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A Hybrid Approach for Compressive Neural Activity Detection with Functional MR Images

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***Abstract*— In this paper, we present a framework for neural activity detection using fMRI data, based on both statistical data analysis (data-driven) and graphical information modeling (model-based). The data-driven approaches do rough prediction when an extraordinary amount of neural activities arise. By proper exploration of spatial, temporal, inter-subject correlations, the model-based approaches can provide more insights to details, and physiological meaning from high data volume, low signal-to-noise ratio (SNR) fMRI measurements. Through temporal cluster analysis (TCA), matched filtering, linear predictive coding (LPC), and variational Bayesian Gaussian mixture modeling (VBGMM), the temporal fMRI signals are converted into event prototypes associated with three neural statuses: activation, deactivation, and normality. As a result, the high volume fMRI data generated from multiple subjects can be statistically modeled as coupled finite-state sequences. Based on the graphical-model representation, the neural activities captured through fMRI can be classified and detected at reduced computational cost. The whole framework consists of three components: 1) image enhancement, event prediction and capture; 2) event feature extraction and modeling; and 3) graphical model based Bayesian inference. The experiment results demonstrate the advantages of the proposed hybrid, compressive signal processing approach in terms of computational cost and robustness against inter-subject variability as well as various artifacts.**

I. INTRODUCTION

FUNCTIONAL magnetic resonance imaging (fMRI) is currently one of the most widely used techniques for neuroscience studies. Data mining techniques used in fMRI studies can be characterized into two major schemes: model-based and data-driven. Model-based methods, such as general linear models (GLM) and graphical models, demand repeatable and stable patterns in brain activities. Those methods can provide insights into how a particular cognitive process is implemented in a specific brain area instead of merely identifying where such a process is located [1]-[3]. However, they cannot be used when the signal responses are not known as *a priori*. Data-driven methods like temporal clustering analysis (TCA), independent component analysis (ICA) and principle component analysis (PCA), have more flexible frameworks for data analysis in the absence of *a priori* model of brain activities, but not fully exploiting the spatial, temporal correlations between adjacent data.

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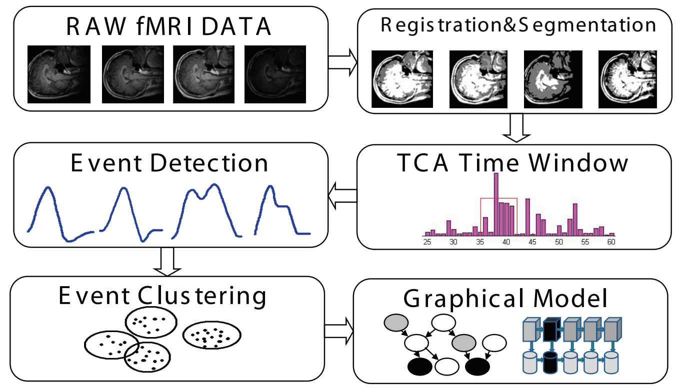

Fig. 1. System diagram of the proposed hybrid approach.

Despite having many achievements, the existing fMRI data mining approaches have to address the following technical challenges:

1) artifacts caused by random subject movements under various experiment conditions;
2) insufficient utilization of temporal, spatial, and inter-subject correlations among neural activities, typically associated with data-driven approaches; and
3) increased computational complexity and cost, typically associated with model-based approaches.

To tackle the above challenges, it requires innovation and development of techniques for:

1) effective image registration and segmentation to reduce artifacts and improve the SNR,
2) efficient representation of neural activity dynamics in the fMRI signal space, and
3) effective statistical inference mechanisms.

