Superiority of OPDC and gOPDC measures against PDC and gPDC

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Abstract - ***This paper is an attempt to study & analyze behavior of brain connectivity measures i.e. partial directed coherence (PDC),Generalized partial directed coherence (gPDC), Orthogonalized partial directed coherence (OPDC) & Generalized orthogonalized partial directed coherence (GOPDC).The behavior of this approach studied using simulation a signal for time invariant & time variant model. .For simulation models optimal model order estimated by SBC method for entire data using the ARFIT toolbox. The results demonstrate gOPDC connectivity measure can remove the intermittent interactions between variables***

Key Words:*PDC, gPDC, OPDC, GOPDC*

1 INTRODUCTION

Neuroscience has concept of brain connectivity which shows how cortical regions communicate & it is used to understand the organized behavior of different cortical regions. It represents the direction and strength of the information flow between cortical areas. During the recording of EEG, artifacts can be identified by technologist. Technologist should be skilled in identification & elimination of artifacts. The removal of artifact an important issue of EEG application in clinic..The problem of brain connectivity has been gaining more and more interest in the last years. There are different connectivity measures for an EEG signal. [15]

In this paper, I develop generalized version of OPDC to handle the numerical problem produces with different variance of amplitudes of signals. GOPDC is compared with the classical PDC and gPDC. This comparison done using simulated time-invariant and time-varying models These testing shows with time–frequency (T–F) connectivity maps Orthogonalized version of the PDC is where combined idea of orthogonalization and imaginary part of coherence functions .Effect of this combination is reduces volume conduction effects.

2 METHODS

2.1 MVAR Model

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

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

where $\boldsymbol{w}$ is a vector white noise, the matrices $\boldsymbol{A}_r$ are given by:

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

for $r = 1, \ldots, p$ and A number of time-varying connectivity measures based on the following transformation of the MVAR parameter. In frequency domain ($\boldsymbol{A}_r(n)$)

$$A(n,f) = I - \sum_{r=1}^{p} A_r(n) z^{-r} \Big|_{z=e^{j2\Pi f}} \quad \ldots\ldots\ldots\ldots\ldots [2]$$

2.2 Dual Extended Kalman Filter (DEKF)

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. There are two estimation state estimation & weight estimation.

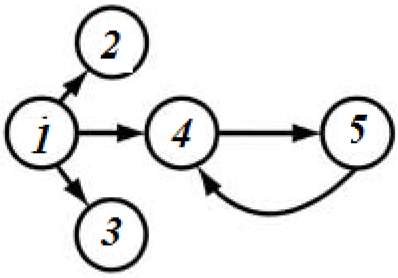
This filter is used to estimation of parameter i.e MVAR parameters (A_r(n)).[4]

2.3 Time-invariant Simulated Model

For testing integrity of connectivity analysis this model is designed by adding random interactions between channels

x(n)=Vy(n)

This equation used for simulation purposes in which x(n) is the multichannel scalp EEG, v represents the lead field matrix and y(n) models the lagged source time traces in the form of an MVAR process.[15]



$y_1(n)=0.95\sqrt{2}y_1(n-1)-0.9025\ y_1(n-2)+10w_1(n)$

$y_2(n)=0.5y_1(n-2)+5w_2(n)$

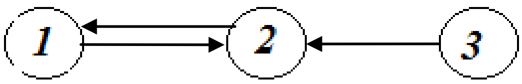
$y_3(n)= -0.4\ y_1(n-3)+w_3(n)$

$y_4(n)=-0.5y_1(n-2)+0.25\sqrt{2}y_4(n-1)+0.25\sqrt{2}y_5(n-1)+1.5w_4(n)$

$y_5(n)= -0.25\sqrt{2}y_4(n-1)+ 0.25\sqrt{2}\ y_5(n-1)+2w_5(n)$.............. [3]

where $w=[w_1w_2w_3w_4w_5]^T$ is a normally distributed white noise vector

2.4 Time-varying Simulated Model



$y_1(n)=0.59y_1(n-1)-0.20y_1(n-2)+b[n]y_2[n-1]+c[n]y_3[n-1]+w[n]$

$y_2(n)=1.58y_2(n-1)-0.96\ y_2[n-2]+w_2(n)$

$y_3(n)= 0.60y_3(n-1)-0.91\ y_3[n-2]+w_3(n)$.......................... [4]

