COMPARATIVE ANALYSIS FOR CONNECTIVITY MEASURES OF EEG WITH IMPROVEMENT IN SNR

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Abstract

This paper represent an effective method for removing artifacts & improving signal to noise ratio (SNR) of electroencephalography (EEG).With artifacts it is difficult to analyze a EEG. It is extremely challenging to determine where this artifact added. For this reason it is necessary to design a filter so dual extended kalman filter (DEKF) is used here. This filter is used here for estimating parameters which are going to used in MVAR model. This model is used with brain connectivity measures. for comparative analysis two connectivity measures are used here i.e Partial Directed Coherence (PDC) & Generalized Orthogonalized Partial Directed Coherence (GOPDC).from comparison based on SNR it is proved that GOPDC method have better performance than PDC.

Keywords— PDC, GOPDC,DEKF, MVAR,SNR

1 INTRODUCTION

EEG is a voltage signal that is measured with placement of electrodes on the scalp. EEG signal contains information about the health status of a patient's brain. [7] EEG signal is electrical signal which shows strength of flow of information. During the collection of EEG, artifacts can be added to EEG. For measurements of these artifacts are difficult & challenging task for skilled persons

The removal of artifact an important aspect of EEG in clinical research. . In this paper, We develop generalized version of OPDC to handle the numerical problem associated with potentially different variance of signal amplitudes .GOPDC is compared with the classical PDC on the basis of SNR. Orthogonalized version of the PDC is combination of orthogonalization and imaginary part of coherence functions .Effect of this combination is reduces volume conduction effects. Partial Directed Coherence (PDC), which is used to determine the directional influences between channels in a signal. This connective measure designed with multivariate autoregressive (MVAR).

2 Proposed Method

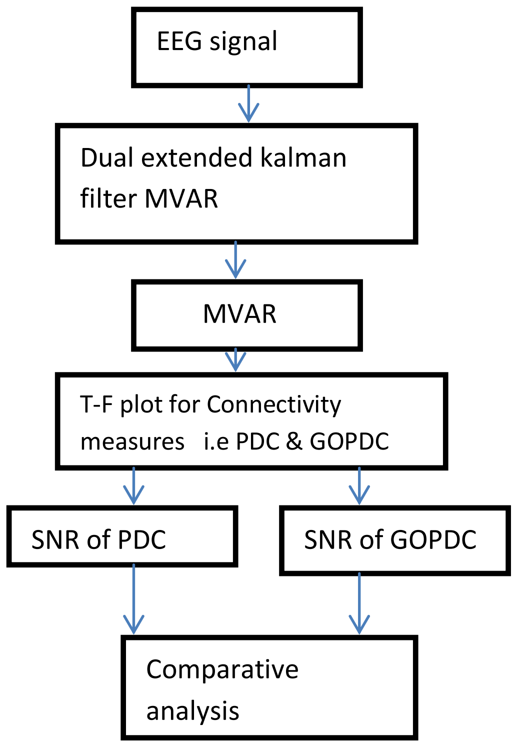


Fig-1:-Proposed method

2.1 EEG signal

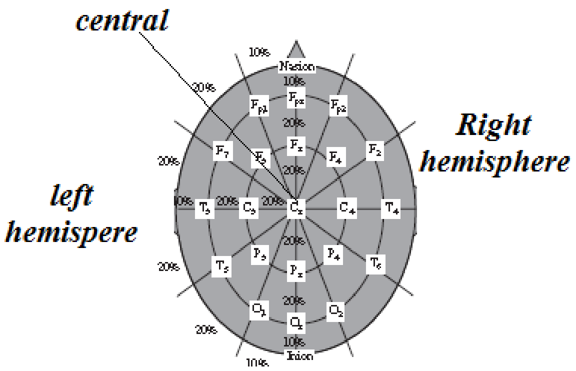


Fig-2:-placement of electrodes

We used 20-channel EEG recordings of four full-term newborns with sampling rate of 256 Hz .We selected five monopolar channels (Cz as the reference) from left hemisphere (O1,C3,P3,T3,T5)

2.2 Dual Extended Kalman Filter

For nonlinear model kalman filter is extended so this filter is called extended Kalman filter (EKF) & For dual estimation Dual extended kalman filter(DEKF) is used. There is sequential & iterative methods are developed.This filter is used to estimation of parameter i.e MVAR parameters (A_r(n)).

