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Person re-identification based on gait via Part View Transformation Model under variable covariate conditions☆

Imen Chtourou [a,*], Emna Fendri [b], Mohamed Hammami [b]

[a] University of Sfax, MIRACL Laboratory, ENIS, Road Sokra km 4, BP 1173, 3038 Sfax, Tunisia
[b] University of Sfax, MIRACL Laboratory, FSS, Road Sokra km 4, BP 802, 3038 Sfax, Tunisia

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ABSTRACT

Human gait represents an attractive biometric modality to re-identify a person as it requires non contact and it is perceivable at a distance. However, the view angle variation and the presence of covariate factors cause significant difficulties for recognizing gaits. In order to deal with such constraints, this paper presents a Part View Transformation Model (PVTM) for gait based applications. Compared with previous methods, the PVTM is applied on selected relevant parts chosen through a semantic classification step. Conducted on the CASIA-B gait database, experimental results show that the proposed method outperforms well known multi-view methods even under covariate factors (*i.e.* carrying bag, clothing).

1. Introduction

Over the past few years, human gait has been receiving an exceptional attention from pattern recognition and computer vision communities as an attractive soft-biometric cue. Several studies have been conducted on the visual analysis of human motion and automated person re-identification and/or recognition. Cognitive and psychological studies have emphasized that humans are able to identify each other by their distinct gait signature. Human gait includes both of the body appearance and the dynamics of walking [1]. Therefore, gait is considered to be pertinent in visual surveillance scenarios. This refers to the fact that gait analysis does not require explicit user cooperation, it is perceivable from a distance and it is unique for each individual. During the last decade, a number of gait analysis techniques have been oriented towards person re-identification [2,3] and/or recognition [4]. Re-identification is the process of identifying the same individual in different time instances either in the same camera or in different cameras. Person re-identification and/or recognition is still a difficult problem. Particularly, the presence of covariate factors (*i.e.* carrying bags, wearing coat) and the view angle variation affect and decrease considerably the performance of gait based applications in real situations. In fact, as shown in Fig. 1, the covariate factors affect considerably the appearance of the same person. These latter may cover (wearing coat) or extend (carrying bags) human body, which has a bad impact on gait information collection and analysis. Moreover, in real life applications, people may walk in different directions. Basically unlike existing methods like [5–7], in this paper a new method for gait based person re-identification is proposed under varying view angle and covariate factors (*i.e.* carrying bag and clothing). To deal with the view angle challenge, the proposed method is based on Part View Transformation Model (PVTM). Meanwhile, for covariate factors, we suggest a dynamic selection of relevant parts extracted from images. The definition of parts is conducted using a semantic classification step [8].

The rest of this paper is organized as follows. State of the art about gait based re-identification methods is reviewed in Section 2. An overview of the proposed method is exhibited in Section 3. In Section 4, experimental results and analysis are highlighted. Finally, in Section 5 we summarized our work and set forward our conclusions.

2. State of the art

In the literature, gait based methods can be categorized into: single-view angle based methods and multi-view angle based methods.

2.1. Single-view methods

The single-view gait based context is where both gallery and probe gait sequences are captured at the same viewing angle. In fact, previous research has demonstrated that the side view is the most discriminative view angle. Han and Bhanu [9] proposed a gait sequence representation method called the Gait Energy Image (GEI). The GEI is an image constructed by averaging human silhouettes over one complete gait cycle.

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* Corresponding author.
E-mail address: imene.chtourou@gmail.com (I. Chtourou).

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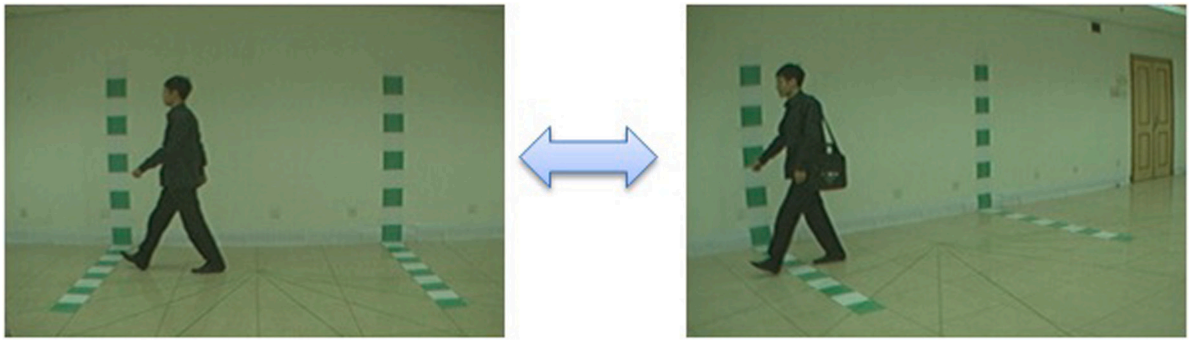

Fig. 1. Walking images of the same person with different covariate factors.

