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A vision-based analysis system for gait recognition in patients with Parkinson's disease

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ABSTRACT

Recognition of specific Parkinsonian gait patterns is helpful in the diagnosis of Parkinson's disease (PD). However, there are few computer-aided methods to identify the specific gait patterns of PD. We propose a vision-based diagnostic system to aid in recognition of the gait patterns of Parkinson's disease. The proposed system utilizes an algorithm combining principal component analysis (PCA) with linear discriminant analysis (LDA). This scheme not only addresses the high data dimensionality problem during image processing but also distinguishes different gait categories simultaneously. The feasibility of the proposed system for the recognition of PD gait was tested by using gait videos of PD and normal subjects. The efficiency of feature extraction using PCA and LDA coefficients are also compared. Experimental results showed that LDA had a recognition rate for Parkinsonian gait of 95.49%, which is higher than the conventional PCA feature extraction method. The proposed system is a promising aid in identifying the gait of Parkinson's disease patients and can discriminate the gait patterns of PD patients and normal people with a very high classification rate.

1. Introduction

Most of the current methods used for evaluating Parkinson's disease (PD) rely heavily on human expertise, e.g., the use of the unified Parkinson disease rating scale (UPDRS) (Martın et al., 2004). UPDRS is a rating tool that follows the longitudinal course of PD. It is composed of 5 separate categories including mentation, behavior, mood, activities of daily living and motor examinations, all evaluated by interview. Some sections require multiple grades assigned to each extremity.

The analysis of gait characteristics, as documented by Knutsson (1972), shows that PD patients exhibit large gait variability. Compared with normal people, PD patients' walking speed is slower, duration of gait cycle is longer, stride length is shorter, and amplitude of range of movement of joints is decreased. These specific gait patterns (e.g. festinating gait, freezing gait) are widely accepted as a prominent feature of PD (McDowell, 1971). However, since posture and gait movement can vary from person to person, the evaluation of Parkinsonian gait tends to be subjective and depends greatly on the experience and judgment of the clinician (Blin, Ferrandez, & Serratrice, 1990; Lubik et al., 2006; Melnick, Radtka, & Piper, 2002; Shan et al., 2001; Salarian et al., 2004; Sofuwa et al., 2005; Stern et al., 1983; Vokaer, Azar, & Beyl, 2003).

In addition to evidence-based practice, therapists also use objective, quantitative methods to improve diagnosis of Parkinsonian gait. As a result, engineering-oriented machine learning-based methods have attracted more and more attention in this field (Engin et al., 2007; Fahrenberg et al., 1997; Makikawa & Iizumi, 1995; Sekine et al., 2002; Veltink et al., 1996). Many previous studies have used dc and ac accelerometers to assess gait patterns. They classified the accelerometer signals into different types of walking and correlated them with energy consumption. Nevertheless, those methods often used a number of sensors, causing patient discomfort.

Vision-based gait analysis systems avoid this problem. Since these systems require no physical contact, they are more comfortable and acceptable to the patients. Vision-based gait analysis is divided into two main categories, model-based and holistic. Model based approaches fit their model to the image data (Cunado, Nixon, & Carter, 1999; Yam, Nixon, & Carter, 2002). These image processing systems use markers on the body and record several steps of the patient. An average of three or more walks is then computed. The temporal characteristics of gait, e.g., stride length, width, cadence and velocity are measured (Melnick et al., 2002). In one study (Cunado et al., 1999) the gait signature was extracted using a Fourier series to describe the motion of the leg and temporally

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correlate this leg motion to determine the dynamic model from a sequence of images.

Holistic methods (Huang et al., 1999a, 1999b; Little and Boyd, 1998) extract posture cues by preserving the silhouettes of people when walking, derive statistical information directly from the gait image and attempt to correlate various features for biometric authentication. The holistic approach has a high human identification rate. For instance, Murase and Sakai (1996) captured the complete gait images of people which they then subtracted and matched using spatial–temporal correlation.