2.3 MVAR Model

A time-varying N-variate AR process of order *p* can be represented as:[15]

$$\begin{bmatrix} x_1(n) \\ \vdots \\ x_N(n) \end{bmatrix} = \sum_{r=1}^{p} A_r(n) \begin{bmatrix} x_1(n-r) \\ \vdots \\ x_N(n-r) \end{bmatrix} + \begin{bmatrix} w_1(n) \\ \vdots \\ w_N(n) \end{bmatrix}$$

where *w* is a vector white noise, the matrices A_r are given by:[15]

$$A_r(n) = \begin{bmatrix} a_{11}(r,n) & \cdots & a_{1N}(r,n) \\ \vdots & \ddots & \vdots \\ a_{N1}(r,n) & \cdots & a_{NN}(r,n) \end{bmatrix}$$

for *r* = 1, ..., *p* and A number of time-varying connectivity measures can be defined based on the following transformation of the MVAR parameters (A_r(n)) in frequency domain:[15]

$$A(n,f) = I - \sum_{r=1}^{p} A_r(n) z^{-r}\Big|_{z=e^{i2\pi f}}$$

2.4 Connectivity Measures

2.4.1 Partial Directed Coherence(PDC)

The time-varying version of the PDC is by

$$\pi_{kl}(n,f) \triangleq \frac{|A_{kl}(n,f)|}{\sqrt{a_l^H(n,f)a_l(n,f)}}$$

A_{kl} shows the direction of the information flow. for Eg. channel 1 affects channel 2 and channel 2 affects channel 3, i.e., 2←1, 3←2,where the arrows shows direction of flow.

2.4.2 Generalized Orthogonalized Partial Directed Coherence (GOPDC)

$$\tilde{\Psi}_{kl}(n,f) = \frac{1}{\lambda_{kk}^2} \frac{|\mathrm{Real}\{A_{kl}(n,f)\}|}{\sqrt{a_l^H(n,f)\Sigma_w^{-1}a_l(n,f)}} \cdot \frac{|\mathrm{Imag}\{A_{kl}(n,f)\}|}{\sqrt{a_l^H(n,f)\Sigma_w^{-1}a_l(n,f)}}$$
$$\text{if } k \neq l.$$

Where where λkk are the diagonal elements of Σw

2.5 Time-invariant Simulated Model

This model is designed by adding random interactions between channels

x(n)=Vy(n)

This equation shows x(n) is EEG signal , v represents the lead field matrix and y(n) models the lagged source time in MVAR process.

$y_1(n)=0.95\sqrt{2}y_1(n-1)-0.9025y_1(n-2)+10w_1(n)$
$y_2(n)=0.5y_1(n-2)+5w_2(n)$
$y_3(n)= -0.4\, y_1(n-3)+w_3(n)$
$y_4(n)=-0.5y_1(n-2)+0.25\sqrt{2}y_4(n-1)+0.25\sqrt{2}y_5(n-1)+1.5w_4(n)$
$y_5(n)=-0.25\sqrt{2}y_4(n-1)+0.25\sqrt{2}y_5(n-1)+2w_5(n)$............... [3]
where $w=[w_1w_2w_3w_4w_5]^T$ is a normally distributed white noise vector

3 DISCUSSIONS AND INTERPRETATION OF THE RESULTS

3.1 Time domain plot

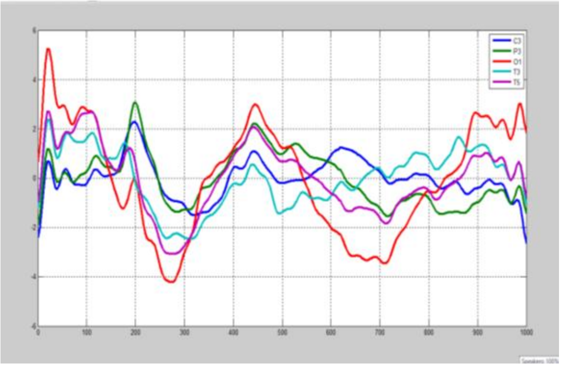


Fig-3: Time domain analysis of EEG

This is graph of EEG signal in time domain.EEG signal collected from five channel of left hemisphere of brain C3,P3,O1,T3,T5.

