Low cost EEG signal acquisition for health care and person identification

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Abstract— The task of monitoring human health invasively and maintaining the security of any system is challenging in the current scenario. The proposed system integrates the health monitoring and biometric authentication for a healthy as well as secure world. The initial module comprises of analysing the change in EEG signals when blood pressure increases for the sick and elderly people while the latter module for security purposes. EEG signal is acquired from the subject. The acquiring of the signal undergoes several steps which include the filtering and amplification. The alpha wave which is unique is extracted, that avoids spoofing attacks is considered for biometry while the beta waves which alter the state according to the human mind state is considered for health monitoring. Data reduction along with SVM classifier and Hilbert transform is implemented in the proposed model.

Keywords— *Security, Electroencephalogram (EEG), Blood Pressure, Acquiring, Amplification, Robustness, Spoofing*

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I. INTRODUCTION

According to the statistics, among the 1.237 billions of people in India, about 100 millions of people are elderly & sick persons who are alone in home. As the new generation is running after the money & comforts they rarely have time to look after their elders and sick. EEG is the only brain imaging modality with a high temporal and fine spatial resolution that can easily be analyzed further.

The technology used to characterise human beings on the basis of biological traits is called biometry. Biometry is identified based either on the physiological which include the fingerprint, iris, face, hand, DNA, veins etc or behavioural traits of a person. The behavioural traits are the gait, signature and voice. The new emerging technology for biometric identification is brain-wave signals. The main purpose of person identification is to find out the identity of a person from N number of sets.

In this paper we study the use of EEG signal for health monitoring and biometric authentication. The advantages of use of brain wave for health care and person authentication include its uniqueness, difficulty in imitating and the impossibility to steal it.

II. BRAIN SIGNALS

The brain signals are measured using electroencephalography. It is a technique used to examine the electrical activity under the scalp. The brain comprises of a large no of neurons that communicate between each other using electricity. The combination of the electrical activity of the brain is called the brain wave pattern. The brain rhythms increase or decrease depending on mental states. The brain waves are classified as shown in the below figure 1:

Frequency(Hz)	Wave types	Characteristics
0.5-3	Delta	Deep Sleep condition
4-7	Theta	After death condition
8-15	Alpha	Relaxed state but not in sleep
16-32	Beta	Excited state
>30	Gamma	Conscious state with any motor function

Fig. 1 Brain waves.

III. METHODOLOGY

The below block diagram shows the complete process being done.

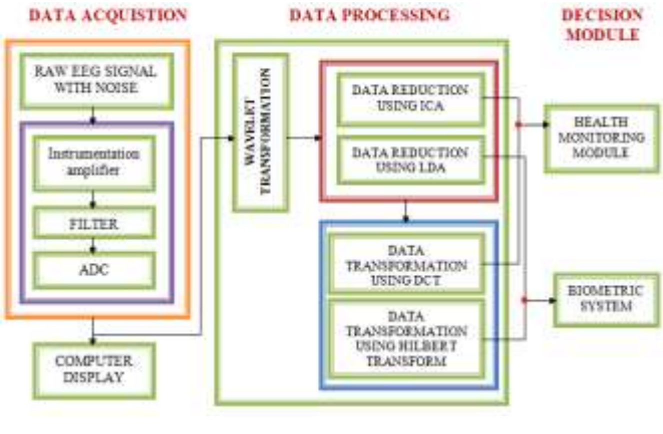

Fig. 2 Block diagram.

The block diagram can be divided into 3 parts, the data acquisition part, the data processing pat and the decision module part.

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The initial segment is used to remove the noise signals by filtering and the amplification along with the analog to digital convertor which is given to a display module.

The data processing part can be defined in simple terms to be processing the individual data in order to make a identification. This outflow is followed for both the health monitoring s well as authenticating purpose.

The decision module comes up with the decision based on the output of the matching process.

The EEG signal is undergone through the several steps stated below:

A. Data Acquisition

The EEG signal is recorded using EEG electrodes. These electrodes along with electrode gel is applied on the subject`s scalp. The positions of placing the electrodes are specified using the international 10/20 system.

The below figure 3 shows the initial first stage circuitry which include the instrumentation amplifier, LPF and an integrator.

