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Efficient Psychological Disorder Analysis With Multimodal Fusion of Brain Imaging Data

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Abstract – The mental disorders can be defined generally through a combination of features that reflect the feelings of a person or his actions and explain his thinking and perceptions. Mental illnesses include psychological or behavioral configurations that are frequently correlated with distress or disability. Thus, around 80% of Bipolar disorder patients who are going through depressive episodes receive an incorrect diagnosis. Depression and mania are thought to be heterogeneous illnesses that can result from dysfunction of numerous neurotransmitters or metabolic systems. Several neuroimaging studies have directly compared patients with (Bipolar Disorder) BD, (Unipolar Disorder)UD, (Major Depressive Disorder) MDD using magnetic resonance imaging (MRI), which provides noninvasive observation of the structural characteristics and functional states of the brain. Feature selection is often considered necessary for classifying neuroimaging data. For neuroimaging data processing, conventional univariate feature selection approaches ignore the mutual information among features with certain independence or orthogonality assumptions, As a

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data-driven technique, multivariate pattern analysis based on whole-brain resting-state functional MRI data can complement both seed-based and univariate statistical analyses. Whole-brain functional connectivity analysis, unlike those analyzing several predefined regions or networks of interest, can ensure the optimal use of the wealth of information present in the brain imaging data. In particular, multivariate pattern analysis methods can both find potential neuroimaging-based biomarkers to differentiate patients from healthy controls at the individual subject level and potentially detect exciting spatially distributed information to further highlight the neural mechanisms underlying the behavioral symptoms of major depression. It is possible to consider the appropriate grading of depression as mild, moderate, and severe by applying that techniques to identify the level of depression.

Keywords—Bipolar Disorder and Major Depressive Disorder, Multimodal Fusion, Neuroimaging, MRI Data, Data Driven Techniques.

I. INTRODUCTION

Depressive disorder is one of the most severe psychological disorders. It is around three hundred million people globally suffer from depression. Now a days, depression occurs in adolescents is growing and the number of suicidal depression is increased annually. Showing depression is the first step in the evaluation of symptoms and severity of depression. Consequently, the diagnosis failures are cannot specify and analyze the sequences of depressive symptoms clearly. Depressive episodes usually present more often than manic or hypo-manic symptoms, even as sub threshold manic symptoms can also be secret in a mixed episode. Most of the Depressive disorder patients who are going throughout depressive episodes obtain an incorrect diagnosis within the earliest of seeking treatment leading to inappropriate and longer medication periods, poorer prognosis and greater health care expenses. The main source of the difficulty in classifying mental disorders is incomplete understanding of their causes and figures.

In recent times, collecting various types of brain data from the same individual using various non-invasive imaging techniques (MRI, DTI, EEG, MEG, etc.). Every imaging technique provides a different view of brain structure or function. For example, magnetic resonance imaging (MRI), this provides noninvasive observation of the structural characteristics and functional states of the brain. Functional magnetic resonance imaging (fMRI) measures the hemodynamic response related to neural activity in the brain dynamically; structural MRI (sMRI) provides information about the tissue type of the brain Diffusion tensor imaging (DTI) can additionally provide information on structural connectivity among brain networks. Another useful measure of brain function is electro-encephalography (EEG), which measures brain electrical activity with higher temporal resolution than fMRI.

Generally these data are analyzed individually; however separate analyses do not enable the examination of the joint information between the modalities. By distinguish,

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combining modalities may uncover previously hidden relationships that can combine disparate findings in brain imaging For example, the spatial precision of fMRI could be complemented with the temporal precision of EEG to provide unique spatiotemporal accuracy. The combined analysis of fMRI and magneto encephalography (MEG) measurements can lead to improvement in the description of the dynamic and spatial properties of brain activity. A inferior and different function–structure linkage is often found in patients with brain disorder such as depressive signifying that combination of two brain modalities provides more comprehensive descriptions of changed brain connectivity. Hence, a key motivation for together analyzing multimodal data is to take maximal benefit of the cross-information of the existing data, and therefore may discover the potentially important variations which are only partially detected by each modality. Approaches for combining or fusing data in brain imaging can be conceptualized as having a place on an analytic spectrum with meta-analysis. A chief purpose of multimodal fusion is to access the joint information provided by multiple imaging techniques, which in turn can be more useful for identifying dysfunctional regions concerned in many brain disorders.

