A Robust Speed-Invariant Gait Recognition System for Walker and Runner Identification

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Abstract

In real-world scenarios, walking/running speed is one of the most common covariate factors that can affect the performance of gait recognition systems. By assuming the effect caused by the speed changes (from the query walkers/runners) are intra-class variations that the training data (i.e., gallery) fails to capture, overfitting to the less representative training data may be the main problem that degrades the performance. In this work, we employ a general model based on random subspace method to solve this problem. More specifically, for query gaits in unknown speeds, we try to reduce the generalization errors by combining a large number of weak classifiers. We evaluate our method on two benchmark databases, i.e., Infrared CASIA-C dataset and Treadmill OU-ISIR-A dataset. For the cross-speed walking/running gait recognition experiments, nearly perfect results are achieved, significantly higher than other state-of-the-art algorithms. We also study the unknown-speed runner identification solely using the walking gait gallery, and the encouraging experimental results suggest the effectiveness of our method in such cross-mode gait recognition tasks.

1. Introduction

Gait is a behavior biometric trait, and human identification based on gait has gained considerable attentions in recent years since: 1) it can be applied at a distance without the cooperation from subjects; 2) it works well with low resolution videos, which are desirable properties in forensic applications. However, for vision-based gait recognition systems, covariate factors may affect the performance, *e.g.*, camera viewpoint, carrying condition, clothing, shoe, speed, *etc*. These factors are extensively studied by the previous literatures [4–6, 12, 13, 21, 23, 29], and great performance improvements are made against these covariate factors. Out of these covariates, walking/running speed is deemed as one of the most common factors in real-world scenarios, and this is our motivation in this paper to present a robust walking/running speed-invariant gait recognition framework.

Current walking speed-invariant gait recognition methods fall into two categories [12]: 1) transformation-based and, 2) feature-based. The first category is to transform the features from different speeds into a common one before matching. In [20], Tanawongsuwa and Bobick developed a stride normalization procedure to map gait sequences across speeds. In [22], by claiming that the effect of speed changes is similar to camera viewpoint changes to some extent, Tsuji *et al*. applied the view transformation model concept [14] to walking speed-invariant gait recognition. The second category is to employ (relatively) walking speed-invariant features. In [13], Liu and Sarkar developed a Hidden Markov Model (HMM)-based time normalized gait feature, which suggests certain insensitiveness against walking speed changes. To combat walking speed changes, the feature template Head and Torso Image (HTI) was proposed by removing the unstable leg parts (due to speed changes) from silhouettes [15]. In [16, 18], Tan *et al*. defined gait signatures through projecting the silhouette into different directions, and these signatures lead to reasonable results in cross-speed walking gait recognition experiments. In [10], an adaptive weighting technique named Weighted Binary Pattern (WBP) was employed on the rescaled Gait Energy Image (GEI [6]), and it has competitive performance in the cross-speed walking gait recognition tasks. More recently, methods based on Procrustes Shape Analysis (PSA) [11, 12] have shown great potentials in handling the large changes of walking speed. Kusakunniran *et al*. proposed Higher-order derivative Shape Configuration (HSC) to extract speed-invariant gait features from the PSA descriptors [11]. They further extended the HSC framework using a Differential Composition Model (DCM) by adaptively assigning weights to different body parts [12]. Compared with HSC, the introduction of DCM delivers significant performance improvements (against large walking

speed changes), yet this adaptive weight assigning scheme instead faces two limitations: 1) it is sensitive to unknown speed scenarios that the pre-training set fails to cover; 2) it is highly correlated to the degree of speed changes, and external information is required (*e.g.* video frame-rate) when the absolute walking speed is not available [12]. Nevertheless, these feature-based methods can achieve reasonable performance in some gait recognition scenarios under the influences of walking speed changes.

