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Original Article

Rhythms-Based Coherence Analysis Between Brain and Heart of Sleep Disorder Samples using MSC

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Abstract *- 62% of adults suffer from sleep problems all over the world, and the incidence of these illnesses is anticipated to grow. Unfortunately, many of these problems in scientific practice may go unnoticed and untreated. It has been widely observed in the diagnosis and scientific applications of various sleep disorders that a diligent and fundamental function of watching the heart and brain functions is required. Sleep problems can be studied using various techniques, mainly polysomnography, Electroencephalogram, MSLT, etc. In this work, we propose a new technique for estimating the relationship between cardiology and neurology for identifying cardiac and cerebrovascular anomalies of sleep disorder patients using ECG and EEG rhythms. Sleep problems based on ECG and EEG rhythms are utilized for the analysis and clinical treatment of difficulties associated with heart and brain-related issues. This paper investigated the magnitude squared coherence (MSC) between the ECG and EEG rhythms through a nonparametric power spectrum density estimation (PSDE) using the Welch method in the typical frequency band of 0-35 Hz. All signals are acquired from sleep apnea samples aged 20 to 50, with a sampling rate of thousand samples per second, using physioNet. For each signal, 1000 samples are used for MSC analysis. The MSC between the ECG and EEG rhythms are plotted, and their mean values are computed. ECG and EEG rhythms of two subjects were reported among the 25 subjects investigated. The measurement shows that in sleep apnea sample 1, the value of MSC between the ECG and EEG rhythms are 0.13954, 0.13017, 0.12599, and 0.12197 at beta (β)band, alpha (α)band, theta (θ) and Delta (δ) of EEG rhythms.*

Similarly, in sleep apnea sample 2, the value of MSC is 0.13970, 1.3540, 0.13404, and 0.13092 at the beta (β) band, alpha (α) band, theta (θ) band, and delta (δ) band of EEG rhythms respectively. Finally, in the first sample, the MSC value is higher in the beta and the second-highest in the alpha rhythm. In the second, the highest MSC rating and the second-highest MSC value are obtained by the beta rhythm and alpha rhythm, respectively. In sleep apnea, the patient's brain and heart are closely associated with beta rhythm and the second highest in the alpha rhythms.

Keywords *- Electrocardiogram (ECG), Electroencephalogram (EEG), Rapid eye movement, non-Rapid eye movement, Power Spectrum Density Estimation, Cross Power Spectral Density, Magnitude Squared Coherence (MSC).*

1. Introduction

Sleep is a complex organic process. Even when we sleep, our brain and bodily functions are still active. They do a lot of important work to help you live a healthy life and work to the best of your ability. So, if you don't get enough sleep, do something that will make you feel drowsy. It can affect your overall health, as well as your way of thinking and day-to-day activities. Sleep problems are conditions that disrupt your regular sleeping pattern. According to a recent consultation, sleep disturbances are also rising in developing countries. Approximately 17% of patients surveyed in eight Asian and African countries reported sleep disturbances [1].

India's population is enormous, and its economy is growing. Until now, little time has been spent on physical.

Health consequences of not getting enough sleep. Good quality sleep is essential for overall health [2] and stiffness relief. Adults should sleep for at least seven to eight hours per night [3], and children should sleep for at least ten hours per night. [4] The general population, on the other hand, is not getting enough sleep. Sleep disorders are extremely common in India. According to one study, the proportion of adults in India who have Insomnia could be as high as 33%. [5] Sleep deprivation has far-reaching health consequences. Adults who are sleepy during the day are less likely to be productive. People who are[6] significantly less capable of making wise decisions are more likely to take pleasure in pain, more likely to be obese, and more susceptible to cardiovascular diseases.[7]Driving while drowsy can be fatal. [8]Inadequate sleep affects schoolchildren's temperament [9] and causes behavioral problems during the day.[10] Even a little lack of sleep has measurable consequences. Failure to get the recommended five hours of sleep on four consecutive nights, for example, reduces assignment performance by 0.6 percent.

It can be quite challenging to consistently get a good night's sleep due to various illnesses known as sleep problems. Sleep troubles in India are becoming increasingly prevalent due to health concerns or excessive stress [11].

1.1. Sleep problems are classified into five types

1.1.1. Insomnia

Inability to sleep or maintain sleep can be caused by jet lag, stress, anxiety, hormones, or digestive issues. Elderly persons, particularly older women, are more susceptible to the illness [12].

1.1.2. Obstructive Sleep Apnea (OSA)

An interruption in breathing during some period of sleep creates sleep apnea. It is a serious health condition where the body doesn't seem to be able to take in enough oxygen. As a result of it as well, you can potentially awaken during the night. [13–14].

1.1.3. Parasomnias

Disorders affecting sleep quality are known as parasomnias. Even if you're asleep, you can have strange actions, conversations, feelings, and behaviors that may make the bedmate believe you're awake.[15–16].

1.1.4.Willis-Ekbom Disease

It is a disease in which a patient's legs strongly need to move. Tingling sensations frequently accompany this desire in the legs. Although these signals can occur during the day, they are most commonly recognized at night [17–18].

1.1.5. Narcolepsy

Narcolepsy is distinguished by "sleep attacks" occurring while the patient awakens. You will experience unusual twitching and nodding without warning [19].

1.2. Diagnosis of sleep disorders

There are three basic ways of analyzing sleep problems [20].

1.2.1 Polysomnography (PSG)

The most frequent test for determining if a patient has obstructive sleep apnea syndrome is polysomnography (PSG), a sleep study.

1.2.2. Electroencephalogram (EEG)

It's a device that measures any ability issues associated with this interest by measuring electrical activity within the brain.

