UNSUPERVISED FEATURE SELECTION METHOD FOR IMPROVED HUMAN GAIT RECOGNITION

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ABSTRACT

Gait recognition is an emerging biometric technology which aims to identify people purely through the analysis of the way they walk. The technology has attracted interest as a method of identification because it is non-invasiveness since it does not require the subject's cooperation. However, "covariates" which include clothing, carrying conditions, and other intra-class variations affect the recognition performances. This paper proposes an unsupervised feature selection method which is able to select most relevant discriminative features for human recognition to alleviate the impact of covariates so as to improve the recognition performances. The proposed method has been evaluated using CASIA Gait Database (Dataset B) and the experimental results demonstrate that the proposed technique achieves 85.43 % of correct recognition.

Index Terms— Biometrics, gait, model free, feature selection, entropy

1. INTRODUCTION

Technology has invaded our lives as never before and the effectiveness of current security systems has become increasingly important. The development of automatic personal identification systems has increased in recent years and worldwide effort has been devoted to broaden and enhance personal identification systems. In particular, biometric recognition has become an area of particular interest and is used in numerous applications. Biometric recognition aims to identify individuals using unique, reliable and stable physiological and/or behavioral characteristics such as fingerprint, palmprint, face, gait, etc. Gait recognition consists on discriminating among people by the way or manner they walk. Gait as a biometric trait can be seen as advantageous over other forms of biometric identification techniques for the following reasons:

- The gait of a person walking can be extracted and analysed from distance without any contact with the sensor.
- The images used in gait recognition can be easily provided by low-resolution, video-surveillance cameras.

Gait recognition techniques can be classified into two main categories: model-based and model-free approach. Model based approach [1, 2] models the person body structure, it uses the estimation over time of static body parameters for recognition (i.e. trajectory, limb lengths etc). This process is usually computationally intensive since we need to model and track the subjects body. On the other hand, the model free approach does not recover a structural model of human motion, instead it uses the features extracted from the motion or shape for recognition. Compared to a model based approach, the model free approach requires much less computation cost (see Tab. 1), furthermore dynamic information results in much improved recognition performance than static counterpart [3]. These reasons have motivated the researchers to introduce new feature representations in model free approach context. The major challenges of methods belong the model free gait recognition are due to the effect of various covariates which are due to the presence of shadows, clothing variations and carrying conditions (backpack, briefcase, handbag, etc). From a technical point of view segmentation and the view dependency are further causes of gait recognition errors. This has motivated the work presented in this paper which aims to mitigate the effect of the covariates and improve the recognition performance.

Table 1. Comparison between model-based and model-free approach gait recognition.

	Model-Free	Model-Based
Complexity	✓	✗
Covariates	✗	✓
Calculation	✓	✗

The rest of this paper is organized as follows: Sect. 2 summarizes the previous works. Sect. 3 gives the theoretical description of the proposed method. Sect. 4 presents the experimental results. Sect. 5 offers our conclusion.

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2. RELATED WORKS

There exists a considerable amount of work in the context of model free approaches for gait recognition. BenAbdelkader et al. [4] introduced a self similarity representation to measure the similarity between pairs of silhouettes. Collins et al. [5] proposed a template based silhouette matching in some key frames. Recent trends seem to favor Gait Energy Image (GEI) representation suggested by Han and Bhanu [6]. GEI is a spatio-temporel representation of the gait obtained by averaging the silhouettes over a gait cycle. It has been found that the different clothing and carrying conditions between the gallery and probe sequences influence the recognition performances [6, 7]. To overcome the limitations of the GEI presentation several works have been proposed. Bashir et al. introduced a novel gait feature selection method named Gait Entropy Image (GEnI) [8]. It consists of computing Shannon entropy for each pixel over a gait cycle; in other terms it aims to distinguish static and dynamic pixels of the GEI. In this case GEnI represents a measure of feature significance (pixels with high entropy correspond to dynamic parts which are robust against appearance changes). In the same context Bashir et al. suggested a new gait representation called flow field [9] in order to represent a weighted sum of the optical flow corresponding to each coordinate direction of human motion, in addition of an unsupervised method which selects GEI pixels based on their intensity value [10]. Dupuis et al. introduced an interesting feature selection method based on Random Forest rank features algorithm [11]. Rida et al. proposed a supervised feature extraction method based on Modified Phase-Only Correlation (MPOC) [12] as well as a feature selection mask based pixels intensity [13].

