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Improving the Recovery Detection of Stroke Diseases based on High Time-Frequency Resolution Protocol

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Overview and results

Brain networks are complex designs comprising more than one hundred billion neurons that work together to produce the associated potential for action, not acting in isolated fields. Decoding the connectome relationship between nerve cells during mental tasks and representing this relationship in a high temporal-spatial resolution is an attractive problem for neuro-connectivity to go beyond these networks. In this sense, the brain connectivity known as Functional Connectivity (FC), Effective Connectivity (EC), and Structural Connectivity are represented in three distinctive concepts (SC). The FC is also known as segregation, which reveals functional patterns between various regions of the brain, while successful integration reveals the impact of causality on a neural region, whether affected by another region's direct or indirect behavior.

Connectivity research emerged from MRI technology, first aiming to construct and discover structural pathways (connectome) in the human brain. The emergence of high spatial resolution functional (1-3 mm^3) MRI (fMRI) made it possible to conduct functional connectivity studies. These investigations led to the identification of several fundamental resting-state and task-based brain networks [1]–[3]. Due to technological limitations, however, fMRI functional connectivity analysis is not suitable for the examination of millisecond range changes typically found, for instance, during cognitive task execution. An alternative to fMRI in connectivity studies is EEG technology that provides superior temporal resolution and measures signals generated directly by neurons as opposed to blood oxygenation changes, such as BOLD fMRI.

EEG functional connectivity can be sensor or source based. If statistical dependence is calculated between the electrode signals, we refer to sensor-level (a.k.a sensor-space) connectivity. If the electrode signals are projected to the cortex by solving the inverse problem that identifies the original sources of bioelectric activities and calculated the association among these cortical regions, we refer to source-level (or source-space) connectivity. Source-level connectivity has the potential to achieve higher spatial resolution (the cortex can be partitioned to thousands of potential source areas) but requires accurate 3D anatomical models and solving the ill-posed inverse problem. For these reasons, sensor-level connectivity would be preferable as an experimental method.

The general process of generating a functional connectivity network from EEG measurements is the following. The cleaned, pre-processed signal is input the first stage of the process that establishes associations between electrodes or cortical sources based on a selected association measure described below. The output of this stage is a square association matrix. Each entry of the matrix represents the strength of the connectivity between two electrodes or sources. This matrix is then used as an adjacency matrix, from which various features can be extracted. To reduce the number of edges in the network graph, normally the association matrix is thresholded and only the top few percent of the edges are kept. The structure of the final connectivity graph can be analysed by the network features and input to statistical tests.

Functional EEG connectivity has the potential to provide more information than fMRI, due to its higher temporal resolution. Oscillations in the brain regions provide a certain coordination mechanism emerging as synchronized rhythms. These oscillations may transfer information from a local network or region to another region. Examining the flow of information between regions may help to reveal the connectivity relation between the neural assemblies either at rest or during task execution. Connectivity information between the distant brain regions may explain how the neural networks are altered e.g. in stroke or neurodegenerative diseases [4]. It can provide new insights about the large-scale neuronal communication in the brain and may help to understand the origins or track the progress of recovery of stroke or monitor the status of brain diseases such as Alzheimer's disease [5], and predict outcome of treatment to many other deficits related to the brain. In this proposal, I provide deep insight about how EEG-based functional connectivity can be used to describe brain plasticity in stroke, which is the brain's natural ability for re-wiring that is essential for successful recovery from stroke.

The most important issue in time-frequency analysis is the principle of uncertainty, which stipulates that one cannot localize a signal with absolute precision both in time and frequency. Long windows are needed for lower frequencies that provide good frequency but reduced temporal resolution, while short windows used for higher frequencies result in better time but lower frequency resolution. Over the past 30 years research to non-stationary signals increasingly has grown resulting in a body of work called "time-frequency" (TF) methods. This included linear TF methods such as the Short Time Fourier Transform (STFT), Wavelet Transform (WT) that involve phase and magnitudes contributions, and non-linear methods that lead to real-valued transforms. STFT, the extension of FT, was modified to show nonstationary characteristics of the signal in the time-frequency domain. It consists of the successive FFT of the overlapped windowed signal, where each frequency distribution being correlated with each window's central time. The main drawback of the method that it has a smeared peak around the peak of the main frequency with decaying side lobes on the selected window. However, side lobes attenuation is associated with increasing of the window [6]. The spectral smearing can be reduced by increasing the length of the time window, but this also reduces the time localization by imposing increased stationarity. Thus, high time localization comes at the expense of the spectral smearing.

I proposed the Using of Hilbert transform as a means to compute instantaneous frequency, promised better results [7]. As an improvement, the Hilbert-Huang transform based on Empirical Mode Decomposition (EMD) and Hilbert Spectral Analysis have been recommended. While used successfully in EEG studies [14] EMD has been criticized for being sensitive for noise and prone to mode mixing. Improvements, such as Ensemble Empirical Mode Decomposition [10] reduced noise sensitivity and mode mixing, while the CEEMDAN method [11], [12] further reduced spurious modes and component noise, and provided completeness, i.e. the recoverability of signals from its immediate mode functions.

I presented solutions for problems related to cleaning the EEG artefacts and increasing the temporal resolution of functional connectivity [7] and went through a collection of used tools that have been developed to give possible solutions then showed how my proposed method can uncover fast-changing connectivity patterns in a finger-tapping task.

The work of research included:

1. The research started by recording the EEG data and filtering the unwanted signals using our smart cleaning algorithms for removing the EOG-ECG artifacts from EEG [13]–[15].
2. Then the research extended the use of the proposed method for identifying brain bio markers [16].
3. Tracking the re-modelling and brain plasticity after stroke and showing the hidden information that cannot be shown in the neuroimaging method as MRI.
4. Identifying reliable biomarkers that characterize progress of Stroke recovery and predict outcome.
5. Exploring the use of high-resolution EEG technology, complementing the use of clinical stroke scales, as an aid to track and measure patient recovery progress.
6. Resting state EEG analysis was carried out easily without the need to move the patients, can be replicated on a regular basis for accurate tracking of progress.
7. The finger tapping experiment have been used to monitor connectivity changes in the motor region of the stroke patient.
8. Functional brain connectivity network identification helped to speed up the recovery and improve the rehabilitation outcome.
9. Introducing a high time-frequency resolution method to track instantaneous high dynamical changes of brain connectivity.

Conclusion:

My research developed a novel approach for resolving issues involving the measurement of EEG brain signals, artefact removal, and brain connectivity. Because our brain connectivity networks evolve at a millisecond rate, conventional time-frequency methods are unable to detect rapid changes in neural connectivity. Therefore, a high-time-frequency resolution approach was used to generate a finer time-frequency resolution on the non-stationary EEG signal and to track the fast-dynamic changes in brain connectivity. The implemented method will aid in the identification of accurate biomarkers that demonstrate brain rewiring and plasticity, as well as describe and predict stroke recovery progress and outcomes.

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