In this paper, we present a hybrid approach to neural activity detection from fMRI data, as shown in Fig. 1. Under this framework, the data-driven approach predicts the time windows in which events of interests will likely be detected; the model-based approach compresses the high volume data, and localize the information of interest efficiently. Through a proper combination of two approaches, the computational cost is reduced, and the efficiency and robustness of the neural activity detection process are improved. The whole procedure includes three stages: (1) fMRI images are enhanced through registration and segmentation. Neural activities are predicted by statistic data analysis, and signal events are captured through matched filtering; (2) signal events are represented by the linear predicative codes (LPCs) and classified into event prototypes through an variational bayesian approach; (3) graphical models are built from labeled event sequences, and are used to classify and detect neural activities from newly acquired data.

The rest of the paper is organized as follows: Section II reviews the related work; Section III describes the the hybrid signal processing framework; Section IV presents the experimental results; Section V concludes the paper and outlines the future works.

II. Related Work

Among data-driven approaches, ICA based methods are robust against inter-subject variabilities at high computational cost, without fully utilizing the spatial and temporal correlations among fMRI signals. PCA can reduce data dimensionality under Gaussian assumption but is sensitive to inter-subject variabilities [4]. TCA is computationally efficient, but subject to motion artifacts caused by different experimental conditions [5]. Among model-based studies, GLM based methods statistically infer neural activities with the prior knowledge derived from experiments yet has the possibility to yield small false activation regions in low SNR environments [6]. Gaussian smoothing filter can reduce such false detections with biased estimation on activation peak locations. An adaptive spatial filter has been developed in [7] to capture spatial features of the neural activities without utilizing inter-subject correlations and can not detect the activation and deactivation at the same time. Spatial modeling techniques like Markov random fields and hierarchical Bayesian models can improve the estimation accuracy, assuming there exists the spatial continuity among fMRI responses. The spatial modeling is primarily limited to the spatially contiguous and locally homogeneous nature of fMRI responses. Usually biased estimation and the sensitivity to inter-subject variabilities are caused by insufficient utilization of the spatial, temporal, inter-subject coherence among fMRI data. In fact, spatial, temporal, inter-subject correlations can be represented by discrete event prototypes and logic sequences. By utilizing the prior knowledge generated by data-driven methods, discrete event based estimation can yield superior performance [8].

TABLE I
Computational Complexity

Case	Computational Complexity
Non-Parametric Kernel-Based ICA	$O(K^2N^2)$
ICA Using Kernel Entropy Est.	$O(KNLogN + K^2N)$ [9]
TCA	$O(KNL)$
Our Approach	$O(KML + KNM)$

K:Subject number. N:Sample number.
L:Pixel number. M:LPC coefficient number.

This study investigates a hybrid approach: 1) use TCA as an exploratory tool to reduce computation cost; 2) use better image registration and segmentation methods to improve the accuracy of TCA; 3) use signal compression techniques to increase the SNR and the robustness against motion artifacts and inter-subject variabilities; and 4) use discrete events prototypes to increase the inference speed and accuracy. Table I shows the computation complexity comparison among different approaches.

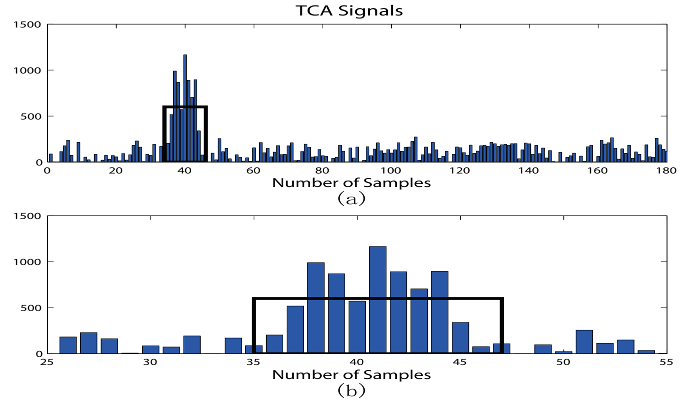

Fig. 2. TCA signals. (a) TCA signals generated by one subject drinking water. (b) Zoomed-in signals to illustrate the generation of time windows.

III. Methodology

The whole framework consists of three components: 1) image enhancement, event prediction and capture; 2) event feature extraction and modeling; and 3) graphical model based Bayesian inference.

