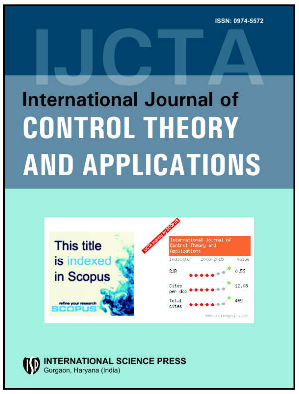

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A Survey on Image and Signal Processing Techniques to Ferret Parkinson's Disease

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Abstract: Parkinson's disease (PD) is a neurodegenerative disorder of the central nervous system. In modern days, research in the field of PD has advanced tremendously. Researchers are trying to find the cause of PD so that it can be terminated before it progresses. Researchers are also trying to reverse the symptoms to re-instate the lost functions. In this paper, an exhaustive survey for identifying PD has been conducted from 2004 to 2016. This work gives a deep understanding on the processing techniques used to automatically identify PD. The survey portrays the processing techniques such as pre-processing, feature extraction, feature selection and classification and how these techniques are used on image and signal data to identify PD.

Keywords: Parkinson's disease, pre-processing, feature extraction, feature selection, classification.

1. INTRODUCTION

In the present era, the economic burden of chronic diseases is increasing day by day due to decreased quality of life and high health care cost. To an extent, these burdens can be minimized through preventive measures, such as following a healthy lifestyle and identifying these diseases as early as possible. Despite the remarkable advancement in the medical field, there are no early detections for Alzheimer, arthritis, depression, psychiatric disorders, PD and urinary incontinence. In this paper, a survey study to identify PD is attempted.

PD is a neurodegenerative disorder [1] which means that the symptoms will grow over time. This disease mostly affects people above the age of 60. PD is associated with motor system disorders. PD normally occurs when the neurons die or malfunction in the substantia nigra of the brain. Neurons produce a chemical called dopamine which helps to control and coordinate movements. As these neurons die or malfunction the amount of dopamine produced will be less. As a result, the person will be unable to control and coordinate movements.

PD is currently diagnosed using clinical criteria. The major clinical symptoms used for diagnosing PD are tremor, rigidity, bradykinesia and postural instability. Other symptoms of PD are depression, difficulty in swallowing, chewing, speaking, constipation and skin related problems. At the later stages, people may face difficulty in walking, talking, etc. The current disease rating scales to diagnose PD are Unified Parkinson's disease rating scale, PD non-motor symptoms questionnaire, Hoehn and Yahr scale, PD non-motor symptom survey, etc. Using these rating scales to identify PD is difficult, particularly to diagnose in its early stages. Therefore it is important to identify PD automatically by using machine learning techniques. Use of these types of techniques, increase the prediction accuracy and help the doctors to make the best decision.

Currently, PD is not curable, but there are some medications that are available to control these symptoms. Levodopa, bromocriptine and pramipexole are some of the medicines that simulate the action of dopamine, allowing the neurons in the brain to respond as they would to dopamine. There are chances that these medicines will not respond to the symptoms. In those cases, surgery can be an alternate option. A therapy called as the Deep Brain Simulation (DBS) can be performed. In this therapy, electrodes are attached to the plus generator which is a small electrical device and this is inserted into the brain. DBS can be programmed externally.

This paper is organized into different sections. Pre-processing techniques applied in the previous work are summarized in section II. Section III gives an idea on feature extraction and selection. Classification is summarized in section IV and the paper is concluded in section V.

2. PRE-PROCESSING

In this phase, the data is pre-processed to remove unwanted information before it is further processed. The main objective of pre-processing is to improve the quality of the data. The different techniques used in pre-processing which are mentioned in the literature are summarized in this section.