To reduce the dimensionality of image data, there are many linear transformation approaches that can be used. These methods are usually expressed as $\mathbf{y} = \mathbf{W}^{\mathrm{T}}\mathbf{x}$, where $\mathbf{x}$ and $\mathbf{y}$ are the original and the dimensionality-reduced image vectors, respectively, and $\mathbf{W}$ is a linear projection matrix such that $\mathbf{y}$ becomes discriminative so as to aid separation of different classes of image sequences.

Many types of optimization criteria can be used to determine an appropriate $\mathbf{W}$, such as maximizing the variance, non-Gaussianity for independancy, negentropy, or the ratio of between- and within-class variations (Hyvarinen et al., 2001; Liu & Wechsler, 1998; Murase & Sakai, 1996). Among them, principal component analysis (PCA) is well-known and widely used (Polat & Güneş, 2007). PCA focuses on computing eigenvectors that account for the largest variance of the data selected, but these directions do not necessarily provide the best separation of gait classes. On the other hand, the ratio of between- and within-class variations (Fisher's linear discriminant criterion) appears to be an especially valid index since it allows simultaneous balancing between the maximization and minimization of the between- and within-class variations. Based on Fisher's linear discriminant criterion, linear discriminant analysis (LDA) then produces a linear projection matrix, which greatly enhances classification.

The aim of this paper is to discriminate PD patients from normal subjects using a vision-based gait analysis approach. The scheme utilizes the holistic image of subjects, and extracts and reduces the feature space by using PCA and LDA. The meaning of the obtained LDA transformation matrix (reduced to a vector in our case) is not only treated as a black box but is also used to describe the posture information of PD patients in a numerical way.

2. Mathematical background used for signal processing

2.1. Principal component analysis (PCA)

PCA is a classic technique used in statistical data analysis, featuring extraction and data compression (Jolliffe, 2002). It is useful in reducing the dimensionality of an input data space by transforming the data from a correlated high-dimensional space to an uncorrelated low-dimensional space. We briefly describe PCA as follows. Suppose that there are N_T vectors being grouped into c classes. We can express these vectors as $\mathbf{x}_{11},\ldots,\mathbf{x}_{1N_1},\ldots,\mathbf{x}_{i1},\ldots,\mathbf{x}_{iN_i},\ldots,\mathbf{x}_{c1},\ldots,\mathbf{x}_{cN_c}$, where $\mathbf{x}_{ij}$ is the jth vector of the ith class and N_i is the number of vectors in the ith class. To proceed, the mean $\mathbf{m}_{\mathbf{x}}$ of the entire set of vectors is given by

$$\mathbf{m}_{\mathbf{x}} = \frac{1}{N_T}\sum_{i=1}^{c}\sum_{j=1}^{N_i}\mathbf{x}_{ij}. \tag{1}$$

To compute the covariance matrix $\mathbf{C}$, we have

$$\mathbf{C} = \frac{1}{N_T}\sum_{i=1}^{c}\sum_{j=1}^{N_i}(\mathbf{x}_{ij}-\mathbf{m}_{\mathbf{x}})(\mathbf{x}_{ij}-\mathbf{m}_{\mathbf{x}})^{\mathrm{T}}. \tag{2}$$

If the rank of $\mathbf{C}$ is K, the eigenvalues of $\mathbf{C}$,λ_1,λ_2,...,λ_K, and the associated eigenvectors $\mathbf{p}_1$,...,$\mathbf{p}_K$ can be computed accordingly. Suppose, without loss of generality, $|\lambda_1| \geqslant |\lambda_2| \geqslant \cdots \geqslant |\lambda_K|$. A partial eigenspace can be spanned using the partial set of $k \leqslant K$ eigenvectors $\{\mathbf{p}_1,\mathbf{p}_2,\ldots,\mathbf{p}_k\}$. Afterwards, the resultant projection $\mathbf{y}_{ij}$ of each vector $\mathbf{x}_{ij}$ on the partial eigenspace can be obtained by

$$\begin{aligned}\mathbf{y}_{ij} &= [\mathbf{p}_1,\ldots,\mathbf{p}_k]^{\mathrm{T}}\mathbf{x}_{ij}\\ &= \mathbf{P}\mathbf{x}_{ij},\end{aligned} \tag{3}$$

where $\mathbf{y}_{ij}$ is also named the PCA coefficients in this paper.

