# Method for gait-based biometric identification robust to changes in observation angle

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***Abstract*—This paper proposes a gait identification technique which is robust to changes in observation angle in one gait cycle. In person identification using gait images, various inherent image features of individuals are extracted from a sequence of gait images taken by a camera. However, for instance, if the subject is close to the camera and the camera captures gait images from the side direction, observation angles between walking direction of the subject and directions of the camera to the subject at all frames are varied during one gait cycle. This unfavorable change induces the decrease of the identification performance. To deal with this problem, the proposed technique in this paper utilizes a 4D gait database consisting of multiple 3D shape models of walking subjects and adaptive virtual image synthesis. In the proposed method, a foot position in each gait image is estimated by the principal component analysis of silhouette images at first. Next, the walking direction of the subject is estimated by applying the least square method to the foot positions, and observation angles between the walking direction of the subject and directions of the camera to the subject at all frames are estimated in one gait cycle. Then, a virtual image in the estimated observation angle is synthesized from the 4D gait database at each foot position. Finally, the subject is identified using affine moment invariants as gait features. Experiments using the 4D gait database of 20 subjects show that the proposed method is robust to the changes of the observation angles in one walking cycle and achieves higher recognition performance than the case using a fixed observation angle in one gait cycle.***

## I. Introduction

Biometric research encompasses a large number of characteristics of a person in order to identify them. These include physiological biometrics, related to the shape of the body, the oldest of which are the fingerprints; and the behavioral biometrics, related to the behavior of a person, the first of which used was the signature. However, in general these systems need special equipment and require interaction with the subject. On the other hand, techniques such as face recognition and image-based gait recognition have the advantage of being unobtrusive because body-invasive sensing is not needed to capture gait information. Gait-based recognition has the further advantage of being used from further distance.

Gait recognition approaches generally fall into two main categories: (1) model-based analysis, and (2) appearance-based analysis. Model-based approaches include parameterization of gait dynamics, such as stride length, cadence, and joint angles [1] [2] [3]. Traditionally, these approaches have not reported high performances on common databases, partly due to their needs for 3D calibration information and self-occlusion caused by legs and arms crossing.

Appearance-based analysis [4] [5] [6] uses measurements of gait features from silhouettes by feature extraction methods, such as gait energy image(GEI) [7], fourier transforms [8] [9], and affine moment invariants [10]. Appearance-based approaches have been used with good results on human identification. However, since image-based gait recognition is sensitive to appearance changes, the correct classification rate gets low in case that subject's appearance is different from that in the database. One of possible situations in which this problem occurs is the case that a subject's observation angle changes compared with those in the database. To deal with this problem, several methods have been proposed so far. Makihara $et\ al.$ introduced a view transformation model to synthesize virtual viewpoint images from captured images [9]. In this method, the view transformation model is obtained from training datasets of multiple people which were taken from multiple view directions. We have introduced a 4D gait database consisting of multiple 3D shape models of walking subjects, and a method which synthesizes virtual viewpoint images from 3D models in the database [11].

However, there is another problem which causes the subject's appearance changes. That is a change of observation angles between walking direction of the subject and directions of the camera to the subject at all frames in one gait cycle (hereafter we call this as "local angle change"). Akae $et\ al.$ showed that the local angle changes in one gait cycle affects the performance of gait identification, especially in case that the distance between a camera and a subject is small and side view images are captured [12]. The reason is as follows: in general, most conventional methods extracted gait features from synthesized virtual images with a fixed local angle at the center position of one gait cycle, so the discrimination capability of gait features gets low in case that local angles vary in one gait cycle.

Conventional methods introduced above did not deal with this problem. So in this paper we propose a method which is robust to local angle changes in one gait cycle by taking the variation of local angles into account. In the proposed method, a foot position in each gait image is estimated by the principal component analysis of silhouette images at first. Next, the walking direction of the subject is estimated by applying the least square method to the foot positions, and observation angles between the walking direction of the subject and directions of the camera to the subject at all frames are estimated in one gait cycle. Then, a virtual image in the estimated observation angle is synthesized from the 4D gait database at each position. Finally, the subject is identified using affine moment invariants as gait features.

