MSC AND PHASE SYNCHRONIZATION ANALYSIS FOR CLASSIFICATION OF EEG

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ABSTRACT

EEG signals are often used for disease diagnosis and behavioral analyses. These signals are highly non-stationary. Therefore a common practice of EEG analysis is, breaking it into many band limited components and then extrapolating the underlying features of these temporal components. This paper is about analysis of mean spectral coherence and phase synchronization of EEG components, across various sub-bands. Coherence is studied for different pair of EEG signals, acquired from corresponding locations of the two hemisphere of brains. Coherence feature is unrestricted to amplitude distortions which are caused by various signal processing steps. This work is centered on MSC computation by using wavelet transform. By using suitable frequency resolutions, or in other ward by using different number of samples while computing FFT for different wavelet sub-band components, wavelet based computation results into time-frequency resolved MSC coefficients. This helps in preserving the underlying less powerful neuronal dynamics, at some frequencies, which would otherwise disappeared due to presence of more powerful harmonically related frequencies. The results show that similar synchronization or association exist between MSC peals and the corresponding phase across the sub-bands, however this association varies in specific ways depending on external stimulus. For this experimentation external stimulus is considered through five different tasks performed by subjects during EEG acquisition. The variations are better observable in theta, beta and gamma sub-bands.

Keyword *Magnitude spectral coherence (MSC), wavelet transform (WT), EEG, Phase synchronization*.

1. INTRODUCTION

Of late EEG devices have become wireless and portable. Cost-benefit ratio EEG acquisition has been augmented significantly. It has become the most preferred method of brain activity recording in clinical studies, lab experimentations, brain computer interfacing, behavioral studies and even deception detection. EEG signal processing carries serious challenges. Due to non-stationary nature of the EEG, selection of an appropriate time-frequency method is tricky. The basic idea of EEG processing is to separate the spectrum into sub-spectral components and then process them individually, based on the application. Unlike to ECG, EEG signals have no special forms. In the analysis of EEG, various statistical and parametric methods, such as autocorrelation, cross-correlation, PSD, wavelet transform, time-frequency analysis are used. The five frequency ranges of waves that are considered for an EEG analyses, from the highest to the lowest frequency are: 1) Gamma waves (30-60Hz) which may be related to coherent consciousness among various parts of the brain, 2) Beta waves (12-30Hz) are the ones registered on an EEG when the subject is awake, alert, and actively processing information 3) Alpha waves (8-12Hz) are typically found for an awake but relaxing or meditating state, 4) Theta waves (5-8Hz) are associated with memory, emotions, and activity in the limbic system and 5) Delta waves (0.5-3Hz)are observed when individuals are in deep sleep or in a coma. Neuronal activities are due to synchronization associated with two processes. One is related to stimuli causing increase or decrease in amplitude of neuronal oscillation due to the number of active neurons firing synchronously. Second process refers to the phase synchronization among few spatially separated oscillatory sources with similar frequency. In this paper an attempt has been towards establishing a hypothetical relationship between magnitude spectral coherence and phase synchronization while performing various tasks.

Data used in this study is from the work of Keirn and Aunon [2] which were collected from 7-subjects while performing five different tasks. Electrodes were positioned at C3,C4, P3, P4, O1 and O2 as defined by the international 10/20 standard. For all the trials impedance of all electrodes were below 5-KOhms, data were recorded at 250Hz over a period of 10 secs and by using a 12bit A/D converter. Signals were amplified and then filtered by an analog bandpass filter with 0.1-100Hz passband. Eye blinks were recorded in a separate EOG channel by two electrodes placed above and below the left eye. The five tasks are namely base line rest, composing letter mentally, compute mental multiplications, visualize rotation of a 3-D object and finally count a sequence of displayed number without vocalizing.

2. WAVELET DECOMPOSITION

Dynamics of alpha and beta oscillatory phenomena have been extensively reported in literatures on EEG based task classification, brain computer interfacing and disease diagnosis. In [5] authors have reported power spectral density (PSD) based mental arithmetic task recognition and have reported significant changes in alpha band when the subject was doing mental arithmetic task. Besides PSD features, autoregressive model coefficients were successfully applied for mental arithmetic task in [3]. A multi-fractal spectrum analysis based task classification approach has been reported in [4]. Spectral analysis of EEG signal is possible by using short-time Fourier Transform (STFT) or Wavelet Transform (WT). Fourier transform decomposes a signal into its frequency components in order to determine their relative strengths. Non-stationary signals are processed by STFT, which introduces a local frequency parameter so that local FT looks at the signal through a window through which signal looks approximately stationary. In comparison to STFT, the wavelet transform (WT) can be thought of as an extension of Fourier transform working on multi-scale basis. In multi-scale framework each scale represents a particular coarseness of input signal. For large scales dilated wavelets take 'global views' of a subsampled signal, while for small scales, contracted wavelets analyse small 'details' in the signal. The basis functions of WT, called wavelets, are obtained from scaling and translating a prototype mother wavelet function. The prototype mother wavelet function can be thought of similar to a band-pass filter and the notion of scale is introduced as an alternative to frequency. Continuous time wavelet transform (CWT) of any signal f(t) is defined as:

$$W_x(a,b) = \int_{-\infty}^{\infty} x(t) \frac{1}{\sqrt{a}} \Psi^* \left(\frac{t-b}{a} \right) dt \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots(1)$$