2.2. Linear discriminant analysis (LDA)

Suppose that ΦO_i represents the set of the vectors $\{\mathbf{y}_{i1},\mathbf{y}_{i2},\ldots,\mathbf{y}_{iN_i}\}$. The mean vector of Φ_i is given by

$$\mathbf{m}_{\mathbf{y}_i} = \frac{1}{N_i}\sum_{j=1}^{N_i}\mathbf{y}_{ij}. \tag{4}$$

Hence, the mean vector of the entire set $\Phi = \{\Phi_1,\Phi_2,\ldots,\Phi_c\}$ is given by

$$\mathbf{m}_{\mathbf{y}} = \frac{1}{N_T}\sum_{i=1}^{c}N_i\mathbf{m}_{\mathbf{y}_i}. \tag{5}$$

The within-class matrix $\mathbf{S_w}$ and the between-class matrix $\mathbf{S_b}$ of the entire set of vectors can be calculated by

$$\mathbf{S_w} = \frac{1}{N_T}\sum_{i=1}^{c}\sum_{j=1}^{N_i}(\mathbf{x}_{ij}-\mathbf{m}_{\mathbf{y}_i})(\mathbf{x}_{ij}-\mathbf{m}_{\mathbf{y}_i})^{\mathrm{T}} \tag{6}$$

and

$$\mathbf{S_b} = \frac{1}{N_T}\sum_{i=1}^{c}N_i(\mathbf{m}_i-\mathbf{m}_{\mathbf{y}})(\mathbf{m}_i-\mathbf{m}_{\mathbf{y}})^{\mathrm{T}}. \tag{7}$$

Maximizing the between-class variance and minimizing the within-class variance simultaneously is equivalent to maximizing

$$J(\mathbf{W}) = \mathrm{Trace}\{(\mathbf{W}^{\mathrm{T}}\mathbf{S_w}\mathbf{W})^{-1}(\mathbf{W}^{\mathrm{T}}\mathbf{S_b}\mathbf{W})\}. \tag{8}$$

By solving the eigenvectors of the matrix $\mathbf{S_w}^{-1}\mathbf{S_b}$, we can obtain $c-1$ eigenvectors $\mathbf{w}_1,\ldots,\mathbf{w}_{c-1}$ to span a canonical space. Thus, we can further project a vector $\mathbf{y}_{ij}$ on the partial eigenspace to a vector $\mathbf{z}_{ij}$ on the canonical space by

$$\begin{aligned}\mathbf{z}_{ij} &= [\mathbf{w}_1,\ldots,\mathbf{w}_{c-1}]^{\mathrm{T}}\mathbf{y}_{ij}\\ &= \mathbf{W}\mathbf{y}_{ij},\end{aligned} \tag{9}$$

where $\mathbf{z}_{ij}$ is also named the LDA coefficients in this paper.

Consequently, the mean vector of the ith class on the canonical space can be computed by

$$\mathbf{m}_{\mathbf{z}_i} = \frac{1}{N_i}\sum_{j=1}^{N_i}\mathbf{z}_{ij}. \tag{10}$$

2.3. Minimum distance classifier (MDC) (Duda, Hart, & Stork, 2000)

In this study, MDC is used to classify an input vector $\mathbf{u}$ to the ith class whose centroid $\mathbf{m}_i$ minimizes the Euclidian distance from $\mathbf{u}$ (using either PCA or LDA coefficients). The minimum distance classifier can be expressed as

$$i = \arg\min_i(\mathbf{u}-\mathbf{m}_i)^{\mathrm{T}}(\mathbf{u}-\mathbf{m}_i). \tag{11}$$

3. System used for detection of PD gait patterns

As shown in Fig. 1, we propose a gait analysis system which can detect the gait pattern of Parkinson's disease using computer vision. This system comprises three main parts: (1) preprocessing,

