

GENDER PREDICTION BY GAIT ANALYSIS BASED ON TIME SERIES VARIATION OF JOINT POSITIONS

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ABSTRACT

In this paper, a novel gender prediction scheme based on a gait analysis is proposed. For the gait analysis, we propose a novel feature extraction scheme that uses the time series variation in the joint positions directly. Here, normalization by linear interpolation is adopted to set the number of samples of a walking period as the same constant for all target humans. The classifier for gender prediction is constructed with a support vector machine using the feature extraction scheme. To evaluate our proposal, we carried out an experiment for gender prediction using six male and six female humans who are in their twenties. The experimental results show that the classification accuracy is 99.12% when three-dimensional coordinates are used directly for feature extraction and 99.12% if two-dimensional features are used in the best case.

1. INTRODUCTION

The acquisitions of personal properties based on image processing has become a very popular topic because these properties are very useful for several applications; they can be used to construct robust security systems, to analyze consumer behavior, etc. The most popular visual cue used for this purpose is the human face, which has enables prediction of the age, sex, emotion, etc. in recent studies. In addition to these applications, face images can be used for identification for passport control and at the entrances of secured buildings, where highly accurate classification is required. As described above, face images can provide a considerable amount of information with sufficient accuracy to obtain personal properties when face image are captured at high resolution. However, it is not practical to predict personal properties by only face images if they cannot be captured at sufficient resolution owing to the distance between the camera and the target. This situation often occurs in images captured at generic outdoor

scenes.

To solve this problem, different approaches that use the whole part of the human body have been proposed because the whole part of the human body can be obtained at moderate resolution, even if the cameras are far away from the target persons. A part-based representation[1], a biologically-inspired approach[2], and a HOG-based approach[3] are schemes based on this idea, which strongly depend on the appearance of the target humans. On the other hand, other schemes that use geometric measurements of the entire body have been also proposed. For example, [4] proposed gender prediction based on metrology of the entire body and a copula model to improve gender classification has been proposed in [5]. These schemes using geometric measurements achieve excellent accuracy but cannot be applied in most applications because specialized devices that are not used in actual environments are necessary to obtain geometric measurements.

In addition to the above schemes using the whole part of the human body, there are other approaches for analyzing personal properties; a gait analysis analyzes the human motion caused by walking. Many studies on kinematics using a gait analysis are published, and they can be applied to prediction of personal properties; for gender prediction, previous studies [6], [7], and [8] have achieved an accuracy of 96%, 94%, and 83%, respectively. The image-based gait analysis in the above schemes is very useful for predicting personal properties because higher accuracy has been achieved without any specialized sensing devices. To improve the prediction accuracy of this type of schemes, the significant features of a gait for prediction should be determined. However, existing studies have not shown a detailed analysis of a gait for the prediction of personal properties. Therefore, a new hypothesis for significant information for gender prediction included in a gait is proposed and confirmed in this paper.

We think that the most significant information in a gait is how to step forward when walking, and it is contained in

time series variation in the joint positions. In particular, when only gender is predicted, it is expected that the time series variation in the joint positions is significantly different between men and women owing to difference in the anatomical structures around the pelvis. To confirm this hypothesis, the accuracy for gender prediction by our proposal is evaluated using actual data obtained from 12 persons who are in their twenties. In this experiment, the three-dimensional geometry of the joint positions is measured by the Kinect v2 produced by Microsoft Corporation. For the gait analysis, we propose a novel feature extraction scheme that uses the time series variation in the joint positions directly and classification is performed with a support vector machine. In this evaluation, feature extraction is executed with the two-dimensional information of the joint positions to estimate the classification performance when the entire body images are captured by a generic camera that cannot obtain three-dimensional information in addition to feature extraction using the three-dimensional information directly.

This paper is organized as follows. Section 2 describes existing studies on a gait analysis. Section 3 presents a novel feature extraction scheme based on the time series variation in the joint positions, and an evaluation using actual data obtained from 12 persons via Microsoft Kinect v2 is presented in Section 4. Finally, Section 5 concludes this paper.

