Gait-based person identification method using shadow biometrics for robustness to changes in the walking direction

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Abstract

Person recognition from gait images is generally not robust to changes in appearance, such as variations of the walking direction. In general conventional methods have focused on training a model to transform gait features or gait images to those at a different viewpoint, but the performance gets worse in case the model is not trained at a viewpoint of a subject. In this paper we propose a novel gait recognition approach which differs a lot from existing approaches in that the subject's sequential 3D models and his/her motion are directly reconstructed from captured images, and arbitrary viewpoint images are synthesized from the reconstructed 3D models for the purpose of gait recognition robust to changes in the walking direction. Moreover, we propose a gait feature, named Frame Difference Frieze Pattern (FDFP), which is robust to high frequency noise. The efficiency of the proposed method is demonstrated through experiments using a database that includes 41 subjects.

1. Introduction

Person recognition methods are useful for various applications, such as surveillance applications for security operations and service robots coexisting with humans in daily life. Gait is one of biometrics which do not require interaction with subjects and can be performed at a distance. In general, existing gait recognition methods assume that cameras are placed at locations where an entire body shape of a person can be observed. However, if cameras are placed at high locations, such as on UAV or the rooftops of tall buildings, for the purpose of wide area security operations, the correct classification rate decreases. This is because the human body area, which is used to extract gait features, cannot be captured sufficiently from overhead cameras.

To deal with this problem, we proposed shadow biometrics, which is a biometrics method that uses the projected body area of the subject [8] [9]. The projected body area of the subject, i.e. the shadow of the subject, is used to extract biometric information from images taken by overhead cameras. In [9], we focused on images taken at an oblique angle with the ground so that both body and shadow areas of the subject are captured enough. In these images, we can consider that body and shadow areas contain body information captured from two different viewpoints - camera and Sun direction. Thus the use of both information from shadows and information from directly observed body can provide a higher correct classification rate than from either taken alone. However, if the subject's walking direction and the position of the Sun are different from that in the database, the appearances of both body and shadow areas are different from those in the database. This causes that the correct classification rate decreases.

The problem of appearance variations due to changes of the subject's walking direction compared with that in the database is a common problem in gait recognition, and gait researchers have been working on this topic [5] [12]. Kusakunniran et al. proposed a view transformation model using Support Vector Regression to synthesize virtual viewpoint images from captured images [10]. Felez et al. proposed an approach which casts gait recognition as a bipartite ranking problem [3]. The proposed method can learn features invariant to covariate condition changes from different people and different datasets. However, if training datasets to learn models do not include images [10] / features [3] of the same condition with the subject's one, the performance gets worse. We proposed a visual hull-based approach which synthesizes gait images at virtual viewpoints using sequential 3D model of the walking subject [5]. This method has an assumption that 3D models of the walking subject are reconstructed in advance. However, if the 3D models are not available, the visual hull-based method cannot be used. Muramatsu et al. proposed a method, which overcomes the drawback of [5], to generate an arbitrary view transformation model [12]. The model is constructed using a 3D gait database composed of non-subject multi-

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ple people's 3D models. However, since the subject's 3D model is not included in the training dataset to learn the view transformation model, the synthesized image may not coincide to the real one.

1.1. Proposed method

In this paper we propose a novel gait recognition approach which differs a lot from existing approaches in that the subject's sequential 3D models and his/her motion are directly reconstructed from captured images, and arbitrary viewpoint images are synthesized from the reconstructed 3D models for the purpose of gait recognition robust to changes in the walking direction. There are three challenges we deal with in the proposed method.

1. To estimate the subject's motion, markerless motion capture technology [13] [2] can be used. In general the markerless motion capture system prepares a 3D shape model with bones in advance and fits the shape model to a reconstructed 3D model of a subject for motion estimation (Fig. 1 (a)). However, if the 3D shape model of the subject is not available, the motion of the subject cannot be estimated (Fig. 1 (b)). Thus the 3D shape model of the subject should be estimated at the same time with the estimation of his motion.

