Investigating body motion patterns in patients with Parkinson's disease using matching pursuit algorithm

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Abstract—*Several recent studies have quantified abnormalities in Parkinsonian gait. However, few studies have attempted to quantify the regularity of body motion during walking in patients with Parkinson's disease. The aim of the paper was to characterise body motion patterns in healthy, elderly subjects and patients with Parkinson's disease during walking. Body motion was recorded during walking for 16 patients with Parkinson's disease and ten healthy, elderly subjects using a tri-axial accelerometer device. To characterise the body motion patterns, time–frequency patterns of the body acceleration signal were estimated using a matching pursuit algorithm. Data from the study showed that the healthy, elderly subjects and patients with Parkinson's disease had different time–frequency patterns. The time–frequency patterns were classified into four distinct patterns based on their time durations: vertical (<0.15 s), circular (0.15–0.5 s), short horizontal (0.5–2.0 s) and long horizontal (>2.0 s). The data showed that the energy of the long horizontal patterns, representing long-term smooth and regular (rhythmic) activities, significantly decreased, but the energy of the circular patterns, representing irregular activities, increased in the patients with mild Parkinson's disease, compared with those of the healthy, elderly subjects ($p < 0.01$). Futhermore, these features were seen more clearly in the body motions of severe case patients than is that of mild case patients. It was concluded that these differences are probably due to a lack of ability to control normal and smooth movement is Parkinson's disease.*

Keywords—*Parkinson's disease, Body motion, Acceleration signal, Gait, Time–frequency patterns, Matching pursuit algorithm*

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1 Introduction

PARKINSON'S DISEASE is a degenerative disorder of the central nervous system. Although the actual cause of Parkinson's disease is not known, it has been postulated that a lack of dopamine may be the cause of the disease (SIAN *et al.*, 1999). Dopamine is a neurotransmitter that helps transmit messages to the striatum for the initiation and control of movement and balance. These dopamine messages make sure that muscles work smoothly and without involuntary movement. Therefore a severe reduction in dopamine causes several major symptoms of Parkinson's disease, such as resting tremor, rigidity, bradykinesia and postural instability (HOEHN and YAHR, 1967, SIAN *et al.*, 1999).

Resting tremor is seen mostly in the hands and fingers of patients with Parkinson's disease. Rigidity is an increased tone or stiffness in the muscles during movement. Bradykinesia causes slowness of movement and is characterised by a delay in initiating movements. Postural instability is impaired balance and co-ordination. Some patients experience repeated falls owing to poor balance. During walking, patients with Parkinson's disease also show characteristic symptoms, including a decreased or non-existent arm swing, short or shuffling steps, festination or pulsion and difficulty in initiation of movement known as freezing (HOEHN and YAHR 1967; SIAN *et al.*, 1999).

Recently, several research groups have quantified spatiotemporal, kinematic and kinetic characteristics of Parkinsonian gait (MURRAY *et al.*, 1978; STERN *et al.*, 1983; FORSSBERG *et al.*, 1984; BLIN *et al.*, 1990; OBERG *et al.*, 1993; MORRIS *et al.*, 1994; 1998; 1999; MILLER *et al.*, 1996; HAUSDORFF *et al.*, 1998; 2000; ZIJLSTRA *et al.*, 1998; EBERSBACH *et al.*, 1999; MESURE *et al.*, 1999; VAN EMMERIK *et al.*, 1999; KIMMESKAMP and HENNIG, 2001). Their data suggested that, in comparison with healthy, age-matched subjects, patients with Parkinson's disease demonstrate a decrease in walking speed associated with a decreased step length and an increase in double support duration and step width (MURRAY *et al.*, 1978; BLIN *et al.*, 1990; OBERG *et al.*, 1993; HAUSDORFF *et al.*, 1998; 2000; ZIJLSTRA *et al.*, 1998; MESURE *et al.*, 1999; MORRIS *et al.*,

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1999). A decrease in limb flexion-extension has been also reported (STERN *et al.*, 1983; FORSSBERG *et al.*, 1984). MURRAY *et al.* have suggested that hip, knee and ankle rotation in the sagittal plane are reduced, depending on the stage of Parkinson's disease (MURRAY *et al.*, 1978).

