Cross-View Gait Recognition Using Correlation Strength

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Abstract

Among various factors that can affect the performance of gait recognition, changes in viewpoint pose the biggest problem. In this work, we develop a novel approach to cross-view gait recognition with the view angle of a probe gait sequence unknown. We formulate a Gaussian Process (GP) classification framework to estimate the view angle of each probe gait sequence. To measure the similarity of gait sequences captured at different view angles, we model the correlation of gait sequences from different views using Canonical Correlation Analysis (CCA) and use the correlation strength as similarity measure. This differs significantly from existing approaches, which reconstruct gait features in different views either through 2D view transformation or 3D calibration. Without explicit reconstruction, our approach can cope with feature mis-match across view and is more robust against feature noise. Our experiments validate that the proposed method significantly outperforms the existing state-of-the-art methods.

1 Introduction

Gait is a behavioural biometric particularly useful for non-intrusive and/or non-cooperative person identification from a distance in unconstrained public spaces. However, such environments also increase the difficulties in gait recognition compared to a more controlled one with constantly known view angle. This is largely because that various factors can affect gait including people walking in different clothes, under different carrying conditions, at variable speed, in different shoes and from arbitrary views. In particular, changes in view angle pose one of the biggest challenges to gait recognition as it can change significantly the available visual features for matching (see Fig. 1).

Early works on multi-view gait recognition fall into two categories: 1) extracting view invariant features, and 2) view synthesis based on 3D calibration. Approaches in the first category aim to extract gait features that are invariant to view change. Self Similarity Plots (SSP) is one such feature that has been exploited for both action recognition [10] (inter-class) and gait recognition [2] (intra-class). However, SSP lacks sufficient discriminative power for effective intra-class discrimination required by gait recognition, as demonstrated by the findings in [2]. Alternatively, a statistical method for extracting view invariant features from

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Gait Energy Images (GEI) was proposed by [7] by which only parts of gait sequences that overlap between views are selected for constructing a representation for gait matching across views. The approach cannot cope with large view angle changes under which gait sequences of different views can have little overlap. Extracting normalized trajectories of body parts is another view invariant feature based approach [9]. However tracking of body parts is unreliable due to self-occlusion. In addition the problem of body parts becoming invisible given large view angle change remains. Approaches in the second category either use a single camera and assume the subjects to be far away from the camera and perform a view synthesis for an arbitrary view using planar imaging geometry [5, 11], or use cooperative multi-camera set-up to extract 3D structure information via camera calibration [3, 17, 21]. Methods based on the planar view assumption have a disadvantage in that these methods cannot cope with large variations in view angle. On the other hand techniques based on 3D reconstruction are only suitable for a fully controlled and cooperative multi-camera environment such as a biometric tunnel [16].

Recently a number of approaches [12, 14] based on view transformation have been presented which have the potential to cope with large view angle changes and do not rely on camera calibration. These approaches aim to learn a mapping relationship between gait features of the same subject observed across views. When matching gait sequences from different views, the gait features are mapped/reconstructed into the same view before a distance measure is computed for matching. An advantage of these methods is that they have better ability to cope with large view angle change compared to earlier works. However, a view transformation based method also has a number of drawbacks 1) it suffers from degeneracies and singularities caused by features visible in one view but not in the other when the view angle difference is large. 2) The reconstruction process propagates the noise present in the gait features in one view to another thus decreasing recognition performance.

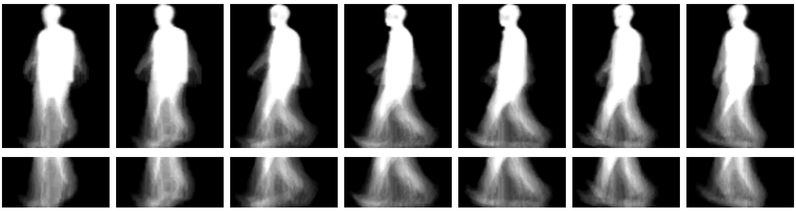
In this paper we propose a novel approach to cross view gait recognition by addressing the problems associated with the view transformation model. Specifically we model the correlation of gait sequences from different views using Canonical Correlation Analysis (CCA). A CCA model projects gait sequences from two views into two different subspaces such that they are maximally correlated. Similar to the existing view transformation methods, the CCA model also captures the mapping relationship between gait features of different views, albeit implicitly. However, rather than reconstructing gait features in the same view and matching them using a distance measure, we use the CCA correlation strengths directly to match two gait sequences. This brings out two key advantages: 1) by projecting the gait features into the two subspaces with maximal correlation, features that become invisible across views are automatically identified and removed. 2) without reconstruction in the original gait feature space, our approach is more robust against feature noise. In this paper we also address the problem of view angle recognition using Gaussian Process (GP) classification [18] in order to build a complete gait recognition system with probe sequence view angle unknown. This differs from existing approaches which assume the probe view angle is known. Experiments are carried out to demonstrate that 1) our GP classification based view angle recognition method effectively identifies the view angle and is superior when compared to an SVM based method; 2) The gait recognition performance of our method significantly outperform those of the existing view transformation models [12, 14] even when they assume known probe sequence view angle.

