TWO DIMENSIONAL HISTOGRAM BASED HUMAN GAIT RECOGNITION

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Abstract- This paper has demonstrated the merits of 2D histogram in the field of gait biometric recognition. In this paper, a new gait representation method i.e. local transitional energy image (LTEI) is proposed in order to capture the spatio temporal characteristics for an individual. LTEI is obtained by averaging all backward and forward frame difference images. Then, 2D histogram is constructed by using the local dynamic characteristics of LTEI and the same is used as the feature matrix. Further, a simple nearest neighbour classifier is used for the classification procedure. The extensive experiments are conducted on standard datasets i.e. CASIA (Version B) and CASIA (Version C) in order to verify the robustness of the proposed approach. The comparative analysis on current existed gait approaches have shown that our proposed approach works well even in the presence of gait covariates i.e. clothing, carrying, back pack and different walking speed condition.

***Keywords*:** Human gait; Local transitional energy image; Two dimensional histogram.

1. Introduction

Human gait recognition is an evolving research area in the biometrics research field. The gait recognition does not need any physical cooperation and even attentiveness of an individual. A lot of researchers are currently working on vision based systems due to high demanding necessities for security issues. Also, many of them used gait recognition in other fields such as early finding of Parkinson disease and running sport training etc. The considerable amounts of gait literatures have already marked the significance of gait recognition in the field of human identification. However, the current gait literatures have been thoroughly studied and reviewed in this section.

[Yumi et al., (2013)] have used several blocks of GEI for the gait representation. They have incorporated affine moment invariants for the feature extraction. [LI et al.,(2013)] have proposed part based representation called SGEI (i.e. structural gait energy image). Further, they have applied PCA on SGEI to reduce the dimension and LDA was used to achieve the class discrimination. [Kale et al., (2003)] have explored the width vector by using outer contour of the human body. [Han et al.,(2006)] have proposed a novel gait representation i.e. GEI (Gait Energy Image). Further, they have applied PCA on GEI to reduce the dimension and LDA was used to achieve the class discrimination.

[Jyoti et al.,(2011)] have explored a novel graph based method by using 4 points from each silhouette. They have constructed the graph by connecting the frames using these four points. [Chen et al.,(2014)] have explored a new gait representation called AGDI (i.e. the average gait differential image) by differencing the frames. [Luo et al.,(2015)] have investigated a fusion based method by using moment invariants of GEI and AFDEI. [Lili Liu et al.,(2011)] have investigated contour based approach. They have used Principal Component Analysis (PCA) to reduce the dimension and also, used Multiple Discriminant Analysis (MDA) to optimize the separability.

[Sungjun Hong et al., (2009)] have proposed the width vector mean based gait recognition approach. [Lishani et al.,(2014)] have applied the Haralick feature extraction method on the sub regions of GEI. [Sungjun et al.,(2007)] have explored a mass vector based features by counting the pixels. [Iwashita et al.,(2013)] have partitioned the human body into several areas. [bo ye et al.,(2006)] have investigated the different scanning directions based approach by considering the outer contour of binarized silhouette. [Arora et al.,(2015)] have explored a novel GGI (Gait Gaussian Image) for the effective gait recognition. [Makihara et al.,(2006)] have used the frequency domain based features.

2. Proposed Approach

2.1. *Pre-processing*

In this paper, we have used Chinese Academy of Sciences dataset i.e. CASIA (Version B & C) which is publicly freely available, considerably prime datasets in current gait literature. These datasets provides the raw silhouettes to the gait biometric research community. In these datasets, each subject's gait is represented as the sequence of silhouettes.

For each frame, morphological operators are applied in order to reduce the noise and, to fill the holes in the contour of the silhouette. Then, bounding rectangle is used to crop the human body. Further, it is resized to fixed dimension (i.e. 128 X 88) and aligned horizontally. The same procedure was applied to all silhouettes of an individual.