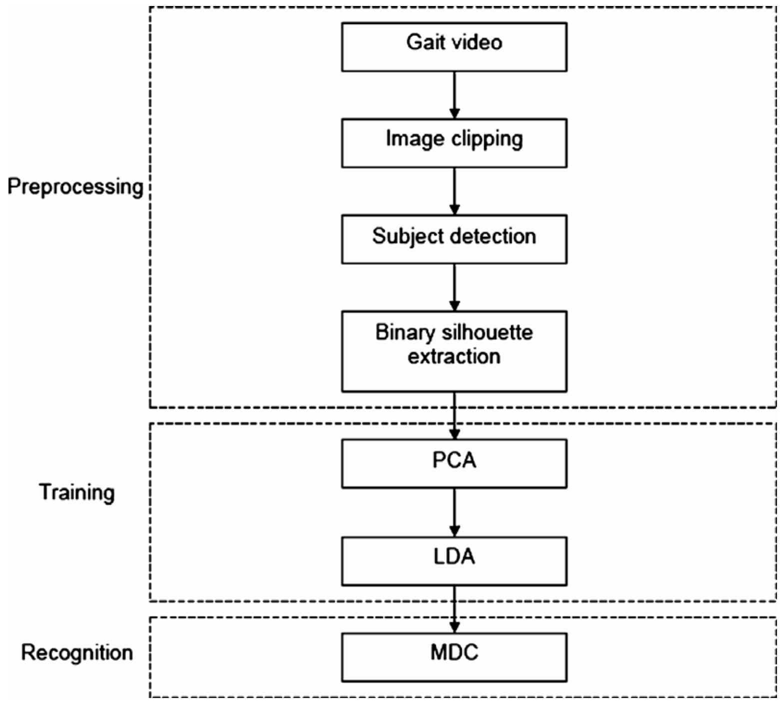

Fig. 1. Flow chart of the proposed system.

(2) training and (3) recognition. In this study, we first captured several videos of both normal subjects and patients with PD. We then processed the images from the videos to characterize the subjects. All subjects were encoded as vectors such that we could use PCA and LDA to extract features. An MDC was then used as the classifier. The flow chart of the proposed system is shown in Fig. 1.

3.1. Environment set-up, image acquisition and subject detection

A structured environment—a corridor with a deep blue curtain—was utilized and the room was well illuminated as shown in Fig. 2. Image acquisition equipment, including a CCD camera connected to a PC or a handy DV, was also used.

There are many background models proposed (Haritaoglu, Harwood, & Davis, 2000), to help extract clear foreground objects. For simplicity, the background model was constructed by taking a photograph of the environment beforehand. Both normal subjects and PD patients were asked to wear light-colored clothing to achieve high color contrast between the background and their profiles. Each subject was instructed to walk from the left to the right end (and then walk back if needed). Afterwards, the subjects' image sequences were captured, as illustrated in Fig. 3.

The difference between the background and each of the image frames was then computed. The absolute value of the difference was then calculated such that every pixel of the input image was judged to belong to the foreground object pixel if the corresponding absolute value exceeded a threshold. This threshold depended on the color contrast of the curtain and the clothing of the subjects and the illumination condition. As a result, we binarized each of the images during walking (see Fig. 4a).

To obtain a more compact silhouette size, we projected the binary image to the vertical axis. The histogram of the projection is shown in Fig. 4(b). From this plot, it is clear that the upper and lower bounds of the silhouette can be computed by using a threshold

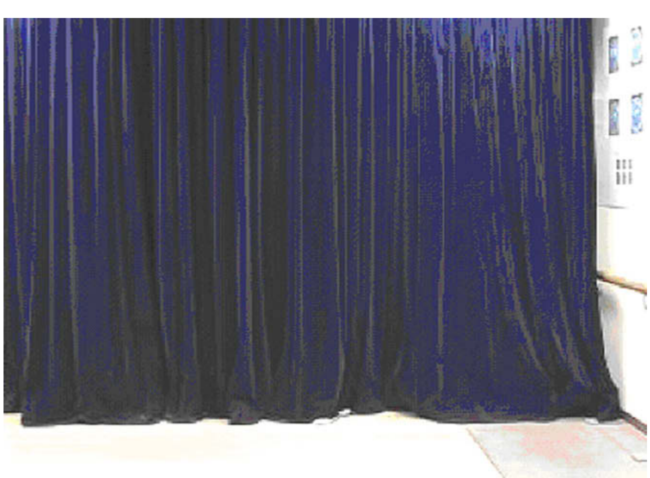

Fig. 2. The set-up of the laboratory.