1.2.3.Multiple Sleep Latency Test (MSLT)

The MSLT is a daylight sleep test performed with the PSG to identify drowsiness. The cardiovascular and nervous systems are the two critical structures in the human body. The coronary heart and brain are the two most important organs of the cardiovascular and nervous systems.

The human coronary heart is a mediastinum organ. It consists of four chambers, four valves, arteries (also known as blood vessels), and a working machine. Cardiac function can be divided into two parts: left and right. The proper coronary heart receives blood from the frame through the upper and lower vena cava. It sends blood to the lungs via the pulmonary artery, and the left heart receives it from the lungs.

The body's central nervous system includes the brain, a key organ, and the spinal cord, which houses crucial alarm systems. The cerebrum, brainstem, and cerebellum are all parts of the brain. Most human systems are controlled by it, which processes, compiles, and coordinates data stored within the nervous system and makes decisions based on the commands received during the frame. The bones of the skull within the head protect the brain.

The correct practical association of these structures is known as coherence, and it is essential for the healthy life of the human frame. Electrocardiogram (ECG) rhythm (Fig.1) and Electroencephalogram (EEG) rhythm (Fig.2) are very often employed to establish a good relationship between the heart and the brain. Tables 1 and 2 show the characteristics of those signals, respectively.

1.3. Electrocardiogram (ECG)

The electrocardiogram (ECG) monitors both the rate and rhythm of the coronary heart and provides an improvement warning of changes in the electrical activity of the myocardium. An electrocardiogram depicts the electrical movements of the heart muscle groups. Its miles are a mash-up of a wide range of motion potentials derived primarily from various components of the heart muscle groups. It is by far the most commonly used in the study of coronary heart disease [21-22]. It is crucial in the investigation and analysis of cardiac conditions. It is a simple test for determining the heart's health [23–24]. Figure 1 depicts the ECG rhythm. Table 1 depicts the properties of the ECG rhythm.

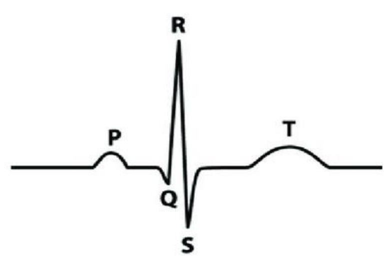

Fig. 1 Presents the ECG rhythm [26]

Table 1. The properties of ECG rhythms

ECG rhythm	Function
P wave	Depolarization of the atria.
Q wave	Activation of the ventricular myocardium's anteroseptal region.
R wave	Ventricular myocardium depolarization.
S wave	Activation of the ventricular myocardium's posterior basal region of the ventricles.
T wave	Repolarization of the ventricle in a short period.

1.4. Electroencephalogram (EEG)

An electroencephalogram (EEG) is a brain probe that detects electrical impulses. Brain cells interact with each other through electrical impulses. An EEG may be used to help counteract potential brain activity disturbances. Brain waves reveal via an EEG. An EEG is an electrical signal recorded from the surface of the skull using a conductive medium with sensing electrodes. EEG has been utilized to explore shocks, brain injury, sleep disturbances, brain tumors, and epilepsy, to name a few supernatural issues. Delta (δ) band, theta (θ)band, alpha (α)band, and beta (β)band are the vital brain rhythms. [25-26].Figure 2 shows the illustration of the EEG rhythm. Table 2 presents the EEG rhythm's characteristics.

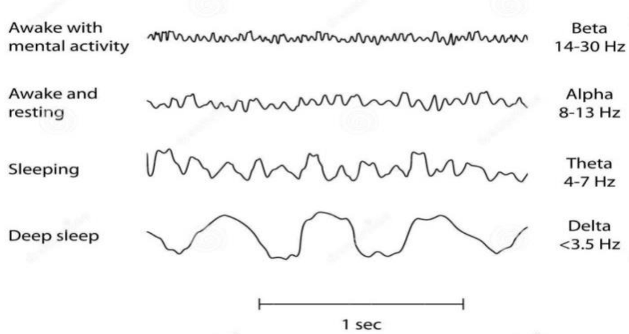

Fig. 2 Illustrate EEG rhythms [26]

1.5. Related Work

The following explains the various sleep states and their connection to Electroencephalogram [28, 29, 30, 31, 32].

1.5.1. Wakefulness (WA)

Wakefulness (WA) is a state in which a person awakens before going back to sleep. The EEG signal changes quickly, with alpha waves (8–13 Hz) being the most prominent.

1.5.2. NREM sleep state 1 (NREM1)

NREM1, known as the sleepiness state, is the initial stage of sleep. Brain activity gradually decreases during this period, frequency band (4–8 Hz) of theta waves becomes increasingly dominant. In the meantime, the eyeballs start to rotate slightly.

1.5.3. NREM sleep state 2 (NREM2)

The EEG amplitude increases, sleep patterns (11– 15 Hz) occur, and K-complexes arise in this stage. In the meanwhile, the eyeballs have stopped running.

1.5.4.NREM sleep state 3 (NREM3)

NREM sleep state 3, commonly known as deep sleep, is the third stage of NREM sleep. Delta waves (2–4 Hz) make up 20–50% of EEG signals at this time, whereas theta waves make up the balance. Some persons may experience sleep paralysis, anxiety attacks, or bed wetness.

1.5.5. NREM sleep state 4 (NREM4)

The fourth stage of NREM sleep, or NREM 4, is an extension of deep sleep. It is known as NREM sleep state 4 (NREM4). It is also referred to as slow-wave sleep. At this moment, between 0.5 to 2 Hz, or more than half of the EEG frequency, fluctuates (delta wave).