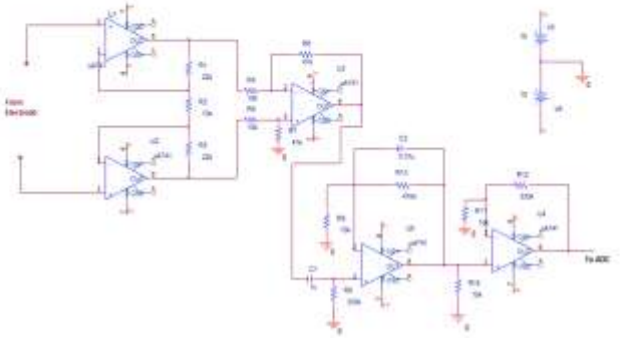

Fig. 3. Circuitry including instrumentation amplifier, LPF & integrator.

The output of the integrator is fed into the controlling unit which has an inbuilt ADC. The controlling unit is the microcontroller Atmega 8. The above is depicted in figure 4.

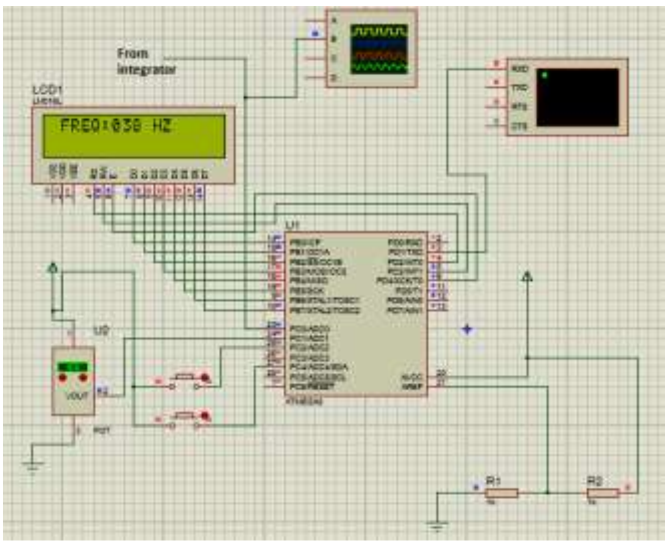

Fig. 4 Signal Aquisition Module

B. Discrete wavelet transformation

The splitting of the EEG signal into different frequency bands should reveal the traits which would be hidden in the original signal. To produce a result for the same we opt for discrete wavelet transformation.

The EEG signal comprises of frequencies more or less below 40 Hz and so we consider the 5 level decomposition of the EEG signal for the purpose of analysis. The Daubechies mother wavelet of order 4 (db4) with 5 level decomposition lets the signal into 5 frequency bands. The data in the table corresponds to the same.

TABLE I
FREQUENCY BANDS EXTRACTED USING DB4 WITH FIVE DECOMPOSITION LEVELS

Decomposition levels	Frequency Bandwidth (Hz)	Frequency bands
D1	64-128	Noises
D2	32-64	Noises (Gamma)
D3	16-32	Beta
D4	8-16	Alpha
D5	4-8	Theta
A5	0-4	Delta

In this work we consider the alpha waves and beta waves which correspond to the D4 and D3 decomposition level.

C. Data reduction technique: Independent component analysis

Independent component analysis (ICA) is a statistical and computational technique for revealing hidden factors that underlie in the sets of random variables, measurements, or signals. ICA usually defines a generative model for the observed multivariate data, which is usually given as a large database of samples. In the model, we will assume the data variables to be linear mixtures of some unknown latent variables, and with an unknown mixing system. The latent variables are assumed to be non gaussian and mutually independent and so they are called the independent components of the observed data. These independent components, called as the sources or factors, can be found by applying ICA.

The ICA method is used based on the following assumptions that the time series recorded on the scalp:

- are spatially stable mixtures of the activities of artifactual sources and the temporally independent cerebral , that
- the summation of potentials emerging from the different parts of the scalp, brain, and body is always linear at the electrodes, and that
- propagation delays from the sources to the electrodes are considered as negligible.

In EEG analysis, the rows of the input matrix X, are the EEG signals recorded using different electrodes and the columns are measurements recorded at different time points using Neuroscan software. ICA will find an `unmixed' matrix, W, which further decomposes or linearly unmixes the multi-channel scalp data into a corresponding sum of temporally independent and spatially fixed components. The rows of the output data matrix, U = WX, are time courses of activation of the ICA components. Independent Component Analysis (ICA) is used for removing artifacts in EEG signals.

