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HMM BASED PARKINSON'S DETECTION BY ANALYSING SYMBOLIC POSTURAL GAIT IMAGE SEQUENCES

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Abstract— **Detection of Parkinson's disease (PD) at an early stage is necessary for its treatment. The commonly used methods available in the literature use observation of certain symptoms such as Tremor, Loss of Smell and Troubled Sleeping, Moving or Walking. The motion pattern in this disease can be characterized by a spatio-temporal phenomenon that signifies gait recognition as reported in the literature. However, non-invasive methods such as use of Gait image sequences are handy in terms of cost and comfort. In this paper we propose a statistical approach for detection of Parkinson's diseases by considering segmental feature of gait image sequences by using Hidden Markov Model (HMM). A set of key features from the image frames is identified during the gait cycle. The input binary silhouette images are preprocessed by morphological operations to fill the holes and remove noise. An image feature vector is created from the outer contour of the image sequences. From the feature vectors of the gait cycle, a set of initial exemplars is constructed. The similarity between the feature vector and the exemplar is measured by the inner product distance. An HMM is trained iteratively using the Viterbi algorithm and Baum-Welch algorithm and then used for detection of Parkisonian gait. The characteristics of one dimensional HMM best fit to one dimensional image vector thus the proposed method reduces image feature from the two-dimensional plane to a one-dimensional vector. The statistical nature of the HMM makes it robust to PD gait representation and recognition. The proposed HMM-based method in LabVIEW and MATLAB is evaluated using the CMU MoBo database as well as our own prepared database for PD detection.**

Keywords— **Pattern classification, sequential data, similarity measure, Hidden Markov Model and Parkinson's disease.**

I. INTRODUCTION

Development of non-invasive methods for the identification of specific gait patterns is an important issue in the detection of Parkinson's disease (PD). The main noticeable point is that every individual seems to have a distinctive way of walking, which can be easily understood from a biomechanical point of view [1]. Human locomotion consists of synchronized integrated movements of hundreds of muscles and joints. Gait can be defined as the coordinated, cyclic combination of movements that results in human locomotion [2].Gait patterns vary from one person to another in certain aspects such as their relative timing and magnitudes.

In this paper, a computer vision-based gait analysis approach is developed towards the detection of PD using a Hidden Markov Model (HMM). People with PD commonly present gait disorders that affect their walking ability. As natural body movements can be transformed into essential spatial-temporal parameters with video-based motion analysis techniques, this analysis helps us to identify PD, from motion patterns if a person is suffering from PD.

In this work, sixteen PD patients and sixteen healthy subjects with no neurological history or motor disorders within the past six months are considered and separated according to their "Non-PD", "Drug-On", and "Drug-Off" states. The participants were asked to wear light-colored clothing and perform three walking trials through a corridor decorated with a navy curtain at their natural pace [3]. We have captured participants' steady-state walking for gait analysis using a high quality video camera at 30 fps, 640x480 resolutions. From the videos, some of the walking images were transformed into binary silhouettes for noise reduction and compression. Using the developed HMM based method, the features within the binary silhouettes was extracted to quantitatively determine the gait cycle time, stride length, walking velocity, and cadence [3]. First binary silhouette of a walking person is detected from each frame. Subsequently, features from each frame are extracted using image processing techniques. Here center of mass, step size, length, and cycle length are selected as the features. Finally HMM has been used for the PD gait pattern recognition.

The major contribution of this paper is extended gait detection techniques for identification of PD. The algorithm has been implemented in Matlab as well as LabVIEW.

The paper is organized as follows. Section 2 gives a review of previous works. Section 3 describes the proposed model. Section 4 discusses the HMM based classification of gait sequences. Section 5 gives the results while Section 6 concludes the paper.

II. LITERATURE REVIEW

A number of intervention studies have been carried out to investigate the detection of PD. In [4], the authors used the olfactory acuity of 22 patients for detection of Parkinson's disease. Ten of 22 patients with PD showed significant decrease in olfactory acuity. Nine of these 10 patients had moderately or rapidly progressive disease.

