AN IMPROVED COMPUTATIONAL MODEL FOR CLASSIFICATION OF 3D SPATIO TEMPORAL *f*MRI DATA

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In the name of Allah, Most Gracious, Most Compassionate.

I praise and thank Allah.

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ABSTRACT

3D spatial temporal functional magnetic resonance imaging (*f*MRI) for classification has gained wide attention in the literature to be applied in the application of data mining techniques. Similarly, Spiking Neural Networks (SNN) has successfully applied in many problems to process and classify *f*MRI data. However, the network still has a drawback in terms of processing noise, redundant and irrelevant features especially in *f*MRI data. To an extent, standard machine learning techniques has effectively process and classify *f*MRI data. Although, these techniques are only best at dealing spatial data, which completely neglect the temporal information inside the data. In order to achieve higher classification accuracy, there is a need to filter out noise from the dataset. Studies have shown that the presence of noise in the data effects the classification process thereby reducing the classification accuracy. In this study, the feature selection technique has been used as a filter at the pre-processing part of the dataset. Thus, this study proposed a feature selection technique called *i*ReliefF to overcome the complexity in selecting the important features in *f*MRI dataset. This technique has been trained and tested by using StarPlus dataset. Based on the obtained results, the new computational model with proposed method *i*ReliefF has shown better performance by achieving 85% accuracy compared to the existing model which is 80%. Therefore, it can be concluded that the proposed *i*ReliefF has achieved reasonable accuracy and is very effective as well as ideal for *f*MRI dataset.

ABSTRAK

Functional magnetic resonance imaging 3D (fMRI) untuk klasifikasi telah mendapat perhatian luas dalam kerja-kerja yang berkaitan untuk diterapkan dalam teknik perlombongan data. Begitu juga, Spiking Neural Networks (SNN) telah berjaya digunakan dalam menyelesaikan banyak masalah untuk memproses dan mengklasifikasikan data *f*MRI. Walau bagaimanapun, rangkaian ini masih mempunyai kelemahan dari segi mengenal *noise*, ciri yang berlebihan dan tidak relevan dalam data *f*MRI. Setakat ini, teknik pembelajaran mesin standard telah memproses dan mengklasifikasikan data *f*MRI secara berkesan. Tetapi, teknik-teknik ini hanya terbaik untuk menangani data *spatial* atau ruang, dan mengabaikan maklumat temporal atau masa yang berada di dalam data. Untuk mencapai ketepatan klasifikasi yang lebih tinggi, terdapat keperluan untuk menapis *noise* dari dataset. Kajian telah menunjukkan bahawa kehadiran *noise* dalam data memberi kesan kepada proses klasifikasi dengan itu mengurangkan ketepatan klasifikasi. Dalam kajian ini, teknik pemilihan ciri-ciri data telah digunakan sebagai penapis di bahagian pra-pemprosesan data set. Oleh itu, kajian ini mencadangkan teknik pemilihan ciri yang dipanggil *i*ReliefF untuk mengatasi kerumitan dalam memilih ciri-ciri penting dalam dataset *f*MRI. Teknik ini telah dilatih dan diuji dengan menggunakan dataset StarPlus. Berdasarkan hasil yang diperoleh, model komputasi baru dengan kaedah yang dicadangkan *i*ReliefF telah menunjukkan prestasi yang lebih baik dengan mencapai ketepatan 85% berbanding dengan model sedia ada yang hanya mencapai 80% ketepatan. Oleh itu, dapat disimpulkan bahawa *i*ReliefF yang dicadangkan telah mencapai ketepatan yang tinggi dan lebih berkesan serta sesuai untuk dataset *f*MRI.