This paper is organized as follows. Section 2 describes the details of the proposed person identification method. Section 3 describes experiments performed using the 4D gait database. Conclusions are presented in section 4.

## II. Person identification robust to local angle changes in one gait cycle

In this section, we explain the local angle changes in one gait cycle, and then introduce the proposed method.

### A. Local angle changes in one gait cycle

The local angle at each frame in one gait cycle is defined with the azimuth angle $\theta^a_{P_n}$ and elevation angle $\theta^e_{P_n}$ at each position $P_n$ in one gait cycle. In case that the azimuth angle is around $\pm 90$ degree and the elevation angle is small (front/back view images are captured), the local angle changes among frames in one gait cycle are small. On the other hand, in case that either the azimuth angle is small or the elevation angle is around $\pm 90$ degree, the local angle changes among frames in one gait cycle are big. Nevertheless, most of conventional approaches utilize a fixed local angle $\boldsymbol{\theta_{P_c}} = (\theta^a_{P_c}, \theta^e_{P_c})$ at the center position $P_c$ in one gait cycle. However, local angle changes in one gait cycle affect the performance of the gait identification, since the subject's appearance changes due to local angle changes.

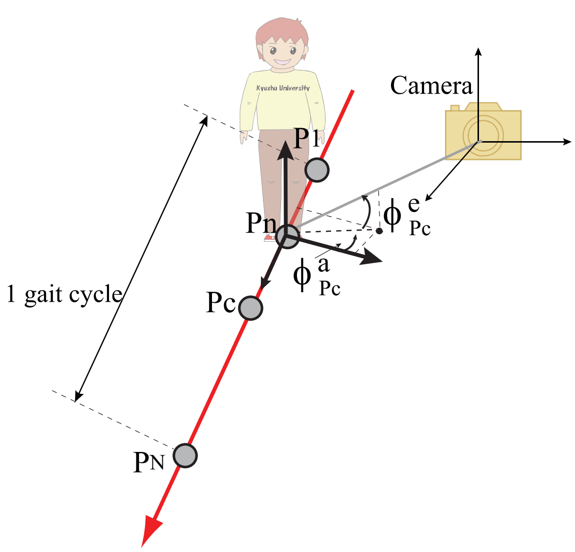


Fig. 1. Local angle changes in one gait cycle.

### B. The proposed person identification method

*1) Estimation of local angles:* To estimate local angle at each frame in one gait cycle, at first we estimate foot position and walking direction in 3D space from each captured image. Here, we assume that external and internal camera parameters and the position of the floor are known.

A background subtraction method is applied to captured images to extract silhouette areas, and the foot positions on the images are estimated as follows: (1) principal component analysis is applied to a silhouette area of each image, and (2) the foot position on the image is estimated as the position whose value along the first principal component is minimum in the silhouette as shown in Fig. 2.

Next, foot positions in 3D space are determined by projecting the estimated foot positions on 2D images onto the floor, and the walking direction of the subject is estimated by fitting a line to the foot positions by the least square method. Then azimuth angle $\theta^a_{P_n}$ and elevation angle $\theta^e_{P_n}$ at foot position $P_n$ ($0 \leq n < N$, $N$ is the number frames in one gait cycle) are calculated from the pose of the camera, the subject's walking direction, and one's foot position in 3D space.

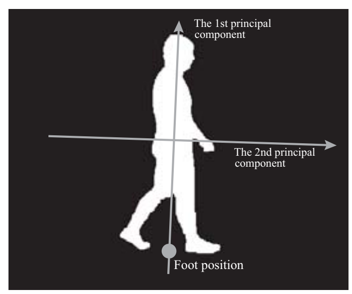


Fig. 2. Foot position detection.

