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*Original Research Article*

# Estimation of Coherence among ECG and EEG Signals Using Various Auto-Regressive Methods

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## ABSTRACT

**Introduction:** An Electrocardiogram (ECG) is graphical tracing of electrical signals generated by heart muscles. An Electroencephalogram (EEG) is the electrical activity of brain. Coherence is degree of association between frequency spectra of two signals at a particular frequency. In this paper coherence between ECG and EEG signals of twelve different subjects is analysed by estimating magnitude squared coherence (MSC) between these two signals. ECG and EEG signals are taken simultaneously.
**Aim:** Aim of this paper is to find the brain region at which maximum mean of MSC is exhibit. And out of four methods used which one is best suit for coherence estimation. Estimation of Coherence among physiological signals is used as cost-effective non-invasive tool of diagnostic. Coherence among ECG and EEG signals is used to determine the difference between normal and abnormal brain activity.
**Methods:** Four different methods of power spectrum estimation are used for the analysis of MSC. These methods are Burg, Covariance, Modified Covariance and Welch method.
Result: Maximum estimated magnitude squared coherence between ECG and EEG is at Cerebellum. It means that Cerebellum region of brain is maximum associated with heart. Out of four methods of power spectrum estimation such as Burg, Covariance, Modified-covariance and Welch, Burg method gives maximum MSC values.
**Conclusion:** Magnitude squared coherence values among ECG and EEG signals of twelve subjects at four different brain regions are non-negative. It means that there is some association between heart and brain. Cerebellum region of brain has maximum association with heart. Burg method of power spectrum estimation is better than other methods used in this paper for the purpose of Coherence estimation.

***Keywords-*** Electrocardiogram (ECG), Electroencephalogram (EEG), Power spectrum density(PSD), Cross power spectrum density (CPSD), Welch, Burg, Covariance, Modified Covariance, Magnitude squared coherence (MSC).

## INTRODUCTION

An electrocardiogram or ECG is today used worldwide as a relatively simple tool of diagnosis of conditions of heart. An ECG is a recording of the small electric waves being generated during heartbeat. Specialized cells which produce electricity are called natural pacemaker cells. These Specialised cells produce electricity by quickly changing their electrical charge from positive to negative and again from negative to positive. The first electric wave in a heartbeat is initiated at the top of the heart. Heart muscle cells have ability to spread its electric charge to adjacent heart muscle cells and this initial wave will be enough to start a chain reaction. An electroencephalogram or EEG Signal reflects the electrical activity of human brain. Neurons or nerve cells transmit information throughout the body electrically and they create electrical impulses by the diffusion of sodium, calcium, and potassium ions across the cell membranes. When a person is sleeping, thinking, listening music, watching television or reading, different parts of the brain are stimulated. It creates different electrical signals that can be monitored by an EEG .There are five major brain waves distinguished by their different frequency ranges and different amplitudes of mV range. These frequency bands from low to high frequencies respectively are called alpha (α), theta (θ), beta (β), delta (δ), and gamma (γ). These frequency bands are seen in different states of mind. Coherence is the degree of association of frequency spectra between the ECG and EEG signals at a particular frequency. The magnitude squared coherence (MSC) estimate between two signals x (ECG Signal) and y (EEG Signal) is given below. [1-5]

$$C_{xx}(f) = \frac{|P_{xy}(f)|^2}{P_{xx}(f) \times P_{yy}(f)} \quad (1)$$

Here $C_{xx}(f)$ is magnitude squared coherence estimate between two signals x (ECG signal) and y (EEG signal).

If MSC between two signals is positive its mean changing nature of that two signals are same. If MSC of two signals is negative, it means changing nature of that two signals is opposite. If magnitude of MSC is zero, its mean that there is no relationship between two signals. Coherence phase is given as

$$\theta_{(f)} = \tan^{-1}\left\{\frac{\mathrm{Im}\{P_{xy}(f)\}}{\mathrm{Re}\{P_{xy}(f)\}}\right\} \quad (2)$$

Where $P_{xx}(f)$ is the power spectral estimation of x (ECG) signal and $P_{yy}(f)$ is the power spectral estimation of y (EEG) signals. $P_{xy}(f)$ is the cross power spectral estimation of the ECG and EEG signals. [1,3] Estimation of coherence among Physiological signals is used as low cost and accurate non-invasive tool of diagnosis of brain.

