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Technical Note

The OU-ISIR Gait Database Comprising the Treadmill Dataset

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Abstract: This paper describes a large-scale gait database comprising the Treadmill Dataset. The dataset focuses on variations in walking conditions and includes 200 subjects with 25 views, 34 subjects with 9 speed variations from 2 km/h to 10 km/h with a 1 km/h interval, and 68 subjects with at most 32 clothes variations. The range of variations in these three factors is significantly larger than that of previous gait databases, and therefore, the Treadmill Dataset can be used in research on invariant gait recognition. Moreover, the dataset contains more diverse gender and ages than the existing databases and hence it enables us to evaluate gait-based gender and age group classification in more statistically reliable way.

Keywords: gait database, treadmill, multiple views, walking speed, clothing

1. Introduction

In modern society, there is a growing need to identify individuals in many different situations, including for surveillance and access control. For personal identification, many biometric-based authentication methods have been proposed using a wide variety of cues, such as fingerprints, irises, faces, and gait. Of these, gait identification has attracted considerable attention because it provides surveillance systems with the ability to ascertain identity at a distance. In fact, automatic gait recognition from public CCTV images has been admitted as evidence in UK courts [36], and gait evidence has been used as a cue for criminal investigations in Japan.

Recently, various approaches to gait identification have been proposed. These range from model-based approaches [4], [37], [40], [41], [46] to appearance-based approaches [3], [6], [10], [14], [16], [17], [25], [26], [39]. In addition, several common gait databases have been published [7], [29], [31], [33], [44] for fair comparison of gait recognition approaches. These databases are usually constructed taking the following into account: (1) the variation in walking conditions, and (2) the number and diversity of the subjects.

The first consideration is important to ensure the robustness of the gait recognition algorithms, since walking conditions often differ between enrollment and test stages. For example, observation views are often inconsistent due to the positions of the CCTV cameras on the street and/or walking directions possibly being different. In addition, walking speeds can change depending on whether the person is merely taking a walk in the park or is walking to the station in a hurry, and clothing almost certainly changes depending on the season.

The second consideration is also important because the number of subjects determines the upper bound of the statistical reliability of the performance evaluation. In addition, if the database is used not only for person identification, but also gender and age estimation from gait, the diversity of subjects in terms of gender and age plays an important role in the performance evaluations of such applications.

In this paper, we describe a large-scale gait database composed of the **Treadmill Dataset** based on the two considerations. The **Treadmill Dataset** is a set of gait datasets with variations in walking conditions, comprising 25 surrounding views, 9 walking speeds from 2 km/h to 10 km/h with a 1 km/h interval, at most 32 clothes combinations, and gait fluctuation variations among gait periods. The proposed gait dataset thus enables us to evaluate view-invariant, speed-invariant, and clothing-invariant gait recognition algorithms in a more extensive range. Moreover, it comprises 200 subjects of both genders and including a wide range of ages. The proposed gait database thus enables us to evaluate gait-based gender classification and age group classification.

The outline of this paper is as follows. First, existing gait databases are briefly considered in Section 2. Next, the Treadmill Dataset is addressed with related performance evaluations of gait recognition algorithms in Sections 3. Section 4 contains our conclusions, discussions, and future work in the area.

2. Related Work

The existing major gait databases are summarized in **Table 1**, with brief descriptions of the frequently used ones given below. A good summary of the other gait databases is found in Ref. [28].

The USF dataset [33] is one of the most widely used gait

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Table 1 Existing major gait databases.

Database	#Subjects	#Sequences	Data covariates
CMU MoBo database [7]	25	600	6 views, 2 speeds, 2 slopes, baggage (ball)
Georgia Tech database [35]	24	288	4 speeds (0.7, 1.0, 1.3, and 1.6 m/s)
Soton database [23], [29]	115	-	Views
	25	∼2,000	Time (0, 1, 3, 4, 5, 8, 9 months), 12 views, 2 clothes
USF dataset [33]	122	1,870	2 views, 2 shoes, 2 surfaces, baggage (w/ and w/o), time (6 months)
CASIA dataset [44]	124	13,640	11 views, clothing (w/ and w/o coat), baggage (w/ and w/o)
	153	612	3 speeds, baggage (w/ and w/o),
TokyoTech database [1]	30	1,602	3 speeds
OU-ISIR Large-scale dataset [30]	1,035	2,070	2 views

datasets and is composed of a gallery and 12 probe sequences under different walking conditions including factors such as views, shoes, surfaces, baggage, and time. As the number of factors is the largest of all the existing databases, and despite the number of variations in each factor being limited to 2, the USF database is suitable for evaluating the inter-factor, instead of intra-factor, impact on gait recognition performance.

The CMU MoBo Database [7] contains image sequences of persons walking on a treadmill captured by six cameras. As the treadmill can control the walking speed and slope, the database includes gait images with speed and slope variations as well as view variations. As a result, this database is often used for performance evaluation of speed-invariant or view-invariant gait recognition [16].

