Human Body Part Selection by Group Lasso of Motion for Model-Free Gait Recognition

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***Abstract*—Gait recognition is an emerging biometric technology that identifies people through the analysis of the way they walk. The challenge of model-free based gait recognition is to cope with various intra-class variations such as clothing variations, carrying conditions and angle variations that adversely affect the recognition performance. This paper proposes a method to select the most discriminative human body part based on group Lasso of motion to reduce the intra-class variation so as to improve the recognition performance. The proposed method is evaluated using CASIA Gait Dataset B. Experimental results demonstrate that the proposed technique gives promising results.**

***Index Terms*—Entropy, gait recognition, group lasso.**

I. Introduction

GAIT recognition discriminates people by the way they walk. Techniques can be classified into two main categories: model-based and model-free approach. Model-based approach [1]–[3] models the person body structure that estimates static body parameters over time. This process is computationally intensive since it needs to model and track the subject body. The model-free approach does not recover a structural model of human motion. It uses the features extracted from the motion or shape and hence requires much less computation. Furthermore, dynamic information results in better recognition performance than its static counterpart [4]. These motivate researchers to develop new feature representations in model-free approach context.

There exists a considerable amount of work in the context of model-free approach. BenAbdelkader *et al.* [5] introduced a self-similarity representation to measure the similarity between silhouettes. Collins *et al.* [6] proposed a template based silhouette matching. Hayfron-Acquah *et al.* [7] suggested a contour representation by analyzing the symmetry of human motion. Lee *et al.* [8] introduced a novel spatiotemporal representation called SVB frieze pattern that captures the motion information over time. Kobayashi *et al.* [9] used Cubic Local Auto-Correlation to extract gait features. Lu *et al.* [10] used multiple feature representations based on independent component analysis and genetic fuzzy support vector machine. Huang *et al.* [11] presented a manifold-based approach for cross-speed recognition. Hu *et al.* [12] proposed an incremental framework based on optical flow. Liu *et al.* [13] integrated gait recognition in person re-identification. Hu *et al.* [14] suggested a view-invariant discriminative projection method by a unitary linear projection. Hu *et al.* [15] introduced a gait modeling method for gender classification.

Recent trends seem to favor Gait Energy Image (GEI) representation suggested by Han and Bhanu [16]. It is a spatio-temporel representation of the gait obtained by averaging the silhouettes over a gait cycle. A considerable amount of works use GEI representation. Yu *et al.* [17] applied a template matching on GEI. Tao *et al.* [18] used Gabor filters to extract information from GEI and a General Tensor Discriminant Analysis for recognition. Xu *et al.* [19] presented an extension of Marginal Fisher analysis to address the problem of gait recognition.

The main challenge of model-free gait recognition is coping with various intra-class variations caused by the presence of shadows, clothing variations and carrying conditions. Segmentation, view angle are further causes of recognition error [16], [17], [20]. To overcome the limitations of GEI presentation, several approaches have been proposed. Bashir *et al.* [21] introduced a feature selection method named Gait Entropy Image (GEnI). It computes entropy for each pixel to distinguish static and dynamic pixels of GEI. The GEnI represents a measure of feature significance. In the same context Bashir *et al.* [22] suggested a gait representation by a weighted sum of the optical flow corresponding to each direction of human motion. An unsupervised method is used to select GEI pixels based on their intensity value [23]. Dupuis *et al.* [24] introduced a feature selection method based on Random Forest feature rank algorithm. Rida *et al.* [25] estimated a mask based on pixel variations. Jeevan *et al.* [26] introduced a gait representation called Gait Pal and Pal Entropy Image. Kusakunniran [27], [28] proposed a framework to construct gait feature directly from a raw video. Rokanujjaman *et al.* [29] introduced a novel frequency-domain gait entropy representation. Choudhury *et al.* [30] proposed a view-invariant multiscale gait recognition method (VI-MGR). Zeng *et al.* [31] introduced a novel method to cope with the problem of walking speed. Recently, Rida *et al.* [32], [33] used the Modified Phase-Only Correlation to extract the feature.

