

## **NBE-E4530 - Human brain connectivity**

### **Final essay:**

### **Source level functional connectivity for SEF (Somatosensory Evoked Field) MEG data with right hand finger stimulation**

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### **Introduction:**

Brain connectivity describes networks of functional and anatomical connections across the brain. The connectivity techniques for quantifying the brain networks use signal processing techniques that have been around for many decades [1]. EEG and MEG records electrical and magnetic signals outside the brain so they lack the anatomical information like MRI. This sensor level signals make the functional connectivity vague. Source level functional connectivity has greater importance over sensor level connectivity because of source specific neuronal data with less background and device noise.

In this study, source level functional connectivity and its network metrics are calculated for a somatosensory MEG dataset. The sensor level data was acquired using 306 channels MEG system while the source level data is calculated using LCMV (Linearly Constrained Minimum variance) beamforming source localization technique [2]. The motivation behind the study is to present a robust pipeline for source level functional connectivity [3, 4] analysis of MEG data.

### **Methods:**

In this study, we utilized a single subject MEG data recorded on a healthy 31 year old male participant using a 306 channel Elekta Neuromag TRIUX MEG system with active shielding on. Laser stimulation was delivered to the palmar aspect of four fingers D2 to D5 (represents index, middle, ring and little finger respectively) of the right hand of the subject (D2 – D5). 176 structural MRI images (T1 images) were also recorded to provide anatomical information to the analysis and to map the results.

We used here somatosensory stimuli where stimulation was controlled via a constant laser stimulator. The duration of each laser pulse was 0.2 ms with a jittered inter-stimulus interval (ISI) between 1320 and 1997 ms. Sensory threshold of the stimulus was determined and the stimulus used for data acquisition was delivered at twice the sensory threshold (~1.2 mA).

The data was acquired in MSR (Magnetic shielded room) with active shielding to remove the environmental magnetic field for improving the SNR (signal to noise ratio). The data was acquired at 1000 Hz sampling rate. While recording the participant was sitting on a non-magnetic chair keeping his head in MEG helmet (sensor array) in such a way to cover his whole head. The subject was asked to move his head as less as possible to avoid large movement artifact in the data.

We present here only little finger (D5) data results to make it simple. The raw MEG data was first MaxFilter'ed to remove active shielding and head movement artifact from the data. The data was then band pass filtered between 1-200Hz. Two bad channel having large signal jumps were removed from the data. The data was then epoched with -500 ms to 500 ms reference to stimuli markers. We selected -80 ms to -20 ms pre-stimuli data and averaged those for noise covariance. The same was done with 20 ms to 80 ms post-stimuli data for data covariance.

Since MEG and MRI data are acquired by separate system and there is no information exchange between them. They are often different in position in 3D space so that it is mandatory to coregister them to provide an accurate anatomical information. We used MriLab (an Elekta software) and coregistered both data on the basis of fiducial points. Then we defined forward BEM model after segmenting brain 3D model from MRI images.

Then we estimated neuronal sources underneath the MEG data using LCMV beamformer. Beamformers are basically spatial filters which scan whole head data to estimate the underneath sources. It uses the epoched (time-locked) data and forward BEM model to calculate leadfield matrix and then uses the noise and data covariance matrices (which is mentioned earlier) to estimate the sources.

After estimating the sources, we calculated the peak local maxima and calculated the source signal using leadfield and spatial filter designed previously for LCMV beamforming. We got here 9 local maxima which are called as virtual sensors. These are nodes for our network and the signal at these nodes are time series to estimate the connections among them. We epoched these source level data within -500 ms to 500 ms referring to stimuli triggers and then averaged them.

The covariation matrix between these 9 nodes is calculated and plotted. The weighted connectivity among these 9 nodes are plotted over 3D coregistered brain mesh using Fieldtrip[5] to visualize the actual source network. The network metrics are then calculated to show the nodes and link properties within the networks. We calculated the degree, clustering coefficient, transitivity, modularity, betweenness centrality, efficiency and other network metrics for the nodes and whole network.

