International Journal Of Computational Engineering Research (ijceronline.com) Vol. 2 Issue. 7

FPGA implementation of wavelet-based denoising technique toanalysis of EEG signal

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Abstract

The electroencephalogram (EEG) is widely used clinically to investigate brain disorders. However, abnormalities in the EEG in serious psychiatric disorders are at times too subtle to be detected using conventional techniques. This paper describes the application of the wavelet transform, for the classification of EEG signals. The data reduction and preprocessing operations of signals are performed using the wavelet transform. Five classes of EEG signals were used: Alpha,beta,Gamma,Delta,Theta. The EEG signal is generated with the help of MATLAB. After several iteration we found the suitable wavelet coefficients which will able to correctly classify all five class of EEGs, respectively. The wavelet transform thus provides a potentially powerful technique for classification of EEG signals. Finally we carried out FPGA implementation of these resulting parameters.

Keywords: FPGA,Wavlet,MATLAB,etc.

1. Introduction

The purpose of this paper is to illustrate the potential of the High Resolution EEG techniques when applied to the analysis of brain activity related to the observation of TV commercials, political advertising, and PSAs to localize cerebral areas mostly emotionally involved. In particular, we would like to describe how, by using appropriate statistical analysis, it is possible to recover significant information about cortical areas engaged by particular scenes inserted within the video clip analyzed. The brain activity was evaluated in both time and frequency domains by solving the associate inverse problem of EEG with the use of realistic head models.

Successively, the data analyzed were statistically treated by comparing their actual values to the average values estimated during the observation of the documentary. Statistical estimators were then evaluated and employed in order to generate representations of the cortical areas elicited by the particular video considered Electroencephalography (EEG) is the recording of electrical activity along the scalp produced by the firing of neurons within the brain.[2] In clinical contexts, EEG refers to the recording of the brain's spontaneous electrical activity over a short period of time, usually 20–40 minutes, as recorded from multiple electrodes placed on the scalp. In neurology, the main diagnostic application of EEG is in the case of epilepsy, as epileptic activity can create clear abnormalities on a standard EEG study.[3] A secondary clinical use of EEG is in the diagnosis of coma, encephalopathies, and brain death. EEG used to be a first-line method for the diagnosis of tumors, stroke and other focal brain disorders, but this use has decreased with the advent of anatomical imaging techniques such as MRI and CT Derivatives of the EEG technique include evoked potentials (EP), which involves averaging the EEG activity time-locked to the presentation of a stimulus of some sort (visual, somatosensory, or auditory). Event-related potentials (ERPs) refer to averaged EEG responses that are time-locked to more complex processing of stimuli; this technique is used in cognitive science, cognitive psychology, and psychophysiological research.

The processing of information takes place by the “firing” or pulsing of many individual neurons. The pulse is in the form of membrane depolarization travelling along the axons of neurons. A series of pulses in the neurons, also known as a spike train, can be considered the coded information processes of the neural network.The EEG is the electrical field potential that results from the spike train of many neurons. Thus, there is a relationship between the spike train and the EEG and the latter also encodes information processes of the neural-network asurement and analysis of the EEG can be traced back to Berger’s experiments in 1929. Since then it has had wide medical applications, from studying sleep stages to diagnosing neurological irregularities and disorders. It was not until the 1970’s that researchers considered using the EEG for communication.

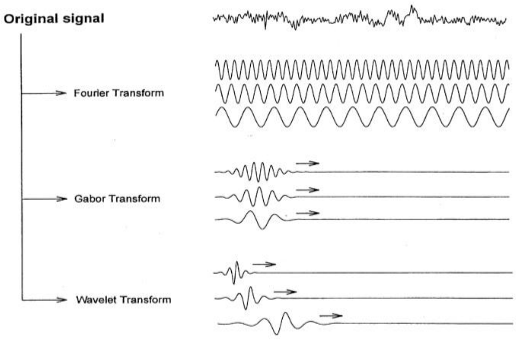


Fig. 1.1 variousmethods of EEG signal Analysis

2. 2.Analysis Methods

2.1 QUANTITATIVE EEG ANALYSIS

In quantitative EEG analysis the spectral contents of measured EEG can be quantified by various parameters obtained from the power spectral density (PSD) estimate. Typically several representative samples of EEG are selected and an average spectrum is calculated for these samples. Traditionally EEG is divided into four bands: δ (0 - 3.5 Hz), θ (3.5 - 7 Hz), α (7 - 13 Hz) and β (13 - 30 Hz). PSD estimates can be calculated by either nonparametric (e.g. methods based on FFT) or parametric (methods based on autoregressive time series modeling) methods.