2. RELATED WORK

Gender prediction by gait analysis has been tackled in several research fields including medical science, cognitive science, and information science since Kozłowski et al. initially proposed initial stage of this type of study in [9]. In this study, a subjective evaluation for discriminating gender by the motion of right sources attached to testees' joints showed that the gait can be used as a cue to classify the gender of the testee by his or her gait. After that, to obtain personal properties from a human's gait, several studies proposed that not only the appearance of human motion but also the information of the acceleration of several parts of a human[10], the sounds and pressure of step[11], and the distance between the ground and a foot[12] are cues to the gender of the target. However, these methods have critical problem for practical applications; the target humans must wear a specialized device to measure the metrology.

In contrast, recent studies based on image processing do not require the target humans to wear such specialized devices; they only use a camera to capture the appearance of the classification target. These image-based schemes can be classified into two major approaches; one extracts features from the captured image directly, and the other estimates the motion of the target humans based on captured images before classification of the personal properties. The most popular approach using the appearance of the target human directly extracts their silhouette from the captured images. For exam-

ple, the scheme proposed in [8] constructs frequency-domain features using several images captured from various angles to classify personal properties, as shown in Fig.1. On the other hand, many classification schemes that estimate a target's motion extract the body parts or joint positions of a human from the captured images. For example, [6] proposed a feature extraction scheme using a motion analysis with a stick-based model, and Lee et al. estimated positions of the arm, head, torso, etc. by ellipse fitting[7], as shown in Fig.2.

Experimental results using the existing schemes show that feature extraction based on the motion of body parts improves the classification accuracy. Therefore, the ideal classification accuracy is evaluated when the geometry of joint positions is obtained accurately in this study. To simulate this condition, geometry data captured by Microsoft Kinect v2 is used in this study.

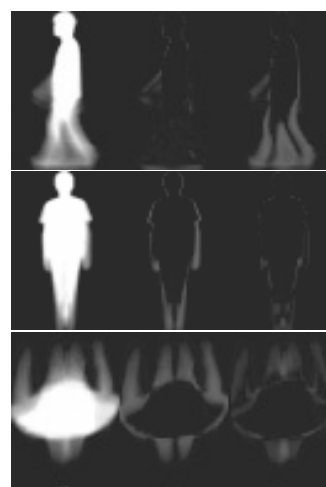


Fig. 1. Frequency-domain features proposed in [8]

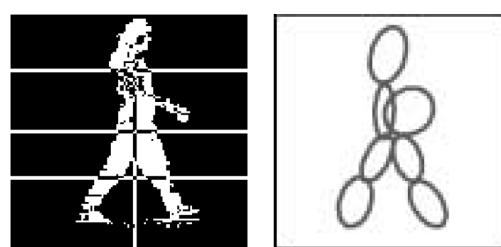


Fig. 2. Modeling by ellipses proposed in [7]

3. GENDER PREDICTION BASED ON THE TIME SERIES VARIATION IN THE JOINT POSITIONS

In this section, the basic idea of the proposed scheme is shown, the joint positions obtained by the Kinect v2 are ex-

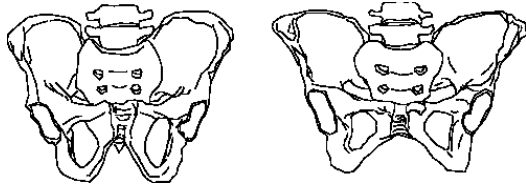


Fig. 3. Structure of human's pelvis

plained, and a novel gender prediction scheme based on the time series variation in the joint positions is proposed.

3.1. The basic idea of the proposed scheme

The largest difference between men and women in their skeletal structure is the pelvis, whose shape is shown in Fig.3. In this figure, the left and right illustrations correspond to male and female pelvises, respectively. As you can see, they are quite different, even though they are located near the central part of the human body. Owing to this difference, the angle between the body axis and the thighbone in men tends to differ from that in women. Considering these differences, it is natural that the optimal way of walking including how to use the joints becomes different.

