

e-ISSN:2582-7219



# INTERNATIONAL JOURNAL OF MULTIDISCIPLINARY RESEARCH IN SCIENCE, ENGINEERING AND TECHNOLOGY

Volume 6, Issue 2, February 2023



INTERNATIONAL  
STANDARD  
SERIAL  
NUMBER  
INDIA

**Impact Factor: 7.54**



6381 907 438



6381 907 438



ijmrset@gmail.com



www.ijmrset.com



# Brain Regions Using Statistical Region for Identifying Abnormalities

Dr.M.Geetha, Sivaranganathan K

Associate Professor, Department of Computer Applications (MCA), K.S.R. College of Engineering (Autonomous),  
Tiruchengode, India

Department of Computer Applications (MCA), K.S.R. College of Engineering (Autonomous), Tiruchengode, India

**ABSTRACT:** Functional magnetic resonance imaging or functional MRI (fMRI) opens up the opportunity to study human brain function in a non-invasive way and it relies on the blood-oxygen-level-dependent (BOLD) effect. It allows indirectly imaging brain activity by changes in the blood flow. To understand, the complex interaction patterns among brain regions, clustering technique is performed. In existing system k-means (IKM) algorithm is used 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.

## 1. 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.

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. 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

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.

First pre-processing is performed 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. After Pre-Processing, feature extraction is performed based upon the density of the image.

In existing system Interaction K-means (IKM) [2] 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 objet 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.

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.

## II. BACKGROUND TECHNIQUES

### 2.1 SCANNING

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.

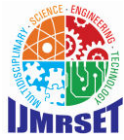
FMRI <sup>[1]</sup> produce images at higher resolution than PET. It involves rapid scanning of the brain to see which area of brain becomes activated. It is highly sensitive so small changes also detected and multiple scans can be done on the same subject. By using concentration level we can identify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

### 2.2 CLUSTERING

In this section, we elaborate our cluster notion based on characteristic interaction patterns. We want to find clusters of objects, which are represented by multivariate time series <sup>[10]</sup> sharing a common cluster-specific interaction pattern among the dimensions. Hidden Markov models <sup>[11]</sup> it measure only the similarity nerve cells only. Sequence Clustering Refinement <sup>[12]</sup> algorithm it acts as a K-means but it does not cluster different regions. Independent component Analysis <sup>[13]</sup> cluster it measures only the independent nerve cells. Nearest hyper plane distance neighbor clustering algorithm <sup>[14]</sup> that can be applied to high dimensional data, it cannot be applied to low dimensional data and it does not provide efficient clustering.

An Automatic Unsupervised Classification <sup>[15]</sup> observed that the grey matter distance can best separate the Alzheimer's disease patients from the cognitively normal control but it takes more time to diagnose the diseases. Fuzzy clustering <sup>[16]</sup> algorithms classify the tissues based on single channel MRI-Images but after clustering noise and misclassification error may present. Hierarchical clustering analyzes micro array data and makes it easier to interpret the results of a cluster analysis but it diagnoses only Alzheimer's disease only. Recently, compression-based similarity measures have been proposed.

In existing Interaction K-means (IKM) <sup>[2]</sup> a partitioning clustering algorithm suitable to detect clusters of objects with similar interaction patterns. Previous approaches to clustering multivariate time series 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. 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. But IKM clusters only particular region. So result is in accurate.

### 2.3 SEGMENTATION

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>[17]</sup> is used to estimate the parameters of this model; the resulting pixel-cluster memberships provide a segmentation of the image. According to<sup>[18]</sup> the EM algorithm has demonstrated greater sensitivity to initialization than the K-Means or FCM algorithms. The Markov Random Field (MRF)<sup>[19]</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>[20]</sup>. Unsupervised region merging<sup>[21]</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>[22]</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.

