2020 4th International Conference on Computer, Communication and Signal Processing (ICCCSP)

Recurrence Quantification Analysis based Emotion Detection in Parkinson's disease using EEG Signals

2020 4th International Conference on Computer, Communication and Signal Processing (ICCCSP) | 978-1-7281-6509-7/20/$31.00 ©2020 IEEE | DOI: 10.1109/ICCCSP49186.2020.9315244

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Abstract— **Emotional disturbances are Parkinson's disease (PD) patients is typical, and this work aims to identify the emotional disturbances in PD using Electroencephalogram (EEG) signals. Clinicians assess the emotional impairment in PD using International standard questionnaires, and most of the time, this assessment becomes inaccurate since the verbal responses of PDs are not precise to express their internal feelings. EEG based emotional impairment detection in PD gained significant attention due to its robustness, flexibility, and non-invasiveness. In this work, we utilized the EEG dataset consists of 20 subjects each in PD and 20 Normal Control (NC), and EEG signals are collected using 14 channel wireless EEG device over six types of emotions (happiness, sadness, anger, fear, disgust, and surprise) at a sampling rate of 128 Hz. The 6th order IIR Butterworth filter with a cut-off frequency of 0.5 Hz – 49 Hz is used to filter the noises and other external interferences. Two features from Recurrent Plot (RP) such as, Maximum Diagonal Line Length (MDLL) and Maximum Vertical Line Length (MVLL) are extracted from alpha, beta, and gamma frequency bands of EEGs. These emotional relevant features are mapped into corresponding emotions of PD and NC using the Probabilistic Neural Network (PNN) classifier. The gamma frequency band (30 – 49 *Hz*) feature of maximum diagonal line length gives a maximum mean accuracy of 91.38% and 87.55%, for NC, and PD subjects, respectively.**

Keywords—Emotion detection, Probabilistic Neural Network (PNN), Statistical Analysis, Parkinson's disease, Electroencephalogram (EEG).

I. Introduction

Parkinson's disease is one type of neurological disorder that affects nearly 6 million population over the world. Most of the patients affected by this disease are in the age range of 45 – 85 years. The loss of dopomione chemicals in the Bessel ganglia region in brain is dully responsible for PD. Besides, PD also affects the postures, emotion and cognitive processing ability of the subject's [1-4]. Conventionally, the international standard questionnaires are used in the clinical environment to assess the PD stages, and the disease progression based on the physical symptoms and mental states. Most of the time, the patients are not able to identify and express their precise internal feelings to the clinicians for effective treatment. Hence, the success rate on remedial treatment towards emotional impairment in PD is highly a challenging issue [5-8]. In short, most of the clinicians are looking for an autonomous system that can detect the emotional impairments in PD in non-invasive and computationally efficient methods.

Recently, there are different modalities, based on speech, facial emotional expressions, and lexical approaches are used for identifying emotional disturbances in PD. Nevertheless, these methods are highly biased and flop to trail the intrinsic emotions in PD [8]. Neuro analysis based on Magnetic Resonance Imaging (MRI), functional MRI (fMRI), and Electroencephalogram (EEG) are becoming more popular over recent years in identifying the cognitive impairment in PD with higher spatial and temporal resolution. Among these methods, EEG is a computationally, less complicated, and cost-effective method of acquiring the brain's electrical activity of the subjects with acceptable spatial and temporal resolution.

EEG based emotional impairment detection in PD gains attention over recent years by several neuroscientists, and noticeable results on emotional impairment detection in PD are reported in the literature [9-10]. Most of the researchers utilize linear and non-linear feature extraction methods to extract meaningful information from the EEGs about the emotional state changes in PD. However, nonlinear feature methods are more popular and effective in feature extraction over other methods. Since it is assumed that the brain is a chaotic system and highly sophisticated and nonlinear. Thereby, nonlinear feature extraction methods give more detail about emotional state changes. Some of the most common nonlinear feature extraction methods used in the literature on EEG signals are, wavelet transform (WT), empirical mode decomposition (EMD), multiwavelet transform (MWT), recurrence quantification analysis (RQA), and Q wavelet transform [11-12]. In [13]. the maximum mean emotion classification rate of 89.17%, and 84.50% is reported in distinguishing six basic emotions using EEG signals on NC, and PC, respectively.

