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EXTRACTION OF HUMAN GAIT FEATURE FROM ACCELERATION DATA

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Abstract. *This paper addresses a problem of feature extraction of time-series data for analyzing human motion. Human motions are observed by motion sensors such as accelerometers and gyroscopes, which involve time series. In this paper, we discuss the methodology for extracting both of a style and characteristic component from a walking motion. The walking motion is measured using two types of sensor, one is a whole body motion capturing system (MoCap), and the other is four wearable motion sensors for acquiring segmented body motion. To extract the style and characteristic component, we use the singular value decomposition of the measured data and compare the results corresponding to MoCap data with accelerometer data. From these experimental results, it is possible to extract both of a style and characteristic component of motion from both segmented body motion and full body motion. These results suggest that data with segmented body motion can be used to identify individuals.*
Keywords: Human gait features, Singular value decomposition, Accelerometer

1. **Introduction.** The human activity detection and recognition using body-worn sensors are key issues for the wearable sensing technology. In the field of wearable sensing, motion sensors (e.g., accelerometers and gyroscopes) are widely used for understanding human activities such as car driving, sports, healthcare assessments [1, 2, 3, 4, 5]. This paper discusses the problem of human motion analysis from motion sensors, which involves the time sequence data obtained from human behavior. The goals of human motion analysis generally include the classification or characterization of movements of any particular individual. The purpose of classification is to comprehend *what* activity is being performed. On the other hand, the purpose of the characterization is to comprehend *how* any activity is being performed. To achieve these goals, extraction methods for motion features from motion data have been discussed by many researchers in the fields of computer vision, robotics, and computer science. In the field of computer visions, Troje [6, 7] has developed a framework for analysis and synthesis of human gait patterns for decomposing biological motion. Mishima *et al.* [8] have proposed an extraction method for similarities and differences in human motion using singular value decomposition. Meanwhile, in the field of intelligent robotics, Okada *et al.* [9] have proposed a dynamics-based

information processing system that encodes sensory data of a humanoid robot in fewer dimensions using attractors. These approaches are used for exploring motion knowledge, that is, information of the individualities of subjects such as differences between beginners and experts, or elderly people and young people. However, these results were obtained from data of whole body motion, which are collected by using a three-dimensional motion capturing (MoCap) system. In the MoCap systems, movements of a subject are usually captured using cameras, magnetic and ultrasound systems. Using these systems, we can collect complete three-dimensional kinematics data of whole body motion. However, they require the dedicated space for measuring, the time needed for the analysis, and also the costly equipment. These constraints have limited the analysis object to the specific human activity. On the other hand, the wearable sensing approach can acquire motions and postures by using such motion sensors as body-worn accelerometers and microphones. This approach does not require specific environment for acquiring human body motion, i.e., indoors or not as measurement field.

To understand human activities in daily life, we need to discuss the effectiveness of conventional extraction methods for the wearable sensing approach. Thus, the aim of this paper is to discuss the methodology for extracting both of a *style* and *characteristic* component from walking motions. In this paper, the style component is defined as a signal component common to all subject obtained from the same walking motion. The characteristic component is also defined as a set of signal components, which are features characteristic of a subject. The motions are measured using two types of sensor, one is a full-body motion capturing system, and the other is the wearable motion sensors for acquiring segmented body motion. To extract the style and characteristic component, we use the singular value decomposition of the measured data and compare the results corresponding to MoCap data with accelerometer data.