3. METHODOLOGY

In this paper among all available feature representations we have chosen GEI, it is an easy and simple representation to compute thus making it an effective compromise between the computational cost and the recognition performance. Fig. 1 shows our framework which is divided into two main modules: the first one consists of selecting features from the GEI which are robust against covariates. The selection method should not be overspecialized for a particular training set [11] as consequence we perform it on a feature selection set independent from training and testing sets (all selected sequences from the feature selection set were removed from the training and testing sets). The second module estimates the performance of our method (Correct Classification Rate) using GEI features selected in the first module.

It has been found that the gait of an individual is characterized much more by the horizontal than the vertical motion [14], as consequence instead to estimate the motion of each pixel by calculating its entropy [8], we estimate the horizontal motion by taking the entropy of each row from the GEI

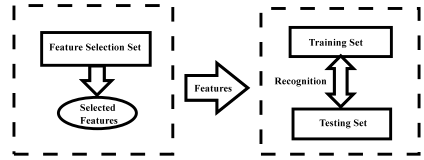


Fig. 1. Scheme of our method.

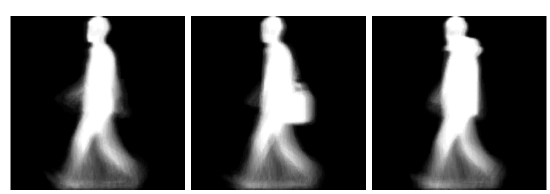
considered as a new feature unit, the resulting vector $\mathbf{e} \in \mathbb{R}^N$ represents the motion based vector (see Sec 3.2). The goal is to find the shared dynamic human body part between different gait sequences which is supposed to be robust again covariates (i.e. the shared human body part between different gait sequences with the highest motion/entropy value). The human body parts based motion are estimated using the group fused Lasso algorithm [15] introduced by Vert and Bleakley which aims to estimate where the most or all the motion based vectors $\{\mathbf{e}_k\}_{k=1}^P$ jointly change (i.e. segment the motion vectors into shared blocks with the same motion value)(see Sec 3.3). In the second module we calculate the performance of the selected human body part (GEI features) using Canonical Discriminant Analysis (CDA) [16](see Sec 3.4).

3.1. Gait Energy Image

GEI is a spatio-temporal representation of the gait patterns. It consists of representing the gait cycle using a single grayscale image obtained by averaging the silhouettes extracted over a complete gait cycle [6]. GEI is computed using the following equation

$$\mathbf{G}(x,y) = \frac{1}{F}\sum_{t=1}^{F}\mathbf{B}(x,y,t) \tag{1}$$

where F is the number of the frames within a complete gait cycle, $\mathbf{B}$ is a silhouette image, x and y are the coordinates of the image and t is frame number in the cycle. Low and high intensity pixels of the GEI correspond to the dynamic and static parts of the body, respectively. Dynamic parts are most informative since they contain the information of the gait while static parts are sensitive since they contain the shape and contour information which can easily be influenced by the covariates [8].



(a) Normal Walk (b) Carrying Bag (c) Wearing Coat

Fig. 2. Gait energy image of an individual under different conditions.

3.2. Motion Based Vector

The motion based vector $\mathbf{e} \in \mathbb{R}^N$ consists on calculating the Shannon entropy of each row from the GEI considered as new feature unit (see Fig. 3), it is given by:

$$\begin{cases} \mathbf{e}(i) = -\sum_{k=0}^{K} p_k^i \log_2 p_k^i \\ i \in [1, N] \end{cases} \tag{2}$$

where p_k^i is the probability that the pixel value k occurs within the feature unit $\{U_i\}_{i=1}^N$ and $K = 255$ (grayscale image). The probability p_k^i is given by:

$$\begin{cases} p_k^i = \frac{\#\mathbf{G}(i,j)=k}{M}; \; \forall j \in [1, M] \\ i \in [1, N]; \; k \in [0, 255] \end{cases} \tag{3}$$

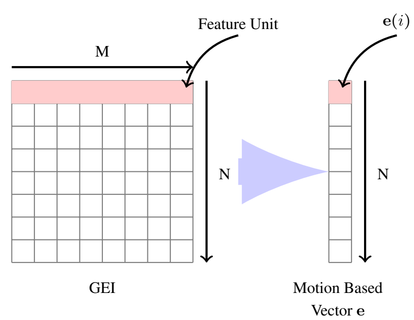


Fig. 3. Illustration of the motion based vector.