Furthermore, some studies have investigated the reproducibility of several gait parameters for patients with Parkinson's disease. Blin *et al.* and Hausdorff *et al.* have reported an increase in the variability of spatiotemporal gait parameters such as stride length and duration (BLIN *et al.*, 1990; HAUSDORFF *et al.*, 1998; 2000). The variability of electromyographic shape in lower limbs also increases (MILLER *et al.*, 1996). In contrast, the variability of the relative loads in the mid- and forefoot regions decreases (KIMMESKAMP and HENNIG, 2001). VAN EMMERIK *et al.* suggested that walking speed was an important factor influencing the stability of gait (VAN EMMERIK *et al.*, 1999). However, few studies have attempted to quantify the regularity of body motion during walking in patients with Parkinson's disease.

Several research groups have used an accelerometry technique to measure body motion (SMIDT *et al.*, 1971; EVANS *et al.*, 1991; AMINIAN *et al.*, 1995; MAKIKAWA and IIZUMI, 1995; VELTINK *et al.*, 1996; BOUTEN *et al.*, 1997; TAMURA *et al.*, 1997; SEKINE *et al.*, 2000*a*; *b* 2002; AUVINET *et al.*, 2002; SCHUTZ *et al.*, 2002). This accelerometry technique has the great advantage of measuring body motion directly without constraining the subject. In fact, the accelerometry technique has been proposed for classifying several daily activities, estimating energy expenditure for several physical activities and quantifying gait abnormalities. In our previous study, we investigated dynamical changes in body motion during walking between young and elderly subjects by using acceleration signals (SEKINE *et al.*, 2000*a*; *b*; 2002). The fractal measure is a representative measure of fractional Brownian motion that provides a useful model for many physical phenomena (FISCHER and AKAY, 1996). Our previous results showed that the fractal measures of the acceleration signals during level walking were significantly higher in the elderly subjects than in the young subjects. The high fractal values suggested that the body motion becomes more complex or irregular during walking. These findings show that the acceleration signal can be used to assess the dynamics of body motion during walking.

In this paper, we hypothesise that the body motion in patients with Parkinson's disease is neither smooth nor rhythmical, and that their body acceleration signals have irregular patterns in the time–frequency domain. To test this hypothesis, we measured the body motion of healthy, elderly subjects and patients with Parkinson's disease using a tri-axial accelerometer device. Then, we estimated the time–frequency patterns of the acceleration signal using a matching pursuit algorithm (MALLAT and ZHANG, 1993). The matching pursuit algorithm was chosen as it provides better time and frequency resolutions than other time–frequency analysis and time-scale analysis methods (MALLAT and ZHANG, 1993). This algorithm also provides detailed information about each time–frequency pattern, including its energy, time and frequency localisation, phase and scale (time duration), which can be used for comparison and statistical analysis (MALLAT and ZHANG, 1993).

2 Method

2.1 *Measurement system*

In this study, our measurement system consisted of an accelerometer device and a data logger. The accelerometer device was constructed using three uni-axial accelerometers* (size: $4 \times 4 \times 3$ mm; weight: 0.3 g; range: $\pm 10\,g$; frequency response: 0–500 Hz). These uni-axial accelerometers were mounted orthogonally to record signals in the anteroposterior (X), lateral (Y) and vertical (Z) directions. We calibrated the accelerometers by measuring their outputs under controlled inclination. To give examples, the outputs were $1\,g$, $0\,g$, $-1\,g$, with the inclination at 0°, 90°, 180°, respectively. Note that g is gravity.

After the accelerometer device had been calibrated, it was fixed on an acrylic plate that had two slits for a waist belt. It was fastened to the subject's back in the lumbosacral region of the vertebral column, close to the subject's centre of gravity when standing. It was attached over their clothes by an elastic waist belt. The accelerometer device was connected to the portable data logger† by an interface circuit of our own fabrication. This data logger consisted of a CPU, a 10-bit A/D converter, an IC card interface and a removable 2 MB IC memory card (MAKIKAWA and IIZUMI, 1995). The interface circuit included three amplifiers and three second-order analogue Butterworth lowpass filters as an anti-aliasing filter for each direction. The output resolutions were approximately $0.01\,g$, and the cutoff frequency was 500 Hz. According to our previous studies, these specifications are sufficient to record the body acceleration during walking (TAMURA *et al.*, 1997; SEKINE *et al.*, 2000*a*; *b*; 2002). The accelerometer outputs were digitised at a sampling rate of 1024 Hz by the data logger and were recorded on the IC memory card. After the measurements were completed, the data were transferred by a card reader to a personal computer for further analysis.