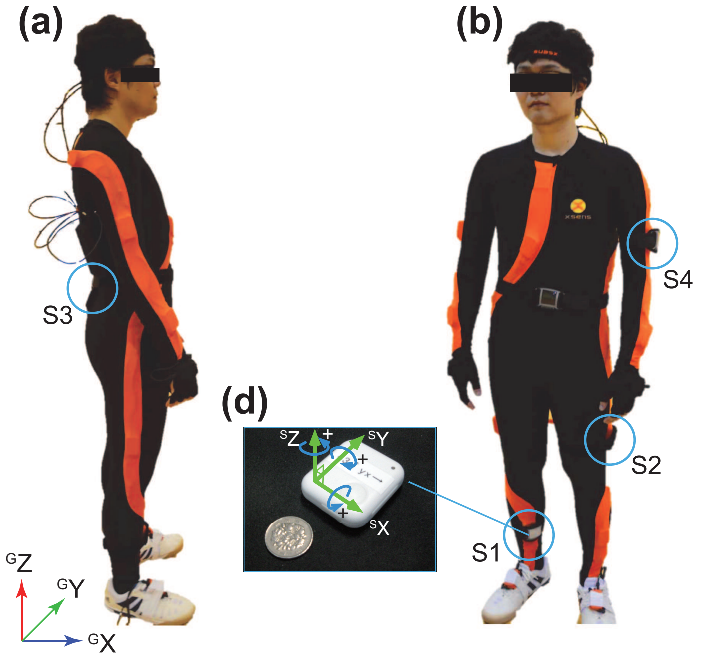
2. **Overview of Experiment.**

2.1. **Capturing body movements.**

To acquire human activities, we have constructed a measuring system shown in Figure 1. This system includes two types of sensors for capturing body movements, i.e., one capturing a full body motion and the other selecting body segment motion.

As the first system, we use an inertial motion capture system (MVN, Xense Inc.) shown in Figures 1(a), 1(b) and 1(c) for recording full body motion of subjects. In this system, subjects wear the motion capture suits, which includes data transmitter and 18 sensor modules, which are placed on the head, shoulders, upper arms, forearms, waist, thighs, lower legs, and feet. The MVN calculates the position and orientation with respect to an earth-fixed reference coordinate system, G. The earth-fixed reference coordinate system used is defined as a right-handed Cartesian coordinate systems: $\left({}^G\mathrm{X}, {}^G\mathrm{Y}, {}^G\mathrm{Z}\right)$ shown in Figure 1(a). And the orientation output is represented using quaternions. All signals from the modules are sampled at 100 Hz and sent to the host computer from the transmitter on the suits. The numbering of the segments for MoCap is given in Figure 1(c).

As the second system, we use a wireless motion sensor (WAA-010, ATR-Promotions Inc.) shown in Figure 1(d). The dimensions of the sensor module are $39 \times 44 \times 8$ mm with a weight of 20 g. The four sensors are worn on the right lower leg, left thigh, lower back and left forearm on a subject, and the numbering of the segments is shown in Figures 1(a) and 1(b). These placements are referred to Bao and Intille [1]. By using this system, the motions of a subject can be collected as both acceleration and angular velocity along with three-axis of local coordinate on the sensor module: $\left({}^S\mathrm{X}, {}^S\mathrm{Y}, {}^S\mathrm{Z}\right)$ shown in Figure 1(d). All signals from the modules are sampled at 100 Hz and sent to the host computer from each sensor module via Bluetooth. Then, to remove high-frequency noise, the signals are filtered by 3rd-order Butterworth LP filter with a cut-off frequency of 12.5 Hz.



(c)

Segment#	Label
1	Pelvis
2	L5
3	L3
4	T12
5	T8
6	Neck
7	Head
8	Right Shoulder
9	Right Upper Arm
10	Right Fore Arm
11	Right Hand
12	Left Shoulder
13	Left Upper Arm
14	Left Fore Arm
15	Left Hand
16	Right Upper Leg
17	Right Lower Leg
18	Right Foot
19	Right Toe
20	Left Upper Leg
21	Left Lower Leg
22	Left Foot
23	Left Toe

FIGURE 1. Inertial motion capture system (MoCap) and wearable accelerometer modules. (a) and (b) show sensor setting on a subject's body, (c) is the numbering of the segments for MoCap, and (d) shows an accelerometer module.

