Feature Selection for Gait Recognition without Subject Cooperation

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Abstract

The strength of gait, compared to other biometrics, is that it does not require cooperative subjects. Previoius gait recognition approaches were evaluated using a gallery set consisting of gait sequences of people under similar covariate conditions (i.e. clothing, surface, carrying, and view conditions). This evaluation procedure, however, implies that the gait data are collected in a cooperative manner so that the covariate conditions are known a priori. In this work, the performance of state of the art gait recognition approaches are evaluated without the assumption on cooperative subjects, i.e. the gallery set consists of a mixture of gait sequences under different unknown covariate conditions. The results show that the performance of the existing approaches drop drastically under this more realistic experimental setup. We argue that selecting the most relevant gait features that are invariant to changes in gait covariate conditions is the key to develop a gait recognition system that works without subject cooperation. To that end, we propose a novel gait recognition approach, which performs automatic feature selection on each pair gallery and probe gait sequences, and seamlessly integrates feature selection with an Adaptive Component and Discriminant Analysis (ACDA) for fast recognition. Experiments are carried out to demonstrate that the proposed approach significantly outperforms the existing techniques.

1 Introduction

Gait is a behavioral biometric that measures the way people walk. Compared to physiological biometrics such as fingerprint, iris, and face, the advantage of gait is that it does not require subject cooperation and can operate without interrupting or interfering with the subject's activity. This makes gait ideal for situations where direct contact or cooperation with the subject is not possible (e.g. medium to long distance security and surveillance applications in public space).

Gait is sensitive to various covariate conditions, which are circumstantial and physical conditions that can affect either gait itself or the extracted gait features. Example of these conditions include clothing, surface, carrying condition (backpack, briefcase, handbag etc), view angle, speed, and shoe-wear type to name a few. The existing works on gait recognition use a gallery set consisting of gait sequences of people under similar covariate conditions and evaluate the performance of the proposed methods on probe sets of possibly different covariate conditions [5, 12, 11, 1, 6, 3, 10]. They therefore make the implicit assumption that the gallery data are collected in a cooperative manner so that the covariate conditions are known a priori. It is well known that given cooperative subjects, gait cannot compete with physiological biometrics in terms of recognition accuracy. It is therefore necessary and crucial to evaluate the performance of the existing gait recognition approaches without the assumption on cooperative subjects, i.e. the gallery set is composed of a mixture of gait sequences under different unknown covariate conditions. To the best of our knowledge, none of the existing work has done such an evaluation.

In this work, we evaluate the performance of state of the art gait recognition approaches under the aforementioned realistic experimental setup. The results show that the existing approaches yield very unsatisfactory performance (a nearly 4-fold decrease in recognition rate in some experiments compared to the result obtained using gallery sequences of similar covariate conditions). We argue that the main reason is that the existing approaches rely on both static appearance features and dynamic gait features for person identification, i.e. the identification is not achieved using gait alone [7, 8]. More specifically, most approaches represent gait using features extracted from silhouettes. By extracting silhouettes, a large part of physical appearance features have been removed from the image representation of human. Nevertheless, a silhouette still contains information about the shape of human body that has nothing to do with gait (e.g. contour of head and upper body). Although recent studies suggest that static shape information is more important than kinematics for most of the silhouette-based gait recognition approaches [7, 8], including static appearance features in gait representation also makes the existing approaches vulnerable to the changes of covariate conditions. To overcome the problem, it is crucial to select the most relevant gait features that reflect the unique characteristics of gait as a behavioral biometric, and importantly are invariant to appearance variations caused by changes of covariate conditions.

To that end, we propose a novel gait feature selection method to automatically select covariate condition invariant features for gait recognition. Gait Energy Image (GEI) is selected for gait representation, which is a spatio-temporal gait representation constructed using silhouettes [1]. GEI represents a gait sequence using a single image; it is thus a compact representation which is an ideal starting point for feature selection. In spite of its compactness, it has been demonstrated that GEI is less sensitive to noise and able to achieve highly competitive results compared to alternative representations [1]. Since in a realistic experimental setup, the covariate conditions for both the gallery and probe sets are unknown, we propose to select a set of features that are unique to each pair of gallery and probe sequences.