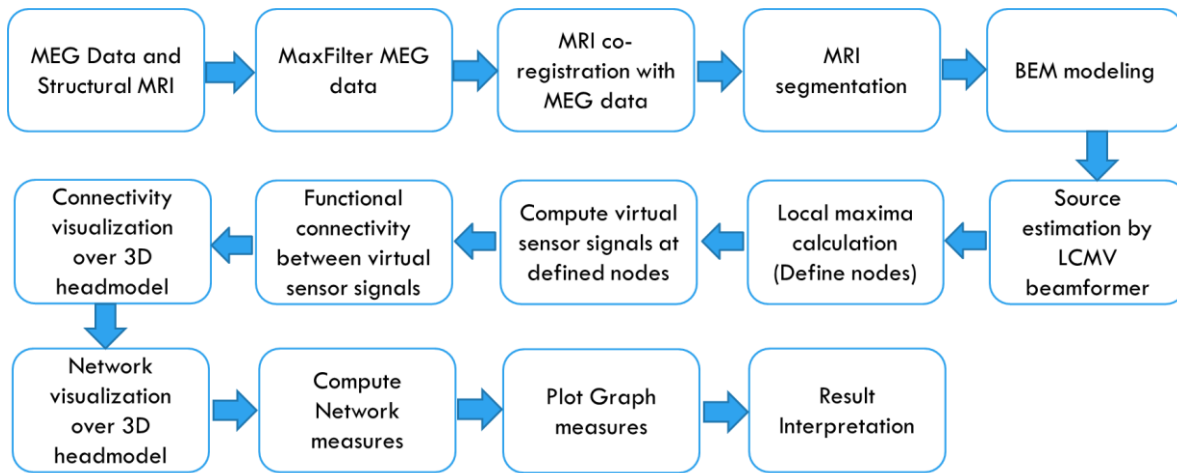


Fig.1: The overall analysis workflow used in the project

## Results:

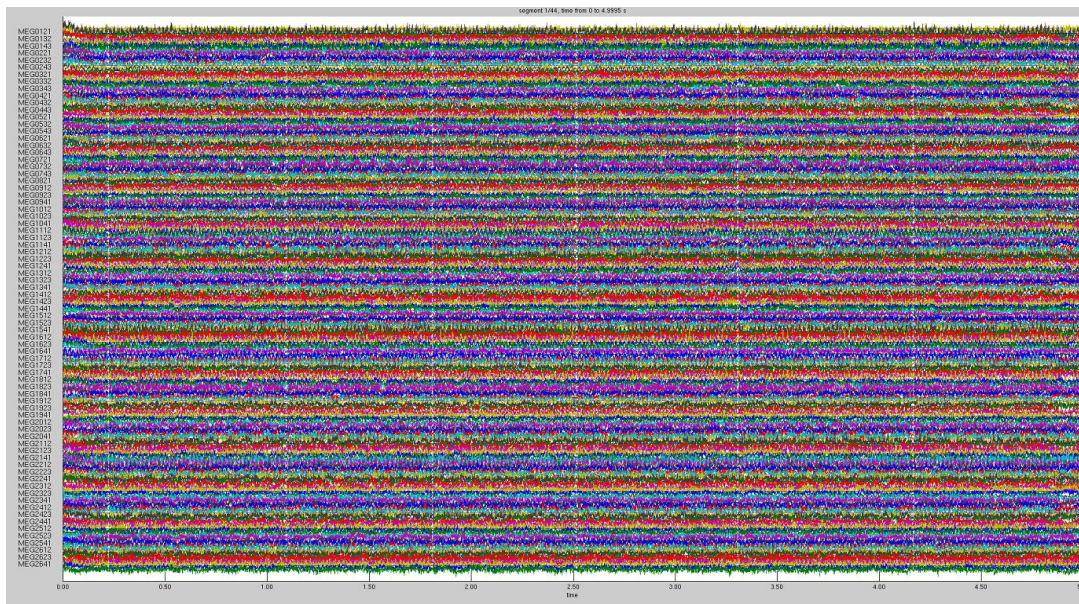


Fig. 2: Raw 306 channel MEG data (visualization in Fieldtrip)

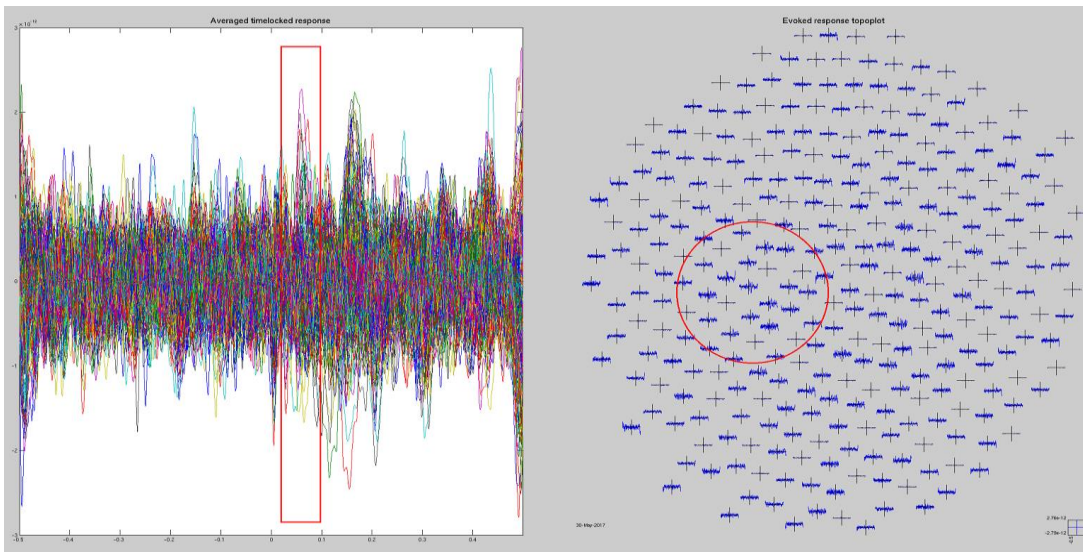


Fig. 3: Averaged epoched data, SEF (red box), Expected area of source (red circle) (in Fieldtrip)

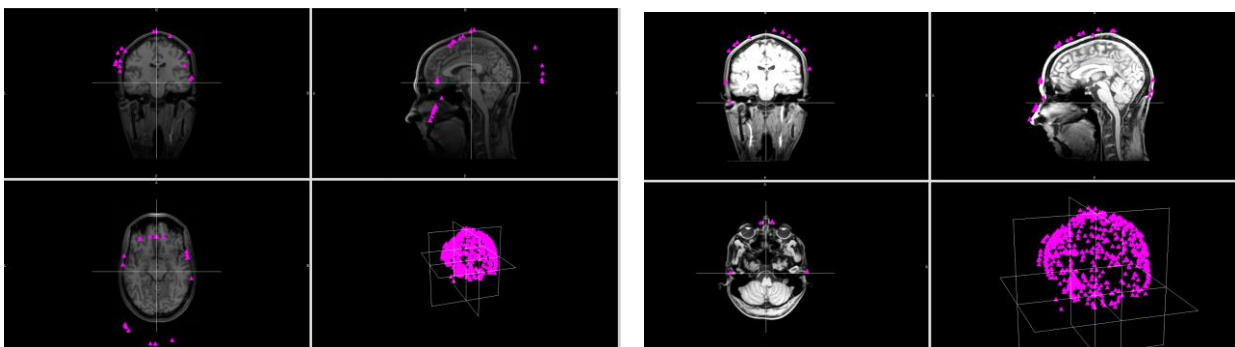


Fig. 4: Uncoregistered and coregistered (later) MRI with MEG data, (in MriLab)