2. The accuracy of motion estimation may not be good enough for person recognition, due to self-occlusion. One possible way of improving the accuracy is to increase the number of cameras which captures images of the subject. However, if the gait recognition system is installed in public areas for security purposes, in general an area is covered by a single camera, not multiple cameras.

3. To obtain position information of the subject, images taken from multiple viewpoints are necessary.

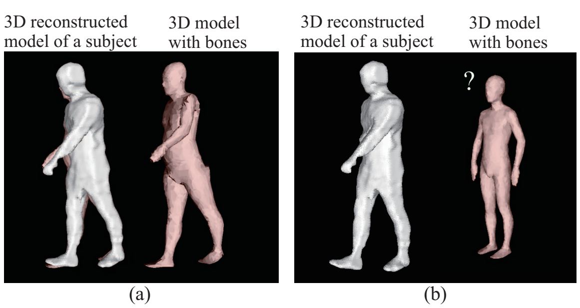


Figure 1. (a) Motion estimation with a 3D shape model with bones, (b) motion cannot be estimated correctly due to a 3D model which does not fit to the subject. For the purpose of showing models clearly, we place objects separately.

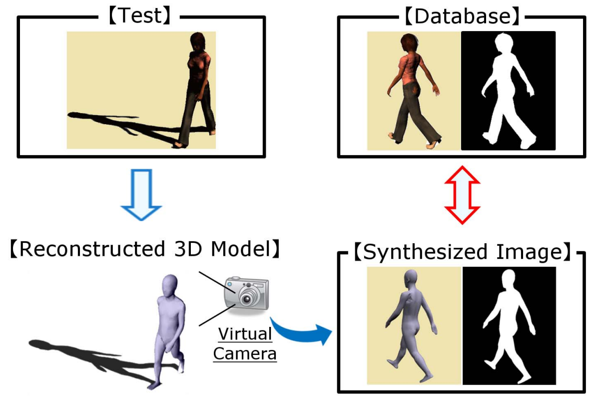


Figure 2. An example scenario using the proposed method.

To solve above three challenges, in the proposed method we utilize a statistical 3D shape model to estimate the 3D model of the subject at the same time with the motion estimation [14] and we introduce a statistical gait motion model to estimate his motion robust to self-occlusion. The statistical 3D shape model consists of an average 3D shape model and several shape parameters, and by changing the shape parameters various types of 3D shapes can be reconstructed [14]. The statistical gait motion model consists of an average gait motion model and several gait parameters, and by changing the gait parameters different gait motions can be generated. In this paper, we call a statistical model which combines both the statistical 3D shape model and the statistical gait motion model. Besides, we take advantage of the shadow biometrics, which allow us to obtain two different viewpoint images using a single camera.

There are three possible scenarios to use the shadow biometrics, in case that we assume that images are taken at an oblique angle with the ground. The first one is that shadows are projected in images of both training and test datasets, so both shadow and body areas are available. The second one is shadows are projected in images of test dataset, thus both shadow and body areas are available in the test dataset but only body area can be used in the training dataset. In this case, after we reconstruct 3D model of a subject using the proposed method as shown in Fig. 2, we synthesize an image from a view point of the training dataset. The last scenario is the other way round of the second scenario. In this paper, we focus on the second scenario.

In the proposed method, first we extract body and shadow areas of the subject, and then we estimate parameters of both statistical 3D shape model and statistical gait model so that the statistical model fits to the reconstructed 3D model of the subject. Next, a virtual image of the statistical model is synthesized from a viewpoint of the training dataset. Finally we extract a newly proposed gait feature, named Frame Difference Frieze Pattern (FDFP), from synthesized images, followed by person identification. The advantage of the statistical 3D shape model and the statistical gait model is that by tuning parameters whole body shape of the subject and motion can change. Thus even though some of body areas are not visible in captured images due to occlusions, the body shape and motion can be estimated by changing parameters of the statistical model using non-occluded areas, which can be obtained in captured images.

The remainder of the present paper is organized as follows. Section 2 describes the statistical 3D shape model and introduces the statistical gait motion model. Section 3 introduces the proposed method to estimate parameters of both statistical models and the newly proposed gait features. Section 4 describes experiments performed to demonstrate the efficiency of the proposed method, and Section 5 presents our conclusions.

