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Denoising of EEG, ECG and PPG signals using Wavelet Transform

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Abstract
Physiological signals such as EEG, ECG and PPG are very sensitive in nature and they are invariably corrupted by Power line and environmental noises. Quite often the frequencies of the signal and the noise overlap. Because of the importance of the underlying signal it is imperative to eliminate the noise without altering the time domain representation of the signals. Hence normal frequency selective filtering alone is not suffice for processing these signals. A wavelet based filtering approach is ideal for this problem as wavelet transforms preserve both time resolution and frequency resolution of the input signal. In this manuscript a Multi-scale wavelet based noise removal algorithm is proposed for processing EEG, ECG and PPG signals. And it is shown that the algorithm not only removes the noise effectively but also keeps the time resolution of the input signal intact. The improvement in noise removal is verified by comparing the signal to noise ratio of signal before and after applying wavelet based filtering algorithm.

1. INTRODUCTION

Biomedical indicators are collection of physiological performance of organisms, ranging from gene and protein sequences, to neural and cardiac rhythms, to tissue and organ photos. Biomedical signal processing pursuits at extracting vast data from biomedical signals. With the resource of biomedical sign processing, biologists can find out new biology and physicians may reveal distinct ailments. Diagnosis of various illnesses is done by analysing biomedical signals. A particular signal can be helpful in detecting a specific condition related to a single organ. Analyzing a combination of signals can diagnose multiple illnesses and give better prediction. Hence Multi signal processing is an attractive research area in Biomedical Signal Processing field.

There are different types of biomedical signals are available. But this work deals with the following three signals: ECG, EEG and PPG. The purpose of the work is to expand an well-organized multi signal processing system based on wavelets to remove the various noises present in the ECG, EEG and PPG signals and extract the features of interest for accurate diagnosis of illnesses and monitoring of people's health status.

2. LITERATURE SURVEY

A feature detection algorithm (choice-making rule set) is offered as the latest utility, which brings the detail of intelligence into the pulse oximeter layout through enabling onboard signal first-rate verification.

The signals of interest being the electrocardiogram (ECG), photoplethysmography (PPG) and impedance plethysmography (IP) signals.

The work has two main aims; the first being to estimate breathing rates from the signals, the second being to detect apnoeas from the signals.

In this article, we goal to develop methods for the evaluation and type of epileptic EEG signals and additionally for the identification of different categories of MI tasks based EEG indicators in BCI's improvement.

We have proposed a method of abnormality detection in bio signals following an change interpretation of laptop aided analysis. Rather than the traditional scheme of making selections on whether or not a given trial of scientific check is indicative of sickness or now not; we comply with the approach of marking factors of hobbies amongst time for further processing, both through a medical doctor and computationally. We have aimed at shooting a greater sparse illustration of the bio signal by way of lowering it to only activities of potential hobby. This method lets in us to make more flexible selections through being prepared for any sort of distortions and artifacts from recording noise.

Results on noisy datasets had been supplied, illustrating the complications of creating sign-primarily based prognosis inside the presence of full-size noise. The outcomes suggest that we are able to successfully reduce the sign into its big occasions. Our outcomes may lead to a shift in computer-aided analysis technique, in particular in a single dimensional temporal signal, wherein learning on small segments is complicated with problems inclusive of lack of information on whether the occasion exists in part or in entire inside the phase. The processing we have tested looks after such problems by way of pinpointing the correct area of the abnormal occasion within the signal.

The proposed scheme starts with mapping of the bio signal onto an appropriately chosen characteristic area. The choice of this space relies upon on the character of the quantity of interest, and contain prior statistics approximately the modality beneath examine. This trouble shall be mentioned inside the following phase. Once the transformation of the signal is carried out, the intention is to music the evolution of this sign in this new space and hit upon deviations from "everyday" behaviour. Following this concept of deviance detection, we first define what popular or regular behaviour is, and the applicable variance around this popular; so that it will decide "strange" conduct. Based in this definition, the recursive scheme iterates through the temporal sign, predicting at whenever instant how the sign need to evolve. Any deviations from this prediction consequence in an alert or peculiar occasion.

