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Part based clothing invariant Gait Recognition

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ABSTRACT

This paper proposed a new part based representation to address the gait covariate factors especially clothing condition, since clothing may hide the dynamics of human body parts. Based on this observation, firstly GEI (i.e. Gait Energy Image) is split into three robust parts such as HeadEI (Head Energy Image), HandEI (Hand Energy Image) and FEI (Foot Energy Image) by using the anatomical proportion of human body parts. Then, Radon transform is applied separately on each selected part. Next, feature vector is obtained by computing the standard deviations in all the radial lines. At the end, all three part's features are fused to make one feature vector for an individual. Lastly, multi class SVM (i.e. Support Vector Machine) is used for the classification process by adopting the one versus one technique. The considerable amounts of experimental trials are investigated on standard datasets such as CASIA B and OU-ISIR Treadmill Dataset B. The experimental outcome has shown the promising results under different clothing conditions.

Key words: Clothing; Foot Energy Image; Hand Energy Image; Head Energy Image; Part Based

1. INTRODUCTION

Gait biometric systems are becoming increasingly important, since they provide more reliable and efficient means of identity verification. Every person has a unique way of walking, which is referred to as gait. Hence, people can be recognized by their gait. Biometric gait recognition is one of the active research topics in the biometric research. In many cases, gait evidence is more sufficient to recognize the person and it is very difficult to hide, replica, and steal. Gait recognition is broadly categorized into two research areas namely computer vision and sensor based. In this paper, we highlighted the computer vision based gait recognition system, since it is essential required in security sensitive environments. The great volumes of gait literatures have already marked the significance of gait recognition in the field of human identification. However, the contemporary gait literatures have been thoroughly studied and revised in this section.

Huang et al [1] have investigated CST (Canonical space transformation) based gait recognition algorithm. Hayfron et al [2] have explored a symmetry map based gait representation for an individual. Murat et al [3] have proposed a four view directions based representation which calculates the difference between the human silhouette and bounding rectangle in four directions. Wang et al [6] have applied a new shape analysis model on each silhouette and produced mean shape model as a single representation for an individual. Mark et al [7] investigated the different masking procedures to extract the gait features even in the presence of few major real time conditions. Bo Ye et al [9] have performed a contour analysis on human silhouette in different three directions namely horizontal, vertical and diagonal.

Tao et al [10] have extracted the 2D Gabor filter based features from the averaged image i.e. GEI. Further, they have performed GTDA (tensor discriminant analysis) to reduce the feature dimension. Toby et al [12] have generated two contour based templates to capture motion and static information. Martin et al [11] have explored color histograms based methods to address the gait occlusion problem. Hong et al [13] proposed a mass vector by counting the non-zero pixels from the silhouette in row wise direction. Edward et al [18] have extracted the bounding rectangle based features from each silhouette. They have stored the extracted features in form of ranges to effectively address the gait identification under the practical conditions.

Sungjun et al [14] proposed a width vector by calculating the distances between the contour pixels in each silhouette. Pushpa et al [16] have investigated the skeleton model based gait recognition approach. Prathibha et al [20] explored a curve based gait representation model. They have incorporated concept of Bezier curve in their work. Bharathi et al [21] explored the graph based representation by taking 4 points from each silhouette. They have used shortest path distance as the feature vector. Rohit et al [23] have proposed a simple model called EDI (Energy Deviation Image). They have used fuzzy components as features by incorporating fuzzy PCA on EDI.

2. PROPOSED APPROACH

2.1. Pre-processing

In this paper, we have used Chinese Academy of Sciences dataset (i.e. CASIA-B [8]) and Osaka University Datasets (i.e. OU-ISIR Treadmill Dataset B [22]) which are publicly freely available and noticeably prime datasets in current gait literature. Figure 2 and 3 shows the different category of clothing factors available in these datasets. The major advantage of these two datasets is both offers the direct raw silhouettes to the gait biometric exploration community. In these datasets, each subject's gait is represented as the sequence of silhouettes.

For each frame, morphological operators are applied to reduce the noise and also, used to fill the cavities in the contour of the silhouette. Then, bounding rectangle was used to crop the human body. Further, it was aligned horizontally and resized to fixed dimension (i.e. 128 X 88). The same procedure was applied to all silhouettes of an individual. At the end, GEI (Gait Energy Image) is obtained by averaging all silhouette images of an individual. The logic of GEI is simply computing the average of all silhouettes of an individual. In Figure 1, the sub figure (a) shows the GEI representation.

2.2. Part Based Clothing Invariant Gait Representation

This paper demonstrated the robust part based gait representation in order to address the gait covariate conditions especially clothing condition, since few clothing conditions cover the major portion of lower leg part during walking. Hence, leg information may not available for the identification procedure. But, we may get foot movement information to some extent. Hence, it needs to be considered for the robust gait identification process. Figure 1 shows the effect of clothing factor in the gait recognition system where leg movements are hidden by the clothes.

In addition to the above, head and hand parts are also less affected by the different clothing factors. Because, clothing condition usually not cover or hide these body parts. Based on these observations, the proposed approach considered the three robust parts such as head, hand and foot. As per our observations on available gait datasets, it is observed that these body parts are insensitive to the gait covariate factors and also convey the motion information of gait.

