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# Multi-view large population gait dataset and its performance evaluation for cross-view gait recognition

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## Abstract

This paper describes the world's largest gait database with wide view variation, the "OU-ISIR gait database, multi-view large population dataset (OU-MVLP)", and its application to a statistically reliable performance evaluation of vision-based cross-view gait recognition. Specifically, we construct a gait dataset that includes 10,307 subjects (5114 males and 5193 females) from 14 view angles ranging 0°–90°, 180°–270°.

In addition, we evaluate various approaches to gait recognition which are robust against view angles. By using our dataset, we can fully exploit a state-of-the-art method requiring a large number of training samples, e.g., CNN-based cross-view gait recognition method, and we validate effectiveness of such a family of the methods.

**Keywords:** Gait database, Gait recognition, Multi-view large population performance evaluation

## 1 Introduction

Biometric-based human identification methods have been intensively studied for the purpose of various application: access control, surveillance, forensics, etc. As biometric traits, face, voice, fingerprint, hand veins, iris, handwriting, and gait are available for such applications. Among them, gait is one of the most practical trait for video-based surveillance and forensics because it can be obtained from a CCTV footage captured at a distance, as well as applicable to an uncooperative subject. In fact, gait recognition has started to be used in practical cases in criminal investigation [1–3].

However, the availability of gait recognition for uncooperative subjects induces problematic covariates, including view angle, walking speed, clothing, surface, carrying status, shoe, and time elapse. Therefore, for further progress, it is essential that gait recognition is more robust against these covariates. In this paper, we focus on the view angle which is one of the most important covariates and hence deal with cross-view gait recognition.

Cross-view gait recognition has been intensively studied in recent years. Robust approaches against the view

angle are categorized mainly into two families: generative and discriminative approaches. Given a matching pair of gait features under different views, generative approaches generate the gait features under the same view for better matching [4–7]. The generative approaches do not, however, guarantee the optimality in terms of discrimination capability because they essentially optimize not the discrimination capability itself but the accuracy of the generated gait features.

The discriminative approaches aim at optimizing the discrimination capability under view variations by learning discriminant subspaces or metrics. This family usually applies machine learning-based approaches such as linear discriminant analysis (LDA) [8, 9], primal rank support vector machine (RankSVM) [10], and multi-view discriminant analysis (MvDA) [11]. Moreover, discriminative approaches using deep learning [12] has become flourishing recently. Deep learning has achieved great successes in many areas. An advantage of deep learning is that it simultaneously executes feature extraction and recognition within a unified framework using a large amount of training samples. In particular, a convolutional neural network (CNN), which considers spatial proximity using a convolution operation, significantly improves the accuracy of image recognition as demonstrated through a series of ImageNet Large Scale Visual Recognition

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Challenges [13]. Moreover, the effectiveness of a CNN has been demonstrated in research fields that are more relevant with gait recognition, such as action recognition [14], video classification [15], and face recognition [16].

There are some gait recognition studies using a CNN framework [17–20], and they reported that the CNN-based method outperformed the benchmark without using CNN. Though CNN-based method requires a large number of samples for sufficient training or for statistically reliable evaluation, there is no gait database including a large number of subjects with wide view angles at the same time. For example, though CASIA dataset B [21] used for evaluation in [17, 18] contains gait images with a wide range of view angles (11 views, 0 – 180°), it is composed of only 124 subjects. On the other hand, OU-ISIR gait database, large population (OU-LP) [22] used in [17, 19, 20], contains gait images of a large population (4016 subjects) but its range of view angle is narrow (4 views, 55°, 65°, 75°, 85°). Therefore, the evaluation of cross-view gait recognition using such databases may not be statistically reliable.

In order to cope with such a problem, we built a gait database comprising the multi-view large population dataset. Specifically, our dataset named as “OU-ISIR Gait Database, Multi-View Large Population (OU-ISIR, MVLP)<sup>1</sup>” is the largest gait database in the world, comprising 10,307 subjects and including wide range view (14 views, 0°–90°, 180°–270°). Thanks to the dataset, we can evaluate the performance of various approaches to cross-view gait recognition including generative approaches and discriminative approaches with or without a CNN framework, in a statistically reliable way. In particular, since the state-of-the-art CNN-based approaches require massive training samples to get the high accuracy, our dataset can be exploited as the massive training samples in order to draw real state-of-the-art accuracy of the CNN-based approaches.

The outline of the paper is as follows: Section 2 introduces existing gait databases, while Section 3 addresses the construction of our dataset. The performance evaluation for cross-view gait recognition is described in Section 4, and Section 5 presents our conclusions and discusses future work.

## 2 Existing gait databases for cross-view gait recognition

Existing major gait databases with multi-view images are summarized in Table 1.

As the database with a wide range of view angle, there exist Soton multimodal [23] (not released to the public), CASIA database B [21], CMU Mobo [24], AVA [25], WOSG [26], KY 4D [27], and OU-ISIR Treadmill Dataset C [28] (not released to the public). The Soton Multimodal was collected at the biometric tunnel [29] and contains over 400 subjects multi-modal data (gait, face, and ear). The subject’s gait is recorded by 12 cameras and 1 camera records a front face view and 1 camera records a snapshot of the side view for ear recognition. The CASIA database B is frequently used for evaluation of cross-view gait recognition since it contains large view variations from front view (0°) to rear view (180°) with 18-degree interval. This database recorded ten sequences per subject: six normal sequences; two sequences with a long coat; two sequences with a backpack. The CMU Mobo contains 25 subjects walking on a treadmill with six view variation whose range is 0–360°. The subjects perform four different walk pattern; slow walk, fast walk, incline walk, and walking with a ball. The AVA contains videos of 20 walking subjects with a large variety of body size, who walk along straight and curved paths. The database contains six view angles. The WOSG contains 155 subjects with eight view variations. The subjects were captured with the short-wave infrared spectrum (900–1700 nm) in an active, outdoor environment. KY 4D contains sequential

**Table 1** Existing major gait databases with multi-view images

Name	#Subjects	#Views	View range	Environment	Year
CMU Mobo [24]	25	6	0–360	Indoor, treadmill	2001
Soton small database [44]	12	4	–	Indoor	2001
Soton multimodal(*) [23]	> 400	12	–	Indoor	2011
CASIA database A [45]	20	3	0–90	Outdoor	2001
CASIA database B [21]	124	11	0–180	Indoor	2005
AVA [25]	20	6	–	Indoor	2013
WOSG [26]	155	8	–	Outdoor	2013
KY 4D [27]	42	16	0–360	Indoor	2010
OU-ISIR Treadmill Dataset C(*) [28]	200	25	0–360	Indoor, treadmill	2010
OU-ISIR LP [22]	4016	4	55–85	Indoor	2012
<b>OU-ISIR MVLP (Ours)</b>	<b>10, 307</b>	<b>14</b>	<b>0–90, 180–270</b>	Indoor	–

Databases with (\*) are not released to the public. Items in bold indicate our database

3D models and image sequences of 42 walking subjects. The sequential 3D models are generated from gait image sequences captured by 16 cameras. The OU-ISIR Treadmill Dataset C contains 200 subjects with 25 views: a combination of 12 azimuth views with 30° interval and 2 tilt views; and 1 top view. Though these databases contain images with a wide view angle, the number of subjects is insufficient to evaluate of gait recognition in a statistically reliable way.

