Power of Positive and Negative Thoughts Extracted from EEG Signals to Find a Biometric Similarity

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Abstract

The electroencephalogram (EEG) signal is the electrical activity of brain neurons. In this paper, an analysis of the EEG signal is conducted on positive and negative thoughts. Positive thought is defined as the EEG signal that is transmitted when the subject thinks “yes” in response to a question. Negative thought is defined as the EEG signal that is transmitted when the subject answers “no”. The EEG signal was recorded using four channels at positions C4, C3, P4 and P3 with a sampling frequency of 256 Hz. In this paper we discuss on the two main areas that are used for identification: the right/left brain symmetric and the other one is to form a matrix for identification of all person. The power of the signals are used to form a matrix for biometric purposes.

Key words: EEG, Brain Waves, DWT, Wavelet, PCA

1. Introduction

Analyzing brain waves is one of the understanding methods of brain behavior. Stern (2004) showed the brain has different types of frequencies as Delta (0.5-4) Hz, Theta (4-7) Hz, Alpha (8-12) Hz, Beta (12-30) Hz, Gamma (30-70) Hz. The EEG signal is the activity of brain neurons et al. Bruce (2004). In this paper the patient asked the answer the questions with *yes* and *no* only by thinking and the whole procedure takes about 1 minute and four channels used for positions 2*C4, P4 and C3 and number of samples is 15k. In this paper the effect of artifact is not considered. Instead, the patient told to be in relaxing situation and avoid large movement of face or body.

In this paper, the power that is contained in the EEG signal for positive and negative thoughts calculated. Positive thought is defined specifically for when the subject thinks a “yes” in response to a question. Negative thought is defined specifically for when the subject thinks a “no” response to a question. Principle component analysis and discrete wavelet transform are the main algorithms that are used to derive the denoised data.

2.Literature Review

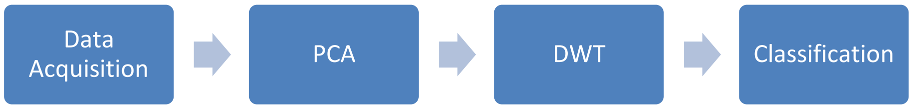

Fig 1: *Organization of paper.*

Kahle (2003) showed the principal component analysis (PCA) is one of the eigenvalue multivariable analysis methods. The PCA has been mostly used to analyze spatial data however; in this paper claimed the PCA is also a useful tool for denoising and artifacts removal. Shaker et al. (2005) used PCA technique to reduce the dimension of the EEG signal. The output of PCA is used for wavelet analysis for classifying EEG. However the organization of this work is similar to Shaker (2005) but here the new classification in energy and alpha power technique is used and used PCA/DWT for denoising. The work shows by using PCA and wavelet has more accuracy than using just FFT or STFT. Lee et al. (2003) found PCA is a useful tool for time series data. Since PCA retains maximum variance, it is predictable to offer features that are robust to small noise. Result of using PCA is about 15% better in Raw and 19% better in Hjorth technique. Jin et al. (2007) used PCA to get the principal features and classified the model based on support vector machines (SVM). Result of using PCA and SVM is about 73.93% for classification which is 12% better than not using it. Jung et al. (1998) used PCA for artifacts removing. Lins et al. (1993) showed ocular artifacts can be removed more effectively by PCA than by regression or by using spatio-temporal dipole models. Result shows error in PCA is 0.0174 while error in dipole is 0.4298 and for regression is 1.8213.

The Discrete Wavelet Transform (DWT) is a tool that widely applicable in signal processing. It is suitable for non-stationary signals and this is a major benefit for spectral studies. The DWT, based on sub-band filtering is a fast computation of the Wavelet Transform. Ocak et al. (2009) used DWT for automatic detection of epileptic seizures in EEG and approximate entropy. It is observed that DWT can find 96% of seizures compared to 72% without DWT. Amine et al. (2009) used DWT to classify EEG via DWT with perfect success in rejecting undesired frequencies. The worked method is up-down sampling for compute the frequency bands. Results showed that combining DWT with Lyapunov and Exponents brings 99.28% of accuracy in classification Naiet (2009).

In this paper we used PCA to compute denoising parameters and DWT for filtering, artifact removal and power analysis.