We also measured average walking speeds in the subjects using two photo-electric sensors‡. The sensors were mounted on an upright pole and were placed at the centre of the walking path. The distance between the sensors was 6 m along the walking path. The height of the sensors was adjusted to the height of the subject's shoulder. The sensor output signals were recorded onto a personal computer. After recordings had been made, the signals were used to calculate average walking speed between the sensors.

2.2 *Experimental design*

In this experiment, the recordings were made from 16 patients with idiopathic Parkinson's disease (PD). The PD patients were categorised into two groups using Hoehn–Yahr stages (HOEHN and YAHR, 1967). The mild case group (stage I or II) included 11 patients (six male, five female; age: 66.0 ± 9.6 years old; height: 1.55 ± 0.12 m; weight: 52.7 ± 12.3 kg; mean ± SD) and the severe case group (stage III or IV) included five male patients (age: 57.4 ± 19.1 years old; height: 1.64 ± 0.92 m; weight: 53.8 ± 7.9 kg; mean ± SD). For comparison, ten healthy, elderly (HE) female subjects with no history of neurological disease (age: 66.3 ± 5.3 years old; height: 1.47 ± 0.05 m; weight: 49.7 ± 4.2 kg; mean ± SD) participated.

The subjects walked along a walking path freely, at their own speed, without any assistance or walking aid such as a cane. Note that the walking path was a part of a 50 m straight corridor in a hospital. Although the length of the walking path depended on the subject's walking ability, it was at least 10 m. The measurement was taken after the subject had walked along the walking path once to determine the length of the walking path and the optimum location of the photo-electric sensors for the individual subject. This study was approved by the Ethics Committee of Fujimoto Hospital, and all the subjects gave written informed consent before examination.

*Type 3031-010, IC-Sensors, USA

†Micro 8, Shimadzu, Japan

‡PZ2-61, Keyence, Japan

2.3 *Signal processing*

Many biological signals are not stationary. Quantitative changes in biological signals have traditionally been estimated using the fast Fourier transform (FFT), despite the requirement for the stationary property. In practice, to satisfy this requirement, investigators used FFT using short data segments while carrying out long-term signal monitoring. This approach is called the short-time Fourier transform (STFT) method. However, the use of a short window results in low spectral resolution, as the FFT requires a long data segment for accurate spectral estimation. The spectral resolution of the STFT method can be improved with the use of a longer data window, at the expense of poor time resolution (MALLAT and ZHANG, 1993; AKAY, 1998).

In this study, an adaptive time–frequency analysis method called the matching pursuit algorithm was used for representing an acceleration whose localisations in time and frequency can vary. The non-stationary biological signal can be expanded into several waveforms (patterns), whose time-frequency properties can be adapted to its local structures. Note that these waveforms can be selected from a redundant dictionary D of time-frequency patterns (atoms), such as dilations, translations and modulations of a single window function $g(t)$ (MALLAT and ZHANG, 1993)

$$g_\gamma(t) = \frac{1}{\sqrt{s}} g\left(\frac{t-u}{s}\right) e^{j\eta t} \tag{1}$$

where t is time, and γ represents the chosen set of parameters including the frequency modulation η, the translation u and scaling parameter s. The energy is concentrated around γ with a spread proportional to s (MALLAT and ZHANG, 1993).

Linear expansion of signal $f(t)$ over a set of vectors was selected from the dictionary to match its local structures. This expansion can be done by successive approximations of $f(t)$ with orthogonal projections on elements of the dictionary. The original signal $f(t)$ can be decomposed into

$$f = \langle f, g_{\gamma 0} \rangle g_{\gamma 0} + R^1 f \tag{2}$$

The second term on the right hand side represents the residual vector after approximating $f(t)$ in the direction of window function $g_{\gamma 0}$, which is orthogonal to the term R^1, the remaining signal. Therefore the power of $f(t)$ can be written as

$$\|f\|^2 = \|\langle f, g_{\gamma 0} \rangle g_{\gamma 0}\|^2 + \|R^1 f\|^2 \tag{3}$$

The original signal $f(t)$ is decomposed into a sum of dictionary elements that are chosen to match its residues best (MALLAT and ZHANG, 1993). Although this decomposition is non-linear, we maintain an energy conservation as if it were a linear orthogonal decomposition. This decomposition is obtained with a strategy similar to the matching pursuit algorithm (see MALLAT and ZHANG, 1993 for the details).

