Gait Recognition across Various Walking Speeds using Higher-order Shape Configuration based on Differential Composition Model

Worapan Kusakunniran, Member, IEEE, Qiang Wu, Member, IEEE, Jian Zhang, Senior Member, IEEE, and Hongdong Li, Member, IEEE

Abstract—Gait has been known as an effective biometric feature to identify a person at a distance. However, variation of walking speeds may lead to significant changes to human walking patterns. It causes many difficulties for gait recognition. A comprehensive analysis has been carried out in this paper to identify such effects. Based on the analysis, Procrustes Shape Analysis (PSA) scheme is adopted for gait signature description and relevant similarity measurement. To tackle the challenges raised by speed change, this paper proposes Higher-order Shape Configuration (HSC) for gait shape description, which deliberately conserve discriminative information in the gait signatures and is still able to tolerate the varying walking speed. Instead of simply measuring the similarity between two gait by treating them as two unified objects, a Differential Composition Model (DCM) is constructed. The DCM differentiates the different effects caused by walking speed changes on various human body parts. In the meantime, it also well balances the different discriminabilities of each body part on the overall gait similarity measurements. In this model, Fisher discriminant ratio is adopted to calculate weights for each body part. Comprehensive experiments based on widely adopted gait databases demonstrate that our proposed method is efficient for cross-speed gait recognition and outperforms other state-of-the-art methods.

Index Terms—Gait recognition, human identification, walking speed variation, procrustes shape analysis, higher-order derivative, differential composition model

I. INTRODUCTION

The study of human gait is innate to human interest and pervades many fields including biometrics, clinical analysis, computer animation and robotics [1]. From a surveillance perspective, gait recognition is an attractive modality because it may be performed surreptitiously and at a distance in an unconstrained environment, which is not possible with other biometric techniques such as face recognition.

In a real-world environment, there are various factors significantly affecting human gait including dressing different clothes, walking while carrying different objects, walking on different surfaces, walking with different shoes, walking under variable speeds and walking being observed from arbitrary views [2]. Among these factors, speed change has been regarded as one of most commonly seen challenging factors. The change of walking speed can significantly change the gait shape description. For example, the reduction of stride length can be caused by slowing down the walking speed [3]. In fact, speed change also affects other body parts including arm, hip, knee and ankle. Moreover, different people may react differently to the change of walking speed because of age, gender, individual body structure, etc., which makes the situation more complicated. In this paper, we will focus on effects of speed change on gait recognition. A new solution is proposed to deal with the challenges raised.

In recent years, several methods [4][5][6][7][8][9] have been proposed for cross-speed gait recognition from different perspectives. Based on their published results, it is observed that they can sort out the problem to some extent, particularly, when the speed changes are small. However, it is still challenging to them when the speed changes are significant. The proposed method will tackle this problem as one of the core research objectives in this paper. To demonstrate the performance improvements by the proposed method, the relevant comparisons have been conducted in this study.

In this paper, Procrustes Shape Analysis (PSA) is adopted for gait recognition because it has been proved as a special shape description which can tolerate the change of orientation of an object [10][11][12]. It can help to conduct shape registrations, in particular, to build up gait features. Somehow, PSA can deal with the changes of gait pose and body size throughout the walking cycle although its original scheme is still constrained to cross-speed gait recognition. The main challenges raised in the current PSA framework are: 1) the existing shape configuration method is based on the static shape description known as Centroid Shape Configuration (CSC). It may not efficiently describe dynamic gait information particularly with the variation of walking speed; 2) the existing
similarity measurement is carried out between two shapes as a whole without differentiating significances between different segments of the shape. It will cause problems if contributions of the different shape segments are not the same.

In order to adopt the PSA and to adapt it for our purpose, we carry out a complete analysis on details of effects caused by various walking speed changes on gait recognition. Moreover, we also demonstrate the various effects on different body parts. Such kind of analysis provides helpful references for future work in this area. According to the analysis, this paper proposes a new Higher-order Shape Configuration (HSC) which well extends traditional CSC to handle the gait shape change caused by the walking speed change. In the meantime, we introduce Differential Composition Model (DCM) which reflects different effects caused by walking speed change on the different body parts. DCM further improves the discriminability of the gait feature based on HSC. Using the proposed method, we have achieved much better performance when compared with the benchmark methods, particularly, when the change of walking speed is remarkable.

The rest of this paper is organized as follows. Related work is reviewed in Section II. Background knowledge of PSA is briefly and the framework of PSA for gait recognition is introduced in Section III. Effects of walking speed change on the PSA-based gait recognition are comprehensively analyzed in Section IV followed by the framework of cross-speed gait recognition based on the revised PSA in Section V. Experimental results are shown in Section VI and conclusions are drawn in Section VII.

II. RELATED WORK

Current works on cross-speed gait recognition fall into two categories: 1) identifying speed-invariant gait features; 2) transforming gait features under various walking speeds onto a common walking speed. Some interesting works in the first category are briefed below. Liu et al. [4] developed a HMM-based time-normalized gait feature. Similarity between two normalized gait features was measured using a sum of shape distances corresponding to gait stances in LDA space. The normalized gait dynamics, which is based on a population based generic walking model, has shown its effectiveness to compensate the hard covariates caused by the walking speed change. Tan et al. [5] used eight kinds of projective features to describe human gait and PCA was applied for reduction of raw gait feature dimension. Mahalanobis distance was used to measure gait similarity. Projective normalization was used to improve the robustness of projective frieze patterns against speed variation. Kusakunniran et al. [6] applied partial LBP concept on Gait Energy Image (GEI) and proposed adaptive weighting techniques to discriminate significant bits of partial LBP in gait features. However, a typical limitation of existing methods in this category is that the performance is satisfying only to the small change of walking speed. They cannot well handle the larger change of walking speed.

The essential of the second category is to learn mapping relationship between gait features under different walking speeds. It transforms gait features using generic speed transformation model. Therefore, gait similarity measurement can be carried out under a common walking speed. Tanawongsuwan et al. [7] applied knowledge learned from the stride length analysis [8]. The linear relationship between stride length and walking speed at the population/global level was used to normalize gaits across different speeds. Tsuji et al. [9] proposed a factorization-based speed transformation model using SVD to transform dynamic gait features from one speed to another.

The challenges to the second category are: 1) they are not applicable to unknown walking speed which is not covered by supervised training for learning the transform relationship; 2) they require model fitting and/or body part tracking; 3) they cannot achieve good performance for the case of large speed changes; although this category of methods can efficiently address cross-view gait recognition [13][14][15]. In our study, we find that walking speed change is a kind of internal factor caused by a walking person, which will present different efforts on different persons. We cannot treat it in the same way as in the case of view change which is a kind of external factor caused by shooting environments. Consequently, seeking a generic solution in the second category to cover any walking person becomes very difficult. Therefore, this study chooses to seek a solution in the first category.