Fig. 3. A subject walked from the left to the right end.

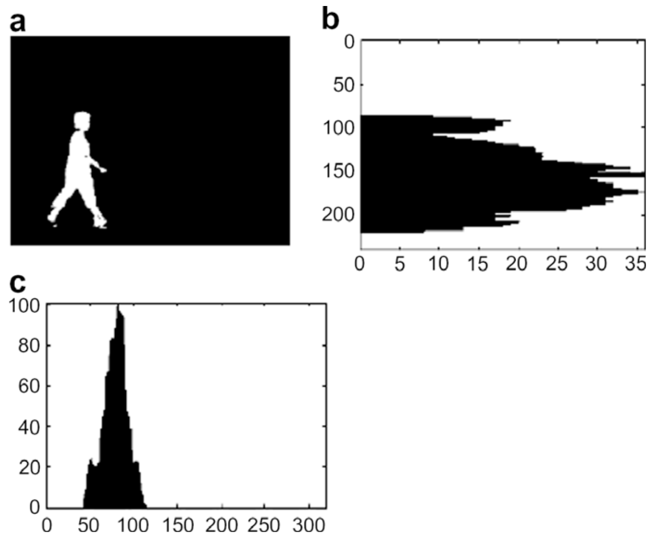

Fig. 4. Subject detection. (a) The detection of a subjection using image differences. The histogram of the detected subject on the (b) vertical and (c) horizontal axes.

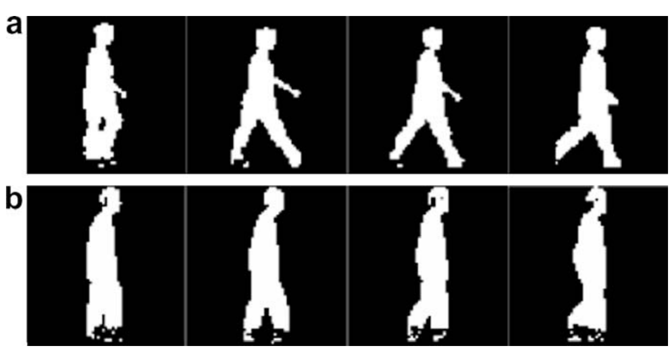

Fig. 5. Two examples of detected subjects: (a) a normal person and (b) a patient of Parkinson's disease.

of 2% of the maximum projection amount. Similarly, the left and right boundaries of the silhouette were also obtained by projecting the binarized image to the horizontal axis. Finally, we show two examples of the sequences of the binarized and truncated images of the normal subjects and PD patients in Fig. 5a and b, respectively. It is noted that the resultant images were normalized to the size of 64×64 pixels to further reduce the computational costs.

3.2. Training and testing

According to the view point of Machine Learning (Alpaydin, 2004), when designing a classifier, we should use *training data*, which are independent of *test data* used in the test phase. Thus, we divided the videos of the subjects into two groups: the first group was used to train the system and the remainder was used to evaluate the classification performance of the system.

3.3. Feature extraction

For comparison purposes, two kinds of feature extraction methods, PCA and LDA, were used in this study, as described below.

3.3.1. PCA coefficient extraction

The silhouette of a subject in an image frame was originally represented as a binary matrix. Since this matrix, in general, contains redundancy, we extracted efficient features by first using PCA. To this end, we reshaped each of the obtained silhouettes as a vector form such that we could collect all the silhouettes to perform PCA.