The graphical plot which represents the nonstationary characteristics in any given time-series data is called Recurrent Plot (RP). It is usually represented by a square matrix with dots. The analysis methods used to calculate the density of dots in RP and to measure the characteristics of diagonal and vertical lines are called Recurrent Quantification Analysis (RQA). Compared to other non-stationary analysis in time-series data, RQA performs better in terms of identifying the recurrent behavior of a system. The analysis of RQA in Parkinson's disease EEG data is relatively new, and there is no researches in the literature discussed about the application of RQA in emotional disturbances detection in PD.

The primary aim of the present work is to improve the emotion detection rate in PD compared to our earlier work using the RQA feature and PNN classifier. Besides, this preliminary work aims to examine the emotion detection rate of PD with normal control (NC) to investigate any emotional impairment problem in PD in perceiving any specific emotions. This work is a continuation of our earlier work on RQA features based emotion classification in PD. The rest of the paper is presented as: (a) Basics of PD, importance of emotional disturbances detection in PD using EEG is presented in section I. (b) the proposed methodology of emotional impairment detection in PD using EEG is discussed in section II (c) section III discusses the numerical results of proposed methodology in emotional disturbances detection in PD and NC, and (d) the conclusion of the proposed work is given in section IV.

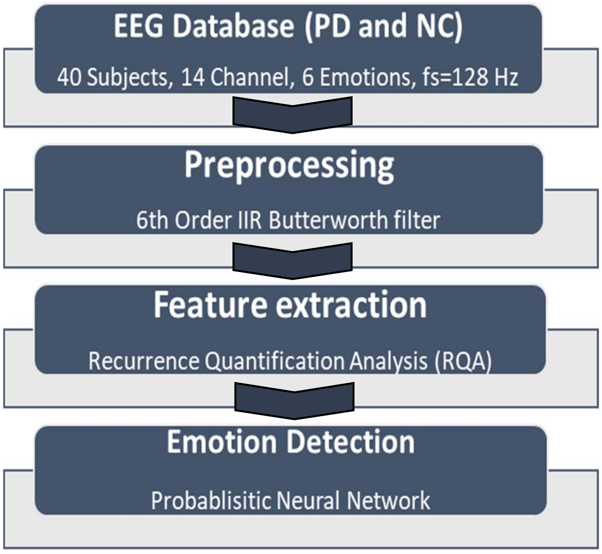

Fig. 1. Emotion classification in NC and PD using EEG signals

II. Research Methodology

The flow of research methodology in identifying emotional disturbances in PD using EEG signals is shown in Fig 1 and discussed eloboratively in this section.

A. Dataset

A quality EEG database is highly essential for developing any clinical diagnosis system. To the best of our understanding, no emotional EEG databset relevant to emotion classification in PD is existing either as an open-source database or pay-use method. The researchers have developed a standard EEG database of 20 PD (ten males and ten females) subjects and 20 NC (nine men and 11 women) subjects from Hospital Universiti Kebangsan Malaysia, Kuala Lumpur, Malaysia, after getting ethical approval from the local ethical committee. EEG data is collected from the subjects using a 14 channel wireless EEG device (Emotiv Epoc Headset) at a sample rate of 128 Hz. Audio-visual stimuli based data acquisition protocol is designed to acquire EEG data from the subjects over six trials on six emotions. The emotion elicitation protocol is framed by combining the audio (International Affective Digitized Sounds) and visual (International Affective Picture System) databases. The duration of each trial is approximately 4-5 min, and the total time required for each session is about 25 – 30 min. All the subjects are optimally medicated (to reduce the tremor), right-handed, and were given written consent before participating experiment and paid USD 20 for their active participation. All the subjects were scored <24 in Mini-Mental Score Examination (MMSE) and Beck Depression Inventory Score <1.8. The complete details of the data acquisition protocol design, clinical history of PD subjects, ethical approval details, inclusion, and exclusion criteria of PD subjects are given in detail in [14-16]. At the end of the experiment, the EEG samples collected on specific labels are sent to further processing, and no self-reported emotions are considered on this work.