2. Statistical models

In this section, we first briefly describe the statistical 3D shape model and then introduce the statistical gait motion model. Both models are generated from training datasets of multiple people.

2.1. Statistical 3D shape model

The statistical 3D shape model [14] was constructed by using an AIST/HQL dataset [1], which consists of 3D models of 97 people (49 male and 48 female). The model consists of an average 3D shape model and 11 shape parameters, and by changing the shape parameters various types of 3D shapes can be reconstructed. Assume that the average 3D shape $\bar{\boldsymbol{x}}$, which is defined as $\bar{\boldsymbol{x}} = \frac{1}{N}\Sigma_{i=1}^{N}\boldsymbol{x_i}$ (N is the total number of 3D models). Here, a 3D model of a person i is defined as $\boldsymbol{x_i} = (x_{i1}, y_{i1}, z_{i1}, \cdots, x_{ik}, y_{ik}, z_{ik})^T$ (k is the number of vertex points of a 3D model). The difference between the average 3D shape $\bar{\boldsymbol{x}}$ and a 3D model $\boldsymbol{x_i}$ is defined as $d\boldsymbol{x_i} = \boldsymbol{x_i} - \bar{\boldsymbol{x}}$. By applying eigenvalue decomposition to $(d\boldsymbol{x_1}, d\boldsymbol{x_2}, \cdots, d\boldsymbol{x_N})^T$, eigenvectors and eigenvalues are obtained. Finally, a statistical 3D shape model is defined as

$$\boldsymbol{x} = \bar{\boldsymbol{x}} + \boldsymbol{E}\boldsymbol{b}. \quad (1)$$

Here, $\boldsymbol{E} = (\boldsymbol{e_1}, \boldsymbol{e_2}, \cdots, \boldsymbol{e_t})$ is eigenvectors and $\boldsymbol{b} = (b_1, b_2, \cdots, b_t)^T$ is shape parameters. $t = 11$ with 95 % contributing rate. By changing the shape parameters, various types of 3D shapes can be reconstructed as shown in Fig. 3.

2.2. Statistical gait motion model

The 3D models used in section 2.1 are the ones of people standing. To generate a statistical gait model we use a 4D gait database [7] consisting of 3D models for the duration of one gait cycle. The database comprises 41 subjects with four sequences for each subject (Fig. 4).

First, we estimate motion of each walking person in the database using a markerless motion capture system [13]. As we mentioned in Section 1.1, a 3D model with bones for each person is necessary, so we estimate the 3D model with bones using the statistical 3D shape model first. In concrete, we estimate parameters of the statistical 3D shape model so that the statistical 3D shape model can fit to the reconstructed 3D model of each person. Moreover, we embedded a bone model, which has 30 degree of freedom in total, to the statistical 3D shape model, so that positions of all joints can move with the change of parameters of the statistical 3D model.

After motions of all gait sequences are estimated, we generate the statistical gait motion model as follows. First, since the number of frames in one gait cycle differs among walking sequences, we normalize the number of frames in one gait cycle into a certain number F (we set $F = 22$ in experiments). We basically use the same methodology to generate the statistical gait model with the method for the statistical 3D shape model, but the difference is that we apply a frequency analysis to motions before we apply the eigenvalue decomposition. The reason why we apply a fre-

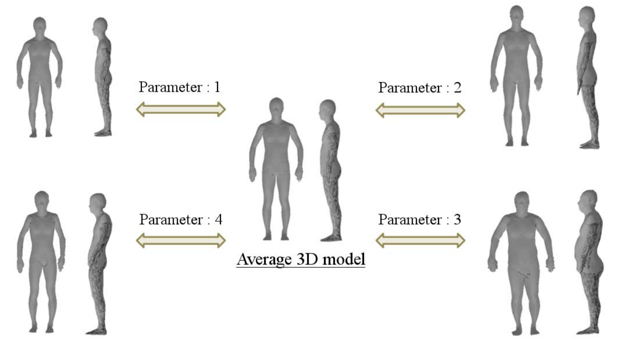


Figure 3. Statistical 3D shape model consisting of an average 3D shape model and shape parameters

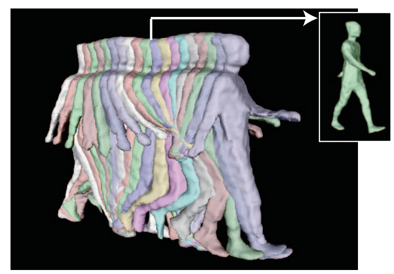


Figure 4. An example sequence of 3D models in the 4D gait database.

