Expert Systems with Applications 39 (2012) 520–526

Contents lists available at ScienceDirect

Expert Systems with Applications

journal homepage: www.elsevier.com/locate/eswa

A vision-based regression model to evaluate Parkinsonian gait from monocular image sequences

You-Yin Chen[a,*], Chien-Wen Cho[a], Sheng-Huang Lin[b,c], Hsin-Yi Lai[a], Yu-Chun Lo[c], Shin-Yuan Chen[d], Yuan-Jen Chang[e], Wen-Tzeng Huang[f], Chin-Hsing Chen[e], Fu-Shan Jaw[c], Siny Tsang[g], Sheng-Tsung Tsai[d]

[a] Department of Electrical Engineering, National Chiao Tung University, No. 1001, Ta-Hsueh Rd., Hsinchu City 300, Taiwan, ROC
[b] Department of Neurology, Tzu Chi General Hospital, Tzu Chi University, No. 707, Sec. 3, Chung Yang Rd., Hualien 970, Taiwan, ROC
[c] Institute of Biomedical Engineering, College of Medicine, National Taiwan University, No. 1, Sec. 1, Jen-Ai Rd., Taipei 100, Taiwan, ROC
[d] Department of Neurosurgery, Tzu Chi General Hospital, Tzu Chi University, No. 707, Sec. 3, Chung Yang Rd., Hualien 970, Taiwan, ROC
[e] Department of Management Information Systems, Central Taiwan University of Science and Technology, No. 666, Buzih Rd., Taichung 406, Taiwan, ROC
[f] Department of Computer Science and Information Engineering, Minghsin University of Science and Technology, No. 1, Xinxing Rd., Hsinchu City 304, Taiwan, ROC
[g] Department of Psychology, University of Virginia, 102 Gilmer Hall, P.O. Box 400400, Charlottesville, VA 22904-4400, USA

ARTICLE INFO

Keywords:
Human motion analysis
Parkinsonian gait
Linear discriminant analysis (LDA)
Classification
Regression

ABSTRACT

Parkinson's Disease (PD) is a common neurodegenerative disorder with progressive loss of dopaminergic and other sub-cortical neurons. Among various approaches, gait analysis is commonly used to help identify the biometric features of PD. There have been some studies to date on both the classification of PD and estimation of gait parameters. However, it is also important to construct a regression system that can evaluate the degree of abnormality in PD patients. In this paper, we intended to develop a PD gait regression model that is capable of predicting the severity of motor dysfunction from given gait image sequences. We used a model-free strategy and thus avoided the critical demands of segmentation and parameter estimation. Furthermore, we used linear discriminant analysis (LDA) to increase the feature efficiency by maximizing and minimizing the between- and within-group variations. Regression was also achieved by assessing the spatial and temporal information through classification and finally by using these two new indices for linear regression. According to the experiments, the outcomes significantly correlated with the sum of sub-scores from the Unified Parkinson's Disease Rating Scale (UPDRS): motor examination section with $r = 0.92$ and 0.85 for training and testing, respectively, with $p < 0.0001$. Compared with conventional methods, our system provided a better evaluation of PD abnormality.

1. Introduction

Parkinson's Disease (PD) is a common neurodegenerative disorder and results from the progressive loss of dopaminergic and other sub-cortical neurons (Jankovic, 2008). PD often causes muscle rigidity, remor, and a slowing or complete loss of physical movement. Previous studies have reported that about 0.1–0.2% of the population is affected by PD (Chien et al., 2006). Several treatments have been reported to be effective, such as drugs like L-dopa and brain surgery with deep brain stimulation (Lin et al., 2008). The clinical diagnosis of PD is typically based on the patient's medical history and clinical presentations. The specific assessment of PD includes observations of some common motor tasks, such as walking a short distance and getting up out of a chair. The Unified Parkinson's Disease Rating Scale (UPDRS; Christopher et al., 2008) is widely used to evaluate PD by clinicians' observations. It consists of four parts includes: (1) mentation, behavior, and mood, (2) activities of daily living, (3) motor examination and (4) complications of therapy. The evaluation of UPDRS relies rather strongly on expertise; therefore, the measurement of UPDRS tends to be subjective. Some studies report a high inter-rater reliability in UPDRS rating (Paulson & Stern, 2004) but according to a study by Richard et al., the motor section in the UPDRS has the best inter-rater consistency, while the other sections have poor results, especially for speech disorder and facial immobility (Richard, 1994).