In this paper, we propose a novel PSA-based method for speed-invariant gait recognition. It has the following significant points which are different from the traditional PSA framework [10][11][12][16][17][18][19][20][21]. First, prior knowledge of human shape structure is embedded in the re-sampling process to more precisely address the point correspondences. Three key positions of human body (i.e. head and feet) are automatically detected and adopted as the reference points for the re-sampling. This assumption is reasonable for gait shape analysis since they are visible normally for standing posture under any speed and view.

Second, to describe gait shape, we propose HSC to replace traditional CSC in PSA scheme which is not efficient to handle speed change problem. HSC describes gait shape using higher-order information of the shape boundary such as tangent and curvature. Such information is consistent to describe gait shape regardless of global appearance change caused by speed change. We apply the Forward Divided Difference approximation for calculating higher-order derivatives [22].

Third, in order to handle the large speed change, we propose DCM which decomposes gait shape boundary into segments. Such segmentation reflects various efforts caused by speed changes on different body parts. Each segment is assigned a weight to differentiate each other. Fisher discriminant is used to calculate the weight values. Then, final similarity measurement between any two gaits is a weighted sum of distance of each corresponding pair of boundary segments.

III. THE PSA-BASED GAIT RECOGNITION

PSA [10][20][21] is a process of performing shape-preserving Euclidean transformation on a set of shapes. It is able to achieve similarity measurement between two sets of shapes by properly superimposing. This property is useful for gait recognition. During superimposition, the positions and the
The core idea of PSA is to find the best way to superimpose one shape onto another shape, by minimizing Euclidean distance of their shape configurations \((Z_1\) and \(Z_2\)) [21] as:
\[
\min \| Z_1 - \alpha_1k - \beta Z_2 \|^2, \quad \alpha, \beta = \| e^{i\angle} \| (1)
\]
where \(\alpha_1k\) represents translation, \(\beta\) and \(\angle\) represent scaling and rotation of \(Z_2\) respectively.

To simplify the discussion, we consider an easy case where two shapes in Eq. (1) have been registered at their centroids. That is, translation can be ignored. The solution of Eq. (1) can be obtained [21] as:
\[
\alpha = 0, \quad \beta = \frac{|Z_1^* Z_2|^2}{\|Z_2\|^2} (2)
\]
where the superscript \(\ast\) represents a complex conjugation transpose. The \(\beta\) presents the similarity between two shape configurations. Therefore, in the framework of PSA, Procrustes Distance (PD) \(d_P(Z_1, Z_2)\) is used to quantify the dissimilarity of two shape configurations as [20][21]:
\[
d_P(Z_1, Z_2) = 1 - \min_{\alpha, \beta} \| Z_1 - \beta Z_2 \|^2 \quad (3)
\]
\[
= 1 - \frac{|Z_1^* Z_2|^2}{\|Z_1\|^2 \|Z_2\|^2}
\]
where the \(\beta\) has been normalized as a value between 0 and 1.

In this paper, PSA is employed for gait recognition. According to our research, PSA is helpful for analyzing gait shapes which may be inconsistent due to several factors such as: 1) various poses and sizes throughout a walking cycle and/or a camera’s viewpoint; 2) inconsistency of individual walking pattern; 3) change of walking pattern caused by the change of walking speed. In this research, we will show that PSA can tolerate these inconsistencies after additional efforts proposed in this paper. First of all, in this section, the existing PSA adopted for gait recognition is introduced in order to demonstrate the challenges of this research.

### A. The framework of PSA-based gait recognition

The framework of PSA-based gait recognition is shown in Fig. 1. Gait should be analyzed within complete walking cycle(s) because it is a periodic action [15].

The method in [15] is adopted to estimate gait period of each gait sequence. A key process is to create a waveform of aspect ratio: width/height of silhouette bounding box along the time series of gait sequence. Instead of using the whole gait silhouette [23], using aspect ratio can significantly reduce computational complexity. Then, normalization and autocorrelation are applied to the waveform to obtain the repeating curve pattern, which can indicate the gait period. The gait cycle i.e. the number of frames in a gait period \((T_{frame})\) can be detected by maximizing the autocorrelation of the normalized waveform of the aspect ratio \((\{a(i)\}_{i=0}^{N_i}\) where \(N_i\) is the size of the waveform or the total number of frames in the gait sequence) as:
\[
T_{frame} = 2 \times \arg \max_{t} \frac{\sum_{i=0}^{N_i} a(i)a(i + t)}{\sqrt{\sum_{i=0}^{N_i} a(i)^2 \sum_{i=0}^{N_i} a(i + t)^2}} \quad (4)
\]
where \(N_i = N_w - t - 1\). The autocorrelation signal contains two local peaks in one gait period because of the bilateral symmetry of human gait under any view except frontal view [15]. Thus, the gait period is estimated as twice the local peaks where \(T_{frame}\) is obtained in Eq. (4).

Given a human walking sequence, a silhouette can be extracted from each frame using the method in [2]. However, some extracted silhouettes are incomplete. In this paper, mathematical morphological operations are used for holes remedy and noise elimination [24]. In order to obtain the shape boundaries from the gait silhouettes, Border Following algorithm [25] is used in our study. In practice, gait shapes of individual can vary in size and pose. For example, gait shapes of leg-crossing pose and leg-apart pose are very different and gait shapes usually appear larger when they are closer to a camera. Thus, a process of shape re-sampling is required for shape normalization and point correspondence between different gait shapes. Selecting proper number of re-sampling points is essential, which can be empirically determined by maximizing the recognition performance on the training dataset.

After gait shapes have been properly re-sampled, CSC is used to describe the normalized gait shapes. It describes the shape by recording the displacement of each boundary point from the shape centroid. Then, Procrustes Mean Shape (PMS) of a set of CSCs in complete walking cycle(s) is computed as a gait feature. Construction of PMS is based on a procedure of superimposition along a set of shapes by considering affine transformation (see Eq. (1)) among them. In Section III-D, Eq. (1) is extended for PMS construction by superimposing of multiple shapes. Finally, Procrustes Distance (PD) is subsequently used to measure dissimilarity between two PMSs of any two gait sequences.

In order to have a detailed understanding on the PSA-based gait recognition, brief discussions of the key components are given below.

### B. Incorporating prior knowledge into the gait shape re-sampling process

The shape re-sampling is used to address the problems of shape normalizations and boundary point correspondences. So that, all shape boundaries will contain the same number
of boundary points and each boundary point approximately corresponds to the same body part. This is an important preprocessing in our gait recognition because: 1) PSA is rigid evaluations and requires a one-to-one point correspondence between the shapes; 2) gait is a dynamic shape model such that it varies in pose and size throughout a walking cycle and camera’s viewpoint; 3) particularly, gait shape changes when walking speed changes (see Analysis-A).