Where 'a' and 'b' are real numbers accounting for scaling and translation of the wavelet operator. One drawback of the CWT is, since coefficients a and b are continuous over R (the real number), representations of the transformed signal is often redundant. If scales and positions are chosen based on powers of two (called dyadic scales and positions) then the analysis become much more efficient and accurate. Such analysis of WT is called the discrete wavelet transform (DWT). From usefulness point of view, DWT is more applicable for real-time processing of EEG signals, due to its short processing time; however, the CWT produces good resolution and performance high enough for use in clinical and research settings. Fig. 1 below shows the PSD plots of various sub-band components, obtained from CWT decomposition, for four different activities; namely: rest, letter composing, counting, and visualizing object rotation.

It can be noticed that, as compared to the rest state, the delta band power has drastically reduced while performing various tasks. Counting exhibits synchronized pattern across theta, alpha and beta bands. Noticeable rise in power spectrum, while visualizing object rotation, can be related to involvement and triggering of neurons from both the hemispheres, resulting into more resilient sub-components. Rise in gamma activity in letter composing task supports recalling the fact from memory and converting into linguistic form, hence more anticipation. PSD analysis though is very efficient, often fails to compare or correlate phenomena because signal power gets affected by irresolute and non-recordable signal normalization that happens during various signal processing steps. Signal attenuation varies across the spectrum, when system order changes and even due to amplitude normalization in CWT processing. This motivates for extracting features from the spectrum coherence and phase synchronizations.