In addition to the difference in the skeletal structure, there are some social factors that cause differences in the way of walking between men and women. A typical example caused by such social factors is the way of walking of women in fashion shows. Fig.4 depicts the joint positions of a female model walking on runway at a fashion show. The most significant characteristic is that the pelvis leans side-to-side according to the motion of the legs. The authors have not obtained statistics on how woman walk, but there are many women that walk in the same way. On the other hand, the fluctuation in the male pelvis while walking is less than that of a woman, as shown in Fig.5. Moreover, the trajectories of the knees and ankles seem different between men and women.

These differences are caused by the skeletal structure and social factors as described above can be characterized by the motion of the joint positions while walking. To confirm this hypothesis, we propose a novel gender prediction scheme using feature vectors created with only the information about the joint positions and evaluate the classification accuracy of the proposed scheme using actual data. To obtain the joint positions, Kinect v2 by Microsoft is adopted in this study.

3.2. Joint positions obtained by Kinect v2

In this study, we modified a sample program named "Skeleton Basics-D2D" provided by Microsoft included in the Kinect for Windows SDK in order to obtain the joint positions of a target human at each sampling time. The program extracts the absolute coordinates of the joint positions of 25 humans,

as shown in Fig.6, where the center of the coordinates is the location of a Kinect v2 device, as shown in Fig.10.

The obtained joints can be represented by index numbers shown as follows: 0 is Spine Base, 1 is Spine Mid, 2 is Neck, 3 is Head, 4 is Shoulder Left, 5 is Elbow Left, 6 is Wrist Left, 7 is Hand Left, 8 is Shoulder Right, 9 is Elbow Right, 10 is Wrist Right, 11 is Hand Right, 12 is Hip Left, 13 is Knee Left, 14 is Ankle Left, 15 is Foot Left, 16 is Hip Right, 17 is Knee Right, 18 is Ankle Right, 19 is Foot Right, 20 is Spine Shoulder, 21 is Hand Tip Left, 22 is Thumb Left, 23 is Hand Tip Right, and 24 is Thumb Right[13].

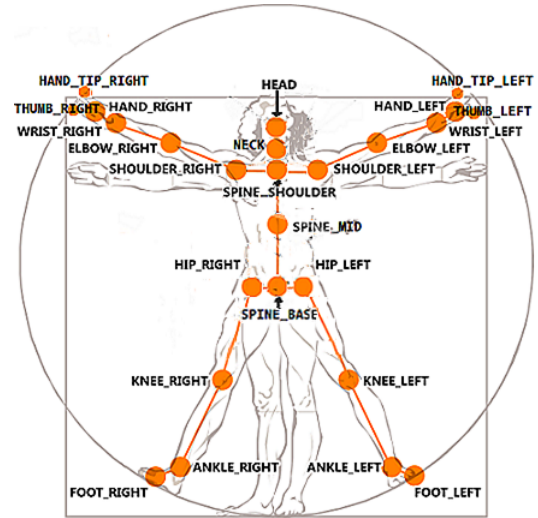


Fig. 6. Joints obtained by Kinect v2[13]

In the rest of this paper, the position of a joint whose index is i is represented by a position vector \mathbf{p}_i defined by the following equation:

$$\mathbf{p}_i = (s_i, t_i, u_i) \quad (i = 0, 1, 2, \dots, 24), \quad (1)$$

where s_i , t_i , and u_i are the x -, y -, and z -components of the position vector \mathbf{p}_i , respectively.

In addition to the joint positions, the Kinect v2 provides a corresponding measure of the reliability as follows:

- 0 means failure,
- 1 means an estimate, and
- 2 means success.

Next, we define the coordinates of a joint position at time t that is necessary for modeling the time series variation by a position vector $\mathbf{p}_{i,t}$, as follows:

$$\mathbf{p}_{i,t} = (l_{i,t}, m_{i,t}, n_{i,t}) \quad (i = 0, 1, 2, \dots, 24), \quad (2)$$

where $\mathbf{p}_{i,t}$ represents a position vector \mathbf{p}_i at time t and $l_{i,t}$, $m_{i,t}$, and $n_{i,t}$ are the x -, y -, and z -components of the vector $\mathbf{p}_{i,t}$, respectively.