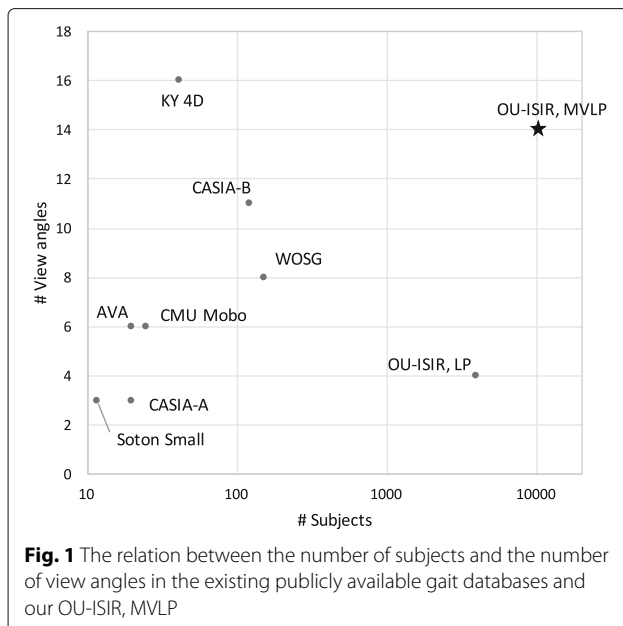
On the other hand, the OU-ISIR LP [22] is the largest dataset w.r.t. the number of subjects besides our dataset. The dataset contains 4,016 subjects with a wide age range from 1 to 94 years old also with an almost balanced gender ratio. Though a large number of subjects data are contained, its view variation is limited to only four view angles (55–85°) within 30° of angular difference.

The relation between the number of subjects and the number of view angles is shown in Fig. 1. In order to evaluate cross-view gait recognition in a statistically reliable way, the database with a large number of subjects from a wide view angle is definitely required.

### 3 The OU-ISIR gait database, multi-view large population dataset

#### 3.1 Capturing system

Our gait dataset, OU-ISIR MVLP, is constructed based on gait images collected in the gait collecting framework introduced in [30]. The gait data is collected in conjunction with long-run exhibition at a science museum (Miraikan) while informed consent is obtained through electrical procedures. Gait images of 1280 × 980 pixels at 25 fps are captured by seven network cameras (cam1–7) placed at intervals of 15° azimuth angles along a quarter



of a circle whose center coincides with the center of the walking course, where a green wall and a carpet are installed for chroma-key, as shown in Fig. 2. Its radius is approximately 8 m and height is approximately 5 m for capturing images at depression angle to consider a surveillance view while the view angles of CASIA dataset B and OU-ISIR LP are almost horizontal. Each network camera continuously capture a video during the opening hours, photo-electronic sensors are built at the walking course to sense a passing time of a subject, which is used to clip a video of the target subject from the whole sequence. The subject repeat forward (A to B) and backward (B to A) walking twice of each, 28 gait image sequences (= 7 (cameras) × 2 (forward and backward) × 2 (twice)) can be captured per one subject. The view angle of our dataset is defined as shown in Fig. 3.

Gait sequence is the same for each of camera view 1 to 7, and camera view 1' to 7' in Fig. 3. Multi-view images from the same gait sequence are preferable for training the generative approaches, because the generative approaches aims at transforming a gait feature of one view to that of another view with being free from intra-subject variations. Hence, they are useful for training the generative approaches within camera view 1 to 7, and camera view 1' to 7', respectively, but not for training them across one of camera views 1 to 7 and another one of camera views 1' to 7'.

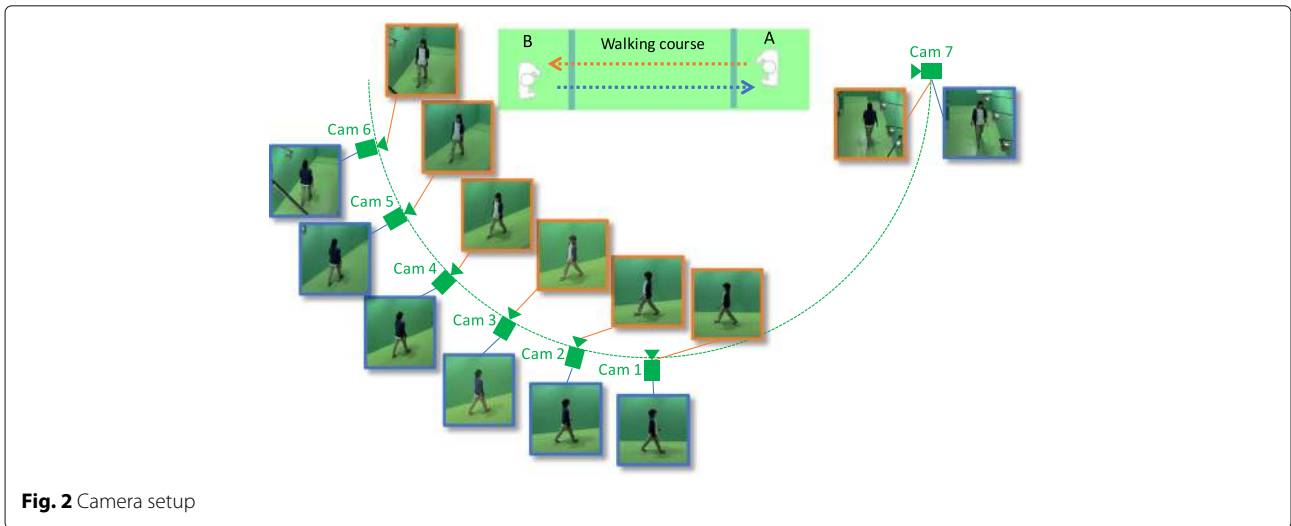
On the other hand, such intra-subject variations of gait itself actually exist between probe and gallery gait sequences in a real situation, and hence we need to cope with them. Discriminative approaches aim at mitigating both view variations and intra-subject variations of gait itself at the same time, and hence the intra-subject variations of gait itself included the training set are rather welcomed to train a better discriminative models. Our database contains intra-subject variations of gait itself for all the camera views because of two gait sequences captured for each camera. Hence, they are also useful for training the discriminative approaches.

#### 3.2 Procedure of gait feature extraction

We extract Gait Energy Images (GEIs) [8], also known as averaged silhouette [31], as gait feature for performance evaluation. GEI is the most prevalent gait feature which is obtained by simply aggregating the silhouette sequence over one gait period. Thus, a GEI represents a mixture of static and dynamic parts.

This section briefly describes how to extract GEIs in our dataset (see Fig. 4). The procedure is as follows:

1. Silhouette sequence extraction. Human region is extracted by a chroma-key technique, i.e., removing green area based on HSV color space within the walking course.



**Fig. 2** Camera setup

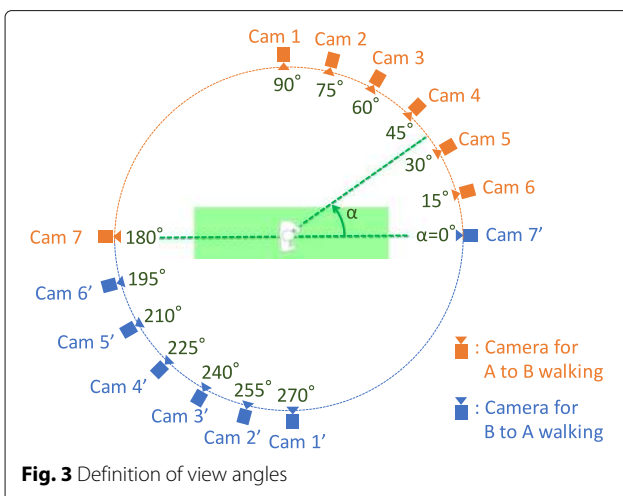
2. Size-normalization. Silhouette extracted in step 1 is normalized by size based on the method used in [22]. First, the top, bottom, and horizontal center of the silhouette regions are obtained for each frame. Second, a moving-average filter is applied to these positions. Third, we normalized the size of the silhouette images such that the height is just 128 pixels according to the average positions, and the aspect ratio of each region is maintained. Finally, we produce an  $88 \times 128$  pixel image in which the average horizontal median corresponds to the horizontal center of the image.
3. Gait period detection. Gait period is detected based on size-normalized silhouette sequences from cam1 by using the method proposed in [22]. We adopt the normalized auto correlation (NAC) of the size-normalized silhouette images for the temporal axis and determine the gait period as the frame shift

corresponding to the second peak of the NAC. Since, in our dataset, gait images captured by seven cameras simultaneously, the gait period detected based on silhouette sequences of cam1 is also used as the gait period for the other six cameras (cam2–7).