Although it is simple and effective for recognizing gaits in normal walking conditions, the GEI is sensible to appearance variations, e.g., those caused by clothing or carrying bag. To deal with this challenge, several works have been performed. The work presented in [10] focused on the relevance of Local binary pattern (LBP) in extracting texture features in the whole GEI image and the region delimited by the legs. Chin Poo Lee et al. [11] reported a combination of spatiotemporal and texture descriptors to extract the temporal patterns in gait cycles. Authors in this paper adopt the Transient Binary Pattern operator (TBP) after dividing the GEI image into equal regions. The method in [12], after dividing the GEI image into five and seven non overlapping regions, applied the Fuzzy Local Binary Pattern (FLBP) on each region of the image. The method in [13] rests on golden ratio. A two dimensional Gabor Filter (2DGabor) is adopted to extract features from GEI. It uses four different clothing models to identify unaltered area of the test GEI that is used for recognition. This method managed to detect the part of clothing, and discarded it. The work accomplished by [14] relies on the Haralick features extracted from GEI. These features are extracted locally by dividing vertically or horizontally the GEI into two or three equal regions of interest, respectively. Alotaibi et al. [15] proposed a feature selection method based on the GEI. They used dictionary learning with sparse coding and Linear Discriminant Analysis(LDA) to seek the best discriminative data representation before feeding the Nearest Centroid (NC) classifier. Authors in this paper attempt to describe an augmentation technique to overcome some of the problems associated with the intra-class gait variations, as well as the amount of the training data whether it is relatively small or not. Ghebleh et al. [16] suggested an adaptive outlier detection method to remove the effect of clothing on silhouettes. It detects the most similar parts of probe and each gallery sample independently and uses these parts to obtain a similarity measure. These previously mentioned methods are applied on the side view angle which makes them unsuitable for the majority of real time gait based applications.

2.2. Multi-view methods

The variation caused by multiple viewing angles brings even more challenges for robust gait based applications. Fig. 2 shows the gait representation features (GEI) of two different subjects under different viewing angles from 0 to 180 . Obviously, the differences between intra-subjects under large view variation are much larger than the differences between inter-subjects of the same view. That is why multiple viewing angles is a problem that still challenging and remains to be solved.

As presented in [17], gait based methods addressing the multi-view can be based on 3D information, invariant features or learning relationships in a subspace.

2.2.1. Methods based on 3D information

Methods in the first category rely on the reconstructed 3D gait model [18–21] [22]. Bodor et al. [18] proposed a 3D visual hull model to construct the gait features using silhouettes from multiple cameras as input. Zhao et al. [19] proposed to use an array of multiple cameras to capture a set of video sequences which are then used to reconstruct a 3D human skeleton model. Iwashita et al. [20] proposed a spatio-temporal 3D gait database directly in order to synthesize gait sequence at each view angle. The person was recognized and his walking direction was estimated by comparing the gait features with those in the database. López-Fernández et al. [21,22] presented a rotation invariant gait descriptor based on 3D angular analysis of the subject's movement for multi-view gait recognition on unconstrained paths. However, the need for multiple cameras and camera calibration limits the feasibility of this first category in real applications.

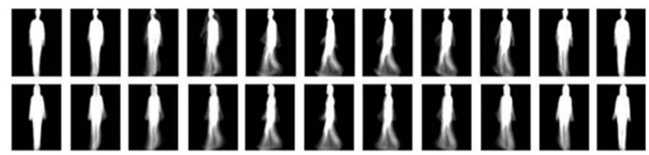

Fig. 2. Gait Energy Image (GEIs) of two persons from CASIA gait database B walking under different angles: 0°, 18°, 36°, 54°, 72°, 90°, 108°, 126°, 144°, 162°, and 180°.

2.2.2. Methods based on view-invariant features

The second category concerns methods that extract view-invariant gait features [23–25]. Jean et al. [23] set forward a method to compute view-invariant gait features which are view normalized feet and head 2D trajectories. Goffredo et al. [24] extracted model-based gait feature, namely angular measurements and trunk spatial displacements, which are then reconstructed using view-rectification method. Kusakunniran et al. [25] transformed gait silhouettes from arbitrary view into the canonical view. Procrustes mean shape was extracted as a feature to measure gait similarity. Xu et al. [26] proposed a gait recognition method based on capsule network. They achieve view invariant recognition using one model. The idea is to consider two different architectures, namely matching local features at the bottom layer based on capsule network and matching mid-level features at the middle layer based on capsule network. When the difference between two views is large, these methods can still perform efficiently. However, these methods in this category are not applicable for front view because the gait feature from front view could not be transformed into side view.

2.2.3. Methods based on subspace projection

The third category learns mapping or projection relationship of gaits across views through a training process. The learnt relationships normalize gait features from different views into shared or associated subspace(s) before gait similarity is measured. The relationship between gait data from different views is established through the learning process. Recent research mainly relies on View Transformation Model (VTM) [27–31] and subspace learning [5–7,32–34].