EEG signal generation using MATLAB

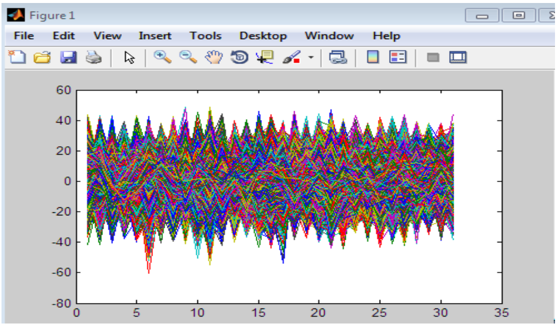


Fig 1.2 EEG signal.

2.2 TIME-VARYING EEG ANALYSIS

In the analysis of non-stationary EEG the interest is often to estimate the time-varying spectral properties of the signal. A traditional approach for this is the spectrogram method, which is based on Fourier transformation. Disadvantages of this method are the implicit assumption of stationary within each segment and rather poor time/frequency resolution. A better approach is to use parametric spectral analysis methods based on e.g. time-varying autoregressive moving average (ARMA) modeling. The time-varying parameter estimation problem can be solved with adaptive algorithms such as least mean square (LMS) or recursive least squares (RLS). These algorithms can be derived from the Kalman filter equations. Kalman filter equations can be written in the form

$$
\begin{aligned}
\hat{\theta}_{t|t-1} &= \hat{\theta}_{t-1} \\
C_{\tilde{\theta}_{t|t-1}} &= C_{\tilde{\theta}_{t-1}} + C_{w_{t-1}} \\
K_t &= C_{\tilde{\theta}_{t|t-1}} \varphi_t \left(\varphi_t^T C_{\tilde{\theta}_{t|t-1}} \varphi_t + C_{e_t} \right)^{-1} \\
C_{\tilde{\theta}_t} &= \left(I - K_t \varphi_t^T \right) C_{\tilde{\theta}_{t|t-1}} \\
\epsilon_t &= z_t - \varphi_t^T \hat{\theta}_{t|t-1} \\
\hat{\theta}_t &= \hat{\theta}_{t|t-1} + K_t \epsilon_t
\end{aligned}
$$

Where θ is the state vector of ARMA parameters, φ includes the past measurements, C denotes for covariance matrices and K is the Kalman gain matrix. All these adaptive algorithms suffer slightly from tracking lag. This can however be avoided by using Kalman smoother approach.Here we demonstrate the ability of several time-varying spectral estimation methods, with an EEG sample recorded during a eyes open/closed test. This test is a typical application of testing the desynchronization /synchronization (ERD/ERS) of alpha waves of EEG. The occipital EEG recorded while subject having eyes closed shows high intensity in the alpha band (7-13 Hz). With opening of the eyes this intensity decreases or even vanishes. It can be assumed that EEG exhibits a transition from a stationary state to another. One such transition from desynchronized state to synchronized state is presented below.

Analysis Based On Modes

The EEG signal is closely related to the level of consciousness of the person. As the activity increases, the EEG shifts to higher dominating frequency and lower amplitude. When the eyes are closed, the alpha waves begin to dominate the EEG. When the person falls asleep, the dominant EEG frequency decreases. In a certain phase of sleep, rapid eye movement called (REM) sleep, the person dreams and has active movements of the eyes, which can be seen as a characteristic EEG signal. In deep sleep, the EEG has large and slow deflections called delta waves. No cerebral activity can be detected from a patient with complete cerebral death.

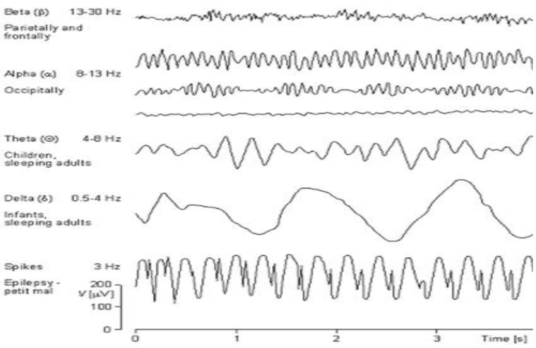


Fig. 1.3 various stages of EEG signal's

Power Spectra Calculation

Using Auto-Regressive (AR) parameter model method to compute the self-power spectra estimated value of the EEG signal [23]: The AR model of the EEG time series x_n is provided by the following formula

$$x_n = -\sum_{k=1}^{p} a_k x_{n-k} + w_n \tag{2}$$

Here p is the order of the AR model; $a_k(k = 1, 2, \cdots p)$ is AR model parameter; w_n is the unpredictable part of x_n, namely residual error. If the model can well match the EEG time series, w_n should be white noise process. According to the AR model