Antonosson and Mann suggested that 99% of the acceleration power during walking is contained below 15 Hz (ANTONSSON and MANN, 1985). The acceleration signals were lowpass filtered (20 Hz) and resampled at 1/8 times the original sampling rate, 1024 Hz. Then we decomposed the acceleration signals into several time-frequency patterns (atoms) using the matching pursuit algorithm, until the summation of atom energies reached 99.5 % of the total energy.

We classified the time–frequency patterns (atoms) into four distinct groups based on their time durations: vertical (<0.15 s), circular (0.15–0.5 s), short horizontal (0.5–2.0 s) and long horizontal (>2.0 s) patterns. The vertical pattern represented impulse type activities. The circular pattern showed irregular activities representing burst type patterns of the acceleration signal. The horizontal patterns showed long-term smooth and regular activities, representing periodic patterns of the signal-like sinusoid.

After categorising the time–frequency patterns, the mean and standard deviations (SDs) of the energies were estimated for each pattern for the HE group and the two PD groups. We also estimated the mean and SD of walking speed for these three groups. Statistical significances between groups were determined using a one-way analysis of variance (ANOVA) and a Scheffe multiple comparison test. The significance level was $p < 0.05$ for all comparisons.

3 Results

Figs 1*a–c* (upper panels) show a typical example of raw acceleration signals in the *X*-, *Y*- and *Z*-directions and their time–frequency energy distributions (lower panels) in an HE subject during walking. It is obvious from these Figures that the acceleration signals in the time domain for the HE subject are periodic and continuous waveforms, especially in the *X*- and *Z*-directions. Also, their corresponding time–frequency energy distributions consisted of several long and short horizontal patterns and a few circular and vertical patterns. The frequency of the dominant long horizontal patterns was approximately 2 Hz, which is related to step frequency. The other high-frequency, long horizontal patterns were harmonics of the dominant one. The vertical pattern representing impulse type activities was present at heel-strike. However, the circular

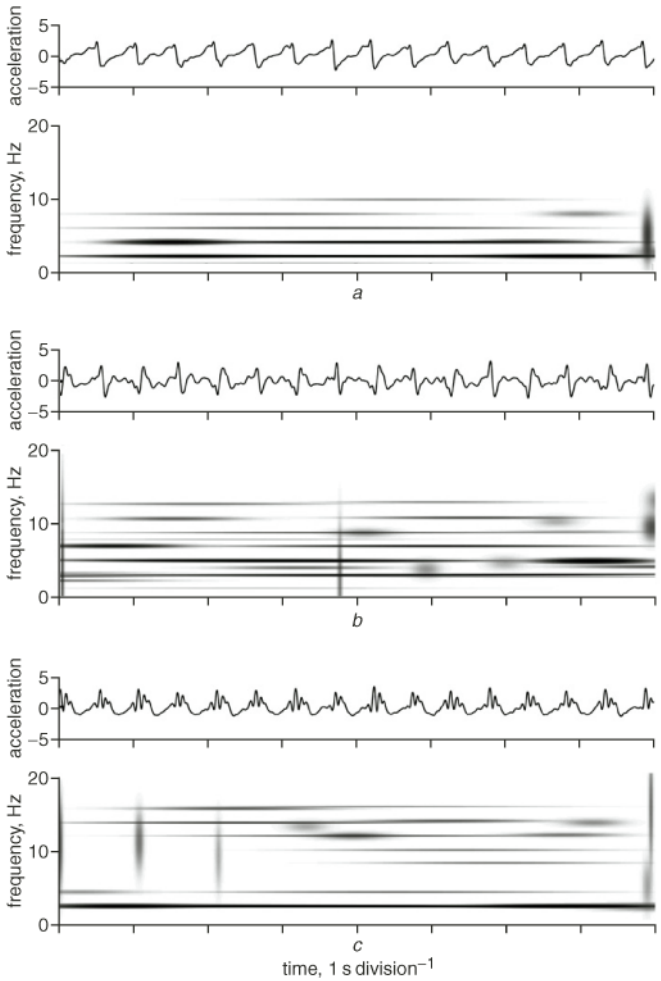

Fig. 1 *Typical example of acceleration signals and their time–frequency energy distributions during walking in HE subject. (a), (b) and (c) (upper panels): Raw acceleration signals in X-, Y- and Z-directions, respectively. Lower panels: time—frequency energy distributions. Note that acceleration signals were normalised by their standard deviations*

patterns representing burst type activities with short time duration were more often present in the acceleration signal of the *Y*-axis than in those of the X- and Z-directions.

