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Classification of acceleration waveform in a continuous walking record

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Abstract: We attempted to distinguish walking on level ground from walking on a stairway using a waist acceleration signal. A tri-axial accelerometer was fixed to the waist and the three acceleration signals were recorded by a portable data logger at a sampling rate of 256 Hz. Twenty healthy male subjects were asked to walk through a corridor, or up and down a stairway continuously without any instruction. The data were analyzed using discrete wavelet transform. Walking patterns were classified according to two steps. At the first step, the times when walking pattern changed were detected using the low-frequency component of the anterio-posterior acceleration (LF_A) and of the vertical acceleration (LF_V). At the second step, three types of walking patterns were distinguished by comparing powers of wavelet coefficients in the vertical direction (P_{WCV}) and in the anterio-posterior direction (P_{WCA}). Changes in walking patterns could be detected by using both LF_A and LF_V. Walking down stairs could be distinguished from the other types of walking by the largest value in P_{WCV}, and walking up stairs could be discriminated from level walking by P_{WCA}. Level and stairway walking could be distinguished by waist acceleration.

I. INTRODUCTION

Monitoring of physical activity has been used to assess energy expenditure in human daily life. When physical activity in elderly people can be measured with an unconstrained physical monitor, it is effective not only to maintain the physical condition but also to inform suitable daily exercise in the elderly.

Energy expenditure has been evaluated accurately by measuring oxygen uptake, but the technique is rather complicated and needs a skillful technique to operate. Acceleration measurements close to gravity are another possible method for estimating energy expenditure [1]. The integral per unit time of an acceleration signal is well-correlated to energy expenditure. Precise evaluation of acceleration, however, requires classification of activities such as walking or running.

In this study, we attempted to classify the acceleration signal for horizontal level and stairway walking using time-frequency analysis of wavelet transforms.

II. SUBJECTS AND METHODS

A tri-axial piezoresistive accelerometer was attached with a belt to the back of a subject at the level of the lumbo-sacral segment of the spinal column, close to the center of gravity of the body in a standing position. The accelerometer was connected to a portable data logger [2] (Micro8, Shimazu, Kyoto, Japan), which has a removable 2 Mbyte IC memory card (Fig.1). The sampling rate was 256 Hz, which gave a sufficient range of analysis for walking [3].

The experiments were performed with 20 male subjects (age 22.7±1.2 years, height 171.8±4.9 cm, weight 65.3±11.0 kg, mean±s). The subjects walked continuously along a corridor then up a stairway, and then along another corridor and down a stairway, wearing their own shoes. Recordings were taken as each subject walked along a 20 m level path and up and down 20 steps at an angle of 30.6 degrees.

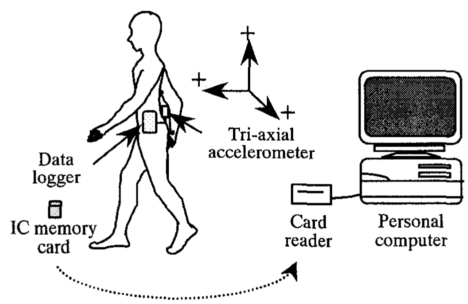

Figure 1 Experimental set-up

After completion of the measurement, the data in the IC memory card were analyzed using a personal computer. Signal processing was carried out using commercially available software (MatLab).

III. SIGNAL PROCESSING

The wavelet transform for walking data was computed using coiflet 3 in the MatLab (The Math Works, USA) package. The analysis was followed. First, we detected a time when the walking pattern changed and then classified the walking pattern during the selected period.