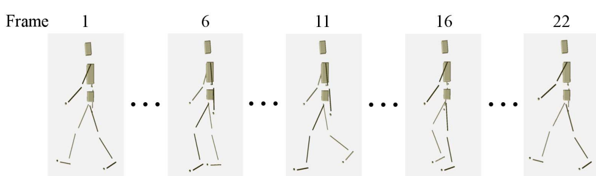
quency analysis is as follows. Gait is a repetitive motion, thus once parameters are tuned properly, gait motion for the duration of one gait cycle can be reconstructed even though gait motion for a part of one gait cycle is not obtained.

Let us define an average angle vector $\boldsymbol{U_j^s} = (u^s_{(1,j)}, u^s_{(2,j)}, \cdots, u^s_{(F,j)})^T$, and $u^s_{(i,j)}$ is defined as an angle of a joint j ($1 \leq j \leq J$, J is the number of joints) and a gait sequence s ($1 \leq s \leq S$, S is the total number of gait sequences). We apply a discrete cosine transform to $\boldsymbol{U_j^s}$ and obtain a power spectrum vector $\boldsymbol{d_j^s} = (d^s_{(1,j)}, d^s_{(2,j)}, \cdots, d^s_{(F,j)})^T$. A power spectrum vector of all joints is defined as $\boldsymbol{D^s} = (d^s_{(1,1)}, d^s_{(2,1)}, \cdots, d^s_{(F-1,J)}, d^s_{(F,J)})$, and finally we define a vector $\boldsymbol{K} = (\boldsymbol{D^1}, \boldsymbol{D^2}, \cdots, \boldsymbol{D^S})$.

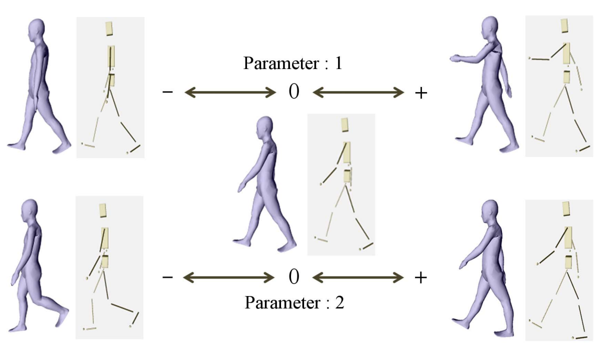
The eigenvalue decomposition is applied to $\boldsymbol{K}$, and the statistical gait motion model is defined as

$$\boldsymbol{K} = \bar{\boldsymbol{K}} + \boldsymbol{N}\boldsymbol{w}. \tag{2}$$

Here, $\boldsymbol{N} = (\boldsymbol{n_1}, \boldsymbol{n_2}, \cdots, \boldsymbol{n_t})$ is eigenvectors and $\boldsymbol{w} = (w_1, w_2, \cdots, w_t)^T$ is gait parameters. $t = 20$ with 95 % contributing rate. To reconstruct joint angles, we apply an inverse discrete cosine transform to $\boldsymbol{K}$. By changing the gait parameters, various types of motions can be reconstructed as shown in Fig. 5.



(a) Average gait model for the duration of one gait cycle



(b) Motion variations with the change of gait parameters

Figure 5. Statistical gait motion model consisting of an average gait motion and gait parameters. (a) average gait motion and (b) motion variations with the change of gait parameters.

3. Person identification robust to viewpoint changes

In this section, we explain details of the proposed method and a new gait feature, named Frame Difference Frieze Pattern (FDFP).