Posture and motor tasks are different for completely healthy people compared with patients with motor disorders due to age, stroke or PD. These patients may have problems with asymmetry of stance, ambulation, and stepping up onto raised structures (Chen et al., 2005; Yang, 2008). As an objective and quantitative approach, gait analysis is especially important for evaluating these motor impairments.

Gait analysis is commonly used to help identify biometric features for personal identification, medical diagnosis support, personalized training systems for various sports and so on (Chien et al.,

* Corresponding author. Tel.: +886 3 571 2121x31233; fax: +886 3 612 5059.
E-mail address: irradiance@so-net.net.tw (Y.-Y. Chen).

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doi:10.1016/j.eswa.2011.07.042

2006; Cunado, Nash, Nixon, & Carter, 1999; Gafurov, Helkala, & Søndrol, 2006; Kohle, Merkl, & Kastner, 1997; Lakany, 1999; Salarian et al., 2004). As an objective and quantitative approach, gait analysis is important for evaluating locomotion. The effectiveness of this approach is supported by Stebbins and Goetz's study (Stebbins & Goetz, 1998). Consequently, more and more gait analysis systems are being developed.

Some quantitative gait analysis systems utilize various types of sensors or equipment attached to the subject's body to record physiological or physical signals over time. For example, Salarian et al. attached gyroscope sensors to subjects' limbs to compute the angular rate of rotation (Salarian et al., 2004). Gafurov et al. used accelerometers attached to subjects' legs to detect acceleration in three dimensions (Gafurov et al., 2006). The force platform is another device that is widely used for measuring walking patterns. Chien et al. evaluated bradykinesia by GAITRite system, which could identify footfall contacts (Chien et al., 2006). Although the above sensor-based approaches can accurately access gait dynamics well, they are often expensive, complicated and uncomfortable for the subject. To avoid those problems, vision-based systems (Cunado et al., 1999; Yam, Nixon, & Carter, 2002; Zhang, Vogler, & Metaxas, 2007) have been developed for gait analysis because of no sensors requirement and are more comfortable for the subjects. For example, Chang et al. segmented the images of the subjects into regions and then computed the distances and angles of their limbs (Chang, Guan, & Burne, 2000). In a study by Melnick et al., the temporal characteristics of gait, such as stride length, width, cadence and velocity, were measured (Melnick, Radtka, & Piper, 2002).

There have been some studies to date on the classification of PD and the estimation of gait parameters as reviewed above. However, it is also important to construct a regression model that can evaluate the degree of abnormality in PD patients because it is important not only to detect whether a subject has PD but also to determine the severity of the disease. Additionally, objective and quantitative measurements are also very helpful in assisting doctors in the assessment of PD for rehabilitation and treatment planning. In this study, we intended to investigate a gait regression model of PD. The regression analysis was designed to predict the severity of motor symptoms among PD patients. We extracted posture and dynamic stride variation data by vision-based approaches. Afterwards, we optimized the discriminant capabilities of these features to form useful gait abnormality indices according to a certain scale determined by experts. Thus, these features had higher correlation coefficients to the given scale. Finally, we combined useful indices by linear regression (Lin, Wang, Chen, Chen, & Yen, 2009) to assess the degree of gait abnormality.

2. Materials and methods

2.1. Overview of the regression model for the gait analysis of patients with Parkinson 's Disease

We proposed a vision-based analysis system for PD gait evaluation that can classify and compute the regression model from the given gait data. The architecture of the gait analysis comprises five main parts: (1) video acquisition, (2) image preprocessing, (3) feature extraction, (4) learning using extracted features and (5) the testing processing. Moreover, the flow of image preprocessing comprises image clipping, background construction, subject detection, and image normalizing and reshaping. For feature extraction, both spatial and temporal features are used in this design. The spatial feature is extracted directly using the silhouettes of the subjects in the images. On the other hand, temporal information is obtained from the time-varying step size. Linear discriminant analysis (LDA; Dogantekin, Dogantekin, & Avci, 2009) is used to simultaneously maximize the between-class variations and minimize the within-class variations.