Compared with walking gait recognition, there are only a few works on running gait recognition [8, 24–27], which is claimed to be more potent (than walking gait recognition) [8, 26, 27]. However, the effect of the running speed has not been studied in these existing works. For the cross-mode gait recognition (*e.g.*, to identify an unknown runner solely using the walking gallery), Yam *et al.* [26] reported there is a unique mapping between the walking and the running gait patterns for each subject. Yet they also claimed that the generic mapping across the population does not exist, since walking/running is highly individual-related. Based on their approach [26], it is unlikely for the unknown runner identification given only the walking gait gallery, which may restrict the gait recognition applications when only the walking gait gallery is available, since criminals often escape by running away.

Our objective is not only to solve the cross-speed gait recognition in a fixed-mode manner, but also to study the effect of the cross-mode gait recognition. In this work, we present a classifier ensemble framework based on Random Subspace Method (RSM) [7] to solve the cross-speed gait recognition problems in a fixed-mode or cross-mode manner. The rationale behind is that we can deem the unstable dynamic features (under unknown walking/running speeds) are the intra-class variations the gallery data fails to capture, and in this case overfitting to the less representative training data (*i.e.*, gallery) may hamper the performance. This problem can be solved by using a general model, and in this work by combining a large number of weak classifiers which have different generalization powers, the generalization errors (caused by unknown walking/running speeds) can be reduced [7].

The rest of this paper is organized as follows: section 2 demonstrates properties of speed changes. We present the RSM framework in section 3. In section 4, we evaluate the robustness of our method on CASIA-C dataset and OU-ISIR-A dataset and section 5 concludes this paper.

2. Problem statement

GEI is a popular feature template and it is widely used in recent gait recognition algorithms due to simplicity and effectiveness [4–6, 10]. GEI is the average silhouette over one gait cycle, which encodes a number of binary silhouettes into a grayscale one, and it has two main advantages: 1) the
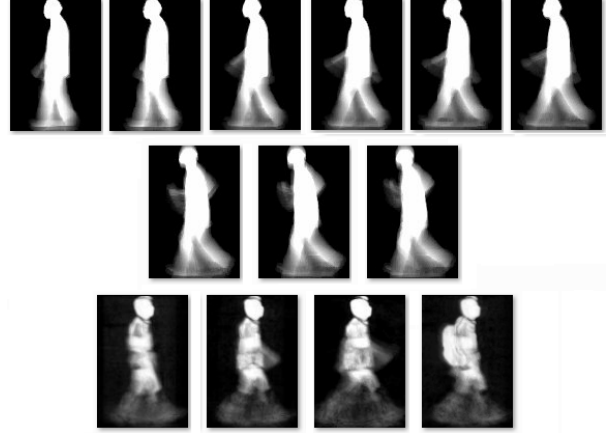

Figure 1. GEI samples from the OU-ISIR-A and CASIA-C datasets. Top row: GEIs from OU-ISIR-A dataset with walking speed ranges from 2km/h to 7km/h (from left to right with 1km/h interval); middle row: GEI samples from OU-ISIR-A dataset with running speed ranges from 8km/h to 10 km/h (from left to right with 1km/h interval); bottom row: from CASIA-C dataset, the GEIs with slow/normal/fast walking speed, and a GEI sample with a bag (from left to right).

segmentation noises can be smoothed; 2) the computational cost can be significantly reduced [6]. Several GEI samples from the OU-ISIR-A [22] and CASIA-C [15] datasets are illustrated in Fig .1.

In real-world scenarios, speed is one of the most common covariate factors. In recent years several methods were proposed to solve the cross-speed (walking) gait recognition, yet most of them are not applicable when the speed changes are large. The only work DCM [12] that can solve the problem of large walking speed changes faces two main limitations, *i.e.*, lack of generalization to unseen speeds, and the requirement of external information [12]. To build a robust system with higher performance and less limitations, in this section we summarize the characteristics of speed changes by using the GEI examples from OU-ISIR-A dataset and CASIA-C dataset. Fig. 1 illustrates the effect on GEIs with respect to different speeds, from which we can observe:

1. For the fixed-mode gait recognition (walking only or running only), the static parts are relatively independent of walking/running speed changes.
2. For the cross-mode gait recognition, from the visual effect, there still may be some similar patterns between fast walking and running, *e.g.*, head, neck, and hip.