B. Preprocessing of EEG signals

Removing the unwanted information such as low-frequency noises, high-frequency noises, power line interference, the effects of eye blinks, eyeball rotation, eyeball movements from EEG signals are highly crucial for getting the meaningful information from EEG signals. Because the human brain is the control center of the whole body and any of the above activity causes significant distortions in the EEG signals. Initially, all the raw EEGs traces are undergone a thresholding process with an amplitude of $\pm 85\mu V$ to reduce the effects of artifacts (due to eyeball movement, eye blinks, muscular movements, etc.). Later, a 6^{th} order IIR Butterworth filter is used with a bandpass frequency of 1 Hz – 49 Hz for filtering the noises mentioned above from the EEG signals. This work investigated several types of filter with different orders. The 6^{th} order Butterworth filter gives the best performance in removing the interferences with less distortion in the output compared to other types of filters.

C. EEG frequency band extraction

In this work, the three most useful frequency bands of EEG signals, namely alpha (8 Hz – 13 Hz), beta (13 Hz – 30 Hz), and gamma bands (30 Hz – 49 Hz), are analyzed for emotion detection in PD. The cognitive activities related to different emotions can be effectively captured from the above three frequency ranges compared to other frequency bands such as delta, and theta bands. In this work, IIR 6^{th} order Butterworth filter with appropriate bandpass frequency ranges of different frequency bands are used to extract the emotional related information from EEG signals of PD and NC. MATLAB toolbox is used for implementing filtering operation to get the filtered (noise-free) data for RQA analysis.

D. Feature extraction and statistical testing of features

The preprocessed signals are used for extracting the RQA features for emotion classification in NC and PD, respectively. From our earlier experiments, the 6-sec segment EEG epoch (time-segment) performs better in identifying six different emotions of NC, and PD compared to other time-segments. Hence, we segmented the input EEGs traces into 6-sec segments, and a set of two RQA features were extracted for emotion classification. Compared to other nonlinear methods which works on extracting the features from the EEGs by assuming a linearity over a certain period of time, RPs are used to envisage and analyze the recurrent property of a system in phase space. This phase space can be projected into either in two or three-dimensional space for visual analysis. Basically, RP consists of an array of dots in the form of a square matrix [17]. The characteristic features of RP

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analyzed through Recurrent Quantification Analysis (RQA) is widely used in several EEG related researches. Recurrence plot (RP) is one of the powerful tools used for analyzing the behavior of any nonlinear dynamic system using visual plots [18-19]. The characteristics of the plot can be quantified through Recurrence Quantification Analysis (RQA). There are several performance measures that can be derived from the RP through RQA and to name a few, recurrence rate (RR), maximum diagonal line length (MDLL), maximum vertical line length (MVLL), laminarity (LAM), entropy (ENT), etc. In this preliminary work, we used to extract the two features, namely, MDLL and MVLL for emotion detection. Besides, we also used to combine the above two features called ALL features to study its significance in emotion classification in PD.

In this work, Maximum Diagonal Line Length (MDLL) and Maximum Vertical Line Length (MVLL) are extracted from the RPs. Here, MDLL is reciprocal of approximate Largest Lyapunov Exponent (LLE) and it measures the system divergence. Its measured as a longest diagonal line in the RP by excluding the line of incidence. Similarly, the mesure of longest vertical line in the RP is measured through MVLL. The total number of features extracted from NC for six emotions of twenty subjects on each frequency band over six trials is 11520 × 14. Consequently, the same dimensional data is extracted from RP for PD subjects. Finally, these features are used to classify the emotions of NC and PD using classifiers.

One way analysis of variance (ANOVA) is used to perform the statistical analysis of the extracted features to calculate the significance level. The significance level has been set into $p<0.01$, and the features which give $p<0.01$ are considered as significant and used for emotion detection using PNN. Before classification, all the notable features are split into training and testing features using a fivefold cross-validation method. Here, a total number of features were divided into five equal sizes feature vector. Initially, the first four splits were used for training and the fifth set used for testing. This process will continue until all the features become a testing feature in the classifiers. Finally, the average accuracy of the feature over five folds are reported in this work.