2.5 Schwarz's Bayesian Criterion (SBC) for model order

$$SBC(p)=\ln(\textstyle\sum_e(p))+\ln(L).p.CH^2$$

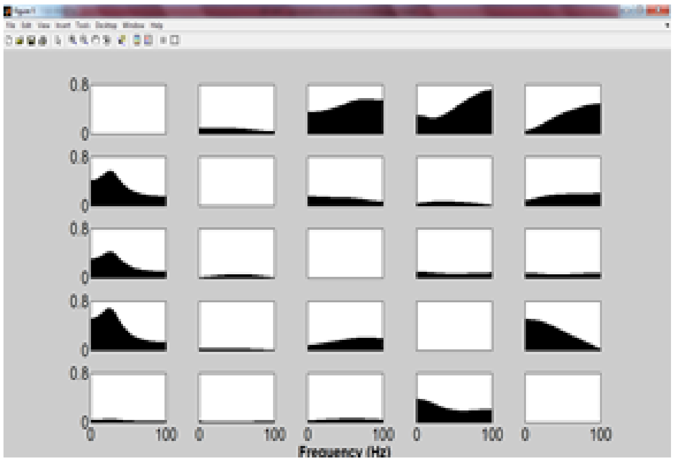
- P:Order of model
- CH: Number of channels
- L: Length of the time series signal

3. DISCUSSIONS AND INTERPRETATION OF THE RESULTS

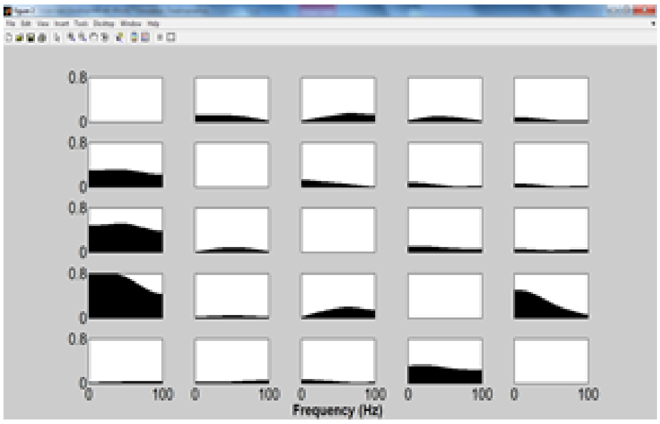
3.1 Time-invariant simulation

In time-invariant simulation an effect of channel 1 & effect of mutual sources are there in PDC.

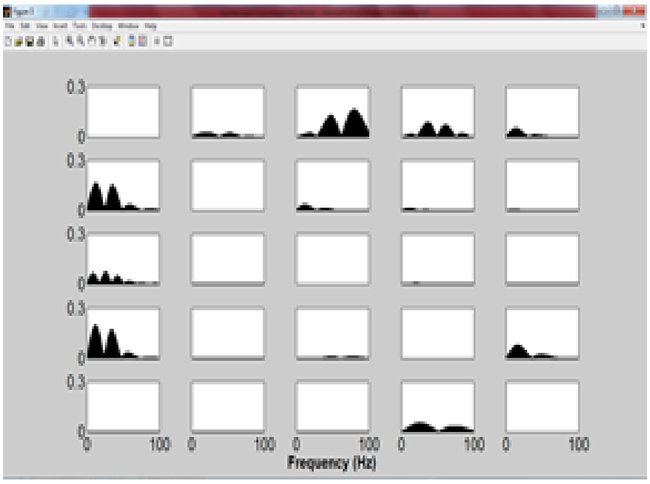
Non-zero values in fig shows there is no connectivity between channels & each channel relates with another expect itself



(a)



(b)



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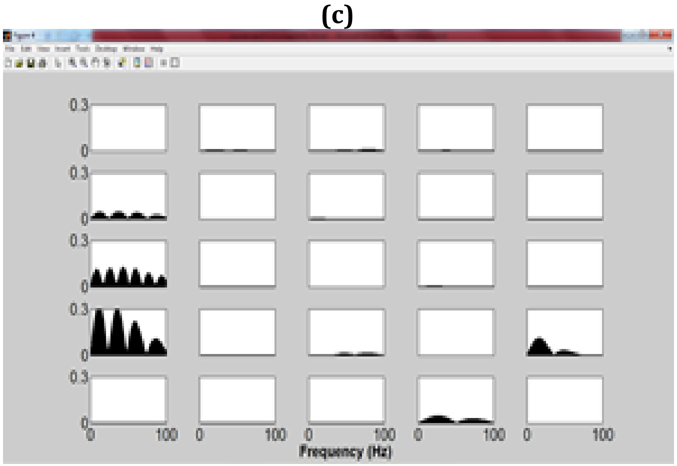
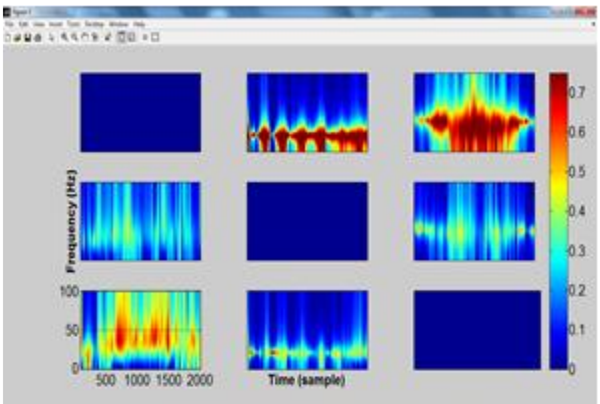