Figs 2*a–c* show a typical example of raw acceleration signals (upper panels) and their time–frequency energy distributions (lower panels) in a mild case PD patient during walking. Note that raw acceleration signals were not as smooth as those in the HE subject (Fig. 1). As shown in Figs 2*a–c*, the time–frequency energy distribution still has long horizontal patterns. However, the energies of the long horizontal patterns were reduced compared with those of the HE subject. Again, like the HE subject, the frequency of the dominant continuous horizontal atoms was approximately 2 Hz. However, the number of circular patterns was increased compared with the HE subject.

Fig. 3 shows the same features for a severe PD patient during walking. Note that the patient did not have a stable walking pattern according to empirical observation by therapists. The patterns of the raw acceleration signals varied for each step. This feature was also apparent in the time–frequency energy distributions, as shown in Figs 3*a–c* (lower panels). The long horizontal patterns were reduced drastically compared with those of the HE subject and the mild PD patient. In addition, the short horizontal and circular patterns were dominant compared with those of the HE subject and the mild PD patient.

These findings were valid for other subjects in our database. Our data suggest that the PD caused changes in the acceleration signal. The major features of the PD patients were a reduction in the long horizontal patterns and an increase in the circular patterns compared with those of the HE subjects. Table 1 shows the mean energies for each of these four patterns for the HE group and the mild and severe PD groups. In the *X*-direction, the mean energies of the long horizontal patterns were significantly different between the three groups ($p < 0.01$). The mean energy of the short horizontal patterns for the severe PD group was significantly different from those for the other groups ($p < 0.01$). However, there was no significant difference between the HE group and the mild PD group ($p > 0.05$). The mean energies of the circular patterns were significantly different between the three groups ($p < 0.01$). The mean energies of the vertical patterns were not significantly different between among the three groups ($p > 0.05$).

In the *Y*-direction, the mean energies of the long horizontal patterns were not significantly different between the three groups ($p > 0.05$). The mean energy of the short horizontal patterns for the severe PD group was significantly different from those of the HE group and the mild PD group ($p < 0.01$). However, there was no significant difference between the HE group and the mild case PD group ($p > 0.05$). The mean energies of the circular and vertical patterns were not significantly different between the three groups ($p > 0.05$).