These observations are consistent with the claims in [22], *i.e.*, although the dynamic gait features can be significantly affected by the speed changes, the static features can be relatively stable. In this case, the covariate speed has the similar properties with some covariates like carrying condition or certain types of clothing, which only affect part of the

human silhouette. It indicates the possibility of using certain carrying-condition-invariant or clothing-invariant gait recognition concept to solve the problems caused by different walking/running speeds.

RSM is an effective framework to enhance the generalization accuracy [7]. Each base classifier is generated by randomly sampling on the original feature set, before the final classifier combination, *e.g.*, through majority voting. The RSM concept was recently introduced to gait recognition area by Guan *et al.* [4] and the experimental results in [3–5] suggest that the RSM framework is robust to a broad range of covariates like shoe, (small changes in) camera viewpoint, carrying condition [4], clothing [5], and covariates caused by the extremely low frame-rate videos (*e.g.*,1fps) [3]. In this work, by assuming the covariate speed may have a similar effect of carrying condition, or certain type of clothing that only deforms part of the silhouette, the RSM concept is employed in this work and our main contributions are:

1. Since the covariate speed only affects part of human silhouette, we claim it has some similar properties with carrying condition or certain types of clothing, and thus borrow the corresponding RSM concept to address this issue. For the fixed-mode gait recognition tasks, the nearly perfect experimental results on the CASIA-C and OU-ISIR-A datasets conform to our claim.

2. We also study the cross-mode gait recognition. Based on our RSM framework, it is possible to identify a runner solely using a walking gait gallery, which is a significantly contribution to the real-world surveillance applications.

3. Speed-invariant gait recognition system

Gabor-filtered GEI (referred to as Gabor-GEI) has been demonstrated to be an effective feature template for human gait recognition [21, 23]. Given a GEI sample, Gabor functions from five scales and eight orientations are employed to generate the Gabor-GEI feature template. For computational efficiency, similar to [23], we use the subsampled Gabor-GEI in this paper. More details about Gabor-GEI can be found at [21]. In the rest of this section, we introduce the RSM framework used for the speed-invariant gait recognition system.

3.1. Feature extraction using RSM

Due to high dimensionality of Gabor-GEI, we use the two-dimensional Principle Component Analysis (2DPCA) [28] to decorrelate the feature space (in column direction). The reasons of using 2DPCA, instead of conventional PCA are two-fold: 1) 2DPCA has a much lower time complexity [28]; 2) the input feature of 2DPCA is based on matrix, which may preserve the data structure to some extent, and

empirical results shows that 2DPCA normally outperforms the conventional PCA in face recognition [28] and gait recognition [29].

Given n Gabor-GEI samples $I_i (i = 1, \ldots, n)$ in the gallery, the scatter matrix S can be estimated by using:

$$S = \frac{1}{n} \sum_{i=1}^{n} (I_i - \mu)^T (I_i - \mu), \qquad (1)$$

where $\mu = \frac{1}{n} \sum_{i=1}^{n} I_i$. The eigenvectors of S can be computed, and the eigenvectors with zero eigenvalues are removed, while the rest are retained as candidates to construct the random subspaces. A total number of L random spaces are generated, and the corresponding transition matrices $R^1, \ldots, R^L$ can be formed by randomly selecting N eigenvectors from the eigenvector candidates. Each Gabor-GEI can be projected into L subspaces, and the coefficients for a certain subspace are the feature descriptors corresponding to certain areas of whole Gabor-GEI, and such areas (*i.e.*, feature dimensions) are less sensitive to other affected areas (caused by the covariates like speed) in this subspace.