A. Image Enhancement, Event Prediction and Detection

1) Image Registration and Segmentation: A 2D deformable image registration [10] and piecewise constant model for level set version of mumford-shah segmentation [11] are used to reduce the motion artifacts in fMRI data and isolate the gray matter, where neural activities are present.

2) Event Prediction: As a data-driven technique, TCA assumes that the number of pixels with extreme values will be greater during the activation periods than during the rest period. We use TCA to predict the time windows in which extraordinary neural activities arise. When the TCA signals are above a certain threshold, it can be regarded as a neural activation (deactivation) period. Fig. 2 (a) shows the TCA signals of one subject drinking water and Fig. 2 (b) shows the zoomed-in signals to illustrate the procedure of time window generation. Using the time windows generated by the data-driven approach, event signals will be detected and modeled.

3) Event Detection: Fig. 3 shows the procedure of event prototype generation. First the temporal sequence of the segmented signal by time windows is normalized by subtracting the mean of the signal. Then the sequenced signal is convoluted with a matched filter (band-pass filter) to reduce the SNR. A threshold manipulation is applied after the convolution to remove the low-information background activities. Then discrete events are isolated from the data sequence. Finally, signal event data sets are categorized into event prototypes for further logic processing.

B. Event Feature Extraction and Modeling

1) Feature extraction: When subjects perform similar activities such as water drinking and glucose intaking, their

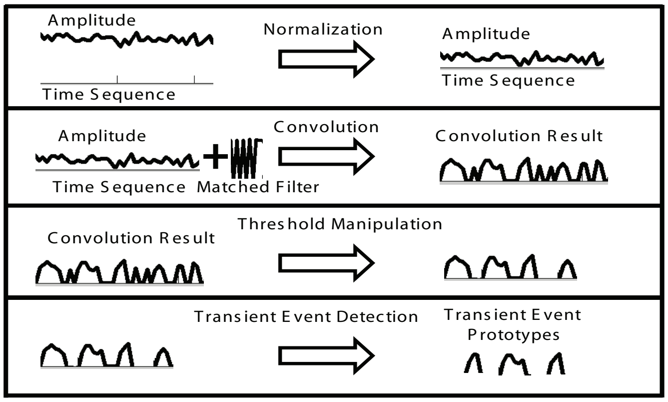

Fig. 3. The procedure of event prototype generation.

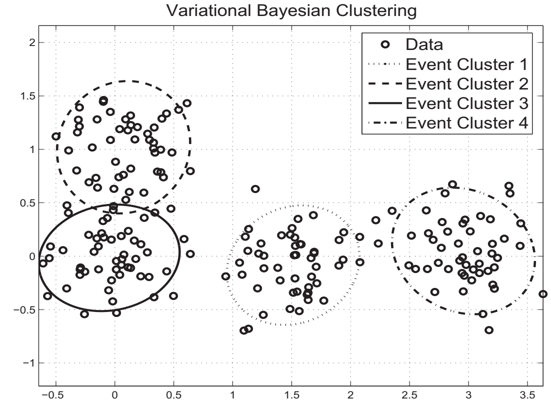

Fig. 5. Clustering of event prototypes using the VBGMM approach.

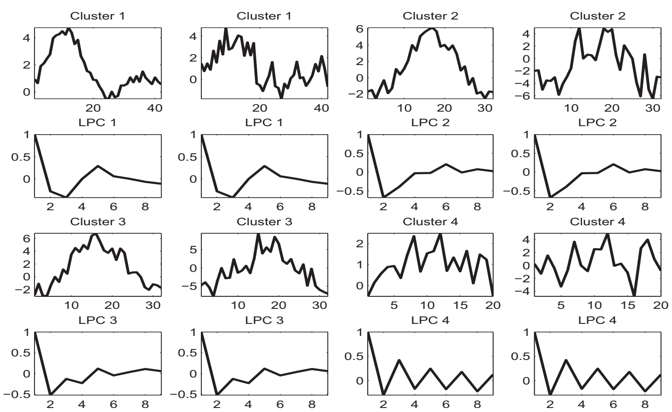

Fig. 4. Compressive linear predicative coding of signal events.