4. GEI extraction. GEI is extracted by averaging the size-normalized silhouette sequences pixel-wise over one gait period. If several gait periods are detected from one walking sequence, the nearest one to the center of the walking course is used. Examples of generated GEIs for each view angles are shown in Fig. 5.

### 3.3 Subject statistics

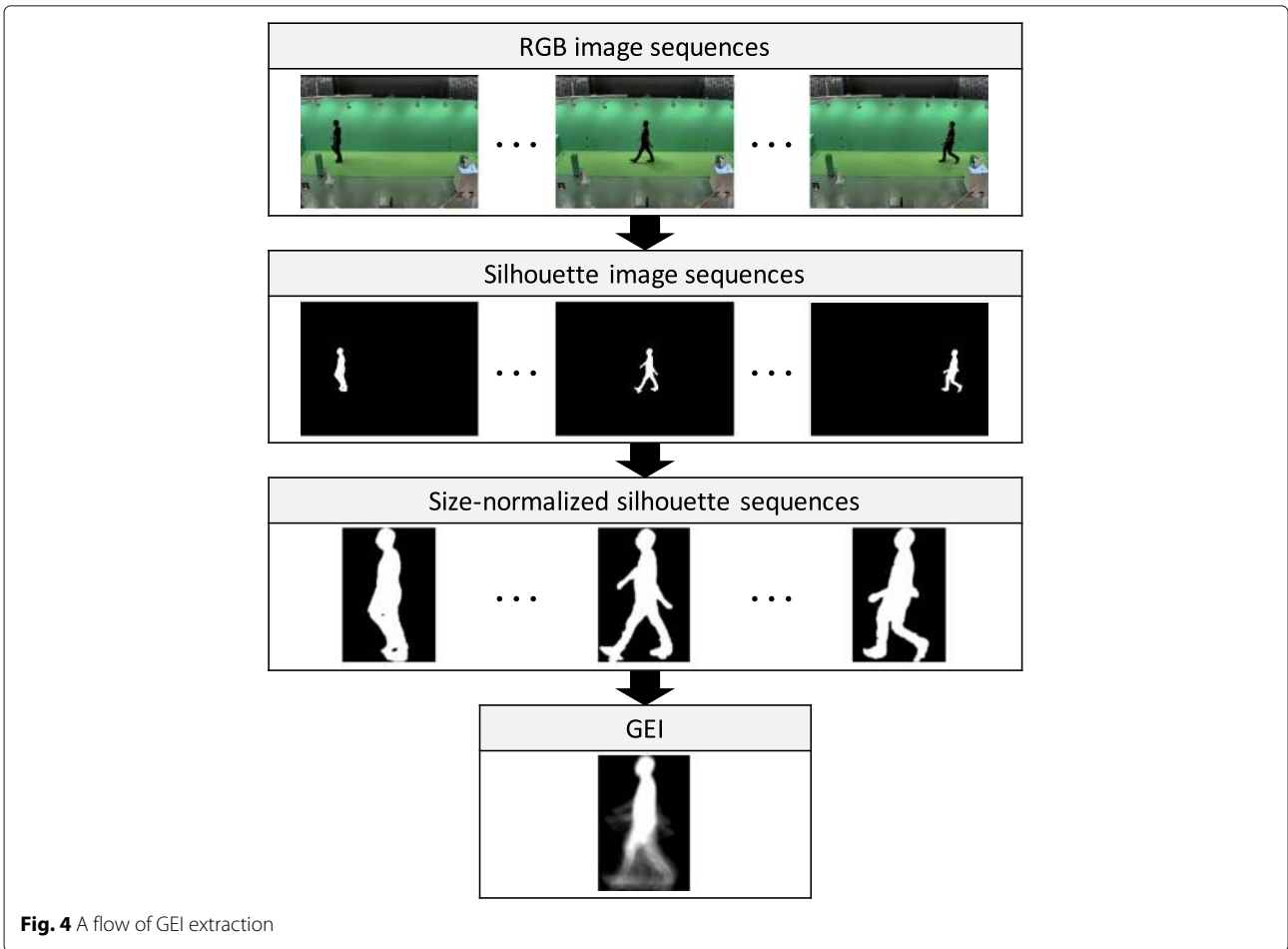
We captured gait images of 78,378 subjects by the framework mentioned above from 15 July 2015 to 27 June 2016 and defined a subset of gait images of 10,307 subjects (5114 males and 5193 females with various ages, ranging from 2 to 87 years) from 14 view angles, ranging  $0^\circ$ – $90^\circ$ ,  $180^\circ$ – $270^\circ$ . Moreover, since they are captured from October to February, subjects wear various clothes according to a season change. Detailed distributions of the subjects' gender and age are shown in Fig. 6. Almost all the subjects are of Asian descent. Over 100 subjects are included for every 5 years from 5 to 69 years old for each gender. Therefore, the dataset is useful not only for cross-view gait recognition but also for age estimation or gender classification. The number of subjects of each view angles is summarized in Table 2. Note that the number of subjects are slightly different among view angles since low quality GEIs with a large loss or blur are removed with visual confirmation.



**Fig. 3** Definition of view angles

### 4 Performance evaluation of cross-view gait recognition

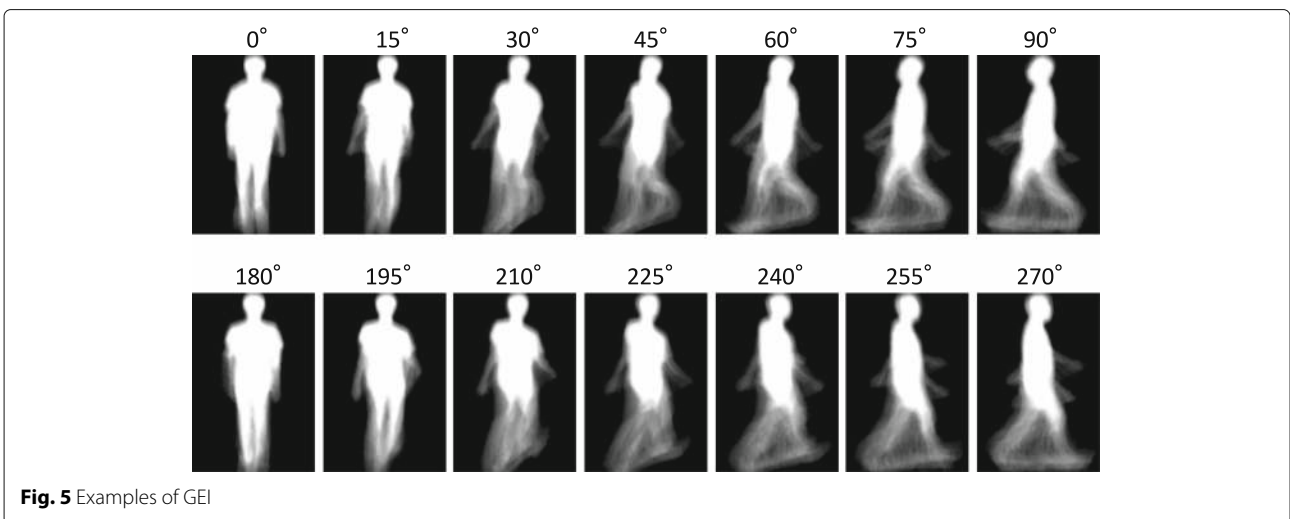
First, we evaluated performances of existing approaches to cross-view gait recognition: generative approaches

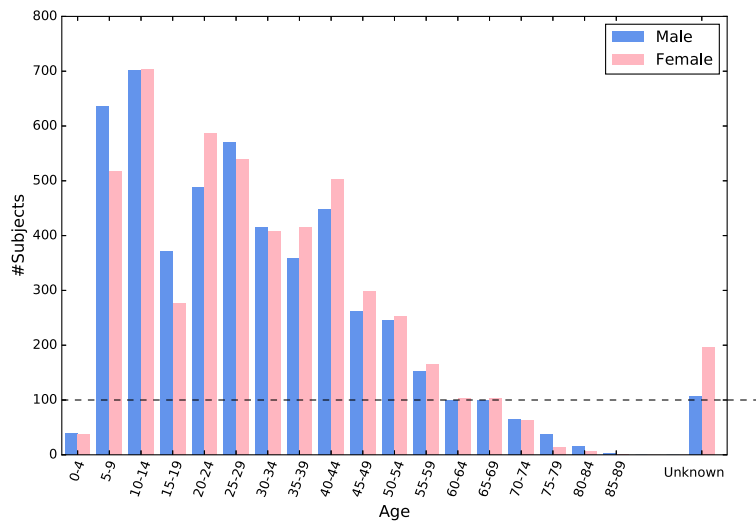


and discriminative approaches. In addition, we considered two settings: recognition with a cooperative gallery subject (i.e., *cooperative setting*) and with an uncooperative gallery subject (i.e., *uncooperative setting*). View angles of the gallery GEIs are the same among enrolled subjects in cooperative setting, whereas

they may differ for each subject in uncooperative setting.