3. METHODOLOGY

3.1 The Electrocardiogram (ECG)

The ECG can be measured as a multi- or single- channel signal, depending on the software. During everyday dimension of preferred clinical ECG, 12 one of a kind leads (channels) are recorded from the body floor (pores and skin) of a resting affected person. In arrhythmia analysis most effective one or two ECG leads are recorded or monitored to research lifestyles-threatening disturbances within the rhythm of the heartbeat.

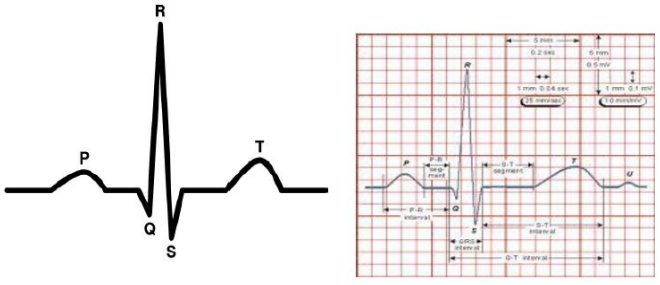


Figure 1: The ECG Waveform

General waveform generated is as shown in Figure 1 which is labelled as:

P wave	Atrial depolarization
QRS complex	Ventricular depolarization
T wave	Ventricular repolarization
U wave	Repolarization of Purkinje fibers
Baseline	Polarized state

3.1.1 Recording of ECG

The Standard 12-Lead ECG

- ECG signal is traced in three various electrode positions.
- Standard Limb Leads(Bipolar Limb Leads) I, II, III
- Unipolar limb leads (Augmented Limb Leads)
- Unipolar chest leads (Standard Limb Leads) – I, II, III
- Every lead offers different reading.
- Total 12-reading is attained where standard leads-3, unipolar leads-3 and chest lead-6.

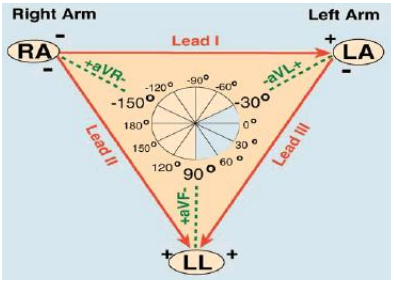


Figure 2: The standard 12-Lead ECG

3.2 The Electroencephalogram (EEG)

The EEG (popularly known as *brain waves)* represents the electrical activity of the brain of an alternating kind recorded from the scalp surface after being picked up with the aid of metal electrodes and conductive media. The EEG measured without delay from the cortical floor is called electrocardiogram at the same time as when the use of depth probes its miles called electrogram. Thus electroencephalographic analyzing is a completely non-invasive method that can be carried out repeatedly to sufferers, everyday adults, and kids with honestly no chance or trouble.

The normally used terms for EEG frequency bands whose sample is shown in Figure 3.

- Delta (δ): $0.5 \leq f < 4$ Hz;
- Theta (θ): $4 \leq f < 8$ Hz;
- Alpha (α): $8 \leq f \leq 13$ Hz: and
- Beta (β): $f > 13$ Hz.

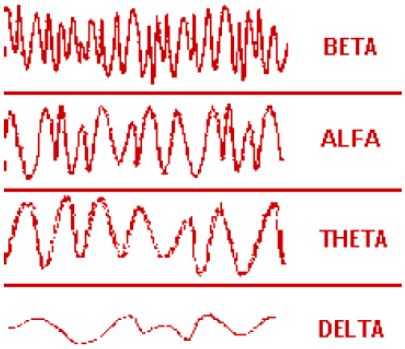


Figure 3: Brain wave samples with dominant frequencies belonging to beta, alpha, theta, and delta band.

EEG signals show off several styles of rhythmic or periodic pastime. (Note: The term rhythm stands for distinct phenomena or activities within ECG and EEG.). Figure 5 illustrates a four second pattern of an EEG data.

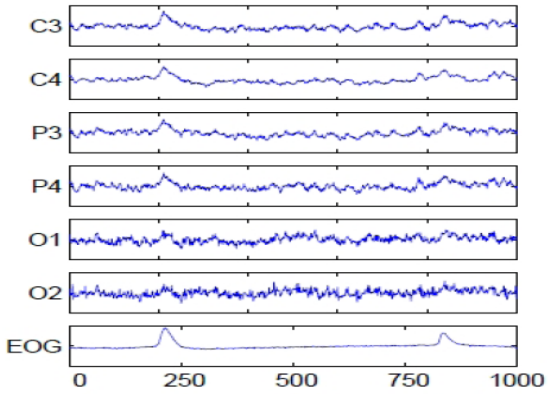


Figure 4: A four second sample of an EEG data

3.3 Photoplethysmogram (PPG)

A pulse oximeter is an optical medical device allowing the non-invasive monitoring of cardiopulmonary parameters. In clinical and homecare applications, this easy to use device, usually in the form of a fingertip clip, has been widely used to acquire and display heart rate (HR) and arterial blood oxygen saturation (*SpO2*).