Makihara et al. [30] introduced VTM to transform gait features from one view into another view. Singular Value Decomposition (SVD) was applied on frequency domain features to construct the VTM. Kusakunniran et al. [28] defined the VTM reconstruction problem as a Support Vector Regression (SVR) problem. They chose local regions of interests based on local motion relationships, instead of global features, to build VTMs through support vector regression. After that, they improved the performance by introducing sparsity to the regression [29]. Zheng et al. [27] established a Robust VTM which is based on Robust Principal Component Analysis (RPCA). Muramatsu et al. [31] proposed an Arbitrary View Transformation Model (AVTM). This is based on combining details of both first and third categories. 3D gait visual hulls were established and used to create training gait sequences under any required angle views. Then VTM was constructed to transform features.

Methods based on subspace learning have been used to transform the gait features obtained from various viewing spaces into a shared feature space. Bashir et al. [32] modeled the correlation of gait sequences from different view angles using Canonical Correlation Analysis (CCA). Hu et al. [33] proposed a unitary linear projection method named View-invariant Discriminative Projection (ViDP), which allows cross-view gait recognition to be conducted without knowing the query view angle. Xing et al. [5] proposed Complete Canonical Correlation Analysis (C3 A) in order to overcome the shortcomings of CCA when dealing with two sets of high dimensional features directly. Nini Liu et al. [34] designed a Multiview Subspace Representation (MSR) method which considers gait sequences collected from different views of the same subject as a feature set and extracts a linear subspace to describe the feature set. Connie et al. [6] demonstrated how to generate virtual views to compensate the view difference in the query and reference sets. This makes it possible to match the query and reference sets using standardized views. The proposed method, which associates multi-view matrix representation and randomized kernel, offers a solution for the problem of changing of view. Xu et al. [17] proposed Coupled Locality Preserving Projections (CLPP) in order to deal with gait recognition under view change using GEI data. Huimin Wu et al. [35] proposed to combine deep features and hand-crafted representations into a globally trainable deep mode for gait recognition tasks. Wu et al. [36] performed multi-view gait recognition via similarity learning by deep Convolutional Neural Network (CNN). They trained deep networks to recognize the most discriminative changes of gait patterns by a small group of labeled multi-view human walking videos. Wanjiang et al. [7] proposed a method, called Multi view Max-Margin Subspace Learning(MMMSL) in order to address the problem of gait across multiple views. The MMMSL based method can obtain single common space shared by all views. In this learnt common subspace, same-class samples from all views cluster together, and each different-class cluster was kept away from its nearest neighbors as far as possible. Li et al. [37] proposed a feature extraction via GEI subspace projections. Authors applied a sequence of three projections to obtain an optimal subspace from the gait energy image. They developed a three-step projection procedure for the GEI data, in order to obtain a low-dimensional discriminant feature vector. First, they defined an importance map and selected regions of high importance. Second, they applied PCA on the selected important regions to reduce the feature dimension while separating data samples of different classes. Third, they conducted LDA to reduce the feature dimension while maximizing the ratio of inter-class to intra-class variances. For the classification, they adopted Collaborative Representation Classifier (CRC). Despite all the above-mentioned efforts, the achieved multi-view gait based method still give relatively low accuracy. In this paper, we aim to handle both the view angle variation and presence of covariate factors (*i.e.* carrying bag, clothing) challenges while keeping the discriminative information so as to achieve better performance.

3. Overview of the proposed method

The overview of the proposed method is illustrated in Fig. 3. After gait features being prepared and the semantic classification is done, the viewing angles of gallery gait data and probe gait data are transformed into the same direction with the generated PVTM. Therefore, gait signatures can be measured. The advantage of our proposed method is the use of the VTM on selected relevant parts. This makes it suitable to deal with several covariate factors. The framework of the proposed method contains an off-line phase and an on-line phase. In the following sub-sections, we will detail each phase.

3.1. Off-line phase

The off-line phase is a training step which is conducted in order to construct the Part View Transformation Model (PVTM).

3.1.1. Gait feature preparation

The well-known Gait Energy Image (GEI) [9] is used as a gait feature. Before the generation of the GEI, a gait period estimation step is necessary. In our work, we have adopted the method used in [38] and [39] to determine the period of each gait sequence. GEI is constructed from a sequence of aligned silhouettes images in a one walking cycle. GEI captures several key information of human gait including the motion frequency, the temporal and spatial changes of the human body and the global body shape. This rich content of GEI will provide a substantial correlation across views. Furthermore, Partial Least Squares (PLS) analysis has attracted increasing attention in image and video processing. It is an efficient supervised dimension reduction algorithm. Inspired by the work of [27], Partial Least Square (PLS) regression is used in this paper as a feature selection algorithm to learn optimal feature representation vectors. The optimized obtained GEI is expected to be better factorized than the original spatial-domain GEI.