1.5.6. REM (rapid eye movement)

Rapid eye movement (REM) sleep is a type of sleep in which the eyes remain closed but move swiftly. The frequency of more prevalent beta waves is greater than 13 Hz.

In 2008, AH Khandoker et al. presented a test of the interplay of EEG asleep and ECG during and after sleep interruption events utilizing spectrum energy measurement techniques. The results of a study that completed the complete integration of ECG and EEG into REM sleep are greater than NREM sleep. However, it is researched further in a vast and extremely distinct model of normal OSA and its end with or without arousal. [33].

A.K. Kokonozi et al. reported utilizing the correlation method in 2008 that the heart and brain rhythm interact and are complex for insomnia [34].

In 2010 Haslaile Abdullah et al. demonstrated the linking of EEG band affections and heart rate variability for sleep apnea severity using experiments in the univariant and inconsistent gaussian methods. They have discovered through cross-correlation analysis that the association of HRV frequency bands with EEG can be employed as an input component for differentiating normal apnea and sleep. [35].

Billy Sulistyo et al. [36] developed a model for detecting sleep problems using heart rate variability (HRV) characteristics acquired from electrocardiogram (ECG) readings. This study analyzed HRV features using several classification techniques, including ANN, KNN, N-Bayes, and SVM linear methods. In 2018, the scheme of subject-specific and subject-independent were used using the subject-specific and subject-independent scheme for categorization.

The results of a study by Tushar K. Routh et al. [37] on identifying sleep disorders based on EEG signal characteristics show that sleep stages may be discriminated and separated more precisely at significant levels (p 0.05). Second, in 2018, dimension minimization based on the canonical correlation analysis (CCA) method was performed using random forest classification, which improves the sleep phases classification at 95.42 percent accuracy by looking at potentially correlated multi-sources.

Based on a single channel EEG analysis of sleep difficulties phases data, Padmaraju Koppireddi et al. [38] identified sleep apnea. This work uses polysomnographic data from the MIT-BIH and EEG datasets from Physionet that were collected and presented by researchers for diagnosing and modeling sleep categories. A machine learning classifier using an ensemble bagged tree classifier achieved an apnea detection accuracy of 95.9 percent in 2021, according to experimental data on 18 records with 10197 epochs.

A discrete wavelet transform, an artificial neural network, and ECG measurements were used by Mahmud Qatmh et al. [39] to identify sleep apnea. Sleep apnea is a sleep disorder that can seriously affect one's health. This study presents an artificial neural network classifier for identifying sleep apnea using ECG signals. In 2022, the testing records acquire 92.3 % accuracy. Based on the above literature study, we proposed a new coherence analysis technique between brain and heart of sleep disorder samples using MSC based upon rhythms of electrocardiogram and Electroencephalogram. The paper is divided into four sections. The materials and methods of the proposed method are described in Section II. Results are presented in Section III, and the work is concluded in Section IV.

Table 2. EEG rhythms characteristics at various frequencies

S.No	Rhythm	Frequency (Hz)	Amplitude (μV)	Pre-dominant Location	Found in	Mental State	Mind State	Diseases
1	**Delta (δ)**	1- 3.5	< 100	Every Where	Infants, Deep sleep, etc.	Deep sleep, severe brain disorder and lack of attention.	Unconscious	Brain injuries, Learning Problems, Inability to think
2	**Theta (θ)**	4 - 7	< 100	Temporal and parietal	Children, sleeping adults, etc...	Emotional stress, creative inspiration and deep meditation.	Unconscious	Attention Deficit Hyper activity Disorder (ADHD)
3	**Alpha (α)**	8 - 13	< 20	Occipital lobe	Light sleep, Eyes closed	Eyes closed and relaxation	Subconscious	Desynchro -nization
4	**Beta (β)**	14 - 30	< 20	Frontal regions	The high state of wakefulness	active thinking, active attention, focus, solving problems	Consciousness	Epilepsy, Seizures
5	**Gamma (γ)**	30-100	< 2	Tomato sensory cortex and Hippocampus regions	Sensory stimulation	various cognitive and motor functions	Consciousness	Schizophre nia and Alzheimer' s Disease
6	**Mu (μ)**	8-13	< 2	Frontal (motor cortex)	Sensory stimulation	Suppression during motor activity	Consciousness	---

2. Materials and Methods

The sleep EDF [Expanded] database [27], used in this study, is accessible to the general public online through PhysioNet. The dataset was gathered at 100 Hz for almost 24 hours and included 61 males and 23 females.

2.1. The methodology

The Welch method uses nonparametric power spectrum density estimation methods to determine the magnitude square coherence (MSC). This work utilizes a data analysis of ECG and EEG from physiobank. Statistical properties such as the highest and lowest amplitudes and the mean of the received signals are computed using the Welch method [41]. The MSC mean is normalized to the [0, 1] range. The hood is most likely determined by the normalized mean of objective rhythm coherence between the four brain and coronary heart rhythms. The source code was developed in MATLAB R2018b [40]. Figure 3 shows the block diagram for the proposed method.

