Robust Gait Recognition Based on Procrustes Shape Analysis of Pairwise Configuration

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Abstract

In this paper, we have further developed Procrustes Shape Analysis (PSA) for robust gait recognition. As a result, a significant improved performance is presented in this paper including the performance on a challenge situation for viewing angle variation. Based on the framework of PSA, Procrustes Mean Shape (PMS) has been well applied in many literatures to extract the signature of gait sequence captured from complete walking cycle(s). Then, similarity of gaits is measured using Procrustes Distance (PD). To describe the shape, conventional PSA uses Centroid Shape Configuration (CSC) as the descriptor which embeds global shape information inside. However, it is not sufficiently accurate to discriminate the identity of individuals from the same class of human walking. CSC significantly limits performance of PSA in our observation for the case of gait recognition. Its nature of global representation cannot address the challenges of gait recognition which involves significant shape (i.e. body pose) changes caused by various reasons such as dressing of individuals, change of walking speed, change of walking direction, change of camera viewpoint, etc. In this paper, a novel Pairwise Shape Configuration (PSC) is proposed as a new shape descriptor in PSA. The proposed PSC well embeds local information of gait as well as relevant global information so it is robust to deal with the challenges mentioned above. From our point of view, a reliable PSC should depend on consistency of boundary point correspondence from the processes of shape re-sampling and normalization which are relevant to the gait similarity measure using PD in the later stage. In this paper, context of body pose through the sequence of gait is introduced, which is significant to assist the body shape re-sampling and normalization. Our method has been tested on large gait databases under various walking environments. The extensive and comprehensive experimental results have shown that the proposed method outperforms several other methods in literature with a big margin including existing PSA-based methods, especially for scenario of viewing angle variation.

1 Introduction

Human gait is an attractive biometric feature for human identification in automatic surveillance system. For the advantages of being easily obtained at a distance, capably measured at low resolution, non-contact, and non-invasive, gait is more preferable compared to other popular biometrics such as face, iris, and fingerprint. Due to increasing interest in gait recognition in the computer vision community, a large number of methods have been continuously contributed, which can be explicitly categorized into two major groups, model-based methods [1] [5] [6] [11] [12] [22] [23] [25] [27] [28] [32] [38] [41] [42] and motion-based methods [2] [3] [4] [8] [13] [17] [20] [21] [26] [27] [30] [33] [35] [36] [37] [39] [43] .

Model-based methods generally aim to model human motion and the kinematics of joint angles. The model matching is operated in each frame of a walking sequence in order to measure the physical gait parameters such as trajectories, limb length, and angular speeds. Cunado et al. [11] considered legs as an interlinked pendulum. Phase-weighted Fourier magnitude spectrum was applied to recognize the gait signatures. Johnson and Bobick [5][23] used activity-specific static body parameters without directly analyzing the dynamics of gait patterns. Lee et al. [25] introduced a framework for simultaneous gait tracking and recognition using person dependent shape deformations based on a nonlinear generative model with kinematic manifold embedding and kernel mapping within Bayesian framework.

Motion-based methods generally analyze the image sequences of walking human to discover gait features regarding motion or shape. Abdelkader et al. [4][3] invented an eigengait method using image self-similarity plots. Chai et al. [8] introduced the Perceptual Shape Descriptor technique to recognize the gesture. Han et al. [20] constructed Gait Energy Image (GEI) as gait signature which was performed on synthetic template and combined information from real templates. He et al. [21] recognized individual gaits via HMMs that used the quantized vector of Hu moments of a silhouette as the input. Wang et al. [39] employed Procrustes Shape Analysis (PSA) to obtain Procrustes Mean Shape (PMS) from a sequence of gait poses as gait feature. Then, Procrustes Distance (PD) was carried out to measure the similarity between PMSs for gait recognition. Inspired by the paper [39], Zhang [43] adopted Shape Context (SC) descriptor to replace PD for PMSs similarity measurement. The method [43] gained favorable performance after combining PMS and SC. However, SC is computational expensive.

The traditional PSA uses Centroid Shape Configuration (CSC) which is a global shape representation [39][43]. CSC might be sufficiently robust and precise to classify objects from different classes, but might not enough precise to identify objects from the same class. Therefore, a local shape representation called Pairwise Shape Configuration (PSC) is proposed to replace CSC. Based on the advantage of local feature, PSC is more robust to noises and variations. In contrast for the global shape descriptor, CSC is entirely miscalculated when shape centroid is misestimated because of noises and shape variations. In particular for gait recognition, shape variations can be leaded from various external and internal factors. The external factors include fault foreground detection in low resolution video, partial occlusion, change of camera viewpoint, and walking when carrying a bag. The internal factors include walking pattern inconsistency of the individual, variation of gait poses acquired from different positions of the gait cycle, change of walking direction, and change of walking speed. PSC is theoretically intended to be more robust to shape variations of gait poses when being compared to CSC.

Normalization of shape boundary is another important task. Gopal et al. [18] chose the equal arc-length sampling to normalize the shapes by selecting candidate points spaced at equal arc length along the shape boundary. This method is not accurate to tackle the point correspondance between leg-crossing and leg-apart poses. The paper [3] [29] [34] used SC to find the best matching points between two human shapes. This method is not suitable to be adopted for gait recognition. First, to create PMS as gait signature from many gait poses, it is hard to select the robust referent pose for boundary point matching. Secondly, it is computational expensive. Thirdly, this method is too overfitting to tackle the point correspondance between leg-crossing and leg-apart poses. Unfortunately, the clockwise boundary information from right foot to left foot, which can be seen in leg-apart pose but cannot be seen in leg-crossing pose, will be ignored. Therefore, we proposes the method that is not too overlossing to mismatch too much the corresponding boundary points and not too overfitting to loss too much gait information.