A. Detection of changes in walking pattern

Changes in gait are characterized mainly by posture changes. The piezoresistive accelerometer can detect a DC component, that is, acceleration-related gravity, so that the static posture can be obtained from the low-frequency component of the signal. In walking, the posture change was clearly seen in the anterio-posterior direction of acceleration. Thus, the low-frequency component, which included posture information, can be classify the different walking styles. The time of posture changes, that is, transient posture changes, can be obtained from the low-frequency component. The original signal was composed to 10 levels. Then the wavelet packet [4] is used and detail -10 was composed. The final wavelet decomposition consists of the approximation -10 and the subset of low-pass filtering component as represented in equation (1).

$$LF_A = \sum_{k\in\mathbf{Z}} c_k^{(-10)}\phi\left(2^{-10}x-k\right) + \sum_{k\in\mathbf{Z}}\left\{\frac{1}{2}\sum_{l\in\mathbf{Z}} g_{2k-l}\, d_l^{(-10)}\right\}\rho\left(2^{-10}x-k\right) \tag{1}$$

where d is the detail of wavelet coefficients, c is an approximation of wavelet coefficients, h is the analysis wavelet,, g is the analysis scaling sequence, j is the level of wavelet decompose, ϕ is a scaling function, ψ is a mother wavelet function, x is time and k, l are time location. ρ is the reconstructing function.

From the calculated value, the threshold level of an individual can be empirically determined and the time of transient gait change is obtained from the crossing of the threshold level.

In addition, the vertical acceleration signal was composed to 10 levels; the detail -9 was composed. The wavelet decomposition consists of the approximation -9 and the subset of both high- and low-pass components with certain weighting functions given in equation (2).

$$\begin{aligned} LF_V = & \sum_{k\in\mathbf{Z}} c_k^{(-9)}\phi\left(2^{-9}x-k\right) \\ & +0.6\times\sum_{k\in\mathbf{Z}}\left\{\frac{1}{2}\sum_{l\in\mathbf{Z}} g_{2k-l}\, d_l^{(-9)}\right\}\rho\left(2^{-9}x-k\right) \\ & +0.3\times\sum_{k\in\mathbf{Z}}\left\{\frac{1}{2}\sum_{l\in\mathbf{Z}} h_{2k-l}\, d_l^{(-9)}\right\}\eta(2^{-9}x-k) \end{aligned} \tag{2}$$

where η is the reconstructing function companion to ρ. The weighting functions are determined empirically and these values affect the decay of filtering characteristics. The times when peak values appeared were chosen for changes in walking pattern.

Times obtained from both anterio-posterior acceleration and vertical acceleration were used to detect changes in walking patterns.

B. Classification of walking pattern

To classify the walking pattern, the signal of one gait cycle of the vertical and the anterior-posterior directions is used. The wavelet coefficients of level -6 and level -7 are composed and the power of signal is calculated. The power of wavelet coefficient for the vertical direction (P_{WCV}) is given by equation (3).

$$P_{WCV} = \frac{1}{N}\sum_{j=-7}^{-6}\left\| d^{(j)}\right\|_2^2 \tag{3}$$

where N is the number of steps in the section of the walking pattern. Walking down stairs was classified from this value. The power of wavelet coefficient for the anterio-posterior direction (P_{WCA}) is calculated from the ratio between the power from level -4 to level -7 and total power, given by equation (4).

$$P_{WCA} = \left(\sum_{j=-7}^{-4}\left\| d^{(j)}\right\|_2^2 \Big/ \left\| f\right\|_2^2\right)\times 100 \tag{4}$$

where f is the original acceleration signal. Level walking and walking up stairs are categorized from the value obtained from equation (4).

IV. RESULTS

A typical example of detection of changes in walking pattern from a continuous walking record is shown in Fig. 2.

Figure 2(a) shows the original acceleration signal in the anterio-posterior direction and LF_A defined by equation (1). When the subject went up the stairs, the LF_A signal represented backward acceleration, that is, the subject was leaning forward compared with other walking patterns. The same feature was shown for all subjects. Therefore, by manually setting the individual's threshold level, it was possible to detect the times of the changes in walking up stairs from crossings of the threshold level. However, the LF_A signal in walking down stairs was unchanged or vertical compared with level walking, and showed no common features among individuals.

Figure 2(b) shows the original acceleration signal for the vertical direction and LF_V defined by equation (2). The LF_V signal showed some peaks, synchronous with changes in walking pattern. It was possible to detect the times of changes in walking down stairs, choosing the times of these peaks.

However, the peaks for walking up stairs disappeared for some individuals.

The changes in walking up stairs were detected by LF_A, and the changes in walking down stairs detected by LF_V. All times when the walking pattern changed could be detected using both LF_V and LF_A (Fig. 2(c)).