E. Probabilistic Neural Network (PNN)

Probabilistic Neural Network (PNN) is used as a machine learning algorithms to map the emotional features into corresponding emotions. PNN classifier has four layers namely, input layer – useful for feeding the input features to be classifiers, radial thickness – helpful in finding the characteristics patters of input features, summation layer – useful for getting the output of radial layers, and output layer – helpful in getting the decision of the network corresponding to the input features [20]. PNN has been widely used in several applications in the literature and its one of the most simple and powerful machine learning tool which require a minimal number of external parameters for performance tuning. In this work, three different statistical features extracted from RQA are used to classify the emotions in NC and PD using PNN. The performance of the classifier is measured by the average emotion classification rate and individual emotion classification rate.

This present work utilizes the MATLAB software and RQA toolbox for feature extraction, SPSS toolbox is used for statistical analysis and Python – Scilearn package is used for PNN classifier implementation. The Intel i7 processor of 8th generation with 16 GB RAM working in Windows operating system is used for performing the computation.

III. Results and Discussion

This section discusses the experimental results of the proposed methodology on emotion detection in PD. This work utilized the EEG samples of six emotions from 20 PD subjects and 20 NC subjects for developing an emotion detection system. Butterworth band-pass filter of 6th order is used for removing the power line interferences and low-frequency noises from the EEGs. Later, these pre-processed signals are used to extract the non-linear features from EEGs using RQA. Three most significant features from the recurrence plot, namely, MDLL, MVLL, and combination of the above two features (ALL), are extracted from alpha, beta, and gamma bands of EEG signals. In the literature, researchers mostly used these frequency bands are mosly used for emotion detection using EEG signals.

In specific, the gamma-band features represents the more meaningful information about the emotional changes compared to alpha and beta bands [14]. The extracted features are statistically tested using a one-way analysis of variance (ANOVA) in distinguishing six emotions in NC and PD with a significance level of $p<0.01$ using the SPSS toolbox [21]. The results of ANOVA confirm that all these features are statistically significant, with $p<0.01$ with high critical value (F value>145). Later, these features were fed into the PNN classifier for emotion detection in PD and NC. In PNN, the amount of standard deviation (sigma – σ) is varied from 0.01 – 1.0 with a step increment of 0.01 using the grid search method and the value of σ at which the classifier gives the highest emotion detection rate is reported in this section. Table I shows the experimental results of the mean accuracy of all three features in three different frequency bands of EEGs in NC and PD.

TABLE I. Classification of Emotions in NC and PD using PNN

Features	Frequency Band	Mean classification rate ± Standard deviation			
		σ	NC	σ	PD
MVLL	Alpha	0.1	80.17±1.54	0.2	78.67±1.57
	Beta	0.09	83.35±1.53	0.08	78.55±0.98
	Gamma	**0.1**	**89.83±1.41**	**0.07**	**82.95±1.70**
MDLL	Alpha	0.11	80.35±0.01	0.1	78.13±0.01
	Beta	0.1	85.9±1.20	0.2	80.45±2.06
	Gamma	**0.1**	**91.38±1.04**	**0.1**	**87.55±1.15**
ALL	Alpha	0.2	80.62±0.01	0.2	78.87±0.01
	Beta	0.2	85.87±1.47	0.2	81±1.47
	Gamma	**0.2**	**90.53±1.09**	**0.1**	**86.53±1.28**

The classification results of PNN classifier confirm that gamma-band features give the highest classification rate compared to the features extracted from alpha and beta bands. Besides, PD gives the lowest emotion detection rate compared to NC. This indicates that PD subjects have an issue with perceiving emotions due to the loss of dopamine and could not differentiate the emotions. Among the three different types of features, MDLL reports higher classification rate of 91.38% in NC and 87.55% in PD. However, the MVLL and the combination of features

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efficiently detect the emotions of NC and PD, and the accuracy of emotion detection is closer to the accuracy of MDLL.

