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CORRELATION-BASED ANALYSIS AND LINEAR REGRESSION MODELING OF SYNCHRONIZED EEG AND ECG SIGNALS MEASUREMENT

Asst. Prof. Dr. Naufel Bahjat Mohammed
Head of Computer Department, KISSR
naufel.bahjat@kissr.edu.krd

Abstract

This research aims to study the correlation between EEG and ECG signals measured at the same time. The correlation analysis of both signals will help to recognize the patient's mental condition and its effect on heart activity.

The data from EEG and ECG signals were converted to time series data then the correlation between them is studied, Linear Regression model between EEG and ECG signals was built.

Keywords: Correlation, EEG, ECG, Linear Regression, Raspberry Pi4.

Introduction:

Many researchers studied the relationship between the EEG and ECG signals and how the mental condition affects cardio activity.

The dynamics between the heart and the brain remain to be a complex subject in need of further research. In neurocardiology, which deals with the interplay between the nervous and cardiovascular systems, there is no question that the two organs are interrelated.

The ECG and EEG recordings increase in value after the subjects performed different stimulating activities. It suggests that heart rate and brain activity have a noticeable correlation with each other. The results did not show any significant differences between males and females (Billones, et al) [1].

While (Gavendra, et al) [2], studies the degree of association or coupling of frequency spectra between the ECG and EEG signals at a particular frequency. Coherence is often interpreted as a measure of 'coupling' and as a measure of a functional association (relationship) between two signals (ECG Signal and EEG Signal), the research study utilized the Welch method for spectral estimation to investigate the coherence between the ECG signal and the EEG signal at a particular frequency and under the different frequency bands. Both signals are completely coherent if the magnitude squared coherence is equal to 1, if MSC is equal to zero then both signals are independent of each other.

Decoding the correlation between Brain and Heart activities studied by

(J. Ramadoss, et al) [3], the research analyzed the complex structure of EEG and R-R signals using fractal theory and sample entropy, and the results indicated that the fractal exponent and sample entropy of EEG signals change more significantly

by moving from the first to the fourth session. The fractal exponent and sample entropy of R-R signals also had similar trends. Besides, it was found that the complexities of R-R and EEG signals are strongly correlated. Therefore, it can be concluded that the activations of the heart and brain are coupled.

The drowsiness detection using joint EEG-ECG data with deep learning was studied by (G. Geoffroy, et al) [4], the research proposed a method based on a deep learning architecture involving convolution and recurrent neural networks.

A very accurate detection was obtained, especially when the learning step involves frames from the target subjects.

Another research by (Silvio Barra, et al) [5], presents a set of preliminary results derived from the investigation of a biometric system based on the fusion of simple features simultaneously extracted from EEG and ECG signals. The reported results show high performance both from the uni-modal approach (higher performance

being EER = 11.17 and EER = 3.83 for EEG and ECG respectively) and fusion (EER = 2.94). However, caution should be considered in the interpretation of the reported results mainly because the analysis was performed on a limited set of subjects.

Research by (Ye Gu) [6]. Conclude that the correlation between EEG each band power and ECG parameters and the correlation between EEG each band relative power and steering wheel related parameters are presented by the correlation coefficients, which confirmed neither the ECG parameters nor the steering wheel related parameters have a strong linear relationship with EEG each band power. This study also shows that the combined parameters which strongly linearly correlate with certain EEG band relative power also do not exist. However, the neural network model did set up close nonlinear relationships between EEG band power and the other parameters, the promising results show that it is very possible to build a high-accuracy driver drowsiness detection system based on these inexpensive and intrusive methods. In order to find out the exact accuracy, the results got from the neural network still need to be used in place of the EEG parameters, and then the results obtained need to be compared with some standard sleepiness scale.

Analysis of ECG and EEG signals to detect epileptic seizures project by

(A. Suvaran, et al) [7], developed an algorithm that predicts if a seizure is likely to occur using Electroencephalogram and Electrocardiogram.

Features like mean and standard deviation of the peak-to-peak interval, QRS amplitude, QRS time PR interval, and QT interval for ECG and spectral power for EEG frequency bands were derived. The power distributions particularly in delta and theta bands were computed to detect the seizures in EEG. Here, both biosignals are processed simultaneously to predict the extract occurrence of seizure.

This paper presents a correlation-based analysis of EEG and ECG signals measured together by transforming both signals into time series data.