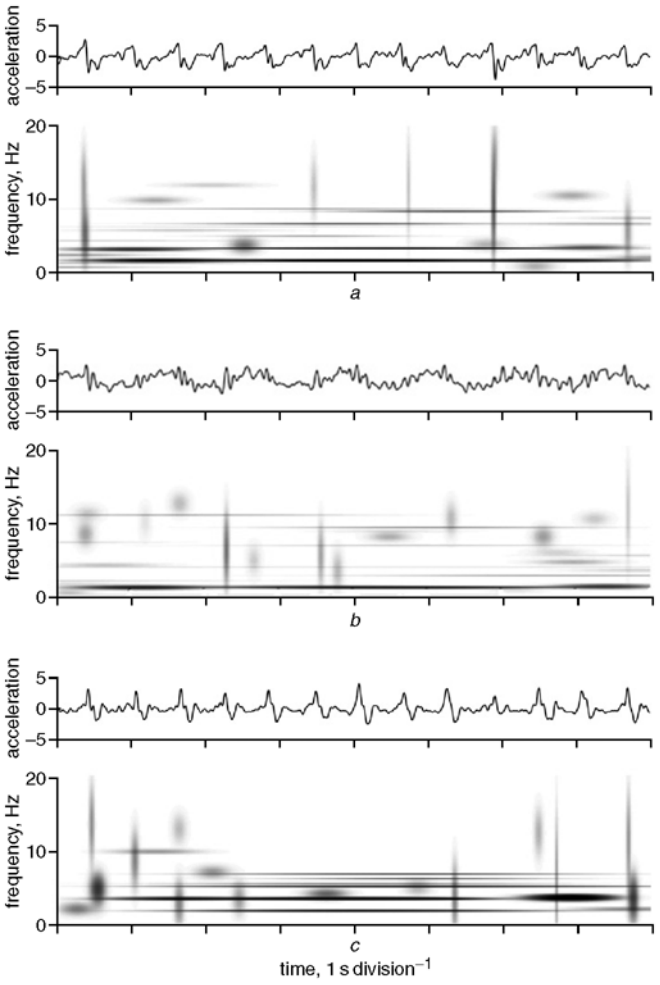

Fig. 2 *Typical example of acceleration signals and their time–frequency energy distributions during walking in mild case PD patient. (a), (b) and (c) (upper panels):Raw acceleration signals in X-, Y- and Z-directions, respectively. Lower panels: time–frequency energy distributions. Note that acceleration signals were normalised by their standard deviations*

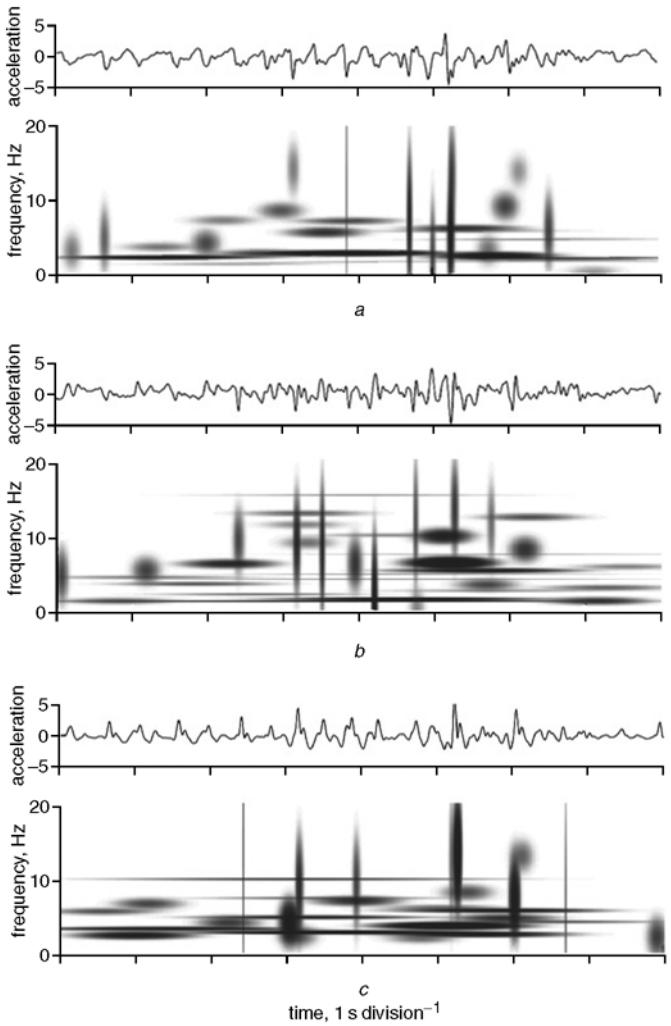

Fig. 3 *Typical example of acceleration signals and their time–frequency energy distributions during walking in severe case PD patient. (a), (b) and (c) (upper panels): Raw acceleration signals in X-, Y- and Z-directions, respectively. Lower panels: time–frequency energy distributions. Note that acceleration signals were normalised by their standard deviations*

Table 1 Comparison of mean energies of four time–frequency patterns, including vertical (VP), circular (CP), short horizontal (SHP) and long horizontal (LHP), between HE group and PD groups

Direction	Time–frequency pattern type	Mean ± SD, %			p-Value		
		HE	Mild PD	Severe PD	HE against mild PD	HE against severe PD	Mild PD against severe PD
X	VP	5.8 ± 3.8	14.0 ± 7.1	16.2 ± 12.8	0.06	0.06	0.86
	CP	3.8 ± 1.2	8.6 ± 2.8	13.6 ± 3.5	<0.01	<0.01	<0.01
	SHP	8.1 ± 3.9	8.3 ± 4.4	21.7 ± 3.6	0.99	<0.01	<0.01
	LHP	81.9 ± 7.2	68.7 ± 9.3	48.0 ± 9.1	<0.01	<0.01	<0.01
Y	VP	9.4 ± 6.4	14.4 ± 8.9	10.2 ± 4.9	0.33	0.98	0.58
	CP	11.0 ± 7.4	14.6 ± 7.5	13.3 ± 7.7	0.56	0.86	0.95
	SHP	11.3 ± 4.3	10.5 ± 4.8	23.8 ± 13.0	0.96	<0.05	<0.01
	LHP	67.7 ± 14.7	60.1 ± 13.7	52.2 ± 18.6	0.52	0.19	0.63
Z	VP	3.5 ± 2.6	9.7 ± 9.1	6.8 ± 3.4	0.10	0.64	0.70
	CP	3.5 ± 2.2	8.7 ± 3.4	13.0 ± 7.5	<0.05	<0.01	0.18
	SHP	6.9 ± 3.2	11.8 ± 4.8	21.9 ± 6.4	0.07	<0.01	<0.01
	LHP	85.6 ± 5.0	69.2 ± 10.2	57.8 ± 8.7	<0.01	<0.01	0.06