In this study, the pose-invariant contexts on the shape boundary, which are head, left foot, and right foot, are used for the process of shape sampling and normalization. These landmarks can be used to achieve more reliable point correspondence. The shape boundary is first segmented into three clockwise curves as head-right foot, right foot-left foot, and left foot-head. Then, the equal arc-length sampling is used to normalize each curve boundary.

Based on the proposed PSC-based PSA combined with the improved shape sampling and normalization using the pose-invariant contexts on the gait shape boundary, we can achieve efficient gait recognition system. The system is also more robust to view and speed changes, compared with the other existing methods. The rest of the paper is organized as follows. Related work is explained in Section 2. The proposed PSA-based method for gait recognition is described in Section 3. Experimental results are illustrated in Section 4 and conclusions are drawn in Section 5.

2 Related Work

Procrustes shape analysis (PSA) [7][14][15] is used to statistically analyze distribution of a set of shape configurations. It is the process of performing a shape-preserving Euclidean transformation by removal of variations in translation, rotation, and scaling. The minimal Euclidean distance between two configurations (Z_1 and Z_2) achieved by translation, rotation, and scaling of Z_2 towards Z_1 is given as [7]:

$$\min_{\alpha,\, \beta} \|Z_1 - \alpha 1_k - \beta Z_2\|^2, \quad \beta = |\beta| e^{j\angle\beta} \tag{2.1}$$

where $\alpha 1_k$ gives the translation of Z_2, $|\beta|$ and $\angle\beta$ gives the scale and the rotation of Z_2, respectively, the two configurations may be considered to represent the same shape. To further simplify the analysis, assume that the shape configurations Z_1 and Z_2 are invariant to the translation, then the full Procrustes fit $\alpha 1_k + \beta Z_2$ has the parameters of:

$$\alpha = 0, \quad \beta = \frac{|Z_1^* Z_2|^2}{||Z_2||^2} \tag{2.2}$$

where the superscript $*$ represents a complex conjugation transpose. This was proved in the paper [15]. Therefore, Procrustes Distance (PD) is used to quantify the dissimilarity of the two configurations that are invariant to the translation as [7]:

$$d_P(Z_1, Z_2) = 1 - \frac{|Z_1^* Z_2|^2}{||Z_1||^2 ||Z_2||^2} \tag{2.3}$$

PSA provides a way to define Procrustes Mean Shape (PMS) as an average shape configuration (Z) for a given set of N shape configurations, $\{Z_i | i = 1, 2, ..., N\}$ [7]. PMS is estimated by minimizing sum of PD between the mean shape (Z) and each configuration (Z_i) in the set as:

$$\min_{\alpha_i,\, \beta_i} \sum_{i=1}^{N} ||Z - \alpha_i 1_k - \beta_i Z_i||^2, \quad \beta_i = |\beta_i| e^{j\angle\beta_i} \tag{2.4}$$

where $\alpha_i 1_k$ gives the translation of Z_i, and $|\beta_i|$ and $\angle\beta_i$ gives the scale and the rotation of Z_i, respectively. Again, the PMS analysis can be further simplified by assuming that the shape configurations are translation-invariant. Then, the mean shape (Z) can be calculated without iteration as the dominant eigenvector of the complex sum of squares and products matrix (S_Z) [7]. The proof can be found for example in chapter 3 of [14].

$$S_Z = \sum_{i=1}^{N} (Z_i Z_i^*)/(Z_i^* Z_i) \tag{2.5}$$

Traditionally, the shape descriptor used in PMS and PD analyses is a Centroid Shape Configuration (CSC) [7][39][43]. CSC is related to r-s Curve that stores the distance r from each boundary point s to origin of the shape which is the shape centroid. CSC stores x- and y-distances from the shape centroid in term of complex number. The method estimates the shape centroid (x_c, y_c) as:

$$x_c = \frac{1}{N} \sum_{i=1}^{N} x_i, \quad y_c = \frac{1}{N} \sum_{i=1}^{N} y_i \tag{2.6}$$

where N is the total number of boundary points and (x_i, y_i) is the boundary point i.

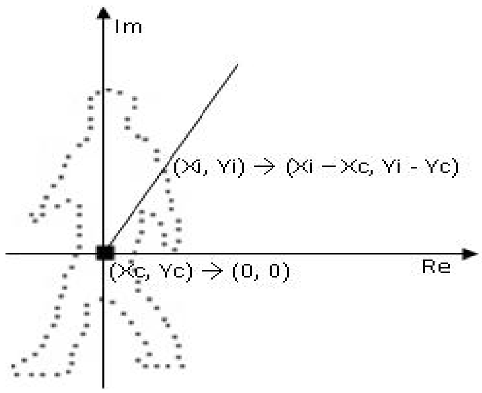


Figure 2.1: Centroid Shape Configuration (CSC). Black square (x_c, y_c) is the shape centroid, (x_i, y_i) is the boundary point, the two axes Re and Im are the real and imaginary part of a complex number respectively, $\rightarrow$ is the translation from the image coordinate into the complex coordinate.