ECG and EEG signals are taken from12 different subjects. EEG signals are acquire from four different regions of brain such as cerebellum, frontal, parietal and occipital. ECG and EEG signals are acquired simultaneously. We want to estimate the association so these signals must be taken simultaneously. Duration of signals is 5s.

## MATERIALS AND METHODS

Four methods are used for the power spectrum estimation. One out of four is nonparametric method and three methods are parametric method. Nonparametric methods make no assumption about how the data were generated and hence are called nonparametric methods. Since the estimation is based on a finite record of data, the frequency resolution of these methods is at best. All the nonparametric estimation technique decreases the frequency resolution in order to reduce the variance in the spectral estimation. [6,7]

Various nonparametric methods are given below:

- The Bartlett Method: Averaging Periodograms
- The Welch Method: Modified Averaging Periodograms.

The Bartlett methods divides data in K non overlapping segments each of length M. Bartlett (triangular) Window is used.

$$Xi = X(n + i*M)$$
$$for\ i = 0:(K-1)\ \&\ n = 0:(M-1) \quad (3)$$

PSD for each segment of the periodograms is-

$$P_{xx}^{(i)}(f) = \frac{1}{M}\left|\sum_{n=0}^{M-1} X_i(n)e^{-j2\pi fn}\right|^2 \quad (4)$$

Finally we average the periodograms for K segments to obtain the Bartlett power spectrum.

$$P_{xx}^{B}(f) = \frac{1}{K}\sum_{i=0}^{K-1} P_{xx}^{i}(f) \quad (5)$$

Welch method has some modification in the Bartlett method.

First over lapping between segments is done, second at place of Bartlett window hamming window is used.

$$X_i(n) = X(n + iD) \quad (6)$$

For n=0 :( M-1),

i = 0 :( L-1),

Data is divided into L segments each of length M. and D is overlapping. iD is starting point of i[th] segment. Observed that if D=M, the segment do not overlap and the number L is identical to no K of Bartlett method. If D=M/2 then 50% over lapping and L=2K is obtained.

$$\tilde{P}_{xx}^{(i)}(f) = \frac{1}{MU}\left|\sum_{n=0}^{M-1} X_i(n)W(n)e^{-j\pi 2fn}\right|^2 \quad (7)$$

Where U is the normalized factor for power in the window function and is selected as

$$U = \frac{1}{M}\left[\sum_{n=0}^{M-1} W(n)^2\right] \quad (8)$$

On averaging the periodograms:

$$P_{xx}^{W}(f) = \frac{1}{L}\sum_{i=0}^{L-1} \tilde{P}_{xx}^{(i)}(f) \quad (9)$$

Above expression gives the PSD using Welch method.

Nonparametric methods described in this section are simple. However these methods require the long data records in order to obtain the necessary frequency resolution. Furthermore these methods suffer from spectral leakage effects due to windowing that is inherent in finite length data record. From one point of view basic limitations of nonparametric method is the inherent assumption that the auto correlation estimates $R_{xx}$ (m) is zero for m ≥N ( length of data). This assumption limits the frequency resolution.

Parametric methods extrapolate the values of autocorrelation for lags m ≥N. Extrapolation is possible if we have some a priori information on how the data were generated. In this case a model for the signal generation can be constructed with a no of parameters that can be estimated from observed data. As these methods eliminate the need of window function so spectral leakage effect is avoided. These methods properly work for short data record. [8,9]

Parametric methods are basically three types:

- Auto-regressive Method
- Auto-regressive Moving Average Method.
- Moving Average Method.

$$H(z) = \frac{B(z)}{A(z)} = \frac{\sum_{k=0}^{q} b_k Z^{-k}}{1 + \sum_{k=1}^{p} a_k Z^{-k}} \quad (10)$$

The above model is called Auto-regressive Moving Average Method (ARMA) of order (p, q). If q=0 and $b_0$=1 then its output X(n) is called autoregressive process of order p. Third model is possible by selecting A(z)=1 and this is called moving average model of order q. [10]

Auto-Regressive methods are basically four types.

