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### Segmentation of Brain Regions Using Statistical Region Merging

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#### Abstract

Functional magnetic resonance imaging or functional MRI (fMRI) is a functional neuro imaging procedure using MRI technology that measures brain activity by detecting associated changes in blood flow, using blood-oxygen-level-dependent (BOLD) contrast. Current result from neuro science suggests modular organization of the brain. To understand, the complex interaction patterns among brain regions, existing system uses k-means (IKM) algorithm, an efficient algorithm for partitioning clustering. A cluster is defined as a set of subjects sharing a similar interaction pattern among their brain regions. IKM clusters only the particular regions or functions of the brain or rest of the nervous system. Hence it is not suitable for different regions of the time series. Hence the proposed Statistical Region Merging (SRM) algorithm is used for image segmentation. The algorithm is used to evaluate the values within a regional span and group them together based on the merging criteria resulting a smaller list and finally abnormality is detected.

**Keywords:** Interaction patterns, Cluster, Segmentation, Region Merging.

#### Introduction

Functional magnetic resonance imaging (fMRI) opens up the opportunity to study human brain function in a noninvasive way. The basic signal of fMRI relies on the blood-oxygen-level-dependent (BOLD) effect, which allows indirectly imaging brain activity by changes in the blood flow related to the energy consumption of brain cells. Recently, resting-state fMRI has attracted considerable attention in the neuroscience community. In resting state fMRI, subjects are instructed to just close their eyes and relax while in the scanner. fMRI data are time series of 3-dimensional volume images of the brain. fMRI produce images at higher resolution than other scanning techniques.

Data from fMRI [1] experiments are massive in volume with more than hundred thousands of voxels and hundreds of time points. Since these data represent complex brain activity, also the information content can be expected to be highly complex. Recent findings suggest a modular organization of the brain into different functional modules. In tracking cognitive processes with functional MRI mental chronometry it says that Functional magnetic resonance imaging (fMRI) is used widely to determine the spatial layout of brain activation associated with specific cognitive tasks at a spatial scale of millimeters. Recent methodological improvements have made it possible to determine the latency and temporal structure of the activation at a temporal scale of few hundreds of milliseconds. Despite the sluggishness of the hemodynamic response, fMRI can detect a cascade of neural activations - the signature of a sequence of

cognitive processes. Decomposing the processing into stages is greatly aided by measuring intermediate responses. By combining event-related fMRI and behavioral measurement in experiment and analysis, trial-by-trial temporal links can be established between cognition and its neural substrate.

To obtain a better understanding of complex brain activity, it is essential to understand the complex interplay among brain regions during task and at rest. Inspired by this idea, a novel technique is proposed for mining the different interaction patterns in healthy and diseased subjects by clustering. At the core of our method is a novel cluster notion: A cluster is defined as a set of subjects sharing a similar interaction pattern among their brain regions. A cluster analysis of motion stream data potentially identifies clusters with similar movements, usually performed by different persons. Time series data are frequently large and may contain outliers. In addition, time series are a special type of data set where elements have a temporal ordering. Therefore clustering of such data stream is an important issue in the data mining process.

Numerous techniques and clustering algorithms have been proposed earlier to assist clustering of time series data streams. The clustering algorithms and its effectiveness on various applications are compared to develop a new method to solve the existing problem. After standard pre-processing including parcellation into anatomical regions, each subject is modeled as a data object which is represented by a multivariate time series.

Each of the dimensions is a time series corresponding to the fMRI signal of a specific anatomical brain region.

The volume of time series data generated by a fiber monitoring system can be huge. This limits the applicability of data mining algorithms to this problem domain. A widely used solution is to reduce the data size through feature extraction. In existing system Interaction K-means (IKM) <sup>[2]</sup> simultaneously clusters the data and discovers the relevant cluster specific interaction patterns. The algorithm IKM is a general technique for clustering multivariate time series and not limited to FMRI data. This may be associated with particular regions or functions of the brain or rest of the nervous system. This is not suitable for different regions of the time series.

So in proposed the Statistical Region Merging (SRM) <sup>[3]</sup> algorithm, is introduced and it is focus on image segmentation and region merging. Region-based segmentation methods are powerful tools for object detection and recognition. These methods aim at differentiating regions of interest (objects / background). Their objective is to divide the image into homogeneous zones to separate the different entities in the image. This is usually a first step in a more complex treatment chain involving pattern recognition. For example in medical imaging, segmentation is very important for representation and visualization as well as for the extraction of parameters and the analysis of images.

Region based segmentation is a specific approach in which one seeks to construct surfaces by combining neighboring pixels according to a criterion of homogeneity. The nature of the considered images and the objective of the segmentation being multiple, there is no unique technique for image segmentation and segmenting an image into meaningful regions remains a real challenge. The algorithm is used to evaluate the values within a regional time and group them together based on the merging criteria, resulting in a smaller list and more number of information is collected and compared with the database and finally abnormality can be detected. In this paper we explain how abnormality is detected in brain regions from FMRI data using SRM algorithm.