For each subspace, to achieve the optimal class separability, two-dimensional Linear Discriminant Analysis (2DLDA) is adopted (in row direction) to project the coefficients of the gallery samples into the canonical space. For the kth subspace, there is a transition matrix W maximizing the ratio of the between-class scatter matrix S_b^k to the within-class scatter matrix S_w^k, *i.e.*,

$$\underset{W}{\operatorname{argmax}} \operatorname{trace}((W^T S_w^k W)^{-1} (W^T S_b^k W)). \qquad (2)$$

For the kth subspace, let W^k and R^k be the canonical space transition matrix and eigenspace transition matrix, then the feature extraction can be performed for the L subspaces given R^k and W^k, $(k = 1, \ldots, L)$. For example, a gait sequence with n_p Gabor-GEIs $I_t (t = 1, \ldots, n_p)$ can be projected into n_p features matrices Y_t^k:

$$Y_t^k = W^k (I_t R^k) \qquad (t = 1, \ldots, n_p). \qquad (3)$$

The new feature descriptors for each gait sequence can be extracted using (3), before the classification is performed in the kth subspace.

3.2. Classification

Assume there are c classes of gait sequences in the gallery, each with $n_j (j = 1, \ldots, c)$ features matrices. For the kth subspace, each class can be represented by its centroid $G_j^k (j = 1, \ldots, c)$. Similar to the set-to-set distance defined in [6], for a probe gait sequence P^k with n_p feature matrices $Y_t^k (t = 1, \ldots, n_p)$, the dissimilarity between P^k and a certain class G_j^k can be measured by the average of

-	# subject	*fn*	*fs*	*fq*	*fb*
Gait Curves [2]	153	91	65	70	26
NDDP [19]	153	98	84	84	16
ODP [16]	153	98	80	80	16
WPSR [1]	153	93	83	85	20
HTI [15]	46	94	85	88	51
HDP [18]	153	98	84	88	36
AEI [29]	153	89	89	90	80
Pseudoshape [17]	153	98	91	94	25
WBP [10]	153	99	86	90	81
HSC [11]	50	98	92	92	-
DCM [12]	120	97	92	93	-
without RSM	153	100	97	97	71
RSM (our method)	153	**100**±0.00	**99.7**±0.24	**99.6**±0.14	**96.2**±0.86

Table 1. Algorithms comparison in terms of CCR(%) on the CASIA-C dataset. *fn*, *fs*, and *fq* denote the speed types of the three probe sets (*i.e.*, normal, slow, and fast); *fb* is the bag-carrying probe set; the speed type of the gallery set is *fn* (*i.e.*, normal).

the distances between each feature matrix and G_j^k, *i.e.*,

$$D(P^k, G_j^k) = \frac{1}{n_p} \sum_{t=1}^{n_p} \|Y_t^k - G_j^k\|, \qquad (4)$$

where $D(\cdot)$ denotes the set-to-set distance for two gait sequences. The gait sequence P^k is then labeled the same as G_m^k if

$$D(P^k, G_m^k) = \min_{j=1}^c D(P^k, G_j^k). \qquad (5)$$

As there are L subspaces/classifiers, the final classification is achieved by majority voting from the L labeling results.

4. Experiments

To evaluate the robustness of our method, two benchmark datasets are used in our experiments, *i.e.*, CASIA-C [15] and OU-ISIR-A [22]. The CASIA-C dataset was collected at night environment using infrared cameras, with a large number of subjects (153) in three different speeds (*i.e.*, slow/normal/fast walking) and a carrying condition. The OU-ISIR-A dataset was collected on a treadmill with a large range of speeds (from 2km/h to10km/h) in terms of walking or running for 34 subjects. In this section, three experiments are designed as follows:

1. Cross-speed walker identification on the CASIA-C dataset.
2. In the fixed-mode manner, cross-speed walker/runner identification on the OU-ISIR-A dataset.
3. In the cross-mode manner, cross-speed runner identification (solely using walking gallery) on the OU-ISIR-A dataset.