The Soton database [29] contains image sequences of a person walking around an inside track, with each subject filmed wearing a variety of footwear and clothing, carrying various bags, and walking at difference speeds. Hence, it is also used for exploratory factor analysis of gait recognition [5]. The recently published Soton Temporal database [23] contains the largest variations, up to 9 months, in elapsed time. It is, therefore, suitable for analyzing the effect of time on the performance of gait biometrics.

The CASIA dataset [44] contains the largest azimuth view variations and hence, it is useful for the analysis and modeling of the impact of view on gait recognition [45].

The OU-ISIR Large-scale database [30] contains the largest number of subjects, while the within-subject variation is limited. Therefore, it is useful for statistically reliable performance evaluation.

In this section, we further discuss three variations related to walking conditions: views, walking speeds, and clothes and also the number and diversity of subjects.

Views: While the CASIA dataset [44] contains sufficient variations in terms of azimuth views, it does not contain any variation in the tilt view. Tilt view variations are quite important because most of the CCTV cameras capture pedestrians from somewhat tilted views. While the CMU MoBo Database [7] includes slightly tilted frontal and rear views, the variation in views is insufficient. Although the Soton Temporal database [23] covers 12 views including azimuth and tilt variations, the range of view variations is still smaller than that in the proposed database.

Walking speeds: Variations in walking speeds are limited to less than three in most of the databases. The Georgia Tech database [35] contains four speeds with a 0.3 m/s (approx. 1.0 km/h) interval. The maximum speed is, however, less than 6.0 km/h and hence faster walking or running sequences are necessary for extensive performance analysis of speed-invariant gait recognition.

Clothes: Variations in clothes are typically limited to normal clothes and a few types of coats and the numbers of variations are significantly small (at most three in the Soton database [29]). To adapt to actual variations in clothes, the database should contain various combinations of outer wear, pants (or skirts), and head wear.

The number and diversity of subjects: Next, we review the number and diversity of subjects. As shown in Table 1, relatively large-scale gait databases with more than a hundred subjects are limited to the following four: the USF dataset [33], Soton database [29], CASIA dataset [44], and the OU-ISIR Large-scale dataset. Although these four databases provide a statistically reliable performance to some extent, the number of subjects is still not sufficient when compared with other biometrics such as fingerprints and faces except for the OU-ISIR Large-scale dataset.

In addition, populations of genders and ages are biased in the databases other than the OU-ISIR Large-scale dataset; e.g., there are no children in the USF dataset, while in the CASIA dataset most of the subjects are in their twenties and thirties and the ratio of males to females is 3 to 1. Such biases are undesirable in performance evaluation of gait-based gender and age estimation and performance comparison of gait recognition between genders and age groups.

The proposed gait database: Contrary to existing databases, the proposed gait database aims to contain sufficient variations in terms of views, speeds, clothes, and subjects as summarized in **Table 2**. The proposed gait database contains gait images with the largest range of view variations (25 views: 12 azimuth views times 2 tilt angles, plus 1 top view), speed variations (9 speeds: 1 km/h interval between 2 km/h and 10 km/h), and clothing variations (up to 32 combinations), and as such, it is can be used for evaluating view-invariant [17], speed-invariant [20] and clothing-invariant [9] gait recognition. Moreover, the genders and ages of subjects are more diverse than the those of current gait database such as the CASIA dataset [44].

Table 2 Proposed gait database.

Dataset	#Subjects	#Sequences	Data covariates
The Treadmill Dataset	34	612	9 speeds (2, 3, 4, 5, 6, 7, 8, 9, and 10 km/h)
	68	2,746	32 clothes combination at most
	200	5,000	25 views (2 layers of 12 encircling cameras and an overhead camera)
	185	370	Gait fluctuation among periods

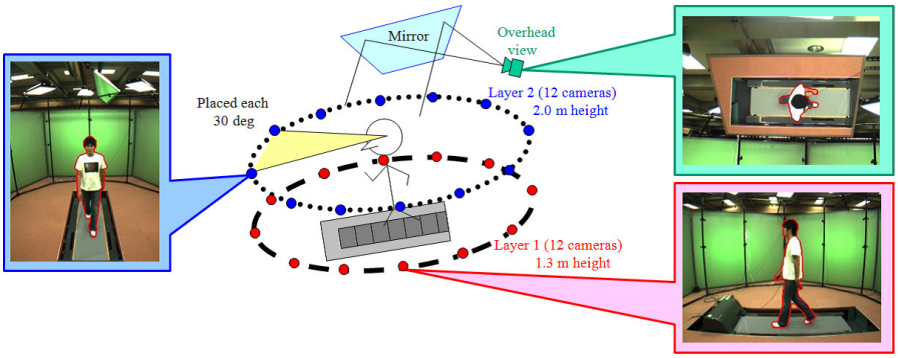


Fig. 1 Overview of multi-view synchronous gait capturing system.

3. The Treadmill Dataset

3.1 Difference between Treadmill and Overground Gait

At the beginning, the difference between treadmill and overground gait is briefly discussed.