The mean vector and covariance matrix of the silhouette vectors can be computed using (1) and (2). Consequently, the features are obtained by evaluating the eigenvalues and the associated eigenvectors through PCA. We rearranged the resultant eigenvectors by ordering their associated eigenvalues from large to small. The largest eigenvectors were selected such that their associated eigenvalues accumulated a certain degree of energy, approximately 90% of the total energy in this study. By (3), each of the original silhouette vectors were thus approximated using a new vector on the space generated by the selected partial eigenvectors so as to reduce the dimensionality of silhouette vectors.

3.3.2. LDA coefficient extraction

Although PCA can reduce the dimensionality of silhouette vectors, it is not used aiming for classification. As a result, further processing is needed to improve the recognition capability of the proposed system. In this study, we focus on two categories of subjects: normal people and patients with Parkinson's disease. The means of the silhouette vectors of each category and of the entire set of vectors were computed by (4) and (5), respectively. After evaluating the LDA transformation matrix, each silhouette vector in the partial eigenspace was mapped to a new vector on the canonical space by (9).

4. Experimental results and discussion

Seven PD patients and seven normal people from Buddhist Tzu Chi General Hospital in Taiwan were enrolled in this study. All the experiments were conducted in the laboratory of the neurosurgery department of the hospital. Under supervision, the subjects were asked to walk from left to right and then to walk back. A SONY HDR-HC3 camcorder was utilized to capture the motion video of the subjects. All video recordings were then extracted to image clips with a sampling rate of 15 frames/s. Because the subjects walked at different speeds, the lengths of the video sequences varied from person to person (see Table 1).

Pixel candidates of the silhouettes of the subjects were labeled to construct binary images in order to ensure that the absolute values of the difference values were larger than an intensity threshold (10, in the experiments). The binarized silhouettes were then obtained by truncating the input image frames and the shapes were normalized to the size of 64×64 matrix. After encoding the detected silhouette images to image vectors, we obtained 3551 vectors.

The mean of the silhouette vectors was computed and the covariance matrix was then calculated. Accordingly, the eigen-

Table 1
The recorded video sequences

Subject number	Status	Length (min)	Sampling rate (frame/s)
1	Normal	3	15
2	Normal	2	15
3	Normal	2	15
4	Normal	3	15
5	Normal	3	15
6	Normal	3	15
7	Normal	3	15
8	PD	3	15
9	PD	2	15
10	PD	2	15
11	PD	3	15
12	PD	3	15
13	PD	2	15
14	PD	2	15

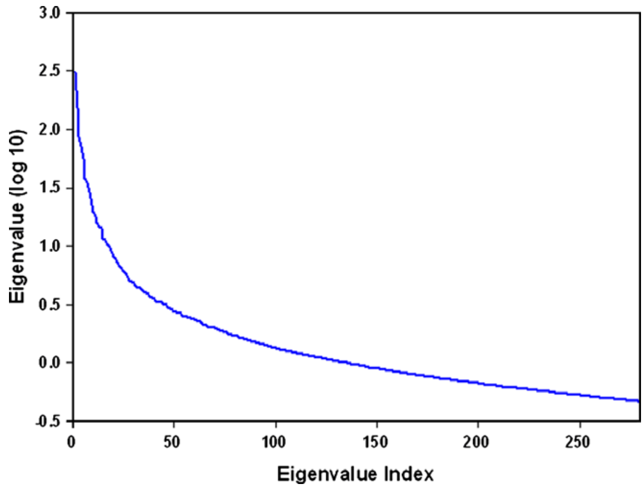

Fig. 6. The sorted eigenvalue diagram.

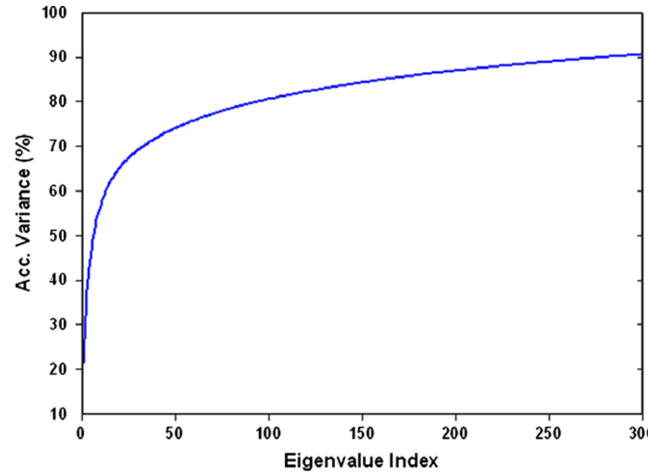

Fig. 7. The accumulated variance diagram.