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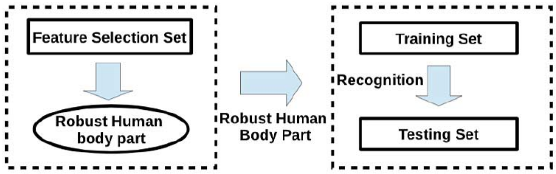

Fig. 1. Scheme of our part-selection, training and testing.

This paper proposes a new framework to mitigate the effect of the intra-class variation of GEI representation. Contributions are summarized as follows:

- A horizontal motion vector is proposed that is more reliable and better characterizes the gait than the pixel-wise motion.
- A human body part selection method is proposed based on group Lasso to cluster the individual dynamic lines into homogeneous parts of human body.
- Feature selection set is separated from the training set to enhance the generalization of body part selection.

II. Proposed Method

Among the available feature representations we choose GEI that is an effective representation, a good compromise between the computational cost and the recognition performance [21]. Fig. 1 shows our framework of part-selection, training and testing, divided into two modules. The first one estimates the human body parts based on motion and group Lasso and selects the discriminative part that is also robust to the intra-class variation. The estimated body parts should not be overspecialized for a particular training set [24]. Therefore, we perform it on a separated feature selection set. The second module applies Component Discriminant Analysis (CDA) to the part of GEI features of the training data selected in the first module. Gait recognition performance is measured by Correct Classification Rate (CCR) on the testing dataset.

It has been found that the gait of an individual is characterized much more by the horizontal than the vertical motion [34]. Therefore, instead to estimate the motion of each pixel [21], we propose to estimate the horizontal motion by taking the Shannon entropy of each row from the GEI. The resulting column vector is named as motion based vector.

To generalize the contiguous human body parts from the motion based vector, we further propose to apply group Lasso learning algorithm to segment the motion based vector into shared blocks with similar motion value. The body part with the highest average motion value over the selection dataset is selected, which is discriminative and robust to the intra-class variation.

A. The Proposed Motion Based Vector

GEI is a spatio-temporal representation of gait pattern. It is a single grayscale image obtained by averaging the silhouettes extracted over a complete gait cycle [16] as

$$\mathbf{G} = \frac{255}{T} \sum_{t=1}^{T} \mathbf{B}(t) \tag{1}$$

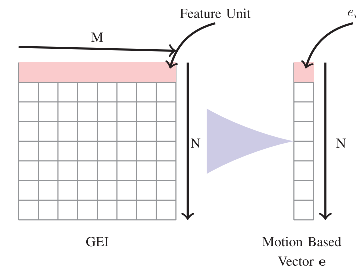

Fig. 2. Illustration of the motion based vector.

Where $\mathbf{G} = \{g_{i,j}\}$ is GEI, $1 \le i \le N$ and $1 \le j \le M$ are the spatial coordinates, T is the number of the frames of a complete gait cycle, $\mathbf{B}(t)$ is the silhouette image of frame t.

For each GEI, a motion based vector $\mathbf{e} \in \mathbb{R}^N$ shown in Fig. 2 is generated by computing the Shannon entropy of each row of GEI. The element of the motion based vector $\mathbf{e}$ is given by:

$$e_i = -\sum_{k=0}^{255} p_k^i \log_2 p_k^i \tag{2}$$

where p_k^i is the probability that the pixel value k occurs in the ith row of image $\mathbf{G}$, which is estimated by:

$$p_k^i = \frac{\#(g_{i,j} = k)}{M}; \quad \forall j \in [1, M] \tag{3}$$

B. Group Lasso For Multiple Change-Point Detection

Let P motion based vectors $\{\mathbf{e}_k\}_{k=1}^P$ of P GEIs stored in $N \times P$ matrix $\mathbf{E}$. The aim is to detect the shared change-point locations across all motion based vectors $\{\mathbf{e}_k\}_{k=1}^P$ by approximating matrix $\mathbf{E} \in \mathbb{R}^{N\times P}$ by a matrix $\mathbf{V} \in \mathbb{R}^{N\times P}$ of piecewise-constant vectors that share change points. This can be achieved by resolving the following convex optimization problem:

$$\min_{\mathbf{V}\in\mathbb{R}^{N\times P}} \|\mathbf{E} - \mathbf{V}\|_F^2 + \lambda \sum_{i=1}^{N-1} \|\mathbf{v}_{i+1} - \mathbf{v}_i\|_1 \tag{4}$$