3.1. Shape and motion estimation using shadow biometrics

The advantage of the use of both body and shadow areas is that we can use two viewpoint images using a single camera. This is useful to estimate the position information of the subject, which is necessary for motion estimation with high accuracy. The position information of the subject can be estimated using both shadow and body areas with the assumption that the pose of the Sun is known with respect to the camera. In this paper, we assume that the position information of the subject for the duration of one gait cycle is known, but instead we focus on showing the effectiveness of the proposed concept. The position estimation will be our future work.

As we mentioned in section 1.1, the scenario we focus on is that both shadow and body areas are available in the test dataset but only body area can be used in the training dataset. Thus, after we estimate a 3D shape and gait motion of a subject, we synthesize an image from a viewpoint of the training dataset as shown in Fig. 2. To estimate the 3D shape and gait motion of the subject, we estimate shape parameters and gait parameters of the statistical model using the following procedure.

1. First, we set an initial position of the statistical model to the position the subject. Here, since we have the information of positions of the subject for the duration of one gait cycle, his walking direction with respect to the camera can be calculated. Next, we virtually project a shadow of the statistical 3D model to the ground using the position information of the Sun, and synthesize an image from a virtual viewpoint as shown in Fig. 6.

2. After we obtain a virtual image, we extract a silhouette area, followed by a contour extraction of body and shadow areas (Fig. 7 (a)). We apply the same process to an image of the subject to extract a contour of the subject as shown in Fig. 7 (b).

3. At each point p_i on the contour of the image of the subject the nearest neighbor point q_j is obtained, and the evaluation value d is calculated by $d = \Sigma_i (p_i - q_j)^2$. The shape and gait motion parameters are estimated using the steepest descent method to minimize the evaluation value.

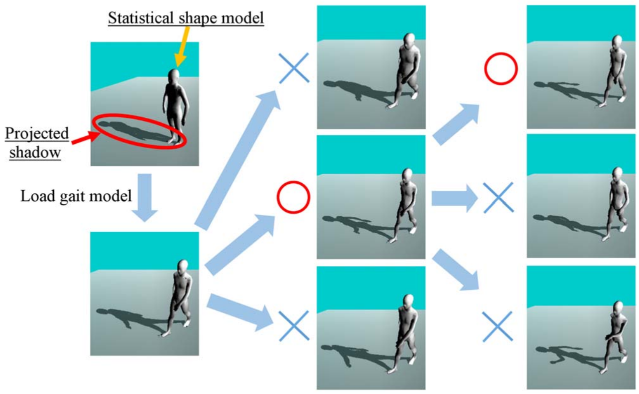


Figure 6. Flow of the proposed method to estimate shape and motion parameters of the statistical model.

(a) Virtual image

(b) Test dataset

Figure 7. Silhouette and contour extraction of a virtual image (a) and an image in the test dataset (b).

4. Step 1 to 3 are repeated for each image of one gait cycle.

After we reconstruct the statistical model with estimated shape and gait parameters, we synthesize a virtual image which are taken with the same viewpoint of the training dataset.

3.2. Frame Difference Frieze Pattern (FDFP)

In the statistical shape model and the statistical gait motion model, we use eigenvectors up to 95 % contributing rate, thus we omit eigenvectors with higher frequency. This causes a small difference between the estimated statistical model and the 3D reconstructed model of the subject, and this may result in higher frequency noise. So in this section, we propose a new gait feature, named Frame Difference Frieze Pattern (FDFP), which is designed to be robust to higher frequency noise. As the name suggests, the FDFP is inspired by the Frieze Pattern [11].

First, we calculate a frame difference image between a frame f and a frame $f - \Delta f$ as follows.

$$S(x,y) = \begin{cases} 255 & (I(f,x,y) = I(f-\Delta f,x,y)) \\ 0 & (I(f,x,y) \neq I(f-\Delta f,x,y)) \end{cases} \quad (3)$$

Here, f is a frame ID in the duration of one gait cycle ($1 \leq f \leq F$ and F=22), and Δf is set from 1 to 15. Example images of $\Delta f = 1$ and $\Delta f = 2$ are shown in Figs. 8 (a) and (b). The FDFP is calculated using frame difference images which are generated from silhouette images for the duration of one gait cycle. The FDFP has two feature vectors, one is $FDFP_{row}$ generated along the vertical axis and the other one is $FDFP_{col}$ generated along the horizontal axis.

$$FDFP_{row}(y,f) = \Sigma_x S(x,y,f) \quad (4)$$

$$FDFP_{col}(x,f) = \Sigma_y S(x,y,f) \quad (5)$$

Examples of $FDFP_{row}$ and $FDFP_{col}$ are show in Fig. 8 (c).