In [5], oxidative stress and mitochondrial respiratory failure was used as a tool for the detection of PD. The authors have reported results of immunochemical studies using polyclonal antibodies directed against HNE-protein conjugates to label the site of oxidative damage in control subjects (ages 18-99 years) and seven patients that died of PD (ages 57-78 years). There results indicate the presence of oxidative stress within nigral neurons in PD, and this oxidative stress may contribute to nigral cell death.

The work in [5] reports evidence to indicate apoptosis in the substantia nigra of PD patients. The authors studied the midbrains of 7 patients with late onset PD, 4 patients with young onset PD and 6 control subjects using the nick-end labeling method. Intense nuclear staining indicating apoptotic process was observed in 8 out of 11 parkinsonian patients studied.

The work in [6] describes an ambulatory gait analysis method using body-attached gyroscopes to estimate spatio-temporal parameters of gait. They have validated their method against a reference system for normal and pathologic gait. Later, ten Parkinson's disease (PD) patients with sub-thalamic nucleus deep brain stimulation (STN-DBS) implantation participated in gait measurements using their device. The method provides a simple yet effective way of ambulatory gait analysis in PD patients with results confirming those obtained from much more complex and expensive methods used in gait labs.

The methods described above are invasive and contact based. In this approach, we propose a non-contact image based method of detection of PD.

III. OVERVIEW OF THE PROPOSED MODEL

Silhouette extraction and features extraction are two major tasks used in this gait recognition system processing. In this proposed model, first the frames from the recorded videos are extracted. These frames are subsequently converted into silhouette image sequences.

The dataset consists of 32 subjects of which 16 are PD patients and 16 are healthy persons. The subjects were walking at their natural pace on a corridor. There are about 16 cycles in each sequence. Half of the cycles were used for training and the other half for testing. The data was collected using a high quality video camera at 30 fps, 640x480 resolution, mounted on a tripod. The following gait variables can be evaluated based on their clinical relevance and reported association with cognitive function:

1) step length
2) stance phase
3) swing phase
4) single support/double support time ratio
5) cadence
6) velocity
7) step length variability
8) swing time variability.

The features within the binary silhouettes were extracted to quantitatively determine the gait cycle time, stride length, walking velocity, and cadence for HMM training and testing purpose. In order to reduce the large number of gait variables to a smaller number of factors, a factor analysis was performed. Furthermore, we assessed all patients with an extensive neuropsychological battery and correlated the composite scores of three main cognitive domains, viz. episodic memory, executive and visuo-spatial domains with the gait factors scores. We also evaluated correlations between gait factors and clinical measures.

A. Silhouette extraction

The motional individual silhouette must be detected before getting the gait feature. Background subtraction has been used for the same. The method described in [7] which uses bottom up cues has been used for background subtraction. The figure below gives an example of gait detection.

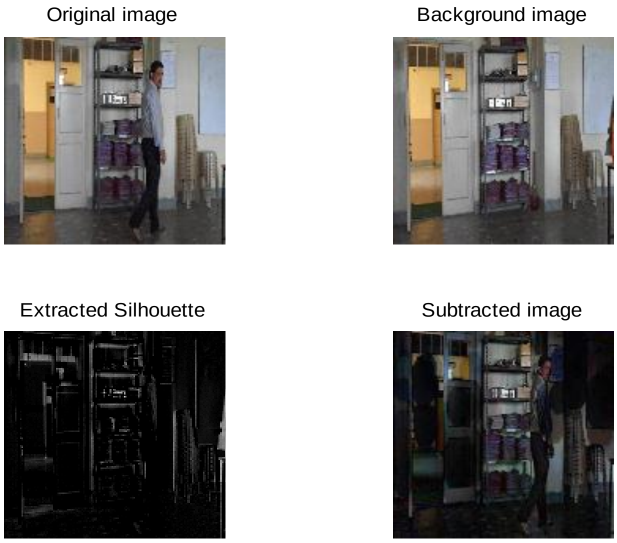

Fig. 1 Example of gait detection. (a) Original image; (b) Background image; (c) Extracted silhouette; (d) Subtracted image

Morphological Erosions applied to the background subtracted image to improve the quality of extracted silhouette and reduce noise [8] [9].