3. Research Methodology

EEG is the method to record the electrical activity of brain along scalp. Data was acquired from 13 male subjects, aged between 18 to 29 years old. The recordings were made in a quiet lab, with the subjects seated comfortably on a reclining sofa. The subjects were fixed with a EEG cap onto which electrodes were placed at locations C3, P3, C4 and P4 respectively, following the standard 10-20 international system. These electrodes are independent from each other and they are in the areas of brain witch related to sensory, somatosensory association, vision and language comprehension Norton (2009). Choi et al (2005) these places are better for estimation of power in low frequency parts of EEG. Figure 5 shows the location of electrodes and C3, P3, C4, P4 regions. The signals were recorded using a gMobilab+ console with a sampling frequency of 256 Hz. The gMobillab+ has four electrodes to record the data in the appropriate places. These electrodes set on the center of scalp and most of EEG experiments use these electrodes for their work. Jiang (2006), Babiloni (2001) Prior to the acquisition process, subjects asked to answer some personal information (e.g., what is your favorite color? What is your favorite sport?).

In the EEG test with duration of one minute, subjects are asked to answer 10 of the questions in a way that answer of the first five questions is *yes* while the rest of questions are answered with *no*. The subject had 6 seconds to answer the questions through thought by thinking of *yes* or *no*. This procedure happened for four times for each person. For clarification purposes, the subject was required to answer the same questionnaire at the end of the experiment, this time in writing.

4. PCA Analysis

In the PCA method the greatest variance by any projection of the data comes from the first principal component, and the second greatest variance is in the second coordinated and so on Sandararajan (2003), Percival (2000).

The PCA is the optimum transform for the data by the terms of least square et al. Mohseni (2006). In this case the data that we have here is in matrix X and there is the transformation that shows $PX=Y$ which Y is a matrix with the same dimension as matrix X which is related to a linear transformation P so the covariance matrix defined to the data X is

$$C_X \equiv \frac{1}{n-1} XX^T \tag{1}$$

And for the matrix Y we have

$$C_Y = \frac{1}{n-1} YY^T \tag{2}$$

$$= \frac{1}{n-1}(PX)(PX)^T$$

$$= \frac{1}{n-1} PAP^T \tag{3}$$

where $A \equiv XX^T$.

The PCA focuses most of the data content in a few principal components, providing an estimation of the embedded space dimension Shelnes(2005).

5. Multivariable De-noising by DWT and PCA

The method used here combines DWT and PCA to compute the denoised matrix, therefore analyzing the function would be simpler Shagass(1992).

The signal X (t) can be represented as:

$$X(t) = f(t) + \varepsilon(t) \quad t = 1, \dots, n \tag{4}$$

We assume $\varepsilon(t)$ is centered Gaussian white noise with variance of δ^2.

There are three steps for the denoising procedure in each decomposition level. The first step is to decompose the signal up to level J. For each level of decomposition j the signal is divided to two parts of approximate coefficients and detail coefficients. The approximate coefficients contain high frequency components and detail coefficients contain low frequency components. We break the signal for 4 levels (J=4). The second step is using PCA. There are two methods for performing PCA. The old method is to calculate the PCA of the signal after level of J from DWT. The new method is to compute the PCA from each level of DWT. Here we compute the noise covariance matrix $C_\epsilon = P\Lambda \mathrm{P}^{\mathrm{T}}$ where Λ=diag $(\lambda_i, 1 \leq i \leq p)$.Then we apply the $D_j P$ for each level of decomposition. The last step is reconstructing the de-noised signal from threshold of detail coefficients by the inverse wavelet transform et al Daubechies(1992), Keinert(2005). Figure 2 shows the result for one channel denoising and compressing in time domain up to level 4 and figure 3 shows the denoised signal with actual length.

5.1 Removing Artifacts

The artifacts in EEG consist of muscle movement and eye blinking and heart beat et al Kahle (2004). Examples of artifacts are blinking, moving a part of body and heart beat. Artifacts can add extra power to the signal and this can affect the energy and power of the signal so artifact removal is important. Here we use soft thresholding techniques to remove the artifact signal.

Abramovich (1998) shows in (5) there is a thresholding method and we used it to produce a line and cut the extra signal and remove the artifacts. Figure 4 shows this technique.

$$Thr = \begin{cases} sign(cD)(|cA| - delta) & if\ |cD| > delta \\ 0 & if\ |cD| \leq delta \end{cases} \quad (5)$$

Delta is the biological value but we can compare this to the actual EEG signal.

