Gait Regeneration for Recognition

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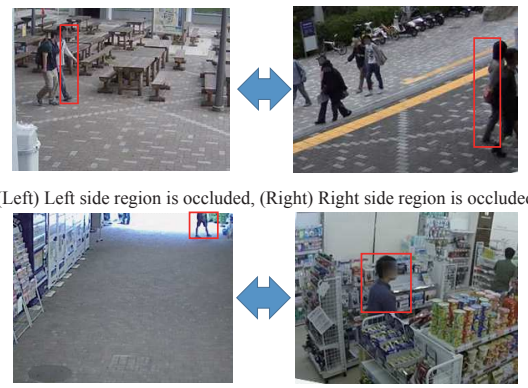
Abstract

Gait recognition has potential to recognize subject in CCTV footages thanks to robustness against image resolution. In the CCTV footage, several body-regions of subjects are, however, often un-observable because of occlusions and/or cutting off caused by limited field of view, and therefore, recognition must be done from a pair of partially observed data. The most popular approach to recognition from partially observed data is matching the data from common observable region. This approach, however, cannot be applied in the cases where the matching pair has no common observable region. We therefore, propose an approach to enable recognition even from the pair with no common observable region. In the proposed approach, we reconstruct entire gait feature from a partial gait feature extracted from the observable region using a subspace-based method, and match the reconstructed entire gait features for recognition. We evaluate the proposed approach against two different datasets. In the best case, the proposed approach achieves recognition accuracy with EER of 16.2% from such a pair.

1. Introduction

Walking styles are different among subjects, and features extracted from the walking style are used for person recognition; this method is called gait recognition [22]. Many biometric person recognition methods have been proposed and used in the world [12], gait recognition has remarkable characteristics which other methods do not. The characteristic is that gait features can be acquired even from the unconscious/uncooperative subject using a camera placed at a good distance, and the gait features extracted even from relatively low spatial resolution (e.g., a person with 30-pixel height in an image) have discrimination ability. These characteristics enable to recognize subjects from CCTV footage, and therefore, gait can be useful clue to recognize a perpetrator for forensics [3, 9, 15–17, 20].

On the other hand, because gait image sequences are captured from uncooperative subjects in the footage, gait recognition from the footage should tackle several problems, which makes gait recognition much more challenging. Such typical problems are covariate factors and missing data. The covariate includes, but not limited to observation views, walking speeds, clothing, and belongings. The missing data includes temporal missing caused by low transmission bandwidth and/or limited storage capacity, and spatial missing occurred caused by occlusions and/or cutting off caused by limited field of view.



(Left) Left side region is occluded, (Right) Right side region is occluded

(Left) Upper body region is cut off, (Right) Lower body region is occluded

Figure 1. Examples of the target gait recognition task. Bounding box in each image shows observable region of a target subject.

Against the covariates' problem, many approaches have been proposed (e.g., against view [13, 14, 18, 21], speed [7, 19], clothing [8, 11], and belongings [23]). Against the temporal missing data problem, temporal super resolution approaches [1, 2, 5] can be effective. On the other hand, against the spatial missing data problem, a part-dependent approache [4, 11] can be applied if the pair share common observable region (COR); however, otherwise this approach fails, and no effective approach for gait recognition have not been proposed to the best of our knowledge. We therefore, focus on such a recognition task where the matched pair do not share COR as shown in Figure 1, and propose an approach that enables recognition from such a matched

pair. In the proposed approach, we firstly generate subspace of the entire gait features from the non-target (independent) multiple subjects, and reconstruct entire gait feature from the spatially missing (partial) gait features extracted from the partial observable region. We thereafter compare the pair of the reconstructed entire gait features originating from the partial gait features. Thanks to the reconstruction of the entire gait features, our proposed approach can recognize a subject even in the case where the matched pair do not share COR.

The contributions of this paper are summarized in the following three points:

1. Regeneration of a entire gait feature from a partial gait feature

An entire gait feature is regenerated from a single partial gait feature using subspace-based method. Even though, a partial gait feature is extracted from only observable partial region where several observation region are occluded/missing, features corresponding to the occluded/missing observation regions are regenetated from the partial gait feature.