Second, we analyzed a sensitivity of the number of training subjects on the recognition accuracy when we adopt the state-of-the-art cross-view gait recognition, i.e., CNN-based method.





**Fig. 6** Distributions of the subjects' gender and age. "Unknown" indicates the cases where declared ages are judged strange by visual confirmation

**4.1 Benchmarks**

We describe eight existing methods used for evaluation experiments. Two of them are generative approaches, five of them are discriminative approaches, which further fall into those with and without CNN respectively, and the other one is direct matching without any training, i.e., Euclidean distance between GEIs (call it *DM*) as a baseline.

**Generative approach**

- View transformation model (*VTM*) [5]:  
As general approaches to cross-view gait recognition, a family of *VTM* [6, 32, 33] have been widely studied and a singular value decomposition-based *VTM* [5] is the most basic one among them. We then exploit it as a baseline for the generative approach. The method obtains the *VTM* with training data of multiple subjects from multiple view angles. In a recognition phase, the *VTM* transforms gallery features into the same view angle as that of an input feature, and the features match under the same view.
- Double quality-dependent *VTM* (*wQVTM*) [34]:  
Among the family of *VTMs*, *wQVTM* is the most advanced one, and hence we exploited it as the state-of-the-art of the generative approaches. This *VTM*-based method incorporates a score

normalization framework with quality measures that encode the degree of the fitness of the trained *VTM* to gallery and test data.

**Discriminative approach without CNN**

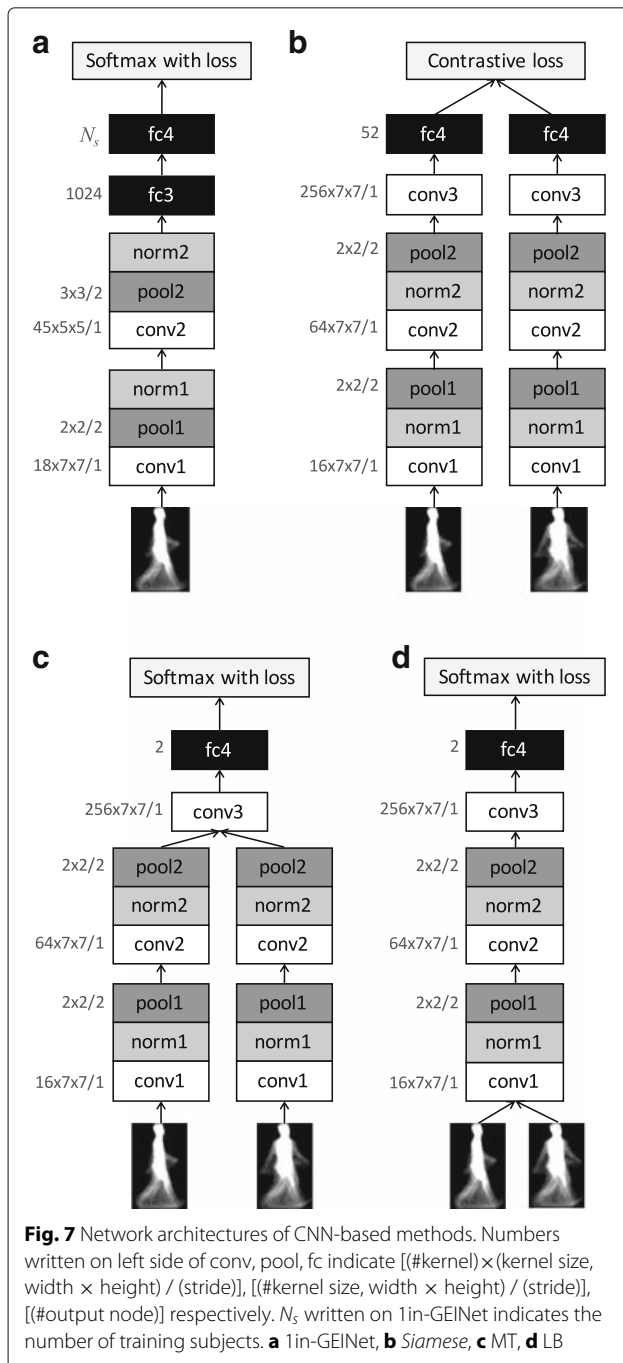
- Linear discriminant analysis (*LDA*) [35]:  
The method is based on linear discriminant analysis, which is the most conventional approach and hence widely exploited in many fields (e.g., Fisher face [36]). We therefore adopt this as a baseline for the discriminative approach. Specifically, we first apply principal component analysis (*PCA*) to an unfolded feature vector of *GEI* to reduce dimension and subsequently apply *LDA* to get discriminant features.

**Discriminative approach with CNN**

- *1in-GEINet* [19](see Fig. 7a):  
The method is based on one of the simplest *CNN* where one input *GEI* is fed and the number of nodes in the final layer (*fc4*) is equal to the number of training subjects. Soft-Max value calculated from output of the final layer is regarded as a sort of probability of matching up to a corresponding subject.

**Table 2** The number of subjects in OU-ISIR MVLP

	Observation angle [deg]													
	0	15	30	45	60	75	90	180	195	210	225	240	255	270
Total	9441	9715	10,151	10,099	9581	10,175	10,165	9430	9751	10,197	10,113	9579	10,197	10,085
Male	4643	4782	5017	4996	4742	5040	5040	4635	4799	5055	5004	4742	5053	5019
Female	4798	4933	5134	5103	4839	5135	5125	4795	4952	5142	5109	4837	5144	5066



- Siamese [20, 37, 38] (see Fig. 7b): The method is based on two parallel CNNs known as Siamese network with shared parameters. In the network, output of fc4 layer is regarded as a feature vector of each input GEI. A contrastive loss for each pair is defined as  $d^2$  (squared L2 distance of the feature vectors of two input GEIs) if they are the same subject, or as so-called hinge loss, i.e.,  $\max(\text{margin} - d, 0)^2$  if they are different subjects.

- Mid-level at the top (MT) [17] (see Fig. 7c): The method is based on two parallel CNNs with shared parameters where two non-linear projections are applied before computing the differences between pairs of images on conv3 layer. The pixel-wise summation of weighted entries by using pair-filter is calculated as output of conv3 layer. Soft-Max value indicates a probability of an event that they are the same subject.
- Local at the bottom (LB) [17] (see Fig. 7d): The method is based on CNN whose structure is similar to MT except for a layer where we compute the differences between pairs of images. A linear projection is applied before computing the differences between pairs of GEIs on conv1 layer.

### Direct matching

- Direct matching (DM) [22]: The method based on direct matching, i.e., L2 distance in the original feature space. We regard GEIs as feature vectors whose dimension is equal to the number of pixels in GEI and compute L2 distance of two GEIs as a dissimilarity.