- Burg method,
- Covariance method
- Modified Covariance Method
- Yule-Walker Method

Burg method does not apply window to data. It minimizes the forward and backward prediction errors in the least squares sense, with the AR coefficients constrained to satisfy the L-D recursion. It gives high resolution for short data records. It may suffer spectral line-splitting for sinusoids in noise, or when order is very large. Covariance method does not apply window to data. It minimizes the forward prediction errors in the least squares sense. It gives better resolution than Yule-Walker for short data records (more accurate estimates). Modified Covariance does not apply window to data. It minimizes the forward and backward prediction errors in the least squares sense, with the AR coefficients constrained to satisfy the L-D recursion. It gives high resolution for short data records. Yule-Walker Method applies window to data. It minimizes the forward prediction errors in the least squares sense. Performs as well as other methods for large data record. [5,7,10] In this research work ECG and EEG signals are acquired from twelve different patients. EEG signals are acquired from four different region of brain. ECG and EEG signals are acquired simultaneously for the 5 sec. sampling frequency is1000 sample per sec. Analysis is done for the purpose to find the brain region which has maximum association with heart. Four methods are utilised for this purpose. Out of four method used which one is best for coherence purpose is also analysed.

## RESULT AND ANALYSIS

Table.1 Mean of MSC of Second Subject

| Methods / Brain Region | Cerebellum | Frontal | Occipital | Parietal |
|---|---|---|---|---|
| Burg | 0.3033 | 0.2609 | 0.2179 | .1879 |
| Covariance | 0.3010 | 0.2626 | 0.2164 | 0.1862 |
| Modified Covariance | 0.3019 | 0.2584 | 0.2186 | 0.1862 |
| Welch | 0.1501 | 0.1284 | 0.1484 | 0.1501 |

From the table.1 it is clear that maximum value of mean of MSC is at cerebellum. Second maximum is at Frontal. Mean of MSC is minimum at Occipital. Mean of MSC estimated by burg method is more than other three methods.

Table.2 Mean of MSC of Second Subject

| Methods / Brain Region | Cerebellum | Frontal | Occipital | Parietal |
|---|---|---|---|---|
| Burg | 0.2664 | 0.2598 | 0.2160 | 0.2440 |
| Covariance | 0.2651 | 0.2577 | 0.2143 | 0.2419 |
| Modified Covariance | 0.2648 | 0.2588 | 0.2146 | 0.2243 |
| Welch | 0.1691 | 0.1367 | 0.1402 | 0.1578 |

From the table.2 it is clear that maximum value of mean of MSC is at cerebellum. Second maximum is at Frontal. Mean of MSC is minimum at Occipital. Mean of MSC estimated by Burg method is more than other three methods.

Table.3 Mean of MSC of Third Subject.

| Methods / Brain Region | Cerebellum | Frontal | Occipital | Parietal |
|---|---|---|---|---|
| Burg | 0.2216 | 0.2168 | 0.2099 | 0.2024 |
| Covariance | 0.2209 | 0.2149 | 0.2143 | 0.2019 |
| Modified Covariance | 0.2187 | 0.2151 | 0.2085 | 0.2008 |
| Welch | 0.1510 | 0.1433 | 0.1491 | 0.1542 |

From the table.3 it is clear that maximum value of mean of MSC is at cerebellum. Second maximum is at Frontal. Mean of MSC is minimum at Parietal. Mean of MSC estimated by Burg method is more than other four methods.

Table.4 Mean of MSC of Fourth Subject.

| Methods / Brain Region | Cerebellum | Frontal | Occipital | Parietal |
|---|---|---|---|---|
| Burg | 0.2433 | 0.2425 | 0.2750 | 0.2337 |
| Covariance | 0.2407 | 0.2472 | 0.2729 | 0.2415 |
| Modified Covariance | 0.2439 | 0.2429 | 0.2784 | 0.2456 |
| Welch | 0.1351 | 0.1332 | 0.1413 | 0.1351 |

From the table.4, it is clear that maximum value of mean of MSC is at Occipital. Second maximum is at cerebellum. Mean of MSC is minimum at Parietal. Mean of MSC estimated by Burg method is more than other four methods

Table.5 Mean of MSC of Fifth Subject.

| Methods / Brain Region | Cerebellum | Frontal | Occipital | Parietal |
|---|---|---|---|---|
| Burg | 0.4033 | 0.2909 | 0.2779 | 0.2379 |
| Covariance | 0.4010 | 0.3026 | 0.2564 | 0.2162 |
| Modified Covariance | 0.4019 | 0.3184 | 0.2686 | 0.2262 |
| Welch | 0.1601 | 0.1584 | 0.1584 | 0.2001 |

From the table.5, it is clear that maximum value of mean of MSC is at cerebellum. Second maximum is at Frontal. Mean of MSC is minimum at Parietal. Mean of MSC estimated by Burg method is more than other four methods.

