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STUDY OF INDIVIDUAL CHARACTERISTICS IN HUMAN MOTION BY USING 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 our previous researches, a method of extracting both similarities/style and differences/characteristic components from a walking motion was discussed. However, the physical meanings of the similarities/style and differences/characteristic components of a subject from the motion data could not be understood. Toward the understanding of physical meanings of them, in this paper, we discuss a method of determining which segment data contributes to the similarities/style and differences/characteristic components. The results suggest that the classification of the segment data contributing to similarities/style and differences/characteristic components is possible.*
Keywords: Human gait features, Singular value decomposition, Accelerometer

1. **Introduction.** Recently, it is possible to collect the huge amount of data of human motion by using body-worn sensors. Therefore, many researchers deal with the problem of human motion analysis from motion sensors (e.g., accelerometers and gyroscopes) to understand human activities, such as the car driving, sports, and healthcare assessments [1, 2, 3, 4, 5]. The goals of human motion analysis generally include the classification and/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, the extraction methods for motion features from motion data have been discussed by many researchers in the fields of computer vision, robotics, and computer science.

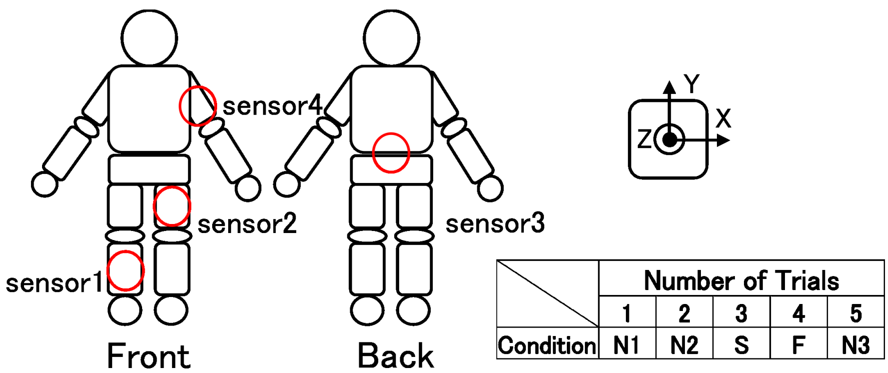
Mishima *et al.* [6] proposed an extraction method of similarities/style and differences/characteristic in human motion using singular value decomposition (SVD) by using a three-dimensional motion capturing (MoCap) system. In the MoCap system, movements of a subject are usually captured using cameras, magnetic and ultrasound systems. These systems allow a complete three-dimensional kinematics of whole body motion and they required dedicated space for measuring, the time needed for the analysis, and also the cost of 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. Akiduki *et al.* [7] discussed a method based on [6] of extracting both similarities/style and differences/characteristic components from walking motions using two types of sensor; one is a MoCap system, and the other is the wearable motion sensors for acquiring segmented body motion. By comparing the results corresponding to MoCap data with accelerometer data, they pointed out that it was possible to extract both the similarities/style and differences/characteristic components of motion from both segmented body motion and full body motion. These results suggested that data with segmented body motion can be used to identify individuals. In [7], they did not discuss the physical meanings of the similarities/style and differences/characteristic components of a subject from the motion data.

If we can know which segment data contributes to the similarities/style and differences/characteristic components, it can be helpful to understand the physical meanings of the similarities/style and differences/characteristic components. Therefore, the aim of this paper is to discuss how to determine which segment data contributes to the similarities/style and differences/characteristic components. In addition, we confirm the effectiveness of the proposed method by using the walking motion data.

The paper is organized as follows. In Section 2, we give an overview of the experiment to collect the walking motion data. In Section 3, we briefly review the method of extracting similarities/style and differences/characteristic components based on SVD. Moreover, we explain how to determine which segment data contributes to the similarities/style and differences/characteristic components. In Section 4, the experimental results and discussion are presented. Section 5 is devoted to a summary.