2.2. *Local Transitional Energy Image*

Gait is a dynamic biometric source which means gait changes over the time. Hence, the extracting the spatio temporal characteristics are more essential in the context of human identification under different gait covariate conditions. However, local transitional energy image (LTEI) based gait representation is presented in this paper. The below Fig. 1 clearly show the representation of local transitional energy image.

For each frame 'I_i' of an individual except first and last frame, the backward difference image is obtained by subtracting the current frame (I_i) from the previous frame (I_{i-1}) and forward difference image is obtained by subtracting the current frame from the successive frame (I_{i+1}). The same procedure is applied to all frames of an individual. At last, local transitional energy image is obtained by averaging all backward and forward frame difference images. The below Eq. (1) shows the computation of proposed gait representation method.

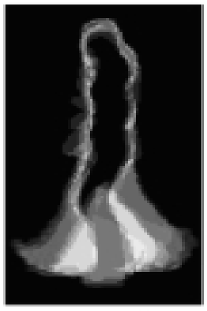

Fig. 1 Proposed Representation: Local Transitional Energy Image

$$LTEI = \frac{1}{2(N-2)} \sum_{i=2}^{N-1} |I_i - I_{i+1}| + |I_i - I_{i-1}| \tag{1}$$

Where 'N' is the number of frames

2.3. *Two Dimensional Histogram*

For LTEI of size M X N, 3X3 neighbourhood (F) is considered for each pixel 'p'. The Fig.2 (a) depicts the sample 3X3 neighbourhood. Firstly, the minimum (M^-) and maximum (M^+) values are calculated for a pixel 'p' by considering its 8 neighbours. Next, two values (V_1^{ij}, V_2^{ij}) are obtained for a pixel 'p' by subtracting the 3X3 neighbourhood from the M^- & M^+ respectively. The both first value (V_1^{ij}) and second value (V_2^{ij}) are calculated as the mean of 8 subtractions. The Eq. (2) and Eq. (3) shows the proposed calculation procedure. The same procedure is applied to all pixels of LTEI. Finally, each pixel of LTEI is represented as a pair of two values i.e. V_1^{ij} & V_2^{ij}. The Fig. 2 (b) depicts the matrix 'V' which consists of 'MXN' number of pairs. Lastly, two dimensional histogram (i.e. H) is constructed by mapping the V_1^{ij} as the row wise and V_2^{ij} as the column wise. Hence, the size of the matrix 'H' is P X Q (i.e. 255 X 255). Since, the maximum intensity in LTEI is 255. The same matrix 'H' is used as the feature matrix for an individual. The Fig. 2(c) depicts the matrix 'H' where each cell contains the occurrence of combinations of V_1^{ij} & V_2^{ij}.

$$F = \begin{pmatrix} p_1 & p_2 & p_3 \\ p_4 & p & p_5 \\ p_6 & p_7 & p_8 \end{pmatrix} \qquad V = \begin{pmatrix} (V_1^{11}, V_2^{11}) & \cdots & (V_1^{1,N}, V_2^{1,N}) \\ \vdots & \ddots & \vdots \\ (V_1^{M,1}, V_2^{M,1}) & \cdots & (V_1^{M,N}, V_2^{M,N} \end{pmatrix}$$

(a) (b)

$$H = \begin{pmatrix} C_{1,1} & \cdots & C_{1,Q} \\ \vdots & \ddots & \vdots \\ C_{P,1} & \cdots & C_{P,Q} \end{pmatrix}$$

(c)

Fig.2. Sample Matrices: (a) Sample 3X3 Neighborhood (b) Matrix 'V' (c) 2D Histrogram

$$V_1^{i,j} = \mu\left(M^+ - p_1, M^+ - p_2, ..., M^+ - p_8\right) \forall i = 1, ..., M \ \& \ j = 1, ..., N \tag{2}$$

$$V_2^{i,j} = \mu\left(p_1 - M^-, p_2 - M^-, ..., p_8 - M^-\right) \forall i = 1, ..., M \ \& \ j = 1, ..., N \tag{3}$$

