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Diagnosis of Parkinson's disease using Gait Dynamics and Images

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Abstract

Parkinson's disease is a neuro-degenerative disorder in which dopamine producing neurons in the brain structure called substantia nigra has damaged entire over time. PD leads to number of modal problems and mental disabilities. This paper presents a gait dynamic technology for the early stage prediction of Parkinson's disease and a discussion on the Image processing technologies related to PD diagnosis. The analysis of gait in Parkinson's disease helps to understand the behaviour of the neural system and so the early detection of Parkinson's disease is possible. This can help neurologists to improve their treatment and to give guidance in reintegrate programs. This paper introduces an efficient multi-sensor data analysis of gait force in PD with respect to healthy subjects using PARAFAC model. Tensor decomposition is proposed in the work for the analysis of multi-sensors data. The data are collected from PhysioNet gait database consist of multichannel recording from force sensors of 93 patients with PD and 73 healthy subjects.

Keywords: Parkinson's disease (PD); Substantia Nigra; Gait Dynamics; Parallel Factor Analysis (PARAFAC); Tensor decomposition.

1. Introduction

Parkinson's disease (PD) is a movement disorder with the dopamine producing neuron in substantia nigra of the brain undergoes degeneration. Dopamine is the neurotransmitter that sends signal which control the activity of muscle movement. PD is one of the common neurological disorder and progressive adult onset disease. The cause of

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PD is usually not known, but sometimes it's because of some genetic factors. In worldwide more than 10 million people are suffering from this disease and in India is around 247 out of 100000 is suffering from PD. The count of PD affected people is increasing day by day and expected to be happen more than double the current count by the year of 2030 [1]. The below figure 1 shows the structural difference between a Healthy Brain and a Parkinson's Brain, where PD brain with diminished substantia nigra.

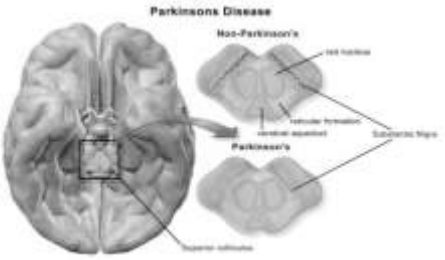


Figure 1. Structural difference between a Healthy Brain and a Parkinson's Brain [39]

The death of dopaminergic neurons in substantia nigra leads to the occurrence of PD. In PD the patient will have a diminished substantia nigra. The clinical features of PD are involuntary shakiness, rigidity, difficulty in movement and postural instability. The chance of getting Parkinson's disease increases with age. A critically disturbed gait can lose their postural balance and coordination, voice disorder etc. [3, 4].

2. Literature Survey

In this paper the survey is carried out into sections: Using gait dynamic technology and using image processing technique. The first section of the literature survey portrays how the Gait analysis technology used in the diagnosis of Parkinson's disease and the second section about image processing.

i) Gait Dynamic Technology

With the advancement of sensor technology in health monitoring that grabs the interest of researchers and leads to analyse health of patients for various causes. Different works based on the Gait dynamic technology is discussed below:

Jeffrey M Hausdorff, et.al [4] described typical gait changes seen in PD patients and find that stride length, fractal scaling and gait variability were impaired. The main focus was to update the gait properties like correlation and fractal measurements in PD to identify the relation between features of gait with other properties. It opens the way to further study to better map these properties with the progression of PD on various probes.

Wu and Krishnan, et.al [5] proposed a five step procedure to estimate the gait variability in patient with PD. They estimated probability density function of stride, swing interval and stance intervals using parzen window. It was found that parameters of stride interval were highly associates with swing interval. The stride intervals were used to form feature vectors for classification using LS-SVM with polynomial kernels and got accuracy of 90.32%.

Khorasani and Daliri [6] used hidden Markov model for modelling the raw gait data with Gaussian mixture to classify PD patient from the healthy subjects. The model could effectively classy the gait data with an accuracy of 90.3% in terms of stride interval of PD patient and healthy subjects. The dimensions of gait dataset used were low. It was consistent with 16 healthy and 15 PD subject so proposed model is not generalised.