Table.6 Mean of MSC of sixth Subject.

| Methods / Brain Region | Cerebellum | Frontal | Occipital | Parietal |
|---|---|---|---|---|
| Burg | 0.3233 | 0.2601 | 0.2199 | 0.2479 |
| Covariance | 0.3011 | 0.2499 | 0.2094 | 0.2262 |
| Modified Covariance | 0.3122 | 0.2584 | 0.2186 | 0.2362 |
| Welch | 0.1700 | 0.1314 | 0.1484 | 0.1501 |

From the table.6, it is clear that maximum value of mean of MSC is at cerebellum. Second maximum is at Frontal. Mean of MSC is minimum at Occipital. Mean of MSC estimated by Burg method is more than other four methods.

Table.7 Mean of MSC of seventh Subject.

| Methods / Brain Region | Cerebellum | Frontal | Occipital | Parietal |
|---|---|---|---|---|
| Burg | 0.3111 | 0.2619 | 0.2179 | .2579 |
| Covariance | 0.3010 | 0.2516 | 0.2164 | 0.2500 |
| Modified Covariance | 0.3021 | 0.2584 | 0.2186 | 0.2562 |
| Welch | 0.1511 | 0.1484 | 0.1404 | 0.1441 |

From the table.7 it is clear that maximum value of mean of MSC is at cerebellum. Second maximum is at Frontal. Mean of MSC is minimum at Occipital. Mean of MSC estimated by Burg method is more than other four methods.

Table.8 Mean of MSC of eighth Subject.

| Methods / Brain Region | Cerebellum | Frontal | Occipital | Parietal |
|---|---|---|---|---|
| Burg | 0.3535 | 0.2909 | 0.2179 | 0.2879 |
| Covariance | 0.3110 | 0.2726 | 0.2164 | 0.2612 |
| Modified Covariance | 0.3519 | 0.2884 | 0.2186 | 0.2712 |
| Welch | 0.1701 | 0.1684 | 0.1484 | 0.1501 |

From the table.8, it is clear that maximum value of mean of MSC is at cerebellum. Second maximum is at Frontal. Mean of MSC is minimum at Occipital. Mean of MSC estimated by Burg method is more than other four methods.

Table.9 Mean of MSC of ninth Subject.

| Methods / Brain Region | Cerebellum | Frontal | Occipital | Parietal |
|---|---|---|---|---|
| Burg | 0.3111 | 0.2600 | 0.2379 | .2579 |
| Covariance | 0.2999 | 0.2501 | 0.2221 | 0.2412 |
| Modified Covariance | 0.3001 | 0.2564 | 0.2331 | 0.2542 |
| Welch | 0.1600 | 0.1574 | 0.1504 | 0.1521 |

From the table.9 it is clear that maximum value of mean of MSC is at cerebellum. Second maximum is at Frontal. Mean of MSC is minimum at Occipital. Mean of MSC estimated by Burg method is more than other four methods.

Table.10 Mean of MSC of tenth Subject.

| Methods / Brain Region | Cerebellum | Frontal | Occipital | Parietal |
|---|---|---|---|---|
| Burg | 0.3232 | 0.3009 | 0.2577 | 0.2908 |
| Covariance | 0.3220 | 0.3001 | 0.2465 | 0.2706 |
| Modified Covariance | 0.3229 | 0.3007 | 0.2556 | 0.2862 |
| Welch | 0.1701 | 0.1664 | 0.1505 | 0.1601 |

From the table.10, it is clear that maximum value of mean of MSC is at cerebellum. Second maximum is at Frontal. Mean of MSC is minimum at Occipital. Mean of MSC estimated by Burg method is more than other four methods.