D. Data reduction technique: Linear Discriminant Analysis

The data reduction technique used here is linear discriminant analysis (LDA). LDA performs dimensionality reduction keeping all the class information preserved. This technique is used to find the linear combination of features which characterises the different classes. LDA differs from PCA as it considers the scatter *within-classes* but also *between-classes* while PCA uses the scatter of the entire dataset.

LDA approaches the problem by assuming that the conditional probability density functions are both normally distributed with mean and covariance parameters and, respectively. LDA makes the additional simplifying based on homoscedasticity assumption (*i.e.* that the class covariances are identical).

LDA is estimated using the following equation:

$$(\vec{x}-\vec{\mu}_0)^T\Sigma_0^{-1}(\vec{x}-\vec{\mu}_0)+\ln|\Sigma_0|-(\vec{x}-\vec{\mu}_1)^T\Sigma_1^{-1}(\vec{x}-\vec{\mu}_1)-\ln|\Sigma_1| \ < \ T$$

where $\vec{x}$ represents a set of observations, $\vec{\mu}_0$ represents the mean and Σ_0 represents the covariance.

The linear transformation is a matrix *U* whose columns are the eigenvectors of $S_w^{-1} S_b$ (called *Fisherfaces*).

$$\begin{bmatrix} b_1 \\ b_2 \\ \dots \\ b_K \end{bmatrix} = \begin{bmatrix} u_1^T \\ u_2^T \\ \dots \\ u_K^T \end{bmatrix} (x-\boldsymbol{\mu}) = U^T(x-\boldsymbol{\mu})$$

The eigenvectors are solutions of the generalized eigenvector problem:

E. Discrete cosine transform

DCT is a transformation method for converting a signal in a time domain into its corresponding frequency components. A discrete cosine transform (DCT) expresses a finite sequence of discrete data points into the sum of the cosine functions terms oscillating at different frequencies. The discrete cosine transform (DCT) helps us to analyse the signal into parts or spectral sub-bands of differing importance. The DCT is similar to the discrete Fourier transform as it transforms a signal or image from the time domain to the frequency domain but we prefer DCT as we need only discrete values. DFT is not preferred as it includes complex values also. The equation of DCT is given by

The DCT equation (Eq. 1) computes the i,jth entry of the DCT of an image.

$$D(i,j)=\frac{1}{\sqrt{2N}}C(i)C(j)\sum_{x=0}^{N-1}\sum_{y=0}^{N-1}p(x,y)\cos\left[\frac{(2x+1)i\pi}{2N}\right]\cos\left[\frac{(2y+1)j\pi}{2N}\right]$$

$$C(u)=\begin{cases}\frac{1}{\sqrt{2}} & \text{if } u=0\\ 1 & \text{if } u>0\end{cases}$$

F. Hilbert Transform

The hilbert transform can be defined by:

$$H(x)=\frac{1}{\pi}\int_{-\infty}^{+\infty}\frac{g(t)}{x-t}dt$$

Hilbert transform is not equivalent to the original signal, rather it is a completely different signal. Hilbert transform does not involve a domain change, i.e., the Hilbert transform of a signal x(t) is another signal denoted by $\hat{x}(t)$ in the same domain (i.e., time domain).The Hilbert transform of a signal x(t) is a signal has exactly the same frequency components present in x(t) with the same amplitude–except that there is a 90° phase delay.

The Hilbert transform can be reduce to a filtering *operation*, where

$$H(\Omega)=-j\,\mathrm{sgn}(\Omega).$$

The Hilbert transform gives the phase of the data and so it can be represented in polar coordinates as shown in figure 6

IV. OBSERVATION

The below figure fig 5 shows the EEG waves which is obtained through the microcontroller after passing through the filtering and amplification modules.

Fig. 5 Oscilloscope output

The below figure fig 6 and fig 7 shows the alpha waves corresponding to a normal subject and abnormal subject respectively after application of wavelet discrete transform. Y axis shows the amplitude while x axis the samples.

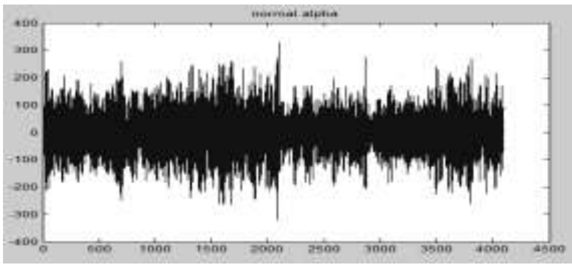

Fig. 6 Alpha waves of a normal person obtained by applying DWT.