2. Recognition from a pair of gait image sequences those include no COR

Thanks to the reconstruction of entire gait feature, recognition from the pair of partial gait features are possible even though the pair do not share COR. To the best of our knowledge, this is the first work to realize gait recognition from the pair of gait features originating from the fully different observation region.

3. Wide variety of accuracy evaluations

We consider multiple patterns that realize occlusion/missing of gait features by changing the observable/available location and area, and evaluate the accuracy of the proposed method against all the combinations of the considered patterns where the matched pair do not share COR. Moreover, these evaluations are conducted againt gait features from mulple different observation views.

2. Related work

In this section, we mainly summarize work related to gait recognition from occluded gait features.

Many part-dependent approaches [4, 8, 11] have been proposed, and they have potential to recognize subjects from a partial gait features. For example, Iwashita et al. firstly divide human body into multiple area, and then estimate matching weight to each area; finally they identify a subject by weighted integration of similarity from each body area. The part-dependent approaches can be useful for gait recognition with occlusion, however, these approaches are not applicable to the recognition task where the matched pair do not share COR.

On the other hand, Xu et al. proposed a method using patch distribution feature [27]. In the paper, they generate image-specific GMM of augmented Gabor features from a universal background model by MAP adaptation. This method may has potential to be applied to the recognition task where the matched pair do not share COR, but the applicability is not discussed.

An approach that focuses on incomplete silhouette issue is also proposed by Chen et al. in [6]. They generate frame difference energy image (FDEI), extract a feature vector from the FDEI, and calculate a score using the feature and hidden Markov model for recognition. Employing the FDEI suppress the problem cuased by temporal silhouette incompletion, however, this approach fails if the matched pair do not share COR. An approach explicitly uses partial body region is proposed by Shaikh et al. [24]. They extract the useful portion from the whole body region, and use only the useful portion including he matched pair share COR, namely, the body part containing hand dynamics. Veres et al. [25] investigate important features in a silhouettehand dynamics. Although, this approach uses a partial region, it assumes that t-based gait feature. They conclude that whole body silhouette-based feature includes redundant information, and static component of gait (head and body) are the most important features. We think the formar conclusion is interesting, because it implies that the common information can be acquired from the different body region thanks to its redundancy.

For the face recognition with occlusion, an approach via space representation is proposed by Wright et al. [26] and achieves good recognition accuracy even aginst faces with occlusion. This approach is applicable to gait recognition with occlusion, however, applying this approach to the target gait recognition task have difficulty, because this approach assumes that the training data contain the data from the target subject which share COR with the test data.

To the best of our knowledge, any efficient approach for gait recognition from the matched pair without COR, has not been proposed and/or discussed so far.

3. Problem setting

3.1. Target task

Two gait image sequences are given as a gallery and a probe for verification. Different from the normal biometric person recognition tasks, entire gait feature cannot be extracted from these two image sequences, in place a pair of partial gait features are available for recognition in the target task; for example, only data from the upper body part are given as a gallery, and data from the lower body part are given for a probe as shown in Figure 1. In this paper, we assume that occluded/missing reagions are known, in other words, available regions are known[1]. Note that even if occluded/missing region are known, direct comparison of

[1]For localizing available region, an approaches [] are useful

the extracted appearance-based gait features is meaningless, because data of the corresponding region does not exist in the gallery and the probe.

3.2. Feature representation

In this paper, we describe an entire gait feature by a K-dimension vector. So, in case that a target gait feature is image-based (2D) features, we transform the 2D feature to a K-dimension vectors by mean of raster scan as shown in Figure 2. Two types of gait features are utilized: entire gait features extracted from entire observation regions, and partial gait features extracted from observation regions with occlusion/missing in which occluded/missing regions are known. We call the first type as full-dimensional (FD) gait feature, and the latter type as partial-dimension (PD) gait features. In this paper, both types of gait features are represented by a K-dimensional vector in order to make explaination simple and systematic. However, information from the dimensions that corresponding to occluded/missing region are undefined[2] and unavailable for the PD gait features. We therefore, employ indicator vectors which elements show if the information associated with the corresponding dimension is extractable from the input image sequence, and generate selection matrix to extract the available data from the K-dimensional vectors. Let $\boldsymbol{q}^G$ and $\boldsymbol{q}^P$ be an indicator vector of a gallery and a probe, respectively, and let $\boldsymbol{Q}^\chi, \chi = \{G, P\}$ be a selection matrix of the gallery and probe, respectively. Indicator vectors $\boldsymbol{q}^{\chi\in\{G,P\}} \in \mathbb{R}^{K\times K}$ are defined by

$$\boldsymbol{q}^\chi = [q_1^\chi, q_2^\chi, ..., q_i^\chi, ..., q_K^\chi], \tag{1}$$

$$q_i^\chi = \begin{cases} 1 & \text{if } i\text{-th dimension is available} \\ 0 & \text{otherwise} \end{cases}. \tag{2}$$

