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MFCC based feature extraction for diagnosing schizophrenia disease

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***Abstract*—This paper concerns the diagnosis of schizophrenia using an electroencephalogram signals. This study, MFCC based feature extraction was compared with the result of Hjorth parameters, Autoregression, Fractal dimension, and Phase slope index. Decay brain emotional learning based fuzzy inference system (DBELFIS), inspired by the limbic system of the brain emotional learning was used to classify schizophrenia from control participants.**

***Index Terms*—Electroencephalography, Spectrogram, Fuzzy, Schizophrenics, Amygdala, Orbitofrontal, Emotional learning**

I. INTRODUCTION

Schizophrenia can be defined as a serious psychiatric disorder and falls within the scope of psychotic illnesses with a worldwide lifetime prevalence of 1%. The name schizophrenia conducted from the recent scrutinization that the illness is symbolized by the disjunction or fragmentation of the different psychotic functions [1]. Patients with schizophrenia would have some types of symptoms feature, including disorganized speech, turbulence in thought, effects, perception and problem in social connectivity between people, the problem in understanding peoples thoughts and reacting emotionally to others [2]. The cognitive or intellectual deficit in schizophrenia that is not clear needs various investigation procedures, including an analysis on daily living or occupational therapists working in cognitive-behavioral therapy. The recent study set up a link between certain electroencephalographic (EEG) test and patients cognitive and psychological damage [3-4]. EEG signal demonstrates the electrical activity of the brain that analyzes useful features that can be used for the diagnosis of different diseases[5]. Patterns of EEG may correspond with the normal or impaired function of the central nervous system disease based on an experimental basis [6]. Previous studies using EEG have investigated the emotion recognition [7], analysis of epileptic activity [8], Attention-deficit/hyperactivity disorder (ADHD) [9], schizophrenia [10], depressive symptomatology [11], cognitive processing [12], brain damage [13] and many other functions. As various literature reviews show, significant problems with executive function, working memory and episode memory, reasoning, problem solving and speed of processing, in different cognitive domains have been demonstrated by people with schizophrenia [14-15]. However, emotional states are dynamic and may have been modified by involving in the task, despite having complicated brain process for emotion analysis, different emotional tasks are identifiable by measuring and describing of physiological signals [16]. Most emotions based studies have been studied that schizophrenia patients show mainly alternations in functional connectivity. There are also cognitive abnormalities with people with chronic schizophrenia [17]. Cognitive processes and emotions, both need the cortex connections involving the limbic system[18]. There have been various model free EEG studies between schizophrenics and other groups. Among the studies imply differentiating between the target patients population and appropriate comparison groups [19-21], denoted increased slow wave is observed significantly more in schizophrenia populations. Winterer el al [22], reported increased frontally pronounced delta-activity and decreased the signal power of the N100/P200 amplitude, then he deduced that schizophrenics represent impairment of the frontal lobe. Some studies validated frontal localization of EEG abnormalities of schizophrenics [19], [23-24]. Sponheim et al [25] reported distinguishable omnipresence of slow wave abnormalities between schizophrenics and bipolar patients. Shagas et al [26], compared the EEG of schizophrenics with affective disorders, personality disorders, and healthy controls. They obtained a sensitivity of 50% and specificity of 90% and when comparing largely similar group, 78 % sensitivity, and 85% specificity were reported. It has been studied that the amplitude of abnormal EEG was twice as great among people with schizophrenia as among affective disorder [27]. In addition, the EEG measure named Global Field Synchronization(GFS) that approximates functional connectivity of brain processes in a different EEG frequency band, was proposed; GFS analysis indicated a loss of mutual association of memory functions in schizophrenia patients[28]. Several feature extraction methods, including Shannons entropy, spectral entropy, approximate entropy, Lempel-Ziv complexity, and Higuchi fractal dimension were extracted from EEG signals, then two classification methods, including LDA and Adaboost were examined, the results proved that EEG signals can be a useful tool for differentiating between the schizophrenic and control participants[29] . The neural basis of the emotional brain is represented by the limbic system (LS) theory of emotion. The limbic system is a group of regions in the brain containing the hippocampus, the amygdala, the thalamus, the sensory cortex and the orbitofrontal cortex. Among this structure, the amygdala plays a major role in emotional learning and in keeping emotional experiment and responses. Thalamus is the first part of the limbic system that receives emotional stimuli and is responsible for the provision of high-level information about the stimulus. LeDoux [30] announced that there are two different paths to access amygdala, one is short and fast but inaccurate and comes directly from the thalamus, the other is slow and long distance but accurate and arisen from the sensory cortex. Sensory cortex partitions the incoming signal between amygdala and orbitofrontal cortex. Orbitofrontal cortex processes stimulus, learning the stimulus-reinforcement association and evaluates the amygdalas response. It also evaluates the reinforcement signal and forbids the amygdala from provision of inappropriate responses[31-32]. MacLean said interaction sensation from the world with information from the body causes emotional experience, he proposed his limbic model of emotion [33]. Lazarus announced the case for emotion involving cognition [34]. A computational model of emotional learning in the amygdala was proposed by Moren and Balkenius[31]. Brain emotional learning as a controller for heating, and air conditioning (HVAC) control system was introduced [35]. The supervised version of brain emotional learning was named FDBEL(supervised fuzzy decay brain emotional learning) was conducted for predicting Geomagnetic Index [36]. Diagnosing the complexity of the dynamic system by using a reinforcement-recurrent fuzzy rule based on the brain emotional learning was designed [37]. Khashman [38] presented altered back propagation learning algorithm namely, the emotional back propagation (EmBP) learning algorithm and examined the effect of the applied emotional factors on learning and decision making potentially of the neural network. The results showed that inserting emotional parameters boost the performance of the neural network and have high recognition rates. Khashman [39] attempted to model natural intelligence and emotions in machine learning. This approach demonstrated that emotion must be measured through simulation maps by analyzing the integration of emotion at the structural level of cognitive systems by adding emotional factors on learning and decision-making capabilities of the neural network. The model was named DuoNeural Network (DuoNN). The result showed that the DuoNN architecture, configuration, and the additional emotional information processing, obtained recognition rates with high accuracy. Kashman [38-40], assumed that the anxiety level at the beginning of a learning task is high and the confidence level is low. Brain emotional learning based fuzzy Inference system (BELFIS) integrates the idea of the previous emotional model with neuro-fuzzy inference system for predicting solar activity forecasting, it utilized adaptive networks that the number and type of membership function can be different.The results indicated that BELFIS is a reliable, nonlinear predictor model for solar activity forecasting but suffers from the curse of dimensionality and related issue; thus, it is not workable for high dimension applications [41]. Lotfi [42] modified version of brain emotional learning (BEL) applied in various control applications and proposed brain emotional learning based picture classifier (BELPIC), and the result showed the high accuracy and low time complexity for image classification. Lotfi and Akbarzadeh [42], proposed the limbic-based artificial neural network (LiAENN) that models emotional situation including anxiety and confidence in the learning process, the forgetting process, the short path and inhibitory mechanisms of emotional brain. The model showed higher accuracy than other applied emotional networks such as brain emotional learning (BEL) and emotional back propagation (EmBP) based networks. Javadi and Setayeshi[43] presented the DBELFIS (decay brain emotional learning based fuzzy inference system), was applied to diagnose schizophrenia patients. The DBELFIS model is a merge of the biologically-inspired model of the limbic system, and adaptive neuro-fuzzy inference system that used fusion fuzzy inference system into amygdala and orbitofrontal learning. The results showed the proposed model diagnoses schizophrenia disease with high accuracy. The rest of the paper is organized as follows. Section A describes the data collection methods used in this work, and Section B explains the feature extraction method applied to the collected data. Section III presents the experimental results. Finally, the conclusion is drawn in Section IV.