Su. et.al [7] proposed gait asymmetry measures the difference in the walking pattern of PD and healthy subjects. This was measured by comparing ground reaction force (GRF) features of left and right feet or hand. The wavelet transformation used in the proposed work decomposes the GRF into different frequency components with an accuracy of 86.2%.

Zeng and Wang [8] proposed a method to evaluate the difference in Parkinson disease subjects and healthy subjects using gait analysis using the principle of deterministic learning. The method consists two phases: i) training phase and ii) classification phase. Radial basis function (RBF) helps to generate gave gait patterns from gait. In the classification phase, estimators were having prior knowledge of all training patterns. The test gait pattern is compared with the sets of trained gait pattern of PD patients. The accuracy of this method is 96.39%.

Muniz and Nadal [9] demonstrated gait analysis using PCA with 38 healthy subjects and 13 subjects in lower limb fracture, where 5 out of 13 were evaluated after physiotherapeutic treatment (FGA) to determine normal and abnormal gait. The parameter GRF was considered in this study. The PCA give additional insights into gait analysis. The Principal component coefficient (PCC) was obtained by SVD using parameter GRF of complete stride. The main classification was given by first PCC, which point out to the higher loading factor. The performance of classification with two PCC was 92.2%, 94.1% with four PCC and 96.1% with six PCC. Definitely, there would be a chance of further improvement in performance by increasing number of subjects, nonlinear classifiers and more gait variable.
Pham, et.al [10] presented an approach which was quite different from conventional methods for gait analysis by changing the data from time series to images. They used fuzzy recursion plot algorithm to change time series data into images and then applied texture analysis to retrieve the texture features from image and GLCM (Grey-Level Co-occurrence Matrix for pattern analysis for the classification of healthy subjects and PD. They used right stride interval data of 4 groups that shows the performance of proposed approach.

ii) Image Processing Technology

Now a day's Image processing technology is mainly focus on the automation for classifying different categories in medical (diagnosis of diseases), agricultural (categorizing pests), weather forecasting fields etc. This paper mainly focus on the diagnosis of PD (a kind of dementia) to assist a doctor for a better treatment. Different works based on the image processing technology for detecting the presence of Parkinson's disease is discussed below:
Aprajita, et.al [11] used component extraction and unsupervised bunching procedures in MRI images. They used a self sorting out guide (SOM) algorithm for grouping the pixels to recognized classes that distinguished classes are Normal or PD. Parkinson's ailment gets determined in cerebrum stem portion with the help of Clustering method. The main advantage is that by using the Neuro Fuzzy approach with SOM overcomes the limitation of Artificial Neural Network.
R. Prashant, et.al [12] presented the ongoing neuro- imaging strategies, for example, dopaminergic imaging use Single Photon Emission Computed Tomography (SPECT). They identified the disease in its beginning stage itself. They utilized the Striatal Restricting Qualities (SBR) that was ascertained from the PPMI (Parkinson's) database. SVM grouping classified whether the person influenced by Parkinson's disease.
Shaohua Wan, et.al [13] proposed a deep multi-layer Perceptron (DMLP) for the behaviour analysis to estimate the progression of PD using cell phones. The behavioural information is gathered with cell phones and physically marked as sitting, standing and walking activities for accelerometers and gyroscopes. Butterworth low-pass filter is used to denoise and standardize the data. At long last, the component vector made out of include values was utilized as preparing information. Deep learning is applied here for the classification of single person behaviour activity movement gathered from cell phones to PD or healthy case.
He-HuaZhang,[14], proposed grouping algorithm that includes a multi-edit nearest neighbour (MENN) algorithm and an ensemble learning algorithm. The MENN algorithm was connected to carry on ideal preparing discourse tests iteratively. Next, a group learning calculation, random forest (RF) or decorrelated neural network ensembles (DNNE) was utilized to create prepared samples from the gathered preparing tests. In conclusion, the prepared group learning algorithms were connected to the test samples for PD characterization. This proposed technique was analyzed utilizing public datasets and compare with other algorithms for validation.
Yue PENG et.al worked to do traditional Medicine Diagnosing Parkinson's Disease using Entropy Chain Multi-Label Classifiers. In algorithm they used were classifier chains. The advantage of that work was low memory consumption. Main drawback of the method was less accuracy compared to other automated approaches [21]