B. Feature Extraction

Feature selection is primarily performed to select relevant and informative characteristics from the image data. Our gait image feature vector is comprised of parameters of moment features in image regions. The feature extraction must be reasonably robust to the varying illumination conditions and with varying subjects. Intuitively, the silhouette appears to be a good feature to utilize, since it captures the motion of most of the body parts and also encodes its structural as well as transitional information [10].Since silhouette contains most of the body parts and is independent of the clothing, illumination and textures, the image database is extracted in silhouette form in this work. The figure below shows different gait cycles of different subjects.

Fig. 2 Different gait cycles of different persons

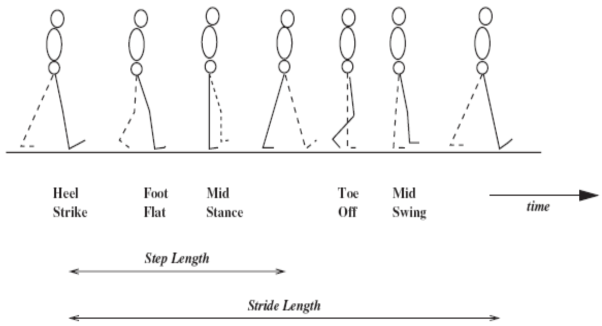

Fig. 3 Extraction of hidden features from the gait image sequences

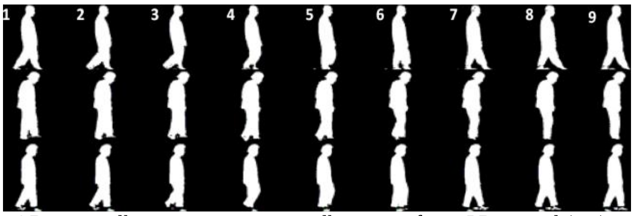

Fig. 4 Binary walking image sequence silhouettes of non-PD control (top) and Parkinson's disease (PD) patients in the "Drug-Off" (middle) and "Drug-On" (bottom) states

The image measurements comprises of a head strike, mid strike and toe strike for the detection of PD patients for further proceedings. The feature vector formed is an n dimensional vector that contains these measurements. This vector can be used to classify an object or to provide us with condensed higher-level image information. A feature is robust if it will provide consistent results across the entire application domain. The images are stored in the form of a two- dimensional data array [11].

At the time of walking, the human body center of mass changes from instance to instance, so we are using center of mass as a feature and this center of mass show the brighted weighted average of x and y coordinates pixels in the frame. Center of mass of the white pixels area for binary images is the same as the center of mass if we consider the intensity at a point as the mass of that point. In binary image we can calculate center of mass coordinate by using following formula [12].

B (i, j) = the brightness of the image at the point (i, j)

$$\bar{x} = \frac{\sum_{i=0}^{n}\sum_{j=0}^{m} j * B(i,j)}{A} \qquad \textbf{(1)}$$

$$\bar{y} = \frac{\sum_{i=0}^{n}\sum_{j=0}^{m} i * B(i,j)}{A} \qquad \textbf{(2)}$$

Here $\bar{x}$ and $\bar{y}$ are center of mass points in image. Here m and n is dimension of matrix which store image in matrix form, A is the area of region, and it can be calculated by following formula:

$$A = \sum_{i=0}^{n}\sum_{j=0}^{m} B(i,j) \qquad \textbf{(3)}\textit{3}$$

Another feature of gait is its periodicity. By observing, the width of the silhouette was changing periodically with the time-lapse. The width of the silhouette will reach a maximum when the two legs are farthest apart (full stride stance) and drop to a minimum when the legs overlap (heels together stance). At the same time, the height of silhouette has slight change in the procedure. Consequently, we can get the estimation of gait cycle.

