Investigation of Gait Representations in Lower Knee Gait Recognition

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Abstract: This paper investigates the effect of lower knee gait representations on gait recognition. After reviewing three emerging gait representations, i.e. Gait Energy Image (GEI), Gait Entropy Image (GEnI), and Gait Gaussian Image (GGI), a new gait representation, Gait Gaussian Entropy Image (GGEnI), is proposed to combine advantages of entropy and Gaussian in improving the robustness to noises and appearance changes. Experimental results have shown that lower knee gait representations can successfully detect camera view angles in CASIA Gait Dataset B, and they are better than full body representations in gait recognition under the condition of wearing coat. The gait representations involving the Gaussian technique have shown robustness to noises, whilst the representations involving entropy provide a better robustness to appearance changes.

1 INTRODUCTION

Gait recognition is a biometric technique which has become a challenge research area in the last few decades. This technique classifies people by the way their walk that does not directly contact with human body. Input images can be captured in a long distance with low resolution and it does not disturb the target activity. Therefore gait recognition can cooperate with CCTV which has become a common facility in surveillance systems.

Gait representating are divided into two categaries based on previous gait research (Shirke et al., 2014). The first categary is model-based that creates the target model which is used in gait feature extractionv. Another is model-free which directly extracts gait features from sequence of human silhouette (Rong et al., 2004, Hu, 2011). This study focuses on the second approach.

There are various gait features which have been used in the model free approach such as the center of mass, width, height, step-size, height of knee, unwrapping boundary, and area or number of pixels (Zeng et al., 2014, Nandy et al., 2014). The whole silhouette could be also used as a gait feature. A sequence of silhouettes has been combined to represent gait, called Gait Energy Image (GEI) (Han and Bhanu, 2006). This technique is commonly used because it is very simple, fast, and representative to some extent. However it is sensitive to some conditions, such as object carrying and clothing. Hence there are emerging research that aim to improve the performance of the whole silhouette gait representation, such as Gait Entropy Image (GEnI) (Bashir et al., 2010), Active Energy Image (AEI) (Zhang et al., 2010), Flow Histogram Energy Image (FHDI) (Yang et al., 2014) and Gait Gaussian Image (GGI) (Arora and Srivastava, 2015).

We proposed a new gait representation which combines Gaussian and Entropy concepts together, namely Gait Gaussian Entropy Image (GGEnI). It takes advantage in correlation between image frames from Gaussian membership function and motion information capturing from Entropy technique.

Different walking conditions affect gait classification results, such as cloth, object carrying, speed transition (Mansur et al., 2014), view angle (Haifeng, 2014, Zheng et al., 2011), curve projection (Iwashita et al., 2014) and incomplete gait cycle (Chattopadhyay et al., 2014). This study begins with view angle detection. We assume that all training sample have already been labelled with camera view angles. When an unknown person is tested, the recognition system first identifies the view angle, and then compares the input images with the sample images only in the same view angle.

Most walking motion parts in a body are clearly

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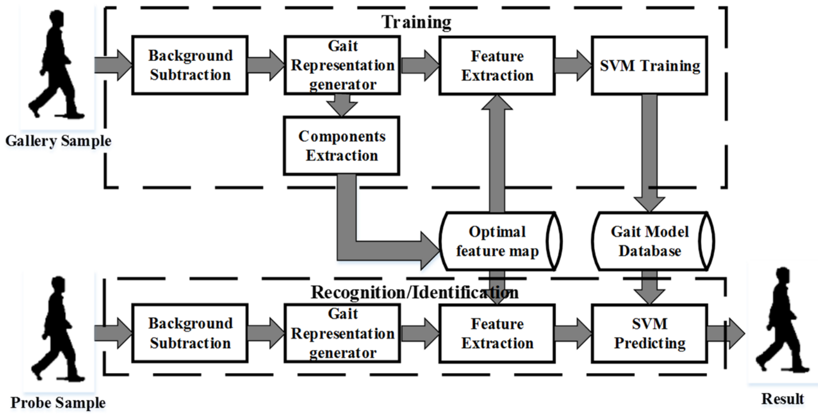

Figure 1: Overview of Gait Recognition System.

arms and legs. Nevertheless, people usually intend to change cloth and object carrying in different seasons and weather conditions, for example sweater, coat, jacket, shorts, skirt, shoe, scarves, gloves, hat and bag. These changes most likely affect above knee appearance except of heel shoe, boots and long skirt. This study also discusses and compares gait recognition based on both full body and lower knee.