values and associated eigenvectors of the covariance matrix were computed. Figs. 6 and 7 show the sorted magnitudes and accumulated variance of sorted eigenvalues, respectively. Among the eigenvectors calculated, the first 280 eigenvectors corresponding to the largest 280 eigenvalues (accumulating 90% of the total variance) were selected as the bases of the partial eigenspace. The image vectors were then projected onto the obtained partial eigenspace to extract the PCA coefficients.

To further discriminate among each class of silhouette vector, the obtained PCA coefficients of the silhouette vectors were processed using LDA. First, the mean vectors of each class and of the entire set of the vectors on partial eigenspace were computed. Then, maximization of the ratio of between-class variance and within-class variance was carried out. Accordingly, the ratios before and after LDA were 0.0446 and 16.0000, respectively. It is clear that LDA raised the ratio. Finally, the LDA coefficients of the silhouette vectors were calculated.

To visualize the different features obtained by PCA and LDA, the distributions of the first two components (for illustration purposes) of PCA and only one LDA coefficient of silhouette vectors of normal and PD subjects are plotted in Figs. 8 and 9, respectively. In the figures, the red "O" stands for the normal subjects and the green "△" for PD patients.[1]

We observed that the PCA coefficients of different groups of silhouette vectors had large overlaps for both vertical and horizontal axes. On the other hand, the LDA coefficients of different groups of silhouette classes clearly separated from one another. Note that, although we illustrated the scatter plots by using only two and one coefficients for PCA and LDA, respectively, we adopted 280 and one coefficients for PCA and LDA, respectively, during the classification of normal people and PD patients. Since the LDA coefficients' dimensionality is only one, the counting index is then used as the horizontal axis of Fig. 9 to show the scatter plot.

For further insight, we investigated the LDA projection matrix carefully (in this study, it reduced to a vector). We computed the absolute values of this vector and shifted and scaled the obtained projection vector elements to fall in the range from 0 to 255. We reshaped this vector to match the shape of captured images. Therefore, we could visualize the projection vector and correlate it to the silhouettes of subjects. We show the image form of the projection vector in Fig. 10. The image pixels with higher intensity in Fig. 10 had more discriminating ability according to LDA projection. The

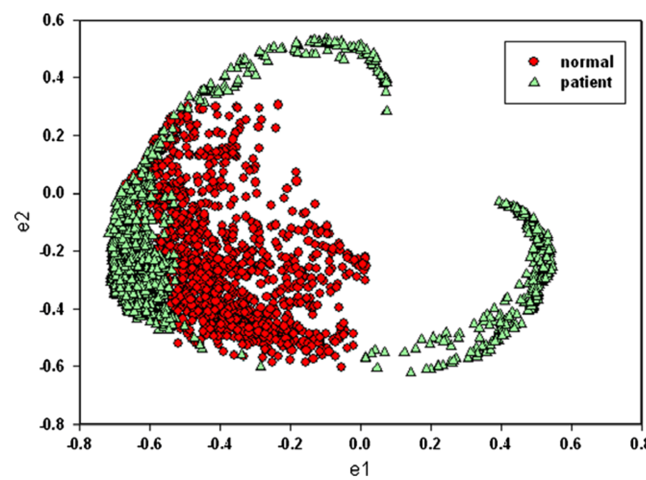

Fig. 8. The distribution of the first two components of PCA coefficients of the training silhouette vectors.