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LIST OF SYMBOLS AND ABBREVIATIONS

*f*MRI	-	Functional Magnetic Resonance Imaging
STBD	-	Spatio And Spectro-Temporal Brain Data
EEG	-	Electroencephalogram
DTI		Diffusion Tensor Imaging
MEG	-	Magneto Encephalography
NIRS	-	Near-Infrared Spectroscopy
SNN	-	Spiking Neural Networks
eSNN	-	Evolving Spiking Neural Network
BOLD	-	Blood-Oxygen-Level Dependent
*i*ReliefF	-	Improved ReliefF
DeSNN	-	Dynamic Evolving Spiking Neural Network
SVM	-	Support Vector Machine
k-NN	-	K-Nearest Neighbor
NB	-	Naïve Bayes
DeSNN	-	Dynamic Evolving Spiking Neural Network
3D	-	3 Dimensional
BCI	-	Brain Computer Interface
ECoS	-	Evolving Connectionist System
ANN		Artificial Neural Networks
STDP		Spike Timing Dependent Plasticity
SSTD	-	Spatio Spectro Temporal Data
AER	-	Address Event Representation
BSA	-	Ben's Spike Algorithm
RO	-	Rank Order
CBV	-	Cerebral Blood Volume
PET	-	Positron Emission Tomography

CT	-	Computed Tomography
MRI	-	Magnetic Resonance Imaging
LS-SVM	-	Least Square Support Vector Machine
MI	-	Mutual Information
SD	-	Statistical Dependency
SNR	-	Signal to Noise Ratio
STPR		Spatio Temporal Pattern Recognition
SPAN	-	Spike Pattern Association Neuron
SNNc	-	Spiking Neural Networks cube
ROIs	-	Region Of Interests
ARFF	-	Attribute-Relation File Format
RDLPFC	-	Right Bilateral Dorsolateral Prefrontal Cortex
LDLPFC	-	Left Bilateral Dorsolateral Prefrontal Cortex
LFEF	-	Left Frontal Eye Field
RFEF	-	Right Frontal Eye Field
RPPREC	-	Right Posterior Precentral Sulcus
SMA	-	Supplementary Motor Area
LPREC	-	Left Posterior Precentral Sulcus
RIPL	-	Right Inferior Parietal Lobule
LIPL	-	Left Inferior Parietal Lobule
RSPL	-	Right Superior Parietal Lobe
RIPS	-	Right Intraparietal Sulcus
LSPL	-	Left Superior Parietal Lobe
LIPS	-	Left Intraparietal Sulcus
LIFG	-	Left Inferior Frontal Gyrus
LSGA	-	Left Supramarginal Gyrus
RSGA	-	Right Supramarginal Gyrus
ROPER	-	Right Opercularis
LOPER	-	Left Opercularis
LT	-	Left Temporal Lobe
RT	-	Right Temporal Lobe
RIT	-	Right Inferior Temporal Lobe
LIT	-	Left Inferior Temporal Lobe

CALC	-	Calcarine Sulcus
RTRIA	-	Right Triangularis
LTRIA	-	Left Triangularis
TBR	-	Threshold-Based Representation
TP	-	True Positive
TN	-	True Negative
FP	-	False Positive
FN	-	False Negative
BSA	-	Ben Spiker Algorithm

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CHAPTER 1

INTRODUCTION

1.1 Research Background

The human brain is the most complex organ of the human body which is the fundamental source to process the input information. The cells bring information to all parts of the human body. Over the past few years, the study of human brain received great attention from researchers especially in image processing. A very common and important field in image processing is the Functional Magnetic Resonance Imaging (*f*MRI) (Sclocco *et al.*, 2016). *f*MRI has appeared as a new tool to get the information of activities in human brain, specifically to capture the spatio temporal activation (Yosipovitch *et al.*, 2015). *f*MRI measures the ratio of oxygenated hemoglobin to deoxygenated hemoglobin in the blood at many individual locations within the brain (Mitchell, *et al.*, 2004). The brain is a complex integrated spatio-temporal information processing machine and Spatio and spectro-temporal brain data (STBD) is a most commonly collected data for measuring brain response to external stimuli (Kasabov, 2014). Spatio and spectro-temporal brain data (STBD) has several forms of understanding such as, electroencephalogram (EEG), diffusion tensor imaging (DTI), magneto encephalography (MEG) and near-infrared spectroscopy (NIRS) as part of *f*MRI. These spatial/spectral and temporal components help to generate the sequence of brain slices and brain images.