In this paper, prior knowledge of human shape structure is integrated into the re-sampling process in order to improve the accuracy of point correspondences between different gait shapes. Based on the prior knowledge, the prominent positions of left foot, right foot and head are used as the key reference points to divide the gait shape boundary into three clockwise curves: head-right foot, right foot-left foot and left foot-head. These three points can be automatically estimated based on analyses of projection histogram on major axis [26].

Then, equal arc-length sampling [27] is applied independently in each boundary segment instead of a whole shape boundary. The equal arc-length sampling selects key points with the interval of equal arc length along the shape boundary. The space between two consecutive key points is given by \( \frac{L}{K} \) (where \( L \) is the perimeter of the boundary and \( K \) is the total number of re-sampled points). The optimized total numbers of re-sampled points on each segment are empirically determined by maximizing the recognition performance on the training dataset. In our experiment, each boundary segments are tested with five different values of \( K \) (i.e. 5, 10, 15, 20, 25). The optimal combination is 15, 10 and 15 points for the boundary segments of head-right foot, right foot-left foot and left foot-head respectively.

For further analyses, the re-sampled gait shape boundary will be re-considered as a whole. In the rest of this paper, boundary points mean the points identified by the re-sampling process above along the gait shape boundary.

C. CSC-based shape descriptor and its constraint to walking speed change

In the conventional framework [10], the re-sampled shape boundary is described using CSC. By unwrapping the shape boundary into a set of boundary points, CSC can be described as a vector of complex numbers as:

\[
Z = \{ z_i | i = 1, 2, ..., N_p \}^T
\]

where \( z_i = (x_i - x_c) + j*(y_i - y_c) \), \( (x_i, y_i) \) is the \( i^{th} \) boundary point, \( (x_c, y_c) \) is the shape centroid, \( x_c = \frac{\sum_{i=1}^{N_p} x_i}{N_p} \), \( y_c = \frac{\sum_{i=1}^{N_p} y_i}{N_p} \), and \( N_p \) is the total number of boundary points. CSC is a global shape descriptor using the shape centroid as a global reference. The shape centroid is utilized as the origin of the 2-D shape space to register all shapes to a common center, which can handle translation invariance.

However, CSC has some disadvantages due to its global representation. In practice, gait shape of individual can be easily altered by many factors, particularly by the change of walking speed and the inconsistency of walking pattern of the individual. Therefore, position of the shape centroid is not stable. Furthermore, according to our experiments, CSC which describes the shape based on its global shape appearance, is very sensitive to walking speed change. In this paper, HSC is proposed to replace CSC for describing gait shape.

D. PMS-based gait feature

Given a set of \( N_g \) gait shape configurations e.g. CSCs \( \{Z_i\}_{i=1}^{N_g} \) from complete walking cycle(s), PMS is estimated by extending the objective function of Eq. (1), which minimizes a sum of PDs between the mean shape \( Z_G \) i.e. PMS) and each gait shape configuration \( Z_i \) as:

\[
\min_{\alpha_i, \beta_i} \sum_{i=1}^{N_g} ||Z_G - \alpha_iZ_i - \beta_i|Z_i||^2, \quad \beta_i = |\beta_i|e^{j\beta_i}
\]

(6)

where \( \alpha_i \) gives the translation of \( Z_i \), and \( |\beta_i| \) and \( \angle \beta_i \) give the scale and the rotation of \( Z_i \), respectively.

Given \( Z_i \) are invariant to translation (e.g. gait shapes are registered using their shape centroids), the solution of Eq. (6) can be calculated based on least square fit-based technique [20][21]. The corresponding \( Z_G \) equals to the dominant eigenvector of the complex sum of squares and products matrix \( S_Z \).

\[
S_Z = \sum_{i=1}^{N_g} (Z_iZ_i^*)/(Z_i^*Z_i)
\]

(7)

E. PD-based gait similarity measurement and its constraint to walking speed change

Given two PMSs of two gaits \( Z_{G_1} \) and \( Z_{G_2} \), PD can measure the similarity which is invariant to translation, scaling and rotation [20][21] as mentioned in Eq. (3), where \( d_P \in [0,1] \). The smaller value of \( d_P(Z_{G_1}, Z_{G_2}) \), the more possibility that gait features \( Z_{G_1} \) and \( Z_{G_2} \) belong to the same subject.

In fact, each boundary segment corresponding to the different body parts changes differently (i.e. regarding both manners of magnitude and direction) due to the change of walking speed. Thus, it will be inefficient to treat the gait shape as a whole where PD is applied for similarity measurement between the gaits from different walking speeds.

In this paper, DCM is proposed to deal with this constraint. It improves the performance of cross-speed gait similarity measurement. DCM contains key parameters to decompose gait shape boundary into a few boundary segments in a way such that each segment contains boundary points that are similarly affected by walking speed change. Then, PD is applied on each boundary segment instead of the whole shape boundary.

IV. SPEED-CHANGE IMPACTS ON PSA-BASED GAIT RECOGNITION

This section comprehensively analyses the impacts of walking speed change on the PSA-based gait recognition. It will reveal the following key points from different perspectives: 1) how significant the impacts are when the walking speed changes in various degrees? 2) how the individual body parts will be affected when the walking speed changes? 3) how the individual person responds to the change of walking speed differently?
the boundary points from index 10 to 21 (corresponding to back leg) shift to the right side and the boundary points from index 21 to 32 (corresponding to front leg) shift to the left side when speed increases. It is consistent with the observation in Fig. 2 that stride length (index 10 to 32) is longer when walking speed is faster.

From Fig. 3 (d), three major segments are observed to contain significant changes on y-axis component when walking speed changes. They are back upper body (index 1 to 11) which includes back arm, front upper body (index 30 to 40) which includes front arm, and legs apart (index 17 to 25). That is, arms and legs normally lift up higher when walking speed increases.

Based on this analysis, we can locate key boundary points to split the original boundary into a few segments. Inside each segment, the variation trends of the boundary points caused by walking speed change are similar. According to the boundary point variations on Fig. 3 (b), we locate local saddle points which are the points of index 8, 18, 23, 31 and 34. Since the points of index 18 and 31 are too close to the points of index 23 and 34 respectively, without over-segmenting the boundary, the experiment keeps only the points of index 23 and 34. This is because they are more clear to indicate changes of the variation trends (see Fig. 3 (b), (c) and (d)).

Therefore, three reference saddle points (8, 23 and 34) are used to decompose the shape boundary into four segments as shown in Fig. 4. Inside each segment, the variation trends of the boundary points caused by walking speed change are similar. This boundary segmentation will be further optimized and used in the proposed DCM (see Section V-B) in order to improve cross-speed gait recognition performance.