There are two main parameters in our method, *i.e.*, random subspace/base classifier number (L) and random subspace dimension (N). In [7], it was claim that the accuracy does not decrease with respect to the increasing number of

classifiers, and we empirically set $L = 1000$. For the random subspace dimension N, following [5], we set $N = 5$. In this paper, we use the Correct Classification Rate (CCR) to evaluate the performance. Considering the random nature of our method, we run each experiments 10 times, with the mean CCR (with the standard deviation) reported as the result. To demonstrate the effectiveness of RSM, we also implement conventional Gabor-GEI+2DPCA+2DLDA (referred to as *without RSM*) for comparison in the three experiments. Specifically, we set 2DPCA preserves 99% of the variance, while 2DLDA same as the proposed one.

4.1. Cross-speed walker identification on the CASIA-C dataset

The CASIA-C dataset contains three different walking speeds and one carrying condition, *i.e.*, slow walking (*fs*), normal walking (*fn*), fast walking (*fq*), and carrying a bag (*fb*). All the 153 subjects are used in our experiments. For each subject, there are two sequences of *fs*, four sequences of *fn*, two sequences of *fq*, and two sequences of *fb*. We use three *fn* sequences as the gallery set, and the rest sequences are used as the probes. This is the dataset can be used to evaluate the algorithms against the (small) walking speed changes and carrying condition. We compare our method with other classical methods, *i.e.*, Gait Curves [2], Normalized Dual-Diagonal Projections (NDDP) [19], Orthogonal Diagonal Projections (ODP) [16], Wavelet Packet Silhouette Representation (WPSR) [1], HTI [15], Horizontal Direction Projection (HDP) [18], Active Energy Image (AEI) [29], Pseudoshape [17], WBP [10], HSC [11], D-CM [12], and the method *without RSM*. The corresponding experimental results in terms of CCR are reported in Table 1, and the CCRs of our method are nearly 100% in all the three tasks with probe sets in different speeds (*i.e.*, *fn*, *fs*, and *fq*), significantly higher than other state-of-the-art algorithms.
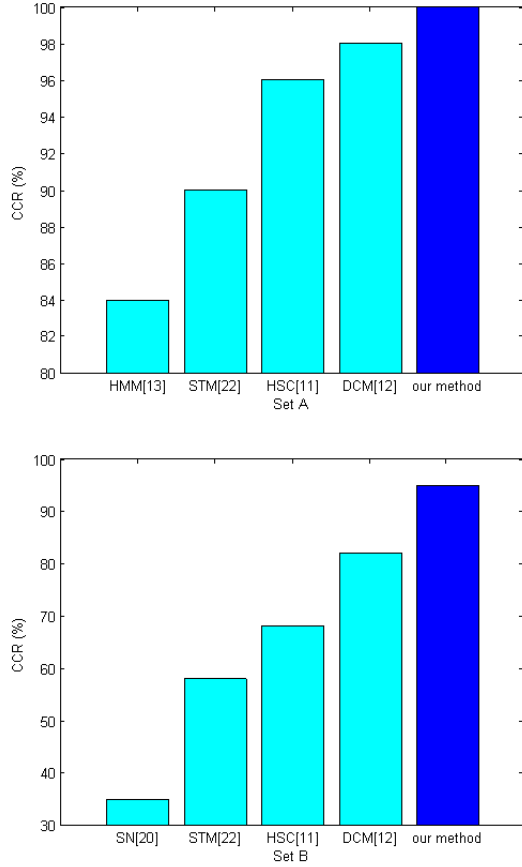
Figure 2. Algorithms comparison in terms of CCR (%) in the two pre-designed experiments [22] with small (*i.e.*, Set A) and large (*i.e.*, Set B) speed changes.

P\G	2km/h	3km/h	4km/h	5km/h	6km/h	7km/h
2km/h	100	100	88	80	80	84
3km/h	100	100	100	88	84	80
4km/h	88	96	100	92	92	84
5km/h	**96**	96	96	96	100	96
6km/h	84	84	96	96	100	100
7km/h	84	88	84	96	100	100

Table 2. The CCR(%) distribution of DCM [12] in the cross-speed walking gait recognition. G/P denotes Gallery/Probe.