2.2. Subjects

Twelve patients with PD before and after drug treatment and twelve normal people from Buddhist Tzu Chi General Hospital in Taiwan were enrolled in this study. Their characteristics are listed in Table 1. All the experiments were conducted in the department of Neurosurgery in the hospital. All subjects were asked to wear light-colored suits and then observed walking back and forth in the 5 m long pathway in front of a dark curtain serving as the background. This is because we intended to compare the motor function of PD patients before and after L-dopa treatment, each PD patient participated twice in this study. Therefore, we obtained a sample of 36 effective subjects.

2.3. Gait imaging protocol

The image preprocessing was accomplished by the following four steps: gait image clipping, background construction, subject detection, and image normalizing and reshaping.

2.3.1. Video acquisition and gait image clipping

The environmental setup was shown in Fig. 1. A camcorder (VPC-HD1010, Sanyo Corp., Ltd., Japan) was settled at the front end of the pathway at approximately 4.5 m, perpendicular to the subjects' walking direction. Subjects stood upright on barefeet and walked along a 4-m pathway at a self-selected speed upon a verbal cue. After the experiments, all videos were clipped with a sample rate of 15 frames/s and an image size of 320×240 pixels. Because the subjects performed at different speeds, the extracted clip numbers of these image sequences varied.

2.3.2. Image background construction and subject detection

First, the background models were constructed by taking photographs of the environments without subjects. Although there are many image segmentation approaches (Haritaoglu et al., 2000; Lu, 2006) for simplicity, we used the image difference and thresholding technique (Cho, Chao, Lin, & Chen, 2009) to segment the subjects' profiles. The differences between the background and each of the frames of the subjects' images were 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 particular threshold. This threshold depended on the color contrast of the curtain and the clothing of the subjects and on the illumination conditions. As a result, we binarized each of the images. To obtain a more compact silhouette size, we projected the binary image onto the vertical and horizontal axes (Cho et al., 2009). The upper and lower bounds of the silhouette were computed by using a threshold of 2% of the maximum projection amount. The resultant images were normalized to the size of 64×64 pixels to further reduce the computational costs. According to the study reported by the previous study (Cho et al., 2009), not only the subject's feet but also other parts of the body can contribute useful information when judging a subject's motion pattern of his gait; therefore, we adopted the whole image of a subject instead of ignoring parts of the subject's body.

2.4. Dimension reduction of gait image

Principal component analysis (PCA) is a classic technique used in statistical data analysis and features extraction and data compression (Jolliffe, 2002). It is useful in reducing the dimensionality

Table 1
The characteristics of PD patients and normal controls in this study.

PD patients							Normal controls		
Subject	Age (year)	Gender (M/F)	Weight (kg)	L-dopa dose/treatment (mg)	UPDRS III Drug off	UPDRS III Drug on	Age (year)	Gender (M/F)	Weight (kg)
1	44	M	73.5	125	10	8	52	M	52
2	61	F	74.7	375	44	26	50	M	71
3	67	M	71	187.5	46	35	57	M	54
4	65	M	72	250	25	23	48	M	72.5
5	57	M	61	250	52	49	67	F	56
6	59	M	71	187.5	21	16	57	F	65
7	57	M	56	250	28	24	48	F	51
8	68	M	68	250	26	18	51	F	60
9	59	F	46	312.5	47	26	57	M	65
10	60	M	78	250	30	25	58	F	67
11	63	F	74	250	40	26	50	F	57
12	59	M	76.5	250	13	9	57	M	75.5
Mean ± S.D	59.6 ± 6.78	9 M/3 F	67 ± 9.7	243.7 ± 68.8	31.2 ± 15.0	23.4 ±12.2	54.4 ± 5.8	6 M / 6 F	62.2 ± 9

The Hoehn and Yahr (H&Y) scale is referred to Drug off condition to drug on condition.
S.D., Standard deviation.

of image data by transforming them from a correlated high-dimensional image vector to an uncorrelated low-dimensional image vector. For image processing, the silhouette of a subject in an image frame was originally represented as a binary matrix. We reshaped each of the obtained silhouettes as a vector form of 4096×1. Afterwards, we collected all the image vectors columnwise and then computed the associated mean vector and covariance matrix. After computing the eigenvectors of the covariance matrix, we projected the original image vectors using the obtained eigenvectors to form a new set of image vectors. We then reduced the dimensionality of the image by ignoring the projected coefficients that resulted from eigenvectors with lower eigenvalues.