3. Proposed Work

A. Method – Using Signals

Tensors are generalization to higher dimensions and can consequently be treated as multi-dimensional field. Tensor decomposition helps to expose hidden lower dimensional structure in the tensor. Tensors are referred to multipath arrays with functions of multiple indices like (i,j,k,……). The applications of tensors are there in the field of data mining, signal processing, machine learning, big data analytics, statistics etc.

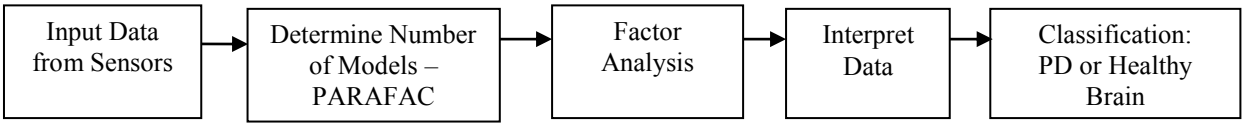


Figure 2: Flowchart for PARAFAC model working on gait analysis

The overall approach of gait analysis for the diagnosis of PD using parafac model is illustrated in Figure 2. The main idea in parafac model is generalization of PCA to higher order arrays, but some of the characteristics of the method are quite different from the ordinary two-way case. Tensor decomposition mainly consists of two different models; i) Canonical Polyadic Decomposition (CPD) or PARAFAC and ii) Tucker Decomposition [15]. The basic steps are to input the multi-way sensors data of subjects to parafac model for parafac analysis with the desired number of components. Model will generate factors of loading matrices then the factor analysis will be applied to find the pattern in the data so that the interpretation of data can help to classify the healthy subjects from those Parkinson's disease subject.

i) Canonical Polyadic Decomposition model (CPD) using ALS algorithm

CPD is a decomposition method, compared to bilinear PCA and also meant as generalization of bilinear PCA. Another name of CPD model is PARAFAC, which stands for Parallel Factor Analysis is given in figure 3. Parafac decomposes tensors of multi-sensor data of higher order arrays with the generalization of PCA. The key concept of Parafac is to express sum of one ranked tensor. The principle of Alternating Least Squares (ALS) [16] algorithm is used in parafac model to estimate the unknown set of parameters by the assumption using known set parameters The ALS algorithm works successively initialize with loading of two modes, find the unknown parameters of last mode, and discover all unknown set of parameters until convergence with small changes. Tensor decomposition of the gait dynamics time series of PD and Non PD with no limitation imposed on loading of four different modes of tensor models.

ii) Tucker Decomposition using HOSVD

In tucker decomposition model, tensor decomposes into core tensor (G) and multiple matrices (A, B, C) which correspond to different core scaling along each mode. It is also known as higher-order PCA. Tucker decomposition is ones turn model, which is based on the possibility of expressing a tensor as the result of n-mode product of another tensor of equal size with different matrices.

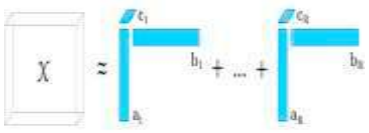


Figure 3: Canonical Polyadic Decomposition

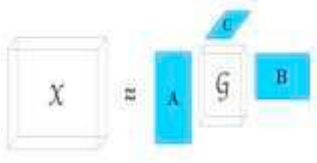


Figure 4: Tucker Decomposition

In Figure 4, G is the core tensor, which shows how different tensor element interacts with each other. Principal components in tensor modes are A, B and C. Tucker decomposition works on the concept of n-rank where n denotes the number of mode used in model. The n-rank of tensor is similar to the column rank of n^{th} unfolding of tensor. This model uses higher order singular value decomposition (HOSVD) to find the best component that captures the variation in mode n.