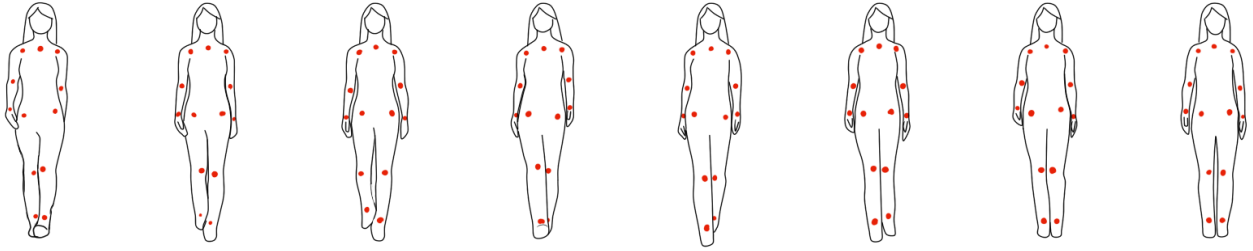


Fig. 4. Women's way of walking

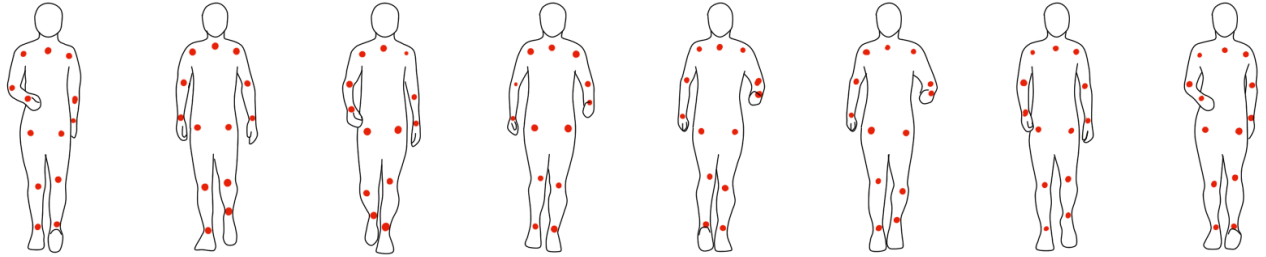


Fig. 5. Men's way of walking

3.3. Feature extraction using the time series variation in the joint positions

The origin of the coordinates of the joint positions obtained by the Kinect v2 is the location of the Kinect v2 device itself. In order to make the joint positions independent from the distance between the target human and the Kinect v2 device, we use relative vector whose start point is the coordinates of joint 0 described by the following equation:

$$\begin{aligned}
 \mathbf{q}_{i,t} &= \mathbf{p}_{i,t} - \mathbf{p}_{0,t} \quad (i = 1, 2, \dots, 24) \\
 &= (l_{i,t} - l_{0,t}, m_{i,t} - m_{0,t}, n_{i,t} - n_{0,t}) \\
 &= (l'_{i,t}, m'_{i,t}, n'_{i,t}), \quad (3)
 \end{aligned}$$

where $l'_{i,t}$, $m'_{i,t}$, and $n'_{i,t}$ are the x -, y -, and z -components of the vector $\mathbf{q}_{i,t}$, respectively. This coordinate transformation in Fig.7, enables feature extraction that is not affected by the distance between the target human and the Kinect v2 device. Here, we would like to construct feature vectors by concatenating the obtained coordinates of the joint positions in the time series order. In order to create a feature vector that only includes the coordinates corresponding to one period of motion of a target human, a feature vector \mathbf{f}_i for joint i should be constructed by the following equation:

$$\mathbf{f}_i = (l'_{i,0}, m'_{i,0}, n'_{i,0}, l'_{i,1}, m'_{i,1}, n'_{i,1}, l'_{i,2}, m'_{i,2}, n'_{i,2} \dots). \quad (4)$$