## Background Review

### Imaging Techniques

To view activities or problems within the human brain without invasive surgery we use scanning techniques. CT(Computed Tomography) <sup>[4]</sup> scan builds up a picture of the brain based on the differential absorption of X-rays but it reveal the gross features of the brain but do not resolve its structure well. EEG(Electro Encephalography) <sup>[5]</sup> measure the electrical activity of the brain by according to the electrodes placed

on the scalp but detecting changes in the brain is done on mille-sec level only. MEG(Magneto encephalography) <sup>[6]</sup> measure the magnetic field produced by electrical activity in the brain e.g. speed of thought. It measures brain activity in 1/1000 of sec but it is more expensive.

ERP (Event related potentials) <sup>[7]</sup> provides the electrodes on the scalp measure voltage fluctuations resulting from electrical activity in the brain. But in ERP patients undergone brain surgery or to localize ERP sources is to place electrodes in the brain. SSPT (Steady State probe Topography) <sup>[8]</sup> measure steady state visually evoked potentials and records at the rate of 13 times per second from 64 electrodes in a light weight skull cap. PET (Positron Emission Tomography) <sup>[9]</sup> measures blood flow by injecting people with radioactive water and measure changes in radiation.

FMRI <sup>[1]</sup> produce images at higher resolution than PET. It involves rapid scanning of the brain to see which area of brain becomes activated. It is highly sensitive so small changes also detected and multiple scans can be done on the same subject. By using concentration level we can identify the abnormality detection as Normal - 90%, Hypothermia – below 90%, Organ Function Changes – below 80%.

### Segmentation Techniques

Our aim in this paper is to propose a path and its milestones from a novel model of image generation. A large number of segmentation approaches have been proposed. In this section, we just were going to analyze the suitable segmentation technique for brain regions.

Expectation Maximization (EM) is one of the most common algorithms used for density estimation of data points in an unsupervised setting. The EM algorithm <sup>[10]</sup> is used to estimate the parameters of this model; the resulting pixel-cluster memberships provide a segmentation of the image. According to <sup>[11]</sup> the EM algorithm has demonstrated greater sensitivity to initialization than the K-Means or FCM algorithms. The Markov Random Field (MRF) <sup>[12]</sup> models are used for the restoration and segmentation of digital images. They can make up for deficiencies in observed information by adding a-priori knowledge to the image interpretation process in the form of models of spatial interaction between neighboring pixels. Hence, the classification of a particular pixel is based, not only on the intensity of that pixel, but also on the classification of neighboring pixels. It has been used for brain image segmentation by modeling probabilistic distribution of the labeling of a voxel jointly with the consideration of the labels of a neighborhood of the voxel <sup>[13]</sup>. Unsupervised region merging <sup>[14]</sup> provide a set of the most relevant region based explanations of an image at different levels of analysis but the result is not so accurate. Watershed segmentation <sup>[15]</sup> invariably produce over segmented

images due to the presence of noise or local irregularities in the source image but it gives results only on the simulation results.

Statistical region merging (SRM) <sup>[3]</sup> algorithm, is used for image segmentation. This approach can be efficiently approximated in linear space; leading to a fast segmentation algorithm tailored to processing images described using most common numerical pixel attribute spaces. The conceptual simplicity of the approach makes it simple to modify and cope with hard noise corruption.

In brain, there are four regions namely Frontal lobe, Temporal lobe, Occipital lobe, Parietal lobe is shown in Figure 1



**Fig 2.2 Brain Regions**

While clustering first it takes time series from all regions then it perform Data preprocessing. Data preprocessing is an important step in the data mining process.

Data pre-processing includes cleaning, normalization, transformation, feature extraction and selection, etc.,. Grayscale images are distinct from one-bit bi-level or black-and-white images, which in the context of computer imaging are images with only the two colors, black, and white (also called bi-level or binary images). For Filtering in this paper Low Pass filter <sup>[16]</sup> is used to filter the Gaussian noise in the image. In smoothing, the data points of a signal are modified so individual points (presumably because of noise) are reduced, and points that are lower than the adjacent points are increased leading to a smoother signal. Next, feature extraction <sup>[17]</sup> in this feature points are extracted from the image based upon the density of the image in the regions.

In existing system Interaction K-means (IKM) <sup>[2]</sup> simultaneously clusters the data and discovers the relevant cluster specific interaction patterns. Existing approaches to clustering multivariate time series <sup>[18]</sup> do not consider interaction information. Most approaches rather extract features from each dimension and cluster the resulting feature vector. To demonstrate that the information on attribute interaction is valuable for clustering multivariate time series, we compare IKM to feature-based approaches <sup>[19]</sup>. As a baseline, we consider classical K-Means clustering with Euclidean distance, which we term *Naive* in the following. The naive algorithm considers the concatenated dimensions of an

object as a feature vector. Similar to classical K-means, IKM is an iterative algorithm, which efficiently converges towards a local minimum of the optimization space. This may be associated with particular regions or functions of the brain or rest of the nervous system. This is not suitable for different regions of the time series.