## III. ABNORMALITY DETECTION

In brain, there are four regions namely Frontal lobe, Temporal lobe, Occipital lobe, Parietal lobe is shown in Figure 3.2



Fig 3.2 Brain Regions

While clustering first it takes time series from all regions then it perform Data preprocessing. Data pre-processing 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>[23]</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>[24]</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. It consider only particular region of the brain region only. So, 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.

#### IV. PROPOSED SYSTEM

In this section, we introduce 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. 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 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.

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 1 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.

#### V. 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 5.1 illustrate the work of SRM algorithm.

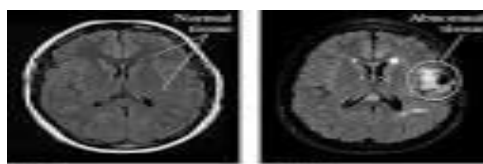
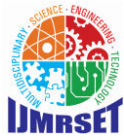


Fig 5.1 Normal & Abnormal brain



## VI. 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.

## REFERENCES

- [1] M. D. Fox and M. E. Raichle, "Spontaneous fluctuations in brain activity observed with functional magnetic resonance imaging," *Nat Rev Neurosci*, vol. 8, no. 9, pp. 700–711, 2007.
- [2] M. Vlachos, J. Lin, E. Keogh, and D. Gunopulos, "A waveletbased anytime algorithm for k-means clustering of time series," in *In Proc. Workshop on Clustering High Dimensionality Data and Its Applications*, 2003, pp. 23–30.
- [3] Richard Nock and Frank Nielson, "Statistical region Merging" vol.26, no.11, Nov 2004.
- [4] Tetsuya Yuasa and Tohoru Takeda, "Fluorescent X-Ray Computed Tomography Using Synchrotron Radiation Towards Molecular Imaging" Prof. Bernhard Schaller (Ed.), ISBN: 978-953-51-0359-2.
- [5] Boris V. Baryshnikov\*, BarryD.van Veen, *Fellow, IEEE*, and Ronald T. Wakai "Maximum-Likelihood Estimation of Low-Rank Signals for Multiepoche MEG/EEG Analysis" in *IEEE TRANSACTIONS ON BIOMEDICAL ENGINEERING*, VOL. 51, NO. 11, NOVEMBER 2004
- [6] Ryusuke Kakigi, Koji Inui, Diep Tuan Tran Yunhai Qiu, Xiahong Wang, Shoko Watanabe Minoruhoshiyama, "Human Brain Processing and Central Mechanisms of Pain as Observed by Electroand Magnetoencephalography" in Ryusuke Kakigi *et al. Journal of the Chinese Medical Association Vol. 67, No. 8*
- [7] L. Xiao, H. Begleiter, B. Porjesz, W. Wenyu, and A. Litke, "Event related potentials during object recognition tasks," *Brain Research Bulletin*, vol. 38, pp. 531–538(8), 1995.
- [8] J. Hamilton, G. Chen, M. Thomason, M. Schwartz, and I. Gotlib, "Investigating neural primacy in major depressive disorder: multivariate granger causality analysis of restingstate fmri time-series data," *Mol Psychiatry*, vol. 16, no. 7, pp. 763–72, 2011.
- [9] Ahmadreza Rezaei<sup>1</sup>, Michel Defrise<sup>2</sup>, Girish Bal<sup>3</sup>, Christian Michel<sup>3</sup>, Maurizio Conti<sup>3</sup>, Charles Watson<sup>3</sup>, Johan Nuyts<sup>1</sup>, "Simultaneous Reconstruction of Activity and Attenuation in Time-of-Flight PET".
- [10] T. Oates, "Identifying distinctive subsequences in multivariate time series by clustering," in *Proc. ACM SIGKDD*, 1999, pp. 322–326.
- [11] T. Oates, L. Firoiu, and P. R. Cohen, "Clustering time series with hidden markov models and dynamic time warping," in *In Proceedings of the IJCAI-99 Workshop on Neural, Symbolic and Reinforcement Learning Methods for Sequence Learning*, 1999, pp. 17–21.
- [12] Ji Hey, Man Lanz, Chew-Lim Tanz, Sam-Yuan Sungz, and Hwee-Boon Low], "Initialization of Cluster Refinement Algorithms: A Review and Comparative Study" yzSchool of Computing, National University of Singapore, 3 Science Drive 2, Singapore 117543.
- [13] E. H. C. Wu and P. L. H. Yu, "Independent component analysis for clustering multivariate time series data," in *ADMA*, 2005, pp. 474–482.
- [14] J. Lin, M. Vlachos, E. J. Keogh, D. Gunopulos, J.-W. Liu, S.-J. Yu, and J.-J. Le, "A mpaa-based iterative clustering algorithm augmented by nearest neighbors search for time-series data streams," in *PAKDD*, 2005, pp. 333–342.
- [15] A. Trouve and Y. Yu, "Unsupervised clustering trees by nonlinear principal component analysis." *Pattern recognition and Image Analysis*, vol. 2, pp. 108–112, 2001.
- [16] Michel Menard, "Fuzzy clustering and switching regression models using ambiguity and distance rejects" in *Laboratoire d'Informatique et d'Imagerie Industrielle, Universit\_e de La Rochelle, Avenue Marillac, 17042 La Rochelle Cedex 1, France* Received 12 August 1998; received in revised form 7 March 2000; accepted 22 March 2000.