Analysis-B: The change of walking speed vs. the higher-order derivatives of the shape boundary

In this analysis, the impacts caused by walking speed change on the higher-order derivatives of the shape boundary are further investigated. The first three higher-order derivatives of the shape boundary (i.e. tangent, curvature and aberrancy) are briefed here, followed by the generic representation.

Given two boundary points \( P_0 = (x_0, y_0) \) and \( P_1 = (x_1, y_1) \), the first order derivative \( f'(P_0, P_1) \) of a discrete function, tangent, using Forward Divided Difference [22] is:

\[
f'(P_0, P_1) = \frac{y_1 - y_0}{x_1 - x_0} = \frac{y_0}{x_0 - x_1} + \frac{y_1}{x_1 - x_0}
\]  

Given three boundary points \( P_0 = (x_0, y_0) \), \( P_1 = (x_1, y_1) \) and \( P_2 = (x_2, y_2) \), the second order derivative \( f''(P_0, P_1, P_2) \), curvature, is:
Analysis-C: The change of walking speed vs. the impacts on the shape boundary information and is able to better tolerate the speed change has no impact on legs motion (boundary point index 10 to 30) and only has minor impact on arms motion (boundary point index 1 to 4; upper bodies). This is because increasing walking speed will increase the stride length [3]. Naturally, arms will swing higher when the stride length increases.

So, it is better to decompose the original shape boundary into segments properly. Then, further processing is carried out on each segment. This will provide two major advantages for cross-speed gait similarity measurement. First, weights can be assigned to each segment. Larger weight is assigned to the segment which is less affected by the walking speed change and contains higher discriminability for gait recognition. Second, performance of the transformation involved in PD process will be improved by carried on the relevant operations on each segment instead of the whole shape boundary. This finding leads to the new DCM proposed in Section V-B.

Analysis-D: The change of walking speed vs. the response of the individual person

It is shown above that arms swing higher, legs lift up higher and stride length becomes longer when walking speed increases. However, each individual may respond differently to the walking speed change. This is not like the change of view which may cause the relatively same efforts on gaits of different persons [13][14]. In this analysis, we will compare the effects on the individual gait caused by the changes of view and walking speed respectively.

Ten different persons are randomly selected and used in this analysis. The same experiments have been carried out by using more or less than ten randomly selected persons. The similar results were observed. The OU-ISIR gait database is used for analyzing the impacts caused by the speed variation and the CASIA gait database B is used for analyzing the impacts caused by the view variation. Results are shown in Fig 6. Fig. 6 (c) and (d) illustrate correlations of x- and y-coordinates respectively at each boundary point when walking speed changes or view changes. The correlation coefficient of the $i^{th}$ boundary point (x- or y-coordinate) between two different walking conditions (c1 and c2) is given as:

![Fig 5. Efforts caused by the walking speed change on the variance of Euclidean distance, and its $1^{st}$ order (tangent), $2^{nd}$ order (curvature) and $3^{rd}$ order (aberrancy) derivatives respectively at each boundary point. The reference walking speed is 2 km/h. The updated walking speeds are shown on the corresponding y-axis. (a) Variation of position. (b) Variation of tangent. (c) Variation of curvature. (d) Variation of aberrancy. The darker color represents the higher impact.]

$$f''(P_0, P_1, P_2) = \frac{f''(P_0, P_1) - f''(P_0, P_1)}{x_2 - x_0}$$

From Fig 5, it is seen that impacts caused by the speed change on tangent, curvature and aberrancy (Fig 5 (b), (c), (d)) are much less than the impacts on global shape appearance (Fig 5 (a)). Particularly, from Fig 5 (c) and (d), it is seen that the speed change has no impact on legs motion (boundary point index 10 to 30) and only has minor impact on arms motion (boundary point index 4 to 8 and index 30 to 34). Therefore, the higher-order derivatives of shape information are more robust to the speed change than the global shape appearance.

The observations above motivate us to develop a new gait shape descriptor which is based on the higher-order derivatives of shape boundary information and is able to better tolerate the change of walking speed. The details can be referred to Section V-A.

### Analysis-C: The change of walking speed vs. the impacts on the different body parts

From Analysis-A, it has indicated that different boundary segments corresponding to various body parts are affected differently when the walking speed changes. In this analysis, a further investigation is conducted by measuring the difference quantitatively using PD on each boundary segment before-and-after the walking speed changes.

From Table I, we may see, first, larger speed change causes larger shape change; second, walking speed change has the different impacts on the different body parts; third, the effect caused by the speed change on legs motion (segments 2 and 3: lower bodies) is much larger than the effect on arms motion (segments 1 and 4: upper bodies). This is because increasing walking speed will increase the stride length [3]. Naturally, arms will swing higher when the stride length increases.

So, it is better to decompose the original shape boundary into segments properly. Then, further processing is carried out on each segment. This will provide two major advantages for cross-speed gait similarity measurement. First, weights can be assigned to each segment. Larger weight is assigned to the segment which is less affected by the walking speed change and contains higher discriminability for gait recognition. Second, performance of the transformation involved in PD process will be improved by carried on the relevant operations on each segment instead of the whole shape boundary. This finding leads to the new DCM proposed in Section V-B.

### TABLE I

<table>
<thead>
<tr>
<th>Gallery</th>
<th>Probe</th>
<th>Segment1: upper body</th>
<th>Segment2: lower body</th>
<th>Segment3: front body</th>
<th>Segment4: upper body</th>
</tr>
</thead>
<tbody>
<tr>
<td>2 km/h</td>
<td>2 km/h</td>
<td>0.00011</td>
<td>0.00077</td>
<td>0.00072</td>
<td>0.00051</td>
</tr>
<tr>
<td>2 km/h</td>
<td>3 km/h</td>
<td>0.00018</td>
<td>0.00137</td>
<td>0.00204</td>
<td>0.00074</td>
</tr>
<tr>
<td>2 km/h</td>
<td>4 km/h</td>
<td>0.00038</td>
<td>0.00730</td>
<td>0.01009</td>
<td>0.00183</td>
</tr>
<tr>
<td>2 km/h</td>
<td>5 km/h</td>
<td>0.00040</td>
<td>0.01264</td>
<td>0.01709</td>
<td>0.00340</td>
</tr>
<tr>
<td>2 km/h</td>
<td>6 km/h</td>
<td>0.00041</td>
<td>0.01787</td>
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<tr>
<td>2 km/h</td>
<td>7 km/h</td>
<td>0.00044</td>
<td>0.02516</td>
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</table>