3.1.2. Part View Transformation Model (PVTM) construction

As the observation views of the gallery and the probe are different, the extracted gallery and probe gait features have different shapes to each other; direct comparison of such gait features yields degradation of recognition accuracy. We, therefore, transform one of them using a VTM so that both gait features have the same view in common, and calculate a matching score by comparing the gait features with the same view. In our previous work [40], we have proposed a method for gait based person re-identification relying on dynamic selection of human parts. We have focused on controlled environments where individuals are seen from a side view. The proposed method consists in computing a new person descriptor from relevant selected human parts. The selection of the most informative parts was achieved depending on the presence of semantic information. This idea was generalized in order to deal with several view angles. In this paper, for each selected informative part from the GEI image, a Part View Transformation Model (PVTM) is constructed. This phase involves construction of the PVTM using multi-view gait features of multiple training persons. We assume that M pairs of gait features associated with source and destination views θ and ϕ are available for PVTM training. These gait features for PVTM training are associated with independent training subjects which are different from target subjects. Let $X^{m}_{(\theta)}$ and $X^{m}_{(\phi)}$ be N-dimensional gait features of the m th pair with views θ and ϕ respectively. By arraying the gait features, we generate a training matrix D by:

$$D = \begin{pmatrix} X^{1}_{(\theta)} & .... & X^{M}_{(\theta)} \\ .... & .... & .... \\ X^{1}_{(\phi)} & .... & X^{M}_{(\phi)} \end{pmatrix} \tag{1}$$

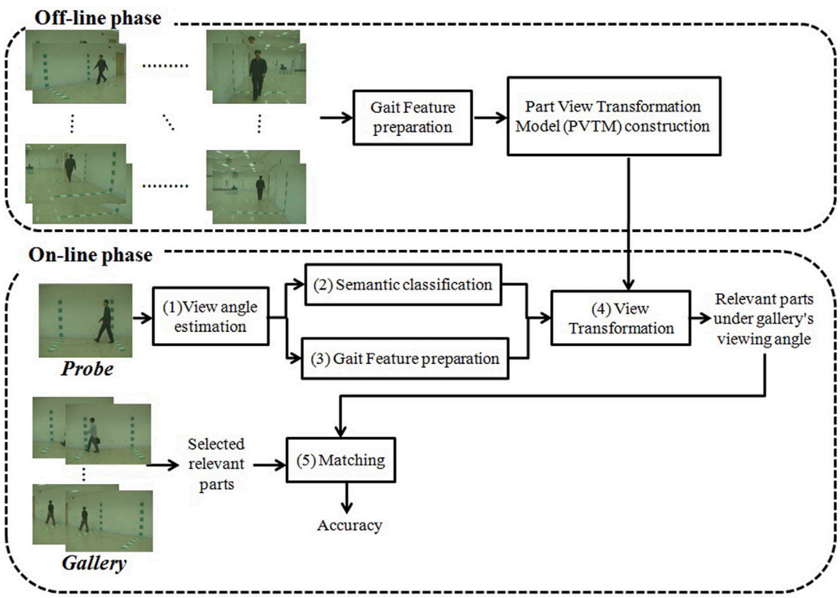

Fig. 3. Overview framework of the proposed method.

We then apply Singular Value Decomposition (SVD) to D. The decomposition-based method using SVD [38] is a conventional approach for VTM construction based on a decomposition concept.

$$D = USV^T \tag{2}$$

$$= \begin{bmatrix} R(\theta) \\ R(\phi) \end{bmatrix} \begin{bmatrix} v^1 & \dots & v^M \end{bmatrix} \tag{3}$$

Here, $U \subset \mathbb{R}^{2N\times M}$ is an orthogonal matrix, $V \subset \mathbb{R}^{M\times M}$ is also an orthogonal matrix, $S \subset \mathbb{R}^{M\times M}$ is a diagonal matrix whose on-diagonal elements are singular values.

$R(\theta)$ and $R(\phi)$ are sub-matrices of U, and they are view-dependent feature-independent matrices. On the other side, v^m is an intrinsic vector, the mth row vector of matrix SV^T, and it is a view-independent feature.

3.2. On-line phase

The on-line phase contains five steps which are (1) View angle estimation, (2) Semantic classification, (3) Gait feature preparation which is detailed in the previous phase, (4) View transformation using PVTM and (5) Matching.

3.2.1. View angle estimation

Our proposed method is based on View Transformation Model. This requires the knowledge of viewing angle for each gait sequence before applying the corresponding view transformation model. For this reason, a viewing angle estimation step is necessary. In our previous work [41], we have proposed a walking direction estimation solution. Such solution can be suitable for real time applications in unconstrained environment where the user walking direction is different and affected by covariate factors. In fact, to classify each view angle into the corresponding class, we adopted a KDD process (Knowledge Discovery in Databases) for extracting useful knowledge from volumes data. The total process of walking direction estimation is based mainly on two steps: a first step which is a models construction step and a second one which is View angle classification step.

3.2.2. Semantic classification

In our previous work [8], we have concentrated on covariate factors that can affect gait representation (*i.e.* Single Shoulder Bag, Back Pack, Hand Bag and Outerwear). These covariate factors can influence and occlude the gait based appearance of the body shape and consequently decrease the performance of gait based applications. The idea was to propose an automatic semantic attribute classification solution which predicts the class of each semantic attribute from walking person image. The classification process is able to identify four semantic attributes corresponding to the examined covariate factors.