The rest of this paper is organized as follows. Section 2 presents a gait recognition system which shows the system overview and techniques used in gait recognition. Section 3 demonstrates experiments and results, and Section 4 summaries this study.

2 METHODOLOGY

The overview of gait recognition system is shown in Figure 1. Both training and recognition phases start with background subtraction which separates human silhouette in each frame of a video sequence. All sequential silhouette images are used to generate gait representation which is described in next section. In the training phase, principal components analysis (PCA) is applied to calculate an optimal feature map for each view angle and condition. Next, gait features are extracted from the optimal feature map as the gait representation. SVMs (Supporting Vector Machines) are used for training and classification.

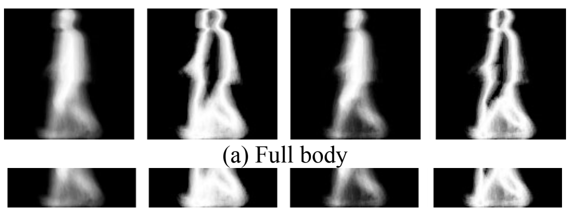

Figure 2: Gait Representation example: GEI, GEnI, GGI and GGEnI (from lef to right).

2.1 Gait Representation

We investigate four gait representations in this research, as shown in Figure 2.

2.1.1 Gait Energy Image (GEI)

This is a common technique in gait recognition. The average silhouette image, calculated from averaging all binarized silhouette images at a same view angle, is used as the representation of personal gait. The final representation is a gray level image. This technique has increased noise tolerance and reduced the memory space.

GEI has been defined as:

$$G(x,y) = \frac{1}{N}\sum_{t=1}^{N} B_t\,(x,y) \quad (1)$$

where N is the number of silhouette frames in walking sequence, t is the frame number in the walking sequence, $B_t\,(x,y)$ is the binary image at time t and *(x, y)* is the pixel coordinate in a frame.

2.1.2 Gait Entropy Image (GEnI)

This technique aims to limit unnecessary appearance information in motion images. Thus it is robust to appearance changes. Same as GEI, sequential silhouette images of a personal gait cycle are used as an input which calculates Shannon entropy by equation (2).

$$GEnI = H(x,y) = \sum_{k=1}^{K} p_k(x,y) log_2 p_k(x,y) \quad (2)$$

where x, y is pixel coordinate and $p_k(x, y)$ is the k^{th}probability which have $K = 2$ because input images are binary image. This paper follows the basic concept in (Bashir et al., 2009) so that $p_2(x, y) = G(x, y)$ in equation (1) and $p_1(x, y) = 1 - p_2(x, y)$.

2.1.3 Gait Gaussian Image (GGI)

GGI is similar to GEI however it uses a Gaussian function instead of the average function. It reduces the noise effect from an individual frame in the interested gait cycle. The Gaussian function is defined as follows:

$$u_i(x) = e^{-\frac{(x_i - \overline{x})^2}{2\sigma^2}} \quad (3)$$

where u_i is Gaussian membership, x_i is the corresponding pixel value of i^{th} frame, $\overline{x}$ is the mean of respective pixel in all frames and σ is the variance of the pixel vector.

Then the output pixel a_j is calculated from the average of the multiplied result between corresponding pixel and Gaussian membership, as shown in equation (4).

$$a_j = \frac{1}{N} \sum_{i=1}^{N} a_i \, u_i \quad (4)$$

where j is the pixel position, i is the frame number, a_i is the pixel value of i^{th} frame and N is the number of frames.

2.1.4 Gait Gaussian Entropy Image (GGEnI)

The aim of this newly proposed gait representation is for improving robustness against appearance changes in GGI, thus the GEnI concept is applied with GGI in this representation. GGEnI is calculated by equation (2), with the probability function changes to Gaussian membership function.

