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**Real-time gait cycle parameters recognition using a wearable motion detector**

**Abstract**

This paper presents the use of an accelerometry-based wearable motion detector for real-time recognizing gait cycle parameters of Parkinson’s disease (PD) patients. The wearable motion detector uses a tri-axial accelerometer to measure trunk accelerations during walking. By using the autocorrelation procedure, several gait cycle parameters including cadence, gait regularity, and symmetry can be derived in real-time from the measured trunk acceleration data. The gait cycle parameters derived from 5 elder PD patients and 5 young healthy subjects are also compared. The measures of the gait cycle parameters between the PD patients and the healthy subjects are distinct and therefore can be quantified and distinguished, which indicates that detection of abnormal gaits of PD patients in real-time is also possible. The wearable motion detector developed in this paper is a practical system that enables quantitative and objective mobility assessment. The possible applications of this system are also discussed.

**Keywords**: accelerometry, accelerometer, Parkinson’s disease, gait, mobility

**1. Introduction**

Gait dynamics reflect one’s mobility which can be affected by physical impairment, age progress and changes in health status. Gait parameters extracted from complex ambulation dynamics can be important measures to assess functional ability, balance
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control and to predict risk of falling. Parkinson’s disease (PD) patients suffer from progressive motor disorders, including resting tremor, bradykinesia, rigidity, and postural instability. The Unified Parkinson’s Disease Rating Scale (UPDRS) [Fahn et al., 1987] and Hoehn and Yahr (H&Y) Modified Scale [Hoehn et al., 1967, Goetz et al., 2004] are the two major clinical measures to assess the PD stages. In addition, the Timed Up-and-Go test (TUG) [Podsiadlo et al., 1991] and the Berg Balance Scale (BBS) [Berg et al., 1989] are also the two assessment tools in terms of mobility.

PD affects gait disorders such as reduced walking speed with increased cadence, reduced step-length, and increased stride-to-stride variability [Lowry et al., 2008]. Shuffling gait is also commonly observed from moderate PD patients. The advanced PD patients may have experienced the episodic gait disorders, such as festination, hesitation and freeze of gait (FOG) that occur occasionally and intermittently and may lead to falling and adverse health outcomes (e.g., hip fracture) [Hausdorff, 2009].

Gait evaluation is frequently based on observational interpretations which are subjective and may vary among clinicians or investigators. As a consequence, monitoring and analysis techniques for the Parkinsonian and pathological gaits have been widely developed and studied. Gait dynamics can be accurately measured by using the optical motion capture systems which utilize high-speed infrared cameras to record the three-dimensional positions of retro-reflective markers attached to the joints and segments of the human body during motion [Melo-Roiz et al., 2010]. Gait detection techniques utilizing pressure sensors embedded in an overground walkway [Menz et al., 2004] or a portable in-shoe pressure measurement system have also been used [Femery et al., 2004]. These techniques detect foot contact (heel strike and toe-off) and even the foot pressure distribution to investigate spatial-temporal gait parameters. However, those systems are expensive, and the sophisticated instrumentation requires specialized personnel. Therefore the uses of those systems are only limited in laboratories or clinical environments.

Accelerometry using wearable systems has drawn a vast amount of research interests in the study of human movement. It is only recently that a few numbers of studies have reported gait analysis using accelerometers while the accelerometer-based trials in movement classification, estimation of energy expenditure and fall detection have been largely studied [Mathie et al., 2004, Yang et al., 2010]. Though the Parkinsonian gaits have been well studied and described, only a few studies have investigated recognizing abnormal gaits using wearable systems. A shank-mounted accelerometer was used to monitor the FOG of the PD patients. A frequency spectra analysis was used to compute the frequency components of gait data. A freeze index is defined as the ratio of two spectral bands of different frequency components 0.5-3Hz and 3-8Hz. However, the power spectral analysis cannot be performed in real-time on compact wearable systems [Moore et al., 2004].
2008]. A wearable system using ARM7 processor was also demonstrated to detect FOG in real-time from every collected 0.32s acceleration data [Jovanov et al., 2009]. Due to the computation constraints, it was reported that a longer sample data will produce longer latency of the system which might not be acceptable for practical uses.