Such differences have actively discussed in the field of applied physiology, biomechanics, medical and health science for the last decades. Van Ingen Schenau [38] concluded that no mechanical differences exist between the two conditions in theory as long as the treadmill belt speed remains constant and that all differences must therefore originate from other than mechanical causes. The constant belt speed assumption is, however, often violated particularly at heal strike moment, and hence the differences may arise. In addition, Lee et al. [12] hypothesized that the differences arose from differences in optic flow subjects received on the treadmill and overground.

Murray et al. [27] reported that no statistical differences in temporal gait parameters but claimed that subjects demonstrated trends for shorter step lengths and gait periods in case of treadmill walking. Although these trends are observed in our case in fact, they are relaxed as much as possible by providing sufficient time for each subject to practice walking on the treadmill. Moreover, in recent work [12], [32], while statistically significant differences between the two conditions are found in several aspects (e.g., kinematic parameter maxima and muscle activation patterns), it was reported that the overall patterns in joint moments and joint powers were quite similar between the two conditions.

Based on the supports from these works [12], [27], [32], we conclude the treadmill gait dataset can be effectively used for the purpose of the vision-based gait recognition as well as the other overground gait datasets.

3.2 Capturing System

Our image capturing system consists primarily of a treadmill, 25 synchronous cameras [*1] (2 layers of 12 encircling cameras and an overhead camera with a mirror), and six screens surrounding the treadmill, as shown in **Fig. 1**. The treadmill (BIOMILL BM-2200) has a walking belt area, 550 mm wide and 2,000 mm long, and can control its speed up to 25.0 km/h with a 0.1 km/h interval. The cameras (Point Grey Research Inc. Flea2 models) are attached to camera poles aligned at the vertices of a regular dodecagon. Of these 25 cameras, 12 cameras in layer 1 are placed every 30 deg at a height of 1.3 m, 12 cameras in layer 2 are also placed every 30 deg at a height of 2.0 m, and 1 camera is placed near the side-view camera in layer 2 to observe the overhead view of a person walking on the treadmill via a large mirror attached to the ceiling. The lens focal length for each of the 24 surrounding cameras is 3.5 mm and that of the overhead view camera is 6.0 mm. The frame-rate and resolution of each camera are set to 60 fps and VGA, respectively, and the recorded format is uncompressed raw data. The surrounding screens are used as a chroma-key background. Sample images captured in the system are also shown in Fig. 1.

3.3 Data Collection

Subjects were obtained through open recruitment or from volunteers and signed a statement of consent regarding the use of their images for research purposes.

After the practice sessions, subjects were asked to walk at 4 km/h or slower if necessary for children and the elderly, except during the data collection for speed variations. Subjects wore standard clothing (long-sleeved shirts and long pants, or their own casual clothes), except during the data collection for clothing variations.

3.4 Preprocessing

In this section, we briefly describe a method for size-normalized silhouette extraction as preprocessing. The first step involves extracting gait silhouette images, by exploiting background subtraction-based graph-cut segmentation [21].

*1 This means that images from all the 25 views are captured at the same time.

Fig. 2 Examples of size-normalized gait silhouettes (every 4 frames).

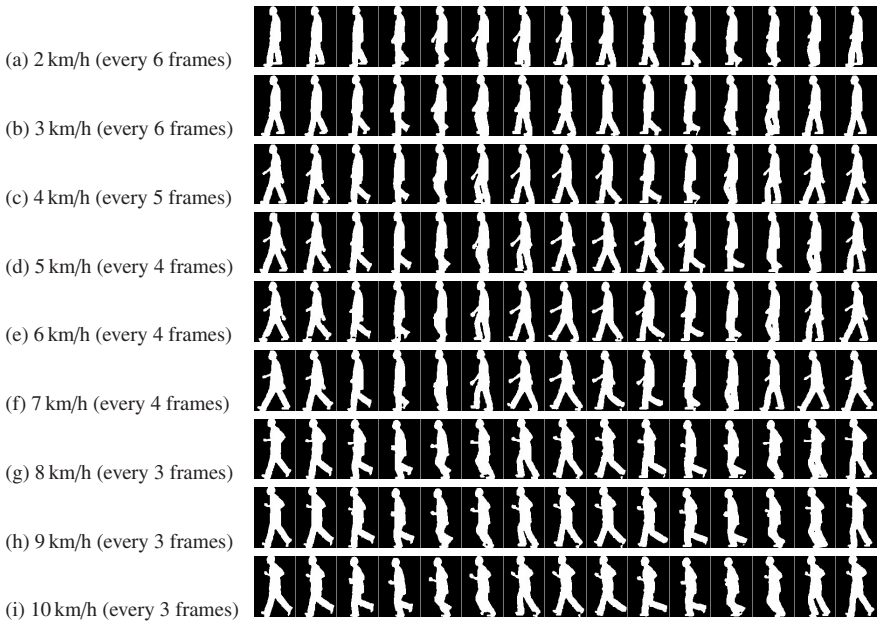


Fig. 3 Examples of size-normalized gait silhouettes for speed variations. Frame interval is adjusted so as to accommodate approximately one gait period.