II. Materials and methods

A. Data acquisition

A study sample of 27 participants including 16 patient and 11 age-matched control participants (all male,18-60) enlisted from consecutive admission to a major psychiatric hospital in perth, Western Australia, provided the basis for this study. All patients had been examined using a structured clinical interview the diagnostic interview for psychosis and final research diagnoses based on the DIP interview and senior consultant psychiatrist review of the clinical case notes. The patients according to DSM-IV and ICD-10 criteria were diagnosed [44-45]. The exclusion criteria for all control participant included if any of their first degree relatives had been diagnosed with schizophrenia, positive history of head injury, neurological disorder, and substance abuse or dependence at the time of testing. Variety of standard neuroleptics at the time of recording with no effort to standardize the dosages were received by patients. Each participant was seated upright with eyes closed and the experiment lasted for 2 min. Electrophysiological data were recorded using a Neuroscan 24 Channel Synamps system, with a signal gain equal to 75 K (150 at the headbox). For EEG paradigms, 20 electrodes (Electrocap 10-20 standard system) were recorded according to the international 10-20 system, EEG data were recorded from 20 electrodes (Fpz, Fz, Cz, Pz, C3, T3, C4, T4, Fp1, Fp2, F3, F4, F7, F8, P3, P4, T5, T6, O1, O2).