5.2 Analysis of Power and the Worst Trial Removal

The Energy of signal gives some information about the dispersion of signal in Time/Frequency domain. For the same person when he/she answers the same questions the energy of signal for each trial must have similar pattern. When we asked a patient to concentrate on the special job and he/she couldn't do that or maybe the patient was thinking about other thing, the energy of signal is changed. This is happened because the other neurons are participated for the task which they are not related to this. In these cases we need to remove the worst trial while the information in that trial is not right. In this test energy of each person calculated in one table for different trials. The following table shows the Energy of the patient. It shows that the highest energy belongs to P3 electrode and the minimum is for C4.

Energy	Highest to Lowest			
Trial1	C4	C3	P4	P3
Trial2	C4	C3	P3	P4
Trial3	P3	C3	P4	C4
Trial4	P3	C3	P4	C4
Trial5	P3	C3	P4	C4
Final Result	P3	C3	P4	C4

Table 1. *Shows the Energy dispersion in electrodes.*

In the first row the majority of highest energy belongs to P3 so in final result also P3 has the most energy and so on.

The table shows that in Trial2 the only proper position of electrode's order is C3, so this Trial must be omitted while we have the worst result. Back to the Trial2 and compare it with other tests, this is observable more noise and artifacts exist on it or the patient couldn't concentrate on the task truly. The final result for this person is energy of P3 is greater than the other electrodes. Here the energy of P3 is greater than C3 and C3 is greater than P4 and the least is C4.

5.3 Justification of Worst Trial Removal

There are two main reasons for removing the worst trials. While we want the student to concentrate on task but the student can't do it. In this case the power of signal is different with what we expect. The case is critical while students focus on hearing or watching something. That's because the different neurons are stimulated which they may not relate to the measured area. The second reason is again for artifacts. However we removed the artifacts before but in cases which signals are full of artifacts, this method couldn't be useful for classification. As it can be seen in figure 6, trial 2 is different with the other trials. Analysis shows that artifact happened in the region C3 that we couldn't remove it.

6. Classification

There are two separate methods to do the classification task. The first method is analyzing Alpha-power used to classify the person as left/right brain and the second method is analyzing the power of yes/no parts for measure and compare with new signal.

6.1 Analysis of Alpha Power

In this part we are looking for hemispheric asymmetry of brain. When the person asked for particular questions the left/right part of brain will activate to answer the question. If the person has more power on left/right side of brain he/she has left/right asymmetry Ocak(2009). The parameter of EEG which is more important in this test is alpha wave, which has been shown to be inversely related to glucose of brain et al. Johnson(2009).

The electrode placement for the test is depicted in Figure 5. The power of alpha activity for a person is shown in Table 2 and its obvious alpha-power of P3 is the highest followed by electrodes P4, C3 and C4 the results shown on the Figure 5, the person recognized as left- brained while figure 6 represents the dataflow direction of brain power.

Alpha Power Activity	C4	P4	C3	P3
Trial No 1	0.0250	0.0666	0.0002	0.2346
Trial No 2	0.0097	0.1267	0.1145	0.1661
Trial No 3	0.0159	0.0541	0.0509	0.2414
Trial No 4	0.0074	0.0756	0.2529	0.7968
Trial No 5	0.0014	0.0082	0.0145	0.1559

Table 2. *Shows the Alpha-power of each electrode.*

6.2 Analysis of Power of Yes/No Parts

Each signal of EEG in this test has two parts. The first part is *yes* thoughts and the second part is *no* thoughts. In this part tried to find a matrix which demonstrates the properties of a person by all 5 trials that already are taken from the patient. Here the statistical method based on signal power deploys to identify a person via the pattern of *Yes/No*.

Power of signal is calculated by

$$P = \frac{1}{n}\sum_{i=1}^{N} |f(n)|^2 \tag{6}$$

Where N is the length of signal and f(n) is samples of EEG signal. For each trial the power of *yes* and *no* parts are calculated so we have the power of *yes* and *no* parts. For the next stage we are looking for the patterns where power of *yes* is more than *no*.

Table 3 shows the percentage of *yes/no* for all of 5 trials and for all electrodes and it's showing for example in Trial1 powers of all electrodes in *no* parts are greater than *yes* parts.