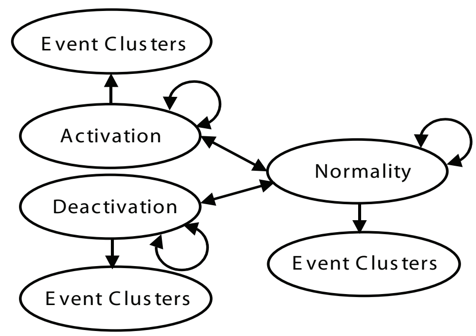

Fig. 6. Graphical model of neural activities in fMRI data.

neural activities should exhibit similar patterns regardless of their anatomical differences. However, due to the inter-subject variabilities and artifacts caused by experiment conditions, the signal patterns may not be exactly the same. For example, some subjects drink water fast, their response signals could have a high-spike in a short period of time. When subjects drink water slowly, the response data might be very flat with little spike. In order to deal with such a disparity and only get the pattern informaton, we utilize linear predictive coding (LPC) which transmits spectral envelope information with tolerance of transmission errors. Fig. 4 shows activities performed by different subjects, resulted in transient event signals which can be represented in LPC coefficients. It can be seen that LPC can reserve the signals' structural similarity and disparity.

2) Events Classification: After the event prototypes were generated. The event features could be classified using variational Bayesian Gaussian mixture model (VBGMM). Fig. 5 shows the event prototype clustering results. It can be seen that the event features are successfully clustered into four different clusters.

3) Graphical Model Based Inference: Probabilistic graphical models are graphs in which nodes represent random variables, and the arcs represent conditional independence assumptions. Hence they provide a compact representation of joint probability distributions. With the classified compressive transient events, our factor graph is showed in Fig. 6. Its hidden states include (1) activation, (2) deactivation, and (3) normality. Each hidden state has various emitted observations of event prototype.

IV. Experimental Results

We tested our methodology with 6 subjects of fMRI data generated by water drinking activity. We used the data of five subjects to train the graphical model using Bayesian Network Toolbox, and used fMRI signals of the remaining subject as testing data. Fig. 8 shows the neural activity detection results in the area of hypothalamus using the proposed hybrid approach. Fig. 8 (a) illustrates a set of average fMRI signals in hypothalamus that is associated with the drinking activities, (b) shows the generation of time windows using TCA, (c) shows the event prototype sequences, and (d) gives the neural activity detection results. We also estimated the likelihood of each subject's data fitting to event sequential models, yielding little variance. Fig.10 shows the comparison between TCA and the proposed method detecting neural activity in the area of hypothalamus for 6 subjects. It can be seen that TCA yields a false alarm for subject 4 and the proposed approach shows robustness against the inter-subject variabilities. Another advantage of the hybrid approach is the reduced computational cost. As the fMRI data is of very high volume, this approach is suitable to analyze the brain