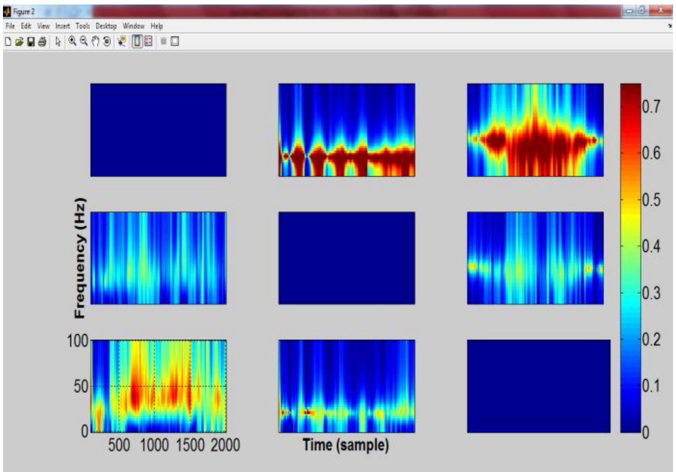
(d)

Fig-1: Diagrams of a)PDC, b)gPDC, c)OPDC and d)gOPDC

3.2 Time-varying Simulation



(a)



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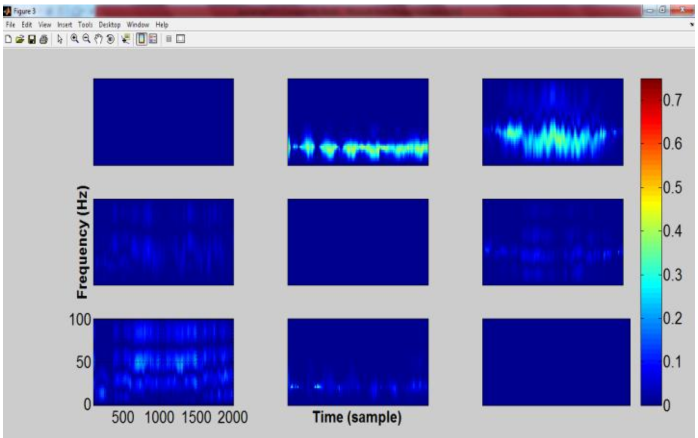

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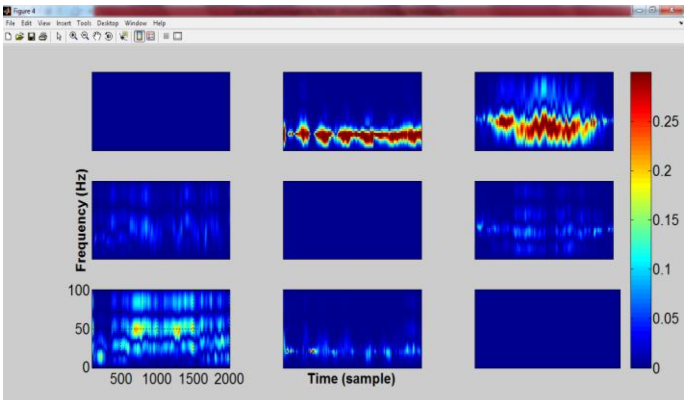

(d)

Fig-2: Diagrams of a)PDC, b)gPDC, c)OPDC and d)gOPDC

4. CONCLUSIONS

Comparison of different connectivity measures by simulation of time varying model & time in-varying simulation. From this simulation we can understand gOPDC can effectively remove the intermittent interactions between variables

In this paper the model order estimated by SBC(Schwarz's Bayesian criteria).The order is kept constant in overall simulation. In time varying simulation the connectivity values for gOPDC have smaller magnitude than the gPDC values (from color bar) i.e orthogonalization step attenuate the mutual sources & OPDC & gOPDC are superior methods than PDC & GPDC for connectivity measures.

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