For calculating step size length, height and gait cycle, we have used boundary box technique [13]. On silhouette a boundary box is created to cover whole object from outside and its right edge boundary touches the back foot back end and left edge touches the front foot front end, this boundary box width recorded as stride length.

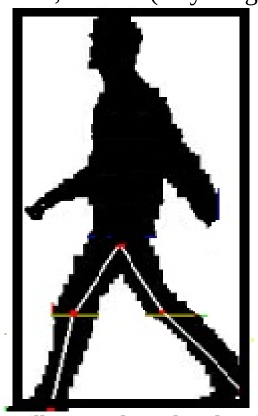

Fig. 5. Silhouettes boundary box image

Stride length, height and gait cycle are obtained. Stride length is estimated by tracking the person, estimating their walking velocity and thus cadence.

IV. PD GAIT PATTERN DETECTION SYSTEM

The schematic of our Gait image based PD detection is shown in figure 6. Firstly the video is captured by a camera, followed by motion detection and segmentation methods which are applied to detect and segment walking person in video. From these segmented images, silhouettes are created for image processing operations to extract the feature for each PD image sequences. Thus database is created using extracted feature and these features represent the special characteristic of walking person[14][15].This paper adopts the Hidden Markov model for classification and detection of PD persons and the maximum recognition rate is 99.6995%.

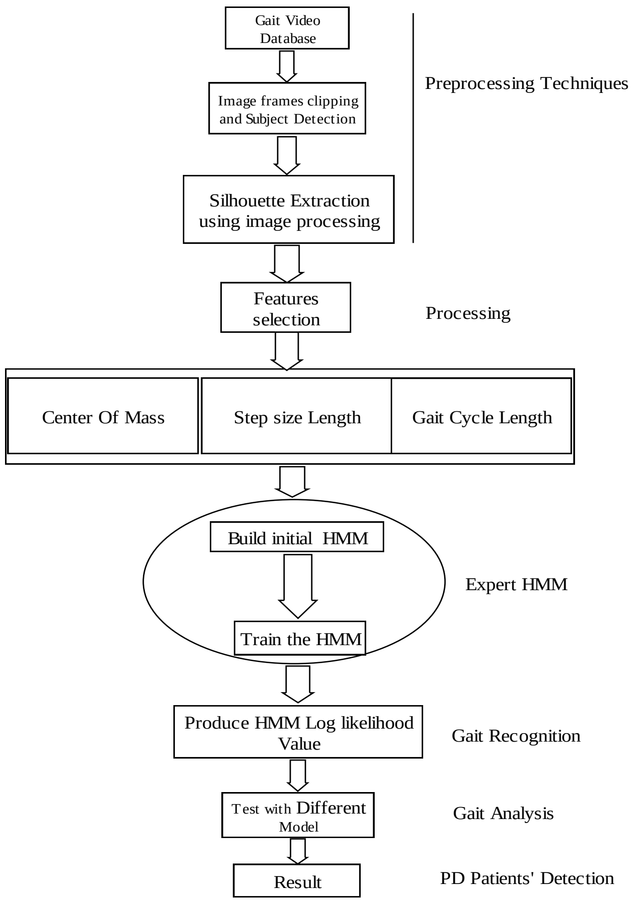

Fig. 6. Schematic overview of the proposed HMM model

V. HIDDEN MARKOV MODEL OF GAIT SEQUENCES

HMM is used to identify the inherent characteristics of a particular motion independent from such variations. An HMM model is a finite state machine. Each state may be modeled as a single Gaussian or a multi-modal Gaussians mixture. Due to the continuous nature of gait image sequences, the PD identified features must be trained by expert HMM and then test by the PD image sequences. The topology of an HMM model for gait image sequences is considered to be left-to-right to meet the observations arrangement criterion. This left-to-right topology authorizes transitions from each state to itself and to right-hand neighbors. HMM model parameters are usually estimated in the training phase by maximum likelihood based or discriminative based training algorithms using sufficient training data sets. A continuous left-to-right HMM model parameters with N states and M mixtures can be stated by. The state and observation sequence of HMM is shown in Fig.6. It generates an observation O_t, with the probability density. It is capable of forming arbitrarily decision boundaries but its performance depends on the network architecture. Using HMM as classifier gives some advantage. First, HMM is data driven self-adaptive methods in that they can adjust themselves to the data without any explicit function. Second, it is function approximation technique in that network can approximate any function [13][14][15]. Third, it is nonlinear model, which can model real world problem.