In the rest of this paper, the following notation where $\mathbf{q}_{i,t}$ is used instead of $l'_{i,t}, m'_{i,t}, n'_{i,t}$ is used to represent the same equation as Eq.4:

$$\mathbf{f}_i = (\mathbf{q}_{i,0}, \mathbf{q}_{i,1}, \mathbf{q}_{i,2}, \dots). \quad (5)$$

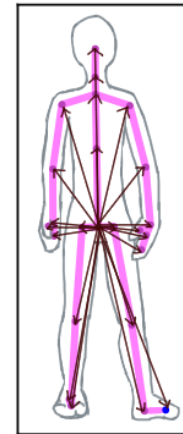


Fig. 7. Coordinate transformation for feature extraction

Here, this notation does not mean that f_i has $q_{i,t}$ as components. Note that this notation indicates that f_i is constructed by concatenating the components of $q_{i,t}$, as in Eq.4.

However, the lengths of the feature vectors obtained from different targets become different if the coordinates obtained by the Kinect v2 that has the constant sampling rate are used directly to construct them because periods of walking corresponding to different target humans tend to become different in general. For example, the periods of walking are clearly different as shown in Fig.8. Therefore, N_A , the length of a feature vector corresponding to one walking period of target A, becomes different from N_B , the length of a feature vector extracted in the same way for target B. Since it is clear that difference in the lengths of the feature vectors makes it difficult to perform accurate classification, the proposed scheme adopts normalization to make the lengths of the feature vectors constant.

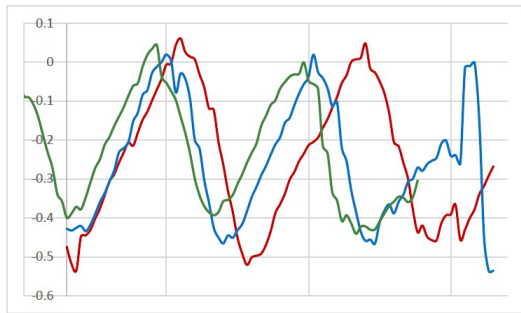


Fig. 8. Difference of walking period

For normalization, the following two operations are applied to a raw feature vector obtained by the above processes. One is a process that expands the walking period of a signal to make it constant for different persons and the other is a process that inserts sample points for the expanded signal to make the number of sample points for the signal corresponding to the walking period constant. Some examples of these processes for normalization are shown in Fig.9. In this figure, the 1st, 2nd, and 3rd rows represent examples for a short period, moderate period, and long period, respectively. Further the 1st, 2nd, and 3rd columns show sample points before normalization, after the expanding operation to make the walking period constant, and the insertion to make the number of sample points per period constant, respectively. In this example, the numbers of sample points for the original signals for the 1st, 2nd, and 3rd rows are four, six, and eight, respectively. The sample points represented by \circ show sample points in the original signals, and the sample points corresponding to \times are sample points after the normalization adopted in the proposed scheme.

Then, the normalization process is detailed using the examples in Fig.9. In this example, the number of sample points after the normalization becomes eight. In the case of the 3rd

row, the sample points after normalization represented by \times are located at the same positions as the sample points of the original input signal represented by \circ . Next, we talk about the case in the 1st row, where the number of sample points of the original signal is four. In this case, four samples must be newly inserted to make the number of sample points after normalization eight. This insertion is performed by two operations described by the 1st row and 2nd column and the 1st row and 3rd column in Fig.9. In the first operation, the sampling interval is extended, as shown in the figure, and the second operation inserts eight samples represented by \times at even intervals. In this example, the four samples represented by \times after normalization are located at the same positions as the extended sample points, and four more samples are inserted at the midpoints of the original sample points because the original signal is extended just twice.