2.2. **Data collection.** In this paper, data on walking motion is collected from 13 subjects (10 men and 3 women aged 24.3±4.3). The subject wears the motion capture suits. At the same time, over the motion capture suits, the four sensors are placed on the position of S1, S2, … shown in Figures 1(a) and 1(b). Authors instruct the subject to walk on the test course with 15 m straight flooring line according to a predefined protocol. In the protocol, each subject has an instruction to perform 5 walking with the following conditions: N1, N2: walking with natural speed, S3: walking with slow speed, N4: walking with natural speed, and F5: walking with fast speed on the course. Before collecting data, we have explained the contents of the experiment. Moreover, we also have obtained informed consent from each subject to use obtained data for research purposes.

3. Feature Computation.

3.1. **Preparation of data matrix.** Consider a sequence of segmented motion data, which is cyclic and consequently has a gait period. Then a set of the time series for subject α ($\alpha = 1, 2, \ldots, M$) from S sensors is as follows:

$$\boldsymbol{x}_p^\alpha = \left(x_p^\alpha(1), x_p^\alpha(2), \ldots, x_p^\alpha(N)\right)^\top \in \mathcal{R}^N, \quad p = 1, 2, \ldots, S,$$

where N is a length of samples, S is the number of time-series, and $\boldsymbol{x}^\top$ represents the transpose of the vector $\boldsymbol{x}$. Moreover, a set of the time series for subject α is also as follows:

$$X^\alpha = (\boldsymbol{x}_1^\alpha, \boldsymbol{x}_2^\alpha, \ldots, \boldsymbol{x}_S^\alpha) \in \mathcal{R}^{N \times S}. \tag{1}$$

For comparing the motions with each subject, we rewrite (1) as follows:

$$\boldsymbol{a}^\alpha = \left(\{\boldsymbol{x}_1^\alpha\}^\top, \{\boldsymbol{x}_2^\alpha\}^\top, \ldots, \{\boldsymbol{x}_S^\alpha\}^\top\right)^\top \in \mathcal{R}^{N \cdot S}. \tag{2}$$

Note that $\boldsymbol{a}^\alpha$ is a column vector, which represents a human gait pattern for subject α. Finally, we define the following data matrix for comparing motions:

$$D = \left(\boldsymbol{a}^1, \boldsymbol{a}^2, \ldots, \boldsymbol{a}^M\right) \in \mathcal{R}^{N \cdot S \times M}. \tag{3}$$

In other words, the matrix D is a set of human gait patterns for all subjects.

3.2. **Singular value decomposition.** In this paper, we suppose that the matrix D contains information on both similarities and differences for each subject. The similarities are a common component of matrix D, and the differences can be defined of a set of components obtained by subtracting the common component from the matrix D. These components can be extracted by using singular value decomposition (SVD) [8]. The SVD of data matrix D is given by

$$D = U\Sigma V^{\top}, \tag{4}$$

where U and V are unitary matrices, and the matrix Σ is a diagonal matrix. The diagonal elements of Σ are called singular values σ_i $(i = 1, 2, \ldots, M)$, which are non-negative real numbers and $\sigma_i \geq \sigma_j$ $(i \leq j)$. Each column vector of U is a left singular vector $\boldsymbol{u}_i \in \mathcal{R}^{N \cdot S}$. Each column vector of V is a right singular vector $\boldsymbol{v}_i \in \mathcal{R}^{M}$. The ith element of each Σ, U and V is called the ith *mode* by Mishima *et al.* [8].