2. **Overview of Experiment.** To acquire human activities, we use a wireless motion sensor (WAA-010, ATR-Promotions Inc.). 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 (sensor1), left thigh (sensor2), lower back (sensor3) and left forearm (sensor4) on a subject, the numbering of the segments is shown in Figure 1. These placements are referred to Bao and Intille [1]. The motions of a subject can be collected as acceleration along with three-axis of local coordinate on the sensor module: $(\mathrm{X}, \mathrm{Y}, \mathrm{Z})$ shown in Figure 1. 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.

In this paper, we measured the walking motion of 13 subjects (10 men and 3 women aged 24.3 ± 4.3). We instructed the subject to walk on the test course with 15 m straight flooring line according to a predefined protocol shown in Figure 1. In the protocol, each subject had an instruction to perform 5 walking with following conditions: N#: walking with natural speed and the number # after N is the trial number of walking with natural speed, S: walking with slow speed, and F: walking with fast speed on the course. Before



	Number of Trials				
	1	2	3	4	5
Condition	N1	N2	S	F	N3

Figure 1. The sensor setting: a subject's body, three-axis of local coordinate on accelerometer module and walking condition

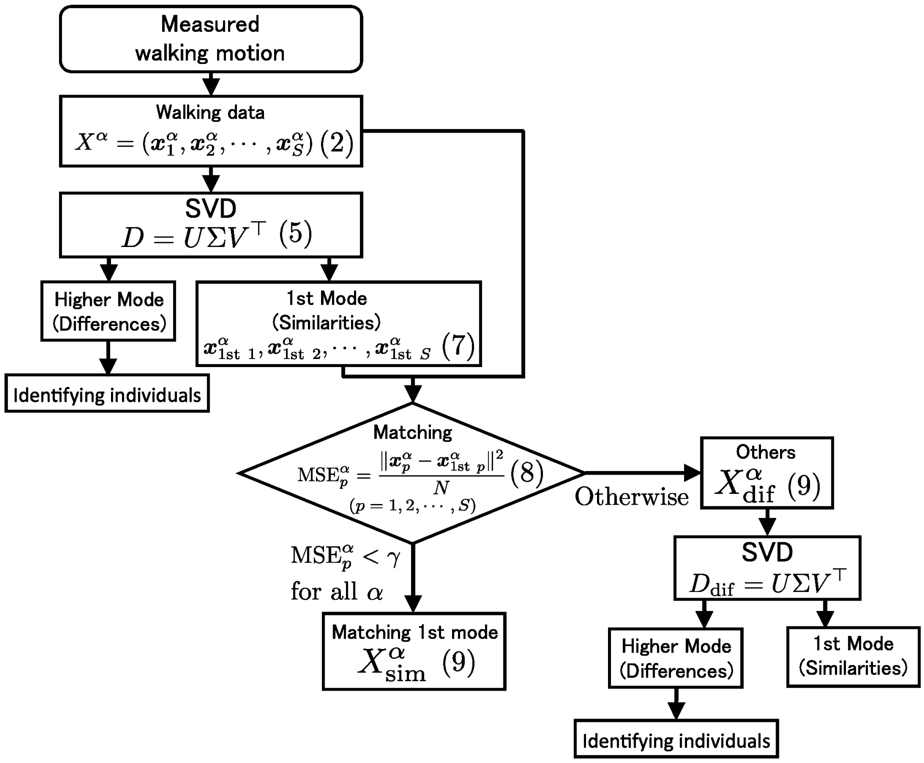


FIGURE 2. The outline of the process

collecting data, we explained the contents of the experiment. Moreover, we also obtained informed consent from each subject to use obtained data for research purposes.

3. **Strategy.** The outline of the process is shown in Figure 2 and we explain the details step by step.