2 Cross View Gait Recognition

We assume that a multi-view gait training dataset is available in which gait sequences of subjects are available in all views. Also the subjects appearing in the training dataset are independent from the subjects in the test dataset in which only a single view sequence is required for each subject. This means that the system can be independently trained on an available dataset and then be tested on a different dataset.

2.1 Gait Representation

Given a human walking sequence, a human silhouette is extracted from each frame using the method of [15]. After applying size normalization and horizontal alignment to each extracted silhouette image, gait cycles are segmented by using the method in [12]. We then compute two gait representations, one for view angle recognition and the other for cross-view gait recognition.



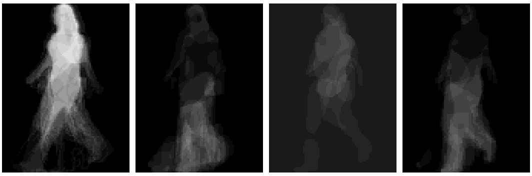
(a) 36° (b) 54° (c) 72° (d) 90° (e) 108° (f) 126° (g) 144°

Figure 1: Top row: GEIs of a same subject for different views. Bottom row: TGEIs obtained from the GEIs in the top row.

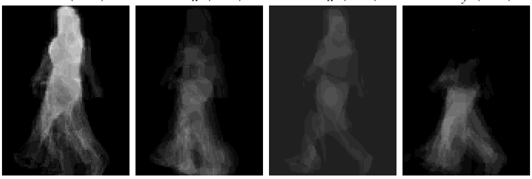
For view recognition, gait sequences are represented using Truncated Gait Energy Images (TGEI). TGEI is simply Gait Energy Image (GEI) [6] without its top part (head & torso) and is generated by only taking the bottom one third of the GEI (see Fig. 1). In this work TGEI is used to learn the Gaussian Process Classifier for view angle recognition. The advantage of using TGEI instead of GEI for view recognition becomes clear on a closer look at Fig. 1. It can be seen that the torso part of the GEI (which constitutes a major portion of it) for view angle 144° and 54° (Fig. 1(b) and (g)) is almost identical. This would make the classification process prone to errors. The same can be said for view angles 72° and 126° (Fig. 1(c) and (f)). In contrast, if we observe the bottom row of Fig. 1 we see that the TGEI for view angles 144° and 54° are completely different and also there are visible changes in TGEI for view angles 72° and 126°. We thus select TGEI as our feature to learn the view classifier.

Gait Flow Images (GFI) [1] are used as a gait feature for cross view gait recognition. GFIs provide more discriminative representation for identity recognition compared to GEI by looking at multiple independent motion of different body parts during a gait cycle [1]. It is robust against various covariate conditions such as carrying and clothing [1]. Gait information is captured in a set of motion descriptors including a motion intensity descriptor (representing shape information) M , and 3 motion direction descriptor M_x^+, M_x^-, M_y^+ (representing motion information) corresponding to the right, left and up directions. Example GFIs for a single subject from 54° and 126° in normal walking conditions are shown in Fig. 2.

The reason why we use different representation for view recognition and gait recognition is clear by comparing Fig. 1 and Fig. 2. In particular, for view recognition, which can be seen as an inter-class classification problem compared with the intra-class one in gait recognition, it is necessary to remove the top two third as most of the information there is invariant to view change (e.g. large part of torso). However, there are useful gait features that contribute towards better recognition performance of gait [1, 4, 13] although this information is largely concerned with appearance not kinematic or motion aspect of human gait. On the other hand, since GFI captures much inter-subject variations, it is good for gait recognition but causes problem for view recognition because these variations now become intra-class variations.