The shape can be unwrapped clockwise into a set of boundary points sampled along its outer-contour in a complex coordinate system where the shape centroid is the origin of the system as illustrated in Figure 2.1. Therefore, CSC can be described as a vector of ordered complex numbers as:

$$Z = \{z_i | i = 1, 2, ..., N_p\}^T \tag{2.7}$$

where $z_i = (x_i - x_c) + j * (y_i - y_c)$, (x_i, y_i) is the boundary point i, and N_p is the total number of boundary points. CSC is a global shape descriptor. This is because the boundary point is represented by using itself and the shape centroid as the global reference.

CSC is translation-, rotation-, and scale-invariant shape descriptor. However, CSC has some disadvantages due to its global representation. In practice, gait shape precision of the individual can be easily altered by many factors such as inconsistency for walking pattern of the individual, variation of gait actions acquired from different positions of gait cycle, partial occlusion, viewing angle change, and speed change. Therefore, the shape centroid can be often misestimated and leading to failure of the entire CSC.

3 Proposed PSA-based method for robust gait recognition

A framework of PSA-based method for gait recognition is shown as following:

Algorithm 1: PSA-based gait recognition framework

Require: A probe gait sequence (G_0) and a set of N_s gallery gait sequences $\{G_i, i = 1, 2, ..., N_s\}$
Ensure: Best identity match of the probe gait in the gallery gait dataset
for $i = 0$ to N_s **do**
  Estimate gait period for G_i
  Capture N_g gait shapes from complete walking cycle(s) of G_i as $\{g_j, j = 1, 2, ..., N_g\}$
  for $j = 1$ to N_g **do**
    Extract shape boundary for g_j as b_j
    Re-sample and normalize b_j as r_j
    Generate shape descriptor for r_j as Z_j
  end for
  Construct PMS as the gait feature (Z_{G_i}) for G_i from $\{Z_j, j = 1, 2, ..., N_g\}$
end for
for $i = 1$ to N_s **do**
  Measure gait similarity (d_p) between probe gait feature (Z_{G_0}) and gallery gait feature (Z_{G_i}) using PD
end for
return Best identity match = $\underset{i}{\operatorname{argmin}}\, d_p(Z_{G_0}, Z_{G_i})$, $i = 1, 2, ..., N_s$

As can be seen from the framework, gait is analyzed from complete walking cycle(s) [24] because it is a periodic action. This paper adopts the technique from [24] to determine the gait period. The idea is to build up a waveform of aspect ratio: width/height of silhouette bounding box, along the time of image sequence. Then, normalization and autocorrelation processes are applied to the waveform to obtain the repeated curve pattern, which may indicate the gait period.

A border following algorithm based on connectivity [19] is used to extract the shape boundary from the gait silhouette. The shape boundary is then re-sampled to a fixed number of points to address boundary size normalization and point correspondence problems. In this work, the shape boundary is first segmented into three curves based on pose-invariant contexts of human shape boundary. Then, equal arc-length sampling [18] is applied to each curve.

Pairwise Shape Configuration (PSC) is proposed as the shape descriptor. PSC describes the sampled boundary point in a complex coordinate system by using its neighboring point as the origin of the system. Given a set of PSCs, $\{Z_j | j = 1, 2, ..., N_g\}$, of a gait sequence from complete walking cycle(s), PMS can be computed as the gait feature as in the equation (2.5).

Then, PD from the equation (2.3) is used to compare two PMSs (Z_{G1} and Z_{G2}) of two gait feature independent of position, scale, and rotation. The smaller value of $d_P(Z_{G1}, Z_{G2})$, the more possibility that gait signatures Z_{G1} and Z_{G2} belong to the same subject.

The main contributions of this paper focus on new PSC-based shape descriptor and pose context-based shape re-sampling which correspond to line 7 and line 6 respectively in the above framework. In the following sub-sections, details of these two points will be explained.

3.1 New shape descriptor using PSC

PSC is proposed to replace CSC to enhance the performance of PSA for robust gait recognition. PSC is similar to $\psi - s$ curve which stores tangent vector at every boundary point by encoding angle of the tangent ψ as a function of the arc length s around the shape. However, PSC is a different boundary descriptor from $\psi - s$ curve because it also records distance between two sampling points where the tangent angle is calculated. PSC stores x-distance and y-distance of each boundary point from its neighboring point in term of complex number.

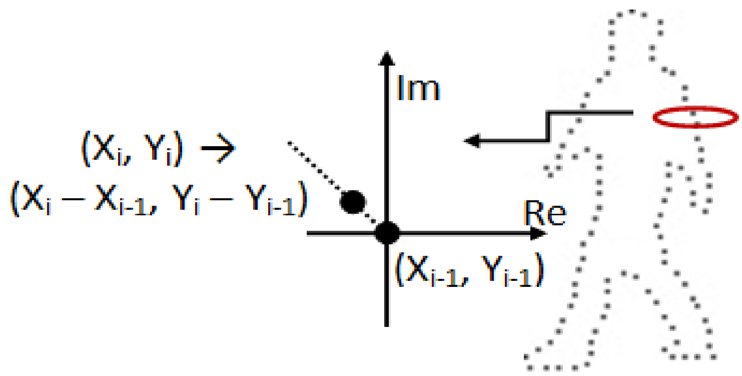


Figure 3.1: Pairwise Shape Configuration (PSC). (x_i, y_i) is the boundary point with its neighbor (x_{i-1}, y_{i-1}), the two axes Re and Im are the real and imaginary part of a complex number respectively, $\rightarrow$ is the translation from the image coordinate system into the complex coordinate system.