Because correspondence between the 2D features and feature vector are specified by the raster scan, we can set $\boldsymbol{q}^\chi$ if the occluded/missing region are known. Note that the gallery and the probe do not have the information from the common dimension in the target task, and therefore, $\boldsymbol{q}^G$ and $\boldsymbol{q}^P$ must be orthogonal; namely, $\left(\boldsymbol{q}^G\right)^T \boldsymbol{q}^P = 0$. And selection matrix is defined by

$$\boldsymbol{Q}^\chi = \text{diag}\left[q_1^\chi, q_2^\chi, ..., q_K^\chi\right]. \tag{3}$$

4. Algorithm

4.1. Overview

The overall algorithm of the proposed approach is depicted in Figure 2. The algorithm is composed of two phase: training and verification. In the training phase, a subspace of FD gait feature is generated. In the verification phase, FD gait feature are extracted from the gallery and probe gait image sequences with occlusion/missing, and FD gait features are reconstructed from the gallery and the probe PD gait features using the generated subspace, and reconstructed FD gait features are compared for recognition. In this paper, we consider K-dimensional appearance-based gait feature from L-dimensional appearance-based PD gait features, where $L \leq \frac{K}{2}$.

[2]Undefined values are padded by value "0"

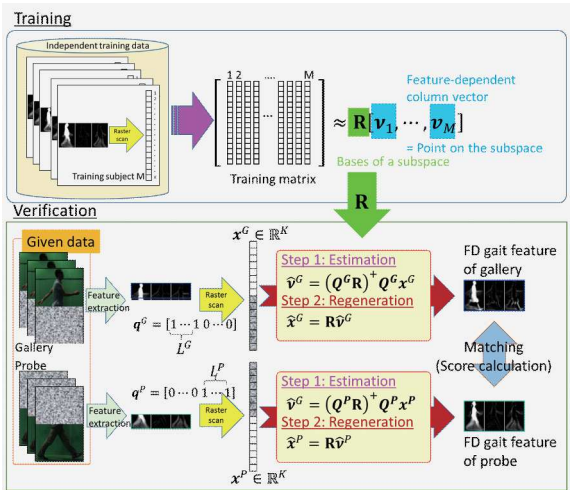


Figure 2. Overall algorithm

4.2. Training

We use M FD gait features from multiple independent subjects for training. Let $\boldsymbol{X}^m \in \mathbb{R}^{K\times 1}$ be a FD gait feature from the m-th subject. We generate training matrix $\boldsymbol{D}$ by arraying the gait features as shown in Figure 2, and decompose the training matrix by singular value decomposition:

$$\begin{aligned} \boldsymbol{D} &= \left[\boldsymbol{X}^1 \boldsymbol{X}^2 \cdots \boldsymbol{X}^M\right] \\ &= \boldsymbol{U}\boldsymbol{S}\boldsymbol{V}^{\boldsymbol{T}} \\ &= \left[\boldsymbol{u}^1, \boldsymbol{u}^2, ..., \boldsymbol{u}^M\right] \begin{bmatrix} s_1 & 0 & \cdots & 0 \\ 0 & s_2 & \ddots & \vdots \\ \vdots & \ddots & \ddots & 0 \\ 0 & \cdots & 0 & s_M \end{bmatrix} \begin{bmatrix} (\boldsymbol{v}^1)^T \\ (\boldsymbol{v}^2)^T \\ \vdots \\ (\boldsymbol{v}^M)^T \end{bmatrix} \end{aligned} \tag{4}$$