### 4.2 Setup

We divided the 10,307 subjects into two disjoint groups of almost the same size, that is, 5153 training and 5154 testing subjects. Additionally, as mentioned previously, each subject had 28 GEIs (14 view angles × 2 sequences).

For the generative approaches, it was assumed that probe and gallery view angles are known and the VTM from a source view to a target view are trained using gait features with possible view angle. On the other hand, for the discriminative approaches, in order to roughly align walking direction in GEIs, GEIs with over 180° view angle, were flipped right-to-left based on perspective projection assumption [39], and parameters of CNN or LDA model are trained for data including all view angle data simultaneously. Note that rough walking direction estimation (leftward vs. rightward) is relatively easily done compared with detailed pair-wise view estimation (30° vs. 45°) required in the generative approaches.

Hyper-parameters of CNN are determined in an ad hoc manner without applying parameter tuning. However, we confirmed that over-fitting was not occurred and learnt parameters were converged sufficiently.

### 4.3 Evaluation criteria

In each setting, we evaluated the recognition accuracy for two tasks; verification, i.e., one-to-one matching and identification, i.e., one-to-many matching. For the verification task, we calculated false acceptance rates (FARs) and false rejection rates (FRRs). We then calculated equal

error rates (EERs) of the FAR and the FRR as a trade-off criterion of the verification capability. Moreover, we calculated rank 1 identification rate as a criterion of the identification capability.

#### 4.4 Results for a cooperative setting

We first evaluated the recognition accuracy of lin-GEINet, the discriminative approach with the simplest CNN, for all possible view angle pairs (14 probe views vs. 14 gallery views) as shown in Table 3. As a result, in the case of the same view angles (e.g., 0° vs. 0°), the accuracy is the highest, and the larger the view differences is, the lower the accuracy become. Moreover, since two GEIs with 180° view difference (one of them is flipped GEI) are virtually regarded as those from the same-view pair due to perspective projection assumption [39] as described in Section 4.2; the trends of 0–90° gallery vs. 0–90° probe (upper left sub-matrix in Table 3) are similar to those of 0–90° gallery vs. 180–270° probe (upper-right sub-matrix in Table 3), 180–270° gallery vs. 0–90° probe (lower-left sub-matrix in Table 3), and 180–270° gallery vs. 180–270° probe (lower-right sub-matrix in Table 3). For the simplicity of the performance evaluation, we focus on four typical view angles (0°, 30°, 60°, 90°) hereafter.

We then evaluated the recognition accuracy of all benchmarks mentioned to in Section 4.1 for all the pairs of the four typical view angles. The rank 1 identification rates and the EERs are shown in Tables 4 and 5, respectively.

**Table 3** Recognition accuracy of 1in-GEINet for all view angle pairs for a cooperative setting

a		Probe view [deg]													
		0	15	30	45	60	75	90	180	195	210	225	240	255	270
Gallery view [deg]	0	75.9	47.5	32.1	15.2	7.0	5.8	7.4	35.9	31.9	25.7	14.0	7.7	6.4	6.4
	15	33.4	87.4	72.9	45.7	18.2	13.0	11.2	27.6	59.1	48.2	33.7	17.7	14.2	11.5
	30	17.3	67.1	89.6	78.1	43.7	29.0	22.7	19.2	47.9	62.6	49.2	30.3	23.9	21.1
	45	6.9	35.5	74.7	89.3	66.4	53.8	37.1	8.9	30.9	48.3	59.2	39.4	36.9	32.6
	60	4.0	16.5	43.4	71.3	86.5	73.5	55.4	5.5	17.2	32.7	44.8	58.0	50.4	46.6
	75	3.2	9.9	26.2	54.6	70.2	88.8	80.8	3.9	13.4	23.8	37.8	46.1	67.3	65.9
	90	3.4	8.6	21.5	36.8	50.2	80.9	90.7	4.8	11.3	22.6	33.5	42.7	64.8	76.6
	180	29.0	33.0	29.8	15.6	8.6	7.8	8.3	83.9	50.5	35.2	17.0	9.5	7.3	7.3
	195	19.5	56.9	52.1	38.1	18.1	15.2	14.2	40.4	89.9	78.8	54.0	22.9	16.5	12.6
	210	13.1	41.0	62.8	52.7	31.0	25.2	24.7	21.6	73.4	91.8	81.4	48.3	31.1	23.1
	225	7.1	26.0	47.0	61.3	41.5	41.5	37.4	9.9	46.7	78.2	91.2	69.9	55.2	36.8
	240	4.4	15.6	33.0	47.0	63.1	53.9	52.1	6.2	22.0	49.9	72.5	88.5	73.2	52.5
	255	3.7	10.7	22.7	40.9	49.1	72.0	71.4	4.7	14.8	30.9	57.7	69.7	89.3	79.3
	270	3.7	9.6	20.9	34.6	47.0	71.5	82.8	4.7	11.7	24.4	38.6	50.0	79.5	89.6

Rank-1 identification rate (%)

b		Probe view [deg]													
		0	15	30	45	60	75	90	180	195	210	225	240	255	270
Gallery view [deg]	0	3.4	6.0	7.4	12.2	16.8	17.7	17.0	6.6	8.1	9.2	12.7	15.7	16.9	16.9
	15	6.2	2.5	3.6	5.7	10.3	12.1	13.1	7.2	4.3	5.7	7.6	10.7	11.9	12.8
	30	7.7	3.7	1.9	2.8	5.4	7.5	8.6	7.8	4.6	3.7	5.1	7.1	8.2	8.7
	45	12.3	5.9	2.9	2.1	3.6	4.8	6.6	11.9	6.2	4.7	4.0	5.8	6.2	6.9
	60	16.8	10.3	5.3	3.7	2.4	3.4	4.6	15.5	10.0	6.9	5.8	4.4	5.1	5.4
	75	17.8	12.3	7.6	4.6	3.4	2.0	2.7	16.8	11.2	8.2	6.3	5.3	3.5	3.4
	90	17.4	13.1	8.6	6.6	4.6	2.6	1.7	16.1	11.8	8.3	6.7	5.5	3.6	2.6
	180	7.3	7.5	8.2	12.4	16.4	16.7	16.4	2.6	6.0	7.5	11.8	15.2	16.2	16.5
	195	8.1	4.2	4.8	6.2	10.2	11.0	11.2	5.7	1.8	2.8	4.5	8.5	9.9	11.5
	210	9.6	5.5	3.4	4.5	6.9	7.7	7.6	7.3	3.0	1.6	2.4	4.4	6.6	7.8
	225	13.1	7.3	4.6	3.8	5.9	5.6	6.1	11.1	4.5	2.6	1.5	3.3	3.8	5.7
	240	15.8	10.7	6.6	5.6	3.9	4.5	4.5	14.8	8.3	4.7	3.4	2.1	3.1	4.4
	255	16.7	11.9	7.8	5.9	4.5	2.7	2.8	15.8	10.1	6.6	3.9	3.2	1.6	2.3
	270	17.4	13.0	8.4	6.5	4.9	2.9	2.0	16.1	11.3	8.0	5.8	4.7	2.5	1.5

EER (%)

Darkness of cells in table indicates goodness of recognition accuracy

Naturally, DM only works for pairs of the same view angle and poorly perform for the pair of the different view angles, since it is directly affected by spatial displacement of the corresponding body parts in GEIs due to view angle difference (i.e., large intra-subject variation). On the other hand, the accuracies of the discriminative approach without CNN, i.e., LDA, and the generative approach, i.e., VTM and wQVTM, are a little bit better than that of DM except for the case of the rank 1 identification rate of wQVTM. This is because the VTM-based method, mitigates spatial displacement of the corresponding body parts in GEIs by view transformation process, while that the discriminative approaches mitigate the intra-subject differences due to view variations. Thus, degree of decrease of accuracy depending on the view angle difference in these cases is limited compared with the case of DM. As for wQVTM, the dissimilarity of GEIs is corrected depending on the quality of generated GEI based on trained VTM. If a GEI for testing is much different from GEIs for training, quality of the GEI for testing becomes low, the dissimilarity is modified based on its low quality so as to lessen the dissimilarity considerably, and hence it behaves as a so-called wolf in Doddington biometric zoo concept [40]. This is why the rank 1 identification rates of wQVTM is worse. This problem would not be revealed when using OU-ISIR LP database or CASIA dataset B. It is because that view angle difference of OU-ISIR LP dataset is small, CASIA dataset B has a small subject variation and both of them have a small walking variation due to capturing under operator’s control. By using our dataset with a large number of subjects from a wide range of view angle, such problem can be evaluated in a statistically reliable way.