*f*MRI contains millions of data points, and has a complex structure in both space and time (Manning *et al.*, 2014). By using a standard machine learning technique, only several data can be processed or understood. Therefore, new computational framework is needed to work with a complicated and huge data points. In recent years, spiking neural networks (SNN) have a similar standard working for mapping, learning and understanding of *f*MRI as well as other spatio temporal data in 3D evolving spiking neural network (eSNN) known as NeuCube architecture (Kasabov, 2014). NeuCube is more efficient to read and process the *f*MRI brain data as compared to traditional machine learning techniques which neglect the temporal component (Enmei Tu, 2016).

1.2 Motivation

The significance of experiments in optimization and machine learning technique is the accessibility to big datasets in real world applications. These datasets are often referred to big data as it consists of vast numbers of data samples as well as features. Similarly, due to the huge quantity of data in *f*MRI, it is necessary to apply some feature selection method to prevent overfitting. Therefore, feature selection technique plays a main role in such a complex dataset as it can assist the extraction of relevant information. It is also a process of selecting subset from novel features according to a certain standard such as feature extraction, feature integrations and etc. As feature selection is an optimization problem by nature, it can improve the performance of decision making models in term of classification accuracy as well as decreasing time complexity by increasing the signal to noise ratio and removing irrelevant, redundant and noisy features. The objective of this research is looking for the most important features that can improve the performance in term of classification accuracy of the model.

1.3 Problem Statement

In recent years, *f*MRI data analysis systems have been widely used to detect the blood-oxygen-level dependent (BOLD) signal from the noisy data and to localize the activated regions in the brain. Due to the complex nature of *f*MRI data, experiments involving *f*MRI data requires high processing time especially in determining the optimal model and thus multiple runs of experiments are required to find the perfect combination of parameters in order to achieve higher accuracy (Salimi-Khorshidi *et* *al.*, 2014). Moreover, *f*MRI is considered as large datasets (up to several gigabytes) and the high levels of noise inherent in *f*MRI data poses a challenge to researchers interested in mining these datasets for information about cognitive processes. Therefore, feature selection technique is needed to find the most relevant features from the raw dataset as to reduce the complexity and improve the classification in term of accuracy. NeuCube as a new SNN architecture is used to map, learn and understand *f*MRI data. This study thereby proposes a feature selection technique called iRelief F to be embedded in the Neucube as a filter method for *f*MRI brain dataset and uses Dynamic evolving Spiking Neural Network (DeSNN) as its classifier.

1.4 Objectives of Study

This study embarks on the following objectives:

(i) To propose a feature selection technique called iReliefF for selecting the important features from the *f*MRI data in the NeuCube.

(ii) To implement the *i*ReliefF in objective (i).

(iii) To evaluate and compare the proposed and existing feature selection techniques in terms of performance accuracy of *f*MRI data in the NeuCube model.

1.5 Scope of Study

This research work only focuses on the proposed feature selection technique to one physical subject data-starplus-04847-v7.mat which contain 4949 features. The results are compared between data without feature selection technique and three other feature selection techniques including (i) Relief (ii) ReliefF and (iii) *i*ReliefF with five different classifiers which are (i) support vector machine (SVM), (ii) *k*-nearest neighbor (*k*NN), (iii) naïve bayes (NB), (iv) Span and (v) DeSNN (NeuCube). The data is a benchmark data of the subjects in human brain which this dataset was originally collected by Marcel Just and colleagues in Carnegie Mellon University (Just, 2014). The data has 2 classes which are Picture and Sentence.

1.6 Thesis Organization

This thesis comprises of five chapters including Introduction and Conclusion chapters. The followings are synopsis of each chapter.

Chapter 1: *Introduction*. Apart from providing an outline of the thesis, this chapter contains an overview of the research background, problem to be solved, objectives to achieve, scope, and expected outcome of the study.