where $\boldsymbol{U} \in \mathbb{R}^{K\times M}$ is an orthogonal matrix that is composed of a set of bases for the subspace: $\boldsymbol{u}^i \in \mathbb{R}^{K\times 1}, i = 1, 2, ..., M$, $\boldsymbol{V} \in \mathbb{R}^{M\times M}$ is also an orthogonal matrix that is composed of a set of bases: $\boldsymbol{v}^i \in \mathbb{R}^{M\times 1}, i = 1, 2, ..., M$, $\boldsymbol{S} \in \mathbb{R}^{M\times M}$ is a diagonal matrix where the on-diagonal elements are singular values: $s_i, i = 1, 2, ..., M$, and superscript "T" denotes transposition operator. Then, we approximate the $\boldsymbol{D}$ by

$$\boldsymbol{D} \approx \begin{bmatrix} \boldsymbol{R}_1 \\ \boldsymbol{R}_2 \\ \cdots \\ \boldsymbol{R}_K \end{bmatrix} \left[\boldsymbol{\nu}^1, \boldsymbol{\nu}^2, \cdots, \boldsymbol{\nu}^M\right], \tag{5}$$

$$= \mathbf{R}\mathbf{N} \tag{6}$$

where $\boldsymbol{R}_j = \left[u_j^1, u_j^2, ..., u_j^\lambda\right], j = 1, 2, ..., K$, $\boldsymbol{\nu}^i = \left[s_1 v_i^1, s_2 v_i^2, ..., s_\lambda v_i^\lambda\right]^T, i = 1, 2, ..., M$; u_j^l is the j-th element of $\boldsymbol{u}^l$, v_l^i is the l-th element of $\boldsymbol{v}^i$, and λ is the dimension of the subspace. The dimension λ is set by considering cumulative proportion of singular values. Note that $\boldsymbol{R}_j, j = 1, 2, ..., K$ is a dimension-dependent transformation vector and $\boldsymbol{\nu}_j \in \mathbb{R}^{\lambda \times 1}$ is a feature dependent vector, and it shows a projected point of the FD gait feature onto the generated subspace. Using these, the m-th training FD gait feature is approximated by

$$\boldsymbol{X}^m \approx \mathbf{R}\nu^m. \tag{7}$$

4.3. Verification

Reconstruction

Two PD gait features are given as a gallery and a probe; they have no common dimension information. We reconstruct a FD gait feature from a PD gait feature. Using equation (7), FD gait feature can be generated by transforming a point on the subspace with $\mathbf{R}$, we therefore, estimate a point on the subspace from the input partial-dimensinal gait feature, and reconstruct the FD gait feature from the estimated point on the subspace. As an estimate of the point on the subspace, we select such a point $\hat{\boldsymbol{\nu}}^\chi \in \{G, P\}$ that

$$\hat{\boldsymbol{\nu}}^\chi = \underset{\boldsymbol{\nu}}{\operatorname{argmin}} \left|\left|\boldsymbol{Q}^\chi \boldsymbol{x}^\chi - \boldsymbol{Q}^\chi \mathbf{R}\boldsymbol{\nu}\right|\right|_2^2. \tag{8}$$

This can be calculated using the least square method by

$$\hat{\boldsymbol{\nu}}^\chi = \left(Q^\chi \mathbf{R}\right)^+ Q^\chi x^\chi, \tag{9}$$

where superscript "+" for a matrix shows pseudo inverse matrix of the matrix.

Thereafter, we reconstruct the FD gait feature from the estimated vector by

$$\hat{x}^\chi = \mathbf{R}\hat{\boldsymbol{\nu}}^\chi. \tag{10}$$

Score calculation

Let $d_{RC}(x^P, x^G)$ be a dissimilarity score calculated from the gallery and probe gait feature using reconstructed gait feature. We calculate it by

$$d_{RC}(x^G, x^P) = \frac{\left|\left|\hat{x}^P - \hat{x}^G\right|\right|_2 - \mu(\hat{x}^P)}{\sigma(\hat{x}^P)}. \tag{11}$$

Here, $\mu(\hat{x}^P)$ and $\sigma(\hat{x}^P)$ is a mean and standard deviation of L-2 norm associated with $\hat{x}^P$ and training data, respectively; and these values are calculated using the $\hat{x}^P$ and reconstructed data from the training data set.