3.3.1 Potential Clinical Parameters Available from PPG Data

Although the regular physiological parameters, HR and *SpO2*, are accounted on a conventional pulse oximeter, the PPGs provided by the pulse oximeter sensor propose other potential clinical parameters as listed in Table 1.

$$C = \Delta V / \Delta P \qquad (1.1)$$

Table 1. Potential clinical parameters that can be obtained from a PPG.

Blood pressure (BP) waveform	**Pulse wave reflection parameters**
o Systolic BP	o Peak-to-peak time (PPT)
o Diastolic BP	o Pulse wave velocity (PWV)
o Mean BP	o Arterial elasticity (*E*)
o Stroke volume (SV)	o Stiffness index (*SI*)
o Cardiac output (CO)	o Reflection index (*RI*)
Venous volume pulsations	**Perfusion index (*PI*)**
o Respiratory rate	Ambient light information
o Venous blood oxygen saturation	Patient motion
o Metabolic rate	Patient identity

Figure 5 illustrates an example volume-pressure curve for an arterial segment. As BP increases, the vessel is more reluctant to dilate and demonstrates decreasing compliance and Increasing the elasticity.

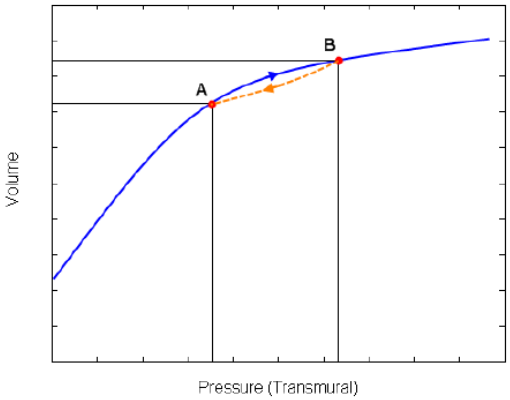


Figure 5. Volume-pressure relationship in an arterial segment.

Once a BP waveform is obtained from a volumetric waveform, systolic, diastolic, and mean BP are subsequently obtainable. Stroke volume (SV) and cardiac output (CO) can also be calculated approximately using a K value calculated with BP information.

Figure 6 demonstrates a single DVP cycle, where the systolic component with height "b" results from the direct transmission of the systolic pressure wave from the aorta to the fingertip.

$$RI = \frac{a}{b} \times 100\% \quad (1.2)$$

$$SI = \frac{Subject\_Height}{PPT} \quad (1.3)$$

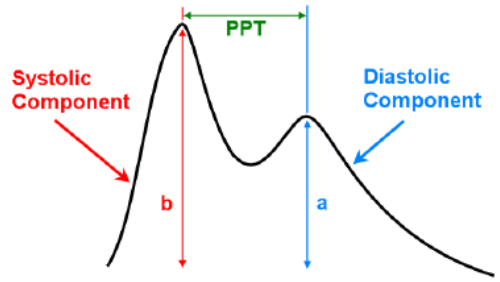


Figure 6. Parameters obtained from digital volume pulse analysis.

PWV can be stated as a function of arterial elasticity (*E*) via the Moens-Kortewea
Equation:

$$PWV = \sqrt{\frac{h \cdot E_{inc}}{2 \cdot r \cdot \rho}} \quad (1.4)$$

where *h* is the arterial wall thickness, *Einc* is the incremental elastic modulus, *r* is lumen radius, and ρ is blood density.

With the factors that (a) veins and arteries are distributed hand in hand and (b) veins are closer to the skin and therefore to a reflectance pulse oximeter sensor, it is believed that venous volume pulse information will be embodied in the photoplethysmographic signal, as in Figure 7.

