Gait Recognition Robust to Speed Transition Using Mutual Subspace Method

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Abstract. Person recognition from gait images is not robust to speed changes. To deal with this problem, generally existing methods have focused on training a model to transform gait features from various speeds into a common walking speed, and the model was trained with gait images with a variety of speeds. However in case that a subject walks with a speed which is not trained in the model, the performance gets worse. In this paper we introduce an idea that an image set-based matching approach, which omits walking speed information, has a potential to solve the problem. This is based on the assumption that speed information may not be critical information to gait recognition, since speed variations are universal phenomena. To prove the proposed idea, we apply a mutual subspace method to gait images and show the effectiveness of the proposed idea with the OU-ISIR gait speed transition database.

Keywords: Gait recognition · Speed transition · Subspace method

1 Introduction

Gait-based person recognition has received an increasing amount of attentions for monitoring and surveillance applications, thanks to the advantages that gait does not require interaction with a subject and can be obtained from a distance. Person identification methods that extract features from gait images taken by a camera have been used with good results. Existing methods using appearance-based gait features, such as gait energy image (GEI) [1], active energy image (AEI) [2] and frame difference frieze pattern (FDFP) [3], reported good performance with publicly available gait databases [4] [5] [6] [7].

However, there are several causes which make the performance of gait recognition worse, and one of them is walking speed change. The walking speed change causes variations in pitch and stride, which result in non-invariant gait features. To address this problem existing methods focused on transforming the gait features from various speeds into a common walking speed [8] or extraction of speed-invariant gait feature [9]. However, since the existing methods assumed

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that the walking speed is constant in one gait cycle, the performance of gait recognition is low in cases in which the subject accelerates or decelerates. The speed transition can happen in daily life, such as acceleration after a ticket gate at a station and deceleration before stop at red traffic signal, and the speed transition problem was firstly reported by Mansur et al. [10]. They proposed a method which synthesized constant-speed gait images based on a cylindrical manifold, which was based on a mapping function trained with an auxiliary training set including gait images under various speeds. Then experimental evaluations of the proposed method was done with a newly released database for speed transition.

As we mentioned above, most of existing methods assumed to have auxiliary training sets to train models. However, in case that a subject walks with a speed which is not included in the auxiliary training set, the performance gets worse. In this paper, we introduce a new idea as follows. Since speed variations are universal phenomena, there is a possibility that speed information does not have to be regarded as critical information to gait recognition. Based on this assumption, we obtain an idea that an image set-based matching approach can solve the gait recognition problem. To show the effectiveness of this idea, in this paper we apply a mutual subspace method (MSM) [14] [15] to gait images under speed transition. Subspace-based methods have been popularly used in face recognition, and the effectiveness of MSM is demonstrated in [16]. Advantages of the use of the image set-based matching approach to gait recognition are as follows: (i) we can directly apply gait images/gait features to the image set-based matching approach without any process such as constant-speed gait image generation [10], and (ii) we do not need any auxiliary training sets. We conducted experiments with the database which Mansur et. al used in [10], and we obtained results with higher performance compared with [10].

There are some existing gait recognition methods using subspace techniques. Liu et al. proposed a gait recognition method which was robust in subject's walking direction changes with respect to a camera [11]. In [11], GEI, which is one of popular gait features, was extracted from gait images at each walking direction. A subspace method was applied to a set of GEI from multiple walking directions, and then a weighted subspace distance was used for person identification. Connie et al. proposed a gait recognition method which formulated a gait subspaces on the Grassmann manifold [12]. This method can be applied to either gait images with walking direction changes or gait images with speed changes, and it also used GEI which was extracted from gait images at each condition (e.g. at each walking direction/speed).

These existing methods need training datasets which include gait images at multiple conditions, such as gait images under multiple walking directions/speeds. We agree that gait images at multiple walking directions are necessary for gait recognition robust to changes in walking direction. However, as we mentioned above, speed information may not be critical information to gait recognition, and thus the proposed image set-based matching approach, which ignores speed information, has a big potential to be efficient to speed changes.

The remainder of the present paper is organized as follows. Section 2 describes gait recognition using the mutual subspace method. Section 3 describes experiments performed to demonstrate the efficiency of the proposed idea using the OU-ISIR gait speed transition database, and Section 4 presents our conclusions.

2 Gait Recognition Using Mutual Subspace Method

In this section we briefly review the mutual subspace method, and then we explain the way how we apply the mutual subspace method as an image set-based matching.

2.1 Mutual Subspace Method

The Mutual Subspace method (MSM) is regarded as one of powerful image set - image set matching techniques. The MSM models template images of each class in gallery dataset and input images in probe dataset as subspaces, and images are embedded to the subspaces. The similarity measure in the MSM is calculated as a canonical angle between template subspace and input subspace.