3.2 T-F plot for PDC & GOPDC

3.2.1 T-F plot for PDC

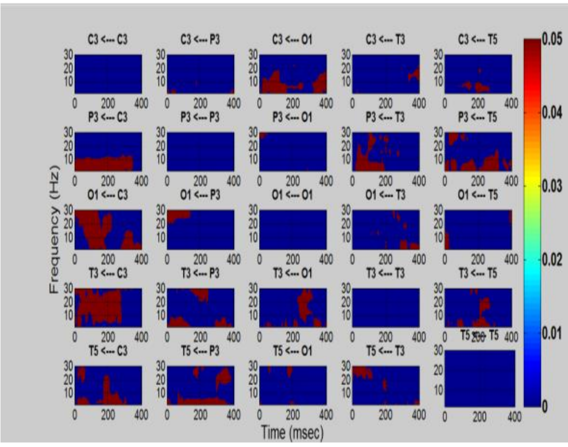


Fig-4: T-F plot for PDC

3.2.2 T-F plot for GOPDC

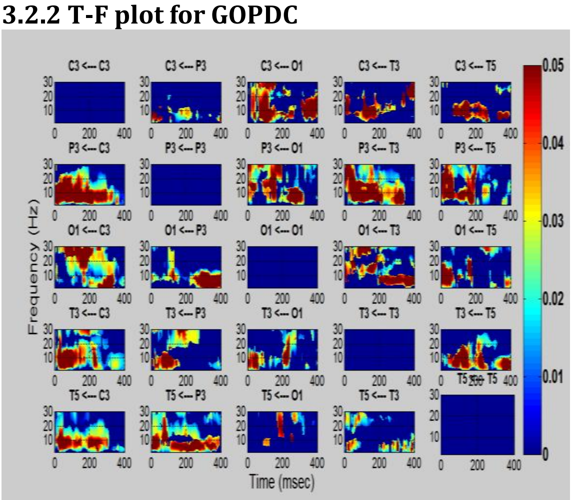
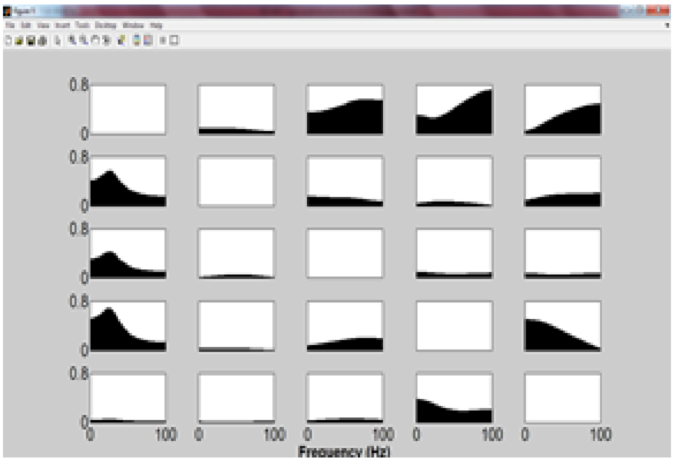


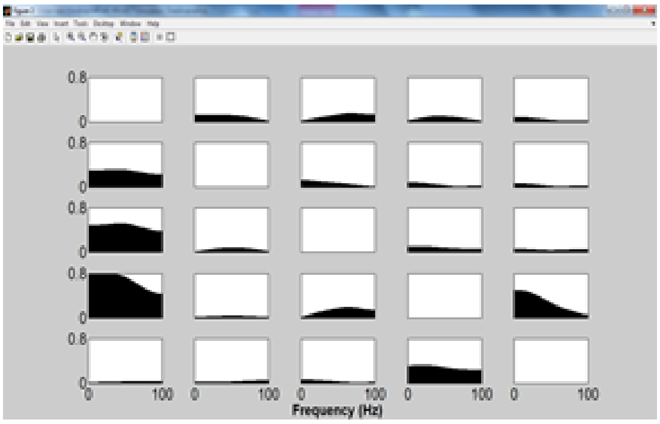
Fig-5: T-F plot for GOPDC

From above result In PDC mutual sources are there (from color bars) .GOPDC much smaller magnitude than the PDC. Observation shows that extra sources are attenuated with GOPDC