The individual emotion classification rate of emotions of three statistical features over three frequency bands is given in Fig 2 – Fig 4. In the case of alpha-band features (Fig 2), MDLL gives high accuracy in detecting sadness and fear emotions, MVLL gives high accuracy in detecting happiness emotion, and ALL features give high accuracy in identifying anger, disgust and surprise emotions. In Fig 3, MDLL and ALL features provide high efficiency in detecting all six emotions. However, MDLL gives high accuracy in detecting all types of emotions in NC and PD compared to other features, and it's high compared to other features in alpha and beta frequency bands. Thereby, a single feature is adequate in detecting different emotional states of NC and PD with a higher recognition rate. In [22], maximum diagonal line length features give the highest emotion detection rate in speech emotion recognition. MDLL and MVLL are the most common types of features which effectively capture the dynamic behavior of signals in emotion classification applications [11].

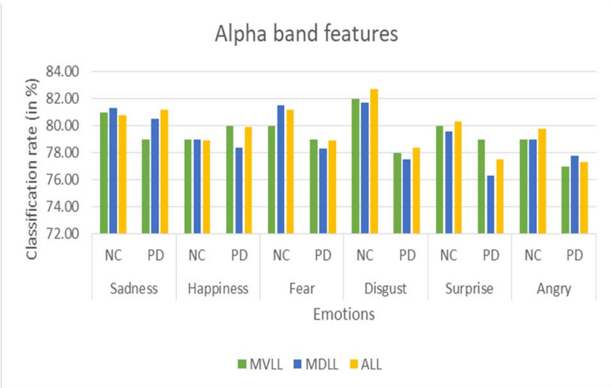

Fig. 2. Emotion classification rate of the alpha band features using PNN

In the PNN classifier, the changes in the value of sigma significantly improve the emotion recognition rate. PNN is one of the simple classifiers which needs a minimal number of external parameters (only one parameter – sigma) for tuning the classifier in mapping the features into corresponding emotions. Besides, this classifier performs well in smaller size data, such as used in this work. PNN is one of the most common types of classifiers used in emotion classification applications in the literature. In this work, the value of sigma varied between 0.01 and 0.9 with a step increment of 0.01. The value of sigma, which gives the highest classification rate, is reported. In this work, PNN offers a higher classification rate in gamma band features in NC and PD. This field of research on emotion detection in PD gained attention over recent years by neuroscience researchers. To the best of our knowledge, there is no international standard database available for comparing the performance of the present work with earlier works in the literature. Table II shows the results of previous works on emotion detection in PD. Our earlier work has started analyzing the RQA features using extreme learning machine (ELM) algorithm, and it is the first work on RQA features based emotion classification in PD and achieved a maximum accuracy of 89.17% and 84.50% in NC and PD, respectively [13]. This present work utilizes PNN classifiers and the same RQA features used in our earlier work and achieved a maximum classification rate of 91.38% and 87.55% in NC and PD, respectively. Thereby, the proposed methodology confirms, the RQA features are highly efficient in capturing the emotional state changes in PD, and the PNN classifier is a simple nonlinear classifier that effectively maps the sensitive features into corresponding emotions with less computational complexity than ELM.