As for discriminative approaches with CNN, we can see their accuracies are relatively better than the other family of approaches. Taking a closer look at those approaches, we also noticed that lin-GEINet yielded the best accuracy for the identification task (i.e., rank 1 identification rate), while the Siamese yielded the best performance for the verification task (i.e., EER). We will discuss these points in Subsection 4.7.

#### 4.5 Analysis of the effect of increasing view angle

In order to analyze the effect of increasing view angle in detail, we rearranged the cross-view gait recognition results by a baseline, i.e., 1in-GEINet shown in Table 3 from viewpoint of the effect of increasing view angle. For this purpose, we picked up 0°, 45°, and 90° as typical view angles of probes and then showed how the accuracy changes as view angle difference between probe and gallery increases in Fig. 8. Here, because our database missed the view angles from 90° to 180° and also those from 270° to 360°, we assume that the accuracies for



**Table 4** Rank 1 identification rate (%) for thinned view angle pairs for a cooperative setting

(a) VTM						(b) wQVTM					
Gallery	Probe				Mean	Gallery	Probe				Mean
	0	30	60	90			0	30	60	90	
0	68.8	0.5	0.2	0.1	17.4	0	0.1	0.0	0.0	0.0	0.0
30	0.7	82.2	2.1	0.8	21.4	30	0.0	81.7	0.0	0.8	20.6
60	0.3	3.2	77.6	5.4	21.6	60	0.0	0.0	78.0	0.0	19.5
90	0.2	1.1	4.2	80.9	21.6	90	0.0	0.0	0.0	0.0	0.0
Mean	17.5	21.7	21.0	21.8	20.5	Mean	0.0	20.4	19.5	0.2	10.0
(c) LDA						(d) lin-GEINet					
Gallery	Probe				Mean	Gallery	Probe				Mean
	0	30	60	90			0	30	60	90	
0	70.0	3.2	0.3	0.2	18.4	0	75.9	32.1	7.0	7.4	30.6
30	4.6	87.1	11.1	1.9	26.2	30	17.3	89.6	43.7	22.7	43.3
60	0.3	9.3	83.3	19.5	28.1	60	4.0	43.4	86.5	55.4	47.3
90	0.1	0.6	12.6	85.9	24.8	90	3.4	21.5	50.2	90.7	41.5
Mean	18.7	25.0	26.8	26.9	24.4	Mean	25.2	46.6	46.8	44.0	40.7
(e) Siamese						(f) MT					
Gallery	Probe				Mean	Gallery	Probe				Mean
	0	30	60	90			0	30	60	90	
0	52.7	23.7	11.1	11.3	24.7	0	70.7	16.7	4.4	3.9	23.9
30	18.4	78.6	32.6	27.6	39.3	30	14.1	88.1	36.9	17.0	39.0
60	8.0	33.5	76.1	39.6	39.3	60	4.0	39.2	85.7	44.2	43.3
90	7.9	26.5	36.5	82.1	38.2	90	3.2	16.2	43.4	89.3	38.0
Mean	21.8	40.6	39.1	40.1	35.4	Mean	23.0	40.0	42.6	38.6	36.1
(g) LB						(h) DM					
Gallery	Probe				Mean	Gallery	Probe				Mean
	0	30	60	90			0	30	60	90	
0	74.4	16.5	3.5	2.8	24.3	0	68.8	0.8	0.1	0.0	17.4
30	13.6	89.3	36.0	16.2	38.8	30	1.2	82.2	1.4	0.3	21.3
60	2.9	36.2	88.4	44.7	43.0	60	0.1	1.1	77.5	5.6	21.1
90	2.2	14.0	41.2	91.7	37.3	90	0.0	0.2	4.1	80.9	21.3
Mean	23.3	39.0	42.3	38.9	35.9	Mean	17.5	21.1	20.8	21.7	20.3

gallery view  $\theta$  can be a good approximation for that for gallery view  $(360^\circ - \theta)$  based on the left-right gait symmetry assumption as introduced in the literature [39], and hence substituted these accuracies for gallery view  $(360^\circ - \theta)$  by those for gallery view  $\theta$  in Fig. 8. As a result, the accuracies for frontal-view (i.e.,  $0^\circ$ ) probe rapidly drop as the view angle difference increases because  $0^\circ$  gait features lack important forward-backward motions (e.g., arm swing and stride) and such motions gradually appear as the view angle increases from  $0^\circ$  to  $90^\circ$ , which makes matching more difficult. On the other hand, the accuracy drop for side-view (i.e.,  $90^\circ$ ) probe is a little bit mitigated compared with  $0^\circ$  probe, because

that the important forward-backward motions are commonly observable in side view (i.e.,  $90^\circ$ ) and oblique views (e.g.,  $60^\circ$ , which corresponds to  $-30^\circ$  difference in Fig. 8). Moreover, it is noticeable that the accuracies for oblique view (i.e.,  $45^\circ$ ) are relatively good even for increasing view angle differences. This can be explained from two points as also introduced in the literature [39]: (1) gait features from oblique view contains both forward-backward motions observed in the side view as well as the body width observed in the frontal view to some extent, and (2) gait features for  $90^\circ$  view difference from the oblique view (e.g.,  $135^\circ$  gallery for  $45^\circ$  probe) is well approximated by the left-right gait symmetry and