Mona K Beyer et al. (2007) [2] have used Voxel-Based Morphometry (VBM) analysis for MR image data pre-processing. The steps involved in this process are as follows: the first step is to create a customized template. Images are normalized with the template provided by the statistical parametric mapping. The normalized images are segmented and then smoothed using a kernel and the result of the smoothed image is applied in the statistical analysis. Giduthuri Sateesh Babu et al. (2013) [3] have used unified segmentation model based on VBM analysis for pre-processing the MR images. The three steps in this process are as follows: unified segmentation, smoothing and statistical analysis. In unified segmentation step, they have combined tissue segmentation, bias correction and image registration. Smoothing step is applied to the segmented and registered gray matter images using gaussian kernel. The general linear model has been used for statistical testing. They have used gray matter volume to design a covariant matrix for this model. Zacharaki et al. (2009) [4] have pre-processed the MR images using the following techniques: noise reduction, bias field correction and rigid intrasubject registration. Mojtaba Zarei et al. (2013) [5] have used Freesurfer software for MR image analysis. The process includes motion correction, hybrid watershed deformation procedure which are used for removing non-brain tissues, automated Talairach transformation, segmentation, intensity normalization, tessellation of gray matter and white matter boundary, automated topology correction and surface deformation. When the cortical models are completed the authors have performed further data processing and analysis which includes surface inflation, spherical atlas registration, parcellation of the cerebral cortex and creating a variety of surface based data which includes maps of curvature and sulcal depth.

Ehsan Adelia et al. (2016) [6] have used MR images in the pre-processing phase. The pre-processing techniques used are skull stripping, cerebellum removal and tissue segmentation. The tissue is segmented into Gray Matter (GM), White Matter (WM) and Cerebrospinal Fluid (CSF). Hongcheng Liu et al. (2016) [7] have used different pre-processing techniques on MR images. As an initial level of dimensionality reduction, the authors have used a fully automatic atlas-based segmentation algorithm to parcel the brain volume into Region Of Interest (ROI). They have used the AutoSeg tool to segment the MR images to get the ROIs. The authors have also used DTIPrep tool to analyze the raw Diffusion Tensor Images (DTI). For pre-processing the patient's records, Sandhya Joshi et al. (2010) [8] have first checked the data for missing values and incorrect values. They have collected the data from Alzheimer's Disease Research Center (ADRC) and 40 % of the patients were diagnosed with PD. In their study, the authors have preprocessed the data by converting the data in alphanumeric type to numeric form.

Bharti Rana et al. (2015) [9] have used Statistical Parametric Mapping version 2008 (SPM8) for MRI image pre-processing. They have first converted the DICOM (Digital Imaging and Communications in Medicine) images to 3D Nifti format. Then with the help of the template provided by the SPM8 the images are spatially normalized. Segmentation is carried out with the normalized images. Unified segmentation routine of SPM8 is used to segment the images into GM, WM and CSF. To preserve the local volume of the tissue, modulation is performed. To correct noise and small variations, the images are spatially smoothed. YanBing Hou et al. (2016) [10] have used SPM8, resting state fMRI analysis toolkit and pattern recognition toolbox for functional image pre-processing and statistical analysis. Two hundred fMRI images are used for the study. The first, ten images are rejected due to signal equilibrium and participants adaptation to scanning noise. Pre-processing is done with the remaining 190 images using the following methods: slice timing, motion correction, spatial normalization and smoothing. Ludovica Griffanti et al. (2016) [11] have used FSL software package for analyzing the resting state fMRI data. For pre-processing, the authors have used the following techniques and they are - brain extraction, unwrapping using the fieldmap data and gaussian kernel which is used for spatial smoothing and high-pass temporal filtering.

Ruben-Dario et al. (2009) [12] have used Microelectrode Recordings (MER) database in their study. Before analyzing the MER signal, the authors have tried to reduce the electrical noise of the raw data by using a preamplifier which is located near the electrode. After the data is amplified, the signal is sampled at a sampling rate of 24 KHz with an analog to digital converter. Then the authors have used an artifacts detector to discard the incorrect entries in the MER signal which is caused due to the movement of the patient. Decho Surangsrirat et al. (2016) [13] attempts to differentiate tremor in PD and Essential Tremor (ET) using tremor signals. They have collected the tremor signals during kinetic and resting state by attaching a triaxial gyroscope sensor to the patient's finger. The authors have preprocessed the tremor signals by filtering the signals with a 10^{th} order butterworth filter and a band pass filter with cut-off frequencies of 3 Hz and 10 Hz. This is done because the PD and ET tremor frequencies are overlapping and also to remove the low-frequency high amplitude movement during the kinetic task. This section gives an idea of the pre-processing techniques used in the previous work. Some of the image pre-processing techniques used for analyzing the data are SPM8, VBM analysis, Freesurfer software, FSL software package, etc.