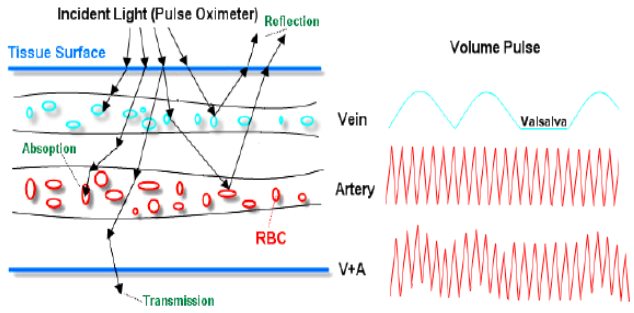


Figure 7. Respiration-induced venous volume pulse and arterial volume pulse. Their Combined volume signal is demonstrated as V+A.

The perfusion index (*PI*), described as the ratio of the pulsatile amplitude (AC) of a PPG to its baseline value (DC) is reported as an index sensitive to proximal sympathectomy. With PIs calculated for the red and near-infrared channels, the calibration coefficient (*R*) for a pulse oximeter can be written as

$$R = \frac{PI_{red}}{PI_{ir}}, \quad (1.5)$$

Where *SpO2* (%) = A*R* + B (A and B are experimentally determined scalars).

3.4 CLASSIFICATIONS OF SIGNALS AND NOISE

(a) Deterministic signal in noise, illustrated by a segment of blood pressure signal recorded using a fluid-filled catheter in the femoral artery

(b) Deterministic signal (in noise) synchronized to an external cue or perturbation, illustrated by an epoch of somatosensory evoked potential recorded from the somatosensory cortex in response to an electrical stimulus to the forelimb

(c) Stationary stochastic signal, illustrated by a segment of EEG from the cortex that shows no specific morphology or shape, but the statistics of the signals are more or less stable or stationary in the absence of any physiological perturbations

(d) Non Stationary stochastic signal, illustrated by a segment of EEG recorded from an adult rat recovering from a brain injury showing bursts of activity, but the statistics of this signal change with time

(e) Chaotic signal that was artificially generated resembles a stochastic signal but is actually generated by a deterministic dynamical system

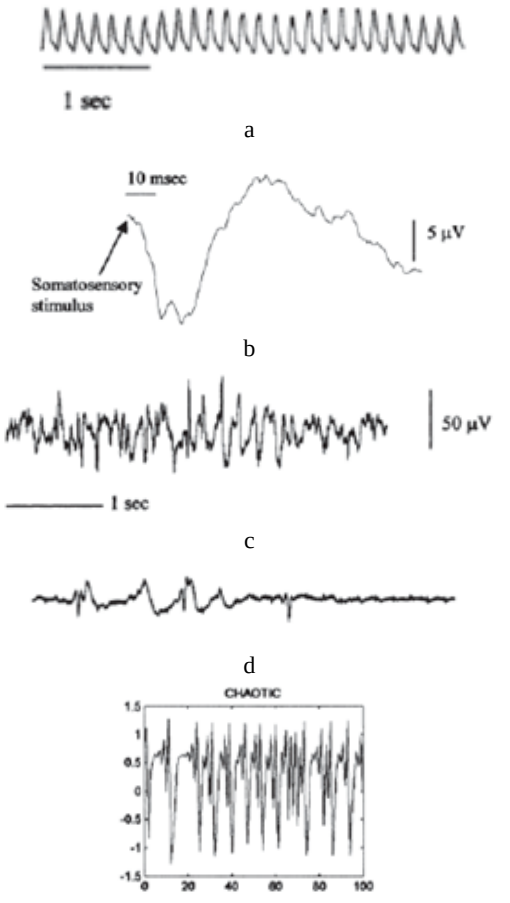


Figure 8: Types of bio signals.

3.5. Wavelet Types

Wavelet Packet Decomposition (WPD), Fractional Wavelet Transform (Fractional WT), Fast Wavelet Transform (FWT), Lifting Wavelets, Multi-wavelet Transforms etc are some of the types of wavelets. However, wavelet transforms are mainly classified into CWT- Continuous Wavelet Transforms and the DWT-Discrete Wavelet Transforms. Multi-wavelet transform is one of the widely adopted techniques, which is explained as follows.