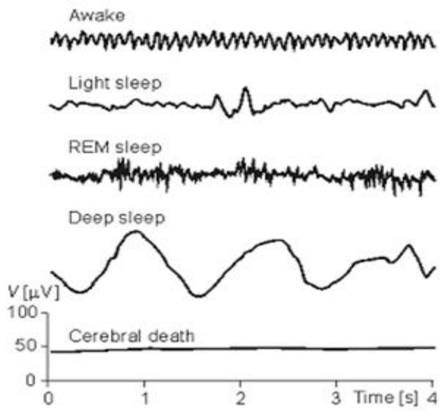


Figure 1.4 EEG activity depends on level of conciousness

given by formula (2), we can get the estimated value of the AR spectra

$$P_x(\omega) = \frac{\sigma_\omega^2}{\left|A(e^{j\omega})\right|^2} = \frac{\sigma_\omega^2}{\left|1+\sum_{k=1}^{p} a_k e^{-j\omega k}\right|^2} \quad (3)$$

Here σ_ω^2 is the variance of AR model residual error. From the formulas (2) and (3), we know the key to get the AR spectra estimation is to estimate the AR parameters a_k(k = 1, 2, ···p) through the EEG time series. Usually, Yule-Walker equation and Levinson-Durbin algorithm are used to estimate AR parameters. In this paper, we use Burg algorithm. Burg algorithm is an auto regression power spectra estimated method, on the premise of Levinson-Durbin recursion restraint, making the sum of the front and back forecast error energy smallest. Burg algorithm avoids the computation of self- correlation function. It can distinguish the extremely close sine signal in low noise signals, and may use less data record to estimate, and the result is extremely close to real values. Moreover, the forecasting error filter obtaining from Burg algorithm is minimum phase.The choice of the model order p is a critical problem in the AR model spectra estimate. If p is too low, it will cause smooth spectra estimate; while if p is too high, it will cause spectral line excursion and spectral line abruption and generate general statistic instability. In this paper, we adopt Akaike information criterion(AIC) to estimate the value of the order

$$AIC(p) = N \ln \hat{\rho}_p + 2p,$$

Here N is the number of the data points, $\hat{\rho}_p$ is the estimated value of the white noise variance (forecasting error power) of p order AR model.

The Determinism Computation of EEG Signals

Whether the brain is a deterministic system, determines the applicability of the nonlinear dynamic method of studying EEG signal [16]. Generally, the deterministic computation of the EEG signal requires much data; and supposes the spread of adjacent lines of EEG series in the phase space are similar. However, unstable data often generates false results. CTM algorithm is a method to express the second-order difference plot (SODP) characteristic of trajectory tangent vector quantificationally. It can be used in the deterministic computation of nonlinear time series effectively. This algorithm is real-time, stable and anti-noisy [17]. The tangent vector of trajectory in the reconstructing phase space is

$$\boldsymbol{Y}(t) = \boldsymbol{x}(t+1) - \boldsymbol{x}(t).$$

The angle between the tangent vectors can be expressed by its cosine value

$$A(t) = \frac{\boldsymbol{Y}(t+1)\cdot\boldsymbol{Y}(t)}{\left\|\boldsymbol{Y}(t+1)\right\|\left\|\boldsymbol{Y}(t)\right\|}.$$

Compared with the angle itself, the cosine value can resist noises better. The SODP of signal expresses the change rate of the tangent vectors angle A(n + 2) - A(n + 1) to A(n + 1) - A(n), its CTM value isThe value of CTM reflects the smooth degree of the attractors' trajectory: the smaller the CTM value is, the less the changes of tangent vector angle, the smoother the trajectory is; and vice versa. The determinacy of the signal S can be measured by the ratio of the CTM value of the EEG series data and the surrogate data. The bigger S is, the stronger the randomicity of EEG signal is. The researches show: the deterministic signal $S < 0.3$; the random signal $S > 0.7$; as to part deterministic signal $0.3 < S < 0.7$.