*2) Synthesis of virtual images from 3D models:* Figure 3 shows an examples of 3D models of a walking person in the database and one of them. A virtual viewpoint image is synthesized from a 3D model $Model^i_m$ ($0 \leq m < M$, $0 \leq i < I$, $M$ is the number of models in one gait cycle of a person $i$ and $I$ is the number of people in the database) according to the azimuth angle $\theta^a_{P_n}$ and elevation angle $\theta^e_{P_n}$ as shown in Fig. 4. Here, the number of frames of the subject in one gait cycle may be different from that of a person in the database, so we align them by $m = \frac{n}{N} \times M$. Besides, we assume that the phase of the first frame of one gait cycle of the subject is the same that of each person in the database. Virtual images are synthesized from all 3D models in the database with respect to each subject.

*3) Extraction of gait features and person identification:* For feature extraction, at first a silhouette area is scaled to a uniform height, set to 128 pixels, and the average image $I^{average}$ from images of one gait cycle is defined by $I^{average}(x, y) = \frac{1}{N}\sum_{n=1}^{N} I(x, y, n)$. Figure 5 shows an example of average images. Then affine moment invariants are extracted from the average image as gait features [10]. Affine moment invariants are moment-based descriptors, which are

(a) Exmaples of 3D models (b) One of (a)

Fig. 3. Examples of 3D models.

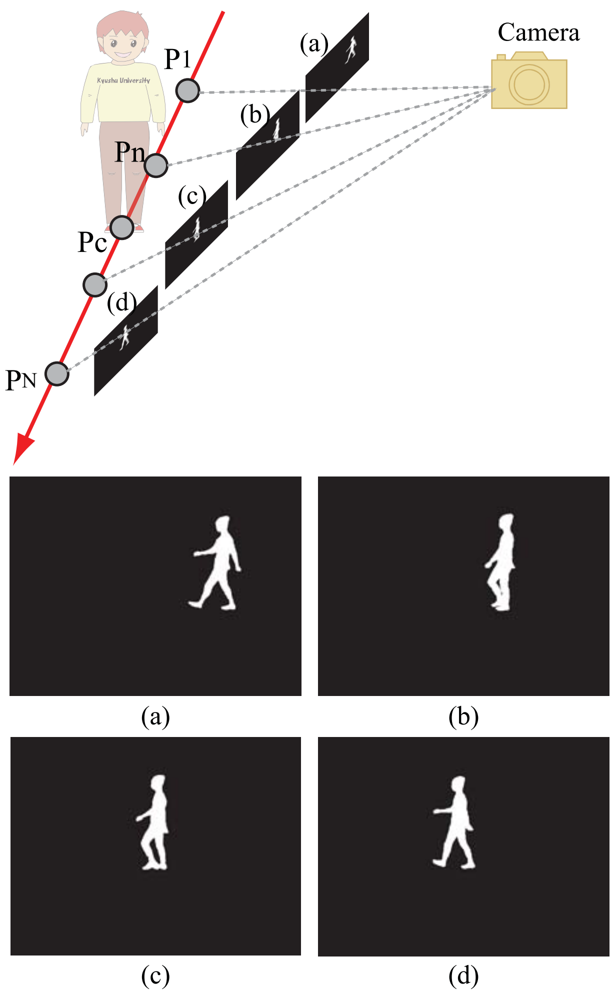


Fig. 4. Examples of synthesize virtual images.

invariant under a general affine transform. The moments describe shape properties of an object as it appears. For an image the centralized moment of order $(p+q)$ of an object $O$ is given by

$$\mu_{pq} = \sum\sum_{(x,y)\in O}(x-x_g)^p(y-y_g)^q I(x,y). \quad (1)$$

Here, $x_g$ and $y_g$ are the center of the object. In our method we used eighty affine moment invariants $\boldsymbol{I} = \{I_1, I_2, \ldots, I_{80}\}$, and we show two of them [13] [14].