Consider a sequence of segmented motion data, which is cyclic and consequently has a gait period. A set of time series of the acceleration of a body part p for subject α $(\alpha = 1, 2, \cdots, M)$ measured by sensors with dimension N is as follows:

$$\boldsymbol{x}_p^\alpha = (x_p^\alpha(1), x_p^\alpha(2), \cdots, x_p^\alpha(N))^\top \in \mathbb{R}^N, \qquad p = 1, 2, \cdots, S, \tag{1}$$

where $\boldsymbol{x}^\top$ represents the transpose of the vector $\boldsymbol{x}$ and S is (the number of sensor worn) $\times$ (the number of its axis). Moreover, a set of the time series for subject α is described as:

$$X^\alpha = (\boldsymbol{x}_1^\alpha, \boldsymbol{x}_2^\alpha, \cdots, \boldsymbol{x}_S^\alpha) \in \mathbb{R}^{N \times S}. \tag{2}$$

For comparing the motions with each subject, we rewrite (2) as follows:

$$\boldsymbol{a}^\alpha = \left(\{\boldsymbol{x}_1^\alpha\}^\top, \{\boldsymbol{x}_2^\alpha\}^\top, \cdots, \{\boldsymbol{x}_S^\alpha\}^\top\right)^\top \in \mathbb{R}^{N \cdot S}, \tag{3}$$

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

$$D = \left(\boldsymbol{a}^1, \boldsymbol{a}^2, \cdots, \boldsymbol{a}^M\right) \in \mathbb{R}^{N \cdot S \times M}, \tag{4}$$

where the matrix D is a set of human gait patterns for all subjects. 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 as 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) [6]. The SVD of data matrix D is given by:

$$D = U\Sigma V^\top, \tag{5}$$

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 $(i = 1, 2, \cdots, M)$, 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: $\boldsymbol{u}_i \in \mathbb{R}^{N \cdot S}$. Each column vector of V is a right singular vector: $\boldsymbol{v}_i \in \mathbb{R}^{M}$. The ith element of each Σ, U and V is called the ith *mode* by Mishima *et al.* [6].

From the results of (5), the column vector $\boldsymbol{a}^\alpha$, which is composed of motion data for subject α, is described as:

$$\boldsymbol{a}^\alpha = \sum_{i=1}^{M} \sigma_i v_{\alpha i} \boldsymbol{u}_i, \tag{6}$$

where $v_{\alpha i}$ is the αth element of $\boldsymbol{v}_i$. At (6), $\boldsymbol{u}_i$ 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 $\boldsymbol{a}^1, \cdots, \boldsymbol{a}^M$, 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 $v_{\alpha i}$ $(i \geq 2)$ have to change with each subject. From these results, we call the similarities and differences the style and characteristic components of motion.

To analyze how the similarities/style (1st mode) and differences/characteristic affect the original data, the column vector of the 1st mode is reconstructed by:

$$\boldsymbol{a}^\alpha_{\text{1st}} = \sigma_1 v_{\alpha 1} \boldsymbol{u}_1 = \left(\{\boldsymbol{x}^\alpha_{\text{1st}\ 1}\}^\top, \{\boldsymbol{x}^\alpha_{\text{1st}\ 2}\}^\top, \cdots, \{\boldsymbol{x}^\alpha_{\text{1st}\ S}\}^\top \right)^\top, \tag{7}$$

where $\boldsymbol{x}^\alpha_{\text{1st}\ p}$ is the reconstructed vector of the 1st mode. We evaluate the degree of matching between the original data vector $\boldsymbol{x}^\alpha_p$ and the vector reconstructed of the 1st mode $\boldsymbol{x}^\alpha_{\text{1st}\ p}$. In this paper, to evaluate the degree of matching, we use the mean square error:

$$\text{MSE}^\alpha_p = \frac{\|\boldsymbol{x}^\alpha_p - \boldsymbol{x}^\alpha_{\text{1st}\ p}\|^2}{N}, \tag{8}$$

where $\|\cdot\|$ indicates the norm of a vector. If the value of MSE^α_p is small with the predetermined value γ, the degree of matching between the original data vector and the vector reconstructed of the 1st mode is good. In this case, we can understand that the original data mainly affects the similarities/style (1st mode). On the other hand, if the value of MSE^α_p is large with predetermined value γ, the degree of matching between the original data vector and the vector reconstructed of the 1st mode is not so good. Thus, we can understand that the original data mainly affects the difference/characteristic, i.e., the original data mainly dose not affect the similarities/style (1st mode). Therefore, in this paper, we classify its original data as follows:

$$X^\alpha_{\text{sim}} = \{\boldsymbol{x}^\alpha_p \mid \text{MSE}^\alpha_p < \gamma \text{ for all } \alpha\}, \qquad X^\alpha_{\text{dif}} = \{\boldsymbol{x}^\alpha_p \mid \text{otherwise}\}. \tag{9}$$