**Table 5** EER (%) for thinned view angle pairs for a cooperative setting

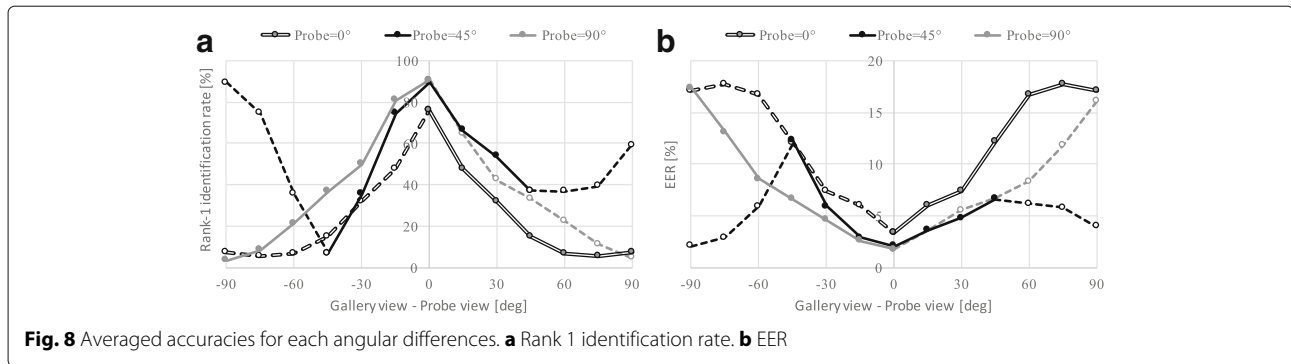
(a) VTM						(b) wQVTM					
Gallery	Probe				Mean	Gallery	Probe				Mean
	0	30	60	90			0	30	60	90	
0	6.9	34.2	40.0	40.7	30.5	0	5.1	30.1	37.8	38.9	28.0
30	32.3	6.0	27.3	31.9	24.4	30	30.8	5.1	22.0	31.3	22.3
60	35.8	22.9	7.1	21.5	21.8	60	34.8	19.1	6.0	16.9	19.2
90	36.2	29.0	22.7	5.9	23.4	90	34.5	25.8	17.7	4.5	20.6
Mean	27.8	23.0	24.3	25.0	25.0	Mean	26.3	20.1	20.9	22.9	22.5
(c) LDA						(d) lin-GEINet					
Gallery	Probe				Mean	Gallery	Probe				Mean
	0	30	60	90			0	30	60	90	
0	7.1	27.3	38.3	40.0	28.2	0	3.4	7.4	16.8	17.0	11.2
30	27.4	5.5	22.1	32.8	21.9	30	7.7	1.9	5.4	8.6	5.9
60	38.8	22.4	6.6	18.6	21.6	60	16.8	5.3	2.4	4.6	7.3
90	40.2	32.8	18.5	5.5	24.2	90	17.4	8.6	4.6	1.7	8.1
Mean	28.4	22.0	21.4	24.2	24.0	Mean	11.3	5.8	7.3	8.0	8.1
(e) Siamese						(f) MT					
Gallery	Probe				Mean	Gallery	Probe				Mean
	0	30	60	90			0	30	60	90	
0	2.5	3.9	6.8	6.0	4.8	0	2.3	6.3	11.2	10.7	7.6
30	4.0	1.4	2.9	2.8	2.8	30	6.3	1.4	3.4	4.8	4.0
60	7.0	2.7	1.4	2.5	3.4	60	11.4	3.5	1.3	3.1	4.8
90	6.2	2.7	2.6	1.1	3.1	90	11.5	5.1	3.0	1.1	5.2
Mean	4.9	2.7	3.4	3.1	3.5	Mean	7.9	4.1	4.7	4.9	5.4
(g) LB						(h) DM					
Gallery	Probe				Mean	Gallery	Probe				Mean
	0	30	60	90			0	30	60	90	
0	2.3	6.4	12.1	11.7	8.1	0	6.9	26.8	43.3	46.0	30.8
30	6.8	1.5	4.0	5.2	4.4	30	27.3	6.0	28.4	39.7	25.4
60	12.8	4.2	1.5	3.2	5.4	60	43.2	29.2	7.1	19.9	24.9
90	12.6	5.7	3.2	1.0	5.6	90	46.5	39.6	19.8	5.9	27.9
Mean	8.6	4.5	5.2	5.3	5.9	Mean	31.0	25.4	24.6	27.9	27.2

weak perspective projection assumption. The accuracy for the oblique-view probe averaged over the view range where the view difference between the probe and the gallery is from  $-90^\circ$  to  $90^\circ$  is better than those for the frontal and side views. This point is more clarified by the averaged accuracies for probe views as shown in Fig. 9.

#### 4.6 Results for an uncooperative setting

We employed the same subject lists as the cooperative setting to evaluate the uncooperative setting. Gallery views are randomly selected from 14 view angles ( $0^\circ, 15^\circ, \dots, 270^\circ$ ) for each subject. The results for the

uncooperative setting are shown in Table 6. Note that we did not evaluate about VTM and wQVTM because they need the information of observation view angle for gait recognition in advance and such an assumption does not suit the uncooperative setting. According to Table 6, the results have almost the same tendency as the cooperative setting: lin-GEINet is the best in terms of identification and Siamese is the best in terms of verification. In comparison of the mean accuracy of cooperative setting using the four typical views and uncooperative setting using all the 14 views, that of uncooperative setting looks much worse. However, one of the reasons for this performance degradation is that uncooperative gallery



view range (14 views) is wider than cooperative one (0°, 30°, 60°, 90°).

Actually the mean rank 1 identification rates for the cooperative setting in 1in-GEINet for all gallery view angles (14 views) and typical probe view angles (4 views), which is shown as the results of Table 3a, are 16.0, 44.9, 42.9, and 42.6% in the cases of 0°, 30°, 60°, 90° probe views, respectively. And these results are comparable (in fact, slightly better) with those of the uncooperative setting shown in Table 6 (15.7, 41.0, 39.7, and 39.5%, respectively). The slight performance degradation of the uncooperative setting is described as the difference between probe and gallery GEIs of the same subject with different view angles is sometimes larger than that of different subjects with the same view angle, which is actually an essential challenging aspect of the uncooperative setting. In other words, this limited performance degradation of the uncooperative setting compared with the cooperative setting means that the discriminative approaches with CNNs overcome the difficulties of the uncooperative setting by effectively

suppressing the appearance changes due to view angle differences while keeping the inter-subject appearance variation.

**4.7 Discussion**

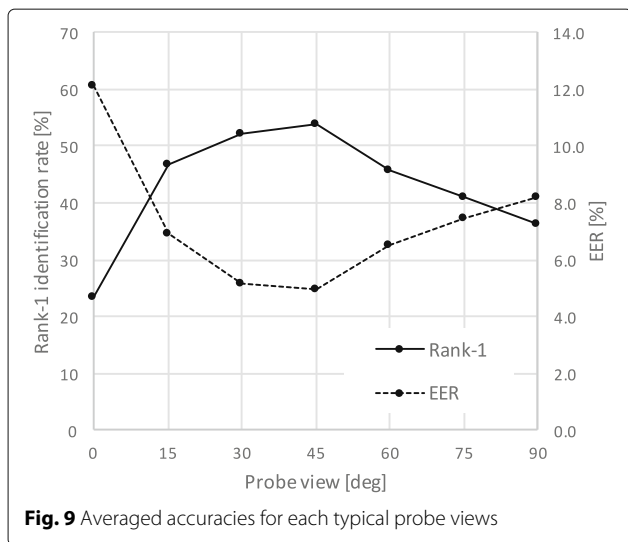
We discussed the experimental results of the discriminative approaches with CNN from several viewpoints.

**1in-GEINet vs. Siamese, MT, and LB** In 1in-GEINet, namely, the method based on CNN with one input, the parameters of CNN are trained so that the soft-max of the node of fc4 layer corresponding to the same subject as input GEI can be high. Specifically, the soft-max loss is calculated as cross-entropy of the soft-max of corresponding node. Since the soft-max normalized scores as that their summation is equal to one, not the absolute value of scores before soft-max but the relative scores against the other subjects are highlighted. Because the identification rate depending not on absolute scores but on this relative scores among the subjects, it is more suitable for the identification task rather than verification task, where absolute score affects the performance.

On the other hand, in Siamese, MT, and LB, namely, the methods based on CNN with two inputs, the parameters are learned so that it is easy to discriminate whether two inputs are the same subject or not. Therefore, these methods look effective as methods for verification task.

In fact, according to Tables 4 and 5, the rank 1 identification rates of 1in-GEINet is better than those of the other CNNs with two inputs. Moreover, EERs of two input CNNs are better than those of 1in-GEINet.

**Siamese vs. MT and LB** In Siamese, a matching pair of GEIs are compared as forms of feature vectors with 52 dimensions, i.e., output of the fc4 layer with full connection, at the last part of the CNN and hence information on spatial proximity is more mixed at the matching stage. On the other hand, In MT and LB, a matching pair of GEIs are compared as forms of images at the middle



**Table 6** Recognition accuracy for uncooperative setting

(a) Rank 1 identification rate (%)						(b) EER					
Method	Probe				Mean	Method	Probe				Mean
	0	30	60	90			0	30	60	90	
LDA	8.1	12.4	12.3	11.8	11.1	LDA	32.1	27.9	28.7	30.6	29.8
1in-GEINet	15.7	41.0	39.7	39.5	34.0	1in-GEINet	14.4	6.3	7.8	8.1	9.2
Siamese	15.6	36.2	33.1	36.5	30.3	Siamese	5.9	2.9	3.8	3.4	4.0
LB	14.2	32.7	32.3	34.6	28.5	LB	9.5	4.7	5.5	5.1	6.2
MT	11.1	31.5	31.1	29.8	25.9	MT	8.9	4.1	4.9	4.8	5.7
DM	7.1	7.4	7.5	9.7	7.9	DM	46.1	40.1	42.2	46.3	43.7

or the first part of the CNN before going through full connection.

Thus, MT and LB is directly affected by appearance difference both derived from inter-subject difference and intra-subject difference due to spatial displacement of the corresponding body parts by view angle differences than Siamese.