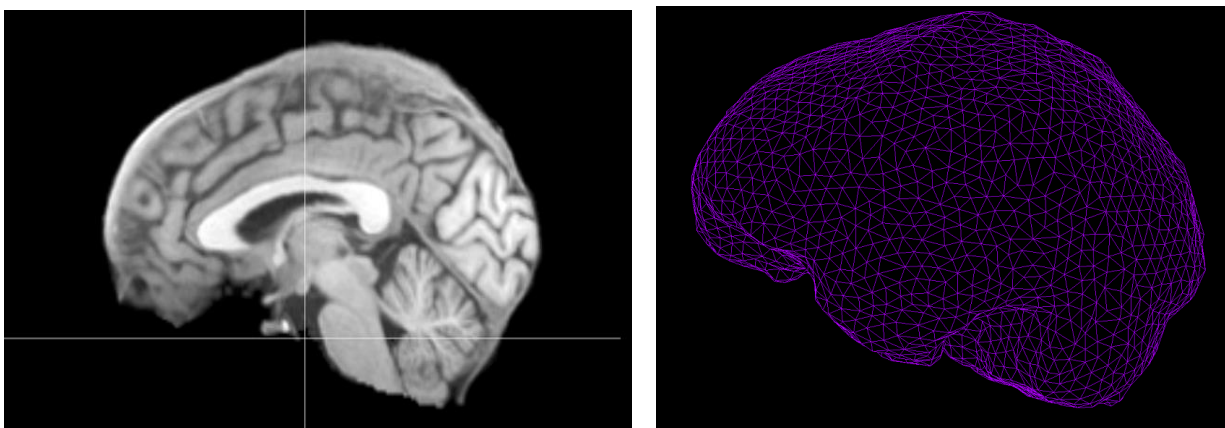


Fig. 5: Segmented brain and BEM mesh (later) (in Elekta's Seglab)



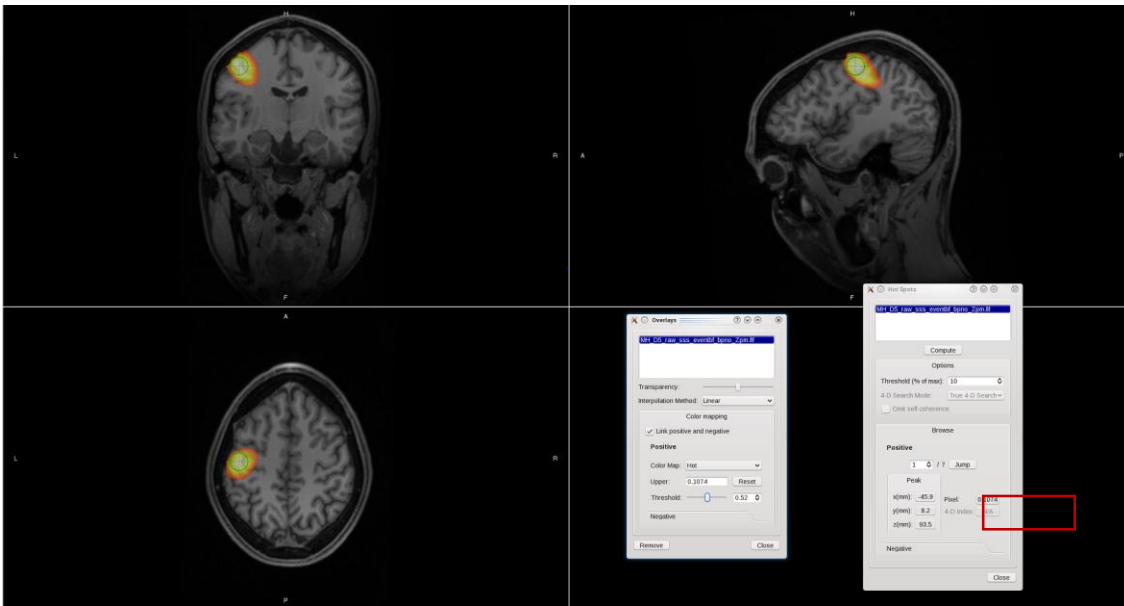


Fig. 6: Primary source estimated by LCMV beamformer (Visualization in Elekta's Mriview)

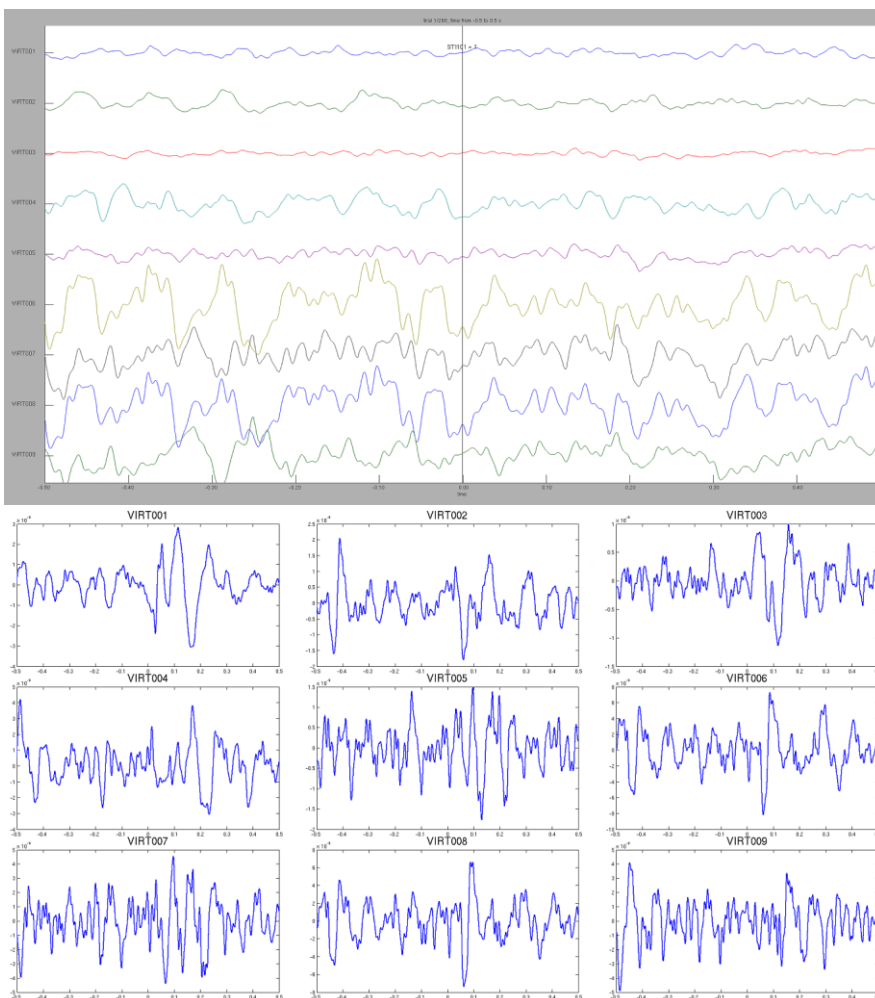


Fig. 7: Virtual electrodes (source nodes) signal and averaged over trial (later), (in Fieldtrip)