2.3 Phase Graph Analysis

Using the phase space reconstruct technique from one-dimensional time series to determine the time delay τ: In the experimental system, it should be through repeated trial method to confirm choice of τ. If τ is undersize, the track of the phase space will approach to a straight line; per contra τ is oversize, the data point will centralize in a small range of the phase space, and we can't get the attractors' local structures from the reconstructed phase graph [13]. Testing repeatedly, we find that selecting τ= 3, data point $N = 2000$, it can well reconstruct the EEG attractors. We construct the EEG attractors of all five kinds of consciousness activities of 7 subjects and find that EEG attractors of various patterns have similar characteristics. Fig.2 is a representative one. As can be seen from Fig. 2, the attractors' track often rotate in an extremely complex way, even smear a group black in the plane, but there is still internal structure when the attractors is magnified. The attractors of relaxation, mental composition of a letter and visualizing a 3-dimensional object being revolved about an axis often distribute in a small ellipse region, while the point in the attractors of mental arithmetic of multiplication and visualizing numbers being written or erased on a blackboard centralize nearby the 45 degree line and there is a large distributing range along the 45 degree line. This is because while proceeding rational computation such as mathematics or imagination, the value of the adjacent sampling points of EEG signals are close, and the amplitude values of the whole EEG signals are great.

FPGA

A field-programmable gate array (FPGA) is an integrated circuit designed to be configured by the customer or designer after manufacturing—hence "field-programmable".

3. Result and Discussion:

Model Sim Output*:*

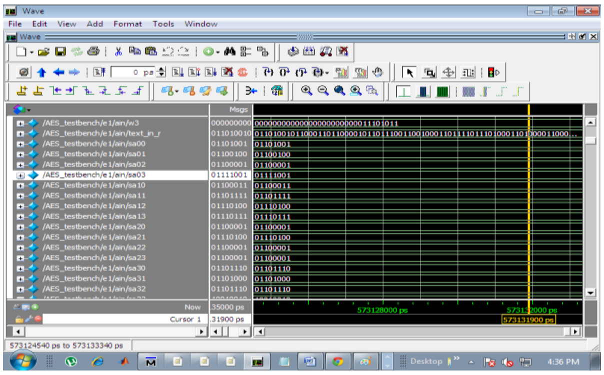


Figure 1.5.Simulated output.

CLASSIFIED EEG SIGNALS.

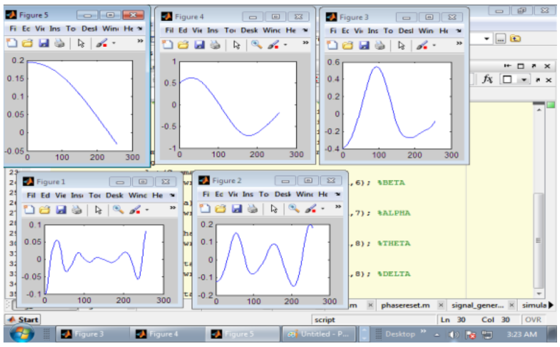


Fig 1.6 classified EEG signals

4. Synthesis Report:

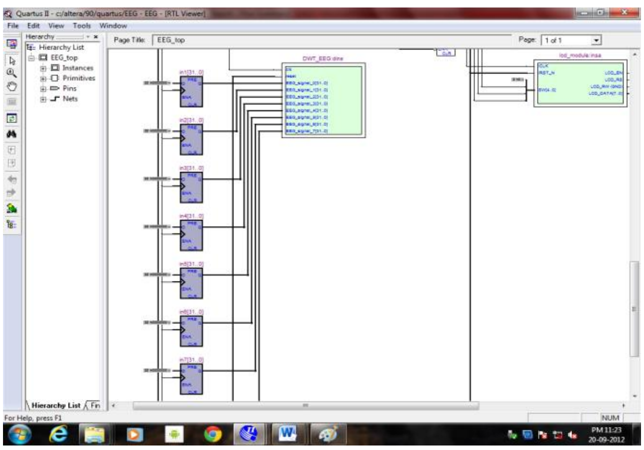
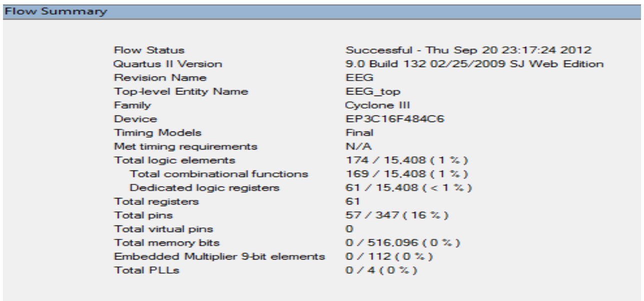