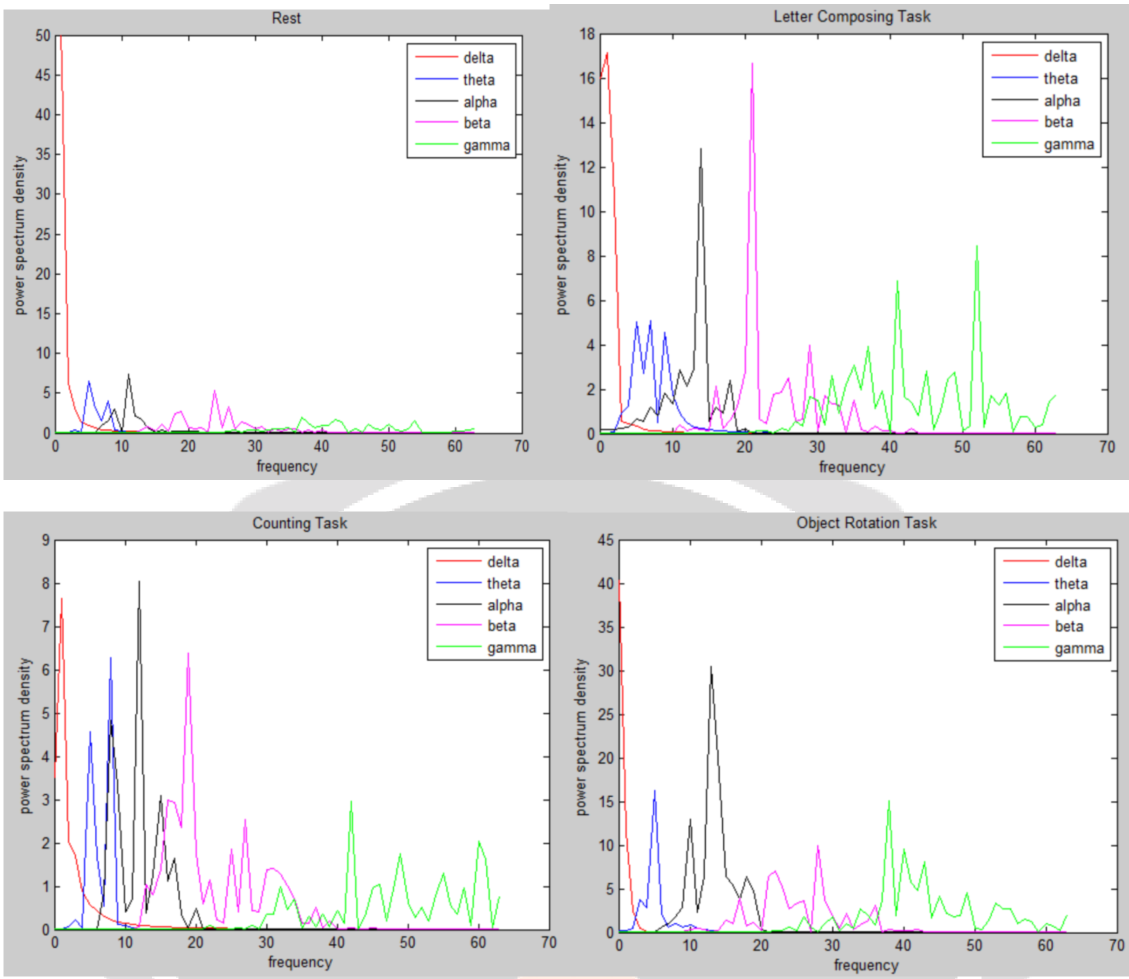


Fig.-1: PSD plot of sub-band decomposed EEG signal from ‘P3’ position.
(a)-Rest, (b)-Letter composing, (c)-Counting and (d)-Visualising rotation.

3. MAGNITUDE SPECTRAL COHERENCE

Usually the left-hemisphere is programmed to do logical processing, i.e. match letters/words with its sound, arranging the phonetics/expressions in right order, and above all identifying the syntax. On the other side right hemisphere understands the big picture of the task like dealing with the sketches, space, patterns, imagination etc. The corpus callosum (CC) is a bridge of nerve cells over which information from one side of the brain gets to the other. As a whole brain administration is a synchronized mechanism. There is strong evidence that one of the fundamental neural mechanisms underlying normal and pathological brain activity is the synchronization of neuronal assemblies and can be explored from quantitative measures of synchronization [7]–[9]. The degree of synchronization in EEG signals is commonly characterized by the time-series measures, namely, correlation, phase synchrony, and magnitude squared coherence (MSC). Cross correlation measures the linear correlation between two temporal signals [21]. Phase synchrony is defined by a phase locking value, ranging from zero (no synchronization) to one (perfect synchronization). MSC identifies the synchrony of spectral components of EEG and the underlying neuronal assemblies. The typical finding is that, for a given neurotic state, which is nothing but combinations of perceptual and cognitive tasks, quantitative measure of EEG correlation, coherence, or synchrony increases (or decreases). [7], [13], [19], [22]–[31].

Cross spectral analysis allows determining the relationship between two band limited and relatively stationary time series signals, as a function of frequency. Given two time series x(t) and y(t) the correlation between x(t) and y(t) is defined as:

$$C_{xy}(w) = \frac{\left|S_{xy}(w)\right|^2}{S_x(w)S_y(w)}$$

It is the magnitude spectrum of cross-spectrum $S_{xy}(w)$ normalized by the power spectrums of x and y. It confines to the range $0 \le C_{xy}(w) \le 1$, subject to the condition that $\left(S_x(w), S_y(w)\right) \ne 0$, power spectrums are non-zero.

Alternatively $$C_{xy}(w)\Big|_{w=w_0} = \frac{\left|\mathrm{E}\left\{ab^*\right\}\right|^2}{\mathrm{E}\left\{|a|^2\right\}\mathrm{E}\left\{|b|^2\right\}} \quad \text{……………..(2)}$$

where E[·] is the expected value of random variable, a and b are Fourier coefficients of x(t) and y(t) at frequency w_0.

Phase synchrony, or mean phase coherence, of x(t) and y(t) can be defined as:

$$R_{xy} = \left|\frac{1}{N}\sum_{j=1}^{N} e^{i\left[\phi_x(t_j)-\phi_y(t_j)\right]}\right| \quad \text{………………………(3)}$$

Where, ϕ_x and ϕ_y denote the phase variables of x(t) and y(t), N is the window sample size, and phase can be computed as $\phi(t) = \arctan\left(\tilde{s}(t) / s(t)\right)$. For an arbitrary signal, $s(t)$ and $\tilde{s}(t)$ are the Hilbert transform pairs.

EEG signals are extremely non-stationary processes. Classical Fourier based spectral and coherence methods are very useful for stationary phenomenon. This stationarity assumption can potentially overshadow the dynamic characteristics required for EEG. The wavelet transform coherence (WTC) method is a known signal analysis tool for neural happenings. The WTC method provides information on the strength of the relationship as a time frequency map. In this way, related signal features can be obtained over specific frequency zones and time points. Desired resolution can be obtained simultaneously for each signal feature; higher temporal resolution for higher frequencies, and higher spatial resolution for lower frequencies.