Fig 6. Fig. 6 (c) and (d) illustrate correlations of x- and y-coordinates respectively at each boundary point when walking speed changes or view changes. The correlation coefficient of the $i^{th}$ boundary point (x- or y-coordinate) between two different walking conditions (c1 and c2) is given as:
where $P_{i,c,1} = (x_{i,c,1}, y_{i,c,1})$ and $P_{i,c,2} = (x_{i,c,2}, y_{i,c,2})$ are the $i^{th}$ point on gait shape boundary under walking condition $c1$ (e.g. walking speed is 2 km/h) and $c2$ (e.g. walking speed is 3 km/h) respectively, $E$ is the expected value operator, $(\mu_{P_{i,c,1}}, \sigma_{P_{i,c,1}})$ and $(\mu_{P_{i,c,2}}, \sigma_{P_{i,c,2}})$ are expected values and standard deviations of $P_{i,c,1}$ and $P_{i,c,2}$ respectively. Eq. (12) can be written as:

$$\rho_{P_{i,c,1},P_{i,c,2}} = \frac{\sum_{j=1}^{N_{s}}(P_{i,c,1} - \bar{P}_{i,c,1})(P_{i,c,2} - \bar{P}_{i,c,2})}{\sqrt{\sum_{j=1}^{N_{s}}(P_{i,c,1} - \bar{P}_{i,c,1})^2 \sum_{j=1}^{N_{s}}(P_{i,c,2} - \bar{P}_{i,c,2})^2}}$$

where $P_{i,c,1}$ and $P_{i,c,2}$ are the $j^{th}$ sample of $P_{i,c,1}$ and $P_{i,c,2}$ respectively in the experimental dataset, $\bar{P}_{i,c,1}$ and $\bar{P}_{i,c,2}$ are the sample means of $P_{i,c,1}$ and $P_{i,c,2}$ respectively, and $N_{s}$ is the total number of samples. The correlation coefficient ($\rho_{P_{i,c,1},P_{i,c,2}}$) shown in Fig. 6 (c) and (d) is calculated as:

$$\rho_{P_{i,c,1},P_{i,c,2}} = \max_{P_{j,c,2} \in S_{i}} |\rho_{P_{i,c,1},P_{j,c,2}}|$$

where $S_{i}$ is a set of neighboring points of $P_{i,c,2}$ in a shared local region.

Refer to Fig. 6, the pattern of shape change caused by walking speed change is much less generic than the pattern of shape change caused by view change. The intuitive explanation on the above observation is that view change is a kind of external dynamic factor which will affect the shooting conditions but is independent to subjects being shot. Thus, it will have the similar impacts to all subjects. However, walking speed change is up to every subject so it is a kind of internal factor strongly related to each individual person. Thus, it is unlikely to use a generic transformation model [7][9] to tackle the speed change problem. Instead, this paper will explore a solution to construct a new speed-invariant gait feature.

V. SPEED-IN Variant GAIT RECOGNITION BASED ON IMPROVED PSA

According to the standard PSA framework for gait recognition in Section III and the comprehensive analyses on the impacts caused by walking speed change in Section IV, we propose a new PSA-based gait recognition which can tolerate the variation of walking speed. The framework of speed-invariant PSA-based gait recognition is shown in Fig. 7. An algorithm pseudo-code is given in Algorithm 1. The preprocessing is referred to Fig. 1 as discussed in Sections III-A and III-B. The proposed techniques to address the challenges of walking speed change are marked by italic and underline in Fig. 7 and will be explained in the rest of this section.

A. Shape descriptor based on HSC

This section is related to line 9 in Algorithm 1 pseudo-code. From Analysis-B, it is shown that walking speed change has no significant impacts on higher-order derivatives of shape boundary such as tangent, curvature and aberrancy. Hence, HSC is proposed for describing gait shape. First, the higher-order derivatives of the shape boundary are calculated on the corresponding x- and y-components separately. Then, they are combined together to replace CSC inside the framework of PSA. $HSC_{r}$ stands for $r$-order derivative of the shape boundary. $HSC_{r}$ is a shape configuration ($Z$) which is written as:

$$\text{Algorithm 1} \quad \text{The speed-invariant PSA-based gait recognition}
$$

**Input:** A probe gait sequence ($G_{0}$) and a set of gallery gait sequences ($G = \{G_{s}\}_{s=1}^{N_{g}}$)

**Output:** Best identity matching of $G_{0}$ in $G$

1. for $i = 0$ to $N_{g}$ do
2. Estimate the gait period of $G_{i}$
3. Capture a set of gait shapes $\{(g_{j})_{N_{s}}\}$ from $G_{i}$ within complete gait period(s)
4. Estimate the gait speed $s_{i}$ of $G_{i}$
5. for $j = 1$ to $N_{s}$ do
6. Extract the shape boundary $b_{j}$ from $g_{j}$
7. Estimate head ($H$) and feet ($F_{L}, F_{R}$) positions of $b_{j}$
8. Compute the re-sampled shape boundary ($r_{j}$) from $b_{j}$ using $H$, $F_{L}$ and $F_{R}$ as reference points
9. Generate the shape descriptor ($Z_{j}$) from $r_{j}$ using the higher-order shape information
10. end for
11. $Z_{G_{i}} \leftarrow$ dominant eigenvector of $S_{Z}$
12. $Z_{G_{i}} \leftarrow$ dominant eigenvector of $S_{Z}$
13. Generate Differential Composition Model ($\Gamma_{i}$) for $Z_{G_{i}}$
14. end for
15. identity $\leftarrow \arg\min_{i \in \{1,...,N_{g}\}} \sum_{k=1}^{N_{d}} w^{sc_{0}}_{k} (Z^{k}_{G_{i}})$, $i = 1,...,N_{s}$ and $sc_{0} = |s_{0} - s_{i}|$
16. return identity
However, from Fig. 10 which shows the discriminability (in terms of Fisher discriminant ratio) of different descriptions (in terms of different orders of derivative) of each boundary segment under various degrees of walking speed change, it can be seen that HSC has higher discriminability for cross-speed gait recognition than CSC.

In practice, given the shape boundary is split into a few segments (see Section V-B1), a proper order of derivative ($\hat{r}$) for HSC can be determined under a degree of speed change ($sc^r$) as:

$$\hat{r} = \text{argmax}_r \sum_{i=1}^{N_d} w_{i,t}^{sc^r}$$

where $w_{i,t}^{sc^r}$ is discriminability of $i$th boundary segment for gait recognition and $sc^r$ stands for the degree of speed change. In Section V-B2, we will propose a method for calculating $w_{i,t}^{sc^r}$. $N_d$ is the total number of boundary segments and $r$ is order of HSC. According to our study, $r \in [0, 4]$ is sufficient (see Tables IV and V for the detailed experimental results).