Figure 3 shows a typical example of relationships between the P_{WCV} and the P_{WCA} in the walking pattern during a selected period. The values of P_{WCV} and P_{WCA} could be classified into three large categories: level walking, walking up stairs, and walking down stairs, as shown in this figure.

The average value and standard deviation of P_{WCV} and P_{WCA} for all subjects are shown in Fig. 4. In P_{WCV}, walking down stairs produced a significant difference (P<0.01) and could be distinguished from the other walks by the largest value. In P_{WCA}, walking up stairs showed a significant difference (P<0.01) and could be discriminated from level walking.

Figure 2(d) shows a typical example of classification of walking pattern from a continuous walking record, using LF_V, LF_A, P_{WCV} and P_{WCA}. For all data sets, we achieved a 98.8% classification rate.

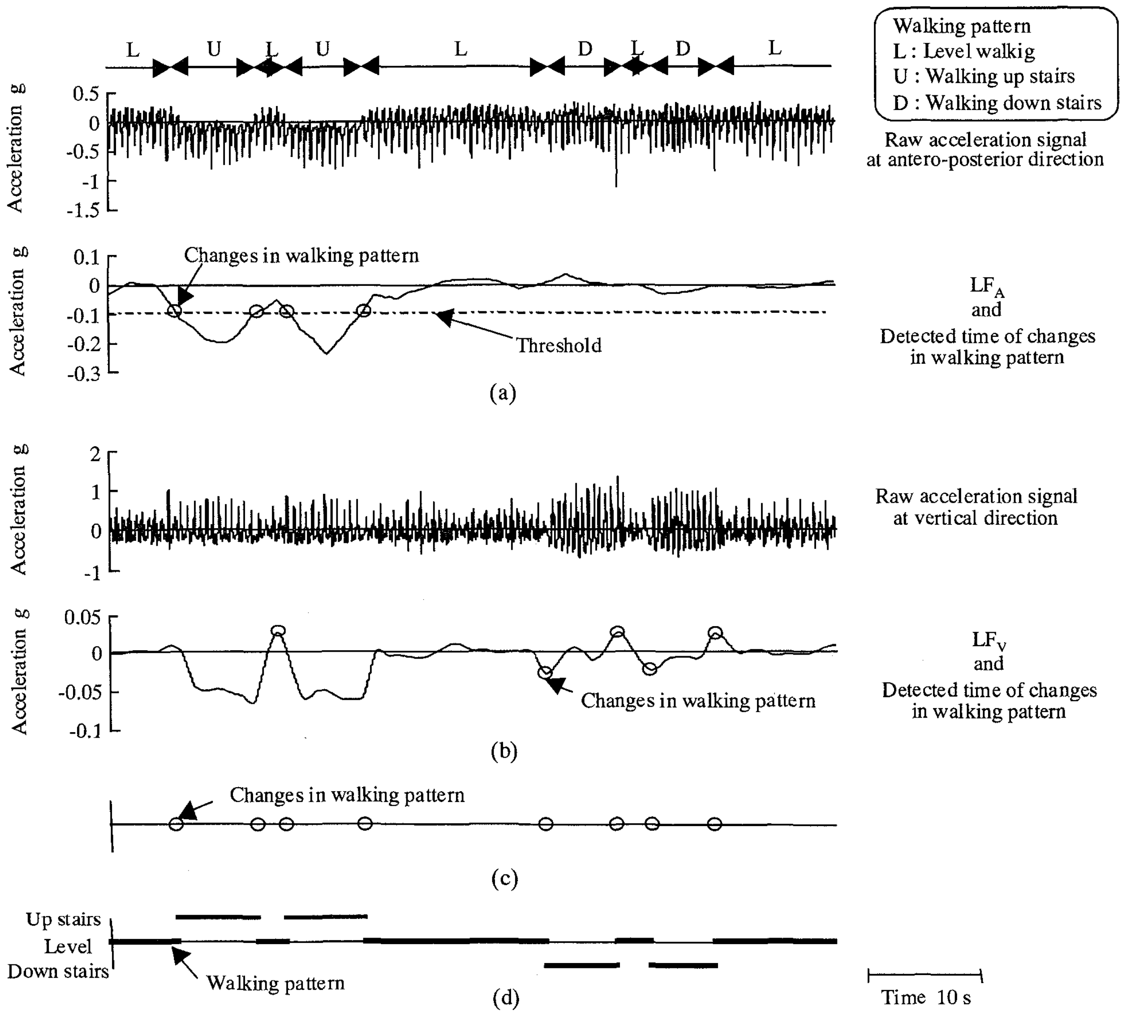

Figure 2 A typical example of detection of changes in walking pattern and classification of walking pattern from a continuous record. (a) Detection of changes in walking pattern using LF_A. (b) Detection of changes in walking pattern using LF_V. (c) Detection of changes in walking pattern using both LF_A and LF_V. (d) Classification of walking pattern using P_{WCV} and P_{WCA}.

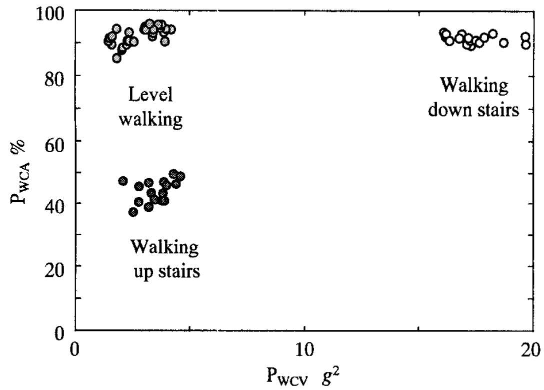

Figure 3 A typical example of the relationship between P_{WCV} and P_{WCA} during selected period

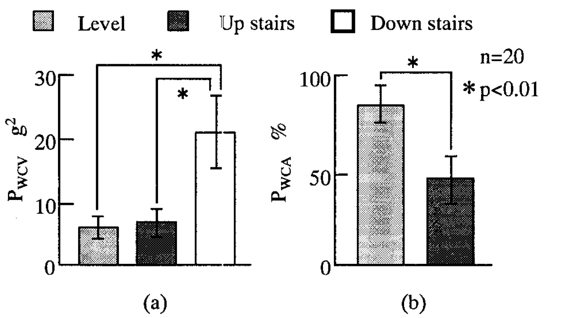

Figure 4 The mean and standard deviation of P_{WCV} (a) and P_{WCA} (b) for all subjects

V. DISCUSSION

In the time domain, the acceleration signal of the vertical direction was used easily to classify the type of walking by visual observations. Level walking has three peaks, and stairway walking has one or two peaks in a walking cycle. In the anterio-posterior acceleration, the signals of level walking and