3.5.1 Multi-wavelet Transforms

The wavelet transform is a kind of signal transform that is normally used in image compression. A new substitute to wavelet

transform is the Multi-wavelet transforms. Multi-wavelets are identical to wavelets but have some significant variations. Wavelets have a related scaling function and wavelet function, whereas multi-wavelet has two or more scaling and wavelet functions.

3.5.2 Continuous Wavelet Transform (CWT)

Since the basic introduction of CWT had been discussed in introduction chapter, we see a mathematical model for CWT here. The CWT adapts a continuous signal into enormously redundant signal of dual continuous variables: translation and scale. The resultant changed signal is simple to understand and precious for time-frequency analysis. The continuous wavelet transform as a wavelet transform with a (properly sampled) continuous-time mother wavelet, a continuous dilation (scale) parameter, and a discrete translation parameter; an additional WT, that achieves no sub-sampling, is the CWT. In CWT the mother wavelet is a continuous function, such as a Mexican hat wavelet (second derivative of a Gaussian). The CWT of the signal x (t) is identified as a convolution of the signal with a scaled and translated version of a base wavelet function which is given by

$$g(c,d) = |d|^{1/2} \int_{-\infty}^{\infty} g(t)\varphi\left(\frac{t-c}{d}\right) d$$

Where c, d$\in$ R, c and d are nonzero real values and they are dilating and translating coefficients respectively.

3.5.3 Discrete Wavelet Transform (DWT)

This thesis focuses on DWT based de-noising and has given the basic characteristics of DWT in the introduction part. A more detailed description and mathematical representation of discrete wavelet transform is given in this section. The discrete counterpart of the WT, named DWT, arose in the situation of the multi-resolution analysis theory as explained in the next chapter of Decomposition and de-noising. It is a multi-resolution illustration of a signal which decays signals into basis functions. It is described by a higher time resolution for high frequency components and a higher frequency resolution for low frequency components.

Discrete wavelet transform as shown in Figure 9 is same as filtering it by a bank of filters of non-overlapping bandwidths which vary by an octave. It is based on sub-band coding which is found to yield a fast calculation of Wavelet Transform. It is easy to implement and diminish the calculation time and resources required. A set of dilations and translations of a preferred mother wavelet is used for signal analysis. It is important to know the behaviour of these filters with these wavelet coefficients. According to the mother wavelet design the coefficients of these filter banks are determined.

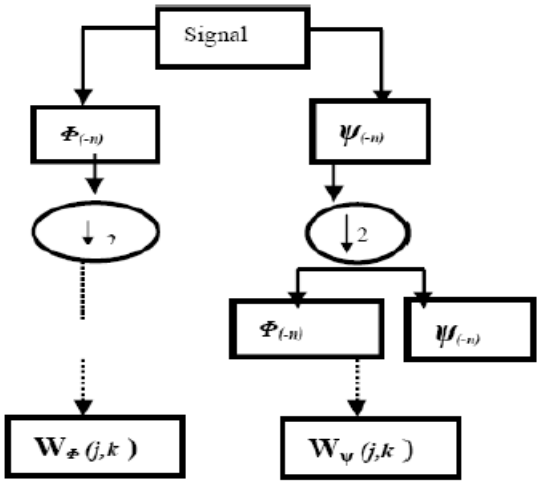


Figure 9: Discrete Wavelet Transform

A common equation for the Discrete Wavelet Transform signal is written as follows from Figure 9:

$$X[e,f] = \sum_{m=-\infty}^{\infty} x[m]\, \varphi_{e,f}\ [m]$$

where, φ [m] be the window of finite length, *f* is a real number recognized as window translation parameter and *e* is a positive real number named as contraction parameter.

3.5.4. Wavelet filters

Discrete Wavelet Transform is completed by way of repeated filtering of the input signal the usage of two filters. The filters are a low skip clear out (LPF) and a high skip clear out (HPF) to decompose the signal into unique scales. All wavelet transforms can be specified in terms of a low-pass filter out h, which satisfies the standard quadrature reflect filter situation:

$$H(Z)\, H(Z^{-1}) + H(-Z)\, H(-Z^{-1}) = 1$$

Where H(Z) indicates the z-transform of the filter H. Its complementary high-pass filter can be described as

$$G(Z) = Z\, H(-Z^{-1})$$

A sequence of filters with increasing length (indexed by *i)* can be attained:

$$H_{i+1}(Z) = H(Z^{2^i})\, H_i(Z)$$

$$G_{i+1}(Z) = G(Z^{2^i})\, H_i(Z),\ i = 0 \ldots\ldots\ldots 1-1$$

With the initial form H0 (Z) = 1. It is conveyed as a two-scale relation in time domain

$$h_{i+1}(t) = [h]_{\uparrow 2^i} h_i(t),\ g_{i+1}(t) = \left[h_g\right]_{\uparrow 2^i} h_i(t)$$

Where the subscript $\varphi(t)\ and\ w(t)$ shows the up-sampling by a factor of m and t is the equally sampled discrete time.