2.5. Classification using the half-length portrait feature

A person's posture is often significantly different from that of others, especially when comparing normal people to patients with movement disorders. For example, healthy people or PD patients may be in flexion, stooped, or have festinating or shuffling gaits. For image processing, the subject's gait in a video can be described by $\boldsymbol{x} = \boldsymbol{x}(t, c)$, where $\boldsymbol{x}$ is the image pixel matrix or, equivalently, a reshaped image vector, t is the time and c is one of the classes. The dimension reduction processing will project $\boldsymbol{x}(t, c)$ to $\boldsymbol{y}(t, c)$ in a new space with a lower dimensionality. If we force each image clip, either $\boldsymbol{x}(t, c)$ or $\boldsymbol{y}(t, c)$ of the same groups of people to be treated as the same class, we can expect that the learned patterns will be the static characteristics in the videos. The so-called static characteristics are the half-length portraits (postures) of the subjects regardless of their dynamic behaviors. We believe that people with specific characteristics, such as movement disorders, will keep some parts of their essential profiles unchanged, which are different from the characteristics of healthy people, even when they are walking.

To perform the above dimension reduction and feature extraction, we chose a transformation to accomplish these two tasks. Parkinson's Disease is typically diagnosed basing on the physician's assessment, we chose a supervised approach to extract gait features because of the superiority of supervised methods of classification. LDA (Cho et al., 2009; Huang, Harris, & Nixon, 1999) is such an algorithm used to obtain these essentially static characteristics because of the mechanism of the suppression of image clip differences of the same class. LDA simultaneously balances the maximization of the between-class variations with the minimization of the within-class variations. Thus, the within-class variations due to silhouette changing with time were minimized. We then expected that the features obtained after LDA will indeed be the static profiles of the subjects.

As a result, we computed the between- and within-class matrices, $\mathbf{S}_b$ and $\mathbf{S}_w$, respectively, and then solved $\mathbf{S}_w^{-1} - \mathbf{S}_b$ to obtain the LDA transformation matrix. We then computed the posture features by projecting the dimension-reduced image vectors to the new space generated by the eigenvectors of $\mathbf{S}_w^{-1} - \mathbf{S}_b$. To classify image feature vectors, the minimum distance classifier (MDC; Duda et al., 2000) was used in this study for its simplicity.

2.6. Classification using lower limb feature

Gait patterns can vary widely, such as walking slowly, shuffling with short steps, and so on. A very straightforward measurement of the gait pattern by a vision system is the computation of the time-varying step size sequence of a subject's video. Furthermore, because posture features rely heavily on the upper half-length portraits, the step size sequences, however, provided the complement of posture feature by computing the dynamic stride range, which is another important information posture cannot cover.

The step size sequences are the temporal information in the videos. However, due to variations in the gait speeds and step sizes of different subjects, the analysis of the step size sequences is complex. There are many feature extraction methods to deal with the time-varying step size functions, such as wavelet and PCA. We used fast Fourier transform (FFT) because it is time-independent (Oppenheim et al., 1999). That is, the variations of time-shift caused by the initiation of the subjects' movement can be removed. In addition, to increase the separability for MDC, we again used LDA to map the power spectra onto a new space. This time, LDA was used to improve the discrimination because the power spectra of the step size sequences had lost their planar image properties.