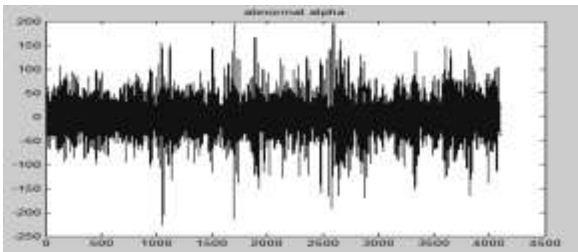

Fig. 7 Alpha waves of an abnormal normal person obtained by applying DWT.

Data reduction is done and plotted .Here we can observe the clear variation in signal for abnormal person, the amplitude is very low compared to normal person as shown in figure 8 (a) and (b).

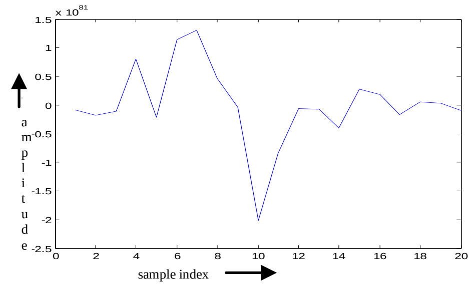

Fig 8. (a)Normal

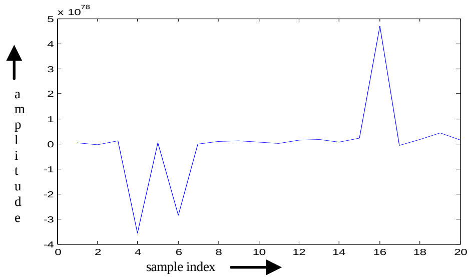

Fig 8. (b) Abnormal

The output after applying discrete cosine transform is shown below in figure 9 (a) and (b). The signal component with higher frequency and strength is taken. . We are getting high peaks in positive side for abnormal person .Here also we can observe a significant change

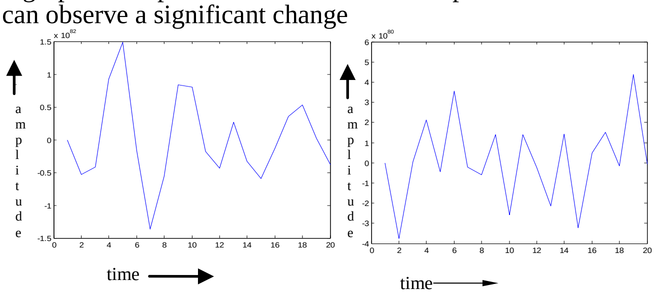

Fig 9 (a) Normal (b) Abnormal

The Hilbert transform gives the phase of the data and so it can be represented in polar coordinates as shown in figure 10.

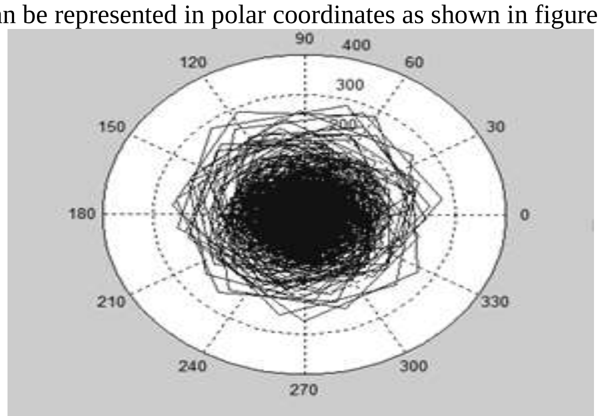

Fig.10 Hilbert transform representation.

V. Conclusion and Future Work

In this study, we found that the beta waves of the EEG signal changes tremendously with the increase of the blood pressure and alpha waves person can be identified by calculating the mean of instantaneous phase of the EEG dataset acquired from the person. Thus contributing this paper for a social cause i.e. Care and motivation to the sick and elderly as well as avoiding forgery in the technologically progressing world.

Future works can include analysis of more parameters related to health of old people and to develop a complete embedded system which will give alert to neighbours or sending messages to doctors or caretakers on the variation of these parameters. The future work is to design a system which can work on the above processing to provide a significant change to the present biometric technology used.

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