Table 3 Number of recorded frames for each speed.

Speed [km/h]	2	3	4	5	6	7	8	9	10
#Frames	420	360	360	420	360	240	240	240	300

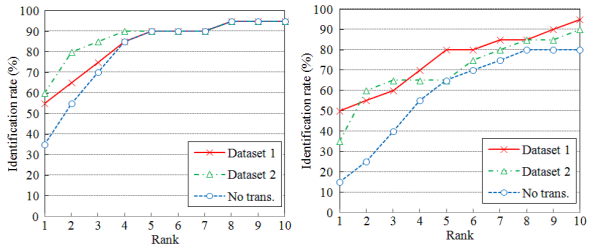
The next step is scaling and registration of the extracted silhouette images [17]. First, the top, bottom, and horizontal center of the silhouette regions are obtained for each frame. The horizontal center is chosen as the median of the horizontal positions belonging to the region. Second, a moving average filter of 60 frames is applied to these positions. Third, we scale the silhouette images so that the height is just 128 pixels based on the averaged positions, and the aspect ratio of each region is maintained. Finally, we produce an 88×128 pixel image in which the averaged horizontal median corresponds to the horizontal center of the image. Examples of size-normalized silhouettes are shown in **Fig. 2**.

3.5 Dataset A: Speed Variations [*2]

Dataset A contains images of 34 subjects walking at speeds varying between 2 km/h and 10 km/h with a 1 km/h interval. The subjects walked for speeds between 2 km/h and 7 km/h and ran (or jogged) to achieve speeds of 8 km/h to 10 km/h. The number of recorded frames for each speed is listed in **Table 3**. Examples of size-normalized gait silhouettes are shown in **Fig. 3**.

This dataset enables us to evaluate the performance of speed-invariant gait recognition algorithms. Thus, we conducted gait recognition experiments based on frequency-domain features [17] with and without a speed transformation model [20] for different speed gait recognition scenarios. The two different sub-

[*2] Partially available on the website [31]. The remainder is being prepared for publication.



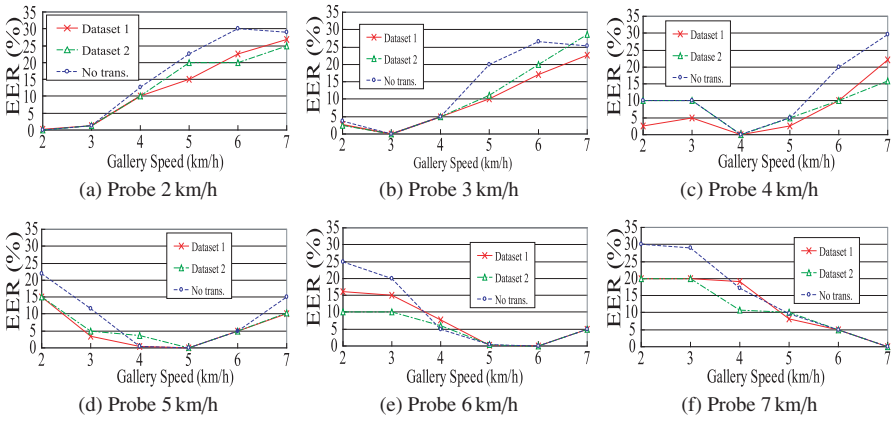
(a) 4 km/h vs. 7 km/h (b) 7 km/h vs. 3 km/h

Fig. 4 Experimental results for gait recognition incorporating speed variations [20]. The horizontal and vertical axes indicate rank and identification rate, respectively. The speed transformation model (Dataset 1 and Dataset 2) improves performance compared with the method without transformation (No trans.).

sets used (called Dataset 1 and Dataset 2) were arranged so as to highlight the effect of the number of subjects used to train the transformation model. Datasets 1 and 2 use 14 and 9 training subjects, respectively, while both datasets have 20 testing subjects in common. In this experiment, speed variations between 2 km/h and 7 km/h were used.

Two typical experimental settings, namely, matching between 4 km/h and 7 km/h, 7 km/h and 3 km/h, are evaluated by the Cumulative Matching Characteristics (CMC) curve which shows rank-k identification rate in the identification scenarios (one-to-many matching) as shown in **Fig. 4**. It is apparent that the speed transformation model (Dataset 1 and Dataset 2) improves performance compared with the method without transformation (No trans.).

Results are also evaluated through the Equal Error Rate (EER) of the false acceptance rate and false rejection rate in the verification scenarios (one-to-one matching) as shown in **Fig. 5**. It



(a) Probe 2 km/h (b) Probe 3 km/h (c) Probe 4 km/h

(d) Probe 5 km/h (e) Probe 6 km/h (f) Probe 7 km/h

Fig. 5 Experimental results for gait recognition incorporating speed variations [20]. The horizontal and vertical axes indicate gallery speed and EER, respectively. The speed transformation model (Dataset 1 and Dataset 2) improves performance compared with the method without transformation (No trans.).