### B. Differential Composition Model (DCM)

This section is related to lines 13 and 15 in Algorithm 1 pseudo-code. It has been shown in Analysis-A and Analysis-C that different boundary segments of gait shape are affected differently by speed change. It will make more senses that different boundary segments have to be treated differently and then integrated in a proper way when analyzing and recognizing gaits. Therefore, DCM is proposed to address this observed challenge. The model ($\Gamma_i$) representing the PMS-based gait feature ($Z_{G_i}$) is described in its general form as:

$$\Gamma_i = \{P_k, w_{k}^{sc}, Z_{G_i}^{k}_{k=1}, N_d\}$$

where $P_k$ is the $k$th decomposition boundary point (see Analysis-A and Section V-B1 for the details), $Z_{G_i}^{k}$ is the $k$th clockwise boundary segment connecting $P_k$ and $P_{k+1}$ on $G_i$, $w_{k}^{sc}$ is a discriminative weight assigned to $Z_{G_i}^{k}$, $sc$ is degree of speed change, $sc = |s_i - s_j|$ for any different values of $s_j$ in the training dataset, $s_i$ and $s_j$ are walking speeds of $G_i$ and $G_j$, respectively, and $N_d$ is the total number of decomposed segments. The calculations of these model parameters will be explained as below.

When two gait features ($Z_{G_1}$, $Z_{G_2}$) are reconstructed in the forms of DCM ($\Gamma_1, \Gamma_2$), overall dissimilarity $D_{\beta}$ between the two gaits is calculated as a weighted sum of PDs as:

$$D_{\beta}(Z_{G_1}, Z_{G_2}) = \frac{\sum_{k=1}^{N_d} w_{k}^{sc} d_p(Z_{G_1}^{k}, Z_{G_2}^{k})}{\sum_{k=1}^{N_d} w_{k}^{sc}}$$

#### 1) Boundary decomposition:
This section is related to Analysis-A (see Fig. 4), gait shape boundary is initially decomposed into four non-overlapped segments, namely segment1 (orange curve, back upper body), segment2 (blue curve, back lower body), segment3 (red curve, front lower body) and segment4 (green curve, front upper body) using the set of reference boundary points ($P = \{P_k\}_{k=1}^{N_d}$) i.e. head position and the other three local minimums. According to Analysis-A, $N_d$ and the initial value of $P$ can be calculated. Given $C_{P_j}$ standing for the movement of boundary point $P_j$ caused by...
walking speed change (see Eq. (8)), the optimal set of $\mathbb{P}$ is given as:

$$\hat{\mathbb{P}} = \arg\max_{\mathbb{P}} \sum_{k=1}^{N_2} \mathbb{P}(C_{P_k}, C_{P_k+1}, C_{P_k+2}, \ldots, C_{P_k+n})$$

(21)

where $\mathbb{P}$ is the total correlation quantifying dependency among the set of variables i.e. $\mathbb{P}$ and $P_k + 1$, $P_k + 2$, ... are boundary points in clockwise direction along the boundary segment connecting $P_k$ and $P_k+1$. Eq. (21) can be regarded as an optimization process which adjusts boundary segments of cohesive boundary points. The total correlation can be calculated [28] as:

$$\Psi(C_{P_k}, \ldots, C_{P_k+n}) = \sum_{c_{P_k} \in C_{P_k}} \sum_{c_{P_k}+1 \in C_{P_k+1}} p(c_{P_k}, \ldots, c_{P_k}) \log \frac{p(c_{P_k}, \ldots, c_{P_k+n})}{p(c_{P_k+1}, \ldots, c_{P_k+n})}$$

(22)

where $H(C_{P_k+j})$ is the information entropy of variable $C_{P_k+j}$ (see Eq. (17)), $H(C_{P_k}, \ldots, C_{P_k+n})$ is the joint entropy of the variable set $\{C_{P_k}, \ldots, C_{P_k+n}\}$, $C_{P_k}, \ldots, C_{P_k+n}$ are training samples of $C_{P_k}, \ldots, C_{P_k+n}$ respectively, and $p$ denotes the probability mass function.

2) Weight calculation: Sets of weights of discriminability ($\{w_k^{sc}\}_{k=1}^{N_2}$) are calculated for the different degrees of speed change ($sc^c$). The weights are calculated based on Fisher discriminant ratio [29][30]. Given training dataset $U_T$ and the estimated walking speeds as:

$$U_{sc,k}^c = \{(Z_p^k, Z_q^k) \mid Z_p, Z_q \in U_T, s(Z_p) = s(Z_q), \}$

$$U_{Ds,k}^c = \{(Z_p^k, Z_q^k) \mid Z_p, Z_q \in U_T, s(Z_p) \neq s(Z_q), \}$

(23)

where $U_{sc,k}^c$ is the set of any two corresponding, $k^{th}$, boundary segments of the same subjects in $U_T$ with the degree of speed change of $sc^c$, $U_{Ds,k}^c$ is the set of any two corresponding, $k^{th}$, boundary segments of different subjects in $U_T$ with the degree of speed change of $sc^c$, $Z_p$ and $Z_q$ are $k^{th}$ boundary segments of $Z_p$ and $Z_q$, $Z_p$ and $Z_q$ are shape configurations of any two gaits in $U_T$, $s(Z_p)$ and $s(Z_q)$ are the subject ID and the walking speed of $Z_p$ respectively. To obtain Fisher discriminant ratio, the relevant means and variances of $U_{sc,k}^c$ are calculated as:

$$\mu_{sc,k} = \frac{1}{N_{sc,k}^c} \sum_{(Z_p^k, Z_q^k) \in U_{sc,k}^c} Z_p^k, Z_q^k$$

$$\left(\sigma_{sc,k}^2\right)^2 = \frac{1}{N_{sc,k}^c} \sum_{(Z_p^k, Z_q^k) \in U_{sc,k}^c} (Z_p^k, Z_q^k) - \mu_{sc,k}^2$$

(24)

(25)

where $N_{sc,k}^c$ is size of $U_{sc,k}^c$. Mean ($\mu_{sc,k}^2$) and variance ($\left(\sigma_{sc,k}^2\right)^2$) of $U_{sc,k}^c$ are calculated in the same way as for $\mu_{Ds,k}^2$ and $\left(\sigma_{Ds,k}^2\right)^2$. Then, inter-class (Between class) variance ($\left(\sigma_{sc,k}^2\right)^2$), intra-class (Within class) variance ($\left(\sigma_{sc,k}^2\right)^2$) and total variance ($\left(\sigma_{sc,k}^2\right)^2$) are calculated as:

$$\left(\sigma_{B,k}^2\right)^2 = I_{sc,k}^c \left(\sigma_{sc,k}^2\right)^2 - \mu_{sc,k}^2$$

$$\left(\sigma_{W,k}^2\right)^2 = I_{sc,k}^c \left(\sigma_{sc,k}^2\right)^2 + I_{Ds,k}^c \left(\sigma_{Ds,k}^2\right)^2$$

(26)

(27)

Fig. 9 and Fig. 10 show analyses of the weights ($w_k^{sc}$) on each boundary segment $k$ using different types of shape descriptor (CSC, HSC$_1$, HSC$_2$) under various degrees of speed change ($sc^c$). Six subjects from the OU-ISIR gait database are used in these analyses.