GGEnI is defined as:

$$GGEnI = \sum_{k=1}^{K} p_k(x, y) log_2 p_k(x, y)$$

$$u_i(x, y) = e^{-\frac{(a_i(x,y) - \overline{a(x,y)})^2}{2\sigma^2}}$$

$$p_2(x, y) = \frac{1}{N} \sum_{i=1}^{N} a_i(x, y) \, u_i(x, y)$$

$$p_1(x, y) = 1 - p_2(x, y) \quad (5)$$

where x, y is pixel coordinate, and $p_k(x, y)$ is the k^{th}probability, $u_i(x, y)$ is Gaussian membership of i^{th} frame, $a_i(x, y)$ is pixel value of i^{th} frame, $\overline{a(x, y)}$ is the mean of all frames at (x, y) coordinate, σ is the variance of pixel vector and $p_k(x, y)$ is the k^{th} probability.

2.2 Principal Component Analysis (PCA)

PCA or Karhunen-Loeve (KL) transformation is a basic statistical technique which has been widely used to reduce data dimensions in pattern recognition and computer vision. The 2D gait representation is reduced into a 1D feature vector through an optimal feature map which is calculated from eigenvectors of input data. The fundamental of PCA is defined in (Jackson, 2003, Jolliffe, 2002). This paper implements PCA with "*cov()*" and "*eig()*" in the MATLAB toolbox.

2.3 Support Vector Machines (SVMs)

SVM is a popular classification method which is basically used as a binary classification. However, it can be extended for multi-class classification by two approaches: one-against-one and one-against-all.

This study implements one-against-all SVM by *libSVM* package (Chang and Lin, 2011). Two important functions are *"svmtrain()"*, and *"svmpredict()"*. The first function receives the training label vector, training data matrix, and a training string as input arguments and returns a model of each subject as the output. Another function receives the probe vector, probe data, model of each subject, and predicts a probability string as the input arguments and returns a probability as the output.

3 EXPERIMENTS

There currently are many gait databases available for research, for example CASIA (Yu et al., 2006), SOTUN (Shutler et al., 2002), and CMU (Ralph, 2001). In the experiments, CASIA gait dataset B was chosen because it includes gait data in three kinds of appearance (normal walking, clothing, and bag carrying) and eleven camera view angles. It provides video sequence, human silhouette and GEIs.

Three main experiments were conducted. The first is view angle detection test.. The second tests the effect of appearance change in case of full body and lower knee gait representation. The third investigates the effect of different number of training dataset in recognition phase.

All experiments set up by the same process that has been shown in Figure 1, nonetheless, training gallery and testing probe are always different. All silhouette images which were used in experiments were cropped, centralized and resized. Image size is 120x120 pixels for full body and 120x36 pixels for lower knee. All experiments used 40 principal components and the polynomial kernel function was applied for SVMs.

3.1 Experiment 1

The first experiment is about view angle detection to understand the view angle of unknown walking direction. Fifty five normal walk gait representation images, five from each view angle, have been used on training. Then all data with unknown view angles, different subjects and different conditions (normal walking, clothing, and bag carrying) were classified by SVM predicting. Results are shown that all four gait representations produce 100% correct rate in view angle detection. And the result of low knee is as good as the full body in view angle detection and provides 100% accuracy.

3.2 Experiment 2

The second experiment tested the correct classification rate (CCR) with different training and testing datasets. All sub experiments used one dataset for training except of the mixed dataset training which has included all three datasets from three kinds of appearance i.e. normal walk, wearing coat and carrying bag.. Results have been shown in Table 1. When all types of appearance datasets have been used in the training phase, the CCR of full body is clearly higher than that of lower knee region. Although full body has higher CCR when gallery and probe are with the same appearance, the CCR of full body gait recognition is significantly affected by appearance change. Especially in the case of individual wearing coat, lower knee classification has shown the higher CCR than that of full body. With regards to the average CCR in Table 1, lower knee and full body give very similar accuracy in the three cases.

In the case of mixed appearance training, the average technique is more robust than the Gaussian technique. GEI and GEnI have higher average CCR than GGI and GGEnI. At the same time, the entropy technique can enhance performance of the average and Gaussian techniques. GEnI has higher CCR than GEI, in the same way, GGEnI has higher CCR than GGI.

Table 1: Average CCR summary.