3. FEATURE EXTRACTION AND SELECTION

Feature extraction is done immediately after pre-processing. Feature extraction is the process of identifying relevant information from the cleaned data. The feature extraction methods used in the previous work are summarized in this section.

Somkait Udomhunsakul et al. (2004) [14] have proposed a feature extraction approach in medical MR imaging. The authors have first removed the noisy pixel by using the spatial and gaussian filters and then the edge detection algorithm is applied. The coefficient details are combined using wavelet transform. To get the final results, the nonmaxima suppression technique is used. The authors have concluded that this method is a useful method for extracting the features in MR images. Yudong Zhang et al. (2010) [15] have extracted the brain MRI features using stationary wavelet transform. In their study, they have compared discrete wavelet transform and stationary wavelet transform. The authors have concluded that the stationary wavelet transform provides a better outcome than discrete wavelet transform with regard to translation invariant property. Sheethal M.S et al. (2013) [16] have used wavelet transformation tool for extracting feature from brain MR images. This tool is expensive and requires large storage space. The authors have used Principal Component Analysis (PCA) procedure for feature reduction. This technique is used to increase the discriminative power and to reduce the dimension of the feature vector. Giduthuri Sateesh Babu et al. (2013) in their work have used the VBM analysis for extracting features from MR images. The authors have used VBM analysis based on unified segmentation model in this study. The steps in this approach are unified segmentation, smoothing and statistical analysis. From the VBM analysis, 2981 features are extracted and this is given as an input to the classifier. The features extracted from the VBM analysis is further reduced by Independent Component Analysis (ICA) feature reduction approach because of the difficulty in predicting PD accurately, as the feature space is high compared to the number of samples in the VBM extracted features. The authors have employed FastICA algorithm to reduce the 2981 features detected using the VBM analysis to combinations of 10 and 50 features.

Bharti Rana et al. (2015) have identified the ROIs in MR images using WFU Pickatlas tool. This tool eliminates the errors which occur while choosing the ROI's manually. In their study the authors have extracted features independently from GM, WM and CSF as follows: features are extracted from individual ROIs, from ROIs in pairs and from ROIs in triplets. For feature selection, the authors have introduced two approaches. The first approach uses the t-test based feature ranking method and this is a univariate approach. The second approach uses mutual information in combination with t-test ranking and this is a multivariate approach. These approaches aid in selecting relevant and non-redundant features. Ehsan Adeli et al. (2016) have used a joint feature-sample selection method for selecting relevant features from MR images. This model helps the authors to identify the relevant features and to discard the redundant features. The extracted features help in improving the learning process.

To remove irrelevant features from the voice dataset Meilin Su et al. (2015) [17] have used a dynamic feature selection approach with respect to fuzzy entropy measures. Hamid Azadi et al. (2015) [18] have used the speech dataset in their study. To rank the features for each specific gender the authors have proposed a gaussian mixture model.

Sandhya Joshi et al. (2010) in their study have considered eleven attributes from their data set. Selection of the most relevant attributes is based on attribute selection technique. Ranker technique is used for selecting the attributes. The authors have used five different attribute evaluation methods in the study and they are chi-squared attribute evaluation, gain ratio, info gain attribute evaluation, one R attribute evaluation and symmetrical uncertain attribute evaluation. Peter Drotár et al. (2015) [19] have used Mann-Whitney U-test to remove irrelevant features and to reduce the input data dimensionality from the handwriting dataset. The features are kept only if they pass the Mann-Whitney U-test with a significance level less than 0.05. As a result, the authors have selected 203 features for further processing. Marziye Keshavarz Shahsavari et al. (2016) [20] have proposed a hybrid Particle Swarm Optimization (PSO) method for selecting the relevant features from the dataset. In this approach, a local search operator is applied to improve the particles located near the local and the global optima. As a result of applying the local search operator on the local optima, particles are forced to jump over the local optimal solution and when the operator is applied on the global optima it causes the particles to converge to the solution.