B. Feature Extraction

Speech signal is non-stationary but in short interval between 5 and 100 ms is 'semi-stationary'. In the processing the speech signal, the windows size was devided typically between 15 ms

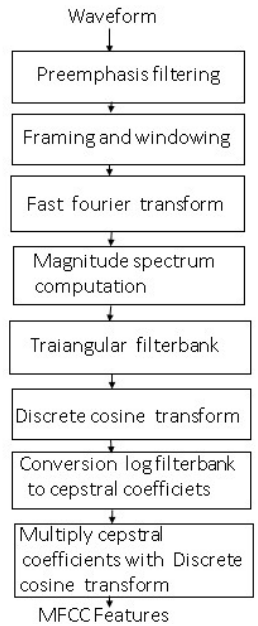

Fig. 1. Process involved to create MFCC features

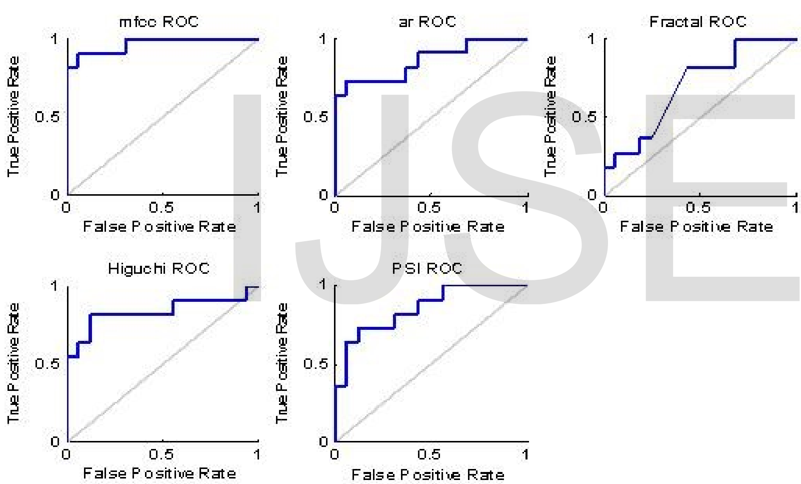

Fig. 2. ROC graphs showing performance of proposed model

and 35ms with a period of 15 ms. We evaluated this method to extract brain wave features from EEG signal and due to low frequency signal we multiplied the windows size by a factor of 10 [46]. Mel-Frequency Cepstral Coefficients feature extraction method is a leading approach for speech feature extraction [47]. The Process of making MFCC features consist of this steps. The first step is filtering signal then dividing the EEG signal into frames, usually by applying a windowing function at fixed intervals. The aim is to model small(typically 20ms) section of the signal that are statistically stationary. The windows function used was hamming windows that removes edge effects then we applied fast fourier transform in order to compute Magnitude spectrum computation, then Triangular filterbank was used which is uniformly spaced filters on mel space. In order to indiviualize part of magnitude spectrum, Trainger filterbank multiplied with magnitude spectrum was applied. Finally, Filterbank converted into cepstrum coefficients. The Fig. 1 shows the process of creating mfcc features. The MFCC feature extraction methods were compared with Hjorth parameters[48], Autoregression [49], Fractal dimension [50], and Phase slope index [51]. The frequency band of 4-40 Hz of EEG signal was evaluated for patients and healthy discrimination. The recorded signal of each channel is divided into short windows. Features were estimated for two-second windows. The window length was defined 400 ms. 5 AR coefficients, 3 Hjorth parameters (activity, mobility, and complexity), and 1 Minkowski-Bouligand fractal dimension were extracted for each electrode site. In the Phase slope index the frequency band of 4-40 Hz was divided into 9 parts including 4-8, 8-12, 12-16, 16-20, 20-24, 24-28, 28-32, 32-36, and 36-40 Hz , for each frequency band, PSI computed. Then, all extracted features were combined to form a feature vector. The receiver operating characteristics (ROC) graph was used for better visualization, and it utilized to prepare and select the best classifier for the proposed system. The ROC curve is a fundamental tool to evaluate a diagnostic test. Each plot in ROC graph presents the performance of the system using the extracted feature, MFCC features have been shown to possess the highest true positive rate than the other applied feature extraction methods when comparing control participant and schizophrenics under ROC graph curve. Fig. 2 indicates that the system works better applying MFCC under DBELFIS classifier[43].

III. Results and discussions

The extracted feature from EEG signals should be labeled, two classes of Patient (A) ,and Healthy (H) were chosen by their values. In the literature, a dimensionality reduction step has been used to classify this dataset. The defined method for the dimensionality reduction is locally linear embedding (LLE) . Some advantage of LLE is to prevent the search from becoming stuck in a local minimum, and also few parameters need to be set. 20% of samples were used as validation, 20% as a test, and 60% as training samples. We extracted four feature extraction methods including MFCC based feature extraction, Hjorth parameters, Autoregression, Fractal dimension, and Phase slope index individually, and the results were compared with DBELFIS classifier [43]. The result showed MFCC based feature extraction method performs well for diagnosing schizophrenia disease.

IV. Conclusion

In this research, EEG signals of 16 schizophrenic patients and 11 age-matched control participants were analyzed. Based on the semi-stationary feature of EEG signal, a feature extration method that is used to extract speech signal, named MFCC based feature extraction, can be applied to extract EEG signals. We evaluated this feature extraction method using DBELFIS. The result showed that MFCC-based feature extraction perfromed well compared to other feature extrcation method for diagnosing schizophrenia.

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