Wavelet cross-spectrum between x(t) and y(t) is defined as:

$$SW_{xy}(\tau,\omega) = \int_{t-\sigma/2}^{t+\sigma/2} W_x(\tau,\omega)W_y^*(\tau,\omega)\,d\tau$$

Where σ is the window size for calculation of coherence and standard practice is to have 50% overlapping between the windows for two consecutive calculations. Finally Wavelet coherence is defined as

$$Coh_w(\tau,w) = \frac{\left|SW_{xy}(\tau,w)\right|}{\left[SW_{xx}(\tau,w)\ SW_{yy}(\tau,w)\right]^{1/2}} \quad \text{……………(4)}$$

As a demonstration fig.3 shows the time-frequency wavelet coherence plot between two signals $x_1(t)$ and $x_2(t)$.

$$x_1(t)=\begin{cases}\sin(4\pi t) & for\ \ 0<t<250ms\\ \sin 160\pi t) & for\ \ 250<t<500ms\\ \sin(80\pi t-135pi/180) & for\ \ 500<t<750ms\\ \sin(20\pi t+60Pi/180) & for\ \ 750<t<1000ms\end{cases},$$

$$x_2(t)=\begin{cases}\sin(4\pi t+30pi/180) & for\ \ 0<t<250ms\\ \sin 160\pi t-90pi/180) & for\ \ 250<t<500ms\\ \sin(80\pi t) & for\ \ 500<t<750ms\\ \sin(20\pi t) & for\ \ 750<t<1000ms\end{cases}$$

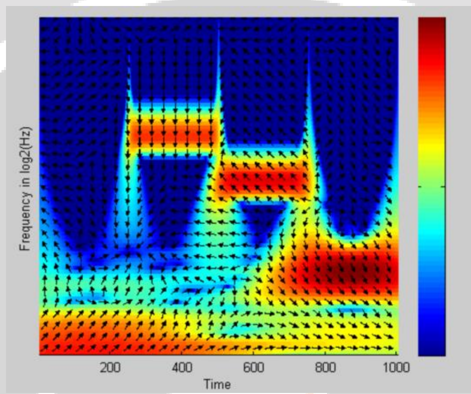


Fig.2-Time-freq coherence plot with relative phase quivers

The phase arrows show the relative phasing between the input time series. Arrows pointing to right corresponds to two signals are in phase. Arrows pointing in N-E directions corresponds to signal $x_1(t)$ lagging $x_2(t)$. Interpretation of the phase as a lead(/lag) is a relative concept. A lead of 90deg can also be interpreted as a lag of 270deg or a lag of 90deg relative to the anti-phase (opposite sign).

EEG signals can be decomposed into non-overlapping spectral sub-bands by means of wavelet decimation. Fig.3 shows the results for EEG analyses for ‘P3’ position for the ‘rest’ and ‘letter writing’ tasks. STFT spectrogram in fig. 3(a) shows less alpha and beta band activities during rest condition as compared to that of letter writing spectrogram shown in fig. 3(b). This comparison is not trivial in WT decimated time series signals shown in fig. 3(c &d). However a significant fall in theta band oscillation is noticed in fig. 3(d) as compared to fig. 3(c). This can be interpreted to the proposition that stronger delta sub-signal characterises mild sleep or rest condition. Spectral and temporal annotations often complement to each other manifesting into a more robust and sensible learning. In [], Koopmans [2] it has been shown that if the phase angle is a rapidly varying 'function of the frequency at which the coherence is to be estimated, the estimated coherence can be supressed to a great extent. The phase bias can mask a strong coherence significantly.

Though spectrogram gives a clear picture of spectral power it suffers from frequency shifting and amplitude distortions caused by local phase gap. In two spectral components phase delay can occur at beginning only or can cause signal shifting randomly through the temporal spread.