P\G	2km/h	3km/h	4km/h	5km/h	6km/h	7km/h
2km/h	100	96	96	96	**100**	84
3km/h	100	100	96	100	100	84
4km/h	100	100	100	100	100	84
5km/h	92	96	100	100	100	96
6km/h	92	92	96	100	100	100
7km/h	88	84	72	92	100	100

Table 3. The CCR(%) distribution of the method *without RSM* in the cross-speed walking gait recognition. G/P denotes Gallery/Probe.

However, in this dataset, since the walking speed changes are relatively small, the appearance of the silhouettes is less affected (see Fig.1). In this case, most of the algorithms can achieve competitive performance. For robustness evaluation, we also conduct experiments on probe *fb*, which involves relatively large intra-class variations. In this case, the performance of most algorithms decrease significantly. Our method consistently yields high performance, with a mean CCR of 96.2%, significantly higher than other methods and the one without using the RSM framework. These experimental results suggest the robustness and effectiveness of the RSM framework, which can nearly perfectly solve this gait recognition problem under the influences of (small) walking speed changes.

4.2. Cross-speed walker/runner identification in the fixed-mode on the OU-ISIR-A dataset

Compared with the CASIA-C dataset, the OU-ISIR-A dataset contains less number of subjects but broader range of walking/running speeds. There are six different walking speeds from 2km/h to 7km/h with 1km/h interval, and three different running speeds from 8km/h to 10km/h with 1km/h interval.

For cross-speed walking gait recognition, Tsuji *et al.* designed two gait recognition tasks [22] for algorithms evaluation given small and large walking speed changes. In both scenarios, we compare our results with other classical methods, *i.e.*, HMM-based time normalized (HMM) [13], Stride Normalization (SN) [20], Speed Transformation Model (STM) [22], HSC [11], and DCM [12]. Note that the results of methods HMM and SN are based on 25 and 24 subjects respectively from other datasets, while STM, HSC, DCM and our method are based on 25 subjects on the OU-ISIR-A dataset. Equivalent scenarios of speed changes are also selected for fair comparison. For small speed changes (*i.e.*, Set A), the result of HMM is based on the speed change between 3.3km/h and 4.5km/h while results of STM, HSC, DCM, and our method are based on the speed change between 3km/h and 4km/h. For large speed changes (*i.e.*, Set B), the result of SN is based on the speed change between 2.5km/h and 5.8km/h while the results of STM, HSC, DCM, and our method are based on the speed change between 2km/h and 6km/h. The results are reported in Fig. 2, and our method significantly outperforms the second best method DCM in both tasks.

For robustness evaluation, we also compare our method with DCM and the method *without RSM* in all the cross-speed matching scenarios, and the corresponding results are

P \ G	2km/h	3km/h	4km/h	5km/h	6km/h	7km/h
2km/h	**100**±0.00	**100**±0.00	**100**±0.00	**97.6**±2.07	97.6±2.80	**94**±2.83
3km/h	**100**±0.00	**100**±0.00	**100**±0.00	**100**±0.00	**100**±0.00	**98.4**±2.07
4km/h	**100**±0.00	**100**±0.00	**100**±0.00	**100**±0.00	**100**±0.00	**90.4**±2.80
5km/h	92.8±1.69	**96.4**±1.26	**100**±0.00	**100**±0.00	**100**±0.00	**96**±0.00
6km/h	**92**±0.00	**94.4**±2.07	**100**±0.00	**100**±0.00	**100**±0.00	**100**±0.00
7km/h	**92**±0.00	**94**±2.11	**94.8**±1.93	**100**±0.00	**100**±0.00	**100**±0.00

Table 4. The CCR(%) distribution of RSM (our method) in the cross-speed walking gait recognition. G/P denotes Gallery/Probe.

P \ G	8km/h	9km/h	10km/h
8km/h	100	96	96
9km/h	96	100	100
10km/h	96	100	100

Table 5. The CCR(%) distribution of the method *without RSM* in the cross-speed running gait recognition. G/P denotes Gallery/Probe.