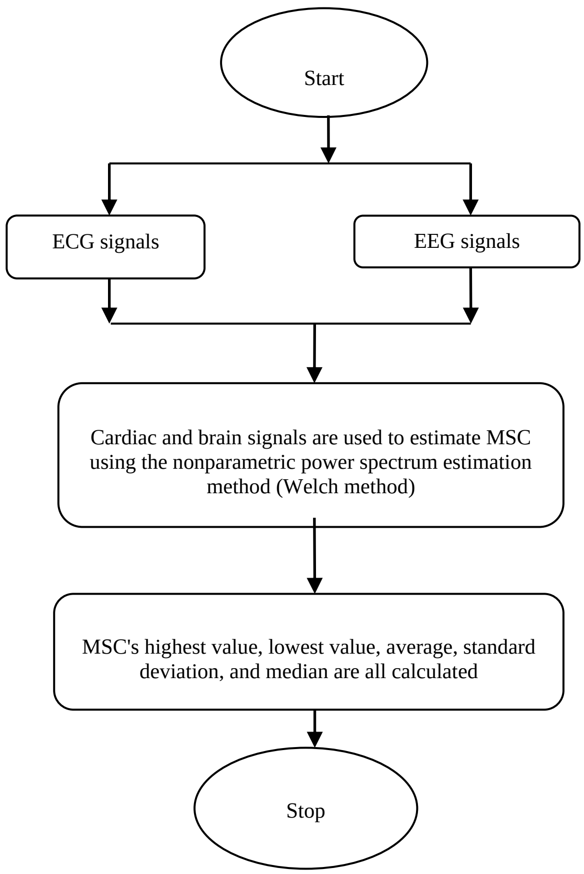

Fig. 3 Block diagram of the proposed method

2.2. Mathematical model for nonparametric Power Spectrum Density Estimation (PSDE) MSC computation between two signals, X (ECG signal) and Y (EEG signal), through Welch Method

One of the most important research areas and applications in signal processing is power spectral density estimation (PSD). Nonparametric or classical methods based on the periodogram are used in PSDE methods and algorithms. The spectral features of signals described as random processes are known as PSD. The power density spectral is the Fourier transform of the autocorrelation function, which provides the transformation from the time domain to the frequency domain [42]. The autocorrelation function of a random signal is the appropriate statistical average that will be used for characterizing random signals in the time domain. This study uses Hamming windows with the Welch Method to develop a PSDE scheme for changing data length. The periodogram is included in the Welch method, which has the advantage of being able to be implemented using the Fast Fourier Transform (FFT).

Consider X(n) signal (ECG signal)

$X_i(n) = X(n+iN)$ n=0, 1, 2, 3……M-1
i=0, 1, 2, 3…..N-1
i^{th} sequence starts from iD (window shift is D) (1)

X(n) signal is subdivided into M overlapping segments. Where each segment has a length N

$$P_{XX}^{(i)}(\omega) = \frac{1}{MU}\left|\sum_{n=0}^{M-1} X_i(n)\omega(n)e^{-j2\pi f_n}\right|^2 \text{, i=0, 1, 2, 3 ……N-1} \quad (2)$$

Where U is a normalization factor for the power in the window function is selected as

$$U = \frac{1}{M}\left|\sum_{n=0}^{M-1} \omega^2(n)\right| \quad (3)$$

$P_{XX}^{W}(\omega)$ is the average of the modified periodogram, which estimates the Welch power spectrum.

$$P_{XX}^{W}(\omega) = \frac{1}{L}\left|\sum_{i=0}^{L-1} P_{XX}^{(i)}(\omega)\right| \quad (4)$$

Assume Y(n) signal (EEG signal)

$Y_i(n) = Y(n+iN)$ n=0, 1, 2, 3……M-1
i=0, 1, 2, 3…..N-1 (5)

Y(n) signal is subdivided into M non-overlapping segments. Where the length of each segment is N

$$P_{YY}^{(i)}(\omega) = \frac{1}{MU}\left|\sum_{n=0}^{M-1} Y_i(n)\omega(n)e^{-j2\pi f_n}\right|^2 \text{, i=0, 1, 2, 3 ……N-1} \quad (6)$$

Where U is the power's normalization factor. The window function is chosen as,

$$U = \frac{1}{M}\left|\sum_{n=0}^{M-1} \omega^2(n)\right| \quad (7)$$

$P_{YY}^{W}(\omega)$ reflects the average of the modified periodogram, which calculates the Welch power spectrum.

$$P_{YY}^{W}(\omega) = \frac{1}{L}\left|\sum_{i=0}^{L-1} P_{YY}^{(i)}(\omega)\right| \quad (8)$$

$P_{XY}(\omega)$ is the cross power spectrum density between two signals X and Y, X (Electrocardiogram) and Y (Electroencephalogram),

$$P_{XY}(\omega) = X(\omega) * \overline{Y(\omega)} \quad (9)$$

Between two signals, X (ECG signal) and Y (EEG signal), there is an MSC of

$$C_{XY}(\omega) = \frac{P_{XY}^{W}(\omega)}{\sqrt{P_{XX}^{W}(\omega) * P_{YY}^{W}(\omega)}} \tag{10}$$

Mean is indicated as

$$C_{XY}(\omega) = \frac{\sum C_{XY}(\omega)}{n} \tag{11}$$

Standard deviation (SD) is denoted by the following

$$\sigma = \sqrt{\sum \frac{(C_{XY}(\omega) - \overline{C}_{XY}(\omega))}{n-1}} \tag{12}$$

Where n represents the total number of samples.

2.3. Steps for MSC calculation between two signals, X (ECG signal) and Y (EEG Signal), using non-parameter Power Spectrum Density Estimation Method (PSDE) via (Welch Method)

- In Welch Method, the first X(n) signal (ECG signal) is subdivided into M overlapping segments. Where each segment has length, N data segments can be allowed to overlap, and second, each data segment is windowed before computing the PSD, then averaging the PSD estimates. i.e. $P_{XX}^{W}(\omega)$
- The first Y(n) signal (EEG signal)is subdivided into M overlapping segments. Where each segment has length, N data segments can be allowed to overlap, and second, each data segment is windowed before computing the PSD and then averaging the PSD estimates. i.e. $P_{YY}^{W}(\omega)$
- Compute the cross power spectrum density PYX (ω) between two signals X(n) signal and the Y(n) signal.
- Substitute $P_{XX}^{W}(\omega)$ value, $P_{YY}^{W}(\omega)$ value, and PYX (ω) value. Calculate the MSC between two signals, X(n) (ECG signal) and Y(n) (EEG signal).