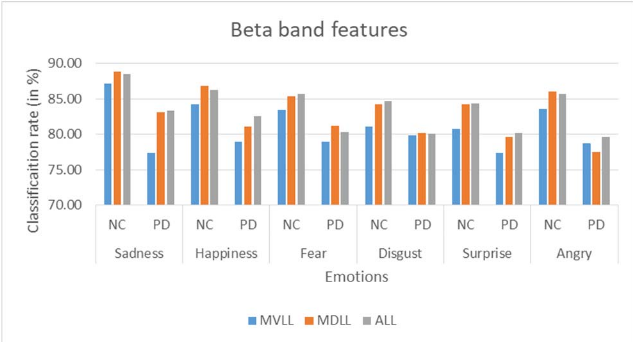

Fig. 3. Emotion classification rate of the beta band features using PNN

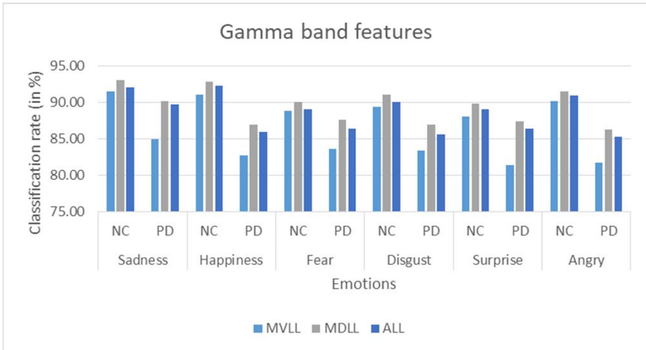

Fig. 4. Emotion classification rate of the gamma-band features using PNN

Although the proposed work achieved higher emotion recognition rate in NC (>90%) and PD (>87%), the present work should consider the following as future works for developing robust emotion detection system, (i) more samples (NC and PD) are essential for testing and validating the proposed method (ii) aims to analyze other types of RQA features. Also, other nonlinear feature extraction methods such as detrended fluctuation analysis (DFA), fractal dimension (FD), etc. (iii) the feature selection methods could be implemented to reduce the computational complexity of the present emotion detection system, and (iv) different machine learning algorithms such as support vector machine (SVM), random forest (RF), decision tree (DT), etc. classifiers for emotion detection could be used.

IV. CONCLUSION

This work aims to develop a methodology for automated emotion detection in PD using EEG signals. Though the EEG signals are highly nonlinear and nonstationary, this work examined the potential of nonlinear features from RQA to detect the emotions in PD and compared with NC. The three most significant features of the recurrent plot through RQA analysis such as MDLL, MVLL, and combination of MDLL and MVLL are used for extracting the meaningful information about emotional state changes in

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PD and NC subjects. These features are extracted from three different EEG frequency bands (alpha, beta, and gamma), and classified using a probabilistic neural network (PNN) classifier. The MDLL feature achieved a high emotion detection rate in both NC and PD compared to our earlier works. The preliminary investigation confirmed that the nonlinear characteristics of emotional EEG signals in the gamma frequency band could be used as a potential feature for emotion detection in PD. Besides, the results also confirmed that the PD subjects have an impairment in recognizing the emotions compared to normal control.

The future work aims to investigate other types of RQA features, different machine learning algorithms for emotion detection in PD. Furthermore, the future work aims to explore the possibilities of developing intelligent real-time emotion impairment detection systems for PD to assist the clinicians for better diagnosis and treatment. Besides, the proposed methodology will investigate its potential in emotion detection with more number of samples collected from PD in the future.

TABLE II. COMPARISON OF EMOTION CLASSIFICATION PERFORMANCE OF PROPOSED METHOD WITH EARLIER WORKS

Ref	Mean (in %)		Happiness (in %)		Sadness (in %)		Anger (in %)		Fear (in %)		Disgust (in %)		Surprise (in %)	
	NC	PD	NC	PD	NC	PD	NC	PD	NC	PD	NC	PD	NC	PD
[8]	87.34	83.70	90.27	85.85	90.29	78.87	77.29	90.84	89.20	80.32	88.05	78.96	88.98	87.36
[9]	71.79	51.66	Not available											
[10]	81.72	82.70	89.26	91.25	76.65	83.35	81.70	80.37	79.25	80.50	70.25	73.50	93.25	87.28
[14]	89.17	84.50	90.90	87.50	91.10	84.30	88	84.10	88.5	82.70	87.4	84.60	89.10	83.80
[15]	**91.38**	**87.55**	**92.80**	**86.90**	**93.10**	**90.20**	**91.10**	**86.90**	**90.00**	**87.60**	**91.50**	**93.10**	**89.80**	**87.40**

ACKNOWLEDGMENT

The authors would like to thank the Kuwait Foundation of Advancement of Sciences for funding this project through an exploratory research grant. (No: PR18-13MM-08).

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