3.2.3. View transformation using PVTM

Given gait features from two different views, the view transformation phase involves the transformation of a gait feature from a view (target view) into that from the other view (source view).

Given, respectively, $x_G^{(\theta)}$ and $x_P^{(\phi)}$ a gallery gait feature with view θ and a probe gait feature with view ϕ, we consider transforming the gallery gait feature with view θ to that with view ϕ. To deal with covariate factors, the GEI image is divided into seven non overlapping parts which are: head, chest 1, chest 2, knee 1, knee 2, foot 1, foot 2. Fig. 4 shows a walking GEI image divided into these mentioned seven parts. Parts affected by any detected semantic attribute are discarded. The transformation is achieved by using the probe gait feature $x^p_{(\phi)}$ for each remaining relevant part, a point on the joint subspace $\hat{v}^P_{(\leftarrow\phi)}$ is estimated by:

$$\hat{v}^P_{(\leftarrow\phi)} = argmin\|x^p_{(\phi)} - R(\phi)v\|_2^2 \tag{4}$$

$$= R(\phi)^+ x^p_{(\phi)} \tag{5}$$

$$where\ R(\phi)^+ = ((R(\phi))^T R(\phi))^{-1} R(\phi)^T \tag{6}$$

where $\|.\|_2$ denotes the L_2 norm.

The probe gait feature of view θ, $\hat{x}^p_{(\theta\leftarrow\phi)}$, is generated by projecting the estimated point on the joint subspace $\hat{v}^p_{(\leftarrow\phi)}$ to the gait feature space of view ϕ

$$\hat{x}^p_{(\theta\leftarrow\phi)} = R(\theta)\hat{v}^p_{(\leftarrow\phi)} \tag{7}$$

3.2.4. Matching

The matching phase involves a score calculation for the final accuracy. We calculate a dissimilarity score between the gallery and the probe in the same gait feature space of view θ by:

$$d(x^G_{(\theta)}, x^P_{(\phi)}) = \|x^G_{(\theta)} - \hat{x}^p_{(\theta\leftarrow\phi)}\|_2 \tag{8}$$

$$= \|x^G_{(\theta)} - R(\theta)R(\phi)^+ x^p_{(\phi)}\|_2 \tag{9}$$

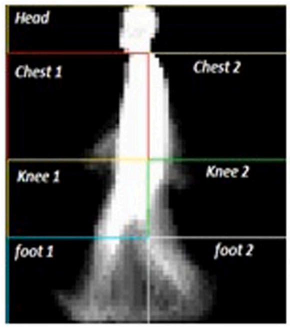

Fig. 4. The GEI division into seven parts: head, chest1, chest2, knee1, knee2, foot1 and foot2.

Table 1
Correct user recognition rate (%) with and without relevant parts selection.

View angle	Without selection of relevant parts	With selection of relevant parts
000	24, 51	21,765
018	12,745	11,568
036	37,059	**38,431**
054	44.51	**46.863**
072	41.764	**47.65**
090	37.843	**46.470**
108	36.471	**43.333**
126	37.451	**41,765**
144	39.120	**48.235**
162	25.294	21.176
180	26.275	25.69

4. Experimental evaluation

In this section, the different experimental setups are detailed in order to validate the performance of our proposed method. In our experimental evaluation, two experimentations have been conducted: The first experimentation validate our proposed method in the case of single view gait sequences. This experimentation is carried out where gallery and probe contain mixed covariate factors. The second experimentation deals with multi-view gait sequences.

4.1. Gait database

The CASIA database is one of the largest gait datasets. CASIA-B [42], in particular, contains gait sequences of 124 subjects captured from multiple angles under several covariate conditions. Each subject was captured from 11 viewing angles (*i.e.*, 0°, 18°, 36°, 54°, 72°, 90°, 108°, 126°, 144°, 162° and 180°). At each viewing angle, each subject was asked to walk naturally along a straight line for 6 times without carrying a bag or wearing a coat, twice carrying a bag and twice wearing a coat.

4.2. Results

4.2.1. Single view gait re-identification

In this experimentation, we aim to validate our re-identification method based on dynamic selection for single view gait sequences. This method has already accomplished promising results for side view [40]. Thus, the gallery and probe sets, from the same view angle, contain a mixture of different conditions (*i.e.* carrying bag, clothing, carrying nothing). In this experiment, we have used only the relevant parts after a semantic classification step. Relevant parts are parts that are not affected by any semantic attribute. Table 1 shows the correct person recognition rate (%) with and without selection of relevant parts. It is obvious that results "with selection of relevant parts" give the better recognition rate (%) for the majority of view angle. In fact, the results confirm the weakness of the gait based method for frontal view angles especially in the presence of covariate factors [43].