Theory:

EEG specifications

An EEG signal is a measurement of currents that flow during synaptic excitations of the dendrites of many pyramidal neurons in the cerebral cortex. When brain cells (neurons) are activated, synaptic currents are produced within the dendrites. This current generates a magnetic field measurable by electromyogram (EMG) machines and a secondary electrical field over the scalp measurable by EEG systems (saeid & Chambers) [8].

Free-running EEG is the brain activity that is present due to the normal operation of the brain. It is there, all of the time, as the brain is operating (Casson, et al) [9].

The amplitude of the EEGs detected over the head is 1-100 µV from top to top and the frequency band is 0.5-100 Hz. Although the EEG signal has a broad frequency band (0.5- 100 Hz), clinical and physiological attention is concentrated between 0.5 and 30 Hz. This frequency range is divided into 5 frequency bands.

• Delta (δ) Signal: In the frequency range of 0.5–3.5 Hz and amplitudes are 20-400 µV. The amplitude tends to be the highest and in the slowest waves. It is normally seen in adults in deep sleep and in infants.

• Theta (θ) Signal: The frequency of these signals is between 3.5-7.5 Hz and their amplitude is between 5-100 µV. Theta is linked to inadequacy and daydreaming. In fact, the lowest waves of theta represent the line between being awake or asleep. In adults, high levels of theta are considered abnormal.

• Alpha (α) Signal: This signal frequency is between 7.5 and 12 Hz and amplitudes vary between 2-10 µV. Hans Berger called the first rhythmic EEG activity he saw an "alpha wave. The interval seen in the posterior regions of the head on both sides is higher in amplitude on the dominant side. It appears by closing eyes and loosening. It is about rest, meditation, and before falling asleep.

• Beta (β) Signal: Beta is a brain signal in which the frequency ranges from 12 Hz to about 30 Hz. Amplitudes vary between 1-5 µV. The symmetrical distribution is usually seen on both sides and is prominent from the front. Beta waves are usually divided by β1 and β2 to obtain a more specific range. Waves are small and fast when resisting or suppressing motion or solving a math task. In these cases, an increase in beta activity was found.

• Gamma Signal: A signal with a frequency range of 31 Hz and above. It reflects the mechanism of consciousness. The amplitudes are less than 2 µV. They carry the characteristic sign of sleep. The gamma wave is seen in REM sleep, learning moments, and moments of extreme happiness and it is very difficult to detect by EEG, fig. (1) shows the waves that can be measured by EEG signals, (Selma) [10].

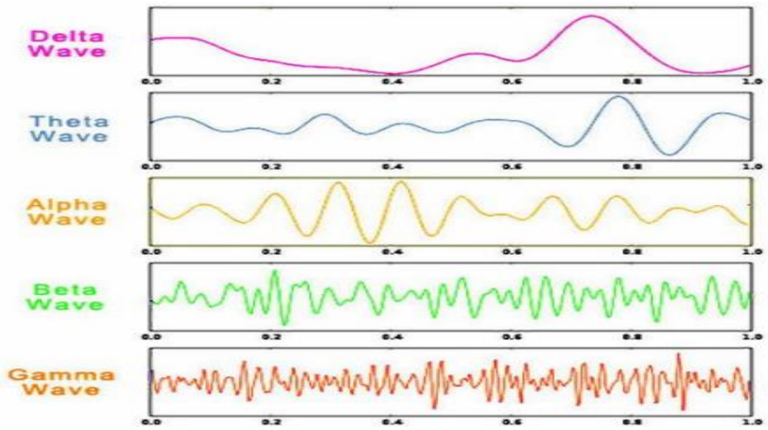


Fig. (1) Brain waves in normal EEG.

ECG specifications

The ECG is the final outcome of a complex series of physiologic and technological processes. First, transmembrane ionic currents are generated by ion fluxes across cell membranes and between adjacent cells. These currents are synchronized by cardiac activation and recovery sequences to generate a cardiac electrical field in and around the heart that varies with time during the cardiac cycle. This electrical field passes through numerous other structures, including the lungs, blood, and skeletal muscle, that perturb the cardiac electrical field. The currents reaching the skin are then detected by electrodes placed in specific locations on the extremities and torso that are configured to produce leads. The outputs of these leads are amplified, filtered, and displayed by a variety of devices to produce an electrocardiographic recording. In computerized systems, these signals are digitized, stored, and processed by pattern recognition software. Diagnostic criteria are then applied, either manually or with the aid of a computer, to produce an interpretation.