So in proposed the Statistical Region Merging (SRM) <sup>[3]</sup> algorithm, is used for image segmentation. It consider different model for different region of time series. The algorithm is used to evaluate the values within a regional time and group them together based on the merging criteria, resulting in a smaller list and more number of information is collected and compared with the database and finally abnormality is detected.

### Proposed System

In this section, we introduce Statistical Region Merging (SRM) <sup>[3]</sup> algorithm focuses on region merging techniques. It aims to propose a path and provide extensions to miscellaneous problems related to image segmentation. First, the key idea of this model is to really formulate image segmentation as an inference problem. Second, the existence of a particular blend of statistics and algorithm to process observed images generated with this model, by region merging, with two statistical properties. With high probability, the algorithm suffers only one source of error for image segmentation: over merging, that is, the fact that some observed region may contain more than one true region. In region merging, regions are sets of pixels with homogeneous properties and they are iteratively grown by combining smaller regions or pixels, pixels being elementary regions. Region merging techniques usually work with a statistical test to decide the merging of regions. A good region merging algorithm has to find a good balance between preserving this unit and the risk of over merging for the remaining regions. The algorithm has some desirable features: It relies on a simple interaction between a merging predicate easily implementable, and an order in merging approximable in linear time. Furthermore, it can be adapted to most numerical feature description spaces (RGB, HSV, etc.). Third, we provide a C-code implementation of this last algorithm, which is a few hundred lines of C, and experiments on various benchmark images, as well as comparisons with other algorithms.

### Algorithm SRM

In image, there are  $N < 2|I|$  couples of adjacent pixels. Let SI be the set of these couples. Let  $f(p, p')$  be a real valued function, with  $p$  and  $p'$  pixels of  $I$ . Our segmentation algorithm, SRM (Statistical Region Merging) is simple. We first sort the couples of SI in

increasing order of  $f(., .)$ , and then traverse this order only once. We make for any current couple of pixel  $(p, p')$   $S \in I$  for which  $R(P) \neq R(P')$  (where  $R(P)$  stands for the current region to which  $p$  belongs) the test  $P(R(P), R(P'))$ , and merge  $R(P)$  and  $R(P')$  iff it returns true. After merging two regions, a simple ordering based on radix sorting with color differences as the keys yields a preordering time complexity  $O(|I| \log(g))$ -linear in  $|I|$ -for our basic implementations of SRM. The merging steps afterward are space/time computational optimal, which makes SRM also optimal from both standpoints. The execution time of our basic implementation of SRM, which is not optimized, segments the largest images ( $512 \times 512$ ) in about one second on an Intel Pentium / IV 2.40 GHz processor. Though running the algorithm does not require tuning its parameters, the control of a statistical complexity parameter makes it possible to adjust the segmentation scale in a simple manner.

## Results and Discussion

Statistical Region Merging (SRM) [3] algorithm focuses on region merging techniques. It aims to propose a path and provide extensions to miscellaneous problems related to image segmentation. It considers different model for different region of time Series. It provides extension to miscellaneous problems related to image segmentation. The algorithm is used to evaluate the values within a regional time and group them together based on the merging criteria, resulting in a smaller list and more number of information is collected and compared with the database and finally abnormality can be detected following fig 4.1 & 4.2 illustrate the work of SRM algorithm.

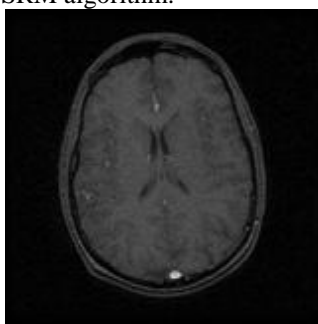


Fig 4.1(a) Normal brain

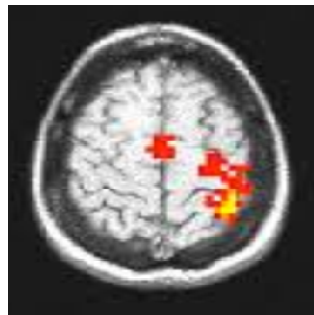


Fig 4.1(b) Abnormal brain

## Conclusion

Cluster is defined as set of objects sharing a specific interaction pattern among the dimensions. Recently, resting-state fMRI has attracted considerable attention in the neuroscience community. Interaction K-means (IKM) simultaneously Clusters the data and discovers the relevant cluster specific interaction

patterns. The algorithm IKM is a general technique for clustering multivariate time series and not limited Human motion stream data can also be extracted from video streams. In this application, it makes sense to regard each movement as a data object. A cluster analysis of motion stream data potentially identifies clusters with similar movements, usually performed by different persons. IKM clusters only the particular region or function of the brain or rest of the nervous system. So Statistical Region Merging algorithm is proposed and it considers different regions while clustering, it performs image segmentation. It provides extension to miscellaneous problems related to image segmentation. The algorithm is used to evaluate the values within a regional time and group them together based on the merging criteria, resulting in a smaller list and more number of information is collected and compared with the database and finally abnormality is detected.

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