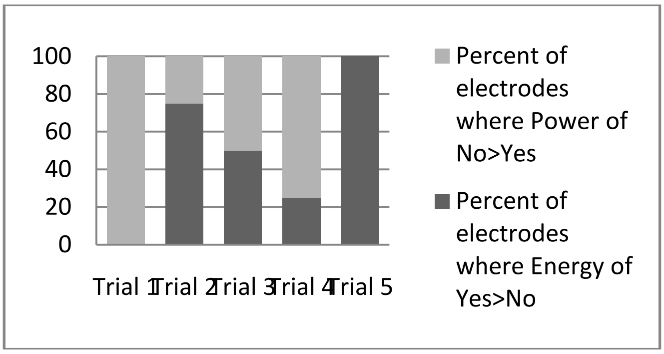

Table 3. *Shows the Percentage of Yes/No for each trial of a person and C4 electrode.*

Matrix *A* with consideration of *Yes* will be: *Yes=1, No=0*. The rows are each trial and columns are C4, P4, C3 and P3.Matrix A belongs to person A.

$$A=\begin{bmatrix} 0\ 0\ 0\ 0 \\ 1\ 1\ 0\ 1 \\ 1\ 0\ 0\ 0 \\ 0\ 1\ 0\ 1 \\ 1\ 1\ 1\ 1 \end{bmatrix}$$

The final result comes in the number of “1” or “0” in one row here for C3 number of “1” is 60%. So the vector of redundancy of “1” in person A is

A= [0.6 0.6 0.2 0.6]

All the test people from A-D describes as identifier matrix:

$$I_M=\begin{bmatrix} 0.6\ 0.6\ 0.2\ 0.6 \\ 0.4\ 0.4\ 0.4\ 0.4 \\ 0.25\ 0.25\ 0.75\ 0.5 \\ 0.5\ 0.5\ 0.5\ 0.25 \end{bmatrix} \tag{7}$$

Here each row belongs to one person and each column stands for percentage of electrodes with the energy of *Yes* more than *No* which averaged over the all trials. This is the Identifier Matrix because the new person will be compared by this Matrix. For the person with the matrix *X=[0.6 0.3 0.2 0.6]* we have best answer in first row for the Matrix related to person A and for 0.3 goes for person C ,0.2 and 0.6 from matrix *X* goes for Person A. so *X=[{A},{C},{A},{A}]* and the *X* matrix is 75% similar to person A.

7. Experimental Results and Discussion

In this method we bring a new method for classification of EEG signals by an identification matrix. Actual EEG signal has noise so we used PCA/Wavelet for denoising and using general thresholding theme for removing artifacts because they are extra potentials and they can change the signal power. There are some features in energy of signal while a person thinks about the specific job so we sort the energy dispersion from biggest to lowest. Here we compare the dominant results and delete the worse trial. For classification the power of alpha wave is taken and sorted the electrodes power from highest to lowest and then we will find the power-flow of the person. Then the matrix is deployed for the power of yes/no parts. If the power of yes is more than no for each electrode we add 1 to the matrix and form the identification matrix and compare the new person with the matrix.

8. Conclusion

In this paper a new method of biometric person identification is discussed, identifying task based on some medic information such as alpha wave power and glucose redundancy in each side of brain plus some statistical signal processing patterns. This method is depended on power, so good artifact removing techniques are needed. While the technique is based on some true brain chemical facts, it is a very robust method for identifying a person. Initial experiments show that over 81% this new method works and identifies the person correctly.