The waveforms and intervals that make up the standard ECG are displayed in Figure 13-8, and a normal 12-lead ECG is shown in Fig, (2). The P wave is generated by the activation of the atria, the PR segment represents the duration of atrioventricular (AV) conduction, the QRS complex is produced by the activation of the two ventricles, and the ST-T wave reflects ventricular recovery. (Mirvis & Goldberger) [11].

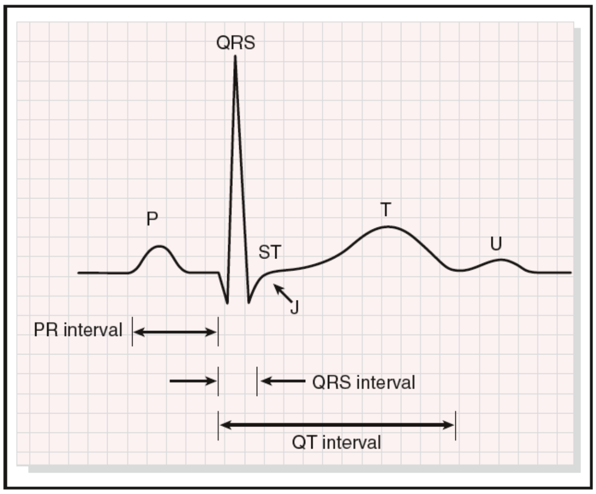


Fig. (2) The waves and intervals of a normal electrocardiogram.

Correlation Analysis

Correlation is a measure of a monotonic association between 2 variables. A monotonic relationship between 2 variables is one in which either (1) as the value of 1 variable increases, so does the value of the other variable; or (2)
as the value of 1 variable increases, the other variable value decreases.

In correlated data, therefore, the change in the magnitude of 1 variable is associated with a change in the magnitude of another variable, either in the same or in the opposite direction. In other words, higher values of 1 variable tend to be associated with either higher (positive correlation) or lower (negative correlation) values of the other variable, and vice versa.

Several approaches have been suggested to translate the correlation coefficient into descriptors like "weak," "moderate," or "strong" relationships, cutoff points are arbitrary and inconsistent and should be used judiciously. While most researchers would probably agree that a coefficient of <0.1 indicates a negligible and >0.9 a very strong relationship, see Table (1), (Schober & Boer) [12].

Table (1) Interpretation of Correlation Coefficient

Absolute Magnitude of the Observed Correlation Coefficient	Interpretation
0.00–0.10	Negligible correlation
0.10–0.39	Weak correlation
0.40–0.69	Moderate correlation
0.70–0.89	Strong correlation
0.90–1.00	Very strong correlation

Correlation analysis is a term used to denote the association or relationship between two (or more) quantitative variables. This analysis is fundamentally based on the assumption of a straight –line, The Pearson Correlation Coefficient formula is as follows: (Gogtay and Thatte) [13]

n = the number of data points, (x, y)
Σx = the sum of the x-values
Σy = the sum of the y-values
Σxy = the sum of the product of x and y in each pair
Σx^2 = the sum of the squares of the x-values
Σy^2 = the sum of the squares of the y-values
$(\Sigma x)^2$ = the square of the sum of the x-values
$(\Sigma y)^2$ = the square of the sum of the y-values
The scatter plot of two-time series data Vs. correlation coefficient is shown in fig. (3), [14].