walking up stairs showed that the body accelerated forward, until the vertical acceleration reaches the maximum value. It then moved into deceleration. The maximum acceleration in the vertical direction was regarded as heel-strike. Lateral acceleration was not significantly different among the walking patterns. Therefore, we selected the vertical and the anterio-posterior acceleration signals for analysis.

By way of comparison, frequency analysis was carried out using FFT. The acceleration signal was divided into each walking pattern and FFT was applied. However, it was difficult to classify walking patterns, because the frequency distribution of the three walking patterns was wide and different for individuals. It is not suitable for dynamic responses such as walking.

We also attempted to design digital filters that imitated the frequency response of using wavelet coefficients. In the method that we proposed, the filters were able to detect changes in walking pattern and to classify walking pattern. However, it was difficult to design directly the filters without the result using wavelet transform.

Therefore, we chose the wavelet method to analyze the acceleration waveform in a continuous walking record. Wavelet transform has characteristics suitable for dynamic response, and performed ideally in decomposing the signal to each frequency component. We could categorize three types of walking pattern with high accuracy using wavelet transform. However, this experiment was only indoors; further experiments are required outside and in a variety of conditions.

In conclusion, we could detect changes of walking pattern in a continuous walking record using the low-frequency component of the acceleration signal, and could classify walking on level floor and on stairways using power of wavelet coefficients.

ACKNOWLEDGMENT

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