In the Z-direction, the mean energy of the long horizontal patterns for the HE group was significantly different from those of the mild and severe PD groups ($p<0.01$). However, there was no significant difference between the mild and severe case PD groups ($p>0.05$). The mean energy of the short horizontal patterns for the severe PD group was significantly different from those of the HE and mild PD groups ($p<0.01$). There is no significant difference between the HE group and the mild PD group ($p>0.05$). The mean energy of the circular patterns for the HE group was significantly different from both the mild and severe PD groups ($p<0.05$ and $p<0.01$, respectively). However, there was no significant difference between the mild and severe PD groups ($p>0.05$). Finally, the mean energies of the vertical patterns were not significantly different among the three groups ($p>0.05$).

Fig. 4 shows average walking speeds for the HE group and the two PD groups. The average speed in the HE group was significantly faster than those of both the PD groups ($p<0.01$). However, there was no significant difference between the mild and severe PD groups ($p=0.692$).

4 Discussion and conclusions

In this study, we used a new analysis method to assess body motion during walking for patients with Parkinson's disease. We employed an accelerometer device to measure the body motion and a matching pursuit algorithm to analyse acceleration signals during walking. Our preliminary data suggested that Parkinson's disease significantly alters the structure of acceleration signals in the time–frequency domain. The time–frequency patterns can also be used to determine the severity of the Parkinson's disease.

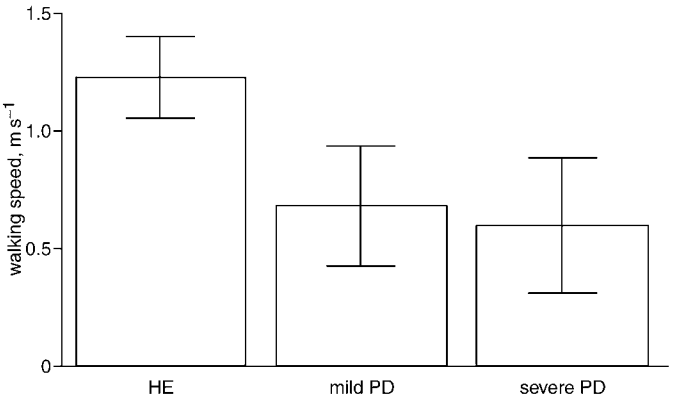

Fig. 4 *Mean and standard deviations of average walking speed for HE group and PD groups*

In the X- and Z-directions, the acceleration signals in PD patients showed a significant reduction in the energies of long horizontal patterns and a significant increase in the energies of circular patterns compared with those of HE subjects. The long horizontal patterns in mild PD patients were still dominant, although the circular patterns had increased. These results suggest that the fundamental ability of periodic and continuous locomotion remained intact in the mild PD patients, although the irregularity of body movement increased during walking compared with that of HE subjects.

In severe PD patients, there were some strong short horizontal and circular patterns around 2 Hz, suggesting that the changes in stepping phase occur frequently. These patterns differ between mild and severe PD patients, as do changes in the step duration. Both the short horizontal and circular patterns can be useful to assess the degree of PD. These findings illustrate that the body acceleration and movement of PD patients become more irregular. We speculated that the decrease in the regularity of the acceleration signal in PD patients is related to the diminished ability to control normal and smooth movement.

However, our results suggested that the acceleration signal in the Y-direction did not play a critical role in characterising body motion during walking in PD patients, compared with the other directions because of body movement mainly effected in sagittal plane during walking. In fact, many changes in kinematic parameters in the sagittal plane were observed, depending on the stage of the Parkinson's disease (MURRAY *et al.*, 1978). Therefore we speculated that the effects of PD could be seen in the X- and Y-directions. We alo suggested that a bi- or uni-axial accelerometric measurement could be sufficient in clinical practice.