Moreover, using the similar way in (2)-(4), we define the matrices:

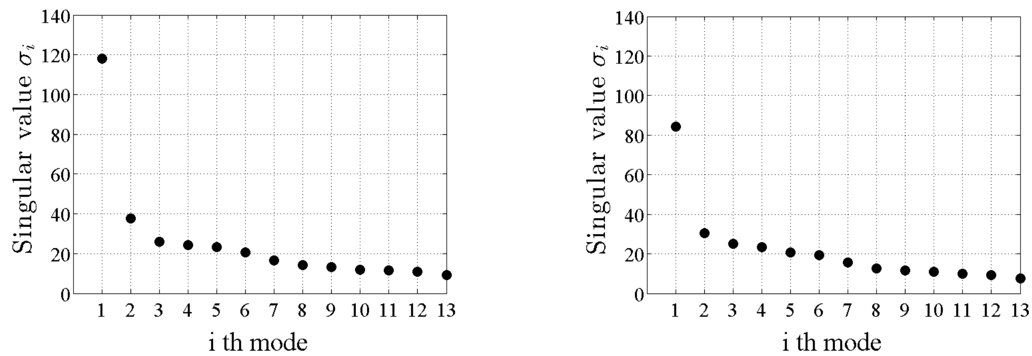
$$D_{\text{sim}} \in \mathbb{R}^{N \cdot r \times M}, \qquad D_{\text{dif}} \in \mathbb{R}^{N \cdot (S-r) \times M}, \tag{10}$$

respectively. Here, r represents the number of data satisfying $\text{MSE}^\alpha_p < \gamma$. Since the matrix D_{dif} in (10) is the data mainly contributing to differences/characteristic, by performing again SVD on D_{dif}, we can confirm the possibility to identify individuals.

4. **Results and Discussion.** We use the data of walking motion with condition N1 in the following part, since we discuss the difference of the subjects and do not discuss the difference of walking conditions in this paper. Before constructing matrix D in (4), time series for one gait cycle are clipped from the whole walking data. Since the length of one gait cycle is different for each subject, the clipped time series have even lengths in between by processing through the cubic spline interpolation algorithm. As the results, the length of clipped time series was $N = 121$. The number of time-series S in (4) was $S = (4 \text{ segments}) \times (3 \text{ axis})$. Also, the number of subjects was $M = 13$.

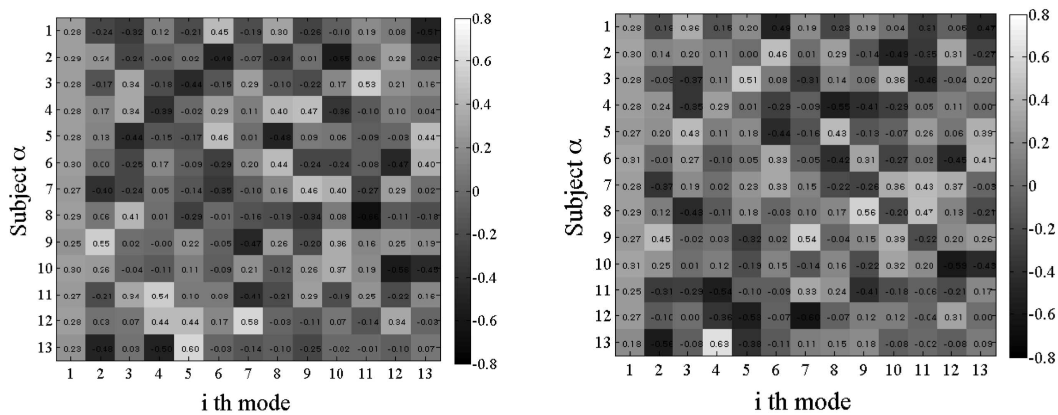
Figure 3(a) shows the results of singular value σ_i of each mode. The singular value at 1st mode reached a peak of $\sigma_1 = 118.0$. The singular value at the 2nd mode dropped suddenly, and after that decreased moderately. Figure 4(a) shows the right singular vector $\boldsymbol{v}_i$ for each subject with a grayscale image. The right singular vector at the 1st mode $v_{\alpha 1}$ remains constant at approximately 0.28 for all subjects. Moreover, Figure 5(a) shows the tree diagram of $V = [v_{\alpha i}]$ for identifying subjects. In Figure 5(a), the right singular values $v_{\alpha i}$ are separated into three groups: Negative/Positive, and Zero at each ith mode based on threshold value v_{th}. The v_{th} is set to 0.1 based on [6].