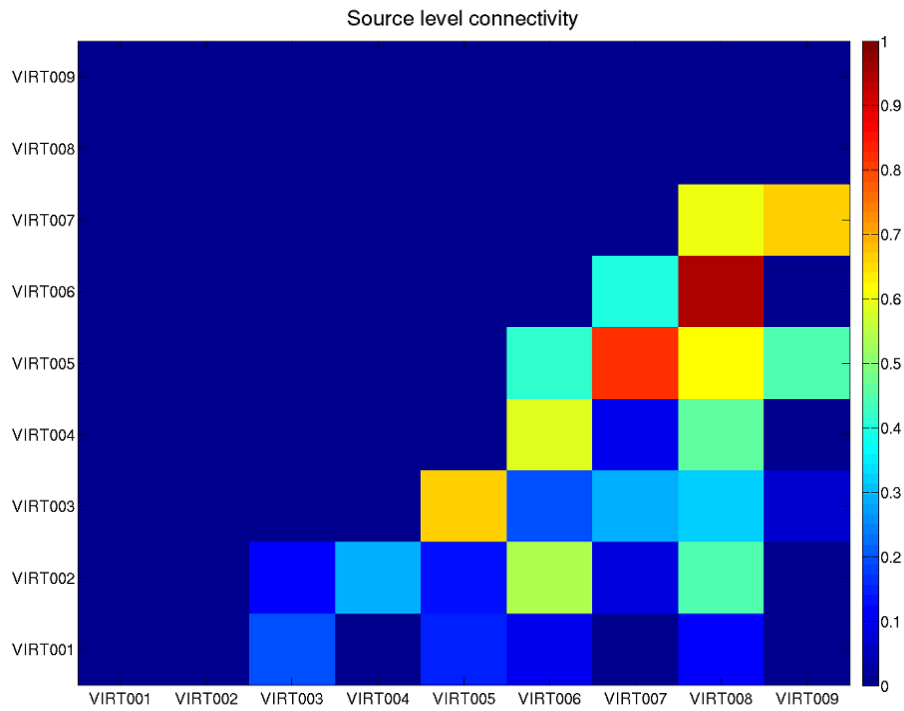


Fig. 8: Correlation base adjacency matrix for 9 nodes (VIRT001,..., VIRT009) estimated inside brain

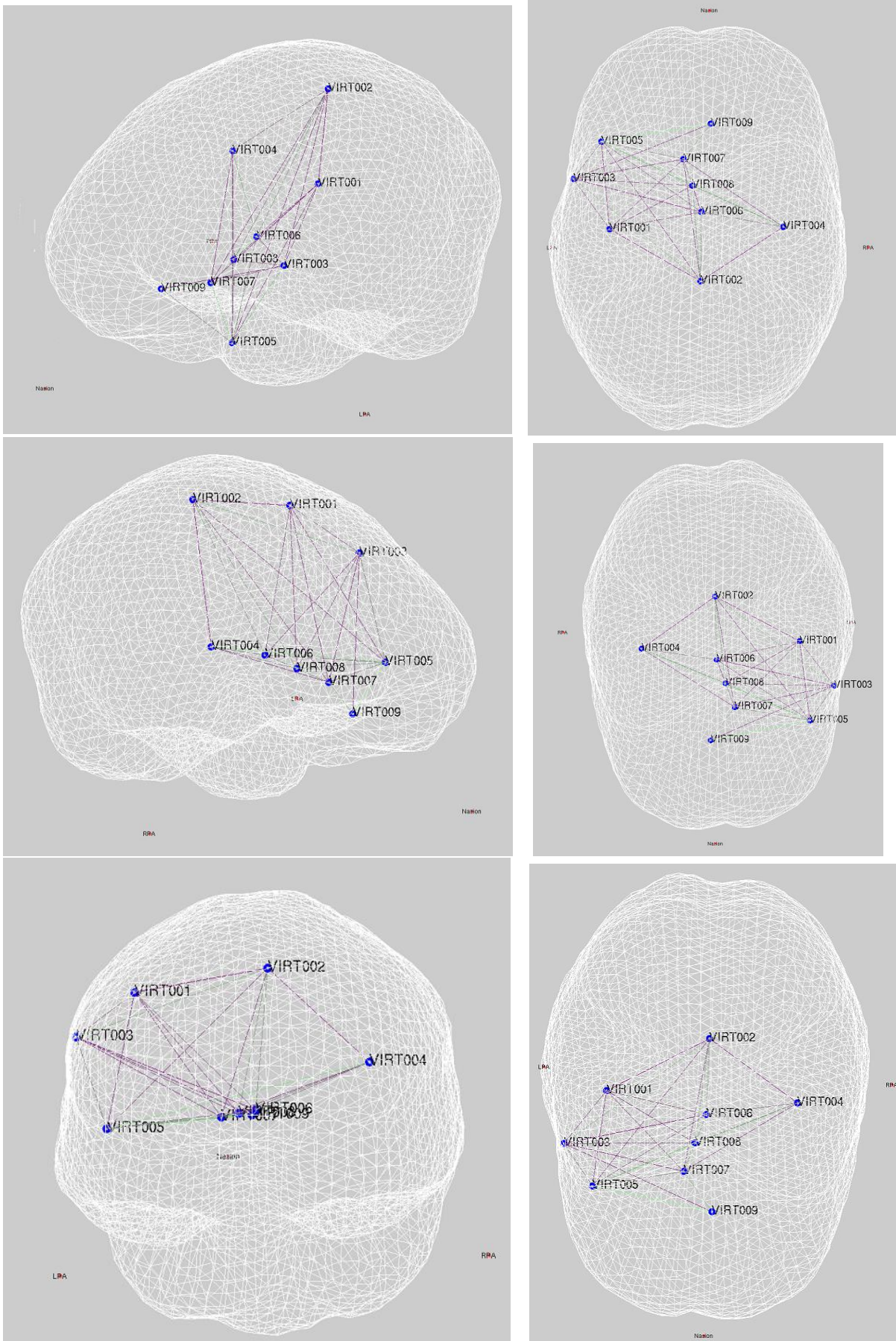


Fig. 9: Brain functional connectivity visualization over participant's co-registered 3D brain model