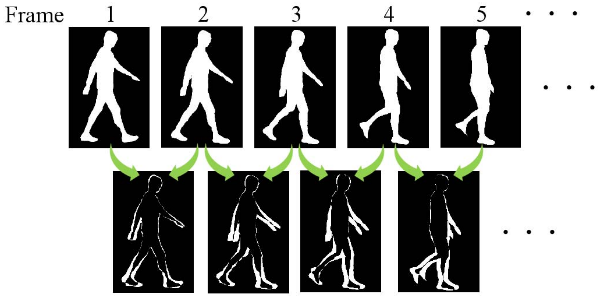
The concept of the FDFP is similar to the Shape Variance-Based (SVB) Frieze Pattern [11], but the difference is as follows. In the SVB Frieze Pattern, the authors set a key frame, which is a double-support position, and calculated a frame difference as the difference between a frame f and the key frame. On the other hand, our FDFP does not require to detect the key frame and a frame difference is calculated as the difference between a frame f and a frame $f - \Delta f$. Moreover, by changing the value Δf, the FDFP can represent much more information.

3.3. Person identification

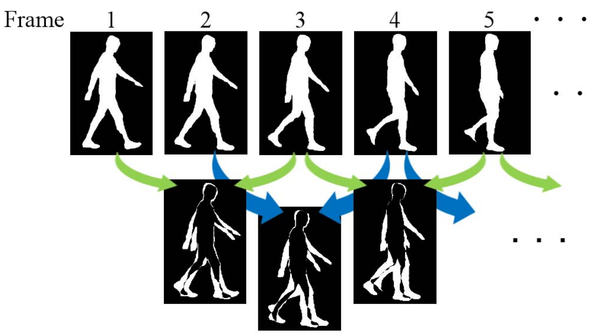
We identify the subject based on the combination of the nearest neighbor approach and the voting-based method [7]. During the training phase, we extract gait features using the FDFP from each image in the training sequences and then build a database. Then, during the identification phase, gait features are extracted from each synthesized image of a subject's sequence in the test dataset. At each frame of the subject's sequence, a person who has the nearest gait feature in the training dataset is voted, and this process is repeated for the duration of one gait cycle. Finally, a person who gets the most votes is chosen as the subject.

4. Experiments

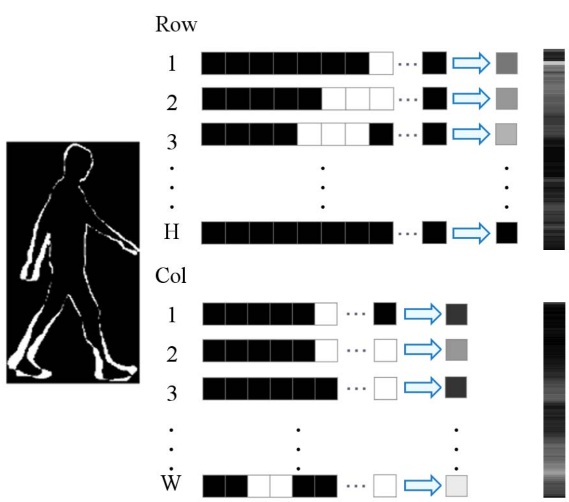
This section presents the results of person identification robust to changes in the walking direction. To prove the



(a) Frame difference ($\Delta f = 1$)

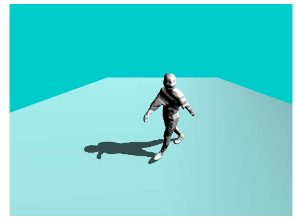


(b) Frame difference ($\Delta f = 2$)

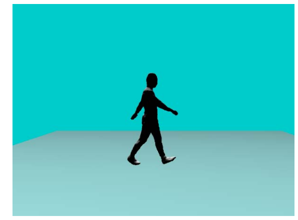


(c) Examples of Frame Difference Frieze Pattern ($\Delta f = 1$)

Figure 8. Frame Difference Frieze Pattern



(a) An example of images taken at a virtual camera θ_1, which are used as test datasets.



