Cross-View Gait Recognition Using Correlation Strength

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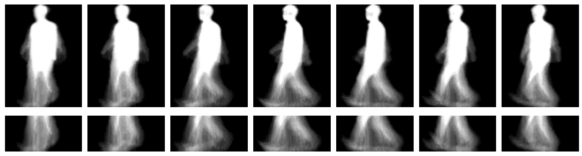
Gait is a behavioural biometric particularly useful for non-intrusive and/or non-cooperative person identification from a distance in unconstrained public spaces. However, such environments also increase the difficulties in gait recognition compared to a more controlled one with constantly known view angle. This is largely because 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. Recently a number of approaches [2, 3] 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 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 [2, 3] even when they assume known probe sequence view angle.

We compute two gait representations, one for view angle recognition and the other for cross-view gait recognition. For view recognition, gait sequences are represented using Truncated Gait Energy Images (TGEI). TGEI (Fig.1(bottom row))is simply Gait Energy Image (GEI) without its top part (head & torso) and is generated by only taking the bottom one third of the GEI.

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].



(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.

Gaussian Process (GP) classifier is trained on the multi view TGEI training dataset. The learned GP gait view classifier is expected to make errors. To minimise such errors 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.

To learn the cross view correlation model we use the computed Gait Flow Images and apply Canonical Correlation Analysis(CCA). This is done 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.

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} can now be recognised by first doing GP classification 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}.

After view classification we use the trained CCA models for $V_{\theta_1} \rightarrow V_{\theta_g}$ and $V_{\theta_2} \rightarrow V_{\theta_g}$ 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. Correlation strength for the two templates are computed using CCA 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

$$\rho^i = \rho^{iM} + \rho^{iM_x^+} + \rho^{iM_x^-} + \rho^{iM_y^+} \qquad (1)$$

The gallery sequence with the largest ρ^i is then identified as the correct match.

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.

[1] K. Bashir, T. Xiang, and S.G. Gong. Gait representation using flow fields. In *BMVC*, 2009.

[2] W. Kusakunniran, Q. Wu, H. Li, and J. Zhang. Multiple views gait recognition using view transformation model based on optimized gait energy image. In *ICCV Workshop*, 2009.

[3] Y. Makihara, R. Sagawa, Y. Mukaigawa, T. Echigo, and Y. Yagi. Gait recognition using a view transformation model in the frequency domain. In *ECCV (3)*, pages 151–163, 2006.