PSC is a local shape descriptor because each boundary point is represented by using only itself and its neighbor. That is a shape can be unwrapped clockwise into a set of boundary points sampled along its outer-contour. The boundary point is written in a complex coordinate system where its neighboring boundary point is origin of the system as shown in Figure 1. Therefore, PSC can be described as a vector of ordered complex numbers as:

$$Z = \left\{ \widetilde{0}, z_i | i = 1, 2, ..., N_p \right\}^T \tag{3.1}$$

where $z_i = (x_i - x_{i-1}) + j * (y_i - y_{i-1})$, (x_i, y_i) is the boundary point i, $\widetilde{0}$ is (0,0), and N_p is the total number of boundary points. Since PSC encodes magnitude and direction of the tangent vector, $\widetilde{0}$ is chosen as a reference frame (zero-degree tangent). The $\widetilde{0}$ is placed at starting point of PSC, then the rest of boundary points is described relative to it.

PSC is translation-, rotation-, and scale-invariant shape descriptor. PSC is also more robust to global shape change and relevant noise than CSC because it can well embed local shape information. In the case of partial of shape is damaged when being described, overall descriptor of PSC will not be significantly miscalculated. The proposed shape re-sampling and normalization in section 3.2 is also used to enhance the optimized efficiency of PSC.

3.2 Shape re-sampling and normalization based on the pose-invariant boundary contexts

In practice, gait shape of individual can vary in size and model along the time sequence of a gait cycle and the position of the individual within a camera's viewpoint. For gait feature construction using PMS and gait matching using PD, the shape boundary of gaits must be sampled to have same number of data points and automatically solve point correspondence between the shapes. The re-sampling process usually needs to consider three functions: 1) boundary size normalization; 2) point correspondence across different shape profiles; 3) boundary smoothing.

In this work, we propose three pose-invariant contexts of human shape boundary which are head, left foot, and right foot to assist in the process of shape re-sampling. The shape boundary is first segmented into three clockwise curves, head-right foot, right foot-left foot, and left foot-head. Then, equal arc-length sampling is applied to each boundary segment. The equal arc-length sampling [18] selects key points spaced at equal arc length along the shape boundary. The space between two consecutive key points is given by L/K, where L is the perimeter of the boundary and K is the number of key points. Examples of boundary shape re-sampling result are shown in Figure 3.2.

As shown in Figure 3.2, the shape outline and the key salient points are successfully extracted through the shape re-sampling process. Noises are also successfully eliminated which can be seen from the smoother shape boundary. The equal arc-length sampling on the boundary segments by the pose-invariant contexts (Figure 3.2(c)) performs better for point correspondence between different poses of individual, when being compared with the equal arc-length sampling on the entire boundary (Figure 3.2(b)). The point correspondence is clearly seen to be unsuccessfully tracked in Figure 3.2(b). For example, left foot in the leg-apart pose (green dot in the top row of Figure 3.2(b)) is wrongly corresponded to left shin in the leg-crossing pose (green dot in the bottom row of Figure 3.2(b)).

Selecting proper number of re-sampling points is essential. The larger number, the more details of shape are presented. However, it might increase computational

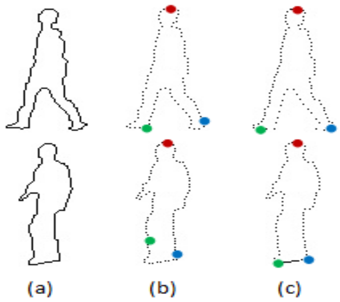


Figure 3.2: Shape re-sampling and normalization. (a) Original shape (b) Equal arc-length sampling on entire boundary (c) Equal arc-length sampling on boundary segments. Red dot is the starting point, blue dot is the point at 40% of the total boundary points, and green dot is the point at 60% of the total boundary points.

complexity and introduce more possible noise around the shape boundary. On the other hand, the smaller number, the less details of shape are presented. Insufficient details can lead to possible poor performance for shape analysis. In the practice, the number of sample points usually is determined empirically in different cases.

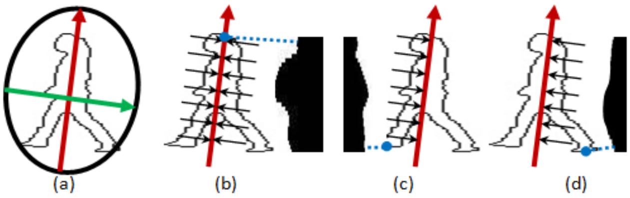


Figure 3.3: Head and feet detections. (a) Red arrow is major axis and green arrow is minor axis. (b) Head detection. (c) Left foot detection. (d) Right foot detection.

In this work, head and feet positions are automatically estimated. First, a major axis is calculated from dominant eigenvector of covariance matrix of the tracked shape silhouette [31]. To make it clear, given $\{(x_i, y_i)|x_i \in \Re, y_i \in \Re, i = 1, ..., N_p\}$ denotes a set of 2D-coordinates of foreground pixels in the gait image, where N_p is the total number of the foreground pixels. The covariance matrix (CM) can be generated as:

$$CM = \begin{bmatrix} COV(x,x) & COV(x,y) \\ COV(y,x) & COV(y,y) \end{bmatrix}_{2\times 2} \tag{3.2}$$

where $COV(x, y) = \sum_{i=1}^{N_p}((x_i - \overline{x})(y_i - \overline{y}))/N_p$ and $\overline{x}$ and $\overline{y}$ are the means of x and y, respectively. Thus, the major axis is the eigenvector of CM corresponding to the larger eigenvalue.