(b) An example of images taken at a virtual camera θ_2, which are used as training datasets.

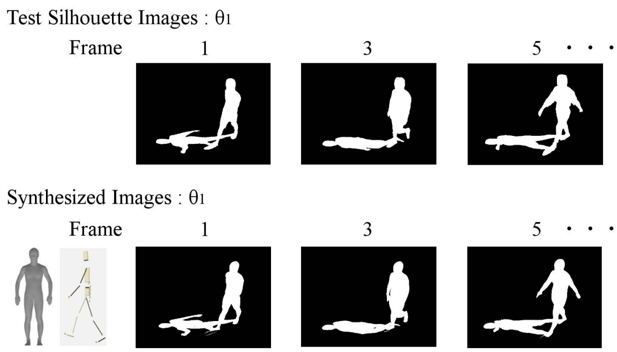
Figure 9. Example images of test and training datasets.

effectiveness of the statistical shape model and the statistical gait motion model, we carried out experiments using the 4D gait database. The database comprises 41 subjects with four sequences for each subject, so totally there are 164 gait sequences. In this experiment, we synthesized images by using a virtual camera which is placed at a viewpoint θ_1 with respect to 3D models in the database as shown in Fig. 9(a), and we used these images as test images. Regarding the training datasets, we placed a virtual camera at a viewpoint θ_2, and synthesized images as shown in Fig. 9(b).

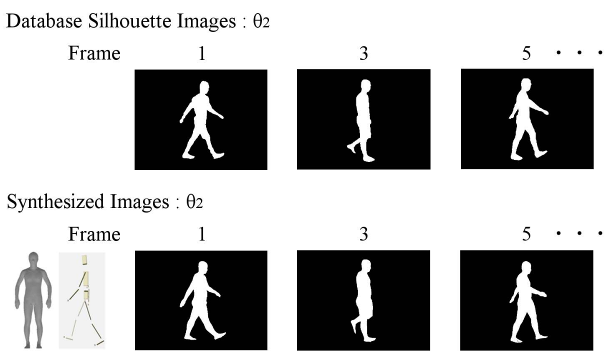
4.1. Evaluation of the estimated statistical model

First we evaluated the statistical model with estimated parameters by the proposed method qualitatively and quantitatively. In a top row in Fig. 10 (a) we show examples of silhouette images at a view point θ_1 in the test dataset. The second row shows example silhouette images synthesized at a view point θ_1 from the statistical models whose parameters were estimated by the proposed method. Since parameters of the statistical models are estimated using images at view point θ_1, it is easily expected that synthesized images from the estimated statistical models are similar to silhouette images in the test dataset. As we mentioned in section 1.1, the advantage of the use of the statistical model is that it can estimate motion and 3D model in areas which are not visible from the camera due to occlusions. To see the effectiveness of the statistical model, let us see the results from a view point θ_2 as shown in Fig. 10 (b). From these results, we can verify the proposed method can reconstruct 3D model and motion in occluded areas.

We evaluated the accuracy of the proposed method quantitatively. Since in experiments test images are synthesized from 3D reconstructed models of walking subjects, we can compare the accuracy of the statistical model with estimated parameters from reconstructed 3D models. We calculated a sum of minimum distances between the statistical model and the reconstructed 3D model at each frame, and we obtain average distance and standard deviation using models for the duration of one gait cycle. Figure 11 (a) shows results of all 41 people in case that no parameters of the statistical model are estimated, and Fig. 11 (b) shows results in case that parameters are estimated by the proposed method. From these results, it is clear the proposed method worked well even though we use just two viewpoint images (i.e. shadow and body areas).