Algorithm steps to be followed for the diagnosis of PD using Gait dynamics is portrayed below:

Dataset: 4-mode tensor (subjects, feet, sensors, VGRF - vertical ground reaction forces)
//All 4-modes are considered at a time in tucker decomposition model.

For each mode, find the A(n) principal component by leading left singular vector of X(n) tensor then core tensor (G) will be the product of X-tensor with all principal component of A without considering other modes.

Repeat until little changes noticed then we can see the classification of Parkinson's and Healthy category.

Method: Using Images - Discussion

For the diagnosis of PD, scanned brain images like MRI (Magnetic Resonance Imaging), PET (Positron Emission Tomography), and SPECT (Single Photon Emission Computed Tomography) can be used. Structural MRI captures intensity at each point of the human brain, Functional MRI measures the activity from changes in blood flow in the brain, SPECT take snapshots of cerebral blood flow and PET is used to observe metabolic process in the body, synaptic activity of neurons etc. The different brain image datasets are processed with most efficient artificial intelligence algorithms [18, 19].

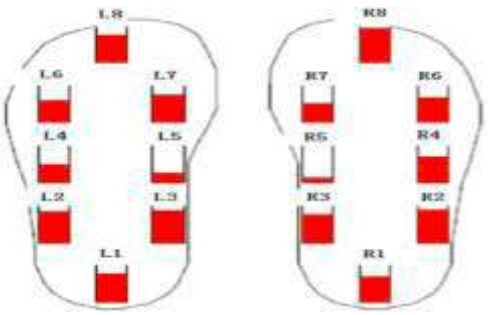
The different steps included in the analysis of digital imaging are:

1) Image acquisition;
2) Pre-processing
3) Feature extraction and reduction;
4) Classification
5) Training and Testing

For Image acquisition, any one of the scanned brain image dataset can be selected. While capturing the scan of the patient there is a chance of adding some noises with it. Noise propagation is affected by scan time, machine type, acquisition mode, distribution of tracer etc. For noise removal and enhancement, the images are pre-processed one by one. Image segmentation is used to convert a digital image into multiple segments. There are number of features available for a digital image like edge, corner, ridges, colours, textures, shapes etc. Proper feature extraction and reduction algorithm helps to select appropriate features for the work. The classification algorithms help to classify the images with proper training methods.

4. Performance Analysis – Gait Dynamics

The database used in this study is downloaded from the public domain of physionet using internet resources [11]. The database record consists of gait with 93 PD patients (56 male and 37 female) and 73 healthy controls (39 male and 34 female). For this dataset, we used 4-mode tensor for the gait dynamics in healthy and Parkinson disease subjects. The four different modes selected are subjects, feet, sensors and VGRF (Vertical Ground Reaction Force). For healthy subjects, first mode vector value is the number of healthy subjects, second-mode vector value is equal to two (left and right), third-mode vector whose value is equal to number of sensors and the fourth-mode vector whose value is equal to the number of VGRF time series of healthy subjects. Similarly, for Parkinson's disease, model gets all mode values.



Sensor	X	Y
L1	-500	-800
L2	-700	-400
L3	-300	-400
L4	-700	0
L5	-300	0
L6	-700	400
L7	-300	400
L8	-500	800
R1	500	-800
R2	700	-400
R3	300	-400
R4	700	0
R5	300	0
R6	700	400
R7	300	400
R8	500	800

Figure 5: Vertical Ground Reaction Force for 8 sensor location under each foot[17] Figure 6 : Locations of 8 load sensors on each foot where "L" and "R" denotes left and right respectively[11].

The sensors location in insole of shoe is represented in figure 5 and a record of 8 load sensors on each foot where "L" and "R" denotes left and right is represented in figure 6. The X, Y coordinates are in arbitrary system which shows the relative positions of sensors that are used insole while working, the sensors are always remains on the same position in insole and individual output is digitally recorded at frequency of 100 Hz.