$$\begin{aligned} I_1 &= \frac{1}{\mu_{00}^4}(\mu_{20}\mu_{02} - \mu_{11}^2) \\ I_2 &= \frac{1}{\mu_{00}^{10}}(\mu_{30}^2\mu_{03}^2 - 6\mu_{30}\mu_{21}\mu_{12}\mu_{03} + 4\mu_{30}\mu_{12}^3 + 4\mu_{03}\mu_{21}^3 \\ &\quad -3\mu_{21}^2\mu_{12}^2) \end{aligned} \quad (2)$$

Gait features from virtual images are extracted in the same way.

In this paper, in the same way with [11], we divide each average image into $K$ multiple areas, and extracted gait features from each area as shown in Fig. 5. Here, $K$ is the number of divided areas.

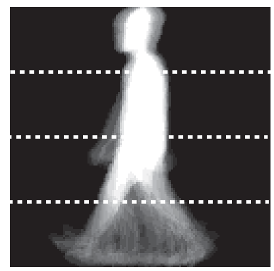

Fig. 5. An example of average images (K=4).

*4) Person identification:* In the proposed method, we use the nearest neighbor as the classifier. In the training phase, we extract gait features by the affine moment invariants from synthesized virtual images, and then build a database. Then in the identification phase, gait features are extracted from silhouette images of a subject and the subject is identified by the classifier.

## III. Experiments

This section shows results of person identification experiments using the 4D gait database. This database comprises of 20 subjects with 4 sequences for each subject, and multiple 3D models were reconstructed by the visual hull technique with 16 cameras placed in a studio as shown in Fig. 6. We utilized sequential 3D models of all subjects as training datasets and captured images from a camera as test datasets. Here, we selected a camera A so that side view gait images were captured. The height of the camera A is approximately 1.2 $[m]$, and the distance from the camera A to the center of the studio is 3.5 $[m]$. Each gait sequence consists of 15 $\sim$ 20 images, and in experiments the correct classification rate is estimated with the leave-one-out cross validation.

### *A. Person identification with the 4D database*

To evaluate the effectiveness of the proposed method, we applied one of conventional methods [11], which utilizes the fixed local angle at the center position of one gait cycle to synthesize virtual images, to the 4D database. This method extracted gait features from average images by affine moment invariants in the same way with the proposed method. The

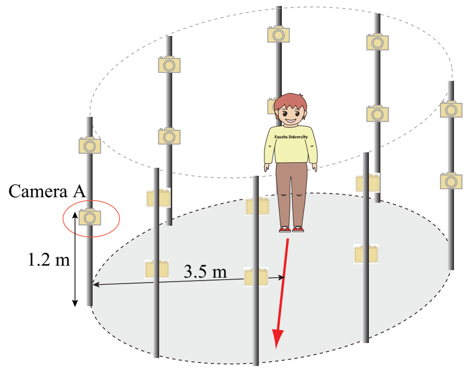


Fig. 6. Experimental setting.

difference between this method and the proposed method is that the angle to synthesize virtual images; the proposed method estimates observation angle at each position of one gait cycle, but the conventional method estimated an angle at the center position of one gait cycle.

In these experiments, we separate each average image into up to 2 areas ($K$=1 and 2), and we combined gait features from areas of $K = 1$ and $K = 2$. Figure 7 shows the results of correct classification rates by the proposed method and the conventional method with respect to the change of number of affine moment invariants. From these results, the highest correct classification rate by the proposed method was 96.4 %, and that by the conventional method was 91.7 %.