5. Experiment

5.1. Overview

In order to evaluate accuracy of the proposed method against wide variety of occlusion/missing scenes, we generated several observable patterns, and considered several matching cases where the gallery and probe do not include the corresponding dimension's data. For the evaluation, we used two datasets those have different properties: subset of OU-ISIR large population dataset [10] (we call this set course dataset) and treadmill dataset. Using the course dataset, we evaluate the recognition accuracy against large population subjects with wide variety of ages. On the other hand, we used treadmill dataset to evaluate accuracy of the proposed approach in different observation view.

5.2. Database

Course dataset

The subset is composed of gait image sequences from 1,912 subjects. Each subjects were asked to walk straight along a course twice in a natural manner, and gait image sequence were captured with 30 fps using a single camera placed approximately 5 m from the course at a height of 100 cm. The course is carpeted, and each subject walked on the course with his/her natural speed. The captured gait image sequences are divided into subset with different observation view: azimuth angle of 55, 65, 75, and 85 deg. The sample images of the course dataset are shown in Figure 3. For the experiment, we randomly divided the subject into two subject groups with the same size of 956 subjects, and used gait image sequences of the subjects in the first group for training data, and gait image sequences from subjects in the second group for evaluation.

Treadmill dataset

This dataset is composed of gait image sequences from 203 subjects. For the data collection, each subject were asked to walk on the treadmill in natural manner, and temporally synchronized 25 cameras positioned around the treadmill captured the walking image sequence of the subject with 60 fps. From this dataset, we select gait image sequences with observation views of 0, 30, 60, 90, 120, 150 and 180 deg captured cameras at height of 200 cm. The sample images of the selected treadmill dataset are shown in Figure 4. Among this dataset, 103 subjects walk on the treadmill only once, and the other 100 subjects walked on the treadmill twice. We, therefore, use gait image sequences from the 103 subject for training, and gait image sequences from the remaining subjects for evaluation. We used the gait image sequence from the first walk of each subject as a gallery, and those from the second walk as a probe.

5.3. Experimental settings

Gait feature

We extract frequency domain feature (FDF) [18] as an appearance-based gait feature from the gait silhouette image sequence. FDF is generated by applying a discrete Fourier transform of the temporal axis to the silhouette images in a gait cycle. In this paper, we use 0, 1, and 2 times frequency elements.

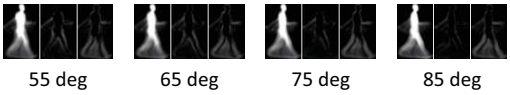


Figure 3. Example of gait features from the course dataset

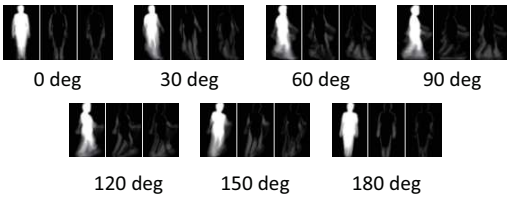


Figure 4. Example of gait features from the treadmill dataset

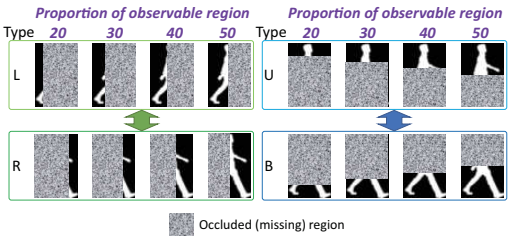


Figure 5. Observable patterns

Observable patterns

In order to realize several different observable patterns, we divided observation region in horizontal/vertical axis, and generated 16 sub-regions as shown in Figure 5. Each region is defined by location labels (type): Left (L), Right (R), Top (T), Bottom (B), and propotion value of the area against full-region: 20, 30, 40, 50 %. For example, "L50" is a 50% region of the left side, and "B20" is the 20% region from the bottom. From a PD gait feature associated with each observable pattern, we reconstruct a FD gait feature.

Matching between non-overlapped region

As for the matching between non-overlapped region, we consider all the combinations of sub-regions without common area. Consequently, gait features associated with observable patterns of label "L"are matched to those of label "R", and gait features associated with the patterns of label "U" are matched to those of label "B".