II. EXITING SYSTEM

Most previous studies of BD and MDD tended to exploit univariate approaches, although the fact that the brain actually functions in a multivariate way. Recent studies have suggested that, when analyzing fMRI data with sophisticated machine learning algorithms, informative fMRI patterns could be targeted to differentiate MDD patients or yet directly discriminate BD from MDD. The existing study, the differential diagnosis between clinically diagnosed BD and MDD patients by implementing a novel feature selection method for use on multimodal MRI data. The main goal of the present study was to identify the informative and biologically relevant features that can efficiently distinguish between patients with BD and MDD. however, the absence of biologically-relevant diagnostic markers of Bipolar Disorder results in misdiagnosis of the illness as major depressive disorder, or recurrent unipolar disorder (UD) depression, in 60% of bipolar individuals seeking treatment for depression.

III. METHODOLOGY

Consequently, we discuss the reasons why misdiagnosis of depressive disorder is so common using current DSM-IV criteria. We then emphasize the limitations of existing clinical strategies for early diagnosis of mental disorder, and focus on the potential utility of neuroimaging studies to identify biomarkers to aid in the differential diagnosis of BD versus Major depressive disorder or other kind of depression. We then discuss future research strategies to study psychotic disorder, including dimensional approaches such as the Research Domain Criteria initiative, in combination with neuroimaging, and discuss the need of prospec tive studies of individuals at risk for

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depression. Finally, we describe the potential of the combination of neuroimaging and machine learning to help identify individuals with, and those at future risk for depressive disorder.

A. Multivariate Method

The multivariate approaches adopted in multimodal MRI fusion can be divided into four classes based on the requirement of previous information and the data type of input, specially the dimension of the used MRI data, where the 'blind' means the source separation process is totally data-driven, thus without any priori; 'semi-blind' means that prior information or human knowledge/interference.

B.Multimodal Fusion of Brain Imaging

The entire of multimodal fusion them are based on linear decomposition and commonly assume that the changes in one data type (e.g. gray matter) are related to another one, such as functional activation. We note that this definition of 'feature' is somewhat different than what is used in conventional machine learning algorithms. Usually the brain imaging data are high dimensional. In order to reduce the redundancy and make possible the identification of relationships between modalities, the raw data can be preprocessed to generate a second-level output, which can be a contrast map calculated from task-related fMRI by the general linear model (GLM), a component image such as the 'default mode' resulting from a first-level ICA, an FA map from DTI data, or a stimulus averaged channel or channels from raw EEG signals.

C.Fusion Method

The fact that conclusions require to be drawn from high dimensional and noisy brain imaging data from only a limited number of subjects. Thus efficient and appropriate methods should be developed and chosen carefully. The methods for data fusion are usually multivariate and can be divided into two classes: hypotheses driven and data driven.

- **Hypotheses-driven approaches:** such as multiple linear regression and confirmatory structural equation modeling have the advantages of allowing testing of specific hypotheses about brain networks implicated in the experimental paradigm; allowing concurrent assessment of several connectivity links, which would have been compromised by the one-by-one assessment of covariance. However, when using these approaches, it is possible to miss important connectivity links that were not included in the a priori hypotheses and they do not provide information about inter-voxel relationships.
- **Data-driven approaches:** include, but are not limited to, principal component analysis (PCA), independent component analysis (ICA) and canonical correlation analysis (CCA). These methods belong to blind source separation approaches, as they do not desire prior hypotheses about the connection of interest; hence, they are attractive for the exploration of the full body of data. However, some methods may be more demanding from a computational

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standpoint. Partial least squares (PLS) is a hybrid which incorporates both hypotheses and data exploration. It is based on the definition of a linear relationship between a dependent variable and a predictor variable (hypothesis) and the data decomposition is achieved by maximizing the covariance between these two variables (data exploration).