Where

$$M^+ = \max(p_1, p_2, ..., p_8)$$

$$M^- = \min(p_1, p_2, ..., p_8)$$

2.4. *Classification*

The $A = (a_{ij})$, $B = (b_{ij})$ are training and testing matrices respectively. Then, distance between A and B can be calculated using the Eq. (4). Suppose that the training samples are $A_1, A_2, \ldots, A_M$ (where M is the total number of training samples) and that each of these samples is assigned a given identity (w_k). Given a test sample 'B', if $d(B, A_l) = \min_j d(B, A_j)$ and $A_l \in w_k$. Then, the resulting decision is $B \in w_k$.

$$d(A, B) = \sqrt{\sum_{i=1}^{n} \sum_{j=1}^{n} (a_{ij} - b_{ij})^2} \tag{4}$$

3. Experiments and Comparative Analysis

3.1. *CASIA Dataset (B)*

CASIA Gait Dataset (Version B) which is one of the prime gait dataset in the field of gait biometric research. This database consists of 124 subjects which are recorded from 11 view angles (i.e. 0^0 to 180^0, with view angle interval of 18^0). Totally, this dataset consist of 13,640 sequences. [Shiqi et al.,(2006)]

In our experimentations, we used only 90^0 view sequences with the occurrence of major gait covariates. Each subject consists of 10 sequences (i.e. 6 normal walking sequences + 2 clothing sequences + 2 carrying bag sequences). For each subject, we considered first 4 normal walking sequences as training set. The remaining 2 normal walking sequences, 2 sequences with clothing and 2 carrying sequences are used as the testing set.

The above same experimental procedure is examined in most of the existed literatures. The below Table 1 show the proposed results for the above mentioned experimental procedure and also, the detailed comparison results on contemporary gait literatures.

Table 1 : Comparative results on CASIA (B) Dataset

Methods	Training Set	Testing Set Correct Classification Rate		
		Normal Walk	**Clothing**	**Carrying**
[Khalid et al., (2010)]	Normal Walk Sequences	98.3%	33.5%	80.1%
[Luo et al., (2015)]		88.7%	91.9%	89.9%
[Arora et al.,(2015)]		98.0%	-	-
Our Proposed Approach		98.79%	94.75%	95.96%

3.2. *CASIA Dataset (C)*

CASIA Gait Dataset (Version C) which is one of the prime speed transition gait dataset in the field of gait biometric research. This database consists of 153 subject's which are recorded in 90^0 view condition. Totally, this dataset consist of 1,530 sequences. [Tan et al.,(2006)]

In our experimentations, we used the gait sequences with the occurrence of different walking speed. Each subject consists of 10 sequences (i.e. 4 normal walking sequences + 2 slow walk sequences + 2 fast walk sequences + 2 backpack sequences). For each subject, we considered 3 normal walking sequences as training set. The remaining 1 normal walking sequence, 2 slow walking sequences, 2 sequences with backpack and 2 fast walk sequences are used as the testing set.

The above same experimental procedure is examined in most of the existed literatures. The below Table 2 show the proposed results for the above mentioned experimental procedure and also, the detailed comparison results on contemporary gait literatures.

4. Conclusion

This paper has explored the benefits of a combination of LTEI and 2D histogram and also, highlighted the better recognition rate compared to contemporary approaches in the literature. In this work, the extensive experiments are conducted on two publicly available, standard datasets. CASIA (Version B) is one of the considerably largest multi view dataset which consist of 124 subjects and CASIA (Version C) is one of the largest different walking speed dataset. Our proposed approach is tested on various gait covariates such as clothing, carrying, back pack and different walking speed condition in order to show the robustness in the real world environment.

Table 2 : Comparative results on CASIA (C) Dataset

Methods	Training Set	Testing Set Correct Classification Rate			
		Normal walk	**slow**	**fast**	**backpack**
[Erhu et al., (2010)]	Normal Walk Sequences	88.89%	89.22%	90.20%	79.94%
[Lee et al.,(2009)]		-	-	-	78.10%
Our Proposed Approach		98.69%	89.86%	91.83%	91.83%

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