Chapter 2: *Literature Review*. This chapter explains basic understanding of Spiking Neural Networks, NeuCube architecture and *f*MRI data. Apart from that, this chapter reviews some of the work on classifiers and feature selection techniques that has already been applied by researchers while solving problems related to accuracy performance.

Chapter 3: *Research Methodology***.** This chapter discusses the research methodology used to carry out the study systematically. First, existing work on Neucube architecture, classifiers and feature selection techniques has been analyzed and by observing the gap analysis the proposed methodology is presented to explain what phases and steps will be taken in this research to achieve the objectives as an outcome. The design and implementation of each step has been taken throughout the experiments to achieve the objectives and expected outcomes of the study.

Chapter 4: *Results and Analysis*. This chapter summarizes the results obtained from different classifiers and feature selection techniques. The comparison has been explained in terms of accuracy performance. The performance evaluation was carried out based on accuracy, precision and recall.

Chapter 5: *Conclusion and Future work*. The contributions of the proposed approach are summarized, and the recommendations are given for further continuation of work.

CHAPTER 2

LITERATURE REVIEW

2.1 Introduction

The overview of this chapter touches on important fields related to the research study which has been found in literature. Furthermore, it also highlights on the different algorithms and techniques generally used in the study domain. These existing related works are reviewed, analyzed and summarized.

The true characteristics of functional Magnetic Resonance Imaging fMRI data are difficult to define, as real data from fMRI consists of a series of three dimensional volumes recorded over an interval of time. Each element of the three-dimensional volume is referred to as a voxel, and the data recorded for each voxel at each time step is a decimal value referred to as the hemodynamic response, correlating to the firing rate of a population of neurons.

Spatio and temporal components are constructed by this technique which generate an image (Alistair *et al.*, 2015). Volume element or also known as voxel is identified as a brain size that can be sub divided into three-dimensional (3D) small cuboids spatial components. Moreover, temporal component is time taken for entire volume on brain scanning. Therefore, the main character of this study is to investigate the brain images of these spatial and temporal data. As magnetoencephalography (MEG), diffusion tensor imaging (DTI), electroencephalogram (EEG), and near-infrared spectroscopy (NIRS) apart from *f*MRI, are also known as spatio and spectro temporal brain data (STBD). Basically, there is a large collection available for researchers' benefit in the Brain Computer Interface (BCI), in areas for education, cognitive sciences, medicine and health.

STBD in particular *f*MRI has complex structure in both spatial and temporal as well as consists of millions of data points. A new computational architecture is needed to handle, process and understand such complex and massive data points where standard machine learning techniques was can only solve partially. Recently, in terms of spike activities, Spiking Neural Networks (SNN) have a similar function as STBD in expecting to be appropriate creation for computational architecture in terms of understanding and learning *f*MRI and also other brain data.

To get a better understanding of the data, an architecture that is based on 3D evolving SNN (eSNN) called NeuCube (Kasabov, 2014) was developed to map and learn STBD. Evolving Connectionist System (ECoS) has inspired to eSNN architecture in its neurons and neurons connections, the principles are developing the structures in time. Furthermore, the structures also provide new features that can be added in advanced stages for the learning process. Therefore, NeuCube is the best architecture that been offered by the advantages of ECoS and eSNN to map, train and learn STBD. Previously, experiments of spatio-temporal stroke data has produced a better accuracy in stroke occurrences predictions and inspired researchers to experiment with others variations of STBD (Othman *et al*,. 2014).

Undoubtedly, standard machine learning frequently neglect temporal component in *f*MRI or others spatio-temporal data where several efforts have been performed to process and model this data. Temporal component of fMRI is very vital and much use in making accuracy decisions equal to the spatial component containing much important information about brain.