The normalized wavelet and scale basis functions can be described as follows:

The output coefficient expanded by the LPF is the approximation coefficient. The scaling function result is in the form of:

$$\varphi(t) = 2\sum_{q=0}^{M} (q)\, \varphi(2t-q)$$

The result of the HPF is the detailed coefficient. The wavelet function result is:

$$w(t) = 2\sum_{q=0}^{M} g(q)\varphi(2t-q)$$

The approximation coefficient is therefore divided into new approximation and precise coefficients. By choosing the mom wavelet the coefficients of such filter out banks are calculated. This decomposition manner is repeated until the required frequency reaction is achieved from the given enter sign.

4. Proposed Algorithm:

Steps:

- Load ECG, PPG, EEG Signal
- Pre allocation, Process the signals as 4 second frames
- Length of each signal, Find Maximum Amplitude. Find peaks above 70% Amplitude.
- Find their mean distance RR Peaks, Mean of RR Peaks

- Find Wavelet decomposition, Mean Amplitude of Peaks.
- Find peaks above 70% Amplitude, mean distance, Mean of RR Peaks
- Detecting R Peaks, Time Duration of Signal
- Initialization of the matrices for storing R-peaks and location.
- Window size represents number of samples in 0.4second (Fs = 1000)
- Finding the peak in each window. Storing the peak and location based on the criteria (0.7 is the threshold). Storing all non zero peaks and locations
- Choosing the higher peak if two peaks are detected in two adjacent windows with location difference shorter than W
- Removing all zero values from resultant matrix, Detecting QRS Output
- Plot ECG, PPG, EEG signal output

5. Simulation Result:

The input signal is processed for different ECG, PPG, EEG signal. Output of ECG, PPG, EEG signal is obtained and the increased percentage SNR values obtained. For different input signal was processed with the proposed algorithm and the various

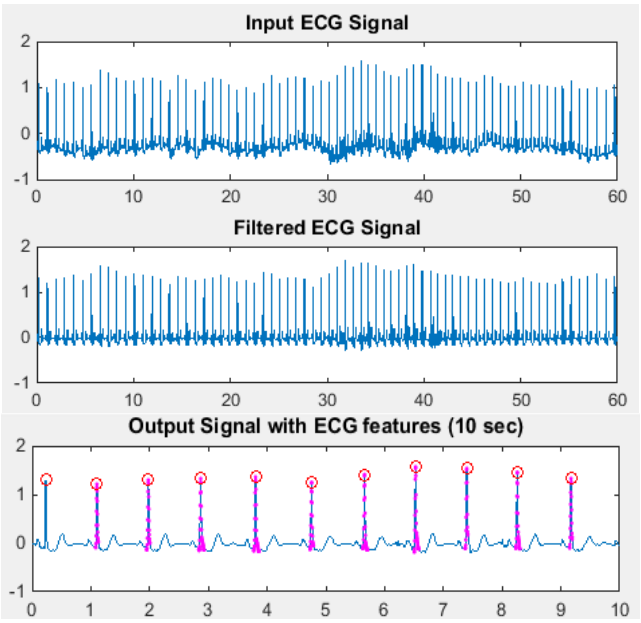
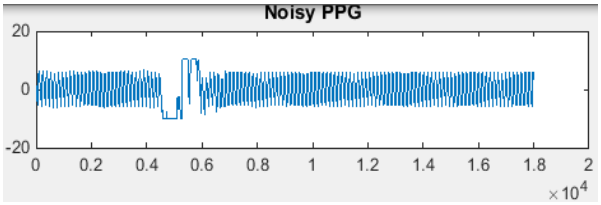