Table 2
Gait recognition rates (%) for bag-carrying image where the viewing angle of probe sequences is 90°° and those of gallery sequences are 54°, 72°, 108°, 126° and 144°.

Gallery view angle	54°	72°	108°	126°	144°	Average
GEI-NNC [42]	13	31	44	15	2	15
GEI-LDA-TSVD [38]	10	31	23	13	10	17.4
GEI-PLS-TSVD [27]	19	59	55	23	10	33.2
GSP-CRC [37]	18	**90**	**83**	24	8	**44.6**
Proposed method	**30**	67	69	**35**	**14**	43

Table 3
Gait recognition rates (%) in coat-wearing image where the viewing angle of probe sequences is 126° and those of gallery are 72°, 90° , 108° , 144° and 162°.

Gallery view angle	72°	90°	108°	144°	162°	Average
GEI-NNC [42]	14	9	6	18	2	9.8
GEI-LDA-TSVD [38]	9	10	20	30	13	16.4
GEI-PLS-TSVD [27]	24	26	53	**88**	**31**	44.4
GSP-CRC [37]	18	16	64	77	7	36.4
Proposed method	**36**	**52**	**71**	60	13	**46.6**

4.2.2. Multi view gait re-identification

This section contains two series of experiments: The first series of experiment shows the advantage of PVTM versus the VTM. The second series of experiment compare our proposed method with some state of the art methods that use the View Transformation Model (VTM).

First series of experiments. In this first series of experiments, we emphasized the advantage of the PVTM versus the basic VTM. PVTM based method uses a VTM for each part (PVTM) of the divided GEI image. Meanwhile, basic VTM based method uses a VTM for the entire GEI image (*c.f.* Fig. 4). We adopted carrying nothing gait sequences in this experiment. We normalized and cropped each GEI to 64 × 64 pixels. For each selected probe view, we tested on the gallery view θ_G from the rest 10 viewing angles except the corresponding probe view. Fig. 5 presents comparison of gait recognition rate using parts and using entire image (the viewing angle of the probe is 126°). From this figure, we notice that using parts provides the best gait recognition rates for the majority of the 10 viewing angles.

Second series of experiments. To evaluate the performance of our proposed method, we compared it with four well known methods from the state-of-the-art.

(1) The gait energy image and nearest neighbor classifier method (GEI-NNC) [42](2) The linear discriminant analysis of GEI and truncated singular value decomposition based (GEI-LDA-TSVD) method [38] (3) The partial least squared regression on GEI and truncated singular value decomposition (GEI-PLS-TSVD) method [27] and (4) The subspace projections of the GEI and collaborative representation classification (CRC) (GSP-CRC) method [37].

For this evaluation, and for fair comparison, we follow the same protocol as proposed in [27]. Samples of the first 24 subjects in CASIA-B Database are used for parameter training while samples of the remaining 100 subjects are invested to form the gallery and probe sets for two tests: bag-carrying walking and coat-wearing walking. The recognition rates for these two tests are given in Tables 2–3, respectively.

Our proposed method goes beyond those presented in [38,42] which use the entire image without taking into account covariate factors (i.e. carrying bag, wearing coat). Concerning the method proposed in [27], although it exceeds our proposed method in the case of coat wearing images (especially in angles 144° and 162°), our average rates remain better. Dealing with the paper [37], although they bring better results than ours in the case of presence of bags, especially for the angles (72° and 108°), they fail in the case of wearing coat in the majority of view angles (except 144°). This confirms that our proposed method is suitable not only for view angle variation but also for covariate factors (carrying bag, wearing coat) presence.

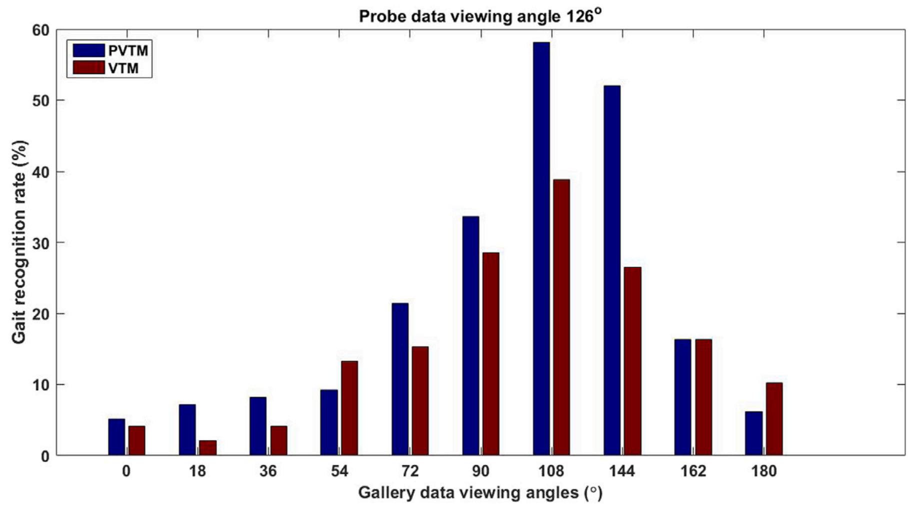

Fig. 5. Comparison of gait recognition rate using Local and Global based method. The viewing angle of the probe is 126°. The viewing angles of the gallery data are the rest 10 viewing angles except the corresponding probe viewing angle.