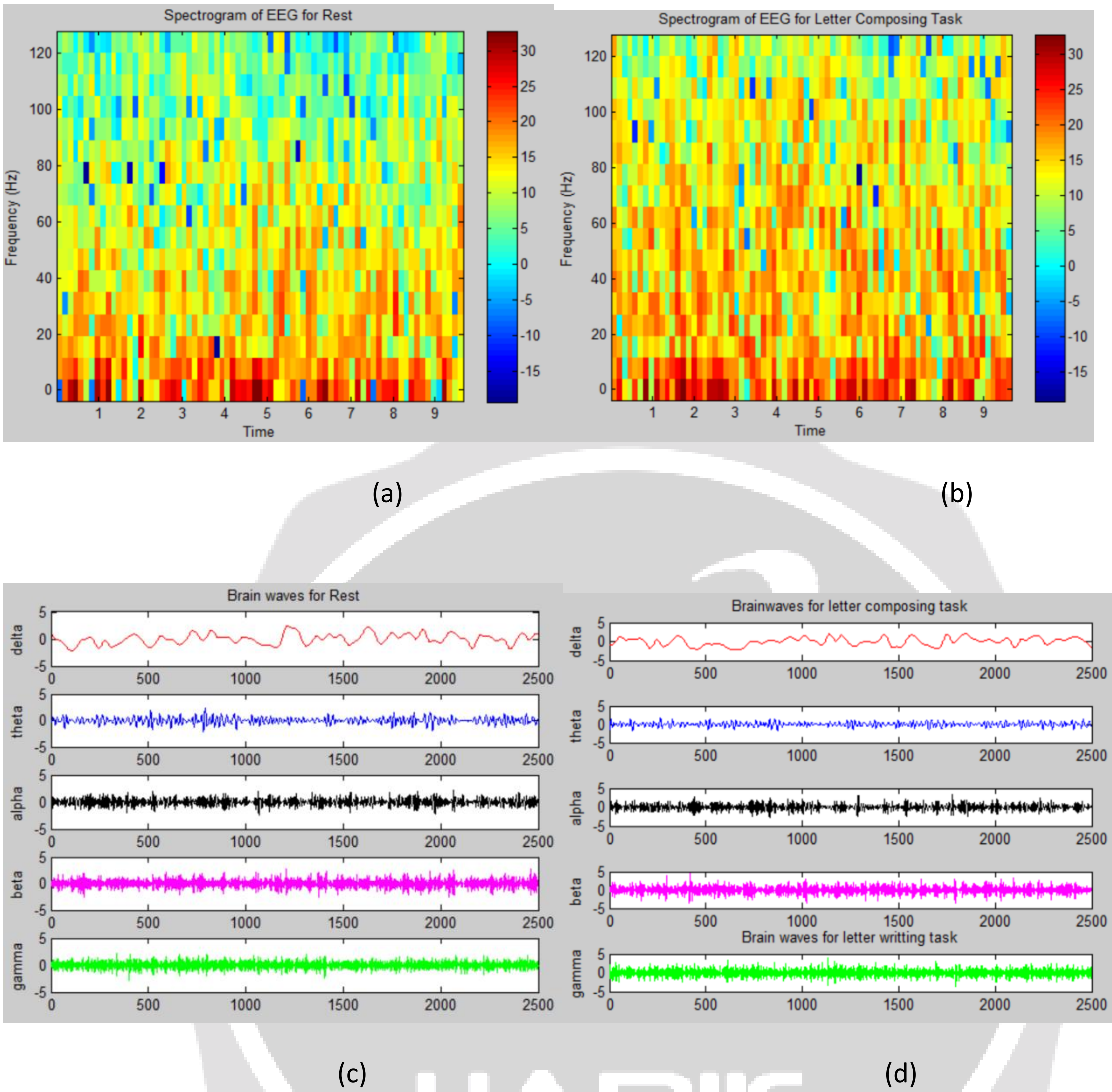


Fig. 3: 'db8' WT decomposed spectrograms and temporal brain waves for P3 position for 'Rest' and 'Letter Writing' Tasks

Effect of misalignment can be looked upon as follows. Fourier transform for two signals $x(t)$ and $y(t) = Ax(t+D) + n(t)$ is given as,

$X(w) = \int_0^T x(t) e^{-j2\pi ft} dt$ and $Y(w) = \int_0^T [Ax(t) + n(t)] e^{-j2\pi ft} dt$, where $n(t)$ is an independent noise signal.

Therefore

$$C_{xy} = \mathrm{E}\left[\frac{1}{T} X(w) Y^*(w)\right] = \frac{A}{T} \int_0^T \int_0^T S_{xx}\left(u - v + D\right) \; e^{j2\pi f(u-v)} du \; dv$$

Substituting $p = u - v$, we get

$$C_{xy} = \frac{A}{T} \int_{-T}^{T} \left(T - |p|\right) S_{xx}\left(p + D\right) \; e^{j2\pi fp} dp$$

For narrow band signals, for which an autocorrelation function decays to zero over a fraction of time T, we can extend the integration limits to infinity and obtain the cross spectral coherence as,

$$C_{xy} \; ; \; A\left(1-\frac{|D|}{T}\right)\int_{-\infty}^{\infty} S_{xx}\left(p+D\right)\; e^{j2\pi fp}dp$$

$$; \; A\left(1-\frac{|D|}{T}\right)C_{xx}\left(f\right)e^{-j2\pi fD}$$

This shows that the cross-power spectrum between to correlated signals is decreased by a factor $A\left(1-\frac{|D|}{T}\right)e^{-j2\pi fD}$. No degradation will appear in either of the auto-power spectral densities. Therefor the magnitude power spectrum is degraded by the square of this factor. Additionally due to the term $e^{-j2\pi fD}$ the in phase and quadrature components will exhibit different degradations. For delays equal to, or greater than, the FFT size, the estimated MSC will become zero. For $|D| = T$, second order term can be exempted leading to a magnitude distortion equal to $\frac{-2|DC_{xx}|}{T}$. For example if time shift is 0.25T, expected value of the estimated MSC will come up to one-half of its true value, which is exceedingly ambiguous. The most useful outcome of the preceding analysis is that for an MSC based exploration of EEG sub-band components Fourier time period (T) selection is very crucial.

4. RESULTS AND CONCLUSION

Goal of this work is to examine if any dependency exist among the MSC, phase values and the corresponding tasks. This association can appear in any of the five sub-bands of EEG. However delta waves being associated with deep sleep conditions are excluded from this study. More attention is given on theta and beta sub-bands. Motivation behind this is theta is likely to have association with memory related activities and beta waves with alertness and logical ability. Fig.4 shows the temporal waves for sub-band spectral components of EEG, which is captured from the location parietal positions one from left and right hemispheres, while the subject was carrying out counting task.