2.7. Classification-based regression

Because LDA maximizes and minimizes the between- and within-class variations simultaneously, the posture features were especially suitable for discrimination. For gait classification, we usually have two classes: patients and normal control. However, for gait regression, we divided the subjects into more classes of different levels according to various rating scales, such as level 0, level 1, level 2, ..., level N. We then assigned each class a grade, such as 0, 1, 2, ..., N, corresponding to the appropriate posture abnormality

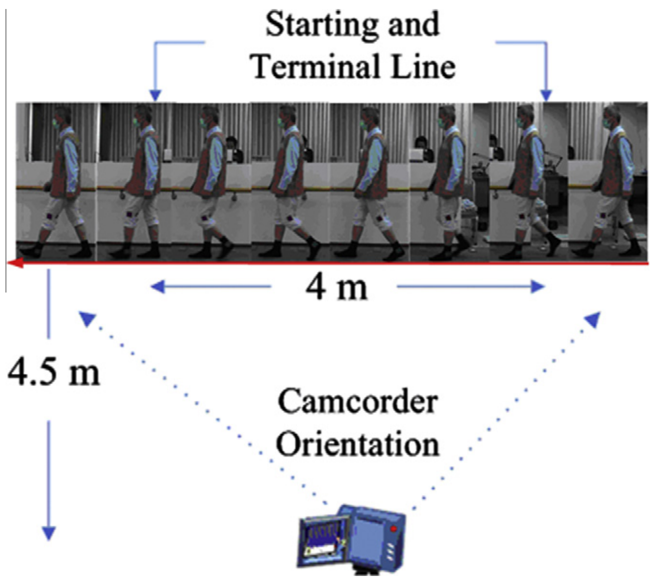

Fig. 1. The environmental set-up and video recording standard.

degree. Thus, the posture abnormality index (PAI) can be simply obtained by determining the level (class) of the given upper-length portrait feature of a subject through MDC classification. Similarly, we can also assign grades for lower limb movement abnormalities to compute the foot movement abnormality index (FMAI) by similar classification process as described above.

2.8. Regression using both PAI and FMAI

As described in the above section, we computed the two indices, PAI and FMAI, for half-length and lower limb movement abnormality for human gait analysis. To proceed, we utilized the linear regression model (Lin et al., 2009) for the assessment of overall motor abnormality (MA) as shown in Fig. 2. The response (as determined by any rating scale or judgment by experts), PAI and FMAI for each subject were fitted by

$$\mathrm{MA} = \beta_0 + \beta_1 \times \mathrm{PAI} + \beta_2 \times \mathrm{FMAI}, \tag{1}$$

where β_0, β_1 and β_2 were estimated using the minimum sum of squares residual criterion. After fitting the model, we then evaluated the correlation coefficients between the outcomes by Pearson's correlation coefficient.

2.9. The evaluation of regression model for the gait analysis of patients with Parkinson's Disease

The regression model for the gait analysis makes use of both spatial and temporal features from gait image sequences. We first individually evaluated the performance of PAI and FMAI by correlating them with UPDRS records provided by doctors. We then further investigated the performance of MA in the same way. Pearson correlation, as the most widely used stochastic measure for the linear dependence of two variables, was used to evaluate the performance of the above linear regression, and the equation was as follows:

$$r = \frac{1}{N-1}\sum_{i=1}^{N}\left(\frac{x_i - \bar{x}}{s_x}\right)\left(\frac{y_i - \bar{y}}{s_y}\right), \tag{2}$$

where x_i is the PAI and y_i is one of the UPDRS Part III sub-scores, $\bar{x}$ and $\bar{y}$ are the associated sample means, S_x and S_y are the associated standard deviations, N is the number of observations, and r is the resultant correlation coefficient.

3. Experiments and results

3.1. Subject detection

To detect the subject, we first subtracted the background image from each current image frame. Pixel candidates of the subjects' silhouettes were then labeled to construct binary images to ensure that the absolute values of the differences were larger than an intensity threshold (10 in this case). The Regions of Interest (ROI) were determined by projecting the binary images onto the vertical and horizontal axes. We selected the ROI rectangles to be square regions. Furthermore, the ROI were normalized to the size of a 64×64 matrix. We encoded the detected silhouette images to image vectors.