After feature selection, the gallery and probe GEIs can be used as templates and the gait recognition problem can be solved by measuring the distance between the templates directly. However, direct template matching has been shown to be sensitive to noise and small silhouette distortions by previous studies [1, 4]. To overcome this problem, statistical feature learning based on subspace Component and Discriminant Analysis (CDA) can be employed to further reduce the feature dimensionality [2]. Nevertheless, since a different set of features are selected for different pairs of gallery and probe GEIs, a conventional CDA based approach is computationally costly because different subspaces have to be constructed given each GEI pair. This problem is addressed by a novel Adaptive Component and Discriminant Analysis (ACDA) proposed in this work. Instead of computing a different subspace for a different pair of gallery and probe GEIs, ACDA adapts a base subspace towards each gallery and probe GEI pair according to the selected features. Experiments are carried out to demonstrate that our feature selection based gait recognition method significantly outperforms previous approaches, especially when the gallery set is composed of sequences under variable unknown gait covariate conditions.

In summary, this work has the following main contributions: 1) For the first time, gait recognition approaches are evaluated without assuming subject cooperation; 2) a novel feature selection method is proposed for gait representation; 3) a novel Adaptive Component and Discriminant Analysis (ACDA) is developed for fast gait recognition.

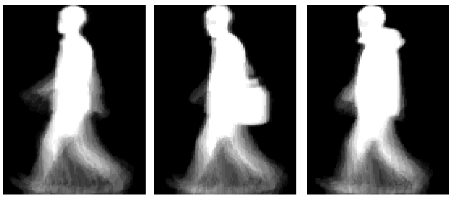
2 Feature Selection on Gait Energy Image

2.1 Gait Representation

Given a human walking sequence, a human silhouette is extracted from each frame using the method in [6]. After applying size normalization and horizontal alignment to each extracted silhouette image, gait cycles are segmented by estimating gait frequency using a maximum entropy estimation technique presented in [6]. Gait Energy Image (GEI) is then computed as

$$G(x,y) = \sum_{t=1}^{T} I(x,y,t), \tag{1}$$

where T is the number of frames in a complete gait cycle, x and y are the image coordinates, and t is the frame number in the gait cycle.



(a) Normal (b) Carrying a bag (c) Wearing a coat

Figure 1: Gait Energy Images of a person under different carrying and clothing conditions.

Examples of GEIs are shown in Fig. 1. Note that pixels with high intensity values in a GEI correspond to body parts that move little during a walking cycle (e.g. head, torso), while pixels with low intensity values correspond to body parts that move constantly (e.g. lower parts of legs and arms). The former mainly contain information about body shape and stance, whilst the latter tells us more about how people move during walking. We call the former static areas of a GEI and the latter dynamic areas of a GEI. The dynamic areas are invariant to human appearance changes; they seem to be the most informative part of the GEI representation for human identification. The static areas of a GEI also contain useful information for identification (e.g. one's hair style). However, since they mainly contain body shape information, they are sensitive to changes in various covariate conditions. For instance, in Fig. 1, three GEIs are computed from three sequences of the same person walking under different conditions. The dynamic areas of the GEI suggest that they are the same person but the static areas suggest otherwise. Based on this observation, an automatic feature selection method is developed to select the most informative gait features from a GEI. These features are mainly from the dynamic areas of a GEI and are thus in general invariant to changes in covariate conditions.