Head position is estimated by analyzing projection histogram of silhouette pixels on the major axis. Head is located at the first point from top of the projection histogram which is above the threshold as shown in Figure 3.3. To estimate left foot position, we create histogram by projecting silhouette pixels on left hand side of the major axis on a direction of the major axis. Then, left foot is located at the first point from bottom of the projection histogram which is above the threshold. Similarly for right foot, histogram is created by analyzing silhouette pixels on right hand side of the major axis. Figure 3.4 shows example results of the proposed head and feet detections. The proposed method can precisely detect the head and feet positions for any walking poses.

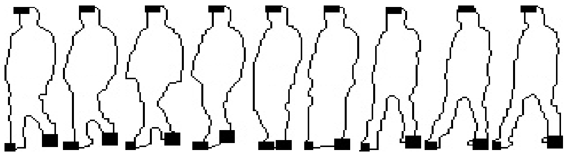


Figure 3.4: Example of head and feet detections.

4 Experiments

The experiments are performed on three well-known gait databases with various testing scenarios. The three databases are CASIA gait database A, CASIA gait database B, and CMU Mobo gait database. Figure 4.1 shows example images from the three databases. The proposed method is verified and compared with other existing methods including PSA-based methods [39][43]. Two existing and three proposed PSA-based methods are used in the experiments. Table 4.1 describes key components of each method.

Figure 4.1: Sample gait images. The first image is from CASIA gait database A, second image is from CASIA gait database B, and the third image is from CMU Mobo gait database.

As shown in Table 4.1, shape boundary can be re-sampled by two different methods which are shape re-sampling using Entire Boundary (EB) and shape re-sampling using Boundary Segments (BS). Shape can be described by two different shape descriptors, namely Centroid Shape Configuration (CSC) and Pairwise Shape Configuration (PSC). Gait similarity can be carried out by two different methods, namely Procrustes Distance (PD) and Shape Context (SC). Method Propose1 enhances PSA using shape boundary segmentation based on pose-invariant boundary contexts to assist the process of shape re-sampling and normalization. Method Propose2 enhances PSA using local shape descriptor, namely PSC, in order to replace global shape descriptor, namely CSC. Method Propose3 enhances PSA using the contributions from both Propose1 and Prppose2.

In this work, the shape boundary is empirically normalized into 40 points which has been proved by Wang et al. [39] that it can be well represented key information of the human shape. The ratio of 2:1:2 (head-right foot:right foot-left foot:left foot-head) is used for the boundary segments. Therefore, the clockwise boundary between head and right foot contains 16 points, the clockwise boundary between right foot and left foot contains 8 points, and the clockwise boundary between left foot and head contains 16 points.

Nearest Neighbor (NN) is used as a classification method and leave-one-out cross-validation rule is used as an unbiased estimation of the true classification rate. The experimental results are shown separately for each database. The different testing scenarios are also verified based on the supplied information of the databases. Figure 4.2

Table 4.1: Two existing and three proposed PSA-based methods

Method	Boundary re-sampling	Shape descriptor	Similarity measurement
Wang et al. [39]	EB	CSC	PD
Zhang et al. [43]	EB	CSC	SC
Propose1	BS	CSC	PD
Propose2	EB	PSC	PD
Propose3	BS	PSC	PD

shows example of PMSs generated from the method Propose3 and Figure 4.3 shows the comparisons between PMSs generated from the method in [39] and the method Propose3. It can be seen that the proposed method (Propose3) can better represent the differences between PMSs from different subjects, when being compared with the method in [39].

4.1 CASIA gait database A

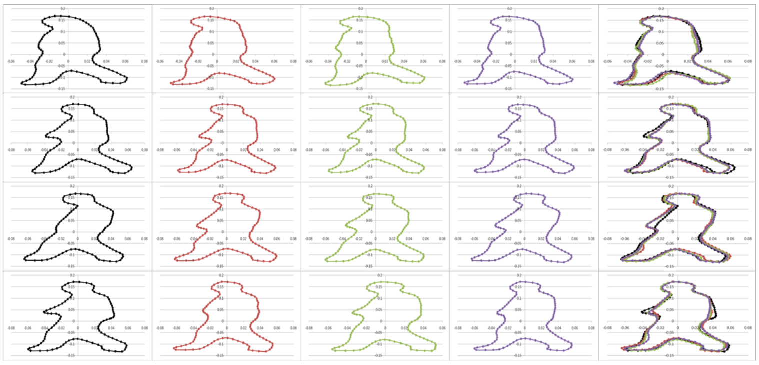
The database includes 20 different subjects from three different views, namely frontal view, oblique view, and lateral view. Four video sequences were recorded for each subject from each view. The database thus includes a total of 240 video sequences. This database is used to verify the performance of the proposed method on normal walking scenario. Table 2 shows comparisons between the proposed methods and other existing methods including PSA-based methods [39][43].

From Table 4.2, it is clearly seen that the proposed method (Propose3) outperforms the other existing PSA-based methods [39][43] for any three views. This proves that the proposed method can enhance the efficiency of PSA for gait recognition. There are two main supporting reasons. First, we propose a better shape boundary re-sampling using boundary segmentation based on pose-invariant landmarks of the human shape. This assists to solve the point correspondence problem between different gait poses. Secondly, the local shape boundary descriptor, PSC, is used to replace the global shape boundary descriptor, CSC. PSC is more robust to variations from the noises and self-shape variation across the gait cycle.