The mean of the silhouette vectors was computed, and the covariance matrix was then calculated. Accordingly, the eigenvalues and associated eigenvectors of the covariance matrix were computed. Among the eigenvectors calculated, the first 280 eigenvectors that corresponded to the largest 280 eigenvalues (accumulating 90% of the total variance) were selected as the basis 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 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 the partial eigenspace were computed. Then the ratio of between-class variance and within-class variance was maximized. Accordingly, the ratios before and after LDA were 0.045 and 16.00, respectively, clearly showing that LDA increased the ratio. Finally, the LDA coefficients of the silhouette vectors were calculated.

3.2. Spatial feature extraction

We extracted the postural features using LDA and PCA for comparative purposes only. The resultant distributions of the four levels of posture abnormality as determined by LDA are shown in Fig. 3. It shows that postural features extracted by LDA had good discriminative capability.

3.3. Correlation between PAI and sub-score 28 (Posture) in UPDRS (Christopher et al., 2008)

Because all the subjects were grouped into four levels of postural abnormality, we computed the correlation coefficients to sub-score 28 (Posture) in UPDRS Part III (Christopher et al., 2008). Vision-based postural abnormality assessment using the LDA algorithm was very consistent with the assessments of the therapist. We found the significant correlation between sub-score 28 (Posture) in UPDRS Part III and PAI computed by means of LDA discrimination ($r = 0.92$, $p < 0.01$ for all subjects). On the other hand, the correlation coefficient by means of PCA discrimination was moderate ($r = 0.68$, $p < 0.01$ for all subjects).

3.4. Temporal feature extraction

The sub-scores 26, 27, and 29–31 are closely related to the subjects' gait by foot movement. We computed the horizontal range of the bright pixels for each subject's binarized image. The dynamic range functions of time were then transformed by FFT to obtain power spectra. To assess the locomotor symptoms, power spectra were further transformed by LDA for regression using a classification-based technique. The resultant distributions of the seven

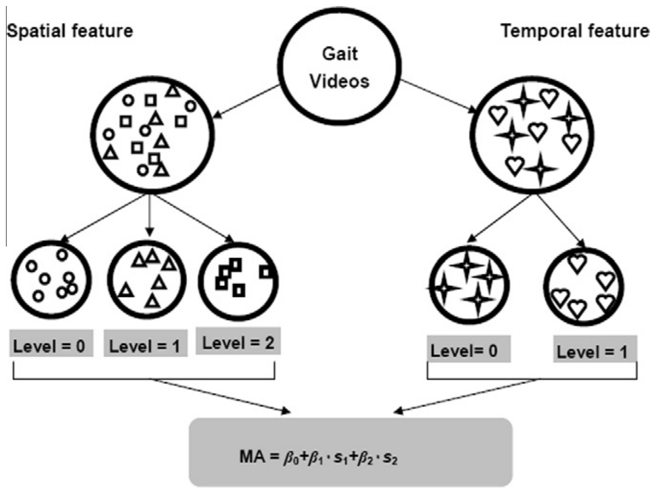

Fig. 2. The illustration of the classification-based regression.

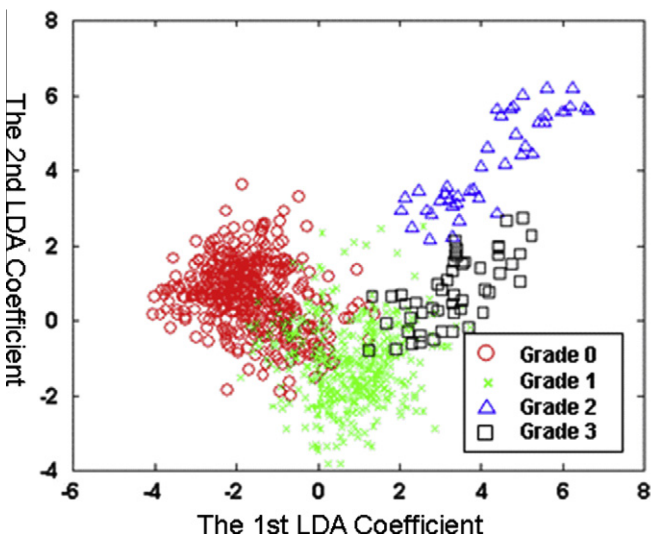

Fig. 3. The distribution of the LDA coefficients of the four levels of postural abnormality of the subjects.