3. Results

Physiobank [36] is used to sample people with sleep apnea aged between 20 and 50 at a rate of 1000 samples per second. We examined a total of samples from ECG and EEG rhythms to evaluate the magnitude squared coherence nonparametric power spectrum density estimation method (PSDE) via the Welch method. Table 3 displays the statistical characteristics of the 25 patients. In table 3, subjects are identified by the letter S, electrocardiograms by the letter X, and electroencephalograms by the letter Y. The maximum and lowest dimensions of the X and Y signals are used to calculate the mean, standard deviation (SD), and median, respectively.

Table 3. Statistical analysis of 25 sleep disorder persons (sleep apnea)

S	Signals	Mean(V)	SD(± V)	Median(V)
1	X	0.01187	0.02164	0.00163
	Y	0.00070	0.00083	0.00093
2	X	0.01318	0.02278	0.00164
	Y	0.00078	0.00076	0.00083
3	X	0.01149	0.02427	0.00163
	Y	0.00076	0.00064	0.00082
4	X	0.01317	0.02576	0.00173
	Y	0.00080	0.00073	0.00082
5	X	0.01757	0.02007	0.00406
	Y	0.00078	0.00063	0.00072
6	X	0.12052	0.38686	0.00193
	Y	0.00078	0.00067	0.00083
7	X	0.02414	0.04467	0.00487

	Y	0.00188	0.00175	0.00113
8	X Y	0.01768 0.00066	0.02786 0.00127	0.00296 0.00182
9	X Y	0.01449 0.00080	0.01521 0.00051	0.00173 0.00162
10	X Y	0.01880 0.00186	0.03305 0.00741	0.04457 0.00082
11	X Y	0.01779 0.00079	0.02764 0.00087	0.00478 0.00082
12	X Y	0.01741 0.00077	0.02678 0.00083	0.00377 0.00072
13	X Y	0.01726 0.00079	0.02819 0.00069	0.00265 0.00082
14	X Y	0.01747 0.00098	0.01854 0.00054	0.00786 0.00082
15	X Y	0.01315 0.00080	0.02584 0.00077	0.00132 0.00112
16	X Y	0.01354 0.00081	0.02460 0.00079	0.00132 0.00082
17	X Y	0.01275 0.00081	0.02598 0.00084	0.00163 0.00072
18	X Y	0.01295 0.00079	0.02626 0.00113	0.00173 0.00092
19	X Y	0.01432 0.01315	0.02533 0.02484	0.00173 0.00132
20	X Y	0.01748 0.00080	0.03751 0.00071	0.00175 0.00082
21	X Y	0.02269 0.00098	0.04368 0.00208	0.00314 0.00192
22	X Y	0.03530 0.00070	0.04373 0.00068	0.00205 0.00082
23	X Y	0.02464 0.00070	0.05402 0.00064	0.00675 0.00072
24	X Y	0.02696 0.01788	0.03591 0.04861	0.00526 0.00375
25	X Y	0.01680 0.00076	0.02505 0.00074	0.00487 0.00046

3.1. MSC analysis

MSC testing is carried out by randomly choosing two samples from 25 samples. The evaluation of MSC between the electrocardiogram and the associated Electroencephalogram of four identified brains (δ). The electrocardiogram and Electroencephalogram of sample1 and sample-2 are proved in figure 7 and figure 9. Rhythms are provided as Delta (δ), theta (θ), alpha (α), and beta (β), respectively, while the parameters of the MSC for Sample-1 and Sample-2 are presented in table 4 and table 5, respectively.