Figure 8 shows examples of silhouette images ((a1) and (a2)), those corresponding synthesized images by the proposed method ((b1) and (b2)), and those corresponding synthesized images by the conventional method ((c1) and (c2)). For instance, in the synthesized image by the proposed method (Fig. 8(b1)) the subject's arm was separated from one's body which was similar to that in the silhouette image (Fig. 8(a1)), but the subject's arm in the synthesized image by the conventional method (Fig. 8(c1)) was connected to one's body. From these results, the proposed method synthesized images similar to captured images compared with the conventional method. It is clear that local angle changes affect the performance for people identification, and the proposed method outperformed the conventional method.

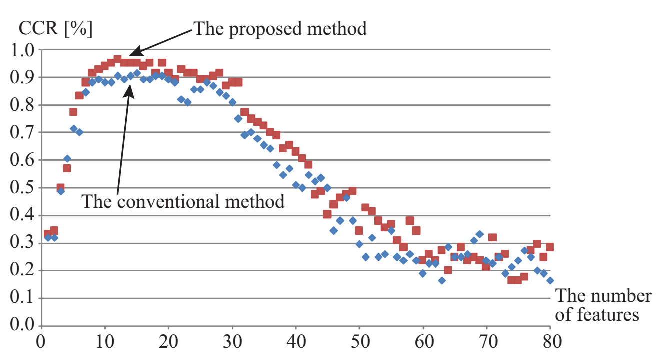


Fig. 7. Correct classification rates.

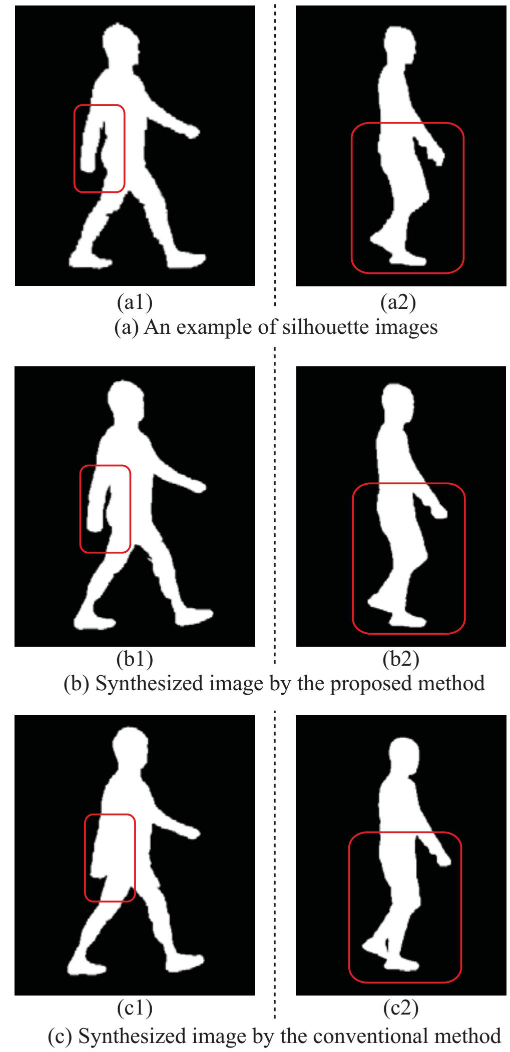


Fig. 8. Comparison of virtual images by the proposed method and the conventional method [11].

## IV. Conclusions

We proposed in this paper the person identification robust to changes in observation angle by utilizing a 4D gait database and adaptive virtual images synthesis. In this method, we estimated a walking direction of a subject in 3D space from foot positions of the subject, and determine the azimuth and elevation angles from the walking direction and foot positions. Next, virtual image based on local angle at each position is synthesized from 3D models of all people in the database. Then the subject is identified by gait features extracted by affine moment invariants. We carried out experiments with the 4D database, and showed the effectiveness of the proposed method. One of our future work is to do more evaluation of the proposed method by applying it to gait images captured by cameras of different viewpoints.

## Acknowledgment


This work was supported by Grant-in-Aid for Scientific Research(C) (23500216).

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