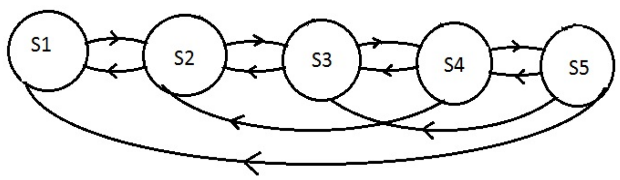

Fig. 7. HMM model for PD gait topology

Finally, HMM are able to estimate the posterior probability, which provides the basic of estimating classification rule. Particular network architecture defined two things, first is the number of hidden layer and second is the number of neuron in each layer. Based on these two things we can create much network architecture, other than these two we can also define different network model and also use different training algorithm. Good architecture determined by experiment result. Design of neural network involves the selection of its model, architecture, learning algorithm, and activation function. A Hidden Markov Model (HMM) is a statistical and probabilistic model that represents the structure or statistical regularities of classes of sequences. In HMMs, state (in our earlier example, the urns) are not observable (i.e., hidden).Observations are probabilistic function of state. State transitions are still probabilistic [15]-[20]. A stochastic process is a sequence of feature extraction code words, the outcomes being the classification of hand gesture path. We formally introduce the elements of HMMs as follows:

Step1. N, the number of states in the model. The individual states are denoted as S_1, S_2, S_3…..S_N.

Step2. M, the number of distinct observation symbols, i.e. the individual symbols. The symbols are denoted as $\Omega=X_1, X_2, X_3….X_N$ .In our case, each observation symbol corresponds to an image frame.

Step3. The state transition probability distribution matrix A= $[a_{ij}]$ where

$$a_{ij} = \Pr[q' = S_j \mid q = S_i], 1 \le i, j \le N \qquad \textbf{(4)}$$

Here q' is the next state; q is the current state; S_j is the state j: S_i is the state i.

Step4: The Observation symbol probability distribution matrix $B = [b_{s_j}(x_k)]$ Where

$$b_{s_j}(x_k) = \Pr[x_k \mid q = S_j], 1 \le j \le N, 1 \le k \le M$$

Here $b_{s_j}(x_k)$ represents the emission probability of an observation symbol x_k in the state S_j.

Step5: The initial state distribution vector $\Pi = \{\Pi_i\}$ where $\Pi_i = \Pr[q_i = S_i]$, $i \le N$.

Step6: λ is the entire model $\lambda = (A, B, \Pi)$.

A. *Training and Testing datasets*

Silhouettes corresponding to a walk cycle are extracted for each person in the database using the silhouette extraction procedure described in Section 2.A. The width vector is generated for each frame and encoded as a compact 5-D observation sequence using the stances of that person. This lower dimensional vector sequence (possibly of varying length) constitutes a training sequence. We train a 5-state, single Gaussian, ergodic HMM for each person. As expected,
the transition probabilities and the observation probabilities turned out to be different for different patients' .We use the holdout method for error estimation. Half of the cycles were used for training and the other half for testing purpose.