(a) $\mathbf{M}(54°)$ (b)$\mathbf{M}_x^+(54°)$ (c) $\mathbf{M}_x^-(54°)$ (d) $\mathbf{M}_y^+(54°)$



(a) $\mathbf{M}(126°)$ (b)$\mathbf{M}_x^+(126°)$ (c) $\mathbf{M}_x^-(126°)$ (d) $\mathbf{M}_y^+(126°)$

Figure 2: Gait Flow Image (GFI) descriptors for a subject under normal walking conditions from the CASIA dataset in (54°) (top row) and (126°) (bottom row).

2.2 Learning a Gait View Classifier Using Gaussian Processes

Gaussian Processes (GP) have been used in regression [19] and classification problems [18]. These models are flexible as no selection of model complexity is required (as compared to e.g. Gaussian Mixture Models). GP are closely related to Support Vector Machines (SVM). A key advantage of GP compared to SVM is that they are probabilistic models that allow to incorporate prior information about data distribution. This often results in more robust and better models.

We assume that TGEI have been calculated from the available multi-view training data. Before we can train our GP classifier dimensionality reduction is required in order to make the computations feasible. Principle Component Analysis (PCA) is used for this purpose. Let $\{\mathbf{x_1},...,\mathbf{x_N}\}$ be $\tilde{d} < d$ dimensional component space representation of N, d-dimensional TGEI templates belonging to C views. The GP Classifier is trained using the reduced dimensional $\mathbf{x_i}$ where $i = 1,...,N$. The classification model uses a latent function $\mathbf{f}$ which is never observed. What is observed are the $\mathbf{x_i}$ values and the class labels y. We define $\mathbf{y}$ as vector of the same length as the latent function $\mathbf{f}$ which for each $i = 1,...,N$ has an entry of 1 for the class which is the label for example i and 0 for other $C-1$ entries. The vector of latent function values at all N training points and C class labels is given by $\mathbf{f} = (f_1^1,...,f_N^1,f_1^2,...,f_N^2,...,f_1^C,...,f_N^C)^T$. The prior over $\mathbf{f}$ has the form $\mathbf{f} \sim \mathscr{N}(\mathbf{0},K)$ where K is the matrix of covariance function values. The covariance function expresses the correlation between the data values. We select the squared exponential covariance function to encode our prior knowledge. This means that points lying close together are closely correlated or in other words gait features that resemble each other (belonging to same view) are highly correlated. The squared exponential covariance function is given as

$$K(x,x\prime) = \sigma^2 exp\left(-\frac{1}{2}(x-x\prime)^T \sum (x-x\prime)\right) \quad (1)$$

where σ defines the magnitude and $\sum = l^{-2}I$, l are the characteristic length scales (learnable hyperparameters of the covariance function) and are associated with the relative importance of different inputs to prediction. The posterior over the training data defined by $p(\mathbf{f}|X,y)$ is not analytically tractable and a Laplace approximation is used instead. More details can be found in [18]. A test point x_* represented in the component space is then classified by computing the predictive distribution of $\mathbf{f}_* = \mathbf{f}(x_*) = (f_*^1,...,f_*^C)^T$ defined by $q(\mathbf{f}_*|X,\mathbf{x}_*,\mathbf{f})$ [18], where X is the matrix of training data.

The learned GP gait view classifier is expected to make errors which in turn will also introduce potentially model mismatch in gait sequence correlation to be described in the next section. To minimise such error propagation, instead of directly using the top label returned from the GP pose classifier, we make a soft decision and look at the top two candidates. This is because the returned labels are rank 2 correct at least 98% on our test dataset (see experiment section). We therefore use a weighted approach and fuse the scores returned from the top two class labels suggested by the classifier. The weights are calculated by normalizing the confidence of the classifier in the top two labels.

Note that as a person moves in space, the view angle with respect to the camera is likely to change continuously. This could mean that two cycles from a gait sequence may be classified into two different views. Our GP classifier caters for this and works on per cycle basis (i.e. a separate TGEI is generated for each cycle).

2.3 Learning Cross View Correlation Model

We use Canonical Correlation Analysis (CCA) [8] to perform recognition across views by using the correlation strength as a measure of similarity. CCA is a linear method[1] and measures the relationship between two sets of multidimensional variables . CCA finds two bases one for each set of variable in such a way that the two sets of variables are maximally correlated.