Table 4 Comparison of speed-invariant gait recognition by the other datasets. P_1 stands for rank-1 identification rate.

Datasets	Literature	Gallery size	Gallery speed (km/h)	Probe speed (km/h)	P_1 (%)
The Treadmill Dataset A	Ref. [20]	25	2.0	6.0	64
Georgia Tech database	Ref. [35]	24	2.5	5.8	40
The Treadmill Dataset A	Ref. [20]	25	6.0	2.0	52
Georgia Tech database	Ref. [35]	24	5.8	2.5	30
The Treadmill Dataset A	Ref. [20]	25	4.0	3.0	96
CMU MoBo dataset	Ref. [16]	25	4.5	3.3	84

is also confirmed that the speed transformation model improves performance as a whole.

We can compare our results with the other results by Tanawongsuwan et al. [35] with Georgia Tech database and also by Liu et al. [16] with the CMU MoBo datasets in terms of the rank-1 identification rate as shown in **Table 4**. Note that the gallery size of the Treadmill Dataset A is increased up to 25 subjects by using the 9 training subjects in the Dataset 2 in order to keep the consistency of the gallery size with those of the other databases. Moreover, we choose pairs of gallery and probe speeds similar to those in the other databases.

Despite the limited speed variation range in the above experiments, it is possible in the future to evaluate how a speed-invariant gait recognition algorithm improves the performance for a much wider range of speed variations compared with the existing speed-variation gait databases [7], [29], [35], [44].

3.6 Dataset B: Clothing Variations *3

Dataset B contains images of 68 subjects with up to 32 combinations of types of clothing. **Table 5** lists the clothing types, while **Table 6** gives the combinations of clothing used in constructing the dataset. **Figure 6** shows sample images of all the combinations of clothing types. All the gait sequences were captured twice on the same day. Thus, the total number of sequences in the dataset is 2,746. The large number of subjects and clothing-variations in the new dataset provides us with an estimate of intra-subject variations together with inter-subject variations for a better assessment of the potential of gait identification.

We evaluated the performance of several gait recognition approaches: GEI [8]-based CSA [42], DATER [43], and CPDA [19], and a part-based frequency-domain feature approach [9]. The dataset was divided into three sets: a training set (20 subjects with all types of clothes), a gallery set (the remaining 48 subjects with a single type of clothes), and a probe set (the remaining 48 subjects with the other types of clothes) to separate the training and test sets in terms of subjects, and to separate the test gallery and test probe in terms of clothing, thereby enforcing strict separation conditions for the experimental evaluations. The gait identification and verification performances were evaluated with CMC and ROC curves as shown in **Fig. 7**, respectively. The results show that CPDA outperforms the other methods in the clothing-invariant gait recognition scenarios.

Table 5 List of clothes used in the dataset (abbreviation: name).

RP: Regular Pants	HS: Half Shirt	CW: Casual Wear
BP: Baggy Pants	FS: Full Shirt	RC: Rain Coat
SP: Short Pants	LC: Long Coat	Ht: Hat
Sk: Skirt	Pk: Parker	Cs: Casquette Cap
CP: Casual Pants	DJ: Down Jacket	Mf: Muffler

3.7 Dataset C: View Variations *4

Dataset C contains images of 200 subjects from 25 views. An example of 25 synchronous images is shown in **Fig. 8**. Naturally, this database enables us to evaluate the performance of multi-view gait recognition [34] and view-invariant gait recognition [17]. Moreover, because the 200 subjects comprise 100 males and 100 females with ages ranging from 4 to 75 years old, (see **Fig. 9** for the age distribution), it can also be used for performance evaluation of gender and age group classification by

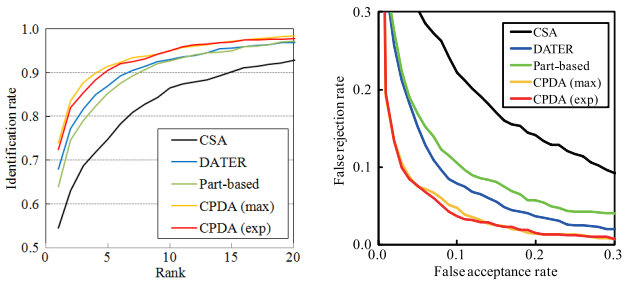
*3 Fully available on the website [31].

*4 To be prepared for publication.

Table 6 Different clothing combinations (#: clothing combination type; s_i: i-th clothes slot).