In the below illustrated figure 7 and 8 show the output of first 20 seconds VGRF time series data with 8 sensors on right foot of Healthy and Parkinson disease subject respectively. There are two type of gait first is normal gait and another is abnormal gait. In normal gait, the VGRF signal shows two peaks, first when heel strikes the ground and second when toe pushed off from the ground that can be seen in figure 7 sensor 8 under the right foot. Generally,

the magnitudes of VGRF signals of healthy subjects are greater than those of PD subjects because of the phases, when subject push off toe from ground and hit heel on the ground.

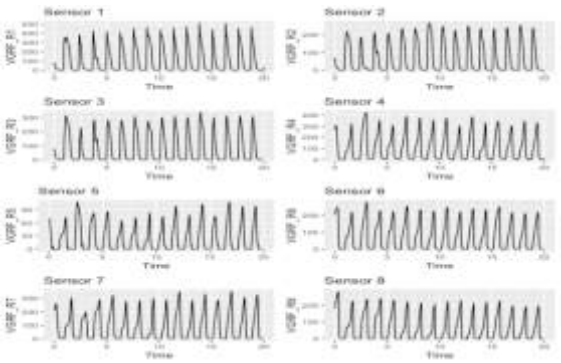


Figure 7

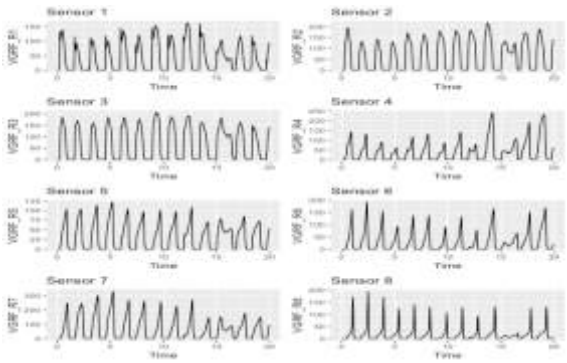


Figure 8

Figure 7 (Left Side): Vertical Ground Reaction Force (VGRF) in Newton of first 2000 instance of time in seconds with 8 sensors placed under right foot of healthy subject.

Figure 8 (Right Side): Vertical Ground Reaction Force (VGRF) in Newton of first 2000 instance of time in seconds with 8 sensors placed under right foot of patient with Parkinson Disease.

After studying the data of 93 PD patient and 73 healthy subjects of multi-sensors gait recorded output with three different methods. We plot the first 2000 instance of time to find some observable differences in the dataset. We have seen a difference in sensor records of R4 of PD and healthy subjects. We apply the parafac model and tucker decomposition models to the data to find the factors and the analysis of factors leads to some pattern in data for classification of healthy subjects from those of PD patients and gets an accuracy of 97%.

For the comparison of results we studied [6, 7, 9] and came with the accuracy value and compared with our proposed system works with PARAFAC and Tucker Decomposition is given in table 1.

TABLE 1: Comparison of performance of proposed work with some existing systems

Method	No. of Modes	Accuracy
PARAFAC + Tucker Decomposition (Proposed)	4	97%
Wavelet Transform + Multilayer Perceptron Neural Network [7]	1	86.2%
Hidden Markov Model + Gaussian Mixture [6]	1	90.3%
PCA [9]	6	96.1%

5. Conclusion

For detection of Parkinson's disease, we saw many techniques that used in past few years. From that we studied diagnosis of any dementia there is a need of inexpensive and efficient technique. Tensor decomposition models for gait dynamics in Parkinson's disease and Healthy subjects can efficiently classify the healthy subjects and PD subjects with less time and good accuracy. It can explore hidden relationship of tensor decomposition factors of Healthy and PD subjects. It can also help to enhance the performance of machine learning by reducing the computation time as tensor decomposition methods for their fast computations.

6. Future Work

To develop the tensor model for gait dynamics in Parkinson's disease for multi-sensors time series data and to make use of image processing technologies for the classification of different types of dementia with help of

scanned images.

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