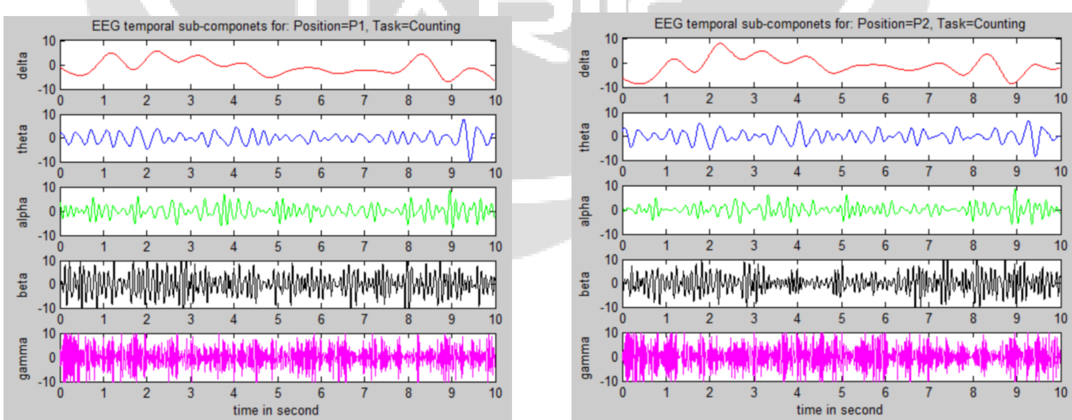
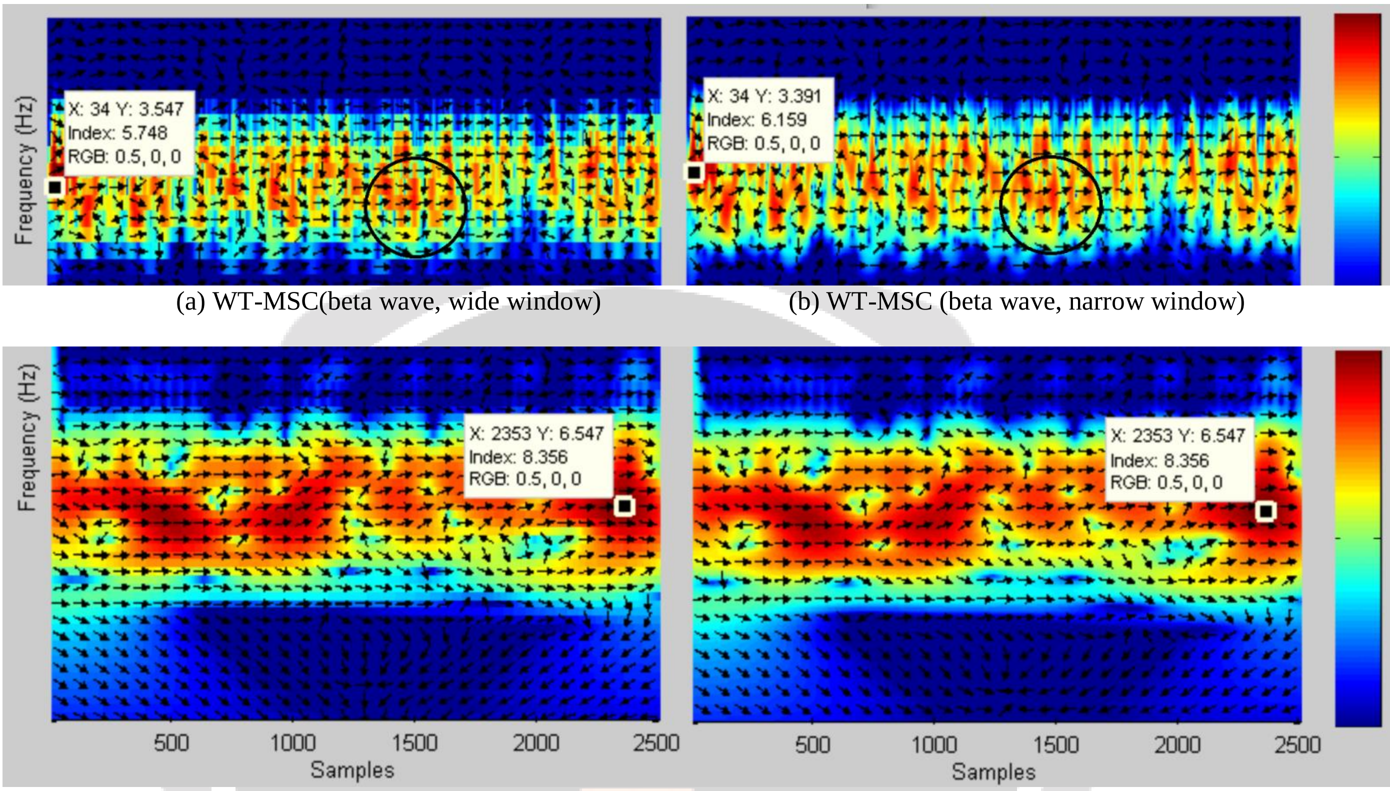