5.4. Experimental results

Reconstructed data

We show the reconstructed FD gait features from several PD gait features associated with three subjects including in the course dataset in Figures 6 and 7. In these figures, the first column shows the PD gait features with several dimension data are missing, and the second, third, and fourth column show the original and reconstructed FD gait features.In these columns, the first rows shows original FD gait features, and the other rows shows reconstructed FD gait features. Although the quality of the reconstructed FD gait features are vary depending on the ovservable pattern, we can see that a FD gait feature is roughly reconstructed from a PD gait features. We can also see that qualities of the reconstructed FD gait features associated with vertical patterns are better than those associated with horizontal patterns. This observation shows that correlations between horizontal region feature are higher than those between vertical regions feature.

Verification accuracy against course dataset

We summarize equal error rates (EERs) of target combinations of observable patterns in tables 1 and table 2. And we draw receiver operating characteristic (ROC) curves of typical combinations in Figures 8. In these figures, gait features from an observation view of 85 deg are evaluated, and observable patterns *L50* and *U50* are used for the gallery. In the cases where the gallery observable pattern of *L50* and the probe observable pattern of *R50* are used, EERs of 17.2 %, 17.6 %, 16.2 % and 16.4 % are achieved even though the gallery and probe features are extracted from the different observation regions; and in the horizontal ovservable cases, EERs of better than 30 % can be achieved from pair of gait features with 60 % of observation region are occluded/missing. In the vertical observable cases, recognion accuracy are worse than those of horizontal observable cases, however, the proposed method achieves much better recognition accuracy than chance-level accuracy even though gait features originating from fully different observation region are used for recognition.

6. Discussion

6.1. Impacts of observation view against recognition accuracy

In order to evaluate recognition accuracy in different observation views, we evaluated verification accuracy against treadmill dataset. We summarize EERs of different observation views and different observable patterns in Figures 10 and 11. In these evaluation, we used observable patterns of L50, L40, T50, and T40 for the gallery, and used oatterns of R50, R40, R30, B50, B40 and B30 for the probe. From these experimental results, we can confirm that our proposed approach can work with reasonable accuracy in all the considered observation views.

6.2. Comparison against matching with bilaterally symmetric assumption

In case of matching between vertical observable patterns, bilaterally symmetric assumption can be useful in specific observation views for recognition. Therefore, we evaluate recognition accuracy of matching under the assumption of bilaterally symmetry (MABS). For this recognition, we simply generate mirrored image sequences, and use the im-

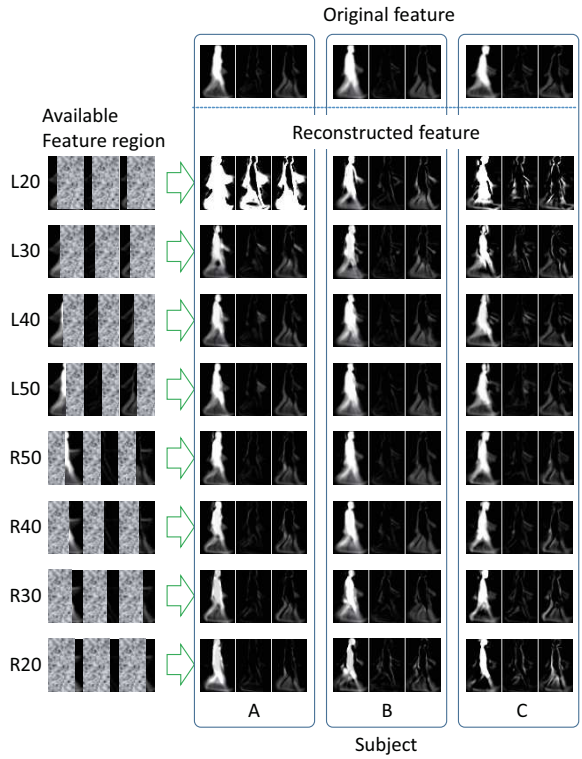


Figure 6. Reconstructed FD gait features from PD gait features with horizontal occlusion