From the results of (4), the column vector $\boldsymbol{a}^{\alpha}$, which is composed of motion data for subject α, is described as

$$\boldsymbol{a}^{\alpha} = \sum_{i=1}^{M} \sigma_i v_{\alpha i} \boldsymbol{u}_i, \tag{5}$$

where $v_{\alpha i}$ is the αth element of $\boldsymbol{v}_i$. At (5), $\boldsymbol{u}_i$ represents a motion feature for the ith mode, $v_{\alpha i}$ indicates the contribution ratio of the subject α to the ith mode, and σ_i represents the contribution ratio of the ith mode to the matrix D. Since the similarities are the common component in the vectors $\boldsymbol{a}^1, \ldots, \boldsymbol{a}^M$, its contribution ratio to the matrix D has to be the largest among all modes. That is, the singular value of the 1st mode σ_1 is the largest among all modes. Moreover, $v_{\alpha 1}$ has to be almost constant for all subjects. On the other hand, the differences are independent of similarities. Then, the contribution ratios at the higher than the 2nd modes to the matrix D have to be smaller than that of the 1st mode. Therefore, the differences might correspond to the higher than the 2nd modes, and $v_{\alpha i}$ $(i \geq 2)$ has to change with each subject. From these results, we call the similarities and differences the style and characteristic components of motion.

4. **Results and Discussions.** In this paper, we used the data of walking motion with condition N1 in the following section. Before constructing matrix D in (3), time series for one gait cycle were clipped from the whole walking data. Since the length of one gait cycle was different for each subject, the clipped time series have even lengths between by processing through interpolation algorithm. In this paper, the cubic spline algorithm was used. As the results, the length of clipped time series was $N = 121$. In the MoCap data, the number of time-series S in (3) was $S =$ (23 segments) $\times$ (3 axes). Note that the orientation output of MoCap was converted quaternions into Euler angles, i.e., roll, pitch and yaw. On the other hand, in the accelerometer data, $S =$ (4 segments) $\times$ (3 axes). Also, the number of subjects was $M = 13$. Figure 2 shows an example of time-series for one gait cycle with subject no.1.

4.1. **Extracting for style and characteristics component of motion.** Figure 3 shows the results of singular value σ_i of each mode. The singular value at the 1st mode reached a peak of $\sigma_1 = 254.2$ in Figure 3(a) and $\sigma_1 = 118.0$ in Figure 3(b). The singular value at the 2nd mode drop suddenly, and after that decrease moderately in both Figures 3(a) and 3(b). On the other hand, Figure 4 shows the right singular vector $\boldsymbol{v}_i$ for each subject with a grayscale image. The right singular vector at the 1st mode $v_{\alpha 1}$ remains constant at approximately -0.3 in Figure 4(a) and $+0.3$ in Figure 4(b) for all subjects. Moreover, Figure 5 shows the tree diagram of $V = [v_{\alpha i}]$ for identifying subjects. In Figure 5, the right singular values $v_{\alpha i}$ are separated into three groups: Negative/Positive,