To learn the cross view correlation model using CCA we compute the GFI for the multiview training dataset. PCA is used to reduce the dimensionality of the GFI descriptors to make the computations feasible. Since the GFI are composed of more than one descriptor, in the following we describe the learning process for one of the gait flow descriptors M. A similar method is used for the remaining descriptors M_x^+, M_x^-, M_y^+. Let $X = \{\mathbf{x}_1,...,\mathbf{x}_N\}$ be matrix of $\tilde{d} < d$ dimensional component space representation of N d-dimensional M templates in view V_{θ_x} and $Y = \{\mathbf{y}_1,...,\mathbf{y}_N\}$ be the component space representation in view V_{θ_y}. Let the linear combinations of canonical variables be $x = \mathbf{w}_x{}^T\mathbf{x}$ and $y = \mathbf{w}_y{}^T\mathbf{y}$. CCA can now be defined as

$$\rho = \frac{E[xy]}{\sqrt{E[x^2]E[y^2]}} = \frac{E[\mathbf{w}_x{}^T\mathbf{x}\mathbf{y}^T\mathbf{w}_y]}{\sqrt{E[\mathbf{w}_x{}^T\mathbf{x}\mathbf{x}^T\mathbf{w}_x]E[\mathbf{w}_y{}^T\mathbf{y}\mathbf{y}^T\mathbf{w}_y]}} \quad (2)$$

which can also be written in terms of covariance matrices as

$$\rho = \frac{\mathbf{w}_x{}^T C_{\mathbf{xy}}\mathbf{w}_y}{\sqrt{\mathbf{w}_x{}^T C_{\mathbf{xx}}\mathbf{w}_x\mathbf{w}_y{}^T C_{\mathbf{yy}}\mathbf{w}_y}} \quad (3)$$

[1] A kernel version of CCA has been tested in our experiments and shown inferior performance, which suggests the linear assumption is valid.

where $C_{\mathbf{xx}}, C_{\mathbf{yy}}$ are the within sets and $C_{\mathbf{xy}}$ the between sets covariance matrices. CCA maximizes ρ by solving for the derivative of Eqn. 3 and setting it to zero. This yields the following eigenvalue equations.

$$C_{\mathbf{xx}}^{-1} C_{\mathbf{xy}} C_{\mathbf{yy}}^{-1} C_{\mathbf{yx}} \mathbf{w}_x = \rho^2 \mathbf{w}_x \tag{4}$$

$$C_{\mathbf{yy}}^{-1} C_{\mathbf{yx}} C_{\mathbf{xx}}^{-1} C_{\mathbf{xy}} \mathbf{w}_y = \rho^2 \mathbf{w}_x \tag{5}$$

where eigenvalues ρ^2 are the square canonical correlations and $\mathbf{w}_x$ and $\mathbf{w}_y$ are the basis vectors.

Once $\mathbf{w}_x$ and $\mathbf{w}_y$ have been computed for V_{θ_x} and V_{θ_y} we do this for all the view combinations in the multi-view training dataset in order to complete the learning process. We are now able to perform cross view gait recognition using GP classification and CCA correlation strengths.

2.4 Cross View Gait Recognition

To perform recognition across view we have gait templates of subjects in view V_{θ_g} as our gallery data. Any probe sequence in an arbitrary view V_{θ_p} and variable covariate conditions for the subjects in the gallery can now be recognized. The essence is to use the correct model to compute correlation strengths for matching across views. This is done by using the learned GP classifier to identify the view angle of the probe sequence. Based on the output from the classifier the corresponding CCA models are then used for computing correlation strengths for matching across views.

Specifically, we first compute the TGEI and GFI templates for the probe sequence. GP classification is then applied using TGEI resulting in the predicted top 2 ranked class labels and the confidence in each. Let the top 2 views identified by the classifier be V_{θ_1} and V_{θ_2} with confidence ω_{θ_1} and ω_{θ_2}, we normalise ω_{θ_1} and ω_{θ_2} so that they sum to 1.