In addition, the proposed method performs better than the other existing methods in the literature except methods [20] and [17] which are comparable to our method. This is because GEI-based method [20] and 3D volume-based method [17] are constructed from a rich gait information by using a shape contour. However, our method uses PMS as gait feature which is constructed from a shape boundary. Nevertheless, rich information does not always well perform. Following experiments will show that the proposed method can significantly outperforms the GEI-based method [20] in a particular scenario which is viewing angle change challenging.

4.2 CMU Mobo gait database

The database contains 25 different subjects from lateral view. Video sequences were captured in an indoor environment. Each subject was recorded under slow walking and



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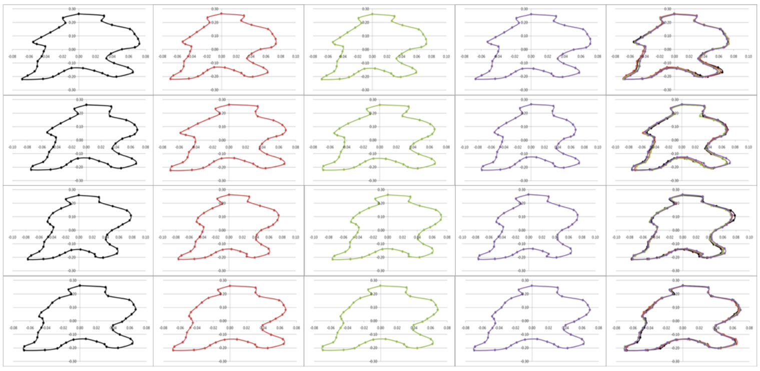

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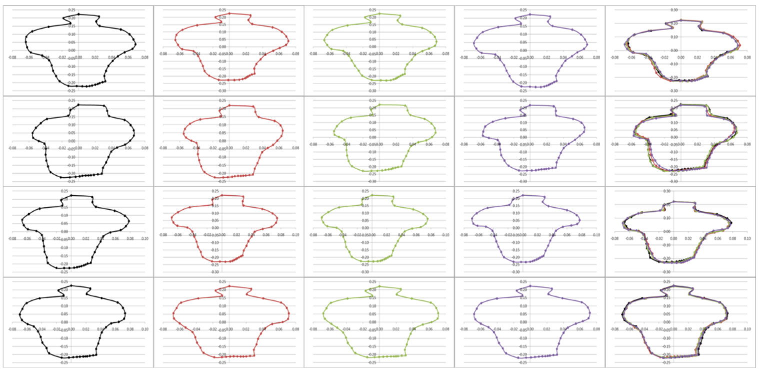
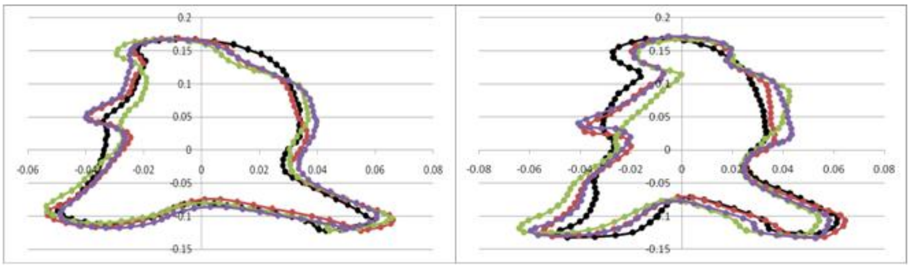


(3)

Figure 4.2: Example of Procrustes Mean Shapes (PMSs). Each row shows the PMSs of the same subject from four video sequences (first four columns), and the last column is the comparison of the four PMSs independent to position, scale, and rotation. (1) is side walk. (2) is lateral walk. (3) is frontal walk.



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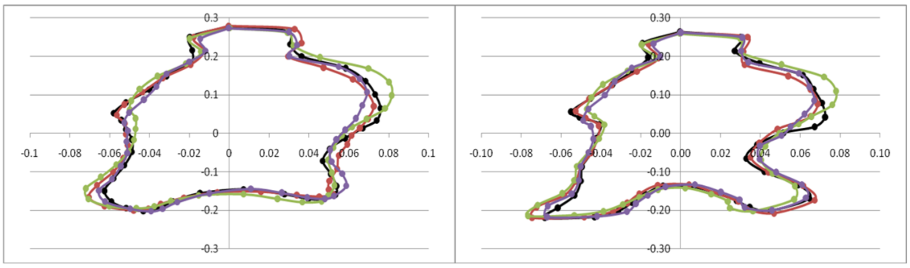

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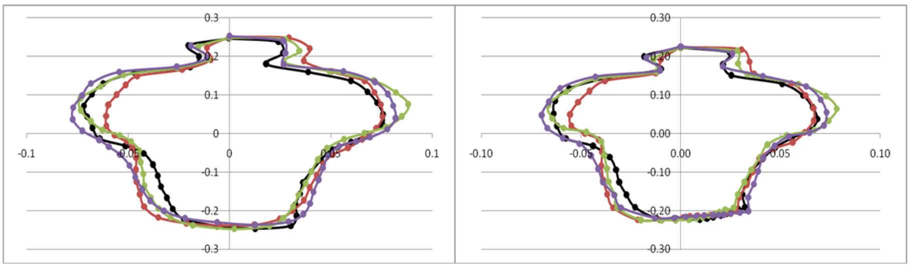


(3)

Figure 4.3: Comparison of PMSs from four different subjects (Black, green, purple, and red). PMSs in the first image are constructed using the method from Wang et al. [39], and PMSs in the second image are constructed using the method Propose3. (1) is side walk. (2) is lateral walk. (3) is frontal walk.