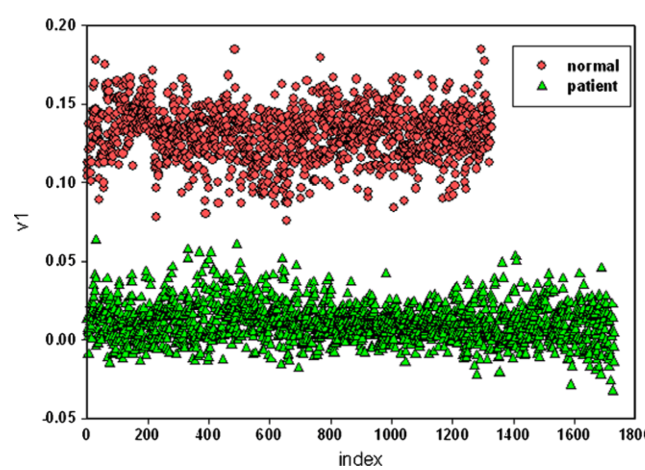

Fig. 9. The distribution of the LDA coefficients of the training vectors.

head and neck (a) were especially emphasized by LDA. The system was able to discern PD patients by "carefully observing" the head and neck parts of the silhouettes of the subjects.

MDC was adopted in this study to evaluate the classification performance of the proposed scheme. During the training phase,

[1] For interpretation of color in Figs. 8 and 9, the reader is referred to the web version of this article.

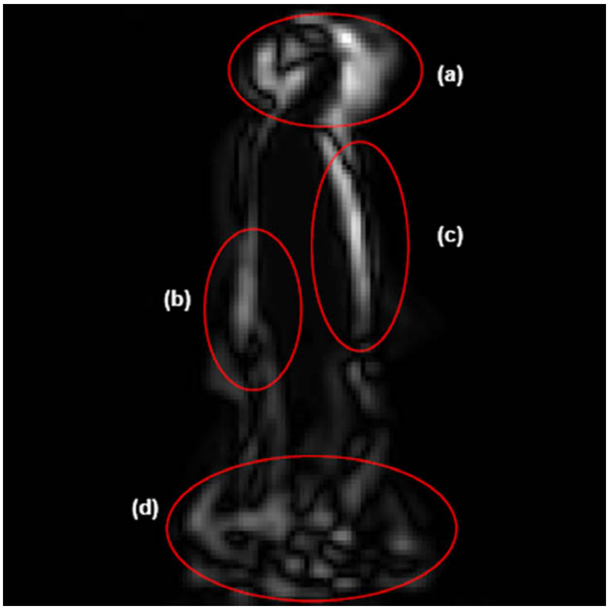

Fig. 10. Visualization of the projection matrix using an image form.

Table 2
Classification accuracy comparison between PCA–MDC and LDA–MDC

Algorithm	Accuracy (%)
PCA–MDC	77.1746
LDA–MDC	95.4872

Table 3
Confusion matrix of PCA-MDC

	Normal	PD
Normal	518	109
PD	240	662

Table 4
Confusion matrix of LDA-MDC

	Normal	PD
Normal	599	28
PD	41	861

both PCA and LDA had classification rates of 100%. Table 2 compares the test performance of PCA–MDC with that of LDA–MDC for 1529 test cases. It is obvious that LDA–MDC outperformed PCA–MDC by 18.31%. Tables 3 and 4 further demonstrate the confusion matrix: LDA–MDC improved the detection rate for both normal and PD subjects. PCA, functioning mainly as a preprocessing of LDA–MDC for data dimensionality reduction, did not separate different groups of silhouette vectors well. As illustrated in Fig. 8, the silhouette vectors of PCA coefficients of the two groups were still close to each another. Although these components corresponded to the eigenvectors with maximum variations of the original vectors, the directions of these eigenvectors were not consistent with the directions that best discriminate between normal subjects and PD patients.

5. Conclusions

The diagnosis of PD is an important issue in the neuroscience field. Although gait analysis is important in the diagnosis of PD, there are limited visual-based methods available. In this paper, we propose an assistance system using LDA to detect PD gait patterns. The proposed system uses the image sequences of human silhouettes during walking and extracts the intrinsic features by LDA. The proposed system can identify normal people and PD patients by their gaits with high reliability and appears a promising aid in the diagnosis of the Parkinson's disease.

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