where $\mathbf{v}_i$ is the i-th row of $\mathbf{V}$ and $\lambda > 0$. Intuitively, when increasing λ enforces many increments $\mathbf{v}_{i+1} - \mathbf{v}_i$ to converge to zero. This implies that the position of non-zeros increments will be same for all vectors. Therefore, the solution of (4) provides an approximation of $\mathbf{E}$ by a matrix $\mathbf{V}$ of piecewise-constant vectors which share change-points. The problem (4) is reformulated as a group Lasso regression problem as follows:

$$\min_{\beta\in\mathbb{R}^{(N-1)\times P}} \left\|\overline{\mathbf{E}} - \overline{\mathbf{X}}\beta\right\|_F^2 + \lambda \sum_{i=1}^{N-1} \|\beta_{\mathbf{i}}\|_1 \tag{5}$$

where $\overline{\mathbf{X}}$ and $\overline{\mathbf{E}}$ are obtained by centering each column from $\mathbf{X}$ and $\mathbf{E}$ knowing that:

$$\begin{cases} \mathbf{X} \in \mathbb{R}^{N\times(N-1)}; \quad x_{i,j} = \begin{cases} 1 & for \quad i > j \\ 0 & otherwise \end{cases} \\ \beta_i = \mathbf{v}_{i+1} - \mathbf{v}_i \end{cases} \tag{6}$$

The problem (5) can be solved based on the group LARS described in [35] which approximates the solution path with a piecewise-affine set of solutions and iteratively finds change-points independently of λ value. The full derivation of the method can be found in [36].

TABLE I
COMPARISON OF CCRS (IN PERCENT) FROM SEVERAL DIFFERENT ALGORITHMS ON CASIA DATABASE USING 90° VIEW

Method	Normal Conditions	Carrying Conditions	Clothing Conditions	Overall	Std
Yu et al. [17]	97.60	32.70	52.00	60.77	33.33
Han et al. [16]	99.60	57.20	23.80	60.20	37.99
Bashir et al. [21]	**100.00**	78.30	44.00	74.10	28.24
Bashir et al. [22]	97.50	**83.60**	48.80	76.63	25.09
Bashir et al. [23]	99.40	79.90	31.30	70.20	35.07
Dupuis et al. [24]	98.80	73.80	63.70	78.77	18.07
Rida et al. [32], [33]	93.60	81.70	68.80	81.37	12.40
Rida et al. [25]	95.97	63.39	72.77	77.38	16.77
Hu et al. [12]	94.00	45.20	42.90	60.70	28.86
Kusakunniran [27]	95.40	60.90	52.00	69.43	22.92
Rakanujjaman et al. [29]	97.61	83.87	51.61	77.70	23.61
Kusakunniran [28]	94.50	60.90	58.50	71.30	20.13
Jeevan et al. [26]	93.36	56.12	22.44	57.31	35.47
Our Method	98.39	75.89	**91.96**	**88.75**	**11.59**

C. Canonical Discriminant Analysis

On the training dataset, Canonical Discriminant Analysis (CDA) is applied to the GEI features of the robust human body part determined by the group Lasso on the feature selection dataset. The CDA applies Principal Component Analysis (PCA) followed by a Multiple Discriminant Analysis (MDA). PCA removes unreliable dimensions that adversely affect the robustness of the classification [37], [38] and hence improves the classification accuracy. MDA maximizes the distance between classes and preserve the distance inside the classes. As suggestion in [16] we retain 2c eigenvectors after applying PCA, where c corresponds to the number of classes (the full explanation is found in [39]). The performance of our method is measured by the Correct Classification Rate (CCR) that is the ratio of the number of correctly classified samples over the total number of samples.

III. EXPERIMENTS AND RESULTS

The proposed method is tested on CASIA dataset B [17] to evaluate its ability to handle the carrying, clothing and view angle variations. CASIA dataset B is a multiview gait database containing 124 subjects captured from 11 different angles starting from 0° to 180°. Each subject has six normal walking sequences (SetA), two carrying conditions sequences (SetB) and two clothing variations sequences (SetC). The first four sequences of setA noted as SetA1 are used for training. The two remaining sequences of SetA noted as SetA2 as well as SetB and SetC are used for testing normal, carrying and clothing conditions, respectively. For each sequence, GEI of size 64*64 is computed. To create our body-part selection dataset, we randomly selected 24 GEIs for each variant (normal, carrying, clothing). All selected GEIs for the feature selection dataset were removed from the training and testing sets. We performed a bagging without replacement of 45 GEIs on the feature selection dataset. The operation was repeated $L = 5$ times.