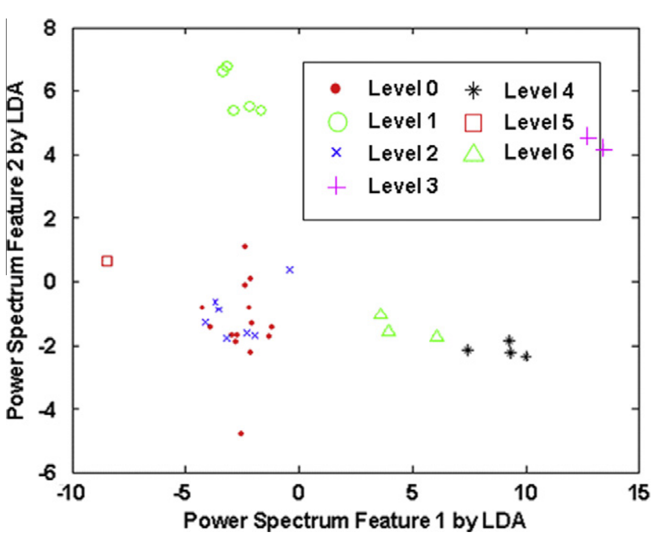

Fig. 4. The distribution of the LDA coefficients of the seven levels of postural abnormality of the subjects.

levels (0–6) of foot-movement-related features extracted by LDA are shown in Fig. 4, which shows that foot-movement-related features extracted by LDA had good ability to separate these groups of temporal features.

3.5. Correlation between FMAI and sum of sub-scores 26, 27, 29, 30, and 31 in UPDRS (Christopher et al., 2008)

Because all the subjects were grouped into seven levels of postural abnormality, we computed the correlation coefficients to subscores in UPDRS Part III (Christopher et al., 2008). Vision-based postural abnormality assessment using the LDA algorithm was very consistent with the assessments of the therapist. We also found the significant correlation between the sum of sub-scores 26, 27, 29, 30, and 31 in UPDRS and FMAI by means of LDA discrimination ($r = 0.98$, $p < 0.01$ for all subjects). On the other hand, the correlation coefficient by means of PCA discrimination was moderate ($r = 0.71$, $p < 0.01$ for all subjects).

3.6. Assessment by linear regression using both PAI and FMAI

Here we further integrated the two above techniques to assess the impairment of PD patients in terms of overall motor ability. We obtained the linear regression parameters $\beta_0 = 2.29$, $\beta_1 = 4.17$ and $\beta_2 = 6.29$. We show in Fig. 5 the correspondence of the subjects' motor impairment score as assessed by our method using linear regression (x-axis) and by the therapist using UPDRS Part III (y-axis). The detailed training and testing results using cross-validation are shown in Table 2, and the very significant correlation in the training phase can be observed.

For comparison, we also implemented some traditional methods using features such as stride time and stride length. We summarize the correlation using stride length, stride time and our method in Table 3, which shows that the linear regression method utilizing both posture and foot-movement outperformed the other methods.

4. Discussion

We proposed a novel regression approach to evaluate the degree of abnormality in the gait of movement disorder patients.

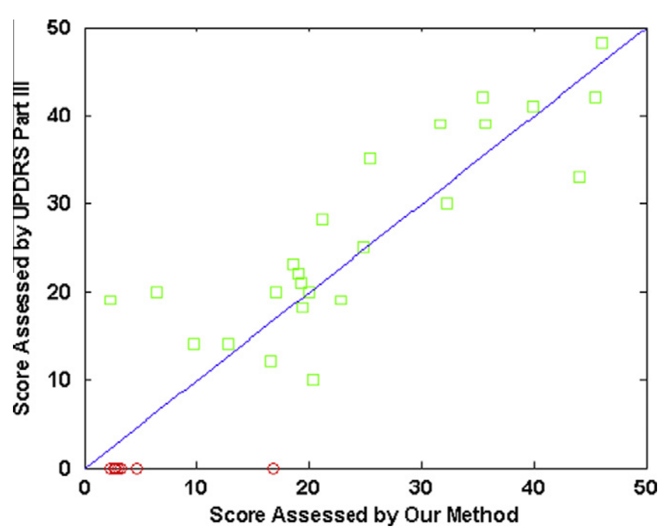

Fig. 5. The correlation of the subjects' motor impairment score (green rectangles and red circles for PD and normal subjects, respectively) assessed by the regression model for the PD gait and by the therapist using UPDRS Part III. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

Table 2
The training and testing results.