Next, the normalization depicted by in the 2nd row of the figure is explained. This example corresponds to a more generic case that the number of sample points after normalization is not represented by an integer multiple of the original samples. In this example, the same operation flow as the 1st row is applied; first the walking period is extended by 1.5 times, and eight samples are inserted at even intervals. Here, only two samples after normalization are located at the same positions where the original sample points exist. For another six samples, the locations of these samples are computed by linear interpolation considering the two nearest sample points of the extended signal. For example, the position of a new sample \hat{q} can be computed by the following equation:

$$\hat{q} = \frac{1}{d_l + d_r} (d_r \cdot q_l + d_l \cdot q_r), \quad (6)$$

where q_l and q_r are the nearest samples on left and right sides, respectively. d_l and d_r represent the distances along the axis of the time direction from a new sample \hat{q} to samples q_l and q_r , respectively. As shown in the equation, new sample points are generated by linear interpolation using the two nearest sample points of the extended signal.

In the proposed scheme, this normalization is applied to all joints represented by $q_{i,t}$ ($i = 1, \dots, 24$) to obtain a feature vector corresponding to each joint i . Therefore, the normalization in the proposed scheme can be represented by the following equation:

$$\hat{q}_{i,t} = \frac{1}{d_l + d_r} \left(d_r \cdot q_{i, \lfloor t \times \frac{N_{old}}{N_{new}} \rfloor} + d_l \cdot q_{i, \lfloor t \times \frac{N_{old}}{N_{new}} \rfloor + 1} \right), \quad (7)$$

where N_{old} and N_{new} are the numbers of samples before and after normalization, respectively. d_l and d_r are computed by the following equations:

$$d_l = t \times \left(\frac{N_{old}}{N_{new}} - \lfloor \frac{N_{old}}{N_{new}} \rfloor \right), \text{ and} \quad (8)$$

$$d_r = t \times \left(\lfloor \frac{N_{old}}{N_{new}} \rfloor + 1 - \frac{N_{old}}{N_{new}} \right). \quad (9)$$

Finally, a feature vector based on three-dimensional information is obtained by the following equation using $\hat{q}_{i,t}$ obtained by the above operations:

$$\mathbf{f}_{3D} = \left(\hat{q}_{1,0}, \hat{q}_{2,0}, \dots, \hat{q}_{24,0}, \right. \\ \left. \hat{q}_{1,1}, \hat{q}_{2,1}, \dots, \hat{q}_{24,1}, \right. \\ \vdots \\ \left. \hat{q}_{1,N_{\text{end}}}, \hat{q}_{2,N_{\text{end}}}, \dots, \hat{q}_{24,N_{\text{end}}} \right), \quad (10)$$

where $N_{\text{end}} = N_{\text{new}} - 1$, and this notation indicates that the vector \mathbf{f}_{3D} is constructed by concatenating the components of $\mathbf{q}_{i,t}$ as in Eq.4.

After this feature extraction, the classifier is constructed by a linear support vector machine with \mathbf{f}_{3D} . Training and classification using actual data are detailed in the following section.

3.4. Feature extraction using two-dimensional information

Next, in order to estimate the classification performance when a walking motion is captured by a camera from an exposure angle, we propose a feature extraction scheme that uses the two-dimensional coordinates generated by a projection from the three-dimensional coordinates obtained from the Kinect v2 onto a two-dimensional plane corresponding to the exposure angle.

After the projection, the feature vector \mathbf{f}_{2D} is obtained in the same way as the above case by the following equation:

$$\mathbf{f}_{2D} = (v_{1,0}, w_{1,0}, v_{2,0}, w_{2,0}, \dots, v_{24,N_{\text{end}}}, w_{24,N_{\text{end}}}), \quad (11)$$

where $v_{i,j}$ and $w_{i,j}$ are obtained by projecting a three-dimensional feature $\hat{q}_{i,j}$ onto a two-dimensional plane corresponding to the exposure angle.

Then, a classifier is constructed with a linear support vector machine using the same way as the three-dimensional case.

4. EVALUATION

In this section, the proposed scheme for gender prediction is evaluated using actual data obtained from six male and six female persons that are in their twenties. The rest of this section describes how to acquire the three-dimensional geometry of the target humans' joints, how to create the training and testing data, and the accuracy of the gender prediction by the proposed scheme.