Table 4.2: Comparison of several different methods on the CASIA gait database A

Method	**Lateral (%)**	**Oblique (%)**	**Frontal (%)**
2001 [4]	72.50	-	-
2002 [3]	82.50	-	-
2002 [10]	71.25	-	-
2002 [26]	87.50	-	-
2002 [33]	78.75	-	-
2003 [39]	71.25	72.50	81.25
2006 [36]	89.31	-	-
2006 [30]	82.50	-	-
2006 [20]	98.75	96.25	95.00
2007 [40]	90.00	90.00	83.00
2007 [16]	90.00	95.00	90.00
2007 [9]	91.25	-	-
2008 [17]	100.00	97.50	91.00
2009 [43]	88.75	-	-
Propose1	91.25	83.75	78.75
Propose2	91.25	88.75	83.75
Propose3	97.50	96.25	95.00

Table 4.3: Comparison of several different methods on the CMU Mobo gait database

Method	**fs:fs (%)**	**fq:fq (%)**	**fs:fq (%)**	**fq:fs (%)**
2003 [39]	93.52	87.04	46.30	32.41
2005 [8]	84.00	73.00	-	-
2006 [35]	93.76	96.53	-	-
2006 [20]	100.00	99.33	75.00	77.78
Propose1	93.52	92.60	50.00	47.22
Propose2	99.07	97.22	59.26	51.85
Propose3	99.07	97.22	77.78	76.85

fast walking scenarios. Six video sequences were used for each subject from each walking speed. The database thus includes a total of 300 video sequences. This database is used to verify the performance of the proposed method on various walking speeds. Table 4.3 shows comparisons between the proposed methods and other existing methods including the PSA-based method [39]. Four different testing scenarios are performed on the database: 1) fs:fs includes slow walking speed dataset for both gallery and probe, 2) fq:fq includes fast walking speed dataset for both gallery and probe, 3) fs:fq includes slow walking speed dataset for gallery and fast walking speed dataset for probe, 4) fq:fs includes fast walking speed dataset for gallery and slow walking speed dataset for probe.

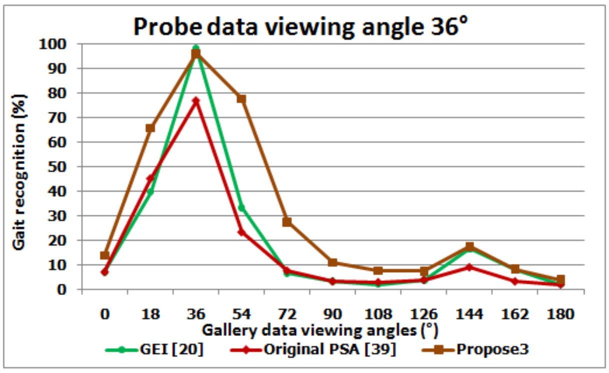
From Table 4.3, it is clearly seen that the proposed method (Propose3) significantly outperforms the existing PSA-based method [39] for both same and across walking speed scenarios. The proposed method also performs better than the other existing methods in the literature except GEI-based method [20] which is approximately equivalent to our method.

4.3 CASIA gait database B

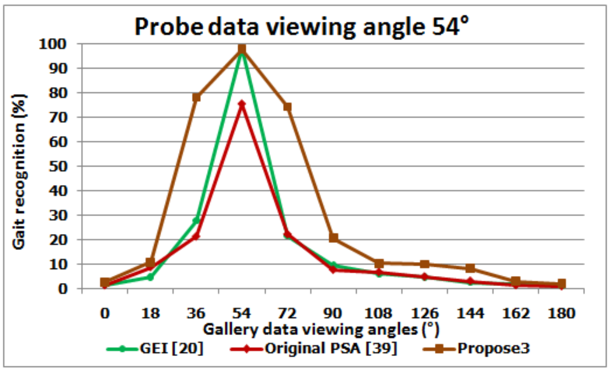
The database includes 124 different subjects from 11 different views, namely $0°$, $18°$, $36°$, $54°$, $72°$, $90°$, $108°$, $126°$, $144°$, $162°$, and $180°$. Six video sequences were recorded for each subject from each view. The database thus includes a total of 8184 video sequences. This database is used to verify the performance and the robustness of the proposed method on viewing angle change problem. Figure 4.4 illustrates the first rank or the top one gait identity matching for multi-view gait recognition by using three different methods, GEI-based method [20], original PSA-based method [39], and the proposed PSA-based method (Propose3).

From Figure 4.4, there are three interesting investigations. First, the proposed method significantly outperforms the original PSA-based method [39] for gait recognition within same view profile. Secondly, the proposed method enhances the original PSA-based method [39] to be more robust to viewing angle change. In PSA, near viewing angle change can be treated as pose-deviation problems. Therefore, the proposed local shape descriptor can deal better with the shape deviations from viewing angle change scenario, when being compared with the original global shape descriptor [39].