A. Clothing and Carrying Conditions

We focus on the effect of the body variations caused by carrying conditions and clothing variations so we carried out our experiments under 90° view angle. Fig. 3 shows the entropy value (y-axis) of all GEIs against feature index (x-axis) for the $L = 5$ experiments The vertical lines represent the limits of human body parts learnt by the group Lasso on the feature selection datasets. From Fig. 3 we see that the group Lasso divides the horizontal motion of human body into 4 parts. The corresponding parts of GEI are shown in Fig. 4. Fig. 3 shows that the part formed by feature units (rows of GEI) from 46 to 64 has the highest mean motion value. It is the most dynamic part from the human body and is also robust to the intra-class variations (see Fig. 4(c) 4(d)), which is selected in this work for recognition. Table I compares the performance of our method against the reported by other methods. It shows that the CCR of our method is marginally lower in the normal and carrying conditions and significantly higher in the clothing variations than all other methods.

It is common in real life that people have different clothes depending on days (warm or cool days) and seasons (summer or winter). Unfortunately, the intra-class variation of the static features (low motion) is mainly caused by the clothing variation that greatly affects the recognition accuracy adversely. It has

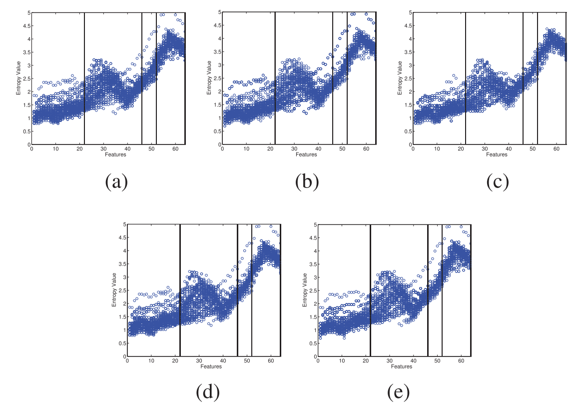

Fig. 3. Values of motion based vectors in selection datasets and parts of shared motion value separated by group Lasso (a) Experiment 1 (b) Experiment 2 (c) Experiment 3 (d) Experiment 4 (e) Experiment 5.

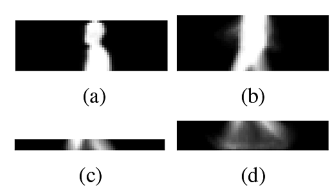

Fig. 4. Human body parts of GEI separated by group Lasso (a) Part1 (b) Part 2 (c) Part 3 (d) part 4.

TABLE II
SELECTED BODY PART CCR (%) WITHOUT PRIOR KNOWLEDGE OF VIEW ANGLE

	Test angle (°)										
	0	18	36	54	72	90	108	126	144	162	180
Normal	97.97	98.79	96.37	96.77	98.39	97.98	97.18	95.56	96.77	97.98	97.58
Carrying	72.76	72.58	75.81	76.42	75.81	73.66	74.60	76.92	76.11	75.10	76.11
Clothing	80.49	83.47	85.08	87.85	91.53	91.07	87.90	86.23	87.45	84.90	83.06
Overall	83.74	84.95	85.75	87.02	88.58	87.57	86.56	86.24	86.78	85.99	85.59

TABLE III
WHOLE BODY CCR (%) WITHOUT PRIOR KNOWLEDGE OF VIEW ANGLE

	Test angle (°)										
	0	18	36	54	72	90	108	126	144	162	180
Normal	100	100	99.19	99.19	99.19	100	99.60	97.98	99.60	99.19	100
Carrying	82.11	77.42	75.81	68.70	59.68	52.68	53.63	60.73	68.02	66.53	72.47
Clothing	26.83	25.81	28.63	27.53	28.63	22.77	23.79	31.17	34.01	29.39	29.84
Overall	69.65	67.74	67.88	65.14	62.50	58.48	59.01	63.30	67.21	65.04	67.44