Figure 13. Input ECG, Filtered ECG, Output of ECG Signal



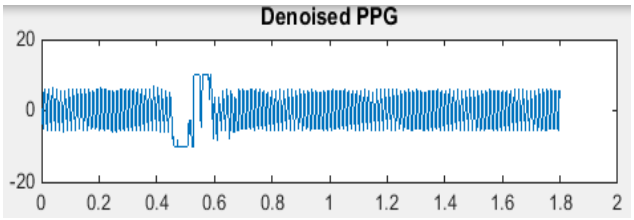


Figure 14. Noisy PPG, Denoised PPG Signal

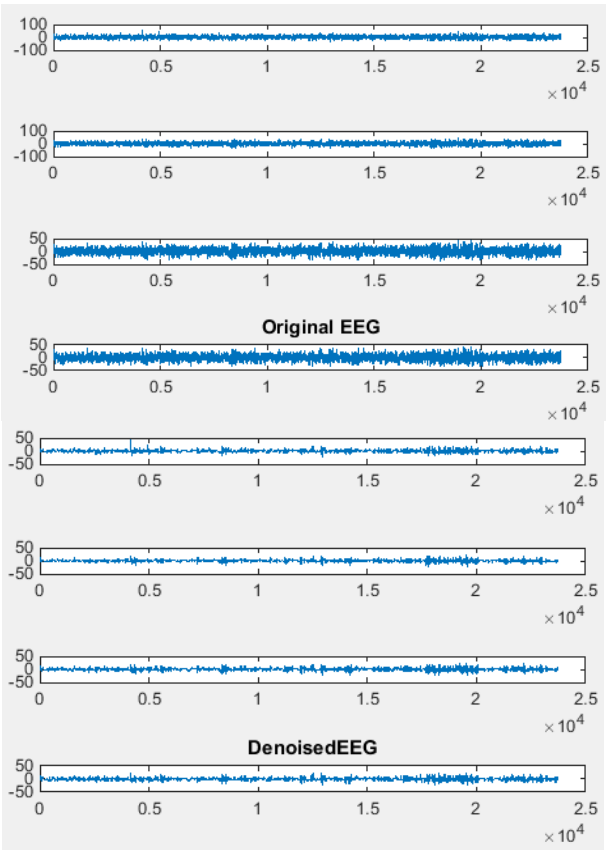


Figure 14. Original EEG, Denoised EEG Signal

Table 2: Different Signal ECG, PPG, EEG - Input, Output and SNR %

Combination	ECG			PPG			EEG		
Signal	Original	Output	SNR %	Original	Output	SNR %	Original	Output	SNR %
ECG1,PPG1,EEG1	-0.92	9.15	89.95	-0.11	35.44	99.69	-3.46	7.25	52.22
ECG2,PPG2,EEG2	-1.06	6.78	84.30	-0.20	31.81	99.38	-22.25	-17.89	224.40
ECG3,PPG3,EEG3	-0.79	7.54	89.49	-0.15	32.92	99.54	-6.18	1.63	277.97
ECG4,PPG4,EEG4	-0.22	12.49	98.26	-0.24	29.54	99.18	-1.52	12.33	87.65
ECG5,PPG5,EEG3	-1.71	6.00	71.59	-0.16	33.19	99.52	-6.18	1.63	277.97
ECG6,PPG6,EEG2	-0.44	11.53	96.16	-0.09	37.25	99.75	-22.25	-17.89	224.40

