Implementation of Machine Learning Algorithm to Exploit Information from Multimodal fMRI/EEG Fused data set

Introduction

Due to our current limited knowledge of the overall brain function various non-invasive multi-modality imaging systems have been developed. Individual Non-invasive functional brain imaging play a vital role in fields such as neurophysiology, cognitive psychology, cognitive science, neurosciece, and other reseach areas in brain functionality (Halchenko & Hanson [8] 2005, pp.223). Over the last five decades the technology of non-invasing functional imaging has florished to the point of the development of diverse types of modalities such as EEG,MEG,PET,SPECT, MRI and fMRI (Halchenko & Hanson [8] 2005, pp.223). However, due to the limitation and inadequacies of individual techniques, there is an interest in ways to integrate these techniques (Halchenko & Hanson [8] 2005, pp.223). This way accumulating the inherent strength of each of the functional modalities into one modality. The combination of various functional modality systems could potential lead to the unveiling of more accurate mathematical maps of the overall brain function and performance. However, due to the major diffuculty of finding a good gold standard, it is rather difficult to assess the truth of combined signals in realistic experiments (Halchenko & Hanson [8] 2005, pp.223). A major challenge in understanding brain function is to localize neuronal activity both spatially and temporally (Halchenko & Hanson [8] 2005, pp.224). The most widely used functional modalities that either directly or indirectly access neuronal activity are the EEG (Electroencephalogram) and fMRI (Functional Magnetic Resonance Imaging). The EEG can capture brain waves/EEG-frequency bands such as: Gamma (>26 Hz), Beta (13-26 Hz), Alpha (8-13 Hz), Theta (4-7.5 Hz), and Dalta (0-5.4 Hz) (Sanei et al., 2013). Therefore, EEG is considered a direct way of capturing neuronal activities. The fMRI is a way to indirectly infer about the different levels of brain activity for a given task. To accomplish this, the fMRI looks at the relative changes in blood flow for different brain regions (Lindquist 2008). Therefore, fMRI is considered as an indirect way to measure neuronal activity because it relies on the fact that the cerebral blood flow and the neuronal activation are coupled. The interesting fact is that the deficiencies of these two functional modalities are complementary to each other. Through the use of EEG, one can acquire data with a high temporal resolution (milliseconds), but limited spatial resolution (Gevins , 1993). On the other hand, fMRI has good spatial resolution (milimeters), but relatively poor temporal resolution (seconds) (Chen et al., 2012). Therefore, it would be optimal to combine these idividual modalities into a single functional multi-modality imaging system. However, acquiring non-corrupted simultaneous recordings of EEG and fMRI is rather straneous task due to interference between the strong MR field and the EEG acquisition (Halchenko & Hanson [8] 2005, pp.224). In order to correct for this there are two possible approaches, which are dependent on the type of study beging conducted. In this experiment, I would liked to foces on applying algorithms to map the EEG data into the corresponding fMRI data set, after their non-simultaneous acquisition times.

This research aims to implement relavent computer learning algorithms to complement and automate the processes of extracting information from multimodal fMRI/EEG fused data. In this study, we will be using a blind method called Joint ICA (jICA), which uses second-level fMRI data, to generate the fusion between fMRI data and EEG data (Sui et al., 2012). After generating the fuse data set by implementing the Joint ICA (jICA), we will implement a machine learning algorithm to automate the process of extracting the results from vast amount of patient under a similar type of study. Besides the computational implications of making the analysis of fused EEG-fMRI data more efficient, this research can also give rise to vital underlining information on the functionality of different brain areas such as the cerebral cortex.

General Goals

The overall objective of this project is to optimize the process of generating fuse fMRI/EEG data, as well as, to extract information from the fused fMRI/EEG data. However, through the analysis of the fused fMRI/EEG data we could potentially encounter information about the overall relationships between the different brain waves/EEG-frequency bands and cerebral hemodynamics. Therefore, another objective would be to find underlining relationships between neuronal activity and cerebral vascular dynamics.