4.1. How to acquire the three-dimensional geometries of humans' joints

An overview of the experimental environment is shown in Fig.10. In this experiment, target humans walk along the z-

axis, as depicted in Fig.10, without any restriction on clothes and shoes. Six male and six female humans in their twenties participated in the experiment. Because not all of the male humans were taller than the female humans, the obtained data are suitable for evaluation to confirm whether gender can be predicted only on the basis of the motion of humans.

4.2. How to create training and testing data

In this experiment, a feature vector corresponding to one period of walking is extracted manually, as shown in Fig.11. This extraction process selects only reliable data on the basis of the information recorded by the Kinect v2. By these operations, we can obtain 231 feature vectors corresponding to each walking period with the gender information of the target. Of these feature vectors, 117 feature vectors and other 114 are used for training and testing, respectively.

4.3. Accuracy of gender prediction

The accuracy of gender prediction was 99.12% when feature vectors were extracted using the three-dimensional coordinates directly. In this case, the number of correctly detected samples was 111, whereas the total number of testing samples was 113. Then, the prediction accuracy was measured using the projected two-dimensional coordinates for the feature vectors. Table 1 summarizes the experimental results considering several exposure angles. In the table, $\theta = 0^\circ$ means the target is located directly in front of the Kinect v2 device, and θ increases as the exposure angle varies in a clockwise manner as shown in Fig.12. From the experiment, the prediction accuracy reached 99.12%.