3.1.1. Sample-1 MSC analysis

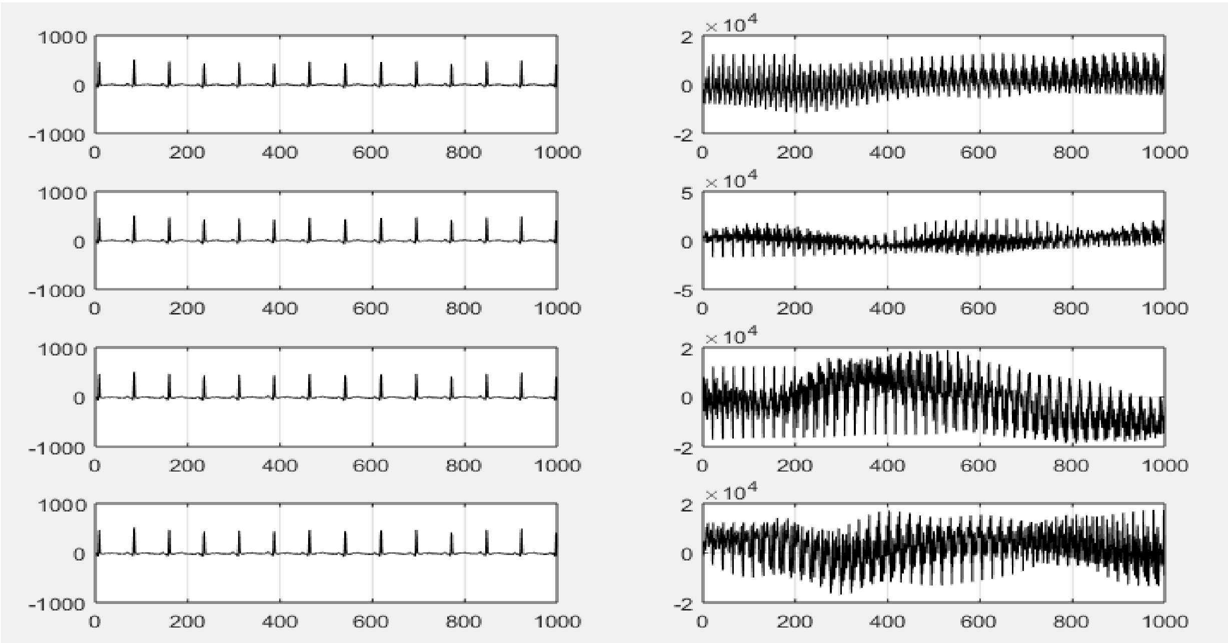

Fig. 4 (a) and (b) ECG signals with associated EEG (beta) signals (each signal sampled at 1000 samples/sec with a sample range of 5006) (c) and (d) ECG signals with associated EEG (alpha(α)) signals ECG signals (e) and (f) and associated EEG (theta (θ)) signal ECG signals (g) and (h) with associated EEG (delta (δ)) signal

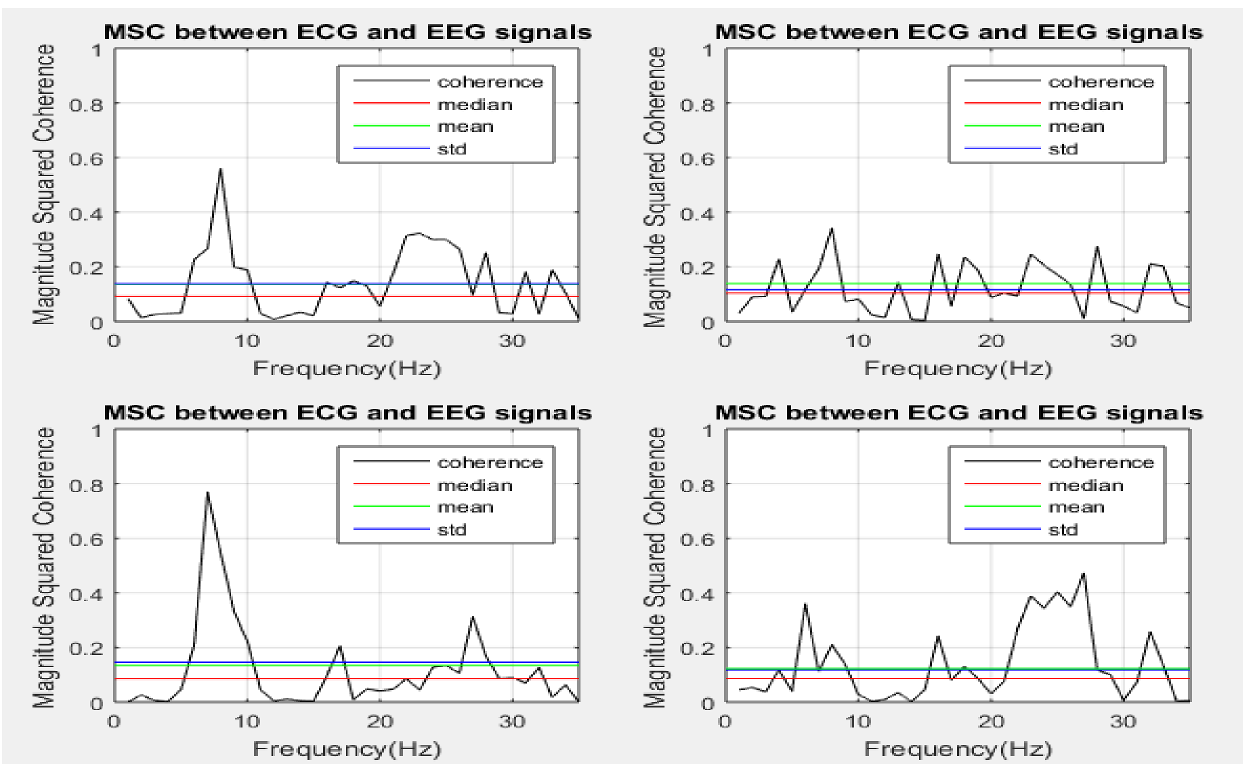

Fig.5 (a) The frequency range (0 to 35 Hz) for MSC sample-1 is connected between the electrocardiogram and electroencephalogram (beta (β)). (b) MSC is calculated using the electrocardiogram and electroencephalogram (alpha ((α)).(c) MSC is calculated using the electrocardiogram and electroencephalogram (theta (θ)). (d) MSC is calculated using the electrocardiogram and electroencephalogram (delta (δ)).

For frequencies between 0 and 35 cycles per second, MSC has an average value of 0.13954 and a maximum value of 0.59601 at 7.5 Hz, shown in Figure 5(a).In the frequency band of 27 Hz to 35 Hz, three more MSC spikes have been found.5 (b), the projected value of MSC in a frequency of 0–35 cycles per sec is 0.13017, and the highest value of MSC near 8.5 Hz is 0.39281. Two more MSC spikes have been found, one around the frequency range of 15.9 Hz and the other at 29 Hz. Within a frequency of 0-35 cycles/sec, the average MSC number is 0.12599, and the highest MSC number is 0.79142, around 7.5 Hz, as shown in Figure 5(c). Every other MSC spike is observed at the frequency of 17 Hz, the other near the frequency of 27 Hz, and 0.33 near the frequency of 35 Hz. Within the frequency of 0–35 cycles/sec, The MSC has an overall average of 0.12198 and a maximum value of 0.99663 at 6.5 Hz, as shown in Figure 5. (d). Other consistent spikes have been identified, one closer to 16 Hz and the other closer to 27 Hz.