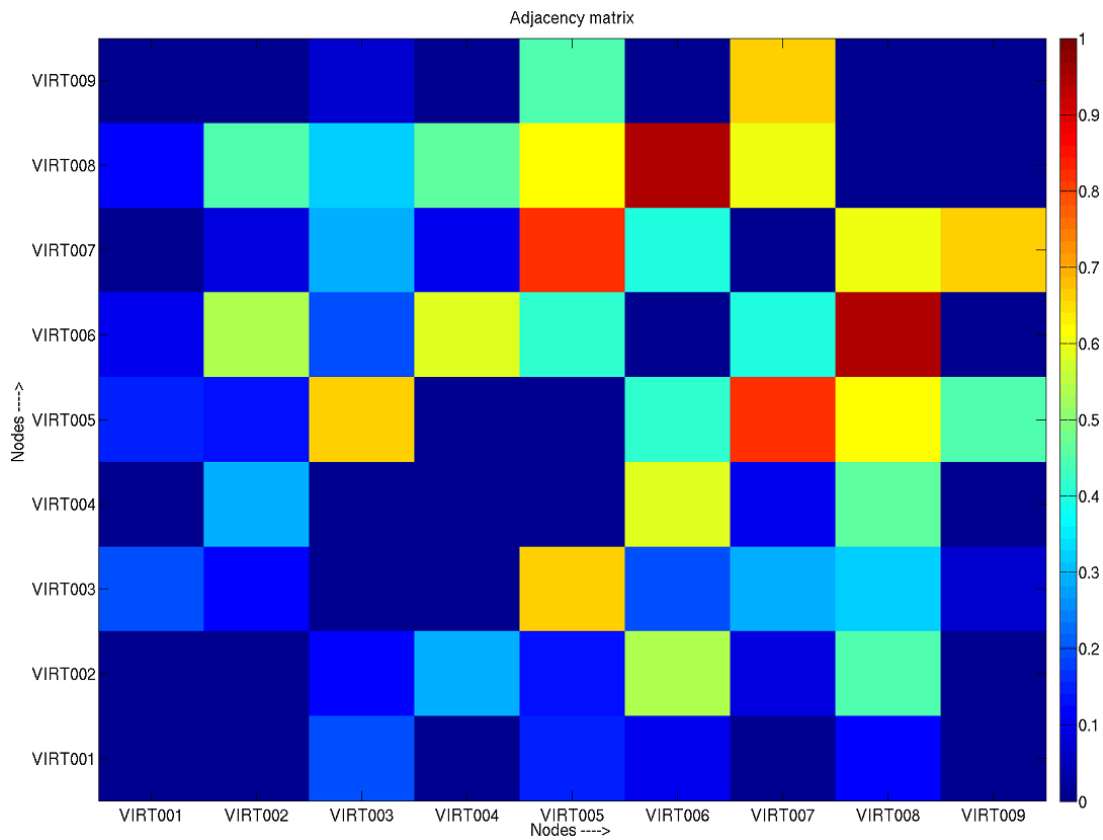


Fig. 10: Adjacency matrix for the nine source nodes

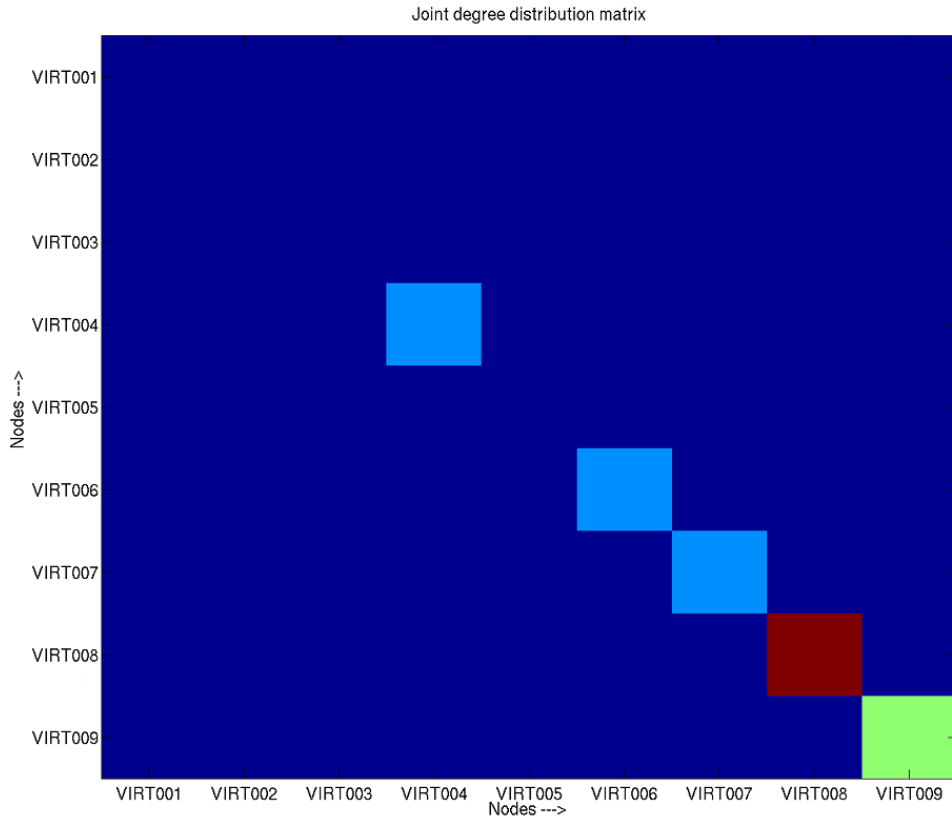


Fig. 11: Joint degree distribution matrix

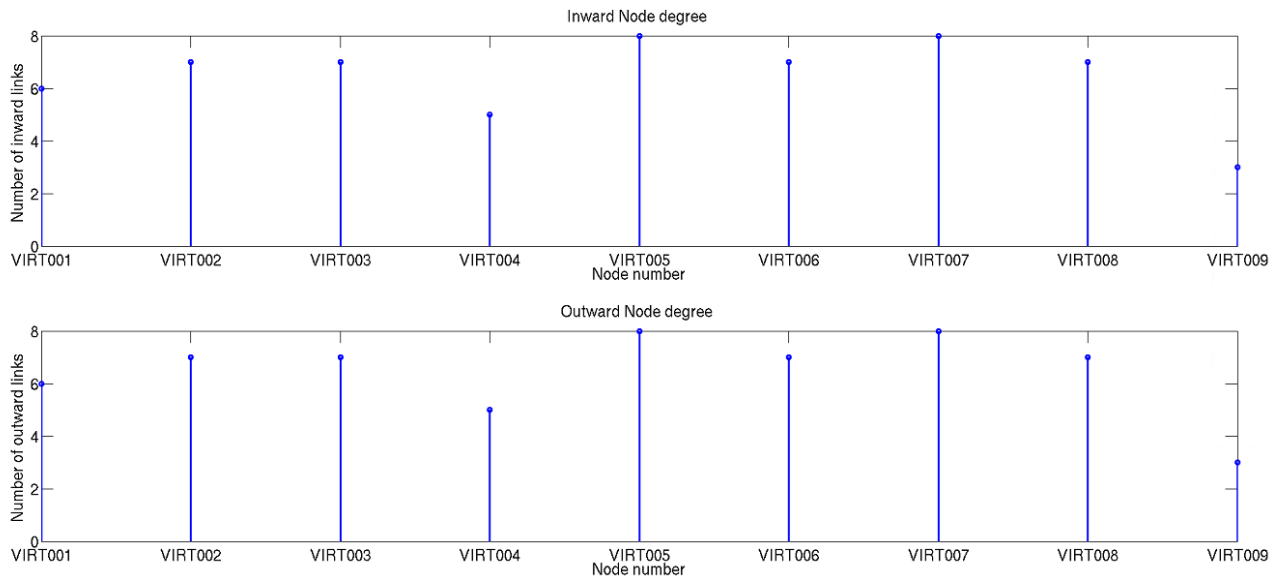


Fig. 12: Node degree (Inward and outward)