D. Multimodal CCA

Multimodal CCA allows a different mixing matrix for each modality and is used to find a transformed coordinate system that maximizes inter-subject co variation across the two data sets. This method decomposes each dataset into a set of components and their corresponding mixing profile, called canonical variates (CVs). The CVs have varying levels of activations for different subjects and are linked if they adjust similarly across subjects. After decomposition, the CVs correlate to each other only on the same indices and their corresponding correlation values are called canonical correlation coefficients (CCCs). Compared to jICA that constrains two (or more) features to have the same mixing matrix, mCCA is flexible in that it allows common as well as distinct level of connection between two features, as shown in Fig. 1, but the associated source maps may not be spatially sparse, especially when the CCC are not sufficiently distinct. Fig. 1 is an application result of multimodal CCA to 16 schizophrenia and 23 controls performing an AOD task. A number of interesting associations are identified by mCCA,three of which have subjects' loadings that are significantly different between groups. The first pair of components, having a correlation given by 0.85, has the fMRI map (fMRI IC 1) performance activations in the temporal lobe (activations enclosed in red circles) and the middle anterior cingulated region and the ERP (ERP IC 1) showing a maximum peak at around 300 ms (P3) after the stimulus onset. This is similar to the result obtained in using jICA on a similar dataset. Another pair of components, having a correlation of 0.66, shows activation in the motor areas (purple box) and the bilateral temporal lobe which are associated with the N2 peak (ERP IC 2).

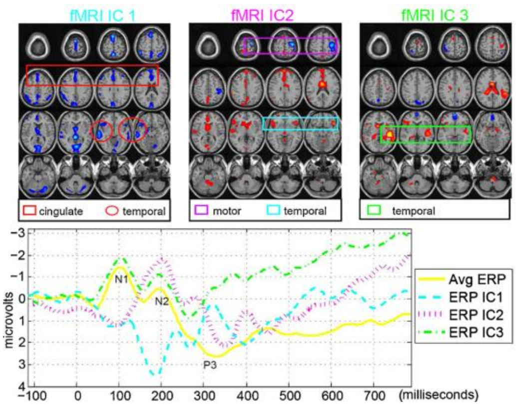

Fig.1 An application result of multimodal CCA

The final pair of components of interest shows significant differences between patients and controls for only the ERP component and not the fMRI component. This finding is not possible with jICA since it assumes the same mixing matrix for both modalities and it is quite plausible that for this particular component pair, fMRI is not sensitive to

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the differences in controls and patients. Multimodal CCA is invariant to differences in the range of the data types and can be used to together analyze very diverse data types. It can also be extended to multi-set CCA to incorporate more than two modalities.

IV. FUTURE WORK

In multivariate pattern analysis-based brain imaging analysis, the features for classification can be various structural characteristics or functional properties extracted from neuroimaging data. For resting-state functional MRI, resting-state functional connectivity measured by the correlation of two functional MRI time series has been used for the discrimination of psychiatric disorders. The purpose of this study was to explore significant disorder-related patterns using whole-brain resting-state functional MRI in medication-free depressed patients without co-morbidity and in carefully matched healthy controls and to discriminate patients from healthy subjects. Functional connectivity, measured by the correlation of two activity time series of anatomically separated brain regions, was used as a classification feature. In feature they can use other techniques to carry for brain resting state functional connectivity patterns to discriminate or identify depressed patients from health controls at the individual subject level with a high degree of accuracy.

V. CONCLUSION

There is great potential advantage in exploring joint information from multimodal brain imaging data. In this paper, we review data-driven multivariate methods that have been applied to multimodal brain imaging data fusion. That method presents a different view in interpreting the multiple datasets based on their various hypotheses. As a data-driven technique, multivariate pattern analysis based on whole-brain resting-state functional MRI data can complement both seed-based and univariate statistical analyses. Whole-brain functional connectivity analysis, different those analyzing several predefined regions or networks of interest, can ensure the optimal use of the wealth of information present in the brain imaging data. In particular, multivariate pattern analysis methods can both find potential neuroimaging-based biomarkers to differentiate patients from healthy controls at the individual subject level and potentially detect exciting spatially distributed information to further highlight the neural mechanisms underlying the behavioral symptoms of major depression. Now a day, there has been increasing interest in multivariate pattern analysis methods to categorize psychiatric patients from healthy controls using structural or functional brain images. If a multivariate pattern analysis based classifier can label new samples with better-than-random accuracy, then the two populations are indeed likely to be different, and the classifier can capture the population differences. Hence, Diagnosis may fail to specify whether the patient is actually suffering from mild or moderate or severe depression. It is possible to consider the appropriate grading of depression as mild, moderate, and severe by applying that techniques to identify the level of depression.

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