These results also indicate that the 1st mode affects equally in all subjects, that is, 1st mode represents the similarities/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 modes represent differences/characteristic component for each subject. Thus, we see that, from the experimental results of Figures 3(a), 4(a)



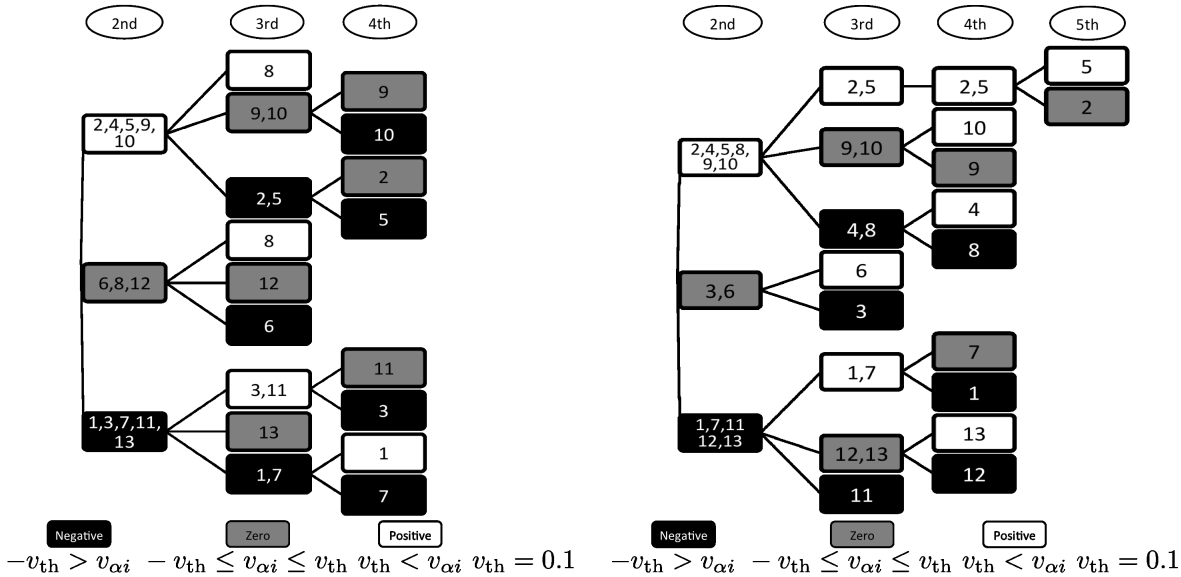
(a) Case of matrix D in (4) (b) Case of matrix D_{dif} in (10)

FIGURE 3. Singular value σ_i of each mode



(a) Case of matrix D in (4) (b) Case of matrix D_{dif} in (10)