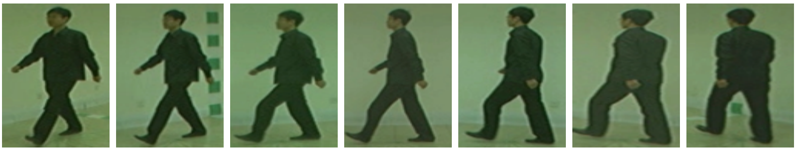
After view classification we use the trained CCA models for $V_{\theta_1} \to V_{\theta_g}$ and $V_{\theta_2} \to V_{\theta_g}$ to compute correlation strength scores between the probe template and a gallery one. Since the GFI comprise of four descriptors for each gait cycle we describe this process for one of the descriptors, M. The same procedure can be applied to the remaining descriptors. Correlation strength for the two templates are computed using Eqn. 3 and are given as $\rho^{iM}_{\theta_1\theta_g}$ and $\rho^{iM}_{\theta_2\theta_g}$ where $i = 1, \ldots, n$ and n is the number of templates in the gallery view V_{θ_g}. The correlation strength for M is then the weighted average of the correlation strength of the two models weighted by the normalized confidence scores and is given as $\rho^{iM} = \omega_{\theta_1}\rho^{iM}_{\theta_1\theta_g} + \omega_{\theta_2}\rho^{iM}_{\theta_2\theta_g}$. Similarly we compute the correlation strength for other descriptors the final score is then computed as follows

$$\rho^i = \rho^{iM} + \rho^{iM_x^+} + \rho^{iM_x^-} + \rho^{iM_y^+} \tag{6}$$

The gallery sequence with the largest ρ^i is then identified as the correct match. Since a test sequence can have multiple gait cycles generating multiple templates in this case we use a simple voting mechanism to generate the output label.

3 Experiments

Dataset–The CASIA Gait Database [20] was used for evaluating the performance of the proposed approach, which is the largest publicly available multi-view gait dataset. The database comprises of 124 subjects. For each subject there are 10 walking sequences consisting of 6 normal walking sequences, 2 carrying-bag sequences and 2 wearing-coat sequences which gives the dataset a coverage of most of the common covariate conditions encountered in real life including the carrying condition and clothing condition. All the sequences are captured from 11 different views starting from 0° with 18° offset resulting in gait view sequences for 0° the front view, $18^\circ, 36^\circ, 54^\circ, 72^\circ$, 90° the front-to-parallel view, $108^\circ, 126^\circ, 144^\circ, 162^\circ$ and 180° the back view. Sample images for different views from the CASIA dataset are shown in Fig. 3.



(a) 36° (b)54° (c) 72° (d) 90° (e) 108° (f) 126° (g) 144°

Figure 3: Sample Images from the multi-view CASIA dataset for different view angles.

We use the gait sequences from 7 views from $36^\circ - 144^\circ$ in our multi-view experiments because views close to the frontal and back views provide little gait information. Each sequence in the dataset contains multiple gait cycles. The original image size of the database is 320x240. The multi-view training set consists of 4 out of 6 normal sequences of 60% of the total subjects in the dataset from views $36^\circ - 144^\circ$. The remaining 40% of the subjects are used for testing, i.e. the subjects used in training and testing are mutually exclusive. For testing we form a gallery set and a probe set. The gallery set consists of the first 4 normal sequences from views $36^\circ - 144^\circ$. The probe set include the last 2 normal sequences (Set A2), the 2 carrying bag sequences (Set B) and 2 wearing-coat sequences (Set C), all from views $36^\circ - 144^\circ$.

View Classification with GP Classifier– We compare GP classification with Support Vector Machines (SVM) for view classification. It can be seen from Table 1 that GP Classification gives better results than SVM and also achieves satisfactory results for the dataset over all covariate conditions and across all different views consistently. In contrast, although good result is obtained for some views, SVM achieved very poor results for others (e.g. 54° and 108°) even using identical feature representation as GP. Table 2 presents rank 2 results for the classification experiment. From Table 2 it can be seen that the correct view is Rank 2 correct almost all of the time for our GP classification whereas SVM lags in terms of performance and again is inconsistent across different views. The excellent rank 2 results lead to the development of algorithm described in Sec. 2.4 in using the confidence score from the top 2 results returned from the GP Classification algorithm.