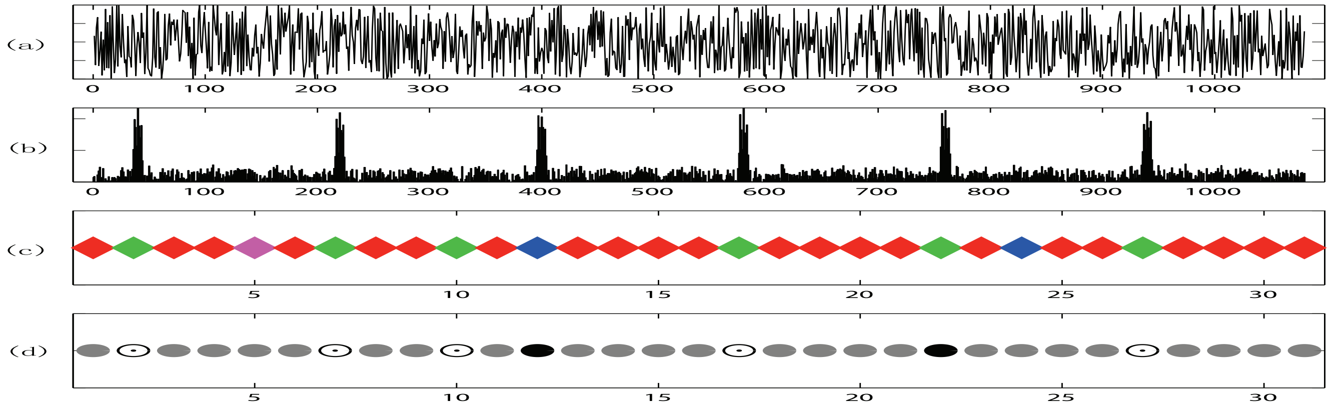

Fig. 7. Detection of neural activities. (a) fMRI temporal signals. (b) Time windows generated by temporal cluster analysis. (c) Labeled event sequence (Red, Blue, Green, and Pink: cluster 1, 2, 3, and 4). (d) Detected neural activity status (Dark: activation; Gray: normality; White: deactivation).

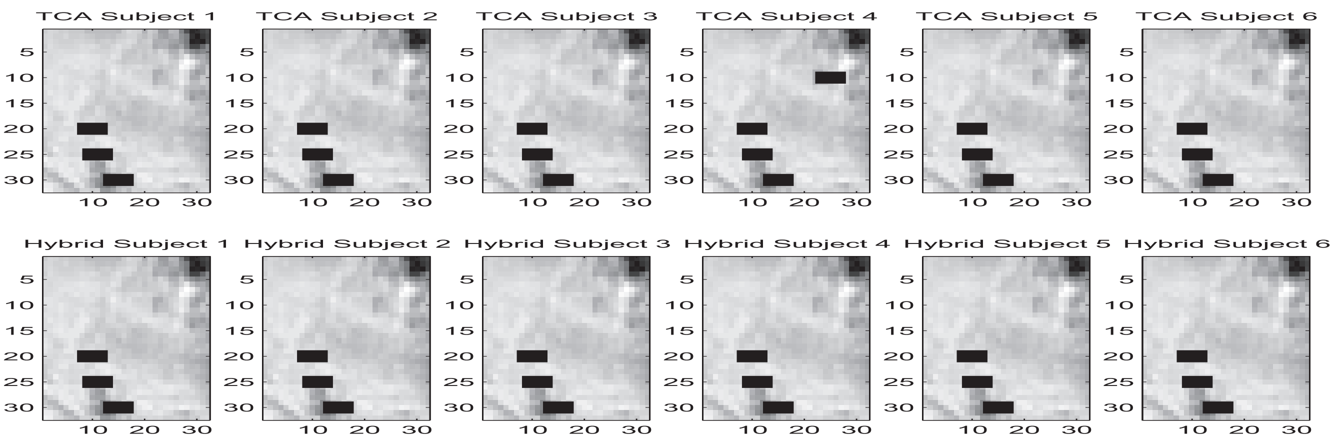

Fig. 8. Neural activity detection performance comparison between TCA (upper) and the proposed Hybrid approach (lower) in the area of hypothalamus.

activities in the long-time experiments such as detecting neural activities in virtual reality.

V. CONCLUSION

We have described in this paper a new framework for detecting neural activities in fMRI data. By integrating data-driven and model-based approaches and using signal compression techniques, the high data volume, low SNR fMRI images can be converted to discrete event sequences. Based on a graphical-model representation, the neural activities can be detected and classified at reduced computation cost with robustness against the inter-subject variability. Future work will focus on finding better event prototype representations and improvement of the event clustering robustness. Spatial correlations among event sequences will be further studied to extend the proposed framework's capability of dealing with applications associated with complex neural activities (e.g. brain study in virtual reality). More effective structural learning methods will be developed for better training of graphical models.

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