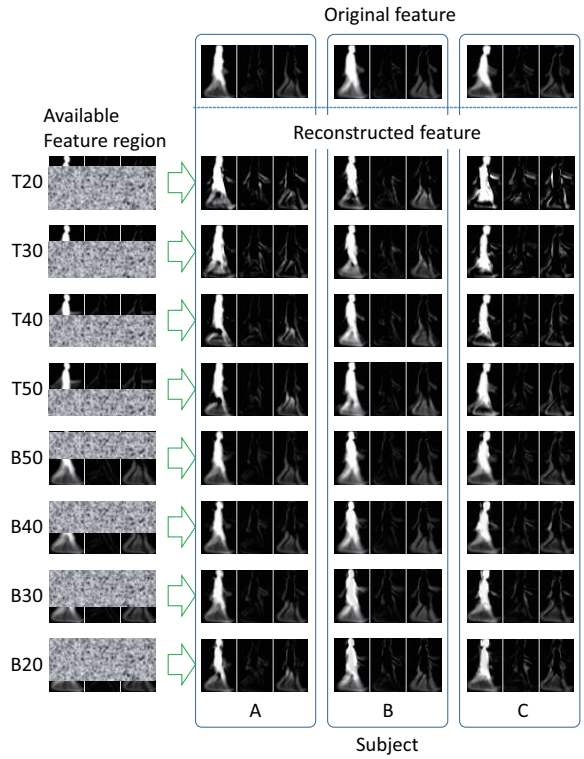


Figure 7. Reconstructed FD gait features from PD gait features with vertical occlusion

age sequence in place of an original image sequence. In this evaluation, we used treadmill dataset, and evaluate the accuracy in multiple observation views using the observable pattern L50 and R50. We summarize EERs of views 0, 30, 60, and 90 deg in Table 3, and show typical ROC cuves in view of 0 and 30 deg in Figure 9. From this table, we can observe that in the case of frontal view, matching with bilaterally symmetric assumption achieve EER of 22.0 %, and this accuracy is slightly better than that of proposed approaches. But in other observation views such as 30, 60, and so on, this assumption results in bad recognition accuracy. This experimental result shows that our approach can achieve recognition in the case where bilaterally symmetric assumption is not true.

7. Conclusion

We focus on a gait recogntion task where a pair of PD gait features without common ovservation region are given as a gallery and probe. For this task, we propose an approach to reconstruct a FD gait feature from a PD gait feature using a subspace-based method, and achieve matching of the pair through reconstruction. We generate a subspace of FD gait feature using features from independent multiple training subjects, and use the subspace for FD gait feature reconstruction. In order to evaluate efficiency of the proposed approach, we consider several observable pattern with different location and area to realize the occlusion/missing in real situations, and evaluate the approach in all the combinations of the pattern without common observation region using large population dataset. The experimental results show the proposed approach achieve reasonable recognition accuracy if gait feature with more than 40% vertical observation area are available, and even though 70% of gait feature are occluded/missing in vertical direction, the proposed approach can achieve much better recognition accuracy than chance-level accuracy. These experimental results show that the proposed approach has a potential to achieve recognition from a pair of PD features without common observation region.

A limitation of the proposed approach is that this approach may be sensitive to the localization accuracy of occluded/missing regions. We will tackle this issue in our future work. Another limitation is its low recognition accuracy compared those with FD gait features. Recognition accuracy can be further improved by generating discriminative subspace, we therefore plan to do it in our future work.

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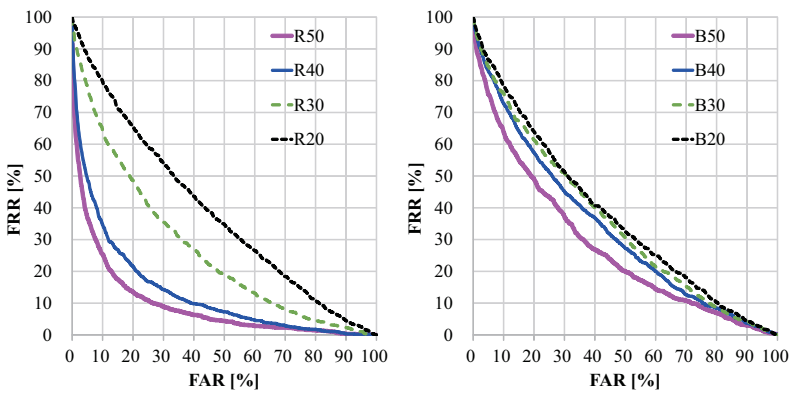

Figure 8. ROC curves; (Left) Horizontal observable patterns against course dataset with view of 85 deg (observable pattern of the gallery is *L50*), (Right) Vertical observable patterns against course dataset with view of 85 deg (obervable pattern of the gallery is *T50*)

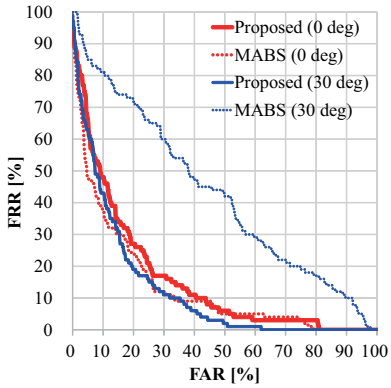

Figure 9. ROC curves of proposed approach and MABS with views of 0 and 30 deg (observable pattern of the gallery and the probe is *L50* and *R50*, respectively.)