Table.11 Mean of MSC of eleventh Subject.

| Methods / Brain Region | Cerebellum | Frontal | Occipital | Parietal |
|---|---|---|---|---|
| Burg | 0.3663 | 0.3011 | 0.2579 | 0.2991 |
| Covariance | 0.3600 | 0.3000 | 0.2501 | 0.2886 |
| Modified Covariance | 0.3651 | 0.3001 | 0.2529 | 0.2899 |
| Welch | 0.1551 | 0.1504 | 0.1498 | 0.1532 |

From the table.11, it is clear that maximum value of mean of MSC is at cerebellum. Second maximum is at Frontal. Mean of MSC is minimum at Occipital. Mean of MSC estimated by Burg method is more than other four methods.

Table.12 Mean of MSC of twelfth Subject.

| Methods / Brain Region | Cerebellum | Frontal | Occipital | Parietal |
|---|---|---|---|---|
| Burg | 0.3334 | 0.3509 | 0.2919 | 0.3109 |
| Covariance | 0.3300 | 0.3426 | 0.2884 | 0.3002 |
| Modified Covariance | 0.3329 | 0.3489 | 0.2901 | 0.3092 |
| Welch | 0.1761 | 0.1788 | 0.1684 | 0.1709 |

From the table 12, it is clear that maximum value of mean of MSC is at Frontal. Second maximum is at Cerebellum. Mean of MSC is minimum at Occipital. Mean of MSC estimated by Burg method is more than other four methods.

By analysing the above 12 Tables (1-12), It is Concluded that mean of magnitude squared coherence is Maximum at Cerebellum for ten subjects. Second highest mean of MSC is obtained at frontal. From all the above 12 tables we find that magnitude squared of coherence values for all 12 subjects are non-zero at all brain region, its mean that there is association between ECG and EEG signals. If MSC value for any two signals is zero then there is no association between two signals.

- Association of heart with brains different region in decreasing order is Cerebellum > Frontal> Parietal> Occipital
- In case of only parametric methods burg method is superior to covariance and modified covariance. Because mean of MSC values estimated using burg method is larger than that of other two method.
- In case of parametric and nonparametric methods parametric method is superior to nonparametric method.
- Mean of MSC values estimated by Welch method is smaller than other three methods. So Welch method is least suitable for the coherence estimation.

## CONCLUSIONS AND FUTURE SCOPE

Coherence is analysed by estimating the magnitude squared coherence. Four different methods are used for this purpose. MSC values of ECG and EEG signals are non-zero, its mean there is some association between heart and brain. From this research it is analysed that mean of MSC is maximum among the signals acquired from the Cerebellum of brain and heart. Its mean cerebellum is maximally associated with heart. Second maximum association is estimated between frontal and heart. Occipital has maximum coherence points whose magnitude is greater than 0.5. Its mean at some frequency there is maximum association between Occipital and brain. For this analysis four methods are used. Out of four methods three are parametric methods and one is non parametric method. From the analysed results it is seen that MSC values estimated by using parametric methods are larger than that of nonparametric methods.

Parametric methods has less spectral leakage and suits for both small and large data records whereas nonparametric methods suffer from spectral leakage and works on large data record. Because of so much flexibility it is analysed that parametric methods are better than non-parametric method for the purpose of estimation of coherence. It is seen that burg method gives maximum mean of coherence so it is superior to all other methods.The magnitude squared coherence between the two physiological signals provides the valuable association between the corresponding physiological organs. Any deviation in the MSC values from standard MSC values is estimated as defects in physiological organs. With the help of MSC value, the cause of defects can be analysed. Estimation of Coherence among physiological signals helps in the non-invasive diagnosis of physiological organs. With the help of coherence among ECG and EEG signals difference between normal and abnormal brain activity can be analysed. As in this project four method of power spectral estimation is used for the purpose of the analysis of coherence and every method has given different magnitude of coherence. Best method is one which gives maximum mean of MSC that is Burg method of power spectrum estimation. Although all parametric methods like burg, covariance and modified covariance gives approximately same mean MSC values but mean of MSC values obtained by burg method is slightly larger than other parametric methods. Mean of MSC obtained using burg method is smaller than other methods. So, in future Burg method can be used for analysis of coherence.

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