Table 4. MSC testing parameters for sample-1

Electrocardiogram and Electroencephalogram	Parameters	Mean(V)	SD(± V)	Median(V)
Beta (β)	MSC	0.13954	0.13353	0.10068
Alpha (α)		0.13017	0.13156	0.10429
Theta (θ)		0.12599	0.12632	0.10266
Delta (δ)		0.12197	0.12031	0.11044

3.1.2. Sample-2 MSC analysis

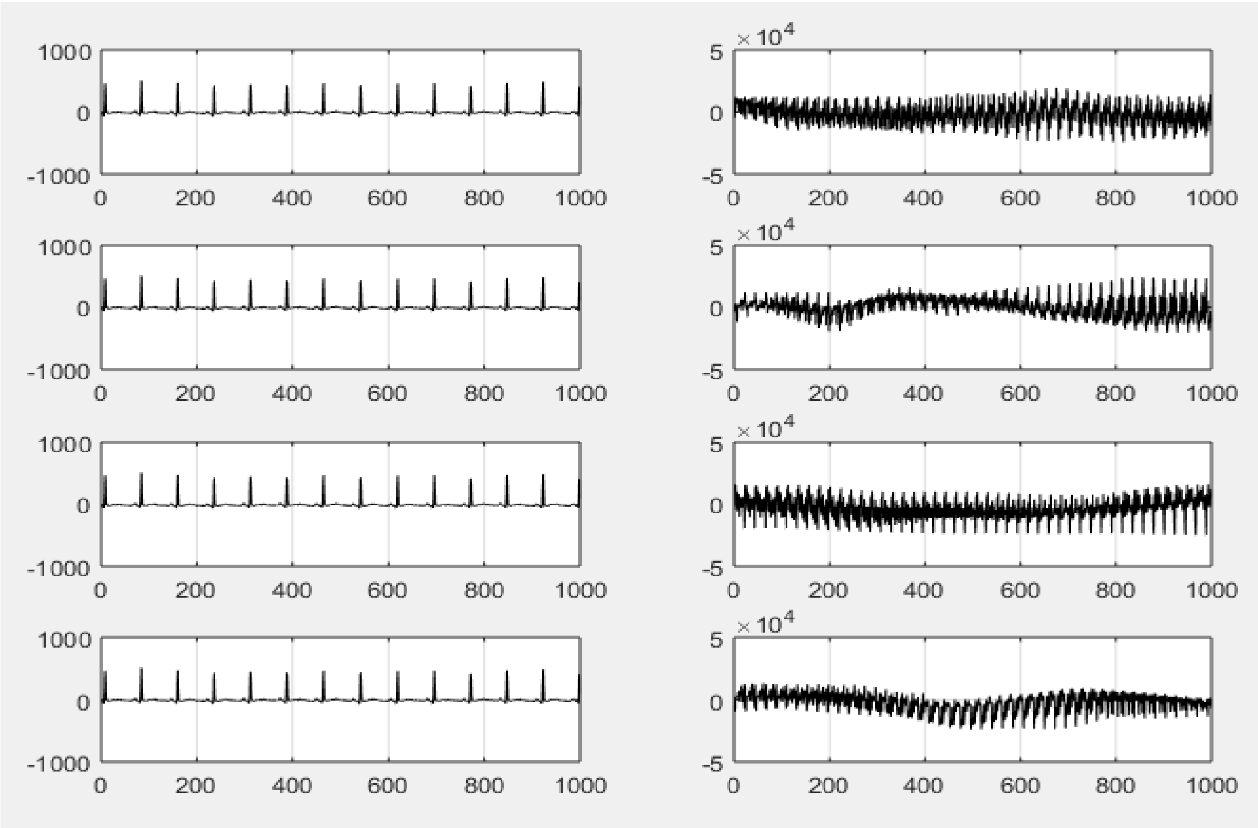

Fig. 6 (a) and (b) show an electrocardiogram and the associated electroencephalogram (beta) signal. Each signal is sampled at a rate of 1,000 samples per second, and many samples are recorded for each signal. (c) and (d) show an electrocardiogram and the associated Electroencephalogram (alpha(α) signal. (e) and (f) Electrocardiogram signals and corresponding Electroencephalogram (theta (θ)) signals. (g) and (h) Electrocardiogram and the corresponding Electroencephalogram (delta (δ)).