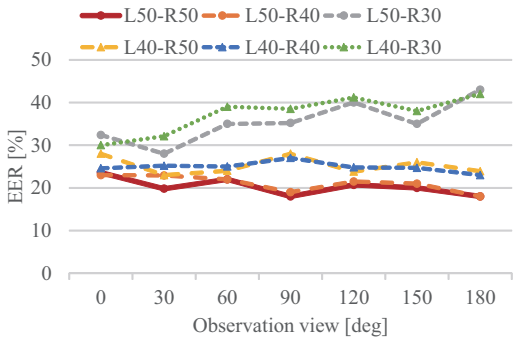

Figure 10. EERs [%] of several matchings with horizontal occulusions in different observation view on treadmill dataset

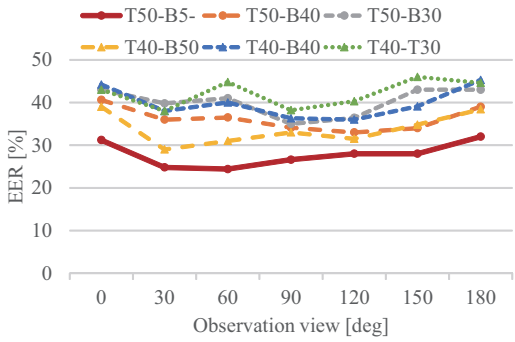

Figure 11. EERs [%] of several matchings with vertical occulusions in different observation view on treadmill dataset

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Table 1. EERs [%] of matching with horizontal observable patterns against course dataset

View	Gallery	L50	L40	L30	L20
55	R50	**17.2**	*22.4*	39.7	48.4
	R40	*21.3*	*25.8*	41.2	48.4
	R30	34.9	36.3	42.7	48.5
	R20	43.6	43.2	45.9	48.8
65	R50	**17.6**	*22.6*	39.0	47.9
	R40	*20.2*	*25.7*	38.9	48.3
	R30	33.7	35.5	42.4	47.6
	R20	43.2	43.7	45.8	47.6
75	R50	**16.2**	*22.4*	39.2	47.9
	R40	*20.3*	*25.7*	40.5	47.5
	R30	33.9	35.5	41.7	48.2
	R20	42.6	42.5	44.5	49.2
85	R50	**16.4**	*23.6*	39.3	47.5
	R40	*20.6*	*25.6*	38.9	48.0
	R30	32.9	34.6	42.2	48.2
	R20	41.8	41.4	44.4	48.7

Table 2. EERs [%] of matching with vertical observable patterns against course dataset

View	Gallery	T50	T40	T30	T20
55	B50	35.0	40.5	44.5	46.9
	B40	40.4	43.4	45.7	47.2
	B30	41.3	43.6	45.9	47.5
	B20	43.8	45.1	46.8	47.8
65	B50	34.4	39.3	42.9	46.9
	B40	38.9	41.2	44.1	47.1
	B30	40.0	42.1	45.2	47.4
	B20	42.4	43.1	45.0	46.8
75	B50	34.0	39.0	42.4	47.6
	B40	37.6	40.9	44.2	47.2
	B30	39.7	42.6	44.7	47.3
	B20	41.9	44.0	46.0	49.0
85	B50	33.2	38.2	42.9	45.9
	B40	38.1	40.7	44.6	46.5
	B30	40.0	41.4	44.7	46.9
	B20	40.6	42.9	46.3	48.1

Table 3. Accuracy comparison between the proposed approach and matching with bilaterally symmetric assumption. In this evaluation, observable pattern of the gallery and probe is L50 and R50, respectively.

View [deg]	0	30	60	90
Proposed	23.6	19.8	22.0	18.0
MABS	22.0	45.0	49.0	47.0

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