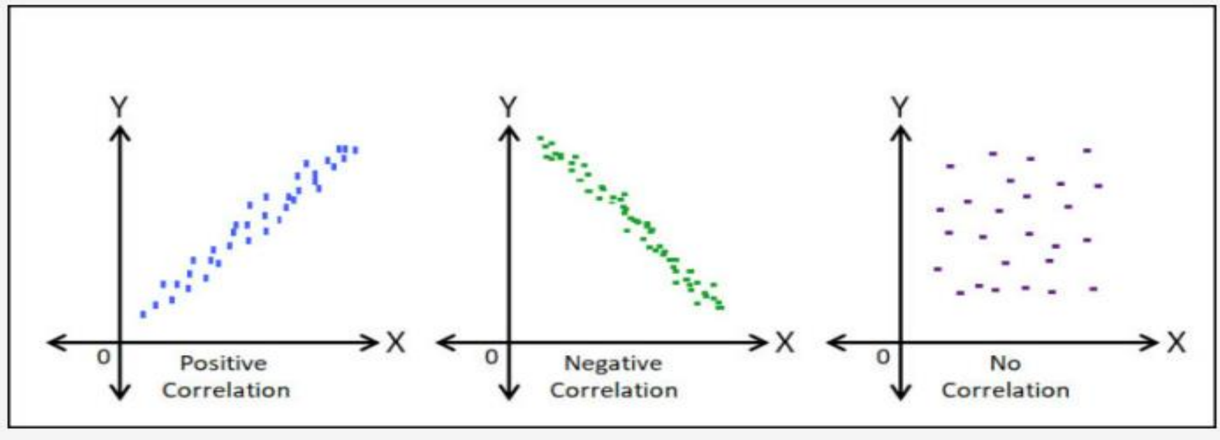


Fig. (3) Scatter plot Vs. correlation coefficient

Linear Regression

Linear regression assumes a linear relationship between the dependent and independent variables. Regression analysis uses the historical relationship between the independent variable and the dependent variable to predict the values of the dependent variable. The regression equation is expressed as follows:

$$Yi = b0 + b1\ Xi + \varepsilon i \qquad \ldots\ldots\ldots.(2)$$

where:

i = 1, …, n

Y = dependent variable

b0 = intercept

b1 = slope coefficient

X = independent variable

ε = error term

b0 and b1 are called the regression coefficients.

The dependent variable is the variable being predicted. It is denoted by Y in the equation. The variable used to explain changes in the dependent variable is the independent variable. It is denoted by X. The equation shows how much Y changes when X changes by one unit. (Lecture Notes) [15].

Experimental Work:

The measurement system for this research is composed of a Raspberry Pi4 as a computer, A Mindwave mobile2 connected to the Raspberry Pi4 Bluetooth BLE5 to measure the EEG signals, an Olimex 328 (Arduino like Board) with an ECG shield to measure the ECG signal.

The measured EEG signal and ECG signal are shown in fig. (4)

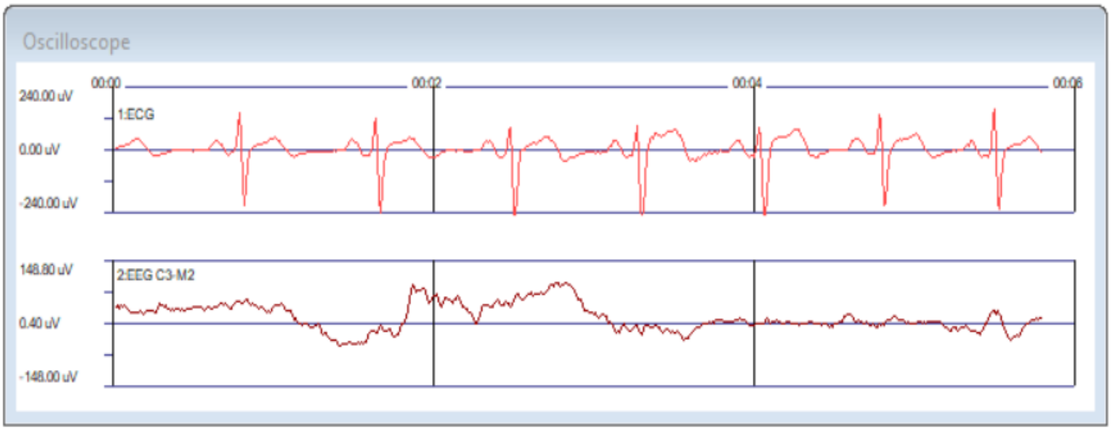
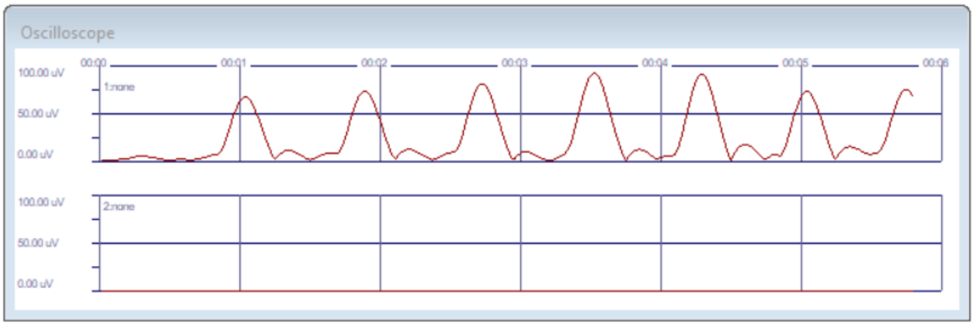
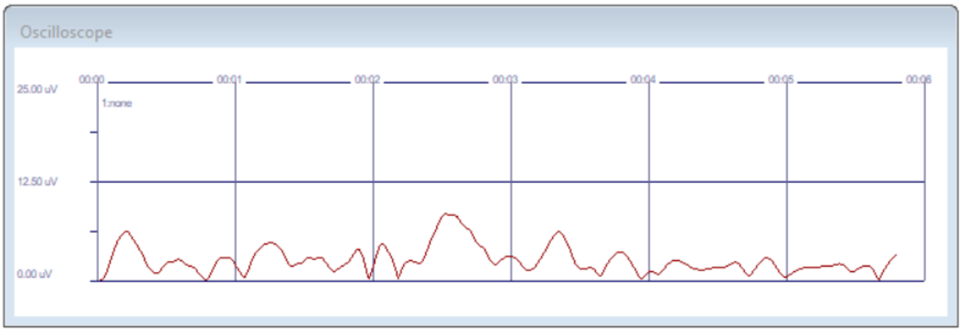