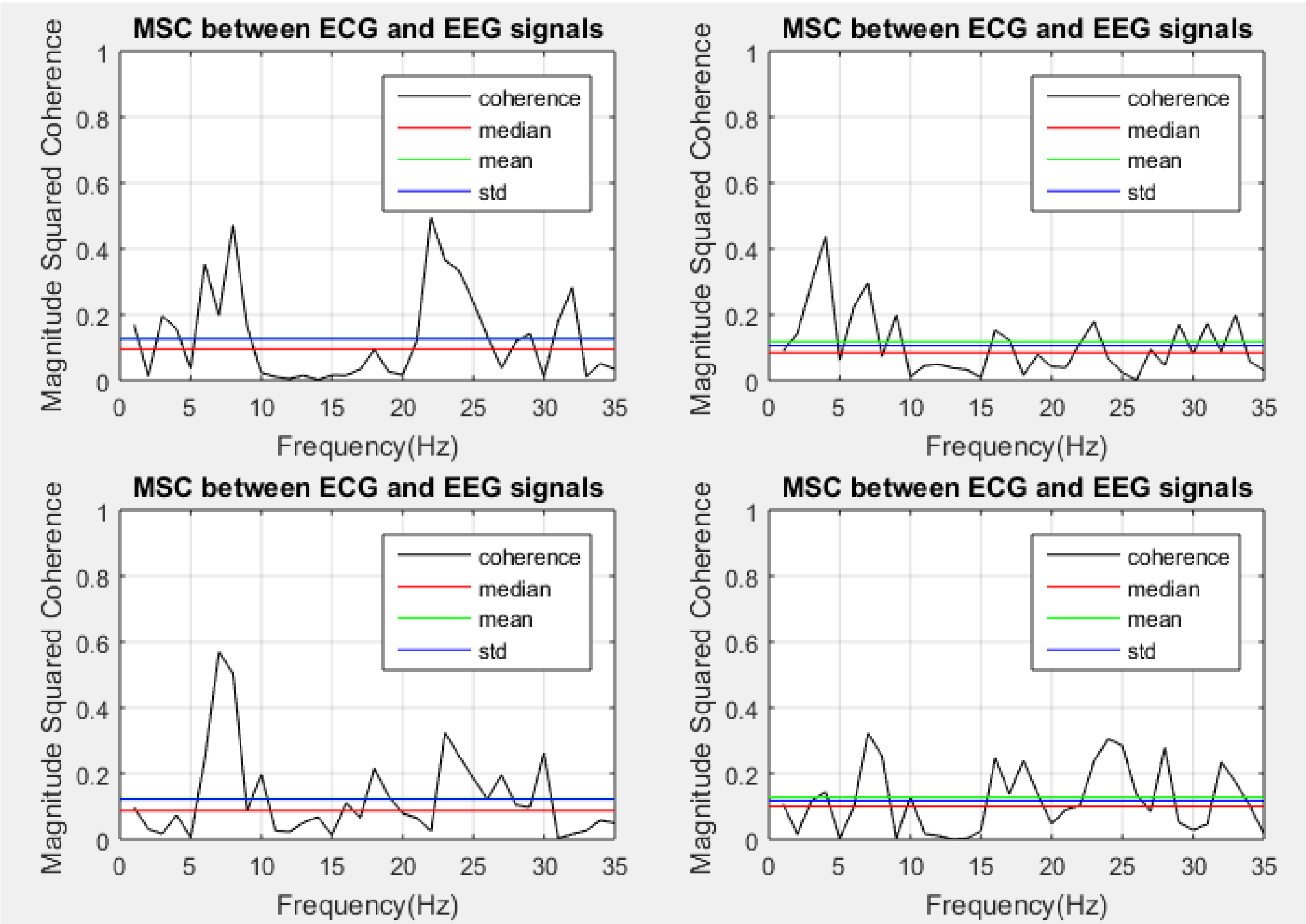

Fig.7 (a) For sample-2, The MSC is calculated using the electrocardiogram, and electroencephalogram (beta (β)) signals are connected within the bandwidth (0 to 35 Hz). (b) The MSC is calculated using the electrocardiogram and electroencephalogram (alpha (α)) signals. (c) The MSC is calculated using the electrocardiogram and electroencephalogram (theta (θ)) signals. (d) The MSC is calculated using the electrocardiogram and electroencephalogram (delta (δ)) signals.

Within a frequency of 0–35 cycles/sec, the MSC's mean is 0.13970, and its maximum value is 0.69819 at 8.8 Hz, as shown in figure 7. (a). A coherence peak is noticed at about 22 Hz. Figure 7 illustrates the MSC's mean value in the frequency range of 0-35 cycles/sec as 0.13540 and its maximum number near 2.5 Hz as 0.42569. (b). An increase in MSC might be seen at about 7.5 Hz. The suggested MSC value is 0.13404, and the maximum MSC value is 5.89829, both of which are within the bandwidth of 0-35 cycles/sec. The MSC value is 0.13404, and the highest MSC value is 5.89829 Hz within the frequency of 0-35 cycles/sec, which is closer to 6.5 Hz (see Figure 7(c)). Three MSC peaks, one at 22Hz and two near 30 Hz, have been identified. The MSC has an average value of 0.13092 throughout the frequency of 0–35 cycles/sec and the maximum value of 0.38381 at 7.5 Hz (see Figure 7 (d)). An MSC is noticed at a frequency of 0, around 17Hz.

Table 5. MSC testing parameters for sample-2

Electrocardiogram and Electroencephalogram	Parameters	Mean(V)	SD (± V)	Median(V)
Beta (β)	MSC	0.13970	0.13312	0.08954
Alpha (α)		0.13540	0.13204	0.07620
Theta (θ)		0.13404	0.13201	0.11145
Delta (δ)		0.13092	0.13033	0.12476

4. Conclusion

This research examines the degree of interaction between EEG and ECG rhythms to measure the rhythm associated with increased brain function with a heart function of sleep apnea patients. The test is done by considering 25 samples of human sleep apnea. Out of those 25 sleep apnea samples, the MSC results of two samples were considered for validation. The MSC rating in the first sleep apnea sample is higher in the beta and the second highest in the alpha rhythm. In the second sleep apnea sample, the highest MSC rating and the second-highest MSC rating are obtained by the beta rhythm and alpha rhythm, respectively. Higher mean MSC values Suggest greater consistency between EEG and ECG rhythms. Lower mean MSC values suggest a negative correlation between EEG and ECG information. With the increased benefit, the beta rhythm of the brain is more active concerning the corresponding heart rhythm. The proposed MSC measurement method is very useful for brain and cardiac abnormalities.

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