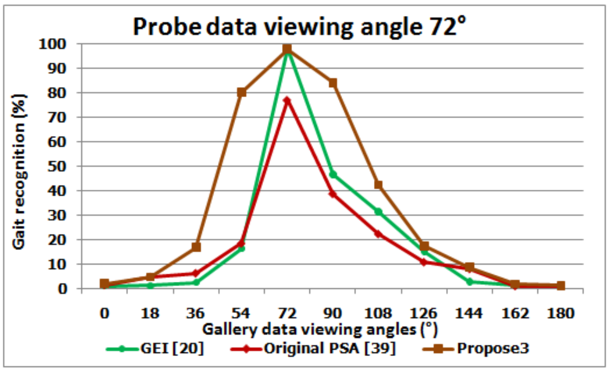
Thirdly, for the same viewing angle recognition, GEI-based method [20] can perform slightly better than the proposed method in some cases. However, the proposed



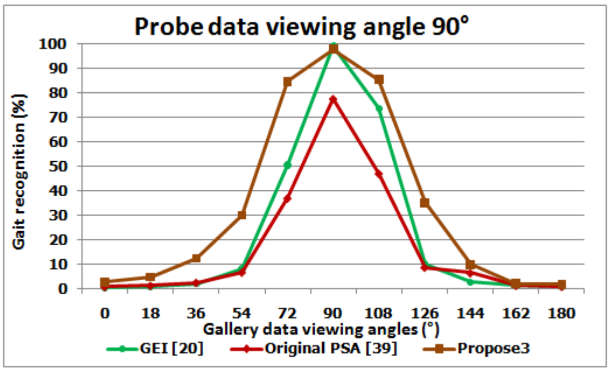
(1)



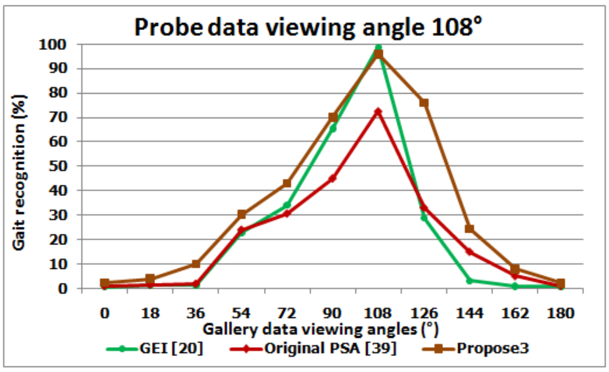
(2)



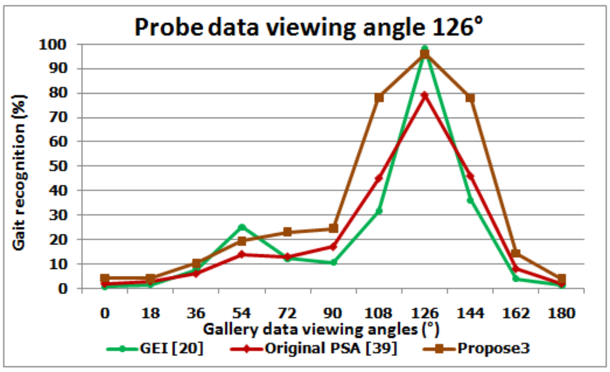
(3)



(4)



(5)



(6)

Figure 4.4: Comparison of several different methods on the CASIA gait database B.

method achieves significantly better performance for viewing angle change scenarios especially for slightly change of viewing angle i.e. $\pm 18^{\circ}$. This is because GEI contains too much view-dependent information. Slightly viewing angle change of the 3D human shape in 3D world is approximately similar to the changes of its projected 2D shape in 2D image. This is because the slightly change of viewing angle does not change a major characteristic of the 2D appearance of the individuals. Besides, PSA can perform a shape-preserving Euclidean transformation, therefore, PSA is robust to the slightly viewing angle change for the gait recognition.

The proposed gait recognition method (Propose3) is more suitable for practical situation than the other existing methods. This is because it is more robust to speed and viewing angle changes which is hard to be avoided in real application. For example, a person regularly walks with small deviation of walking direction and speed.

5 Conclusions

This study has proposed a new method for automatic gait recognition based on Procrustes Shape Analysis (PSA). This paper improves the original PSA-based method [39] by two manners. First, we improve the shape boundary re-sampling and normalization by using the boundary segmentation based on the pose-invariant contexts on the human shape. This can solve the point correspondence problem between different gait poses.

Secondly, the local shape descriptor, called Pairwise Shape Configuration (PSC), is proposed to replace the global shape descriptor, called Centroid Shape Configuration (CSC). This makes PSA more robust to deviations of gait poses. As the result, the proposed method can successfully enhance the performance of the original PSA-based method for gait recognition. It can be seen from the significant improvements shown in the experiments on the three well-known gait databases.

Besides, the proposed method make the PSA-based gait recognition method more robust to changes of viewing angle and walking speed. From the encourage experimental results, it can be said that the proposed method is invariant to near viewing angle change. It has been also proved to be more efficient and/or more robust, when being compared with the other existing methods in the literature. In addition, the use of PSC is expected to improve the performance of PSA for any type of shape and for other applications such as object classification and object retrieval.

The current PSA-based methods for gait recognition have a weak point when PMS is computed as a gait feature. PMS is the compressed representation of a gait sequence by ignoring order of gait poses in the sequence. It loses some temporal gait information. This drawback could be solved by considering history-based or volume-based concepts for PMS. This is leaved out for the future work.

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