2.2 Feature Selection

A binary feature selection mask $M_G(x,y)$ is first generated for a given GEI $G(x,y)$ (either from the gallery or the probe set). As discussed earlier, the intensity values of a GEI can be used to infer the dynamic and static features in the GEI. Apart from this, we can make use of another important observation, that is, more useful gait information is embedded in the bottom part of a GEI than in the top part. Based on this observation, we divide $G(x,y)$ vertically into two parts $G_U(x,y)$ and $G_L(x,y)$ representing the upper two third and the lower one third of the GEI respectively. A base mask $M_B(x,y)$ is then generated as

$$M_B(x,y) = \begin{cases} 0, & \forall(x,y) \ \ where \ \ x > \frac{1}{3}H \\ 1, & \text{Otherwise} \end{cases} \tag{2}$$

where H is the height of the GEI in pixels. The feature selection mask $M_G(x,y)$ is generated from $M_B(x,y)$ as

$$M_G(x,y) = \begin{cases} 1, & \text{if } \ G_U(x,y) < \theta_1 \\ 0, & \text{if } \ G_L(x,y) > \theta_2 \\ M_B(x,y), & \text{Otherwise} \end{cases} \tag{3}$$

where θ_1 and θ_2 are two pre-set thresholds and we have $\theta_2 \approx 2\theta_1$.

Suppose the gallery set contains N GEIs belonging to C classes (subjects). For the ith gallery GEI, we generate a feature selection mask $M_G^i(x,y)$; Similarly $M_G^j(x,y)$ is obtained for the jth probe GEI. Since different set of features are selected for the two GEIs, to compare the similarity between them the features deemed as relevant by both masks will be used. This is achieved by generating a new mask

$$M_G^{ij}(x,y) = M_G^i(x,y) \&\& M_G^j(x,y) \tag{4}$$

where && is the binary 'AND' operator.

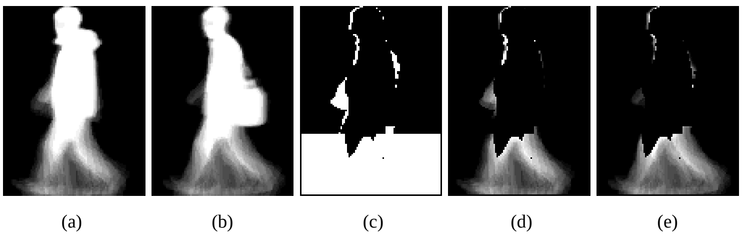


Figure 2: Example of feature selection for a pair of gallery and probe GEIs. (a) gallery GEI; (b) probe GEI; (c) feature selection mask $M_G^{ij}(x,y)$; (d) gallery GEI with $M_G^{ij}(x,y)$ applied; (e) probe GEI with $M_G^{ij}(x,y)$ applied.

Fig. 2 shows an example of applying our feature selection method to a pair of gallery and probe GEIs under different covariate conditions. It is evident that after applying the feature selection mask generated using both GEIs, the effect of the changes in covariate conditions in the gallery and probe sequences is alleviated effectively.

3 Adaptive Component and Discriminant Analysis

After applying a feature selection mask $M_G^{ij}(x,y)$ to each pair of gallery and probe GEIs, gait recognition can be performed by matching a probe GEI to the gallery GEI that has the minimal distance between them. However, direct template matching has been shown to be sensitive to noise and small silhouette distortions [1, 4]. This is because the dimensionality of the GEI feature space is high even after feature selection (typically in the order of thousands). To overcome this problem, subspace Component and Discriminant Analysis (CDA) based on Principal Component Analysis (PCA) and Multiple Discriminant Analysis (MDA) can be adopted which seeks to project the original features to a subspace of lower dimensionality so that the best data representation and class separability can be achieved simultaneously [2].

Suppose we have N d-dimensional gallery GEI templates $\{\mathbf{x}_1,...,\mathbf{x}_n,...,\mathbf{x}_N\}$ belonging to C different classes (individuals), where each template is a column vector obtained by concatenating the rows of the corresponding GEI. To compute the distance between the ith gallery and the jth probe GEI, $M_G^{ij}(x,y)$ is applied to each gallery GEI, which gives us a new set of template $\{\mathbf{x}_1^{ij},...,\mathbf{x}_n^{ij},...,\mathbf{x}_N^{ij}\}$ of dimension d^{ij}. PCA is an orthogonal linear transformation that transform the data to a subspace of dimensionality $\tilde{d^{ij}}$ (with $\tilde{d^{ij}} < d^{ij}$). The PCA subspace keeps the greatest variances by any projection of the data so that the reconstruction error defined below is minimized:

$$J_{\tilde{d^{ij}}} = \sum_{n=1}^{N} \left\| \left(\mathbf{m} + \sum_{k=1}^{\tilde{d^{ij}}} a_{nk}\mathbf{e}_k^{ij} \right) - \mathbf{x}_n^{ij} \right\|^2 \tag{5}$$

where $\mathbf{m}$ is the mean of the data, $\{\mathbf{e}_1^{ij},\mathbf{e}_2^{ij},...,\mathbf{e}_{\tilde{d^{ij}}}^{ij}\}$ are a set of orthogonal unit vectors representing the new coordinate system of the subspace, a_{nk} is the projection of the nth data to $\mathbf{e}_k^{ij}$. $J_{\tilde{d^{ij}}}$ is minimised when $\{\mathbf{e}_1^{ij},\mathbf{e}_2^{ij},...,\mathbf{e}_{\tilde{d^{ij}}}^{ij}\}$ are the $\tilde{d^{ij}}$ eigenvectors of the data covariance matrix with the largest eigenvalues (in decreasing order). Now the gallery template $\mathbf{x}_n^{ij}$ is represented as a $\tilde{d^{ij}}$-dimensional feature vector $\mathbf{y}_n^{ij}$ and we have

$$\mathbf{y}_n^{ij} = M_{pca}^{ij}\mathbf{x}_n^{ij} = [\mathbf{e}_1^{ij},...,\mathbf{e}_{\tilde{d^{ij}}}^{ij}]^T\mathbf{x}_n^{ij}. \tag{6}$$

PCA is followed by MDA which aims to find a subspace where data from different classes are best separated in a least square sense. Different from PCA, MDA is a supervised learning method which requires the gallery data to be labeled into classes. The MDA transformation matrix, W^{ij} maximizes

$$J(W^{ij}) = \frac{|{W^{ij}}^T S_B^{ij} W^{ij}|}{|{W^{ij}}^T S_W^{ij} W^{ij}|}$$

where S_B^{ij} is the between-class scatter matrix and S_W^{ij} the within-class scatter matrix of the gallery data in the PCA subspace $\{\mathbf{y}_1^{ij},...,\mathbf{y}_n^{ij},...,\mathbf{y}_N^{ij}\}$. $J(W^{ij})$ is maximized by setting the columns of W^{ij} to the generalized eigenvectors that correspond to the $C-1$ nonzero eigenvalues in

$$S_B^{ij}\mathbf{w}_k^{ij} = \lambda_i^j S_W^{ij}\mathbf{w}_k^{ij}$$

where $\mathbf{w}_k^{ij}$ is the kth column of W^{ij} and C is the number of classes in the gallery data. Denoting these generalised eigenvectors as $\{\mathbf{v}_1^{ij}, \mathbf{v}_2^{ij}, ..., \mathbf{v}_{C-1}^{ij}\}$, a gallery template is represented in the MDA subspace as:

$$\mathbf{z}_n^{ij} = M_{mda}^{ij}\mathbf{y}_n^{ij} = [\mathbf{v}_1^{ij}, ..., \mathbf{v}_{C-1}^{ij}]^T \mathbf{y}_n^{ij}. \tag{7}$$

Note that the choice of $\tilde{d^{ij}}$ is affected by the dimensionality of the MDA subspace, i.e. $C-1$. In particular, S_W^{ij} becomes singular when $\tilde{d^{ij}} < C$ or $\tilde{d^{ij}} \gg C$. We therefore set $\tilde{d^{ij}} = 2C$ in this paper.