Case study		full body				lower knee			
Gallery	Probe	GEI	GGI	GEnI	GGEnI	GEI	GGI	GEnI	GGEnI
Normal	Normal	96.27%	94.61%	94.61%	93.59%	84.47%	71.57%	82.19%	72.54%
	Bag	51.27%	35.34%	57.49%	40.69%	41.36%	29.72%	48.64%	32.35%
	Coat	35.55%	17.96%	41.36%	18.79%	58.76%	43.15%	59.87%	42.73%
	Average	61.03%	49.31%	64.49%	51.02%	61.53%	48.15%	63.57%	49.21%
Bag	Normal	52.88%	35.02%	57.68%	34.28%	47.05%	30.58%	53.31%	33.37%
	Bag	89.98%	85.49%	90.85%	83.95%	80.61%	69.50%	80.56%	71.94%
	Coat	32.37%	12.40%	40.17%	14.89%	50.36%	26.57%	56.08%	29.56%
	Average	58.41%	44.30%	62.90%	44.37%	59.34%	42.22%	63.32%	44.96%
Coat	Normal	38.07%	17.71%	37.92%	17.98%	61.63%	39.20%	61.16%	40.78%
	Bag	26.25%	11.66%	31.91%	14.66%	39.91%	24.09%	43.53%	26.54%
	Coat	96.97%	94.33%	96.35%	93.39%	87.43%	73.04%	86.29%	75.28%
	Average	53.77%	41.23%	55.39%	42.01%	62.99%	45.44%	63.66%	47.53%
Mix	Normal	94.29%	81.82%	93.87%	83.09%	87.04%	67.93%	86.68%	71.25%
	Bag	89.53%	77.95%	90.06%	78.82%	81.19%	68.42%	81.90%	68.35%
	Coat	94.34%	80.97%	94.83%	81.05%	88.39%	70.56%	88.87%	73.45%
	Average	92.72%	80.25%	92.92%	80.99%	85.54%	68.97%	85.82%	71.02%

3.3 Experiment 3

The third experiment focused on investigation of effects of different number of training datasets on the gait recognition. Normal walk has been chosen for this experiment because there are six normal walk datasets while there are only two wearing coat and carrying bag datasets. Firstly a normal walk dataset has been selected as a probe in the recognition phase and other five datasets have been increasingly used as the gallery in the training phase. Results are shown in Table 2.

Table 2: The effect of number of dataset in training phase.

number of datasets		1	2	3	4	5
Full Body	GEI	96.3%	96.6%	97.2%	97.5%	98.5%
	GGI	94.6%	97.9%	98.6%	98.7%	98.9%
	GEnI	94.6%	96.0%	97.3%	97.5%	98.3%
	GGEnI	93.6%	97.2%	98.3%	98.7%	98.8%
Lower Knee	GEI	84.5%	90.8%	92.6%	93.8%	94.9%
	GGI	71.6%	82.8%	88.9%	91.5%	92.0%
	GEnI	82.2%	89.5%	93.0%	94.4%	94.8%
	GGEnI	72.5%	82.5%	89.0%	92.1%	93.6%

In the full body case, the Gaussian technique (GGI and GGEnI) has higher CCR when the number of training dataset has been greater or equal to two. In the case of lower knee, CCR is greatly increasing when the number of train dataset increases, especially in case of the Gaussian technique. In this experiment, the average technique shows a better result than the Gaussian technique. Nonetheless, in the general trend the Gaussian technique is better than the average technique.

4 CONCLUSIONS

This paper presents the combination gait representative technique between Gaussian and Entropy, called Gait Gaussian Entropy Image or GGEnI. It has been compared with GEI, GEnI and GGI in full body and lower knee gait classification. The contribution can be summaries as follows

(1) The investigation proves that lower knee gait representation is equally good as relevant full body gait representation in camera view angle detection based on the CASIA gait dataset B. It dramatically reduce the computational cost by using lower knee for this purpose.

(2) The lower knee gait representation have a similar classification rate compared to full body when using a single appearance in training and mixed appearance in testing.

(3) The average technique shows a robust way in dealing with appearance change in gait recognition, whilst the Gaussian technique gives better CCR when appearance keeps similar in both gallery and probe samples. The Entropy technique has slightly increased the appearance change robustness, GGEnI has higher CCR than GGI. This proves the hypothesis that the Gaussian technique takes the advantage of statistics to represent gait information.

(4) The Gaussian technique has higher classification rate in case of a fixed appearance when the number of datasets used in training is sufficient. Lower knee classification rate has greatly increased when the number of training datasets increases. All lower knee gait representations give a relatively high CCR over 90% when the number of the training datasets is greater than four.

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