5. Conclusion

The change caused by multiple viewing angles lead to more challenges for robust gait based applications. In this paper, we introduced a Part View Transformation Model (PVTM) based on selected relevant parts of Gait Energy Image (GEI). The proposed method is suitable for multi-view gait based application under different wearing and carrying conditions. The relevant parts are determined based on a semantic classification step. The experimental evaluation proves that the proposed method brings the significant performance on the multi-view gait database. In the future, we plan to evaluate the proposed method on more difficult datasets.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

References

[1] L. Lee, W.E.L. Grimson, Gait analysis for recognition and classification, in: Automatic Face and Gesture Recognition, 2002. Proceedings. Fifth IEEE International Conference on, IEEE, 2002, pp. 155–162.

[2] A. Bedagkar-Gala, S.K. Shah, Gait-assisted person re-identification in wide area surveillance, in: Asian Conference on Computer Vision, Springer, 2014, pp. 633–649.

[3] L. Wei, Y. Tian, Y. Wang, T. Huang, Swiss-system based cascade ranking for gait-based person re-identification, in: AAAI, 2015, pp. 1882–1888.

[4] I. Bouchrika, A survey of using biometrics for smart visual surveillance: Gait recognition, in: Surveillance in Action, Springer, 2018, pp. 3–23.

[5] X. Xing, K. Wang, T. Yan, Z. Lv, Complete canonical correlation analysis with application to multi-view gait recognition, Pattern Recognit. 50 (2016) 107–117.

[6] T. Connie, M.K.O. Goh, A.B.J. Teoh, A grassmannian approach to address view change problem in gait recognition, IEEE Trans. Cybern. 47 (6) (2017) 1395–1408.

[7] W. Xu, C. Zhu, Z. Wang, Multiview max-margin subspace learning for cross-view gait recognition, Pattern Recognit. Lett. 107 (2018) 75–82.

[8] I. Chtourou, E. Fendri, M. Hammami, Semantic attribute classification related to gait, in: International Conference on Intelligent Systems Design and Applications, Springer, 2017, pp. 508–518.

[9] J. Han, B. Bhanu, Individual recognition using gait energy image, IEEE Trans. Pattern Anal. Mach. Intell. (2) (2006) 316–322.

[10] H.M. Kumar, H. Nagendraswamy, LBP for gait recognition: A symbolic approach based on GEI plus RBL of GEI, in: Electronics and Communication Systems (ICECS), 2014 International Conference on, IEEE, 2014, pp. 1–5.

[11] C.P. Lee, A.W. Tan, S.C. Tan, Gait recognition with transient binary patterns, J. Vis. Commun. Image Represent. 33 (2015) 69–77.

[12] A.G. Binsaadoon, E.-S.M. El-Alfy, Gait-based recognition for human identification using fuzzy local binary patterns, in: ICAART, No. 2, 2016, pp. 314–321.

[13] Y. Liang, C.-T. Li, Y. Guan, Y. Hu, Gait recognition based on the golden ratio, EURASIP J. Image Video Process. 2016 (1) (2016) 22.

[14] A.O. Lishani, L. Boubchir, E. Khalifa, A. Bouridane, Human gait recognition based on Haralick features, Signal Image Video Process. 11 (6) (2017) 1123–1130.

[15] M. Alotaibi, A. Mahmood, Reducing covariate factors of gait recognition using feature selection and dictionary-based sparse coding, Signal Image Video Process. 11 (6) (2017) 1131–1138.

[16] A. Ghebleh, M.E. Moghaddam, Clothing-invariant human gait recognition using an adaptive outlier detection method, Multimedia Tools Appl. (2018) 1–21.

[17] W. Xu, C. Luo, A. Ji, C. Zhu, Coupled locality preserving projections for cross-view gait recognition, Neurocomputing 224 (2017) 37–44.

[18] R. Bodor, A. Drenner, D. Fehr, O. Masoud, N. Papanikolopoulos, View-independent human motion classification using image-based reconstruction, Image Vis. Comput. 27 (8) (2009) 1194–1206.

[19] G. Zhao, G. Liu, H. Li, M. Pietikainen, 3D gait recognition using multiple cameras, in: Automatic Face and Gesture Recognition, 2006. 7th International Conference on, FGR 2006, IEEE, 2006, pp. 529–534.

[20] Y. Iwashita, R. Baba, K. Ogawara, R. Kurazume, Person identification from spatio-temporal 3D gait, in: Emerging Security Technologies (EST), 2010 International Conference on, IEEE, 2010, pp. 30–35.

[21] D. López-Fernández, F.J. Madrid-Cuevas, A. Carmona-Poyato, R. Muñoz-Salinas, R. Medina-Carnicer, A new approach for multi-view gait recognition on unconstrained paths, J. Vis. Commun. Image Represent. 38 (2016) 396–406.