Now after three steps of dimensionality reduction (feature selection using $M_G^{ij}(x,y)$, PCA, and MDA), both the gallery and probe GEI feature vectors are represented in a $C-1$ dimensional subspace. This dimensionality reduction process is computationally expensive mainly due to the PCA step. This is because for each new gallery and probe GEI pair, a new mask $M_G^{ij}(x,y)$ is generated and we need to re-do the PCA which involves eigen-decomposition of a $N \times N$ matrix. To make our approach more computationally effecient, we develop an Adaptive Component and Discriminant Analysis (ACDA). More specifically, instead of applying each $M_G^{ij}(x,y)$ to the gallery templates and re-do the PCA on $\{\mathbf{x}_1^{ij}, ..., \mathbf{x}_n^{ij}, ..., \mathbf{x}_N^{ij}\}$, we compute PCA only once for the original gallery templates $\{\mathbf{x}_1, ..., \mathbf{x}_n, ..., \mathbf{x}_N\}$, which results in a base PCA subspace. We then adapt the base PCA subspace towards each gallery and probe GEI pair by applying $M_G^{ij}(x,y)$ directly to the base principal components. Specifically, let $\{\mathbf{e}_1, \mathbf{e}_2, ..., \mathbf{e}_{\tilde{d}}\}$ be the base components, each component can be treated as an eigenGEI, similar to eigenface for face recognition. The adapted components $\{\mathbf{u}_1^{ij}, \mathbf{u}_2^{ij}, ..., \mathbf{u}_{\tilde{d}}^{ij}\}$ are then obtained by applying $M_G^{ij}(x,y)$ to the eigenGEIs. Now Eqn. (6) can be re-written as

$$\mathbf{y}_n^{ij} = M_{pca}^{ij}\mathbf{x}_n^{ij} = [\mathbf{u}_1^{ij}, ..., \mathbf{u}_{\tilde{d^{ij}}}^{ij}]^T \mathbf{x}_n^{ij}. \tag{8}$$

The MDA step that follows will remain unchanged (see Eqn. (7)).

In our Adaptive Component and Discriminant Analysis (ACDA) we approximate $\{\mathbf{e}_1^{ij}, \mathbf{e}_2^{ij}, ..., \mathbf{e}_{\tilde{d^{ij}}}^{ij}\}$ using $\{\mathbf{u}_1^{ij}, \mathbf{u}_2^{ij}, ..., \mathbf{u}_{\tilde{d}}^{ij}\}$ in order to reduce the computational cost. What price we have to pay for this improvement in computational efficiency will depend on the accuracy of the approximation. Intuitively, applying a binary mask $M_G^{ij}(x,y)$ to the gallery data collapses some of the original coordinate axes. $\{\mathbf{e}_1^{ij}, \mathbf{e}_2^{ij}, ..., \mathbf{e}_{\tilde{d^{ij}}}^{ij}\}$ as the subspace expressed in the original coordinate system should also have the corresponding axes collapsed, which is exactly how $\{\mathbf{u}_1^{ij}, \mathbf{u}_2^{ij}, ..., \mathbf{u}_{\tilde{d}}^{ij}\}$ are generated. Theoretically, it can be readily proved that the projection of $\{\mathbf{x}_1^{ij}, ..., \mathbf{x}_n^{ij}, ..., \mathbf{x}_N^{ij}\}$ to $\{\mathbf{u}_1^{ij}, \mathbf{u}_2^{ij}, ..., \mathbf{u}_{\tilde{d}}^{ij}\}$ will have an identical diagonalised covariance matrix as their projection on $\{\mathbf{e}_1^{ij}, \mathbf{e}_2^{ij}, ..., \mathbf{e}_{\tilde{d^{ij}}}^{ij}\}$. More importantly, we demonstrate through experiments in the next section that the approximation is extremely accurate in practice.

4 Experiments

Dataset –The CASIA Gait Database [9] was used for evaluating the performance of the proposed approach. The database comprises of 124 subjects. For each subject there are 10 walking sequences consisting of 6 normal walking sequences (Set A), 2 carrying-bag sequences (Set B) and 2 wearing-coat sequences (Set C). Each sequence contains multiple gait cycles resulting in multiple GEIs. The original image size of the database is 320x240. After size normalization, the size of the GEIs became 128x88 (i.e. the original feature space has a dimensionality of 11264). A sample GEI from each set is shown in Fig. 1. The threshold values of $\theta_1 = 127, \theta_2 = 230$, were used in our experiments. Two experiments were carried out in this study. In the first experiments, the gallery set contains sequences of people walking under similar covariate conditions, i.e. the same experimental setup as the existing work. In the second experiment, the gallery set is composed of a mixture of gait sequences collected under different unknown covariate conditions. This is to evalute the performance of the proposed approach and existing approaches without assuming subject cooperation.