P \ G	8km/h	9km/h	10km/h
8km/h	**100**±0.00	**96**±0.00	**100**±0.00
9km/h	**97.2**±1.93	**100**±0.00	**100**±0.00
10km/h	**99.2**±1.69	**100**±0.00	**100**±0.00

Table 6. The CCR(%) distribution of RSM (our method) in the cross-speed running gait recognition. G/P denotes Gallery/Probe.

-	walking	running
average	98.07	99.16

Table 7. The general average CCR(%) of RSM (our method) in the cross-speed walking (Table 4) and running (Table 6) gait recognition.

reported in Table 2-4. Out of the total 36 tasks including different levels of walking speed changes, the performance of our method is generally better than the other two, especially when speed changes are large (*e.g.*, between 2km/h and 7km/h). It is also worth mentioning that our method does not have the two limitations of DCM, *i.e.*, lack of generalization to unseen speeds, and the requirement of external information. Generally, our method delivers significant improvements in terms of both performance and generalization, which indicates the effectiveness of the RSM concept in solving the cross-speed walking gait recognition tasks.

Based on the 25 subjects, we also apply our method and the one *without RSM* to the cross-speed running gait recognition tasks. The recognition accuracies for these two methods are illustrated in Table 5-6. Both methods can achieve high performance, since in this dataset the running speed range is 8km/h-10km/h and the corresponding intra-class variations are small (see Fig. 1). From the experimental results on CASIA-C and fixed-mode OU-ISIR-A datasets, we can see that when the intra-class variations are relatively small, although method *without RSM* is generally less effective than our method, it can still yield very competitive performance.

Table 7 lists the average CCRs of our method in the fixed-mode gait recognition tasks, *i.e.*, 98.07% average CCR (corresponding to Table 4) for walker identification, and 99.16% average CCR (corresponding to Table 6) for runner identification. The nearly perfect performance suggests the effectiveness of the RSM framework in speed-invariant gait recognition. It is also worth noting that the average identification rate of runner is slightly higher than walker, and this observation is consistent with claims in [8, 26, 27]. In the context of fixed-mode gait recognition, the explanations of this phenomenon are two-fold: 1) the running subjects may have smaller inter-class similarities than the walking subjects [26, 27]; 2) the running subjects may also have smaller intra-class variations which contribute positively to recognition, since normally in real-world scenarios (at least in this dataset), running tends to have smaller speed range (*e.g.*, 8km/h-10km/h) than walking (*e.g.*, 2km/h-7km/h). Nevertheless, for the fixed-mode gait recognition, our method can achieve nearly perfect performance.