[22] D. López-Fernández, F.J. Madrid-Cuevas, A. Carmona-Poyato, M.J. Marín-Jiménez, R. Muñoz-Salinas, R. Medina-Carnicer, Independent gait recognition through morphological descriptions of 3D human reconstructions, Image Vis. Comput. 48 (2016) 1–13.

[23] F. Jean, R. Bergevin, A.B. Albu, Computing and evaluating view-normalized body part trajectories, Image Vis. Comput. 27 (9) (2009) 1272–1284.

[24] M. Goffredo, I. Bouchrika, J.N. Carter, M.S. Nixon, Self-calibrating view-invariant gait biometrics, IEEE Trans. Syst. Man Cybern. B 40 (4) (2010) 997–1008.

[25] W. Kusakunniran, Q. Wu, J. Zhang, Y. Ma, H. Li, A new view-invariant feature for cross-view gait recognition, IEEE Trans. Inf. Forensics Secur. 8 (10) (2013) 1642–1653.

[26] Z. Xu, W. Lu, Q. Zhang, Y. Yeung, X. Chen, Gait recognition based on capsule network, J. Vis. Commun. Image Represent. 59 (2019) 159–167.

[27] S. Zheng, J. Zhang, K. Huang, R. He, T. Tan, Robust view transformation model for gait recognition, in: Image Processing (ICIP), 2011 18th IEEE International Conference on, IEEE, 2011, pp. 2073–2076.

[28] W. Kusakunniran, Q. Wu, J. Zhang, H. Li, Support vector regression for multi-view gait recognition based on local motion feature selection, in: Computer Vision and Pattern Recognition (CVPR), 2010 IEEE Conference on, IEEE, 2010, pp. 974–981.

[29] W. Kusakunniran, Q. Wu, J. Zhang, H. Li, Gait recognition under various viewing angles based on correlated motion regression, IEEE Trans. Circuits Syst. Video Technol. 22 (6) (2012) 966–980.

[30] Y. Makihara, R. Sagawa, Y. Mukaigawa, T. Echigo, Y. Yagi, Gait recognition using a view transformation model in the frequency domain, in: European Conference on Computer Vision, Springer, 2006, pp. 151–163.

[31] D. Muramatsu, A. Shiraishi, Y. Makihara, M.Z. Uddin, Y. Yagi, Gait-based person recognition using arbitrary view transformation model, IEEE Trans. Image Process. 24 (1) (2015) 140–154.

[32] K. Bashir, T. Xiang, S. Gong, Cross view gait recognition using correlation strength, in: Bmvc, 2010, pp. 1–11.
[33] M. Hu, Y. Wang, Z. Zhang, J.J. Little, D. Huang, View-invariant discriminative projection for multi-view gait-based human identification, IEEE Trans. Inf. Forensics Secur. 8 (12) (2013) 2034–2045.
[34] N. Liu, J. Lu, G. Yang, Y.-P. Tan, Robust gait recognition via discriminative set matching, J. Vis. Commun. Image Represent. 24 (4) (2013) 439–447.
[35] H. Wu, J. Weng, X. Chen, W. Lu, Feedback weight convolutional neural network for gait recognition, J. Vis. Commun. Image Represent. 55 (2018) 424–432.
[36] Z. Wu, Y. Huang, L. Wang, X. Wang, T. Tan, A comprehensive study on cross-view gait based human identification with deep cnns, IEEE Trans. Pattern Anal. Mach. Intell. (2) (2017) 209–226.
[37] W. Li, C.-C.J. Kuo, J. Peng, Gait recognition via GEI subspace projections and collaborative representation classification, Neurocomputing 275 (2018) 1932–1945.
[38] W. Kusakunniran, Q. Wu, H. Li, J. Zhang, Multiple views gait recognition using view transformation model based on optimized gait energy image, in: Computer Vision Workshops (ICCV Workshops), 2009 IEEE 12th International Conference on, IEEE, 2009, pp. 1058–1064.
[39] L. Wang, T. Tan, H. Ning, W. Hu, Silhouette analysis-based gait recognition for human identification, IEEE Trans. Pattern Anal. Mach. Intell. 25 (12) (2003) 1505–1518.
[40] E. Fendri, I. Chtourou, M. Hammami, Gait based person re-identification under covariate factors, Pattern Anal. Appl. 22 (4) (2019) 1629–1642.
[41] I. Chtourou, E. Fendri, M. Hammami, Walking direction estimation for gait based applications, Procedia Comput. Sci. 126 (2018) 759–767.
[42] S. Yu, D. Tan, T. Tan, A framework for evaluating the effect of view angle, clothing and carrying condition on gait recognition, in: Pattern Recognition, 2006. 18th International Conference on, Vol. 4, ICPR 2006, IEEE, 2006, pp. 441–444.
[43] R. Imad, Temporal Signals Classification (Ph.D. thesis), École Centrale Marseille, 2017.