The purpose of this section is to find out the feature extraction and selection techniques used in the literature. Some of the common techniques used in the literature to extract the features are spatial and gaussian filters, stationary wavelet transform, WFU Pickatlas tool, etc. From the extensive literature study done it can be seen that most of the literature has commonly used MR images and voice data for feature extraction.

4. CLASSIFICATION

Image classification is a process of labelling the images into a predefined category. Different types of classification techniques used in the previous work is summarized in this section.

Sandhya Joshi et al. (2010) have used different classification techniques such as neural networks and machine learning in their study. In their paper, the authors have used six different types of machine learning methods and they are random forest tree, bagging, decision tree, BF tree, multilayer perceptron and Radial Basis Function (RBF) networks. In the study the random forest tree and the multilayer perceptron classification model have gained an accuracy of 99.25 %. F. Segovia et al. (2016) [21] have evaluated three classifiers to identify PD automatically. The classifiers used are random forest classifier, K-Nearest Neighbour (KNN) and Support Vector Machine (SVM). Marziye Keshavarz Shahsavari et al. (2016) have used Extreme Learning Machine (ELM) to classify the PD patients. ELM is a type of feed forward neural network with a single hidden layer. The authors in this work compares ELM with other classification methods. The study shows that the proposed ELM model has achieved a classification accuracy of 88.72 %. Bjoern M. Eskofier et al. (2016) [22] have mainly concentrated on identifying Bradykinesia. The authors have compared standard machine learning pipelines with deep learning with regard to convolutional neural networks. The study shows that deep learning gives better result over the machine learning algorithm by 4.6% of improved classification rate.

R. Arefi Shirvan et al. (2011) [23] have used KNN classification method to classify the data. Ketan Machhale et al. (2015) [24] have tried to find out normal and abnormal brain MR images. The authors have used SVM, KNN and a combination of SVM and KNN machine learning techniques for classification. From the study, it is found that the highest classification accuracy of 98% is achieved by combining SVM and KNN classifiers. Wahyu Caesarendra et al. (2014) [25] have used SVM for classification. In their study, the authors have found out the classification accuracy in single features, PCA features and Linear Discriminant Analysis (LDA) features. The result shows that the classification accuracy is best in PCA features than LDA and single features. Peter Drotár et al. (2015) have used SVM classifier with the radial gaussian kernel for identifying PD automatically. The classifier is fed with the selected features to diagnose PD. In their study, the authors are able to achieve a classification accuracy of 88.13 % with high specificity and sensitivity values.

Decho Surangsrirat et al. (2016) have used SVM for classification. A 10-fold cross validation is used to test the performance of the classifier. The study shows that the novel features could separate PD and essential tremor patients with 100% accuracy. R. Prashanth et al. (2015) [26] have used four classifiers on SPECT scanned data to identify PD. The classifiers used are SVM, boosted tree, random forest model and naïve bayes. Their study proves that SVM classifier performs better than the other classifiers with a classification accuracy of 97.25%. Wahyu Caesarendra et al. (2015) [27] have used voice feature for multi-stage PD classification. The voice features are extracted by using PCA and LDA. In their study, they have found that PCA feature extraction is better than LDA feature extraction. The authors have used SVM, KNN, adaptive boosting and adaptive resonance theory-kohonen neural network classifiers and these are compared to find the best classifier. The result shows that SVM classifier is better than the other classifiers with a classification accuracy of 79.17 % (for PCA feature extraction) and 29.17% (for LDA feature extraction). To distinguish between PD and healthy people Meilin Su et al. (2015) have used the LDA classifier on the voice dataset.

The aim of this section is to summarize the classification techniques used in the previous work. In the literature, the commonly used classification techniques are SVM, KNN, artificial neural network, decision tree, etc. With the help of these techniques, it is possible to identify if a person is suffering from PD or not.

5. CONCLUSION

This paper gives an overall idea on the processing techniques used on image and voice dataset for identifying PD. A survey of the previous work have been done to find out the common techniques used by other researchers. The most common techniques used in pre-processing, feature extraction, feature selection and classification are explicitly discussed in this paper, helping one to select the best available techniques from the literature. Use of these techniques helps in identifying PD automatically which indeed helps the physicians to diagnose the disease accurately.

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