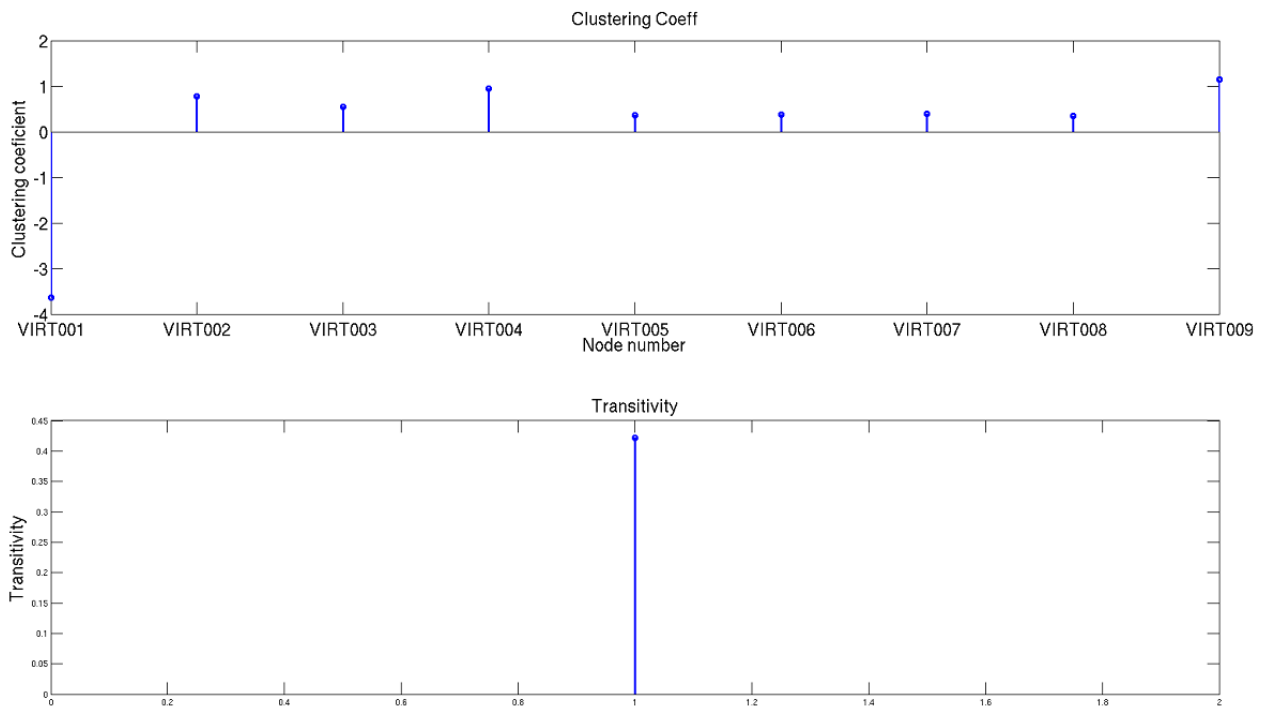


Fig.13: Clustering coefficient for each node and Transitivity of the network



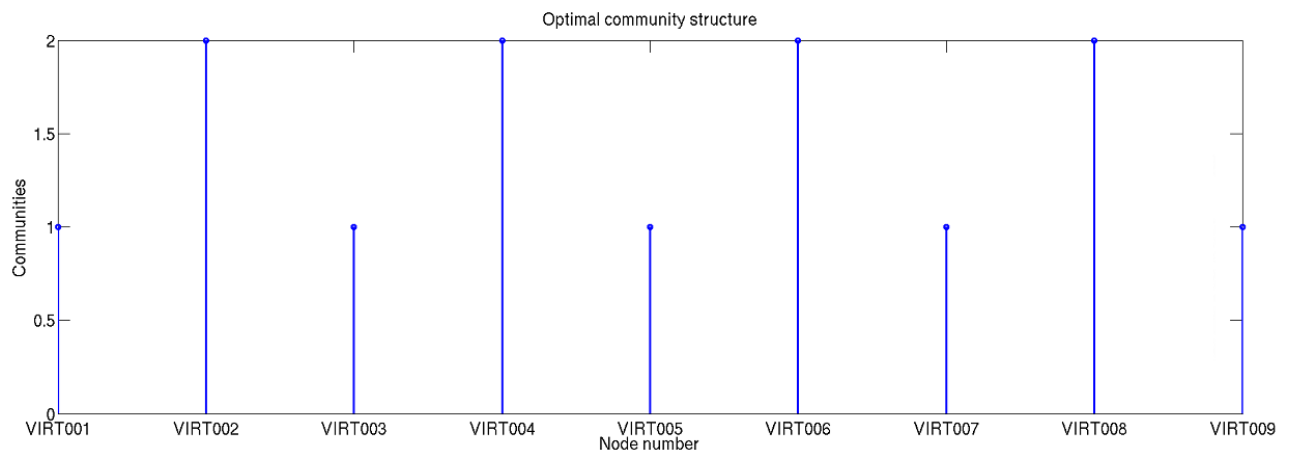


Fig. 14: Optimum community structure for each node

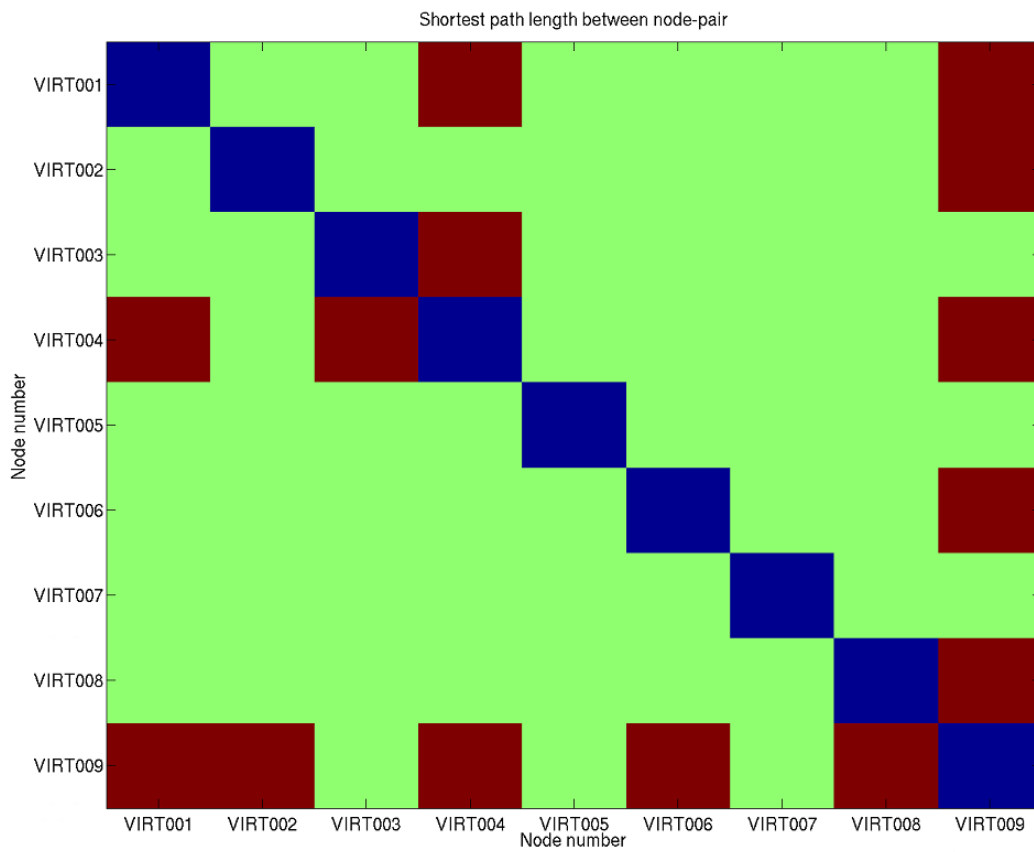


Fig. 15: Shortest path length between each node pair

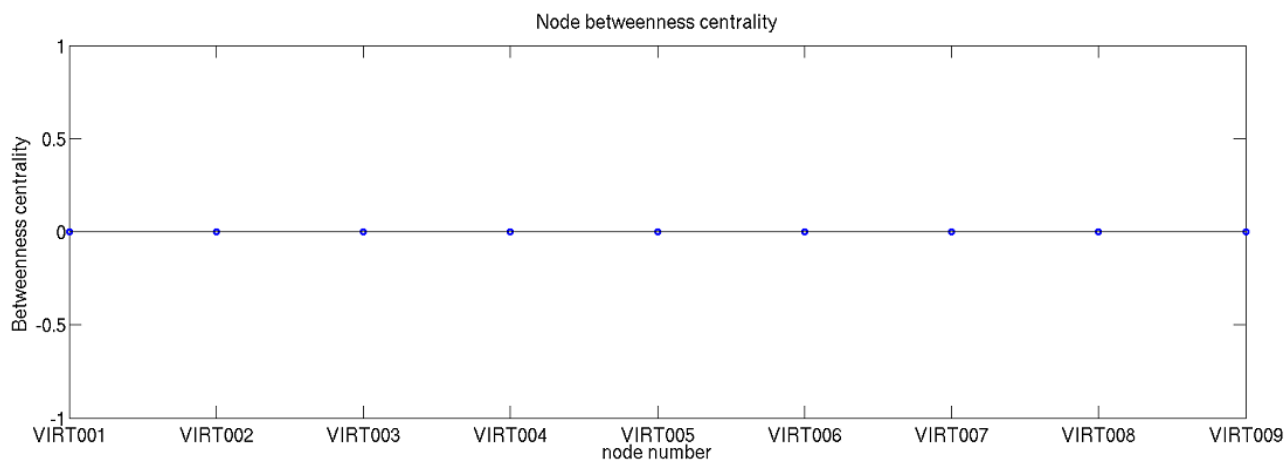


Fig. 16: Nodal Betweenness centrality

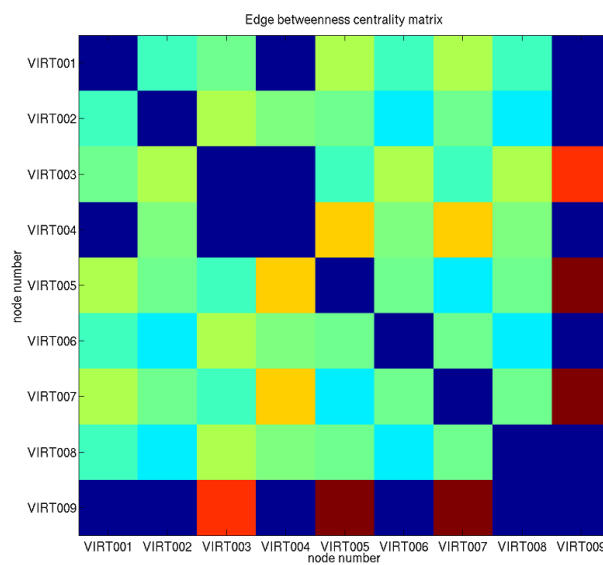
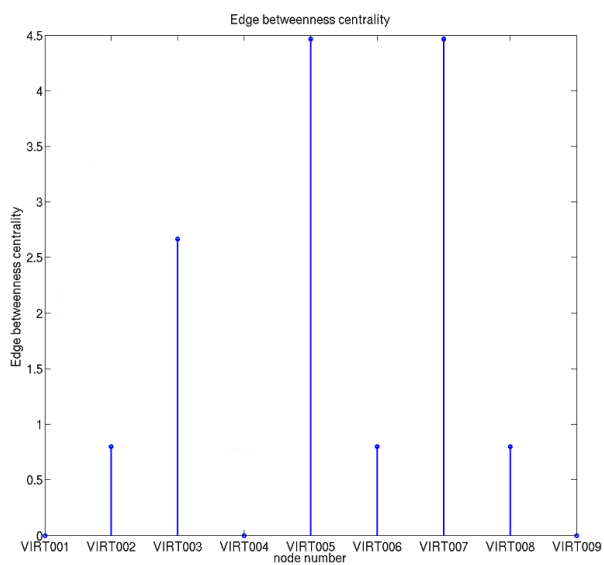


Fig. 17: Edge betweenness centrality

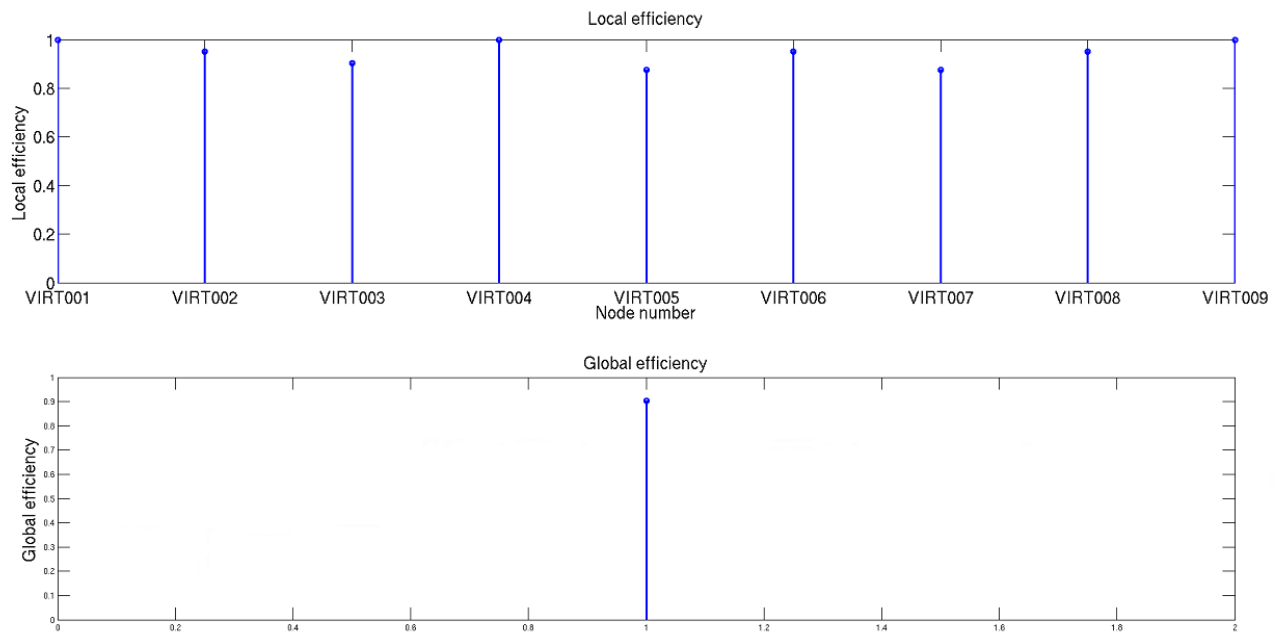


Fig. 18: Local efficiency for each node and global efficiency of the network

#### Link to code:

[https://github.com/amitjaiswal11111/BrainConn/blob/master/NBE\\_E4530\\_AmitJaiswal\\_finalproject\\_script.m](https://github.com/amitjaiswal11111/BrainConn/blob/master/NBE_E4530_AmitJaiswal_finalproject_script.m)

Github address: <https://github.com/amitjaiswal11111/BrainConn>