Fig1.7 RTL Schematic report

Area Utilization Report: Figure



Flow Summary

Flow Status	Successful - Thu Sep 20 23:17:24 2012
Quartus II Version	9.0 Build 132 02/25/2009 SJ Web Edition
Revision Name	EEG
Top-level Entity Name	EEG_top
Family	Cyclone III
Device	EP3C16F484C6
Timing Models	Final
Met timing requirements	N/A
Total logic elements	174 / 15,408 (1 %)
Total combinational functions	169 / 15,408 (1 %)
Dedicated logic registers	61 / 15,408 (< 1 %)
Total registers	61
Total pins	57 / 347 (16 %)
Total virtual pins	0
Total memory bits	0 / 516,096 (0 %)
Embedded Multiplier 9-bit elements	0 / 112 (0 %)
Total PLLs	0 / 4 (0 %)

Fig1.8.Flow summary report

MAP VIEWER:

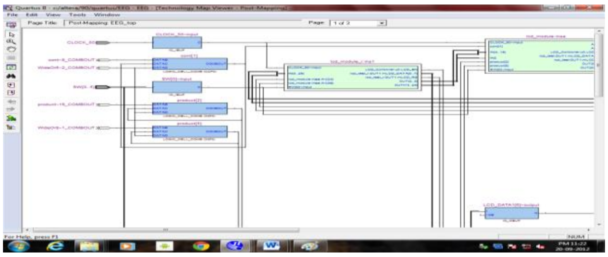
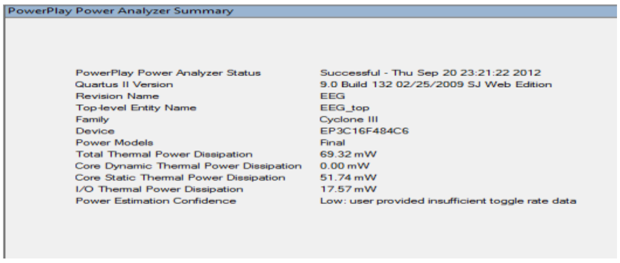


Fig1.9.Technology map viewer

POWER ANALYZES



PowerPlay Power Analyzer Summary

PowerPlay Power Analyzer Status	Successful - Thu Sep 20 23:21:22 2012
Quartus II Version	9.0 Build 132 02/25/2009 SJ Web Edition
Revision Name	EEG
Top-level Entity Name	EEG_top
Family	Cyclone III
Device	EP3C16F484C6
Power Models	Final
Total Thermal Power Dissipation	69.32 mW
Core Dynamic Thermal Power Dissipation	0.00 mW
Core Static Thermal Power Dissipation	51.74 mW
I/O Thermal Power Dissipation	17.57 mW
Power Estimation Confidence	Low: user provided insufficient toggle rate data

Fig.1.10 Power dissipation report

Conclusion

A wavelet-chaos methodology was presented for analysis of EEGs and delta, theta, alpha, beta, and gamma sub bands of EEGs for detection of seizure and epilepsy. Although it is observed that the filters are used for EEG signal denosing classification is not possible with the help of filters. The accuracy of wavlet based EEG classification is for better than any other methods.

References

[1] Seizures and Epilepsy: Hope through Research National Institute of Neurological Disorders and Stroke (NINDS), Bethesda, MD, 2004 .

[2] H. Adeli, Z. Zhou, and N. Dadmehr, “Analysis of EEG records in anepileptic patient using wavelet transform,” *J. Neurosci. Meth.*, vol. 123,no. 1, pp. 69–87, 2003.

[3] P. J. Durka, “From wavelets to adaptive approximations: Time-frequency parameterization of EEG,” *BioMedical Engineering OnLine*,vol. 2, no. 1, pp. 1(1)–1(30), 2003 [Online]. Available: http://www.biomedical-engineering-online.com/

[4] L. D. Iasemidis, L. D. Olson, J. C. Sackellares, and R. S. Savit, “Timedependencies in the occurrences of epileptic seizures: A nonlinear approach,”*Epilepsy Res.*, vol. 17, pp. 81–94, 1994.

[5] H. Adeli and S. L. Hung, *Machine Learning – Neural Networks, GeneticAlgorithms, and Fuzzy Sets*. New York: Wiley, 1995.