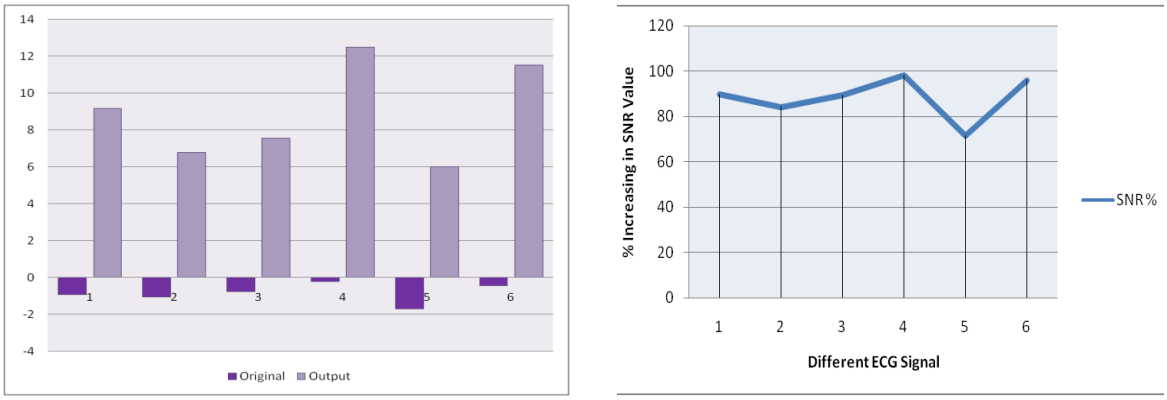


Figure 15. ECG Signal- Input, Output & SNR

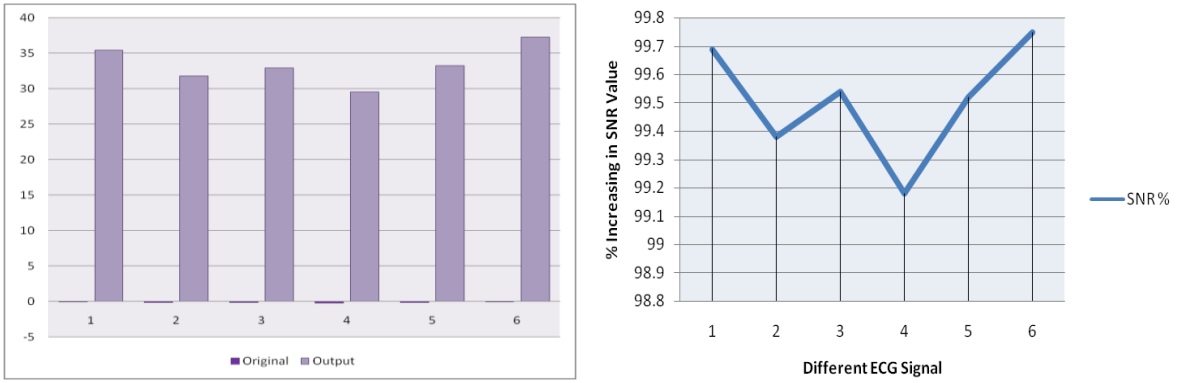


Figure 15. PPG Signal- Input, Output & SNR

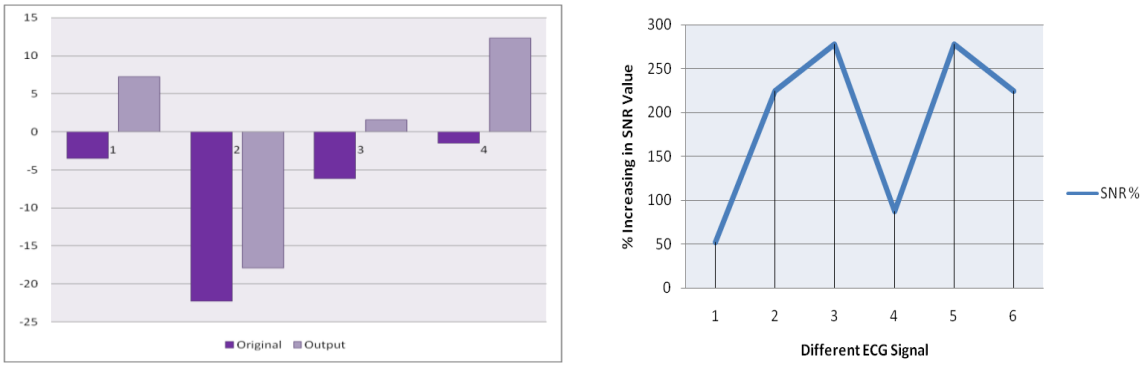


Figure 16. EEG Signal- Input, Output & SNR

CONCLUSION:

The EEG, ECG, PPG indicators can be de-noised the use of Wavelet transform approach. The evaluation of indicators at various levels consisting of de-noised signal may be plotted. Wavelet transform can analyse the indicators in every time and frequency area and additionally indicators with low noise amplitudes may be removed from the indicators through choosing the excellent wavelet to decompose the sign. Wavelet transform may be carried out for EEG, ECG, PPG de-noising. Wavelet packets may be used for de-noising EEG ECG, PPG signals which can provide higher consequences.

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