Refer to CSC-graph in Fig. 9, it can be seen that the discriminative capability of each boundary segment decreases when the degree of speed change increases. That is, larger speed change has higher impact on gait recognition. Besides, walking speed change affects legs’ motion (lower bodies) much more than arms’ motion (upper bodies). According to Fig. 9, we may obtain more weight values for more cases of speed change by a proper interpolation. Examples of interpolated graphs for CSC, HSC$_1$, and HSC$_2$ are shown. Consequently, it can adapt more situations in testing process.

Refer to Fig. 10, it is shown that HSC can efficiently increase the discriminative capability for every boundary segments, when compared with CSC. This is because HSC can describe gait shape boundary in the way that is more robust to gait shape change caused by walking speed change. When the order of HSC increases, the discriminability rises until it reaches the highest value before gradually dropping down. The reason is that HSC can tolerate the shape change caused by walking speed change but on the other hand undesirably captures less gait information. In our study, we recommend to determine the order of HSC according to Eq. (18).
TABLE II
ESTIMATION OF GAIT PERIOD FOR THE CASIA GAIT DATABASE C.

<table>
<thead>
<tr>
<th>Speed</th>
<th>$T_{frame}$</th>
<th>$T_{second}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>fs (slow speed)</td>
<td>29</td>
<td>1.16</td>
</tr>
<tr>
<td>fn (normal speed)</td>
<td>25</td>
<td>1.00</td>
</tr>
<tr>
<td>fq (fast speed)</td>
<td>22</td>
<td>0.88</td>
</tr>
</tbody>
</table>

TABLE III
ESTIMATION OF GAIT PERIOD FOR THE OU-ISIR GAIT DATABASE.

<table>
<thead>
<tr>
<th>Speed (km/h)</th>
<th>$T_{frame}$</th>
<th>$T_{second}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>2</td>
<td>105</td>
<td>1.75</td>
</tr>
<tr>
<td>3</td>
<td>81</td>
<td>1.35</td>
</tr>
<tr>
<td>4</td>
<td>68</td>
<td>1.13</td>
</tr>
<tr>
<td>5</td>
<td>60</td>
<td>1.00</td>
</tr>
<tr>
<td>6</td>
<td>54</td>
<td>0.90</td>
</tr>
<tr>
<td>7</td>
<td>49</td>
<td>0.82</td>
</tr>
</tbody>
</table>

C. Speed estimation

This section is related to line 4 in Algorithm 1 pseudo-code. It proposes a reasonable way to automatically estimate walking speed of each gait sequence.

Usually, walking speed is measured in a unit of km/h or m/s. Alternatively, it can be approximately measured as the period (seconds) of one gait cycle. Shorter period represents higher walking speed. Table II and Table III show estimated period under the various walking speeds based on the CASIA gait database C and the OU-ISIR gait database respectively. Gait cycle in a unit of frame number ($T_{frame}$) is estimated based on the method explained in Section III-A (see Eq. (4)).

When video frame rate is given, gait period in a unit of time e.g. second ($T_{second}$) is calculated as:

$$T_{second} = \frac{T_{frame}}{frame \ rate \ (f/s)}$$  \hspace{1cm} (31)

The CASIA gait database C was recorded at 25 f/s, while the OU-ISIR gait database was recorded at 60 f/s. The CASIA gait database C does not provide any record of absolute walking speed (km/h). However, they can be reasonably estimated using the OU-ISIR gait database as a reference based on $T_{second}$ (see 3rd column in Tables II and III). Therefore, fs, fn and fq in the CASIA gait database C are approximately 4, 5 and 6 km/h respectively.

VI. EXPERIMENTS

In our experiments, four widely adopted gait databases are used to evaluate the performance of the proposed method, which include 1) CASIA gait database C [31], 2) OU-ISIR gait database [9], 3) CMU Mobo gait database [32] and 4) USF gait database [2]. The first three databases directly support the study of gait recognition with respect to the variation of walking speed. The last database is considered as a real scene with non-controlled walking speed. Moreover, from the research perspective, there are different advantages from the first three databases: 1) CASIA gait database C contains a large number of subjects; 2) OU-ISIR gait database includes a large range of walking speeds; 3) CMU Mobo gait database has been widely used by a large number of papers which can be referred for the comprehensive comparison. Fig. 11 shows sample gait images from the four databases. In our experiments, Nearest Neighbor (NN) [10] is used as a classifier.

In our experiments, the algorithm proposed in this paper is implemented using the library functions of OpenCV 2.0 in Microsoft Visual C++ 8.0 environment on the computer with Quad Processor 2.66 GHz and 4 GB RAM.

Regarding the computational complexity, training process may take time but recognition process itself is fast given the trained models. There are three main training components: 1) determination of the order of HSC for each degree of speed change (see Eq. (18)) takes about 5 minutes; 2) segmentation of gait shape boundary in DCM (see Eq. (21)) takes about 10 minutes; 3) weight calculation in DCM for each degree of speed change (see Eq. (30)) takes about 5 minutes. For example, total training time for the CASIA gait database C with 33 training subjects and 3 different walking speeds is approximately 40 minutes. The training process can be done offline beforehand.

In recognition phase, given a probe sequence of gait silhouettes and the trained models, identity matching can be computed in less than 0.1 second. Compared with the standard PSA framework for gait recognition (see Fig. 1), the improved PSA framework for speed-invariant gait recognition (see Fig. 7 i.e. HSC in place of CSC and adding DCM on top of PMS) takes approximately the same amount of time for recognition process.

A. The CASIA gait database C

The database contains 3 different walking speeds, namely slow (fs), normal (fn) and fast (fq). A total of 153 subjects are used in this experiment. 33 subjects are randomly selected and used in the training process and the rest of 120 subjects are used to evaluate gait recognition performance. 8 gait sequences were recorded for each subject (2 sequences for fs, 4 sequences for fn, 2 sequences for fq). Refer to Section V-C, fs, fn and fq are estimated as 4, 5 and 6 km/h respectively.