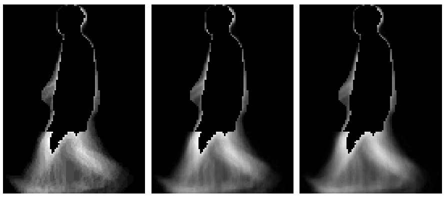
Test Set	TM	CDA	M_G^j+CDA	M_G^j+ACDA	$M_G^{ij}(x,y)$+ACDA
A2	97.6%	99.4%	100%	99.4%	**100%**
B	52.0%	60.2%	84.5%	83.6%	**91.0%**
C	32.7%	22.0%	65.1%	64.0%	**80.6%**

Table 1: Comparing different approaches using a gallery set consisting of sequences under similar covariate conditions (without carrying a bag or wearing a coat). TM–direct GEI template matching without feature selection and CDA [9]; CDA: method in [1] based on CDA without feature selection; M_G^j+CDA: Feature selection mask generated only from the probe GEI and the conventional CDA; M_G^j+ACDA: Feature selection mask generated only from the probe GEI and ACDA; $M_G^{ij}(x,y)$+ACDA: Feature Selection mask generated from each gallery probe GEI pair.

Gallery sequences under similar covariate conditions–The gallery set used for the first experiment consists of the first 4 sequences of each subject in Set A (Set A1). The probe set is the rest of the sequences in Set A (Set A2), Set B and Set C. The performance was measured using recognition rates and is presented in Table 1. Table 1 also lists the results published in [9] which were obtained using direct template matching on the same database and the approach in [1] which is based on the standard CDA without our feature selection methods. The approach in [1] is widely regarded as one of best gait recognition approach and therefore representative of the state of the art. It can be seen that direct template matching gives the worst results. CDA based approach improves on template matching but there is still much room for improvement. Table 1 shows that our approach significantly improves the results for all three probe sets. The improvement is particularly substantial for the probe set with a different clothing condition (Set C), on which poor results were obtained without feature selection.

We also compare the results with a simpler version of the feature selection method. Specifically, we generate a feature selection mask using Eqn. (3) for each probe GEI and apply it to all gallery GEIs. Table 1 shows that using the mask generate from the probe GEI only, the result is much better compared to those of previous approaches without feature selection, albeit it is slightly worse than the result obtained using a mask generated for each gallery-test GEI pair.

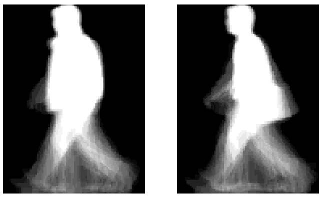
Table 1 also lists the results with feature selection using the probe mask and CDA. It can be seen that our Adaptive Component and Discriminant Analysis (ACDA) method achieves almost identical results as the computationally much more expensive CDA ap-



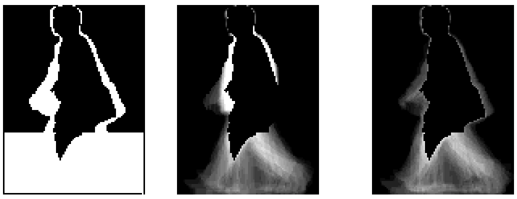
(a) (b) (c)

Figure 3: (a): A GEI with $M_G^{ij}(x,y)$ applied; (b) The reconstructed GEI using $\{\mathbf{e}_1^{ij}, \mathbf{e}_2^{ij}, ..., \mathbf{e}_{d^{ij}}^{ij}\}$; (c) The reconstructed GEI using $\{\mathbf{u}_1^{ij}, \mathbf{u}_2^{ij}, ..., \mathbf{u}_{\tilde{d}}^{ij}\}$. The root-mean-square errors, which are $J_{\tilde{d}^{ij}}$ (see Eqn. (5)) normalized by the image size, was 0.0031 for (b) and 0.0060 for (c).