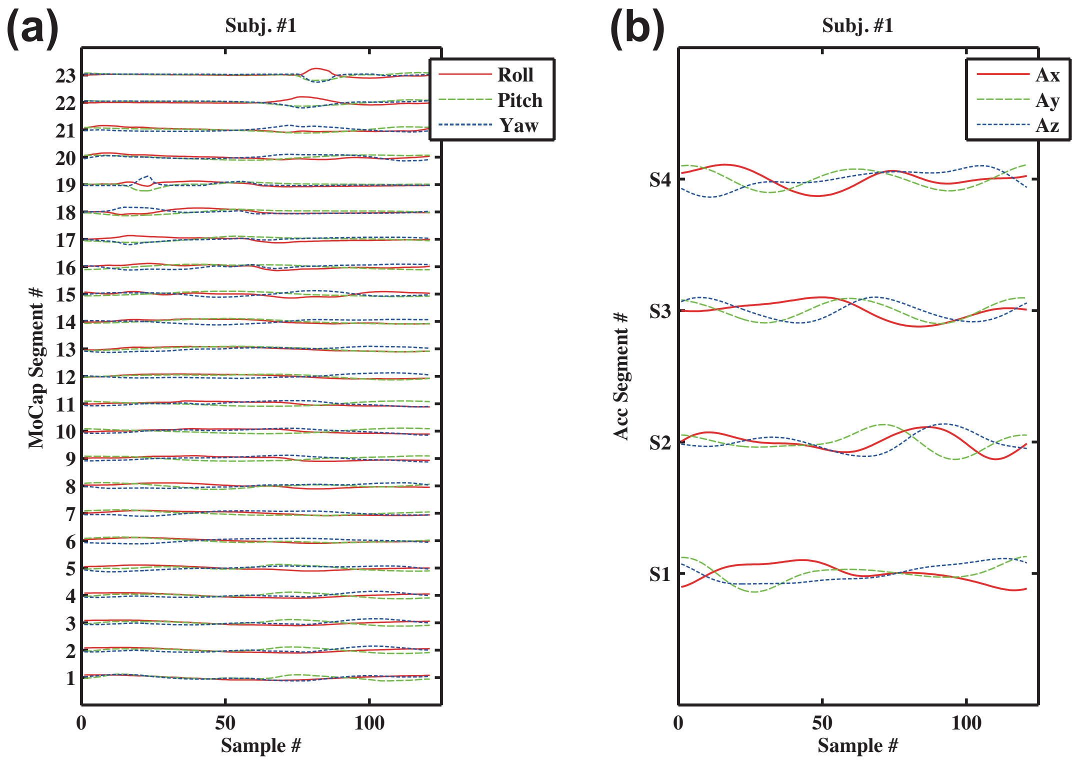
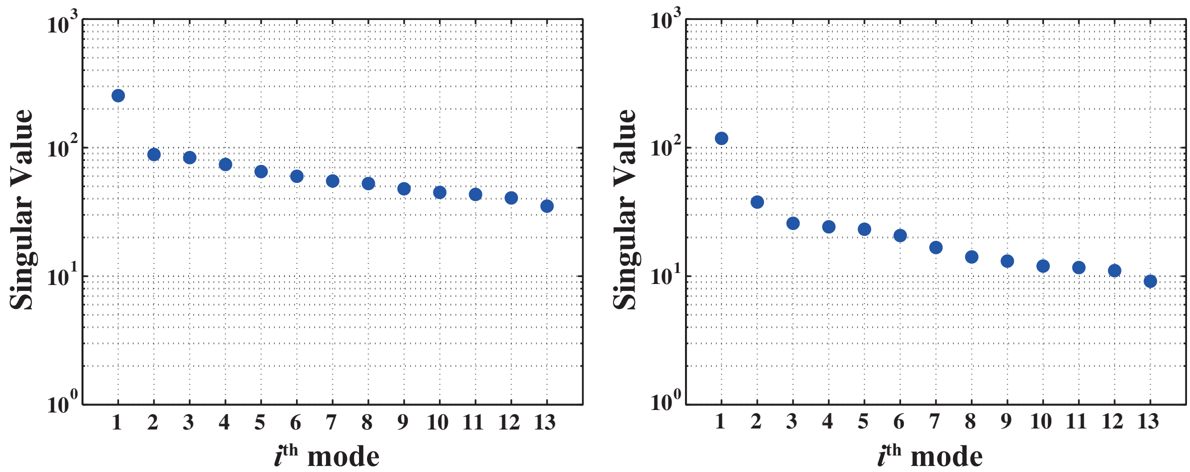


Figure 2. An example of time-series of a gait cycle by a subject. (a) shows MoCap data with 23 segments $\times$ 3 axes, and (b) shows accelerometer data with 4 segments $\times$ 3 axes. These data are standardized for each time-series data.