#### Discussion:

The complete workflow for source level functional connectivity is shown along with graph theoretical network measures. The workflow shows how to proceed with source level functional connectivity and network metrics calculation for other MEG data set using beamformer or other source localization methods.

As we know that beamformers are comparatively precise method for source localization so that it provided here a strong source i.e. VIRT001. The other sources might be because of residual noise. Also we know that the brain area for finger motor response is well localized and the stimulus presented is not higher dimensional stimulus like audiovisual stimulus. Therefore, the estimated sources are very less correlated.

The study is done as to present a workflow for source level functional connectivity. The pipeline is very helpful to find out network between multiple origins of multifocal epileptic MEG data.

#### References:

1. Cabral J, Kringelbach ML, Deco G. Exploring the network dynamics underlying brain activity during rest. *Prog Neurobiol.* 2014;114:102–31

2. Van Veen, Barry D., et al. "Localization of brain electrical activity via linearly constrained minimum variance spatial filtering." IEEE Transactions on biomedical engineering 44.9 (1997): 867-880.
3. Hipp JF, Hawellek DJ, Corbetta M, Siegel M and Engel AK (2012) Large-scale cortical correlation structure of spontaneous oscillatory activity. Nature Neuroscience 15:884-890
4. Schoffelen, Jan-Mathijs, and Joachim Gross. "Source connectivity analysis with MEG and EEG." Human brain mapping 30.6 (2009): 1857-1865.
5. Oostenveld, Robert, et al. "FieldTrip: open source software for advanced analysis of MEG, EEG, and invasive electrophysiological data." Computational intelligence and neuroscience 2011 (2011): 1.