This paper presents the use of the wearable motion detector for real-time recognizing gait cycle parameters of PD patients. A waist-mounted wearable motion detector was designed to measure trunk accelerations during walking. The autocorrelation procedure was applied to derive several gait cycle parameters, including cadence, step regularity, stride regularly and step symmetry. Five PD patients and five young healthy subjects were recruited in a data collection session. The differences in the gait cycle parameters between PD patients and the healthy subjects were compared and discussed. The study in this chapter can lead to a future development of a wearable system for recognizing abnormal gaits, such as shuffling, festinating, or freeze of gait and falls in PD patients in real-time, which can be important and beneficial in PD ambulatory rehabilitation and personal tele-care applications.

2. Method

2.1 Instrumentation

The wearable motion detector is a single waist-mounted device that measures trunk accelerations of human movements. Figure 1 shows the circuit board and the prototype of the wearable motion detector. It uses a tri-axial accelerometer module (KXPA4-2050, Kionix) that senses accelerations in the sensitivity of 660mV/g over the selected range of ±2g. The output of the accelerometer module is firstly low-pass filtered at the cut-off frequency of 50Hz to reduce signal noises. A PIC microcontroller (PIC18LF6722, Microchip) samples the analog output signals via a 10-bit A/D conversion at the sampling rate of 50Hz. Real-time signal processing can be implemented in the PIC microcontroller. The wearable motion detector also uses a wireless ZigBee RF module (XBee 2.0, Digi International) which enables wireless data transmission to a PC via a 2.4GHz ZigBee protocol. Powered by 3 AAA batteries (DC4.5V), the wearable motion detector measures 90mm×50mm×25mm in size and weights 120g.
2.2 Subjects and gait data collection

In order to compare the gait cycle parameters between healthy subjects and PD patients, 5 elder Parkinson’s disease patients (4 males and 1 female, 78±9.8 yr) diagnosed as Hoehn & Yahr (H&Y) stage II to III and 5 young healthy subjects (all males, 26±3.1 yr) were recruited for the gait data collection. The test was approved by the Institutional Review Board (IRB) at the Far-Eastern Memorial Hospital, Taiwan. The subjects were provided with necessary information about the test and they gave their informed consent before the test.

The data collection included the TUG test and the 5-meter-walk test (5WMT) conducted in a laboratory. The TUG test is a validated simple measure to quickly screen mobility of individuals. The subjects were firstly directed to perform the TUG test. In the TUG tests, the subjects were asked to stand up from a seated posture on a chair, then walk forward for 3 meters, turn 180 degrees and walk back 3 meters, then turn 180 degrees and finally sit down on a chair. The time taken to complete the sequential tasks by each subject was measured.

In the 5MWT, the subjects wore the wearable motion detector at their waists while walking on a 5-meter level walkway at their normal and fast walking paces, respectively. The accelerations along the vertical (VT), antero-posterior (AP) and medio-lateral (ML) directions were recorded at the sampling rate of 50Hz. Synchronized video recording was also taken to observe the behaviors of the subjects during the 5MWT.
2.3 Gait cycle parameters recognition

Walking can be generally regarded as a repeated movement of human body. Therefore the measured accelerations during walking should also reveal periodic signal patterns. The autocorrelation procedure is a method to estimate the repeating characteristics over a signal sequence containing periodic patterns and irregular noises. Moe-Nilsson et al. have demonstrated the fundamentals of the autocorrelation procedure for computing gait cycle parameters [Moe-Nilssen et al., 2004].

Consider a time-discrete acceleration sequence containing \( N \) signal points \([x_1, x_2, x_3, \ldots, x_{N-1}, x_N]\). Equation (1) calculates the autocorrelation coefficient \( a_m \), which is the sum of the products of \( x_i \) multiplied by another signal \( x_{i+m} \) at the given phase shift \( m \).