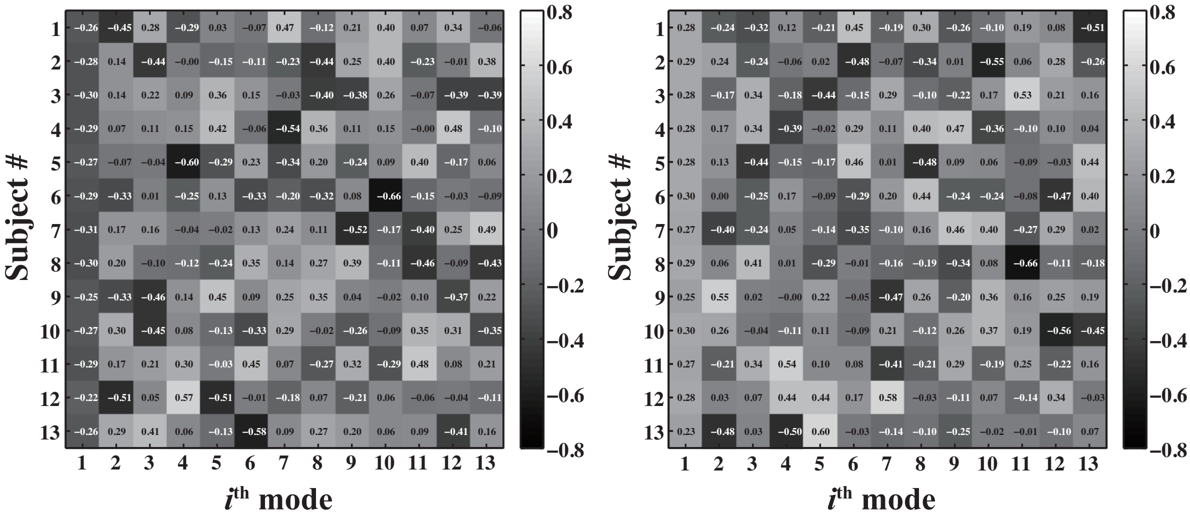
(a) MoCap data

(b) Accelerometer data

Figure 3. Singular value of each mode

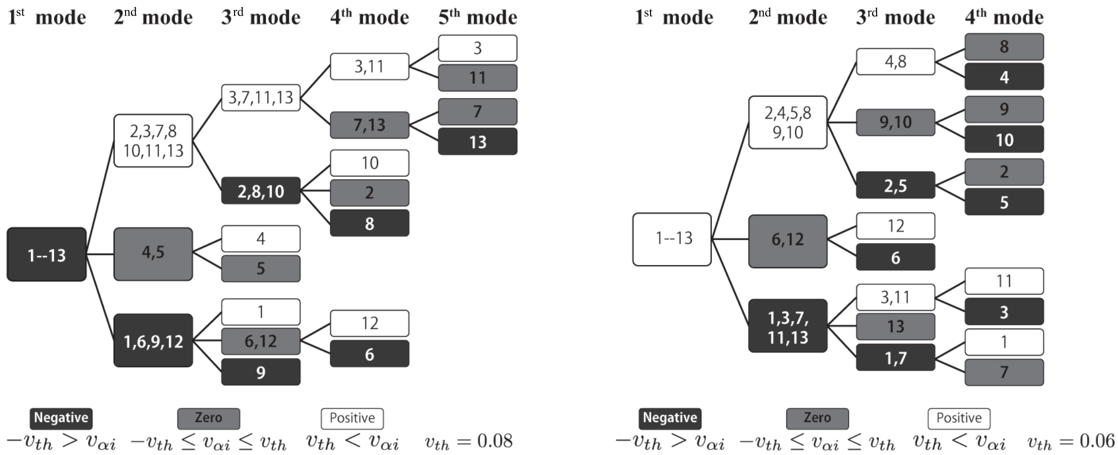
and Zero at each ith mode based on threshold value v_{th}. The v_{th} is set to minimize the mode number to identify all subjects.