#	s_1	s_2	s_3	#	s_1	s_2	s_3	#	s_1	s_2	#	s_1	s_2
2	RP	HS	-	7	RP	LC	Ht	L	BP	Pk	V	Sk	DJ
3	RP	HS	Ht	8	RP	LC	Cs	M	BP	DJ	D	CP	HS
4	RP	HS	Cs	C	RP	DJ	Mf	N	SP	HS	F	CP	FS
9	RP	FS	-	A	RP	Pk	-	Z	SP	FS	E	CP	LC
X	RP	FS	Ht	B	RP	DJ	-	P	SP	Pk	G	CP	Pk
Y	RP	FS	Cs	I	BP	HS	-	S	Sk	HS	H	CP	DJ
5	RP	LC	-	K	BP	FS	-	T	Sk	FS	0	CP	CW
6	RP	LC	Mf	J	BP	LC	-	U	Sk	Pk	R	RC	RC

Fig. 6 Sample clothing images.



(a) CMC curve (b) ROC curve

Fig. 7 CMC and ROC curves for clothing-invariant gait recognition scenarios.

gait [2], [11], [13]. Taking into account both properties of this dataset, we applied it to a multi-view gait feature analysis of gender and age. We defined four typical gender and age classes, namely children (younger than 15 years old), adult males and adult females (males and females between 15 and 65 years old, respectively), and the elderly (aged 65 years and older). Then, we analyzed the uniqueness of gait for each class. **Figure 10** illustrates the average gait features for each class for typical views (side, front, right-back, and overhead) from layer 1 cameras. **Figure 11** shows a comparison of these features for combinations of classes, namely children and adults (C-A), adult males and adult females (AM-AF), and adults and the elderly (A-E).

The results reveal the uniqueness of gait features for the four typical classes from a computer-vision point of view. For example, the arm swings of children tend to be smaller than those of adults since walking in children is less mature. This can be observed in the side and overhead views. Moreover, males have wider shoulders, while females have more rounded bodies; both of these trends are particularly noticeable in the frontal and side views. The elderly have wider bodies than adults due to middle-age spread, and this is clearly observed in the frontal view. See Ref. [22] for more detailed analyses and insights.

In addition to these analyses, the dataset C can be exploited for performance evaluations of view-invariant and multi-view gait recognition, although it remains as a future work.

3.8 Dataset D: Gait Fluctuations *5

Dataset D contains 370 gait sequences of 185 subjects observed from the side view. The dataset focuses on gait fluctuations over a number of periods; that is, how gait silhouettes of the same phase differ across periods in a sequence. As a measure of gait fluctuation, we adopt Normalized AutoCorrelation (NAC) of size-normalized silhouettes for the temporal axis, which is often used for period detection as

$$N_{gait} = \arg \max_{N \in [N_{\min}, N_{\max}]} C(N) \tag{1}$$

$$C(N) = \frac{\sum_{x,y} \sum_{n=0}^{T(N)} g_{x,y,n} g_{x,y,n+N}}{\sqrt{\sum_{x,y} \sum_{n=0}^{T(N)} g_{x,y,n}^2} \sqrt{\sum_{x,y} \sum_{n=0}^{T(N)} g_{x,y,n+N}^2}} \tag{2}$$

$$T(N) = N_{total} - N - 1, \tag{3}$$

where $C(N)$ is the NAC for an N-frame shift, $g(x, y, n)$ is the silhouette value at position (x, y) in the n-th frame, and N_{total} is the total number of frames in the sequence.

Successful gait period detection requires an appropriate search

*5 To be prepared for publication.

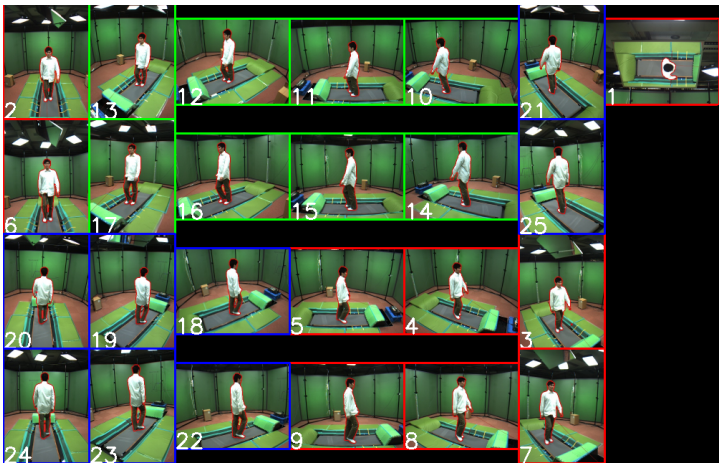


Fig. 8 Example of 25 synchronous images.