2.2 Review of Functional Magnetic Resonance Imaging (*f*MRI)

*f*MRI consist of an arrangement of voxel in its smallest form where it will be used as features and will be experimented and studied. The *f*MRI image actually reproduces the functioning activities that have different parts in brain and the values of features that are actual intensity. Due to these values, it can be directly exploited as features for classification purposes (Mitchell *et al.*, 2005). *f*MRI has been used in medical field by using brain imaging technique and the details will be discussed in the next subsection. For the samples of experiment, previous studies mainly use conventional classifiers and some choose feature in term of classifying the *f*MRI data.

2.2.1 Functional Magnetic Resonance Imaging (*f*MRI)

The visualization of hemodynamic can response in neurons relation activates by certain part of brain in *f*MRI (Buxton, *et* al. 2004). For the particular blood area, the response of hemodynamic is specified by the amount of blood flow. Cerebral blood volume (CBV) and the cerebral blood flow rate has changed based on the components of hemodynamic response as well as change in the oxyhemoglobin and deoxyhemoglobin concentration. There have been several techniques of fMRI to capture the signals' function and generate different components of hemodynamic response. Blood oxygen level dependent (BOLD) technique or also known as one of the greatest mutual techniques that is based on concentration of oxyhemoglobin deoxyhemoglobin component. Combination of BOLD and *f*MRI imaging technique has produced a great number of brain images for instance, spatial and temporal information, while MRI only provides structural mapping of a brain.

Furthermore, *f*MRI generates structural and functional mapping for the brain and takes the advantage of blood to carry oxygen and blood containers that occurs in activation of regions that will be used to measure the changes of neural activity in the brain from stimuli that triggers internally or externally (Haxby, 2011). Accurately, the ratio of oxygenated haemoglobin to deoxygenated haemoglobin in the blood is measured by *f*MRI in detail to control baseline at several individual locations around the brain. Local neural activity influences blood oxygen level and due to this blood BOLD response, it indicates the neural activity (Mitchell *et* al., 2004).

2.2.3 Introduction to Imaging Techniques

Neuroimaging is a structure of brain or other nerve systems that will produce an image of the brain activity and allow researchers to observe the activation of the brain or other nerves. Some might assume the neuroimaging as imaging technique only focuses on human brain. Particularly, images will be used to measure brain diseases and for diagnosing purpose as it can be used to study how the brain is working. The activation of regions in the brain will be activated when a stimulus are showed to the subject and psychologically the brain location will be affected (involves feeling of the subject together with emotions).

Undoubtedly, there are many research facilities and hospitals widely available for a few safe neuroimaging techniques to get around the world such as NIRS, EEG, MEG, Positron Emission Tomography (PET), Computed Tomography (CT), Magnetic Resonance Imaging (MRI) and *f*MRI. Different with the subjects with short-lived radioactive material and x-rays which is PET and CT scans. NIRS, EEG, MEG, MRI and *f*MRI will not expose patients with injecting substance to blood flow or radiation to measure the brain activity. However, MEG and EEG lacks the ability to detect spatial location accurately for the activation. Nevertheless, NIRS have a lower signal-to-noise ratio but has a high correlation with *f*MRI measurement. Therefore, *f*MRI has growing attention for researchers as a counterpart.

Since *f*MRI scan of brain contains hundreds of thousands of voxels, and when the resolution of *f*MRI scanners improves, this amount will only go up. Relevant regions of the brain are often only a small portion of all these voxels. While we could use all the voxels in a machine learning algorithm, it is known that these algorithms perform worse when a lot of unnecessary features are included in the training set. This problem is called overfitting which means that the algorithm tries to fit the classifier variables to every feature, even the irrelevant ones. This results in classification variables that fit the training set very well, but perform poorly on data that is not in the training set. This becomes an even bigger problem when taking into account the fact that the amount of training samples is small, and the amount of noise in the samples is high. So it is important that a trained machine learning algorithm generalizes well.

Therefore, the feature selection method can helps to reduce the amount of features and select more relevant ones by combining features into new ones and to hold more information in less dimensions. Consequently, feature selection has the potential to be used in finding the brain regions responsible for a particular task, and

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