Tables IV and V show gait recognition performance on the CASIA gait database C using the proposed method based on the different types of shape configuration. The results in Tables IV and V are calculated using PD as similarity measurement without and with DCM respectively. For the gait recognition under the same walking speed (see the first three rows in Tables IV and V), HSC$_1$ can achieve the most reliable performance. It works well to handle shape deviation caused by inconsistency of individual walking pattern. For the case of fast walking speed, HSC$_2$ achieves the best performance. This is because the consistency among individual gaits is more unstable when the individual walks faster. For cross-speed recognition (see the last six rows in Tables IV and V), CSC absolutely fails but HSC still maintains high performance.
In our experiments, we may see that $HSC_2$ is sufficient when speed change is not significant e.g. ± 1 km/h (see rows 4-7 in Tables IV and V). For the case involving larger speed change i.e. ± 2 km/h (see the last two rows in Tables IV and V), $HSC_3$ achieves better performance. HSC successfully reduces impacts caused by speed change but also undesirably maintains less discriminative gait information which may have negative effects on gait recognition performance. Thus, the order of derivative (r) for $HSC_r$ has to be properly determined based on Eq. (18). Moreover, the proposed DCM successfully improves the performance as seen in Table V when compared with the results in Table IV.

When compared with other existing methods which use the same database (see Table VI), the proposed method achieves comparable performance when gallery and probe walking speeds are the same ((fn,fn)) but better performance for cross-speed recognition ((fn,fs), (fn,fq), (fs,fq)) significantly for the case of large speed change ((fs,fq)).

### B. The OU-ISIR gait database

The database contains 6 different walking speeds from 2 km/h to 7 km/h with 1 km/h interval. Total 31 subjects are used in this experiment. Six subjects are randomly selected and used in the training process and the rest of 25 subjects are used to evaluate gait recognition performance. Two video sequences were recorded for each subject from each speed.

The advantage of this database is that it includes a large range of walking speeds. The two benchmark methods [7][9] that directly address the challenges of walking speed change will be compared in this experiment. However, [7] uses a non-published gait database. The OU-ISIR gait database is the published database that can closely cover the similar scenarios of walking speed change as adopted in [7]. Thus, [7] is used only in a rough comparison and to indicate the trend of cross-speed gait recognition performance under different cases of walking speed change. The more accurate comparisons can be obtained in the other experimental sections of this paper based on the other 3 gait databases.

Gait recognition performance on this database is shown in Tables VII and VIII. $HSC_1$ is used for gait recognition under the same walking speed. $HSC_2$ and $HSC_3$ are used for cross-speed recognition when speed change is up to 2 km/h and 4 km/h respectively. For other cases of large speed change, $HSC_4$ is used. The proposed method achieves average accuracies of 99%, 98%, 93%, 85%, 83% and 84% for gait recognitions when differences between probe and gallery speeds are 0, 1, 2, 3, 4 and 5 km/h respectively.

The results in Tables VII and VIII are compared as shown in Table IX. DCM significantly improves gait recognition performance especially for large speed change. This is because walking speed change has different impacts on each body part as shown in Analysis-C.

Table X shows the comparison between the proposed method (by using DCM) and the relevant published methods which have been investigated under the same/similar scenarios. The method [9] and the proposed method use the same OU-ISIR gait database of 25 subjects under the small speed change, $HSC_3$ is used. The reported speed change of ± 3.3 km/h (between 2.5 km/h and 5.8 km/h) is close (but less significant) to our case of large speed change.

From Table X, when compared with [9] which uses the same OU-ISIR gait database, the proposed method performs much better for both cases of small and large speed changes. When compared with [7], it can be indicated that the proposed method can well tolerate the large speed change.
C. The CMU Mobo gait database

The database contains 2 different walking speeds, namely slow walking (3.3 km/h) and fast walking (4.5 km/h). A total of 25 subjects are used in this experiment to evaluate gait recognition performance. The trained models are obtained from the training process based on the OU-ISIR gait database in Section VI-B. Therefore, the generic training process across different databases can be evaluated in this experiment. The proposed method is adopted with DCM. $HSC_1$ is used for gait recognition under the same walking speed while $HSC_2$ is used for cross-speed gait recognition.

From Table XI, when compared with other benchmark methods, it can be seen that the proposed method achieves comparable performance when gallery and probe walking speeds are the same. When the walking speed changes, the proposed method demonstrates very promising performance.

D. The USF gait database

The proposed method is further evaluated using the USF gait database which is a real scene captured in an uncontrolled environment. The USF gait database contains a set of 12 challenge experiments which are designed to investigate the effect of five factors affecting the performance of gait recognition. The five factors do not include the change of walking speed. In this database, the walking speed is not specifically controlled. That is, a person walks freely in various walking speeds in a non-controlled environment.

As a case study of real scene, the experiment A from the USF gait database which includes view variation is adopted to verify the proposed method. In the experiment A, probe gait is recorded from the left camera while gallery gait is recorded from the right camera. The two cameras’ lines of sight are verged at approximately 30 degrees. A total of 122 subjects are used in this experiment. 22 subjects are randomly selected and used in the training process and the rest of 100 subjects are used to evaluate gait recognition performance. $HSC_1$ is used in our experiment.

In this section, two different experiments with different data settings are demonstrated here. The first experiment only adopts gait from gallery dataset (but not from probe dataset) of the experiment A, so the views of gaits are the same. A gait sequence of each subject is divided into 2 subsequences of complete walking cycle(s). One subsequence is used as a probe data while another is used as a gallery data. Leave-one-out cross-validation is applied in this evaluation. The proposed method achieves approximately 92% recognition performance.

The second experiment directly adopts the Experiment A of USF gait database which includes both gallery and probe datasets. Thus, both factors of view change and non-controlled walking speed are considered.

Table XII shows that the proposed method is still robust to view change with non-controlled walking speed. It performs better or comparable when compared with other existing methods evaluated on the same database. By taking into account the encouraging performances for the cases of more significant speed changes (see experimental results based on the other databases above), the overall performance of the proposed method is clearly superior. For example, from Table XII, [4] performs slightly better than the proposed method. However, when walking speed change is more significant (see Table XI), the proposed method performs better than [4].

VII. Conclusion

This paper has conducted a comprehensive study aiming to reveal the impacts that different walking speeds exert on gait recognition. Our study has considerably enriched the performance of speed-invariant gait recognition by proposing the method based on the improved PSA. That is, HSC has been proposed as a robust shape descriptor which has been shown to be invariant to walking speed change. In this way, PMS is extracted as a novel speed-invariant gait feature from a set of HSCs describing a sequence of gait shapes from complete walking period(s). Then, PD has been used to measure gait similarity between two PMSs of any two gaits.
To enhance the performance of the cross-speed gait similarity measurement, DCM has been proposed to model PMS as a set of non-overlapped boundary segments. Then, the final gait distance is calculated from a weighted (i.e., Fisher discriminant ratio) sum of PDs corresponding to each boundary segment. Based on comprehensive experimental results, our proposed method has outperformed other existing methods in the literature including the state-of-the-art methods.

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