In this study, the control group and the PD patient groups were not matched for gender. The effect of gender difference was unknown for our results. Gender differences in acceleration signals exist (AUVINET *et al.*, 2002). However, Auvinet *et al.* also suggested that stride regularity and step symmetry were independent of gender (AUVINET *et al.*, 1999; 2002). Therefore we assumed that the time–frequency pattern of the acceleration signal was not influenced as much by gender as by PD.

Previous studies have suggested that several spatiotemporal and kinematic parameters in PD patients are different from those in HE subjects. In general, PD patients walk slowly, with a

decreased step length (MURRAY *et al.*, 1978; OBERG *et al.*, 1993). However, they preserve the ability to modulate cadence in most cases (MORRIS *et al.*, 1994). The cadences of both HE subjects and PD patients are approximately 100–120 steps min^{-1} (MORRIS *et al.*, 1999). Our data furthermore confirm that PD patients still show the dominant patterns around 2 Hz that are associated with cadence. Therefore our results are consistent with previous findings that an unaffected cadence is observed in PD patients.

In addition, several gait variabilities in PD patients have been investigated. Hausdorff *et al.* suggested that the variability of stride duration in PD patients is significantly higher than that in HE subjects (HAUSDORFF *et al.*, 1998; 2000). However, the other studies did not confirm these findings, although they observed some slight increase in the variability of stride duration (BLIN *et al.*, 1990, EBERSBACH *et al.*, 1999). For severe PD patients, our data suggested that acceleration signals contain both short horizontal patterns, and strong circular structured patterns, indicating the variability of stride duration.

Blin *et al.* also suggested that the increase in the variability of stride length in PD patients could be due to the increased variability of force production, less than optimum force control, or a noisier output from the motor system and an inability to produce smooth forces in PD patients (STELMACH *et al.*, 1979; FLASH and TOGAN, 1985; BLIN *et al.*, 1990). In addition, Miller *et al.* suggested that the electromyogram of the gastrocnemius, a muscle critical to gait cycle timing, shows high variability in PD patients (MILLER *et al.*, 1996). As force production and electromyogram activities are directly and closely related to the acceleration signal pattern, our new analysis and pattern recognition approach based on the matching pursuit method can be also used for the analysis of the force production and EMG activities in PD patients during walking.

O'Sullvin *et al.* demonstrated that PD patients improved stride length and walking speed after levodopa treatment and that the gait parameters provided an alternative to clinical rating scales for dopaminergic response in patients with PD (O'SULLVIN *et al.*, 1999). Van Emmerik *et al.* suggested that walking speed is an important factor influencing the stability of gait in PD patients (VAN EMMERIK *et al.*, 1999). They also concluded that systematic manipulation of walking speed could be useful to assess co-ordination and rigidity in trunk movement. Our results showed that the average walking speed in the two PD groups was significantly slower than that in the HE group ($p < 0.01$). Therefore there is the possibility that the irregularity of body motion is related to the decreased walking speed. However, the average walking speeds from the present study showed no significant difference between the mild and severe case PD groups ($p > 0.05$), although the time–frequency pattern of the acceleration signal was significantly different between the two PD groups.

Note that our study was not successful in assessing the severity of the disease and stability of gait using only average walking speed. This discrepancy could be due to a lack of severe cases in the previous study carried out by VAN EMMERIK *et al.* (1999). In this study, some of the severe case patients (Hoehn–Yahr stages III–IV) showed festination gait, which is one of the characteristic symptoms of advanced Parkinson's disease. Therefore the difference between the mild and severe case groups did not appear in the average walking speed. However, the represented time–frequency patterns of acceleration signals can be use to quantify the severity of Parkinson's disease.

In conclusion, body motion during walking shows a deficiency of smoothness and regularity owing to the Parkinson's disease. Our preliminary data also confirmed that the body acceleration signals in patients with Parkinson's disease consist of a few long and short horizontal patterns representing smooth and regular (rhythmic) activities and a significant number of circular patterns representing irregular activities with short durations compared with those of healthy elderly subjects. We are currently using this method to assess the recovery of motor functions in Parkinson's disease patients before and after drug therapy.

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