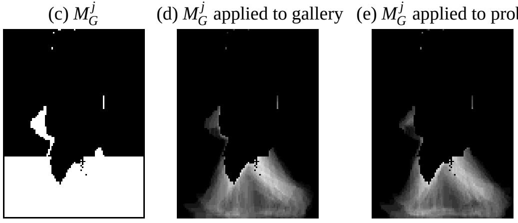
proach. This suggests that our approximation of $\{\mathbf{e}_1^{ij}, \mathbf{e}_2^{ij}, ..., \mathbf{e}_{d^{ij}}^{ij}\}$ using $\{\mathbf{u}_1^{ij}, \mathbf{u}_2^{ij}, ..., \mathbf{u}_{\tilde{d}}^{ij}\}$ is accurate. Fig. 3(b) and (c) show examples of reconstructed GEIs using $\{\mathbf{e}_1^{ij}, \mathbf{e}_2^{ij}, ..., \mathbf{e}_{d^{ij}}^{ij}\}$ and $\{\mathbf{u}_1^{ij}, \mathbf{u}_2^{ij}, ..., \mathbf{u}_{\tilde{d}}^{ij}\}$ respectively. Both of them gave extremely small reconstruction errors.



(a) Gallery GEI (b) Probe GEI



(c) M_G^j (d) M_G^j applied to gallery (e) M_G^j applied to probe



(f) M_G^{ij} (g) M_G^{ij} applied to gallery (h) M_G^{ij} applied to probe

Figure 4: Comparing the feature selection mask M_G^j generated using probe GEI only, and M_G^{ij} generated using both the gallery and probe GEIs.

Gallery sequences under different covariate conditions–In this experiment the gallery set includes a mixture of normal, carrying bag, and wearing coat sequences. More specifically, we selected the first one third of the sequences from Set C, the second one third from Set B and the last from Set A. The probe set for the mixed gallery set is the Set A2, Set B2 which consists of Set B minus one third of Set B included in the gallery set and Set C2 which is Set C minus one third of Set C included in the gallery set. This gives us a challenging set of experiment data closely representing the condition for gait recognition with uncooperative subjects. The experimental results are listed in Tables 2. The results indicate a drastic degradation in performance for the CDA based method without feature selection and the feature selection method based on the probe GEI only. In comparison, our approach achieves much better result, especially for the probe sets with different carrying and clothing covariate conditions. This result suggests that under such a realistic experimental setup, feature selection based on each pair of gallery and probe gait sequences is critical for selecting the relevant gait features. This is evident from an example shown in Fig. 4. It shows that after applying the mask generated using both the gallery and probe GEIs, the gallery and probe sequences can be correctly matched, whilst the mask generated using the probe sequence alone cannot deal with the variations in GEIs caused by changes in covariate conditions resulting in an incorrect match.

Test Set	CDA	M_G^j+ACDA	$M_G^{ij}(x,y)$+ACDA
A2	48.1%	50.0%	**62.73%**
B2	31.9%	36.1%	**54.17%**
C2	9.7%	27.7%	**44.44%**

Table 2: Comparing different approaches using a gallery set consisting of sequences under different covariate conditions.

5 Conclusions

We have investigated the performance of state-of-the-art gait recognition approaches under a realistic experimental setup where no subject cooperation is required. Our experimental results suggest that the existing approaches are unable to cope with changes in gait covariate conditions in a gallery set, therefore are unsuitable for a truly uncooperative person identification task. To overcome this problem, we proposed a novel gait recognition approach, which performs feature selection on each pair of gallery and probe gait sequence, and seamlessly integrate feature selection with an Adaptive Component and Discriminant Analysis (ACDA) for fast recognition. Experiments are carried out to demonstrate that the proposed approach significantly outperforms the existing techniques. It is worth pointing out that the proposed feature selection method is designed mainly for mitigating the effect of changes in covariate conditions that affect gait feature extraction rather than gait itself. Our ongoing work includes further extending the proposed feature selection methods to deal with a wider range of covariate conditions that can affect gait including injury, mood, shoe-wear type, and elapsed time.

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