B. *Results and Discussion*

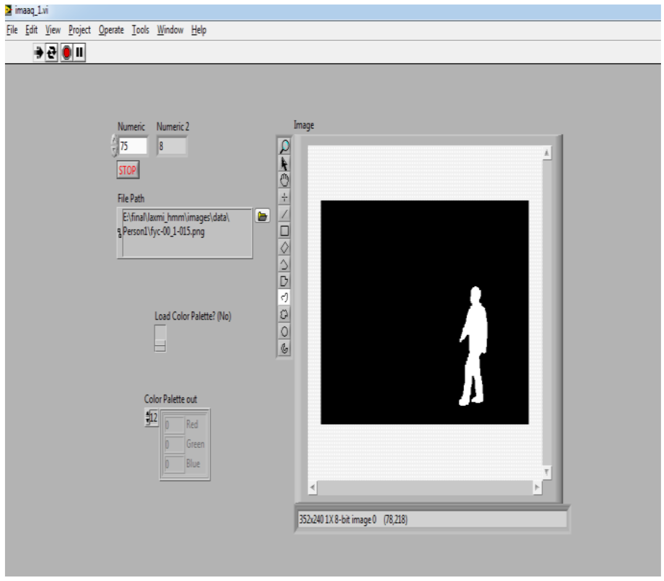

Fig. 8. Training and Testing of Silhoutte image Using LabVIEW

TABLE I
HMM BASED CLASSIFICATION RESULTS FOR CMU DATABASE

Test sequence	Recognition							
	Person1	Person 2	Person 3	Person 4	Person 5	Person 6	Accuracy	Error rate in %
Person1	10	0	0	0	0	0	95.553	4.447
Person2	0	10	0	0	0	0	100	0
Pers	0	0	10	0	0	0	100	0

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on3								
Person4	0	0	0	10	0	0	99.756	0.25
Person5	0	0	0	0	10	0	100	0
Person6	0	0	0	0	0	10	97.675	2.035

TABLE III
CLASSIFICATION RESULTS IN TERMS OF AVERAGE RECOGNITION FOR CMU DATABASE

Feature type	Attempts	success	Recognition
Width of the contour	75	75	100%
Width of the contour+hidden features	75	69	92%

TABLE IIIII
CLASSIFICATION RESULTS IN TERMS OF AVERAGE RECOGNITION FOR CASIA DATABASE

Data sets Group name	Training % age	Testing % age	Training instances	Testing instances
Person 1	80	20	1000	250
Person 2	90	10	1200	125
Person 3	70	30	1155	315

The average best recognition result for our method is 99.6995%.

VI. CONCLUSION AND FUTURE WORK

HMM based classification technique for PD detection presents easy use and installation of the current method which provides clinicians and researchers a low cost solution to monitor the progress and treatment of Parkinson [21]. The ability to evaluate treatments for Parkinson's disease is an important issue. However, previous research has been hindered due to the lack of tools that can be easily installed, provide prompt gait analysis, facilitate data collection and lower a patient's level of exertion during the examinations[22][23]. In this study, a computer vision-based gait analysis approach that is different from other sensor or marker based approaches is developed. The proposed method provides an alternative to perform gait analysis for patients with PD. Alternative to HMM,PD can also be classified by using kernel-based principal component analysis to classify and quantify specific gait patterns [24][25]. Although there are few significant differences among the gait patterns, the proposed method presents encouraging classification accuracy rates of 99.6695% in identifying different PD gaits. This technique provides a practicable reference for clinicians and researchers to obtain the quantitative gait parameters and assess the progression of Parkinson's disease in the motor section of the brain using ambulation patterns recorded in monocular image frames which approaches in classifying "Non-PD" controls and "Drug-Off/ On" PD patients. Our results indicate the feasibility of using gait performance to evaluate the motor function of patients with PD. We propose the use of HMM-based classifiers since they are easy to implement. In the present study, consistent results across cross-validation and test set are achieved with limited training data [26]. The proposed methodology is adopted to derive a low dimensional observation sequence from the PD silhouette during a gait cycle. Learning is achieved by training an HMM for each person over several gait cycles. The method was tested on 3 different databases. In general, the recognition rates were found to be good. As anticipated, drastic changes in clothing adversely affect recognition performance. In spite of its sensitivity to changes in viewing angle beyond ten degrees, the mentioned method is reasonably robust to changes in speed. In the case of human gait recognition we observed in some cases that the stride length changed appreciably with walking speed causing a slight drop in recognition performance. It can also be extended to classify different activities such as walking and running. We are hence convinced of the validity of the HMM based early detection and medication of PD patients.

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