The phase shift \( m \) can be either positive or negative integers which range from 0 to \( N-1 \), or from 0 to \( 1-N \). Therefore, from an \( N \)-point acceleration sequence, its autocorrelation sequence \( A=\{a_{-m}, a_{-m+1}, \ldots, a_0, a_1, a_{m-1}, a_m\} \) can be represented by \( 2N-1 \) autocorrelation coefficients \( a_m \) obtained at every phase shift \( m \). The autocorrelation sequence can either be “biased” or “unbiased”. As shown in Equation (2), the unbiased autocorrelation sequence is preferred because the biased method generates noticeable attenuation of coefficient values next to the zero phase shift from a limited number of data [Moe-Nilssen et al., 2004].

\[
d_m = \sum_{i=1}^{N-\lvert m \rvert} x_i x_{i+m} \\
\]

Equation (1)

\[
a_m^{unbiased} = \frac{1}{N - \lvert m \rvert} \sum_{i=1}^{N-\lvert m \rvert} x_i x_{i+m} \\
\]

Equation (2)

The segments from \( a_{-m} \) to \( a_{-1} \) and from \( a_{1} \) to \( a_m \) in an autocorrelation sequence are symmetric with its zero phase shift \( a_0 \) located at the center of the sequence. Normalized to 1 at the zero phase shift \( a_0 \), the right half segment \( a_0 \) to \( a_m \) of the autocorrelation sequence is only considered for simplicity. Figure 2 depicts an example of an autocorrelation sequence computed from VT accelerations measured at waist during normal walking paces. The first coefficient peak \( D_1 \) next to the zero phase shift indicates the first dominant period, and the second peak \( D_2 \) the second dominant period.
The following gait cycle parameters can be derived from the autocorrelation sequence:

(1) **Step regularity and stride regularity**

The magnitude $D_1$ represents step regularity. This is because the first dominant period indicates the maximal similarity between the acceleration sequence and its m-point shifted duplicate. The m-point span approximates the duration of a step. Similarly, the second dominant period indicates the maximal similarity between the acceleration sequence and its 2-step shifted sequence, and therefore the magnitude of $D_2$ can represent stride regularity. Note that the first and second dominant periods do not represent which of the steps (left-leg or right-leg) as there is no such information given in the autocorrelation procedure.

(2) **Ste symmetry**

The ratio of step regularity to stride regularity, or $D_1 / D_2$ is the step symmetry that indicates the symmetry between two steps of both two legs.

(3) **Cadence**

Cadence ($c$) can be estimated by Equation (3), where $f$ is the sampling frequency and $n$ the amount of the coefficients between the zero phase shift and the first dominant period. This equation estimates cadence without the need of walking speed or distance.
\[ c = 60 \frac{f}{n} \]  

(3)

A sliding window technique is used to cyclically recognize gait cycle parameters in real-time. Take the hardware memory capacity and computation latency of the wearable motion detector into account, the window length is set 3.5s. According to the assumed average cadence of 104 steps per minute, the choice of 3.5-second data can includes approximately 6 steps that should be considered sufficient for real-time processing [Hirasaki et al., 1999].

3. Result and Discussion

To derive the gait cycle parameters, the VT acceleration was used to compute the autocorrelation sequence because the VT component may better carries the characteristics of steps during walking. In this study it is observed that the autocorrelation sequences from the healthy young subjects are more smooth and monotonic, while the counterparts from the PD patients contain subtle fluctuations and are less regular. Figure 3 shows one example of such observations in this study. The magnitudes at the dominant periods from a PD patient’s pattern are relatively lower than that from a healthy young subject’s pattern. Accordingly it implies less regular movements between each step, which can be considered the results from ill-controlled motor behaviors. This requires more PD data to justify this observation.

Figure 4 shows the autocorrelation sequences computed from VT and AP accelerations of a healthy subject and a PD patient. It is shown that the dominant periods on the VT and AP patterns can coincide with each other, though the two patterns vary differently. The comparison of both the VT and AP autocorrelation sequences is helpful in precisely identifying the dominant periods when the dominant periods cannot be clearly determined on the VT autocorrelation sequence alone.
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Figure 3. The example of an autocorrelation sequence (VT acceleration) computed from a healthy young subject (above) and a PD patient (below)

Figure 4. The example of the VT and AP autocorrelation sequences computed from a healthy subject (above) and a PD patient (below)
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Table 1 shows the statistical results of the gait cycle parameters from the 10 test subjects. The average values and its standard deviation are shown. The clinical assessment method TUG Test performance measured in the healthy subject group was 10.6±2.2s while a longer time 23.9±7.9s was measured in the PD patient group. This simple estimate shows a degenerative mobility of the PD patient group.