TABLE IV
VI-MGR CCR (%) WITHOUT PRIOR KNOWLEDGE OF VIEW ANGLE

	Test angle (°)										
	0	18	36	54	72	90	108	126	144	162	180
Normal	100	99	100	99	100	100	99	99	100	100	99
Carrying	93	89	89	90	77	80	82	84	92	93	89
Clothing	67	56	70	80	71	75	77	75	65	64	66
Overall	86.66	81.33	86.33	89.66	82.66	85	86	86	85.66	85.66	84.66

been demonstrated by Matovski *et al.* [20] that clothing is the factor that drastically affects the performance of gait recognition. Thus, alleviating the problems caused by the clothing variation has significant meaning for gait recognition. The proposed method alleviates the clothing variation problem very well as it significantly outperforms all other approaches as shown in Table I. In the normal and carrying conditions, different persons have different clothing conditions but all samples of a same person always have the same clothing condition in the dataset. Thus, the cloths in the normal and carrying conditions in fact undesirably contribute to differentiate persons. Therefore, these recognition rates could be misleading as they do not well reflect the real gait recognition performance. In the next section, we will further see the problems of testing the gait recognition performance using the training and test data in the same cloth for the same persons. Nevertheless, the proposed method performs the best among all approaches on the whole test dataset that contains one-third samples with cloth variation and two-third samples without the cloth variation.

B. View Angle Variations

Although the proposed method in this paper is not aimed at solving the view angle problem, we still test its performances on the view angle variations. We carried out experiments on CASIA database using 11 different angles from 0° to 180°. We propose to recognize individuals without a prior knowledge of the viewpoint. Towards this end, we first estimate the pose of the query subject using the selected human body part. i.e. row 46 to 64 and a simple knn with $k = 1$ to find the group of training samples that have the similar pose to that of the query subject. Then, the query subject is identified among all

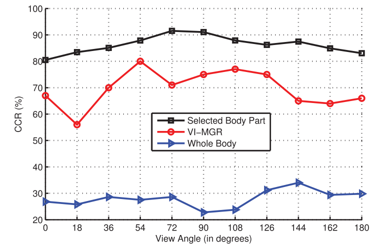

Fig. 5. CCR of different approaches on test data with cloth and view angle variations.

training samples of this group. Results are shown in Table II, Table III and Table IV, which respectively record the CCR of our proposed body part selection approach, the approach that uses the whole body and the View-Invariant Multiscale Gait Recognition method (VI-MGR) [30]. Results in these tables clear show that our body part selection method significantly outperforms VI-MGR and the approach without the part selection for all 11 view angle variations in the case of the clothing variation. On the whole test dataset that contains one-third samples with cloth variation and two-third samples without the cloth variation, the proposed approach outperforms the no-part-selection approach for all view angle variations and outperforms VI-MGR in 8 of the 11 view angle variations.

The problems of the CCR for normal and carrying conditions are shown in Table III and IV. It is well-known that the maximum gait information is captured for the view angle near 90° and the minimum gait information is captured for the view angle near 0° or 180°. However, while perfect or near perfect CCR is achieved by almost all view angles in normal condition, in carrying condition, visibly higher CCR is achieved for view angles near 0° or near 180° than that for view angles near 90°. This shows that the cloths in the normal and carrying conditions in fact undesirably contribute to differentiate persons. Therefore, these recognition rates could be misleading as they do not well reflect the real gait recognition performance. Fig. 5 shows CCR of the 3 approaches on all test data with cloth and view angle variations, which clearly shows the significant performance gain achieved by the proposed approach.

IV. CONCLUSION

In this paper we proposed a method that finds the discriminative human body part that is also robust to the intra-class variations for improving the human gait recognition. The proposed method first generates a horizontal motion based vector from GEI and then applies the group Lasso on the horizontal motion based vectors of a feature selection dataset to learn the discriminative human body part for gait recognition. The learnt human body part is applied to the independent training and test datasets. The proposed method significantly improves the recognition accuracy in the case of large intra-class variation such as the clothing variation. This is verified by the experiments, which show that the proposed methods not only significant outperforms other approaches in the case of clothing variations but also achieves the overall best performance among all approaches on the whole testing dataset that contains normal, carrying, clothing and view angle variations.

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