Probe Set	36°	54°	72°	90°	108°	126°	144°
Set A2 (GP)	84.0%	91.2%	85.3%	74.0%	86.0%	91.2%	93.5%
Set A2 (SVM)	94.9%	40.5%	85.4%	64.3%	24.0%	43.6%	98.0%
Set B (GP)	83.4%	88.7%	84.9%	68.6%	83.0%	92.7%	93.5%
Set B (SVM)	96.1%	41.8%	79.3%	62.6%	28.1%	50.6%	97.9%
Set C (GP)	84.0%	91.2%	85.3%	74.0%	86.0%	91.2%	93.5%
Set C (SVM)	93.7%	50.0%	81.0%	61.2%	22.5%	41.5%	96.6%

Table 1: Rank 1 view classification results for GP and SVM.

Probe Set	36°	54°	72°	90°	108°	126°	144°
Set A2 (GP)	98.0%	99.0%	98.8%	99.0%	99.0%	99.0%	99.0%
Set A2 (SVM)	98.7%	78.4%	92.4%	90.0%	82.9%	71.5%	100%
Set B (GP)	99.5%	99.5%	99.3%	98.8%	99.3%	99.2%	99.3%
Set B (SVM)	98.1%	79.0%	88.7%	88.6%	75.6%	79.2%	99.3%
Set C (GP)	98.1%	98.6%	99.5%	98.3%	98.6%	99.0%	97.9%
Set C (SVM)	97.5%	83.7%	86.0%	86.4%	66.2%	62.9%	97.9%

Table 2: Rank 2 view classification results for GP and SVM.

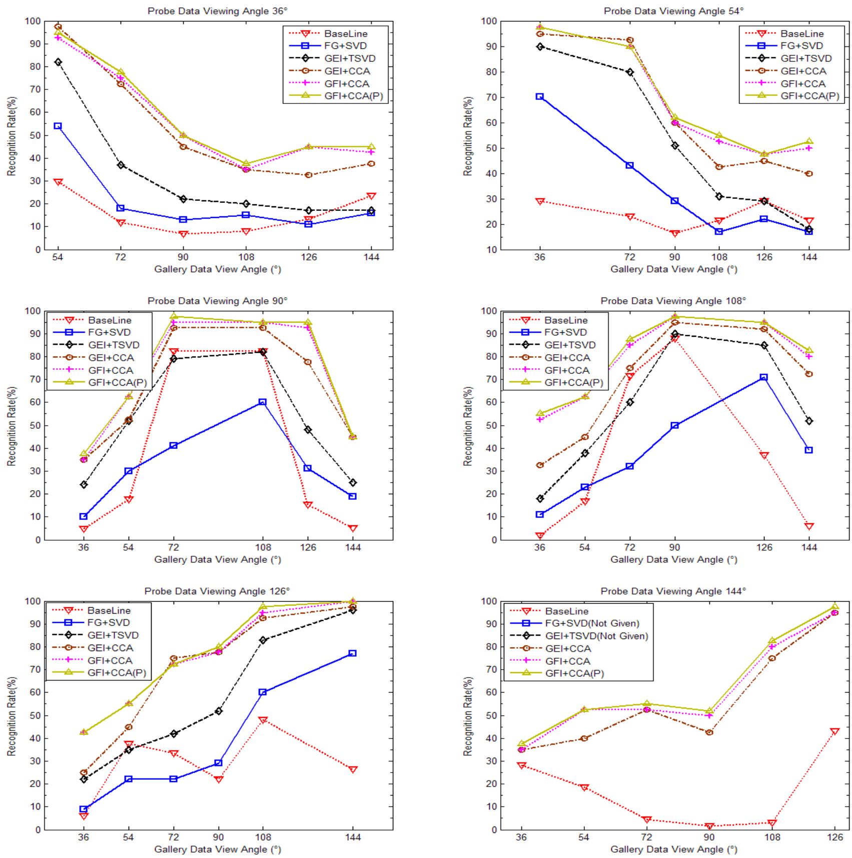


Figure 4: comparison of cross-view gait recognition performance under normal conditions. (For 144° the results of FG+SVD [14] and GEI+TSVD [12] are not available.)

Cross View Gait Recognition using Correlation Strength– After view classification using GP Classification we use correlation strength from CCA to perform gait recognition across multiple views. The results are reported in terms of recognition rate for our method with GFI (GFI+CCA), our method with known probe angle (GFI+CCA(P)), our method with Gait Energy Image for gait representation (GEI+CCA). We also compared our approach with state-of-the-art methods in [14] (FG+SVD), [12] (GEI+TSVD) and the baseline [20] which simply matches GEI across views without any view transformation. Note that we provide the results for gait energy image (GEI+CCA) using our approach to provide a direct comparison with alternative approaches which also use GEI for gait representation. The results obtained using GEI and GFI also give insight on their ability to cope with different covariate conditions such as carrying and clothing.