Fig.4- Wavelet decimated EEG temporal sub-components

As demonstrated in Fig.4, theta waves are slow waves and therefore can be transformed by using less number of spectral components or wider windows. On the other hand beta waves are approximately four times more oscillatory in nature. Narrow windows with more spectral components are appropriate for MSC computation of these waves.

Fig.-5 shows the comparisons of window sizes used for computing MSC of beta and theta waves of EEG. Fig.-5(a) is the MSC plot of gamma wave by using a window width which is twice the size of Fig.-5(b). By doing this resulted in approximately 20% increase in the peak MSC value. Also results of fig.-5(b) are less cluttered, which can be noticed from the components marked with a circle. No such improvement is observable in MSC of theta-wave.



(a) WT-MSC(beta wave, wide window) (b) WT-MSC (beta wave, narrow window)

(a) WT-MSC(theta wave, wide window) (d)WT-MSC (theta wave, narrow window)

Fig.-5: Impact of Fourier window size on spectral power (magnitudes are in db)

Association between MSC and phase: The central objective of this study is to examine if any association exists between cross-hemisphere MSC and phase angle while performing various tasks. This can highlight the contribution by left and right hemisphere towards various tasks. The degree of synchronisation between the left and right hemispheres, while performing tasks, is studied by comparing the peak magnitudes and the corresponding phases of WT-MSC. Possibility of distortion in peak magnitudes, due to initial phase difference or any temporal phase difference, is accounted by taking average power over all the frequencies that ensured peak in one of the epochs. Epochs are nothing but the scaled windows used for wavelet transform. However this processing is later made simpler by first decomposing the raw EEG signals into band-restricted sub-components and then applying the WT-MSC. Fig.-6 is the block diagram of various processing steps. In this study EEG signals are not processed for removing any artifact. EEG signal pairs from parietal, central and occipital lobs are considered independently. Similarly gamma, beta and theta sub-component pairs are considered separately. Motivation behind this is spectra components from different sub-components spans over disjoint frequency bands and hence can't be coherent. However different lobs are likely to possess discriminating spectrums for various tasks. Database used for this study contains EEG from 7-subjects performing 5 different tasks, repeating each task 10 times. Exceptions are: one subject has performed the tasks for only five times, data for five trials of letter writing has not been recorded properly. For each of the tasks 60 trials are considered for this study. Tasks are randomly selected.

