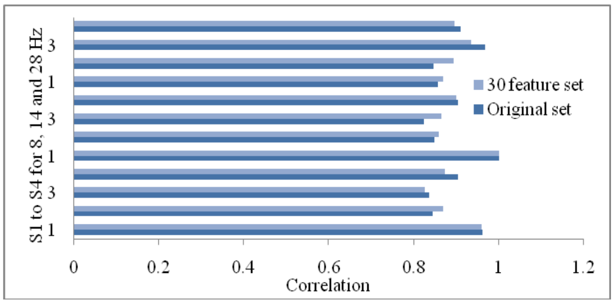

Figure 4: Correlation of S1 at 14Hz with other subjects

It is analyzed that highest correlation for same subject at same stimulus frequency for both original signals and selected feature sets. Also there have little variations for others which lie on acceptable limit. The correlation between S1 of 14Hz and S4 of 28Hz is 0.9100 for original set, where for selected subset it is 0.8965 which can be seen from Fig. 4.

We also measure the interdependencies for 60 feature sets also. This is shown in Fig. 5, for S4 of 28Hz.

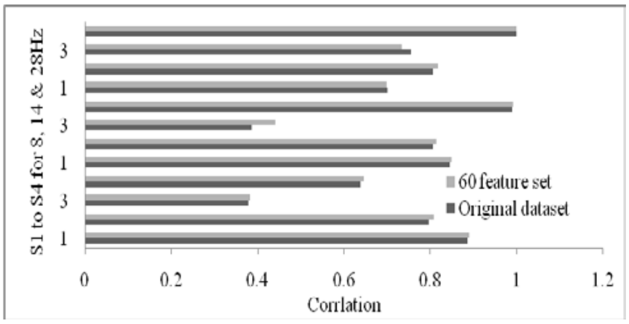

Figure 5: Correlation of S4 at 28Hz with other subjects

It is explored from Fig. 5 that correlations are almost identical for selected 60 features and original dataset. Here correlation is found 0.8053 for original dataset for S4 of 28Hz and S2 of same stimulus as well as for feature set it is seen 0.8176. So, we may claim that effective feature can be selected by using NCCA.

When we run for measuring inter subject dependencies on the basis of correlation, it needs almost 13 to 16 seconds for original dataset but only 50 to 90 milliseconds are required for selecting features. So, this process reduces the cost as well as data size in an effective way.

6. Conclusion

In this paper, ability of NCCA network is tested on the basis of synchronization measure. Firstly features are extracted from EEG signals as a measure of correlation dimensions. The NCCA shows effective way for FS by maximizing correlation. Then the different synchronizations such as cross-correlation, coherency, standard deviation and dependencies are measured from selected feature sets as well as from original datasets. It is obtained that the values of cross correlation are 0.8066, 0.9380, 0.7178 and 0.8006 for original, 20, 30 and 40 selected features respectively of example B, where for example A and C these values are 0.7011, 0.7618, 0.6090, 0.7510 and 0.1168, 0.2315, 0.0356, 0.0412 accordingly. It is seen that highest correlation is found for example B of selected and original features both, so NCCA is suitable for FS. It is also found that coherency and standard deviation is highest for example B of low dimensional EEG data than others at the time of measuring from original and selected features both. High dimensional EEG data shows almost 0.69 cross correlation value for original and selected features both. When dependencies are measured using NCCA, they also shows same result for both selected and original features as correlation between S1 of 14Hz and S4 of 28Hz is 0.9100 for original set, where for selected subset it is 0.8965. But computational time is reduced to analyze feature set than the original data. Though all of these measures show identical comparisons, we may claim that NCCA is a better network for selecting features from time varying signals. It reduces data size as well as computation cost at the same time.

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