fig. (4) Measured EEG and ECG signals

The two measured signals are transformed into time series data, and that is done by taking the average of each ten samples from the measured EEG and ECG to construct the time series. The time series of both signals are shown in fig. (5).



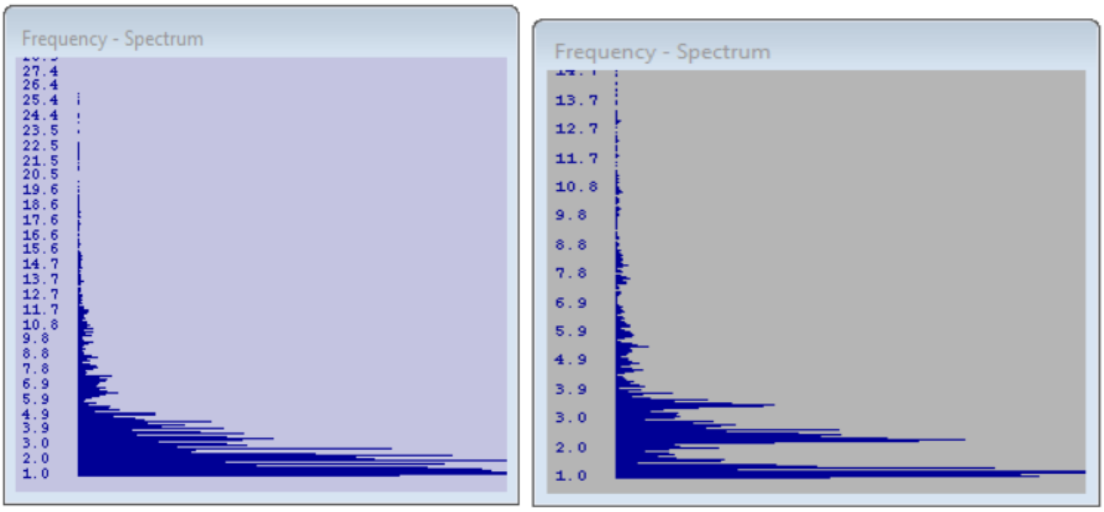
(a)



(b)

Fig. (5) Time series of the measured signals: (a) ECG, (b) EEG

The noise reduction procedure was applied using the Bandpass Besel software filter, the FFT spectrum shows in fig. (6) the noise reduction filtering process is done successfully. The figure shows the high-power components of both signals at the low-frequency period.



(a) (b)

Fig. (6) Spectrum of the filtered signals: (a) EEG, (b) ECG

Results and Discussion:

The first step to calculate the correlation factor is the scatter plot of the EEG and ECG series, fig. (7) shows the scatter plot of both series, from the plot we can see the strong association between them.

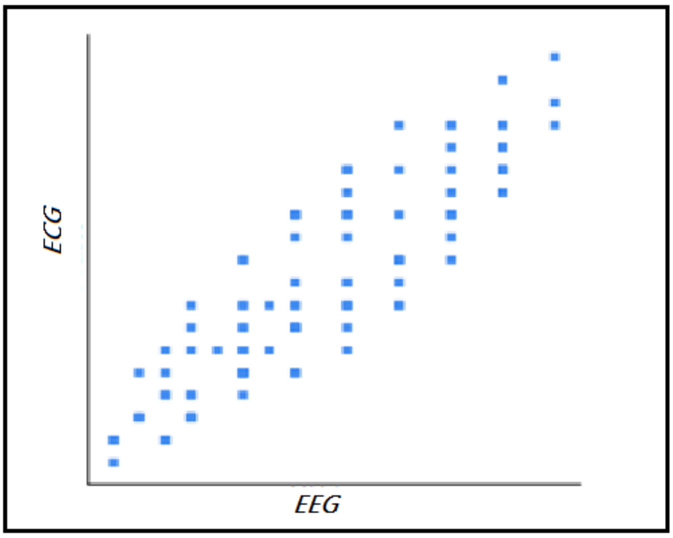


fig. (7) Scatter plot of EEG and ECG Time series

According to equation (1), the correlation factor is calculated as follows:

X Values
∑ = 1048
Mean = 9.193
∑(X - Mx)2 = SSx = 2465.754

Y Values
∑ = 1037
Mean = 9.096
∑(Y - My)2 = SSy = 2227.939

X and Y Combined
N = 114
∑(X - Mx)(Y - My) = 2086.877

R Calculation
r = ∑((X - My)(Y - Mx)) / √((SSx)(SSy))

r = 2086.877 / √((2465.754)(2227.939))
r = 0.8904 Correlation Factor
Where:
X: X Values
Y: Y Values

Mx: Mean of X Values
My: Mean of Y Values
X - Mx & Y - My: Deviation scores
(X - Mx)2 & (Y - My)2: Deviation Squared
(X - Mx)(Y - My): Product of Deviation Scores

The correlation factor value shows a strong association between the EEG and ECG signals. Because of the high association between the EEG signal and the ECG signal, we can use one of the to estimate the other, for that by applying equation (2) the linear regression model is calculated as follows:

Sum of X = 1048
Sum of Y = 1037
Mean X = 9.193
Mean Y = 9.0965
Sum of squares (SSX) = 2465.7544
Sum of products (SP) = 2086.8772
Regression Equation = ŷ = bX + a
b = SP/SSX = 2086.88/2465.75 = 0.84634
a = MY - bMX = 9.1 - (0.85*9.19) = 1.31606
Then the linear regression model as shown in fig. (8) is:

ŷ = 0.84634X + 1.31606 Linear Regression Model

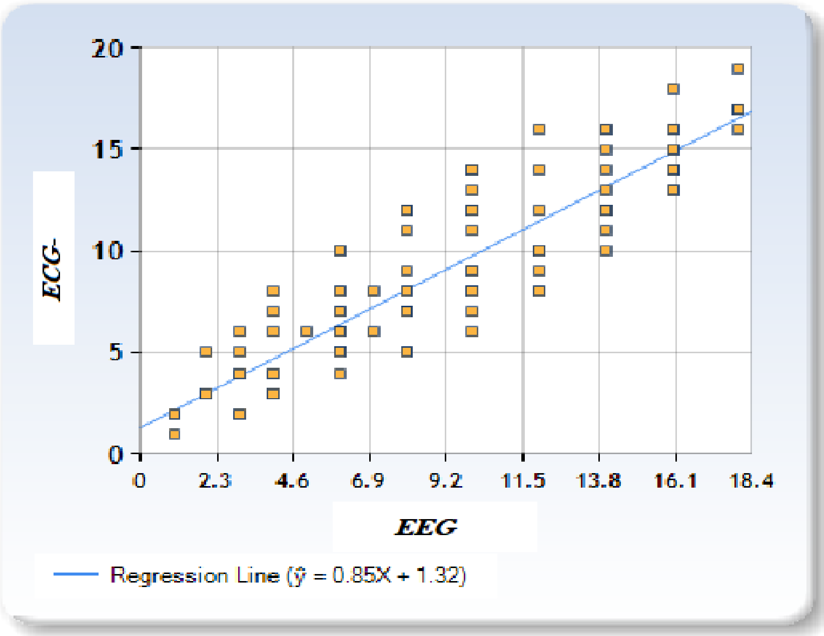


Fig. (8) Linear Regression Model

Conclusion:

This research studied the association between EEG ECG signals measured at the same time, an experimental test designed carefully according to the standards of EEG and ECG measurements. A measurement system for this research consists of Raspberry Pi4 as a computer, Mindwave Mobile2 for EEG measurement, OLIMEX 328 microcontroller, and ECG shield pind to it.

The measured EEG and ECG signals were recorded and transformed into time series data to simplify the association study of the two signals, the association was proved by a correlation factor calculation using the Pearson correlation factor.

The correlation factor results show a high association between EEG and ECG signals according to this research.

To estimate the value of the ECG signal from the EEG signal, the research presents a linear regression model, this model can be used to improve the health monitoring systems or BCI control systems.

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