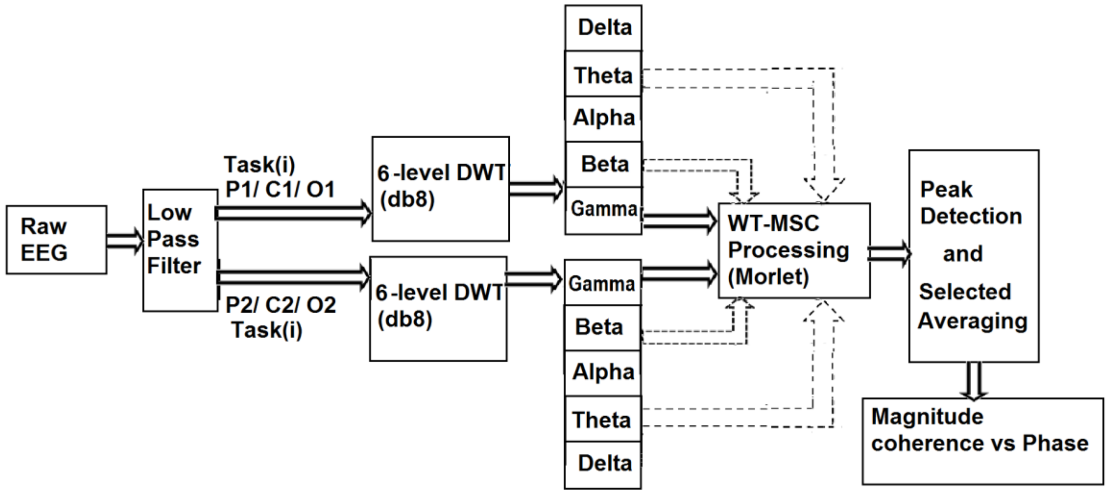
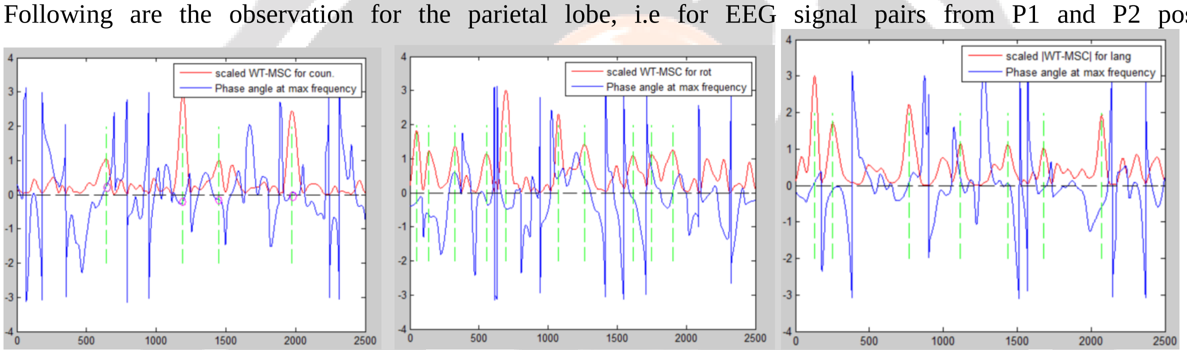
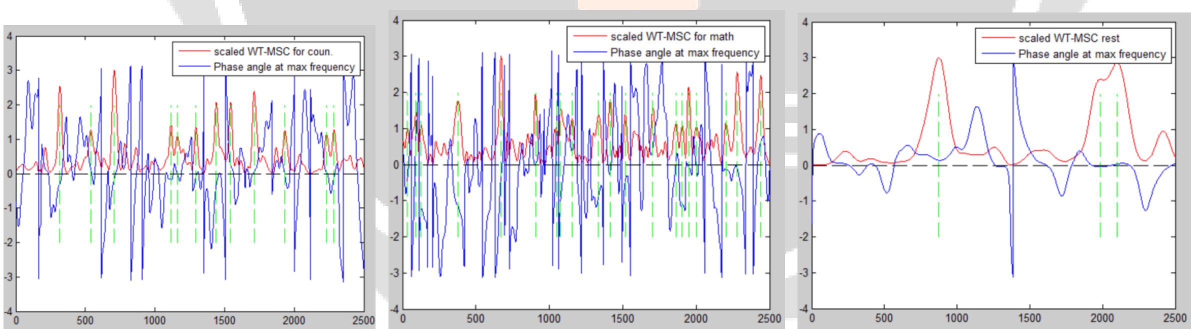


Fig.-6 Block diagram of processing steps for MSC and phase synchronization analysis

Following are the observation for the parietal lobe, i.e for EEG signal pairs from P1 and P2 position.



(a)-'beta', 'counting' (b)- 'beta', 'rotation' (c)- 'beta', 'letter writing'



(d)- 'gamma', 'counting' (e)- 'gamma', 'multiplication' (f)- 'theta', 'rest'

Fig.-7: magnitude spectral-power and phase synchronization plots for EEG signals from P1-P2 positions

Occurrence of a magnitude peak with less phase lag or lead is considered as better synchronisation between the two hemispheres. This can be termed as joint magnitude phase synchronization. MSC peaks for beta waves for 'rest' task lack phase synchronisation. Absolute magnitude is maximum for counting task and minimum for rotation task. Joint magnitude phase synchronisation for counting task is better than the remaining tasks for all sub-components (fig.-7a & 7d). This is can be established as maximum tuning between the parietal lobes for counting task involving both logical and memory coordination. Math and counting tasks exhibits more MSC peaks but with poor phase synchronisation (fig.-7b). Number of peaks for 'letter writing' task is also more, as compared to 'rest', but are better synchronised with phase (fig.-7c). In general gamma-waves better are synchronised except for the math tasks. For

the ‘math’ and ‘rest’ tasks theta waves are more synchronised than other sub-bands (fig.-7f). Synchronization is poor in the theta band for ‘counting’ and ‘letter writing’ tasks. Maximum spectral power exists in theta sub-band.
Peak magnitudes from occipital lobe are less as compared to parietal lobe. For ‘rest’ state gamma band phase plot from O1-O2 pair are more oscillatory. ‘Math’ task bears more MSC peaks but with no significantly visible relationship with corresponding phase component.

This paper is about how to estimate multi resolution magnitude-squared coherence by using wavelet transform of the temporal power in the delta, theta, alpha, beta, and gamma frequency bands, , from the corresponding locations of brain hemispheres. The multi resolution approach is free from shadowing of EEG dynamics associated with low power components due to presence of high power components in the neighbouring spectral sub-bands. Association between the peak locations and phase locations is studied. This study is based on random sample pooling, however use of boot-strap approach followed by some task classification will be more judicious towards establishing the observed association. We observed that association for theta, beta and gamma bands are more task dependent. This work can be interpreted as an complementary feature extraction approach and used to enhance the contribution of EEG towards disease diagnosis, BCI etc.

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