As a result shown in Tables 4 and 5, in the case of the small (no) view angle difference, the accuracy of LB and MT is higher than that of Siamese since leveraging the inter-subject difference is more effective than mitigating the intra-subject difference due to view angle differences in such a case. On the other hand, in the case of a larger view angle difference, Siamese is better than LB and MT, since mitigating the intra-subject difference due to view angle difference is more effective than leveraging the inter-subject difference.

**MT vs. LB** In LB, two raw GEIs are compared at the first part, on the other hand, in MT, two compressed GEIs by convolution and pooling layers are compared at the middle part of the CNN. LB where comparing the raw GEIs more leverages appearance difference considering spatial proximity than MT where comparing the compressed GEIs.

According to Tables 4 and 5, in the case of the small (no) view angle difference, the accuracy of LB is higher, while in the case of a larger view angle difference, the accuracy of MT is higher.

**Discussion summary** We summarize the discussion in this section as follows:

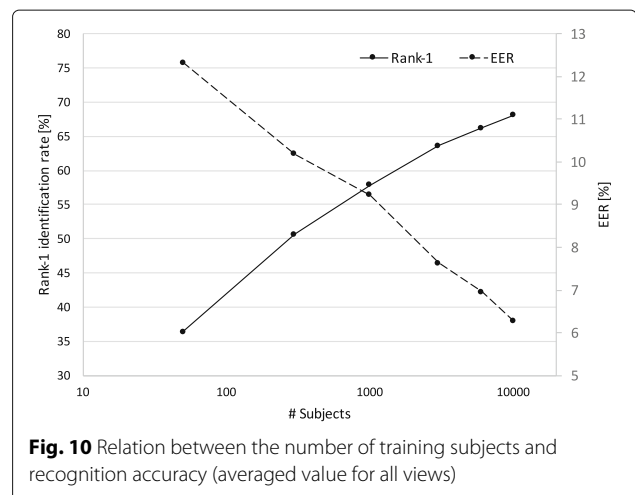
- 1in-GEINet, CNN with one input, is effective for identification task, and Siamese, MT, and LB, CNNs with two inputs, are effective for verification task.
- Compared with CNNs with two inputs, degree of leveraging the inter-subject difference considering spatial proximity is LB > MT  $\gg$  Siamese, on the other hand, degree of mitigating the intra-subject

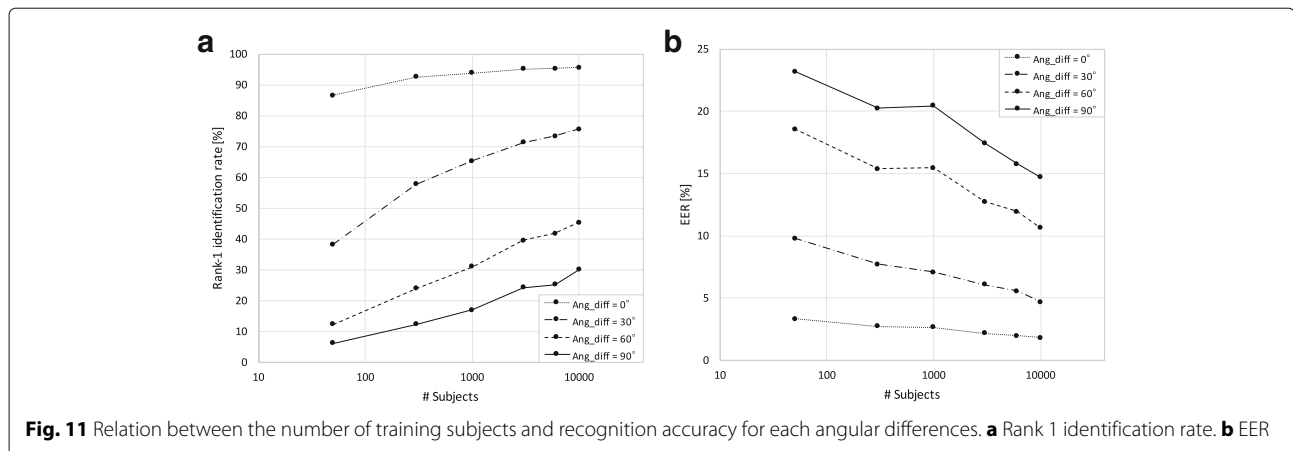
differences due to view angle difference is Siamese  $\gg$  MT > LB.

#### 4.8 Sensitivity of the number of training subjects on recognition accuracy

The accuracy of CNN-based method largely depends on the number of training samples. We analyze the sensitivity of the number of training subjects on the recognition accuracy. Three hundred and seven subjects among 10,307 subjects in our dataset are used for testing data and various number of subjects among the rest 10,000 subjects are used for training data. 1in-GEINet with the simplest network architecture was used in the experiment.

The sensitivity is shown in Fig. 10. Note that the averaged result for all view angle pairs for cooperative setting are plotted on the graph. From this graph, the larger the number of training subjects become the better the accuracy is. Additionally according to Fig. 1, the rank 1 identification rate of 10,000 training subjects is higher by approximately 23% compared to that of 150 training subjects, i.e., the almost same number of subjects for CASIA dataset B and WOSG with the largest population among





the existing databases with wide view angles, and EER of 10,000 training subjects is lower by approximately 5%.

Furthermore, the results for four typically angular difference ( $0^\circ$ ,  $30^\circ$ ,  $60^\circ$ ,  $90^\circ$ ) are shown in Fig. 11. From these graphs, in the case of smaller view difference, the accuracy remain to high even if the number of training subjects decreases. In contrast, in the case of larger view difference, the accuracy drastically drop as an amount of view difference become larger. In such a case, it is not easy to authenticate gait images because intra-subject appearance variations by view differences can be larger than inter-subject appearance variations. Therefore, database with more various view angles would be required for sufficient training.

From the above results, it has been confirmed that the accuracy of the cross-view gait recognition was increased significantly with an increase in the number of training subjects for CNN-based methods which requires a large training data, especially in the case of large view difference. Thus, it indicated the importance of our dataset, OU-ISIR MVLP, with a large subject number and large view variation.

## 5 Conclusion

This paper described the construction of a gait database comprising a large population dataset with a wide view angle and presented a statistically reliable performance evaluation of vision-based cross-view gait recognition. This dataset has the following advantages over existing gait databases: (1) the number of subjects is 10,307, which is more than two times greater than the number of existing public large-scale database, (2) the view angle variation is wide, 14 view angles, ranging  $0^\circ$ – $90^\circ$ ,  $180^\circ$ – $270^\circ$ , (3) the quality of all GEIs is guaranteed by visual confirmation.

Using our dataset, we carried out a statistically reliable performance comparison of cross-view gait recognition by various approaches. Moreover, we confirmed the effectiveness of our dataset with the largest population for

recent CNN-based approaches to gait recognition which generally requires a large number of training samples but achieves the state-of-the-art performance.

Further analysis of gait recognition performance using our dataset is still needed. For example, our dataset enables the evaluation of gender classification or age estimation, cross-database recognition. Thus, evaluating such problems is a future work. Though we evaluated only GEI-based methods in order to compare gait recognition methodologies, there are many gait features that can be used for input images, such as DeepGait [41], CGI (chrono-gait image) [42], and FDF (frequency-domain feature) [43]. Thus, evaluating such gait features is also a future work.

## Endnote

<sup>1</sup>The data have been published in the form of silhouette image sequences and GEIs (Gait Energy Images) in PNG format. <http://www.am.sanken.osaka-u.ac.jp/BiometricDB/GaitMVLP.html>.

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## Authors' contributions

NT and DM participated in the experiments for performance evaluation of gait recognition. YM collected the gait data. NT generated the gait database. NT, YM, and DM prepared the manuscript. YM, DM, TE, and YY gave technical support and conceptual advice. TE and YY designed the study. All authors read and approved the final manuscript.

## Competing interests

The authors declare that they have no competing interests.

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