These results also indicate that the 1st mode affects equally in all subjects, that is, the 1st mode represents the *style* component of walking motion common to all subjects. On the other hand, the higher than the 2nd modes are helpful in identifying individuals, that is, the higher than the 2nd modes represent the *characteristic* component for each subject. Thus, we see that, from the experimental results of Figures 3, 4 and 5, SVD



(a) MoCap data (b) Accelerometer data

FIGURE 4. Value of right singular vector $\boldsymbol{v}_i$ for each subject



(a) MoCap data (b) Accelerometer data

FIGURE 5. Tree diagram of $v_{\alpha i}$ for identifying subjects

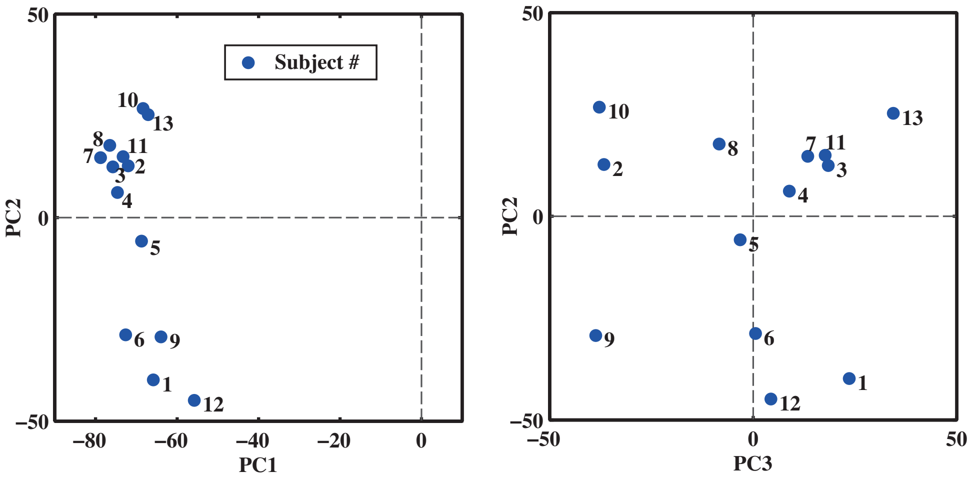
is an effective method for extracting both the style and the characteristic component of motion.

In addition, it is important that both MoCap and accelerometer data denote the same tendency of the 1st mode and the higher than the 2nd modes shown in Figures 3 and 4. This result indicates that both the style and characteristic component of motion can be extracted from both data, i.e., segmented body motion and full body motion data.

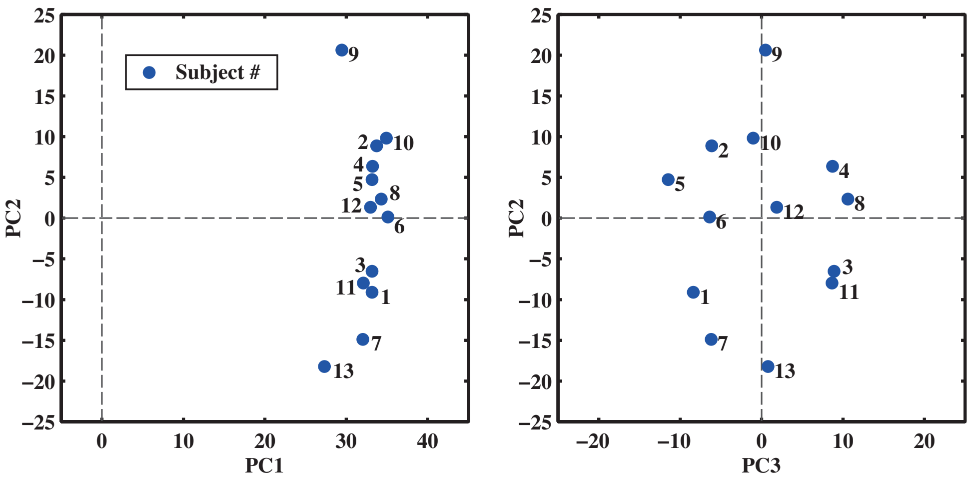
4.2. **Clustering for walking motion.** To visualize the relationships between the subjects and each mode, the dimension of matrix D is reduced. Then the matrix D is approximated by using the left singular vector as follows.

$$D_k = U_k^\top D \in \mathcal{R}^{k\times M}, \quad \text{where } U_k = \left(\boldsymbol{u}_1, \ldots, \boldsymbol{u}_k\right). \tag{6}$$