4.3. Cross-mode runner identification on the OU-ISIR-A dataset

In real-world scenarios, it is also desirable for the cross-mode gait recognition, especially for the runner identification, when only the walking gallery is available. Although Yam *et al*. [26] claimed that cross-mode gait recognition is unlikely due to lack of generic mapping between walking and running across the population, encouraging identification rates are still achieved by our method on the 25 subjects in the OU-ISIR-A dataset, as shown in Fig. 4. To evaluate the effectiveness of RSM, we also conduct the cross-mode gait recognition experiments using method *without RSM* and the corresponding performance are reported in Fig. 3. From which we can see that the general performance of method *without RSM* is significantly worse than the one based on the RSM framework. Although experi-
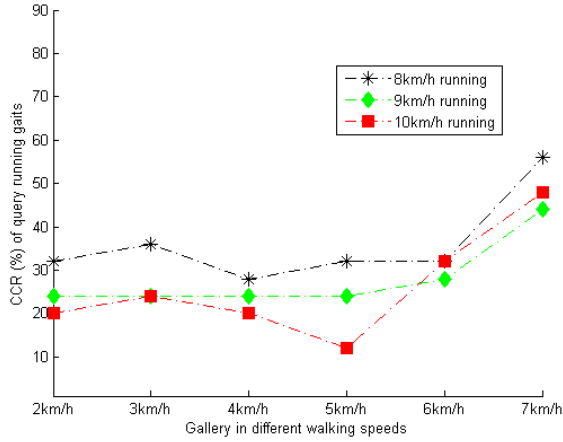
Figure 3. The CCR (%) distribution of the method *without RSM* in cross-mode gait recognition, *i.e.*, to identify unknown runners given the gallery of walkers.
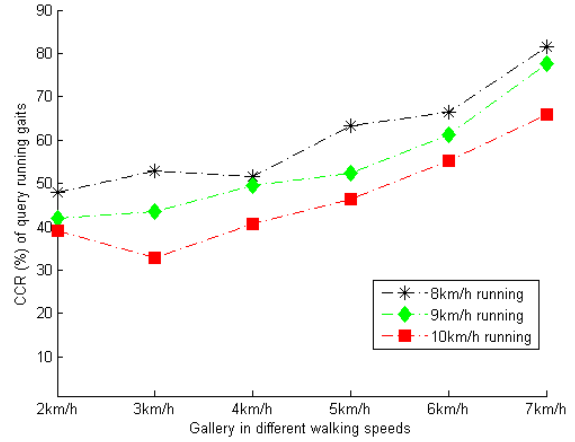

Figure 4. The mean CCR (%) distribution of RSM (our method) in cross-mode gait recognition, *i.e.*, to identify unknown runners given the gallery of walkers.

mental results suggest when the intra-class variations (of the probes) are small, method *without RSM* can yield reasonable performance, its performance drops significantly when the intra-class variations are large. In this case, the training data "dynamically" become less representative when the intra-class variations become large. To combat overfitting to the less representative training data, the RSM framework combines a large number of weak classifiers and it achieves encouraging performance in these challenging cross-mode gait recognition tasks.

Based on the RSM framework, for the query running gaits in different speeds, matching to the gallery sets with fast walkers (*e.g.*, in 7km/h) tends to deliver better performance. Generally, for cross-mode gait recognition, the identification rate is higher when the speed difference is smaller, since there may be more effective features in the common space between (faster) walking and (slower) running. For example, for runner identification in 8km/h, the mean identification rate using a 7km/h walking gallery is 81.6%, and it is significantly higher than using a 3km/h walking gallery with a mean CCR of 52.8%, as shown in Fig. 4. For real-world applications, the results in Fig. 4 suggest that when the running gallery is unavailable, a faster walking gallery is more suitable for runner identification.

4.4. Discussion

For the fixed-mode gait recognition, our RSM framework can perfectly solve the speed changes problem. However, for the challenging cross-mode gait recognition, when the speed differences (between running probe and walking gallery) are large, the performance of our method is unsatisfactory. In this case, the intra-class variations for a subject become extremely large when we deem running and

walking are the same modality, and it is an open question to achieve satisfactory performance under extremely large intra-class variations for unimodal systems [9]. Nevertheless, in real-world applications, it is possible to reduce such speed differences by using the faster walking gait gallery, *e.g.*, with a walking speed of 7km/h, which has nearly perfect performance in walker identification and competitive performance in runner identification.

5. Conclusions

In this paper, we present a classifier ensemble method based on RSM concept to solve the cross-speed gait recognition problems in a fixed-mode or cross-mode manner. For fixed-mode gait recognition, compared with the previous cross-speed walker identification algorithms, our method delivers a significant improvement in terms of performance and generalization. Our method also achieves nearly perfect accuracies in the cross-speed runner identification. Different from fixed-mode, the cross-mode gait recognition is challenging due to the significant differences between walking and running. We study the cross-speed runner identification solely using the walking gallery. The experimental results suggest that a faster walking gallery (*e.g.* 7km/h) is suitable for both the cross-speed runner identification and the cross-speed walker identification. In the further we will investigate how to adaptively prune the redundant weak classifiers to further boost the performance in the challenging cross-mode gait recognition tasks.

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