3.3. Group Fused Lasso For Change-Point Detection

Let P motion based vectors $\{\mathbf{e}_k\}_{k=1}^P$ 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 the vectors in matrix $\mathbf{E} \in \mathbb{R}^{N \times P}$ by a matrix $\mathbf{V} \in \mathbb{R}^{N \times P}$ of piecewise-constant vectors which share change points. It is obtained after resolving the following convex optimization problem:

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

where $\mathbf{V}_{i,\cdot}$ is the i-th row of $\mathbf{V}$ and $\lambda > 0$. Intuitively when λ increases that will enforce many increments $\mathbf{V}_{i+1,\cdot} - \mathbf{V}_{i,\cdot}$ to converge to zero. This implies that the position of non-zeros increments will be same for all vectors, as consequence 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:

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

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

$$\begin{cases} \mathbf{X} \in \mathbb{R}^{N \times (N-1)}; \; \mathbf{X}_{i,j} = \begin{cases} 1 \; for \; i > j \\ 0 \; otherwise \end{cases} \\ \beta_{i,\cdot} = \mathbf{V}_{i+1,\cdot} - \mathbf{V}_{i,\cdot} \end{cases} \tag{6}$$

The problem (5) can be solved based on the group LARS described in [17], it approximates the solution path with a piecewise-affine set of solutions and iteratively finds change-points, the full derivation of the method can be found in [15].

3.4. Canonical Discriminant Analysis

Canonical Discriminant Analysis (CDA) which corresponds to Principal Component Analysis (PCA) followed by a Multiple Discriminant Analysis (MDA). As suggestion in [6] we retain $2c$ eigenvectors after applying PCA, where c corresponds to the number of classes (the full explantation is found in [16]). The aim of the PCA is to be able to represent most of the variations of the original data using only a few principal components which are orthogonal to each others. MDA tries to maximize the distance between classes and preserve the distance inside the classes. The performance of our method is estimated with the correct classification rate (CCR) which corresponds to the ratio of the number of well classified samples over the total number of samples.

4. EXPERIMENTS AND RESULTS

We have used CASIA database (dataset B) [7] to evaluate our method. It is a multivew 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-bag sequences (SetB) and two wearing-coat sequences (SetC). The first four sequences of setA noted as (SetA1) are used for training. The two remaining noted as (SetA2), (SetB) and (SetC) are used for testing the effect of view angle variations, carrying conditions and clothing respectively. In our work we focus on the effect of clothing, carrying conditions and carried out experiments under 90° view using 64*64 GEI resolution. To create our feature selection set, we randomly select 24 subjects without replacement as follows: for each subject 3 sequences are randomly chosen corresponding to the three variants so that 72 sequences are obtained (all selected sequences from the feature selection set were removed from the training and testing sets).

Table 2. Comparison of CCRs (In percent) from several different algorithms on CASIA database using 90° view.

Method	Normal	Carrying-Bag	Wearing-Coat	Mean	Std
Yu et al. [7]	97.60	32.70	52.00	60.77	33.33
Han et al. [6]	99.60	57.20	23.80	60.20	37.99
Bashir et al. [8]	**100.00**	78.30	44.00	74.10	28.24
Bashir et al. [9]	97.50	**83.60**	48.80	76.63	25.09
Bashir et al. [10]	99.40	79.90	31.30	70.20	35.07
Dupuis et al. [11]	98.80	73.80	63.70	78.77	18.07
Rida et al. [12]	93.60	81.70	68.80	81.37	12.40
Our Method	95.56	74.11	**86.61**	**85.43**	**10.77**

To make our feature selection method robust and avoid the overspecialization we have applied the evaluation strategy described in Alg. 1 on the feature selection set for $L = 5$.