Here U_k is a set of k left singular vectors. And the columns and row elements are corresponding to each subject and each mode, respectively. Figure 6 shows the results of (6), where each dot is corresponding to elements of matrix $D_3 = \left(d_{i,j}\right)$. And PC1, PC2, and PC3 shown in Figure 6 are corresponding to the 1st, 2nd, and 3rd principal components



(a) MoCap data



(b) Accelerometer data

Figure 6. Scatter plot of matrix D_3

respectively from principal component analysis. In each two-dimensional space, there are 13 dots which mean similarities between each subject's motion. We can observe the dots in Figure 6 are concentrated in the narrow range of the PC1 axis, and distributed over a wide range of the PC2 and PC3 axis. Then, we can discriminate the walking motion of each subject in the D_3 space using high-order mode. These results suggest that PC1 indicates a role for the *style* component, and high-order modes are corresponding to *characteristic* components.

5. **Conclusions and Remarks.** In this paper, we discussed the methodology for extracting both of a *style* and *characteristic* component from walking motions. The motions were measured using two types of sensor, one is a full-body motion capturing system, and the other is the wearable motion sensors for acquiring segmented body motion. To extract style and characteristic component, we used the singular value decomposition of the measured data, and compared the results corresponding to MoCap data with accelerometer data. From these experimental results, it is possible to extract both of the style and characteristic component of motion from both segmented body motion and full body motion. These results suggest that data with segmented body motion can be used to identify individuals. As further work, we need to investigate the physical meanings of each mode for understanding characteristics of a subject from the motion data.

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REFERENCES

[1] L. Bao and S. S. Intille, Activity recognition from user-annotated acceleration data, *Proc. of PERVASIVE*, Vienna, Austria, pp.1-17, 2004.

[2] M. Tada, F. Naya, R. Ohmura, M. Okada, H. Noma, T. Toriyama and K. Kogure, A method for measuring and analyzing driving behavior using wireless accelerometers, *IEICE Trans. Information and Systems*, vol.J91-D, no.4, pp.1115-1129, 2008.

[3] T. Ploetz, N. Hammerla, A. Rozga, A. Reavis, N. Call and G. D. Abowd, Automatic assessment of problem behavior in individuals with developmental disabilities, *Proc. of UbiComp*, pp.391-400, 2012.

[4] A. Avci, S. Bosch, M. Marin-Perianu, R. Marin-Perianu and P. Havinga, Activity recognition using inertial sensing for healthcare, wellbeing and sports applications: A survey, *Proc. of ARCS*, pp.1-10, 2010.

[5] C. Marcroft, A. Khan, N. Embleton, M. Trenell and T. Ploetz, Movement recognition technology as a method of assessing spontaneous general movements in high risk infants, *Frontiers in Neurology*, vol.5, no.284, pp.1-9, 2015.

[6] N. F. Troje, Decomposing biological motion: A framework for analysis and synthesis of human gait patterns, *J. Vision*, vol.2, no.5, pp.371-387, 2002.

[7] N. F. Troje, Retrieving information from human movement patterns, in *Understanding Events: How Humans See, Represent, and Act on Events*, T. F. Shipley and J. M. Zacks (eds.), Oxford, Oxford Univerity Press, 2008.

[8] K. Mishima, S. Kanata, H. Nakanishi, T. Sawaragi and Y. Horiguchi, Extraction of similarities and differences in human behavior using singular value decomposition, *IEICE Trans. Fundamentals of Electronics, Communications and Computer Sciences*, vol.J94-A, no.4, pp.293-302, 2011.

[9] M. Okada, K. Tatani and Y. Nakamura, Polynomial design of the nonlinear dynamics for the brain-like information processing of whole body motion, *Proc. of the IEEE Int. Conf. on Robotics and Automation*, Washington D.C., USA, pp.1410-1415, 2002.