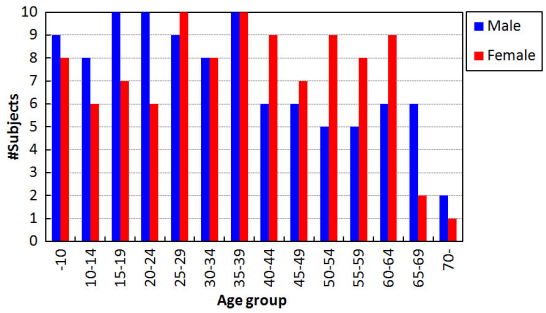


Fig. 9 Distribution of subjects' gender and age.

range setting for the gait period candidate N in Eq. (1). Except for the dataset A (speed variations), it is assumed that each subject walks in a natural way (neither ox walk nor brisk walk), and hence we set the lower and upper bounds of the gait period for such natural walk as 0.83 sec and 1.3 sec, respectively. These bounds are then converted from second unit into frame unit by taking the frame-rate into consideration. For example, in case of 60 fps, the lower bound $N_{\min}$ and the upper bound $N_{\max}$ in frame unit, which are used in Eq. (1), are calculated as $N_{\min} = 0.83\,[\text{sec}] \times 60\,[\text{fps}] \simeq 50\,[\text{frame}]$, $N_{\max} = 1.3\,[\text{sec}] \times 60\,[\text{fps}] \simeq 78\,[\text{frame}]$, respectively.

The NAC increases if gait silhouettes of the same phase across periods are similar to each other (stable gait), and vice versa (unstable gait or fluctuated gait). Hence, we define the two subsets: DB_{high} comprising 100 subjects with the highest NAC, and DB_{low} comprising 100 subjects with the lowest NAC. Examples of size-normalized silhouettes for DB_{high} and DB_{low} are shown in **Fig. 12**. We can see that silhouettes at the same phases for DB_{high} are similar across periods, while those for DB_{low} fluctuate across periods.

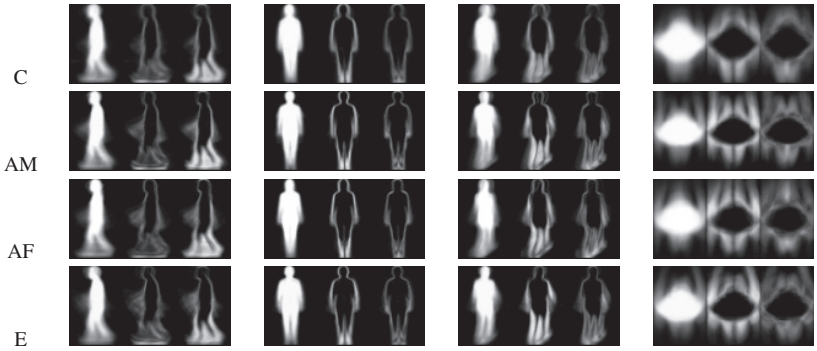
Naturally, the subsets are expected to be used to evaluate how robust the gait recognition algorithms are against gait fluctuations. We evaluated the performance of several gait recognition approaches: Period-Period matching, Sequence-Period matching [24], and Sequence-Sequence matching in eigenspace [26], Average silhouette (or GEI) [8], [15], Frequency-domain feature [17], and Width vector [6]. The experiments were carried out on each subset and for each frame-rate. First, the CMC curves at 4 fps are shown in **Fig. 13**. In addition, EERs for all the frame-rates are shown in **Fig. 14**. The results show that, although Period-Period and Sequence-Period achieve relatively good performance for both subsets, the performance of DB_{low} is significantly degraded compared with DB_{high} as a whole, confirming that gait fluctuations have a large impact on gait recognition performance.

4. Conclusion and Discussion

Conclusion: This paper described a large-scale gait database composed of the Treadmill Dataset for performance evaluation of existing or future gait recognition algorithms. The dataset focuses on variations in walking conditions and includes 34 subjects with 9 speed variations from 2 km/h to 10 km/h with a 1 km/h interval (Dataset A), 68 subjects with up to 32 clothes variations (Dataset B), 200 subjects with 25 views (Dataset C), and 185 subjects with gait fluctuation variations (Dataset D). The variation in the former three factors is significantly larger than that in previous gait databases and therefore the Treadmill Dataset can be used for research on invariant gait recognition. Moreover, the Dataset C contains more diverse genders and ages than the existing databases and hence it enables us to evaluate the gait-based gender and age group classification performance in more statistically reliable way. Finally, several gait recognition approaches were tested using the proposed dataset. It was shown that the proposed database makes it possible to evaluate a wide range of gait recognition problems.

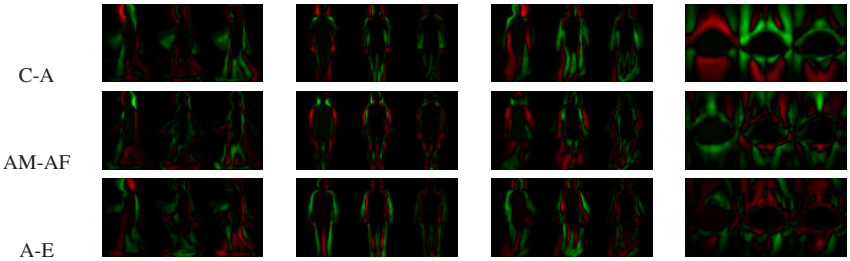
Discussion: While each own gallery set is defined for each dataset in this experimental setup, experimental setup with one common gallery set is beneficial to analysis of the inter-factor impact on gait recognition performance as Sarkar et al. [33] did with the USF dataset. Such experimental setup, however, significantly limits the variety of performance evaluations, particularly in aspects of difficulty ranking caused by variations in gallery sets and the optimal gallery selection.