(a) View point θ_1

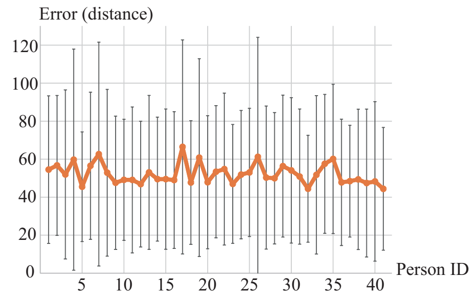


(b) View point θ_2

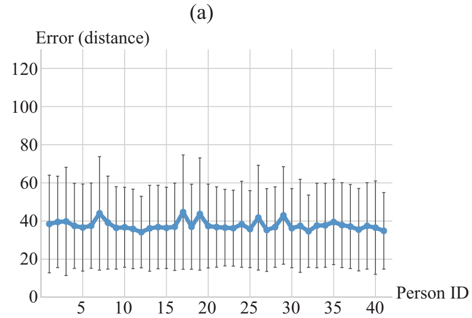
Figure 10. 3D shape and motion estimation. Synthesized images from a viewpoint θ_1 (a) and a viewpoint θ_2 (b).

4.2. Person identification using the proposed method

In next experiments, we identified people using the proposed method and compared the performance of the proposed gait feature (FDFP) with other existing gait features, such as Gait Energy Image (GEI) [4], Active Energy Image (AEI) [15], and Affine Moment Invariants (AMI) [6], which showed good performance in other gait databases. The evaluation was performed using a rule similar to leave-one-out cross validation. In other words, when we selected one gait image sequence from test datasets, we eliminated an image sequence corresponding to this selected image sequence from the database.



(a)



(b)

Figure 11. Average and standard deviation of distances between reconstructed 3D models and statistical models with estimated parameters.Results for statistical models without parameter estimation and (b) results for statistical models with parameters estimated by the proposed method.

First, we used image sequences at the viewpoint θ_1 for test and training datasets, and Table 1 shows results using GEI, AIE, AMI and the proposed FDFP. Here, in the AMI-based method there is a parameter which is used to divide a silhouette area into multiple areas. Thus we changed this parameter in experiments. From these results, it is clear the proposed gait feature FDFP showed the best performance.

Next, we used images sequences at the viewpoint θ_1 for test dataset and images sequences at the viewpoint θ_2 for training dataset, and Table 2 shows results. The results of existing methods, GEI, AIE, and AMI are worse than those of the viewpoint θ_2. On the other hand, the proposed FDFP showed the best performance thanks to the robustness to the high frequency noise.

5. Conclusions

We herein proposed a method by which to identify people robust in changes in the walking direction. The proposed method differs significantly from existing approaches in that the subject's sequential 3D models and his/her motion were directly reconstructed from captured images, by introducing the statistical shape model and the statistical gait motion model. Then arbitrary viewpoint images are synthesized from the reconstructed 3D models for the purpose of gait recognition robust to changes in the walking

GEI [4]	78.66				
AEI [15]	78.05				
AMI [6]	The number of divided areas				
	1	5	9	13	15
	54.27	89.02	90.24	89.02	89.02
Proposed FDFP	Frame interval : Δf				
	1	5	9	13	15
	73.17	98.17	**99.39**	**99.39**	**99.39**

Table 1. Person identification using image sequences at the viewpoint θ_1 for test and training datasets [%].

GEI [4]	34.15				
AEI [15]	46.95				
AMI [6]	The number of divided areas				
	1	5	9	13	15
	9.76	23.78	24.39	28.66	28.66
Proposed FDFP	Frame interval : Δf				
	1	5	9	13	15
	39.02	74.39	84.15	**85.98**	83.54

Table 2. Person identification using image sequences at the viewpoint θ_2 for test and training datasets [%].

direction. We also proposed the new gait feature, named Frame Difference Frieze Pattern (FDFP). We carried out experiments using the 4D database, which included data for 41 people, and demonstrated that the proposed method outperformed conventional methods.

Our future work includes to identify people using images by a camera placed outside.

Acknowledgment

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