Detailed Description of Research Problem

The questions we will be tackling during the summer research at the Technical University of Graz are: What are the most critical findings/parameters that can be extracted from a fused fMRI/EEG data? What machine learning algorithms can be implemented to extract the parameters of interest from the fused data set? After implementation, how accurate is the algorithms in extracting the parameters from a large data set of different patient that fall under the same type of study?

We can also ponder question dealing with the significance of the acquired fused fMRI and EEG data. Such question include: what relationships can be seen between the different brain waves/EEG-frequency bands (gamme, beta, alpha, theta, and delta bands) acquired from the EEG and the cerebral hemodynamics obtained from the fMRI? What does these relationships tells us about the underlining functionally and six neuronal layer organizaion of the cerebral cortex?

Methodological Consideration

To answer these questions we have to consider various components. One major aspect is under what conditions will the EEG and fMRI data be collected. There have been various fMRI studies that have been conducted to determine the organization of the human cerebral cortex. In different studies, intrinsic functional connectivity are used as an estimate of the underlining organization of the cerebral cortex. In one particular study, the organization of networks in the human cerebrum was accessed throught the use of a technique known as resting-state functional connective MRI (Yeo at el., 2011). Individual EEG studies of the human cerebral cortex have also been conducted. Through this project, we will possibly obtain more information about the cerebral cortex by fusing the fMRI and EEG data.

Worksteps

In this research investigation, fMRI and EEG data will be compiled from healthy individuals. Then, the fusion images will be obtained by utilizing a blind method called Joint ICA (jICA). This method will be used because we will be dealing with non-simultanious fMRI and EEG data acquisitions. This method essentially works by first extracting the spatially independent maps for each modality and then coupling the maps together through a share loading parameter (Mohammed at el., 2014). The advantage of the Joint ICA method are: it can be used in identifying some dissorders such as Schizophrenia and it provides a good spatial and temporal resolution in the case of fusing both the EEG and fMRI modalities (Mohammed at el., 2014). The MATLAB Fusion ICA Toolbox (Rachakonda et al., 2012) will be use to perform this Joint ICA method. Then, a machine learning algorithm will be implemented to be able to automate the analysis of a large data set composed of different patient, which fall under the same study type. Lastly, the overall accuracy of the algorithm in analyzing the fusion of the non-simultanious fMRI and EEG data acquisitions will be quantified. This will be done by comparing the analysis of the algorithm to that of a personal in the medical field.

Relevance and Expected Results

Since the relative strengths and weaknesses of EEG and fMRI are complementary, the fusion of the data compiled from these two functional modality, if data is simultaniously acquired, could noninvasively record human brain activity with both high spatial and high temporal resolutions (Huster et al., 2012). Although pathological brain activity can be inferred from EEG measurements, it lacks the spatial resolution need to determine the location within the cortex from where the neural event took place (Huster et al., 2012).

However, fusion of fMRI and EEG data would not have the restriction of neither low spatial nor low temporal resolution. Therefore, the simultaneous measurement and concurrent analysis of EEG and fMRI could have a more optimal presurgical evaluation of epilepsy than any currently used method (Huster et al., 2012). Although, the machine learning algorithm implemented in this investigation would only apply for non-simultanious fMRI and EEG data acquisitions it could serve as a backbone for a more efficient future analysis of simultatiously acquired fMRI and EEG data.

Besides improving the overall process of analyzing fused EEG-fMRI data we can acquire more information on brain structure and function. The fused EEG-fMRI data could give fundemental information on the six layer neuronal structuring of the cerebral cortex. The acquisition of such profound information could lead to a further understanding of the brain functionality. Since, each of the six neuronal layers appear to mark the termination of various subcortical and higher cortical areas it is critical to understanding the overall connections within the cerebral cortex. Due to the rather uniform structure of the cerebral cortex across regions, researchs have hypothesis that there could be a common computational principle operating across the cortex (Barlow 1987). Therefore, the implementation of fused EEG-fMRI may give more fundemental information about the cerebral cortex, which could potentially guide us to find an underlining common computational principle across the cortex.

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