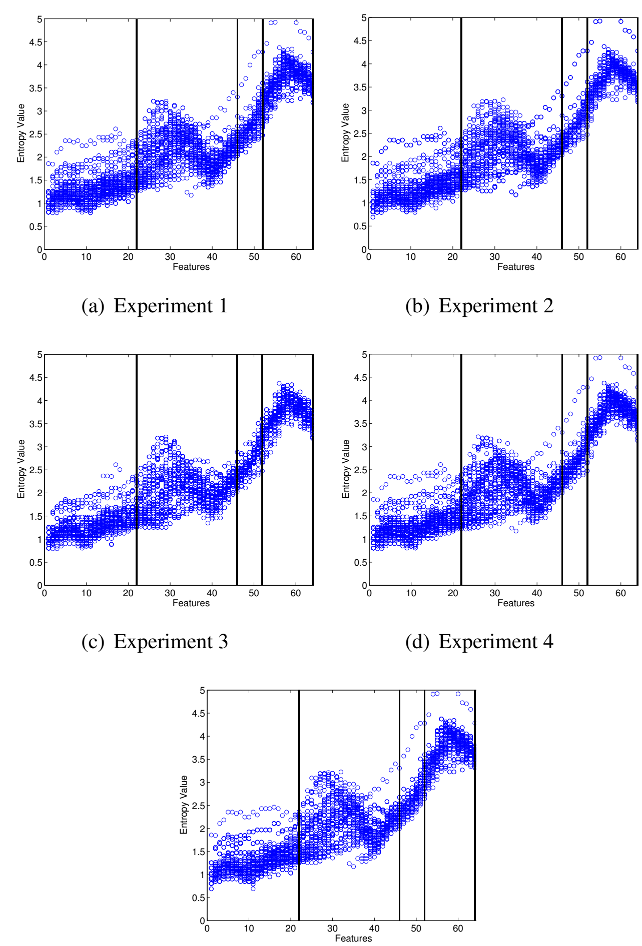
Algorithm 1 The Evaluation Method

Input: feature selection set
for $l = 1$ to L **do**
  Randomly select without replacement of 15 subjects from feature selection set;
  Select related GEI templates corresponding to the three variants (normal, carrying bag, wearing coat);
  Calculate motion based vectors $\mathbf{e}_j$ for all selected GEIs;
  Apply Group Fused Lasso to motion based vectors $\mathbf{e}_j$;
end for

Fig. 4 represents the entropy value of each feature unit (row) of all GEI templates randomly selected for the 5 experiments, it can be seen that the group fused lasso divides the human body based motion into 4 parts; the corresponding parts are shown in Fig. 5. The part between feature unit (row) 52 and 64 from the GEIs has the highest motion value; it corresponds to the dynamic part from the human body (see Fig. 5(d)) which it is used for recognition step.

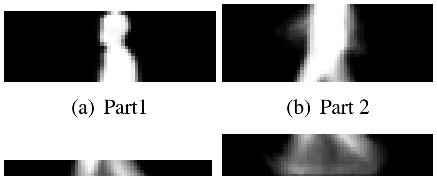
Tab. 2 compares the performance of our method against the reported by other methods, it can be seen that the CCR performance of our method marginally decreases in the normal and carrying-bag walks and considerably increases in the wearing-coat walk comparing with the other methods. The obtained results can be explained that our method takes in consideration only the dynamic features from the human body which are robust against the covariates and have most discriminative power [8] and eliminates the static features which contain the human body shape information. The static features (low motion) are mostly affected in the case of the wearing-coat walk as consequence they influence greatly the recognition accuracy in that case whereas they are discriminative in the case normal and carrying-bag walks.

The advantage of our method is that it loses slightly a bit performance in the normal and carrying-bag walks and considerably increases the performance in the wearing-coat walk which makes a good compromise between different gait walk conditions (normal, carrying-bag, wearing-coat) recognition performance, all that can be seen in the mean and the standard deviation of our method that outperforms the mean and standard deviation of the state of the art methods.



(a) Experiment 1 (b) Experiment 2 (c) Experiment 3 (d) Experiment 4 (e) Experiment 5

Fig. 4. Shared motion value parts selected by group fused lasso.



(a) Part1 (b) Part 2

(c) Part 3 (d) part 4

Fig. 5. Human body parts based motion.

5. CONCLUSION

In this paper we have presented an unsupervised feature selection method for improved gait recognition. The proposed method improves considerably the recognition accuracy in the case of wearing-coat walk and makes the best compromise between different gait walk conditions recognition performances compared with the other existing methods. As future work we will investigate the robustness of our method in the case of view angle variations.

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