	Phase	Correlation coefficients (r)	p-Value
Trial 1	Training	0.95	<0.0001
	Testing	0.86	<0.0001
Trial 2	Training	0.89	<0.0001
	Testing	0.83	<0.0001
Average	Training	0.92	<0.0001
	Testing	0.85	<0.0001

Table 3
The mean and standard deviation of the traditional gait parameters. For each parameter, the correlation coefficients to UPDRS-P3 were calculated.

Statistics	Stride length (pix)	Stride time (s)	Regression model for the PD gait
Mean (pix)	19.4100	1.1593	17.61
Std. (pix)	1.2500	0.1740	14.06
Corr. coeff.	−0.5116	0.1172	0.8451
p-Value	0.0014	1.1556	<0.0001

Traditionally, the evaluation is accomplished by interviews and strongly relies on expertise of the physicians (National Parkinson Foundation, 2009). Engineering-based methods are more objective. Most researchers (Chien et al., 2006; Gafurov et al., 2006; Salarian et al., 2004) use a number of sensors to capture gait dynamics by recording various signals. Vision-based methods (Yam et al., 2002; Zhang et al., 2007) provide an inexpensive and more comfortable way for experimenters to evaluate the static and dynamic characteristics from the videos of patients. However, there are a limited number of studies on the problems with assessment methods. From the results, our method could provide a very accurate and objective assessment of the degree of motor impairment (as listed in Table 3, significant correlation $\boldsymbol{r} = 0.85$ with $\boldsymbol{p} < 0.01$ compared to the doctor's rating records). The method outperformed classical method using either stride time or stride length features.

The linear regression model was developed in the pre-computer age of statistics, but it is still a very effective way of modeling the relationship between the predictors and responses. However, for the application of movement disorder assessment using the monocular image sequence, the model would have failed if we directly fitted it with spatio-temporal information from subjects' videos and UPDRS data due to the large number of variables, high variance in prediction and low interpretation capability. Investigation of the essential correlation between UPDRS and postural and dynamic stride information is straightforward, but the drawback of large numbers of data remains. As reported by Cho et al. (2009), the vision-based pattern recognition technique could be utilized to differentiate between PD patients and healthy people with very high accuracy. However, the study did not provide a quantitative approach to assess the degree of abnormality in PD patients. Thus, in this paper we used UPDRS to train a system to achieve this goal. For example, if an instance of posture information was classified as the third class of abnormality, we knew that the instance would be calculated to have a grade of $3 - 1 = 2$ for posture abnormality. Similarly, we evaluated the dynamic stride abnormality by classifying each instance. Hence, we then used the linear regression model to fit the UPDRS Part III database with the posture and dynamic stride abnormality data.

Finally, we developed a PD gait regression system that is capable of predicting the abnormality degree from gait image sequences. We used a model-free strategy and thus avoided the critical demands of segmentation and parameter estimation. Furthermore, we used LDA to increase the feature efficiency by maximizing and minimizing the between- and within-group variations. According to the experiments, the outcomes significantly correlated to the sum of the UPDRS Part III sub-scores with $r = 0.92$ and 0.85 for training and testing, respectively, with $p < 0.0001$. Compared with conventional methods, our system provided a better evaluation of PD abnormality.

Acknowledgments

The authors are grateful to Tzong-Jer Li and Chung-Yi Wu for their prior system development. We are also very grateful to the volunteers who generously gave their time to assist with this research.

This research is supported by the Grant Nos. 98-2221-E-009-142, 97-3114-E-320-001 and 98-2218-E-320-001 from the National Science Council of the Republic of China in Taiwan.

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