Comparing the cadences derived from the autocorrelation procedure, the PD group had the cadence slightly higher than the healthy group. The cadence of the PD group in fast 5MWT was 108.1±15.6 steps/min., which was approximately 5.8% increased from their normal cadences. The healthy group had the cadence of 113.9±6.2 steps/min. in fast 5MWT, which was approximately 16.9% increased from their normal cadence. This indicates a limited performance margin for the PD group due to their degenerative mobility.

Table 1. Gait cycle parameters of the subjects

<table>
<thead>
<tr>
<th></th>
<th>PD</th>
<th>Healthy</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>TUG-T time</strong></td>
<td>23.9±7.9s</td>
<td>10.6±2.2s</td>
</tr>
<tr>
<td><strong>5MWT (normal)</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Step regularity</td>
<td>0.39±0.16</td>
<td>0.63±0.13</td>
</tr>
<tr>
<td>Samples of a step length</td>
<td>30±4.70</td>
<td>30.5±1.85</td>
</tr>
<tr>
<td>Stride regularity</td>
<td>0.43±0.20</td>
<td>0.80±0.09</td>
</tr>
<tr>
<td>cadence</td>
<td>102.2±15.20</td>
<td>98.6±5.8</td>
</tr>
<tr>
<td>symmetry</td>
<td>0.97±0.3</td>
<td>0.79±0.17</td>
</tr>
<tr>
<td><strong>5MWT (fast)</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Step regularity</td>
<td>0.37±0.17</td>
<td>0.76±0.08</td>
</tr>
<tr>
<td>Samples of a step length</td>
<td>28.2±3.7</td>
<td>26.40±1.4</td>
</tr>
<tr>
<td>Stride regularity</td>
<td>0.47±0.12</td>
<td>0.80±0.08</td>
</tr>
<tr>
<td>cadence</td>
<td>108.1±15.60</td>
<td>113.9±6.2</td>
</tr>
<tr>
<td>symmetry</td>
<td>0.77±0.25</td>
<td>0.94±0.12</td>
</tr>
</tbody>
</table>

For the regularity and symmetry of gaits, the PD group has the step regularity of 0.39±0.16 and the stride regularity of 0.43±0.2 during normal walking paces. The healthy group has higher step regularity (0.61±0.14) and stride regularity (0.79±0.09). Similar trends can be observed in their fast walking paces. Therefore, the PD patients have less regular performance in repeating steps and strides compared with the healthy group. Note that the symmetry during their normal walking speed in the PD group is higher than that in the healthy group, while the symmetry during fast walking in the PD group is lower than that in the healthy group. This mixed results regarding gait symmetry need further investigations.
Several studies have reported the use of the vertical accelerations for autocorrelation procedure [Yang et al., 2010, Moe-Nilssen et al., 2004, Keenan et al., 2005]. In this study the VT, AP and ML accelerations were compared to examine which axis is most sensitive to steps and produces identifiable pattern related to the gait cycle parameters. With visual inspection from the autocorrelation sequences of the 10 test subjects, the ML pattern is considered least descriptive and least sensitive to walking movement.

4. Conclusion

This paper presents the development of an accelerometry-based wearable motion detector for real-time gait cycle parameters recognition. The wearable motion detector is a single waist-mounted device that utilizes a tri-axial accelerometer to measure trunk accelerations during walking. The autocorrelation procedure is used to estimate several temporal gait cycle parameters in real-time. Cadence, step regularity, stride regularity and step symmetry can be derived from the autocorrelation sequences computed from the measured trunk accelerations.

In this study the current focus of research interest here is whether those selected gait cycle parameters can be quantified and distinguishable between PD patients and healthy people without disability. The PD patient group and the healthy subject group recruited in this study show varied characteristics in the gait cycle parameters. The PD patient group with impaired mobility can be found to have reduced gait regularity and symmetry though some details still needs further investigation.

With proper selection of the thresholds for the gait cycle parameters, it is possible that the algorithm can facilitate real-time recognition of abnormal gaits, like shuffling, or festinating gaits from PD patents. Integrated with extended capabilities, such as verbal cueing, movement classification and fall detection, the future development of this study is expected to provide a low-cost system that can benefit and assist ambulation rehabilitation for PD patients and prompt personal tele-care applications.

Acknowledgment

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References

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