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

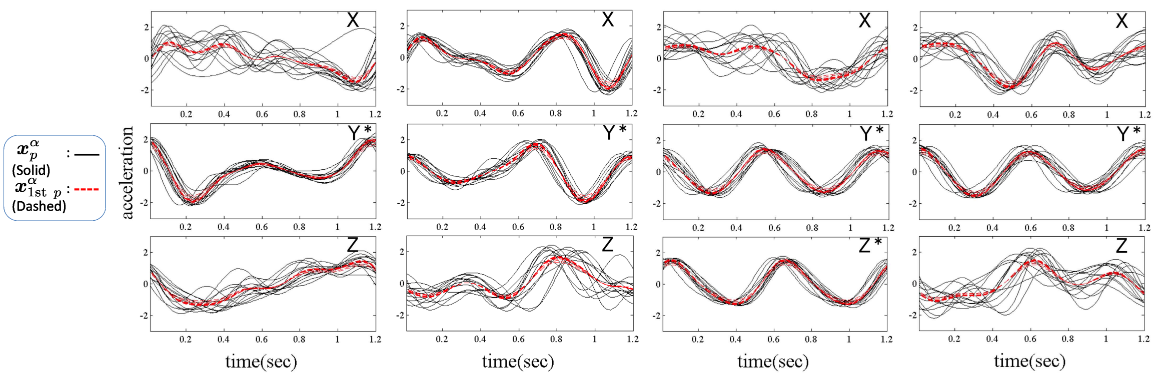


(a) Case of matrix D in (4) (b) Case of matrix D_{dif} in (10)

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

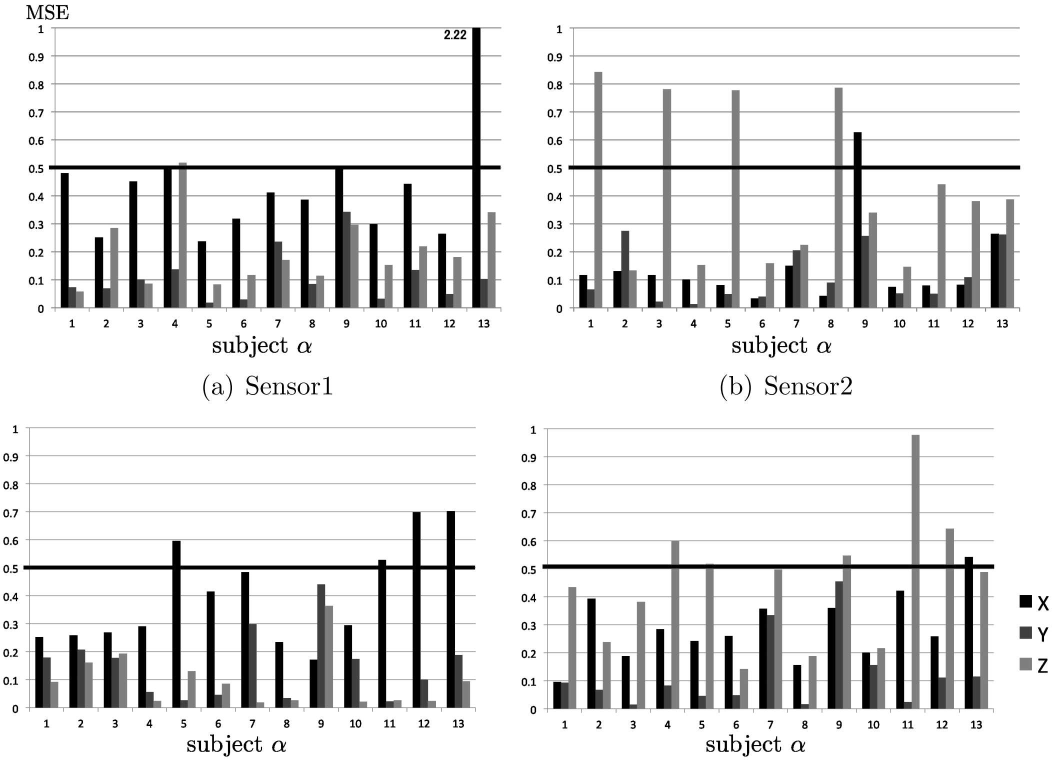
and 5(a), SVD is an effective method for extracting both the similarities/style and the differences/characteristic components of motion. These results are consistent with the claim in [6, 7].