Let us assume C class pattern recognition problem. Patterns in class c are represented in d dimensional vectors $\boldsymbol{x^c}_1, \ldots, \boldsymbol{x^c}_{n^c}$, where n^c is the number of training samples in class c. Bases of the class c template subspace are given by the following eigenequation;

$$\Gamma^c \boldsymbol{\phi}^c = \lambda^c \boldsymbol{\phi}^c, \tag{1}$$

where λ^c and $\boldsymbol{\phi}^c$ are eigenvalue and eigenvector, respectively. Γ^c is autocorrelation matrix of class c training samples,

$$\Gamma^c = \frac{1}{n^c} \sum_{i=1}^{n^c} \sum_{j=1}^{n^c} \boldsymbol{x}_i^c \boldsymbol{x}_j^{cT}. \tag{2}$$

Similarly input images $\boldsymbol{x}_1, \ldots, \boldsymbol{x}_n$ are represented by eigenvector of autocorrelation matrix $\boldsymbol{\psi}$. The similarity measure in the MSM is canonical angle between two subspaces, which are calculated as eigenvalues of following matrix [17].

$$Z^c = (\zeta_{ij})^c = \sum_{m=1}^{M} (\boldsymbol{\phi}_i^c \cdot \boldsymbol{\psi}_m)(\boldsymbol{\phi}_j^c \cdot \boldsymbol{\psi}_m), \tag{3}$$

where M is dimensionality of input subspace. Dimensionalities of training and input images are influential parameters. Roughly speaking the dimensionality is proportional to variation of training and input images. However when the dimensionality increase too large, recognition accuracies are worse, because of the increasing amount of intersections among subspaces. Generally such dimensionalities are defined by cross validation experiments. Finally, class c is chosen, in case that the maximum eigenvalue of Z^c is the highest one among all classes.

2.2 Gait Recognition Using an Image Set-Based Matching

Assume that there are gait images of a subject and silhouette images are obtained as shown in Fig. 1 (a). As a baseline method of the image set-based approach, we directly use intensity values of each silhouette image as a feature vector, and we apply the mutual subspace method to a set of feature vectors from silhouette images. Fig. 1 (b) shows examples of visualizations of principal components. We projected silhouette images to first, second, and third principal components as shown in Fig. 2. Fig. 2 (a) shows projected results of gait image to 1st-2nd principal components, and images of frame ID 1 to 37 are for the duration of the first half gait cycle (one step) and those of frame ID 38 to 74 are for the duration of the last half gait cycle (one step). Fig. 2 (b) shows projected results of gait image to 2nd-3rd principal components.

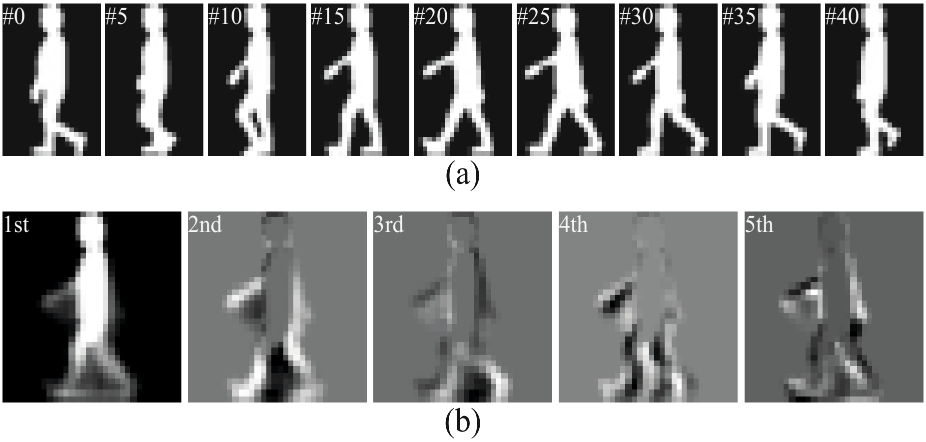

Fig. 1. (a) Examples of gait images and (b) visualization of each principal component (color information is scaled in the range from 0 to 255, for the purpose of visualization).

3 Experiments

In this section, we implement the mutual subspace method and evaluate its performance on the OU-ISIR gait speed transition database [10].