The results under normal conditions are shown in Fig. 4. It can be seen from Fig. 4 that our method significantly outperforms the existing methods over all views. It is interesting to note that the performance of FG+SVD [14] and GEI+TSVD [12] in some cases even falls below the Baseline [20] which does not compensate for view change at all. In contrast our approach beats the baseline approach comfortably. It is also worth pointing out that all alternative methods assume the view angles are known a prior and our approach does not make this assumption and recognise the view angle automatically. Fig. 4 also shows that when probe view angle is known (GFI+CCA(P)), the result is almost identical to the one with GP classification (GFI+CCA) which emphasizes that our classification algorithm based on rank 2 results effectively classifies unknown probe sequences. Comparing GFI+CCA with GEI+CCA it is clear that GFI is a better gait representation. This result is consistent with those reported in [1] for gait recognition under the same view angle.

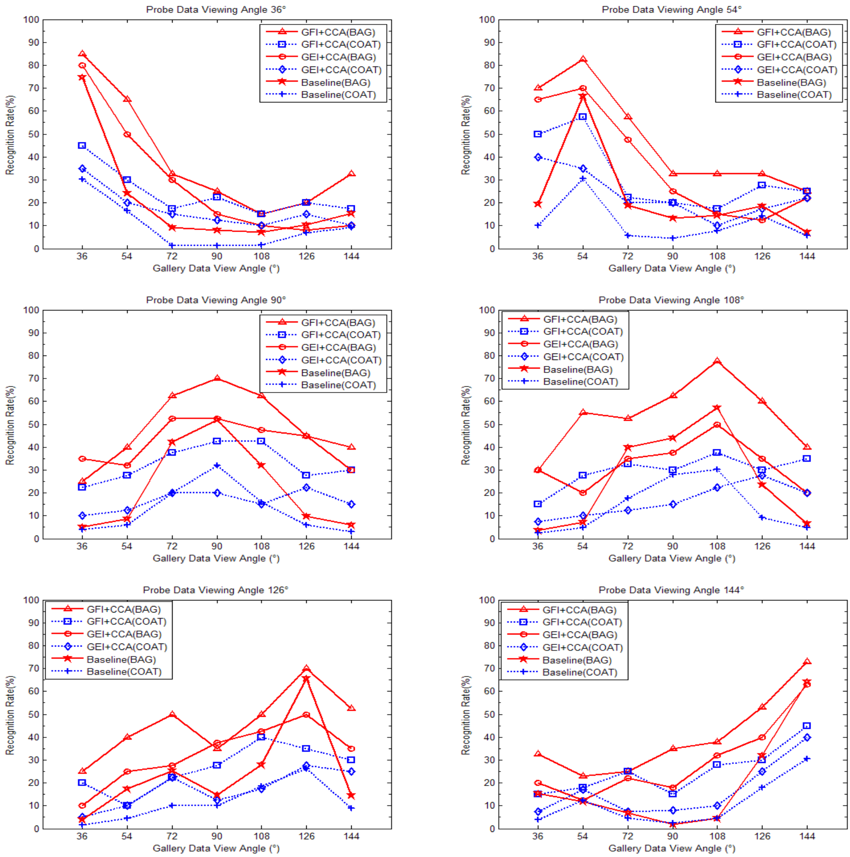


Figure 5: comparison of cross-view gait recognition performance under changing carrying and clothing conditions.

We have also tested the performance of our approach under variable covariate conditions present in the dataset i.e. the clothing and the carrying conditions. We compare the results of our approach (GFI+CCA) with Baseline [20] and with our method using gait energy image (GEI+CCA) only as [12, 14] did not present the results for these experiments. The results are shown in Fig. 5. Again, our approach consistently outperforms the baseline methods. Fig. 5 also shows that the advantage of GFI over GEI become more apparent under changing carrying and clothing conditions as GFI was specifically designed for coping with different covariate conditions [1].

4 Conclusion

We have developed a novel cross-view gait recognition approach using Gaussian Process classification for view recognition and correlation strengths from CCA which act as a measure of similarity across views. Our method works with probe sequence in any view under variable covariate conditions. The system significantly outperforms state-of-the-art on all view combinations and is also effective in dealing with covariate conditions across views.

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