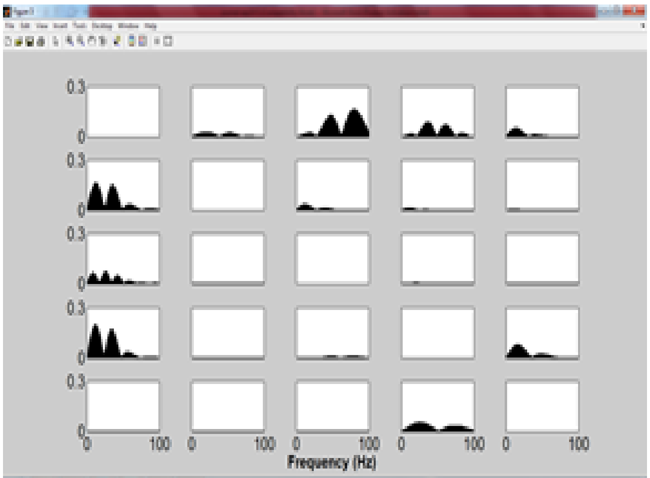
3.3 Time-invariant Simulation



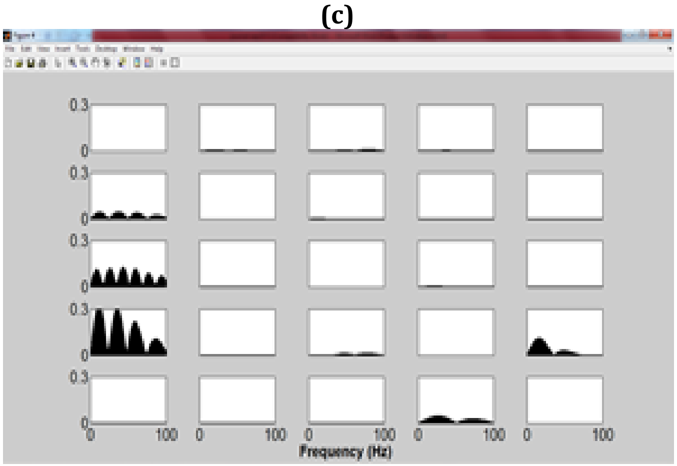
(a)



(b)



(c)



(d)

Fig-6: Diagrams of a)PDC, b)GPDC, c)OPDC and d)GOPDC

From above fig it is cleared that GOPDC eliminate mutual sources & we can take meaningful & necessary information

Non-zero values in fig shows there is no connectivity between channels & each channel relates with another expect itself.

3.3 Signal to noise ratio

Table 1: SNR Values for connectivity analysis measures

Sr.No.	connectivity analysis measures	SNR values(db)
1	Partial Directed Coherence	0.379666
2	Generalized Orthogonalized Partial Directed Coherence	2.336290

Using signal to nose ratio formula SNR are calculated. Hence GOPDC have 2.336290db signal to noise ratio & PDC have 0.379666db. From result it is clear that GOPDC connectivity measure improves signal to noise ratio.

4 CONCLUSION

The various artifacts added in EEG. The main aim of this paper is to get artifact removed EEG signal. For this different methodologies are used. In this methodologies. MVAR model is used with connectivity analysis the coefficients of MVAR model are estimated by Dual extended kalman Filter.

There are two connectivity analysis used i.e Partial Directed Coherence & Generalized Orthogonalized Partial Directed Coherence. These two connectivity analysis are compared. Comparison based on Signal to noise ratio. The performance is evaluated by comparing their corresponding SNR. From result, it is observed that the SNR of the Generalized Orthogonalized Partial Directed Coherence is higher than the Partial Directed Coherence.

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