- [17] A. Dempster, N. Laird, and D. Rubin, Maximum Likelihood from Incomplete Data via the EM Algorithm, J. Royal Statistical Soc., Ser. B, vol. 39, no. 1, pp. 1-38, 1977.
- [18] Z.Yu, O.C, Au,R.Zou, W. Yu, J. Tian, an adaptative unsupervised approach toward pixel clustering and color image segmentation. Pattern recognition. 43(5)(2010)1889-1906.
- [19] F. Forbes, N. Peyrard, Hidden Markov random field model selection criteria based on mean field-like approximations, IEEE Trans. Pattern Anal. Mach. Intell. 25 (9) (2003) 1089–1101.
- [20] Ali, A.A., Dale, A.M., Badea, A, Johnson, G.A., 2005. Automated segmentation of neuroanatomical structures in multispectral MR microscopy of the mouse brain, NeuroImage 27 (2), 425–435.
- [21] Kanak Saxena, Sanjeev Jain, Uday Pratap Singh, “Unsupervised Method of Object Retrieval Using Similar Region Merging and Flood Fill”, in (IJACSA) International Journal of Advanced Computer Science and Applications, Special Issue on Artificial Intelligence.
- [22] Lamia Jaafar Belaid1 And Walid Mourou2,” Image Segmentation: A Watershed Transformation Algorithm” Image Anal Stereol 2009;28:93-102.*Original Research Paper*
- [23] Réjean Fontaine1, François Lemieux1, Nicolas Viscogliosi1, Marc-André Tétrault1, Mélanie Bergeron2, Joël Riendeau1, Philippe Bérard2, Jules Cadorette2, Roger Lecomte2, “Timing Improvement by Low-Pass Filtering and Linear Interpolation for the LabPET™ Scanner”.
- [24] Jonathan S. Anstey and Dennis K. Peters, Chris Dawson, “An Improved Feature Extraction Technique For High Volume Time Series Data”.



**INNO SPACE**  
SJIF Scientific Journal Impact Factor  
Impact Factor  
7.54

**ISSN**

INTERNATIONAL  
STANDARD  
SERIAL  
NUMBER  
INDIA



# INTERNATIONAL JOURNAL OF MULTIDISCIPLINARY RESEARCH IN SCIENCE, ENGINEERING AND TECHNOLOGY

| Mobile No: +91-6381907438 | Whatsapp: +91-6381907438 | [ijmrset@gmail.com](mailto:ijmrset@gmail.com) |

[www.ijmrset.com](http://www.ijmrset.com)