3.1 Experimental Settings

Datasets. The OU-ISIR gait speed transition dataset is the only one dataset which includes gait datasets with speed transition within an image sequence. The dataset consists of two different datasets, dataset 1 and dataset 2. In the dataset 1 the probe set consists of speed transited gait sequences recorded from 26 subjects. More specifically, each subject gradually decreased walking speed and finally stop, and the final gait period of each subject was selected as the

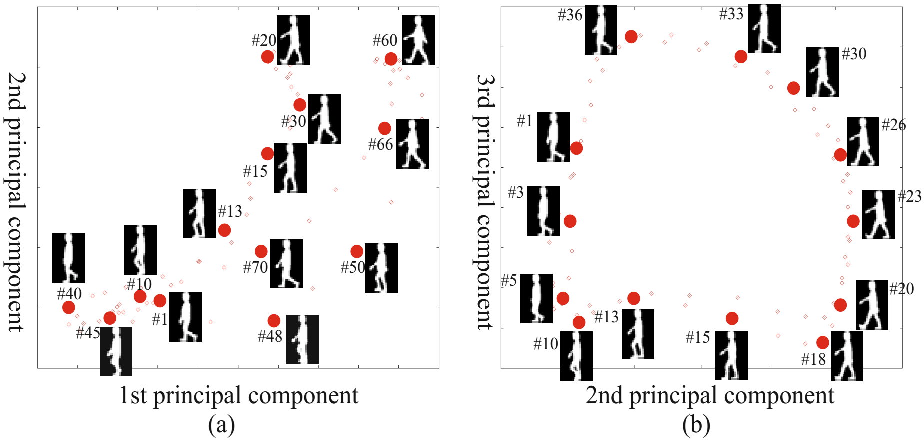

Fig. 2. Projection of gait images to 1st-2nd principal components (a) and 2nd-3rd principal components (b). Frame ID 1 to 37 are for the duration of the first half gait cycle and frame ID 38 to 74 are for the duration of the last half gait cycle.

probe dataset, which contains significant change in stride. The gallery dataset consists of gait sequences from 179 subjects, which include the 26 probe subjects, and the subjects walked at the constant speed (4 km/h) for a few seconds.

In the dataset 2 the probe set consists of 25 subjects and each subject walked twice on the treadmill under the following conditions: (i) accelerations from 1 km/h to 5 km/h and (ii) decelerations from 5 km/h to 1 km/h. For gallery dataset, there are 154 subjects, which include the 25 probe subjects, and each subject walked at a constant speed (4 km/h) for six seconds.

In addition to the two datasets we explained above, the OU-ISIR gait speed transition dataset has an auxiliary training set, which includes 24 subjects under various walking speeds (2, 3, 4, an 5 km/h). It is worth to be pointed out that in [10] the auxiliary training set was used for learning a mapping function to synthesize constant-speed gait images. However, in case that the subject walks with a speed which is not included in the auxiliary training set, the performance gets worse. On the other hand, the proposed approach does not need the auxiliary training set, and thus it can work with subjects walking with arbitrary speeds.

Evaluation Setting. We evaluated the proposed approach with the following two settings.

Setting 1: In general gait features are obtained from a set of images for the duration of one gait cycle. Thus we use gait images for the duration of one gait cycle for both probe and gallery datasets. This is the same evaluation setting of [10]. In [10], GEI was extracted from each gait sequence which includes gait images for the duration of one gait cycle. As we mentioned above, each gallery sequence of dataset 2 is for six seconds and this means the gallery sequences have images for the duration of multiple gait cycles.

Thus each gallery sequence is divided into multiple sequences so that each of them include gait images for the duration of one gait cycle. The divided gait sequences were used as gallery datasets.

Setting 2 (for dataset 2 only): We use gait images for the duration of multiple gait cycle for gallery datasets. As we explained in setting 1, there are multiple gait cycles in the gallery dataset and the proposed approach can use all of them. The use of multiple gait cycles may result in higher performance compared with the use of one gait cycle.

3.2 Evaluation

We evaluated the proposed approach with 2 scenarios: (i) a verification scenario and (ii) an identification scenario. In the verification scenario, we plotted a receiver operating characteristics (ROC) curve, which describes how true positive rate and false positive rate changes as a threshold for the similarity measure changes. In the identification scenario, we plotted a cumulative matching characteristics (CMC) curve (i.e., rank-n identification rates).

Table 1. EER, rank-1 and rank-5 identification rates for dataset 2 (acceleration).