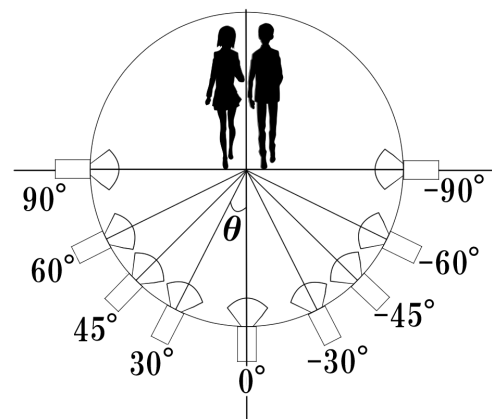


Fig. 12. Exposure angles used in this experiment

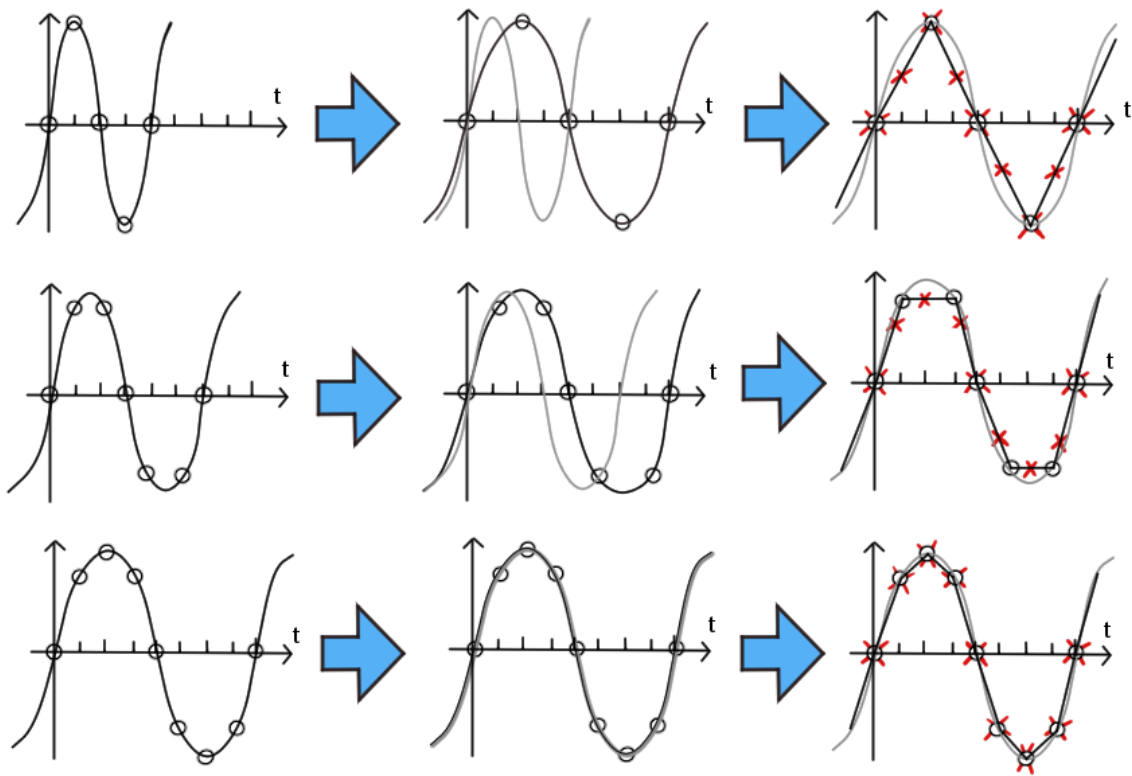


Fig. 9. Interpolation used in the proposed scheme

5. CONCLUSION

In this paper, a novel scheme for gender prediction based on the time series variation in the joint positions during walking was proposed. The feature extraction in the proposed scheme uses samples corresponding to one walking period normalized by linear interpolation in order to make the length of feature vectors uniform. The final classifier for gender prediction is constructed with a support vector machine using the feature extraction scheme.

To evaluate the classification accuracy of the proposed scheme, we carried out an experiment using six male and six female humans that are in their twenties. In the experiment, in addition to the feature extraction using the three-dimensional coordinates of the target's joints obtained by the Microsoft Kinect v2 directly, feature extraction using the two-dimensional coordinates of the target's joints generated by a projection from a three-dimensional space onto a two-dimensional plane was performed considering the exposure angle that captures the target under practical conditions. The experimental results show that the proposed scheme exhibits an accuracy of 99.12% when the three-dimensional coordi-

nates are used directly and 99.12% if the two-dimensional projected data are used in the best case.

The primary purpose of the proposed scheme is to estimate the ideal classification accuracy when the joint positions of a classification target are obtained accurately, and it has two significant problems to be solved to apply it to practical applications. One is how to measure the joint positions of a classification target accurately only by the images captured from a generic camera that cannot acquire depth information. We think that feature point extraction based on machine learning[14] would be a powerful tool for this purpose. The other is how to extract a feature vector corresponding to one period of walking motion accurately, because the manual extraction used in the current proposed scheme cannot be applied to practical applications. It is expected that the detection and synchronization techniques used in digital wireless communication would be useful for solving this problem. In the future, we will construct a robust and practical scheme that overcome these problems.

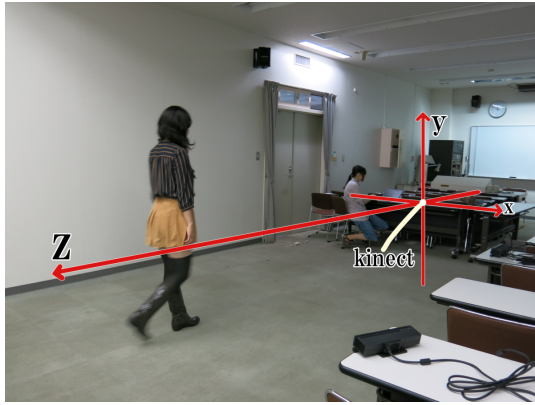


Fig. 10. Experimental environment



Fig. 11. Manual extraction of one walking period

Table 1. Classification accuracy

		Two-dimensional feature								
θ		-90°	-60°	-45°	-30°	0°	30°	45°	60°	90°
accuracy(%)		99.1228	98.2456	98.2456	97.3684	92.9825	96.4912	94.7368	96.4912	99.1228
		Three-dimensional feature								
accuracy(%)		99.1228								

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