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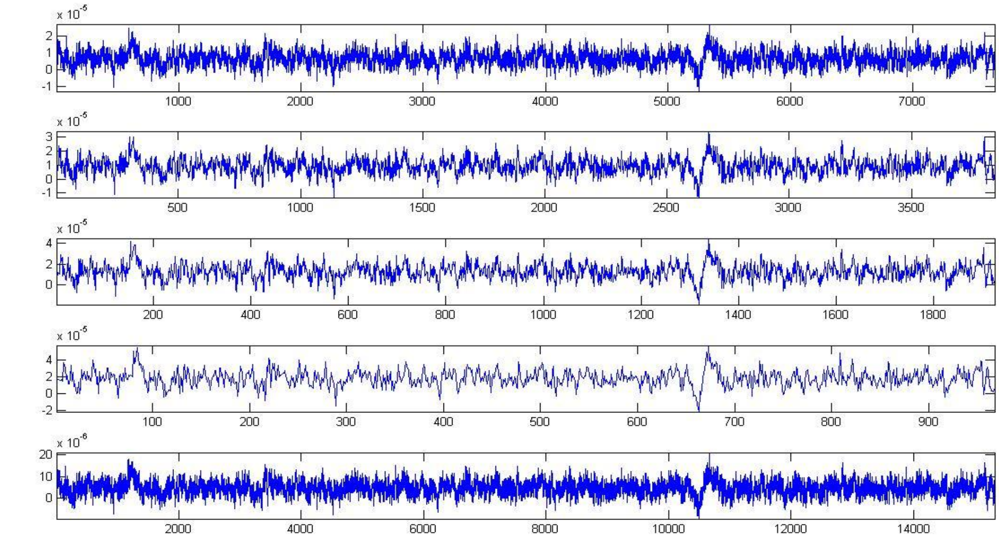


Fig 2: Different wavelet decomposition levels.

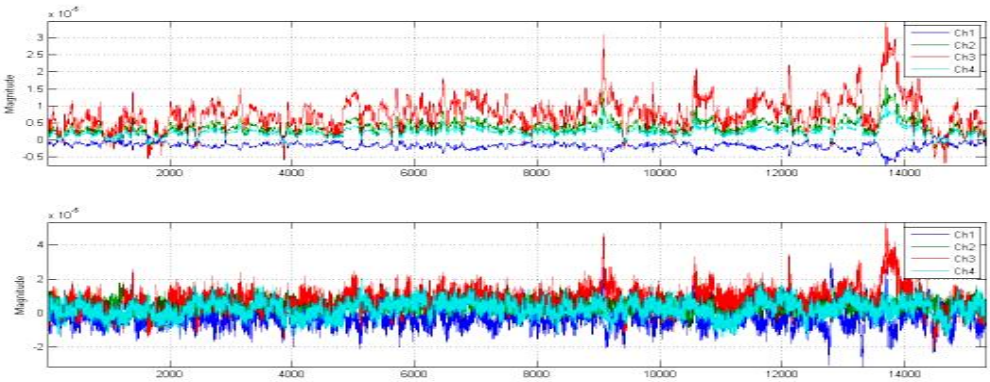
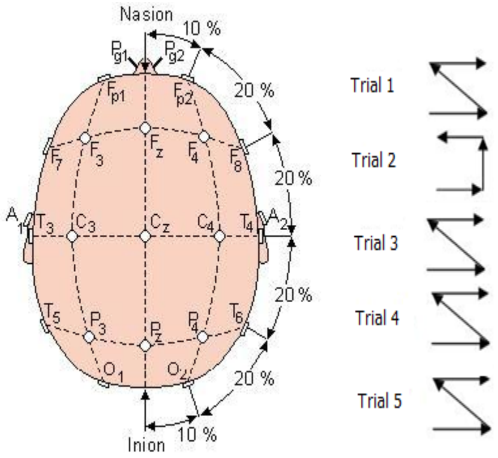
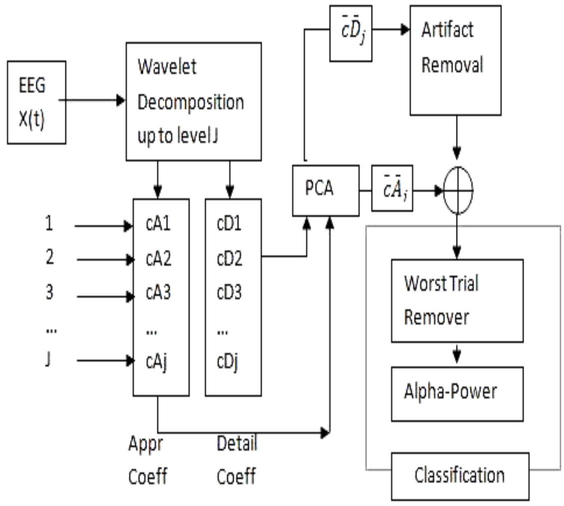


Fig 3: The EEG signal a) after multivariable denoising, b) actual signal.





Figs 5~6: *Location of electrodes as C3, C4, P3, and P4.*

Fig 7: *Flowchart of classification procedure*