	Mansur et. al [10]	***Proposed (setting1)***	***Proposed (setting2)***
EER [%]	8.0	7.0	1.0
Rank-1 [%]	72.0	92.0	96.0
Rank-5 [%]	96.0	92.0	100.0

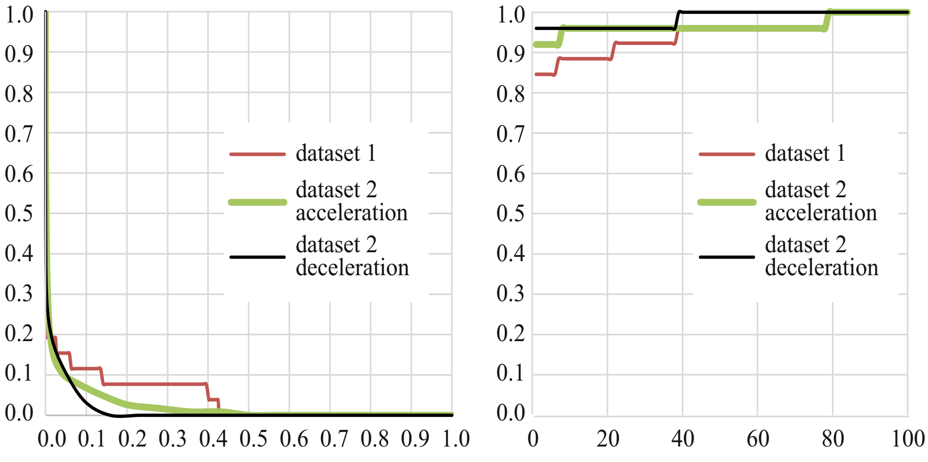

Fig. 3. ROC (left) and CMC curves (right) for dataset 1, dataset 2 (acceleration), and dataset 2 (deceleration) with the setting 1.

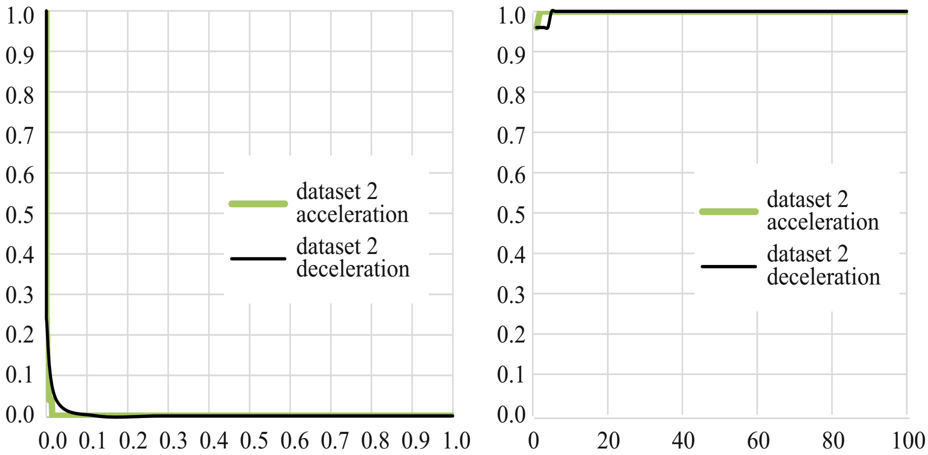

Fig. 4. ROC (left) and CMC curves (right) for dataset 2 (acceleration) and dataset 2 (deceleration) with the setting 2.

We first evaluated the proposed approach with setting 1. Figure 3 shows ROC curves and the CMC curves of the dataset 1, dataset 2 (acceleration), and dataset 2 (deceleration). These results show much higher performance compared to those of [10] (please refer to [10]). These results show higher performance than the existing method [10]. The results of dataset 1 show lower performance compared with those of dataset 2. As the reason is explained in [10], the dataset 1 is more challenging since it contains significant gait fluctuation and very short stride lengths.

Next we evaluated the proposed approach with setting 2. Figure 4 shows the ROC curves and CMC curves of the dataset 2 (acceleration) and dataset 2 (deceleration). Compared with the results of Fig. 3 at setting 1, the results of 4 at setting 2 significantly improved the performance, thanks to the use of all gait cycles in dataset.

Tables 1 and 2 show equal error rate (EER) and rank-1 and rank-5 identification rates of the proposed approach and [10]. These results show the proposed approach outperformed the existing method [10].

Table 2. EER, rank-1 and rank-5 identification rates for dataset 2 (deceleration).

	Mansur et. al [10]	***Proposed (setting1)***	***Proposed (setting2)***
EER [%]	8.0	6.0	3.0
Rank-1 [%]	84.0	96.0	96.0
Rank-5 [%]	92.0	96.0	100.0

4 Conclusions

This paper described a new idea of the use of the image set-based matching approach to solve the gait recognition problem in speed variations. The proposed concept is based on the assumption that speed information may not be critical information to gait recognition, since speed variations are universal phenomena. We implemented a baseline approach using the mutual subspace method, and experimental results with the OU-ISIR gait speed transition database showed that the proposed approach outperformed the existing method. Future work includes applying the proposed approach to different gait datasets, such as OU-ISIR treadmill dataset which includes various speeds. Moreover, we will utilize a kernel mutual subspace method [13] to see if the non-linear subspace method can work better than the linear one.

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