The time series for one gait cycle of each subject $\boldsymbol{x}_p^\alpha$ (solid) and the reconstructed vector of the 1st mode $\boldsymbol{x}_{1\mathrm{st}\ p}^\alpha$ (red dashed) are plotted in Figure 6. We can find that some of the time series for one gait cycle of each subject are almost the same form of the reconstructed vector of the 1st mode. To evaluate the degree of matching between $\boldsymbol{x}_p^\alpha$ and $\boldsymbol{x}_{1\mathrm{st}\ p}^\alpha$, the MSE_p^α in (8) is calculated in Figure 7. From Figures 6 and 7, the form of Y axis of all sensors and Z axis of sensor3 is almost the same as the form of the 1st mode and the value of matching MSE_p^α is small. On the other hand, for example, the form of X axis of sensor1 and sensor3 is different from the form of the 1st mode. The value of matching MSE_p^α is relatively large. Thus, we can understand the data of Y axis of all sensors and Z axis of sensor3 mainly contributed to the 1st mode (similarities/style component) and the other data mainly contributed to the higher mode (differences/characteristic component).



(a) Sensor1 (b) Sensor2 (c) Sensor3 (d) Sensor4

FIGURE 6. The time series for one gait cycle $\boldsymbol{x}_p^\alpha$ of each subject (solid) and the reconstructed vector of the 1st mode $\boldsymbol{x}_{1\mathrm{st}\ p}^\alpha$ (red dashed). * shows its data is categorized into X_{sim}^α.



(a) Sensor1 (b) Sensor2

(c) Sensor3 (d) Sensor4

Figure 7. Value of MSE_p^α

In order to confirm this, we classify the data $\boldsymbol{x}_p^\alpha$ in X_{sim}^α and X_{dif}^α shown in (9). In this paper, we set $\gamma = 0.5$. Thus, if the value of MSE_p^α of the axis in all subjects is less than 0.5, its data is classified in X_{sim}^α. By using the similar way in (2)-(4), we set the matrices: D_{sim} and D_{dif}, respectively.

Since D_{sim} is the similarities/style component, the contribution of this data to the extraction of the difference/characteristic component of motion is small. In other words, since D_{dif} is the data mainly contributing to differences, by performing again SVD on D_{dif}, we can identify individuals.

In this paper, the data Y axis of all sensors and Z axis of sensor3 shown by Y* and Z* in Figure 6 is categorized into X_{sim}^α. The other data is categorized into X_{dif}^α. Thus, $r = 5$. The results of SVD using the only D_{dif} are shown in Figures 3(b), 4(b) and 5(b). From Figure 3(b), although the singular value is smaller than that in the case of D, the tendency is the same as Figure 3(a), i.e., the singular value at the 1st mode reached a peak and the singular value at the 2nd mode dropped suddenly, and after that decreased moderately. The right singular vector at the 1st mode remains constant approximately shown in Figure 4(b). Moreover, Figure 5(b) shows the tree diagram for identifying subjects. We can identify subjects only using the data categorized into X_{dif}^α.

These results indicate that the classification of the segment data contributing to similarities and differences is possible.

5. **Summary.** In this paper, we discussed the method of determining which segment data contributes to the similarities/style and differences/characteristic components from walking motions (see Figure 2) since it could be helpful to understand the physical meanings of the similarities/style and differences/characteristic components. We briefly reviewed the method of extracting similarities/style (1st mode) and differences/characteristic components based on singular value decomposition. After that we explained how to determine which segment data contributes to the similarities/style and differences/characteristic

components. To determine the contribution of the segment data to the similarities/style (1st mode), we evaluated the degree of matching between each segment data and the similarities/style (1st mode) data. In addition, we confirmed the effectiveness of the proposed method by using the walking motion data. From these experimental results, the classification of the segment data contributing to similarities/style and differences/characteristic components is possible. Thus, we concluded that our proposed method is effective to determine which segment data contributes to the similarities/style (1st mode) and differences/characteristic components.

As further work, we need to investigate the physical meanings of the classified segment data for understanding both similarities/style (1st mode) and differences/characteristic of a subject from the motion data.

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