In fact, Sarkar et al. [33] also investigated difficulty ranking caused by variations in gallery sets with eight different gallery sets from the USF dataset. Hossain et al. [9] investigated the difficulty ranking in clothing-invariant gait recognition caused by variations in gallery clothes types with 15 different clothes types from the Treadmill Dataset B and they demonstrated that galleries with a long coat or a down jacket are much more difficult to be recognized than those with a full shirt or a parka.



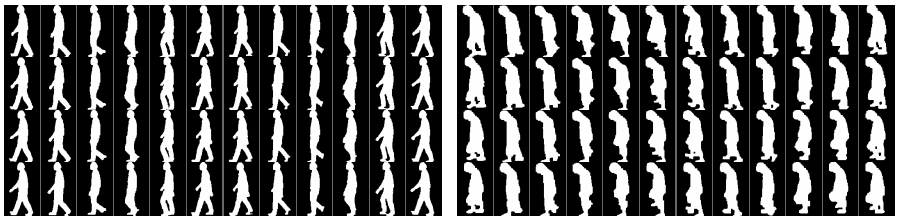
(a) Left (b) Front (c) Right-back (d) Overhead

Fig. 10 Average gait features for four classes (C: Children, AM: Adult Males, AF: Adult Females, E: the Elderly). The features are shown with their 1- and 2-times frequency multiplied 3 times for highlighting purposes.



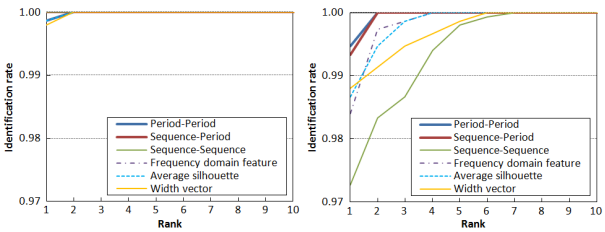
(a) Left (b) Front (c) Right-back (d) Overhead

Fig. 11 Differences in average features. Color is used to denote which class' feature appears more strongly. Red indicates that the feature of the leftmost class (e.g., C of C-A) appears more strongly, while green depicts the opposite. The features are shown with their 1- and 2-times frequency multiplied 3 times for highlighting purposes.



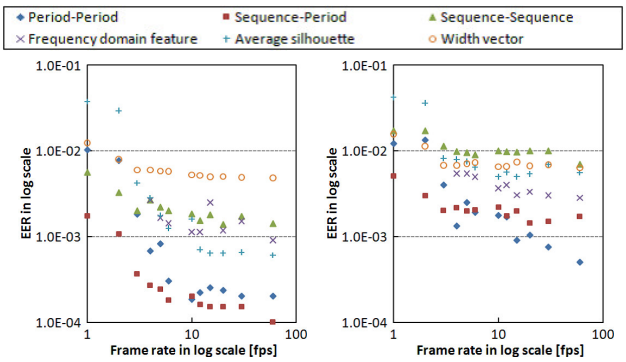
(a) DB_{high} (NAC: 0.96) (b) DB_{low} (NAC: 0.85)

Fig. 12 Examples of size-normalized silhouettes for DB_{high} and DB_{low}. Each row indicates a single period. Silhouettes at the same phases for DB_{high} are similar across periods, while those for DB_{low} fluctuate across periods.



(a) DB_{high} (b) DB_{low}

Fig. 13 CMC curves for Dataset D at 4 fps.



(a) DB_{high} (b) DB_{low}

Fig. 14 EERs for Dataset D.

Moreover, in the context of the view-invariant gait recognition by using view transformation model [17], the optimal view selection of a single-view gallery and the optimal combination of two-view galleries were investigated in Ref. [18]. As a result, it was reported that an oblique-view gallery is better than side-view or front-view gallery in single-view gallery case, and that a orthogonal-view combination is better in two-view gallery case, which is useful information for designing a camera alignment at an enrollment site.

These kinds of useful insights can be never acquired if gallery sets are limited to the common one (e.g., a gallery set where each subject walks at 4 km/h, wears type 9 clothes, and is observed from a side-view camera). In addition, unlike the USF dataset, the strength of the Treadmill Dataset lies in the wide intra-subject

variation for each factor rather than the number of factors, and hence we would rather keep a variety of gallery sets than choosing the one common gallery set in this work.

Future work: Although the proposed database has the largest diversity of all databases up to now, it is still lacking in some aspects, namely, shoes, bag, surface conditions, elapsed time, and scene types (e.g., outdoor scenes). Moreover, the number of subjects is still insufficient for statistically reliable performance evaluation of gait recognition. Therefore, we need to collect the required gait datasets by taking advantage of various demonstration events, such as outreach activities or open recruitment days in the future.

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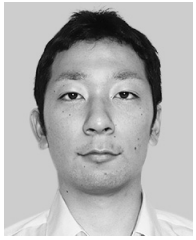

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