In reality, everyone has their own anatomical body proportions with regard to height (H). With the backdrop of anatomical structure, a more accurate human figure is approximated to 7.5 heads tall. The head size is approximated to 0.13H (i.e. foot to neck is 0.870H). Based on these body proportions, three body parts are cropped from the GEI such as FEI (Foot Energy Image), HeadEI (Head Energy Image) and HandEI (Hand Energy Image). The head and foot parts are extracted as shown in the equation (1), (2) respectively. Likewise, to extract hand part, firstly GEI is horizontally split into 4 equal size blocks as shown in the Figure 4.Then, second block is chosen since more hand information is usually occur in that block. In Figure 4, the sub figures (b), (c) & (d) shows the proposed part based gait representation method.

$$Head = 0.13H \tag{1}$$

$$Foot \approx 0.5Head \tag{2}$$

Figure 1: Sample Image (Source: Google)

Figure 2: 32 Clothing Variations in OU-ISIR Dataset [22]

Figure 3: Clothing Variations in CASIA B Dataset [8]

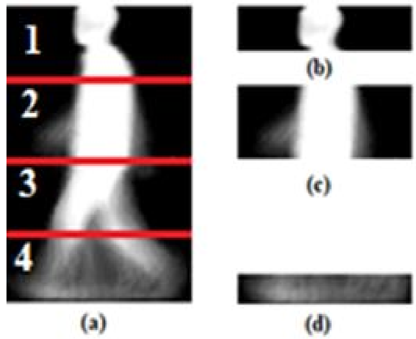

Figure 4: Proposed Representation
(a) GEI (b) HeadEI
(c) HandEI (d) FEI

2.3. Feature Extraction and Classification

In this paper, Radon Transform is applied separately on 3 parts and fuses the features for the classification procedure. The Radon transform maps the 2D image from Cartesian coordinate system (x, y) to polar coordinate system (ρ, θ). The Radon transform on an image f(x, y) for a given set of angles can be considered as the projection of the image along the given angles.

The Radon transform based features are invariant to geometric transformations such as translation, rotation, and scaling etc. Radon transform on an image gives the projection matrix which consists of projection angles. These projection angels which usually ranges from 0^0 to 180^0. The angle 180^0 is not considered since the result would be identical to the 0^0. Hence, all radial lines oriented from 0^0 to 179^0 angles are considered for the feature extraction.

After a Radon transform is applied on particular part, standard deviations (i.e. σ) are computed from the projection angles which ranges from 0^0 to 180^0. So, the length of the feature vector is 180. Further, it is partitioned into number of equal size bins. The value 5 is chosen as the bin size in this work. Then, single value is obtained for each bin by adding the values which fall within the bin. At the end, three part’s features are fused at the feature level. Hence, totally 108 features (3 parts X 36 features) are used for the classification task.

Furthermore, mean (μ) and standard deviation (σ) are computed from the feature vector. Then, each feature value is subtracted from the mean. Next, the subtracted result is dividing by the standard deviation. This procedure enhances the functioning of the support vector machine classifier to finds the support vectors with the minimal time duration.

In this work, we have incorporated the multi class SVM (i.e. Support Vector Machine) classifier by adopting the one versus one technique. SVM is more generalized and powerful classifier in the biometric research field. In this work, we investigated the radial basis kernel, since it finds the hyper plane which bisects the data effectively.

3. EXPERIMENTS AND COMPARATIVE ANALYSIS

3.1. CASIA B Dataset

CASIA Gait Dataset (B) [8] which is one of the main gait dataset in the ground of gait biometric research. This dataset comprises of 124 subjects which are captured from 11 view directions (i.e. 0^0 to 180^0, with view angle interval of 18^0). Totally, this dataset consists of 13,640 sequences. Also, this dataset comprises of few major gait covariate factors.

In our tests, we used only gait sequences with 90^0 viewing angle. Each subject consists of 10 sequences i.e. 6 normal walking sequences + 2 clothing sequences + 2 carrying bag sequences. For each subject, first 4 normal walking sequences are used as gallery set and two sequences with clothing condition are used as the probe set.

The above same experimental plan is considered in most of the contemporary literatures to examine the clothing covariate factor. Table 1 show our proposed result for the above mentioned experimental setup and also, the detailed comparison results on current existing gait literatures.

3.2. OU-ISIR Treadmill Dataset B

OU-ISIR (Treadmill Dataset B) [22] which is one of the largest different clothing variation gait dataset in the field of gait biometric research. This database consists of 32 different type clothing variation gait sequences.

In our experiments, we used the gait sequences with the presence of standard regular cloth (i.e. regular pant and shirt) as a gallery set. The remaining 31 different clothing type gait sequences are used as the probe set. Totally, 856 gait sequences are used for the gait identification under the different clothing factors.

The above same experimental plan is considered in most of the contemporary literatures to examine the clothing covariate factor. Table 2 show our proposed result for the above mentioned experimental setup and also, the detailed comparison results on current existing gait literatures.

4. CONCLUSION

Clothing is one of the prominent gait covariate forms which often encounter in real time scenario. Hence, we highlighted the robustness of the part based representation to address the different clothing confounding factors. This paper demonstrated the benefits of head, hand and feet movements when sufficient gait dynamics not available. The widely used clothing variation datasets such as Chinese Academy of Sciences dataset (i.e. CASIA-B [8]) and Osaka University Datasets (i.e. OU-ISIR Treadmill Dataset B [22]) are used to address the gait identification problem. The large amounts of experimental trials are investigated on these standard datasets and shown the promising results under different clothing variations. The detailed comparative analysis on current gait literatures shown that our proposed part based representation is robust in the real time situations.

Table 1: Proposed and Comparative results on CASIA (B) Dataset

Methods	**Training Set**	**Testing Set & CCR**
		Clothing - Wearing Coat
GEnI [19]	Normal Walk with Regular cloth	33.5%
AFDEI [24]		91.9%
GEI + 2D-PCA [15]		86.7%
Proposed Results		99.59%

Table 2 : Comparative results on OU-ISIR Treadmill B Dataset

Methods	**Training Set**	**Testing Set & Correct Classification Rate (CCR)**
		31 different Clothing conditions
Xu et al [4]	Regular Cloth Sequences	55%
Yan et al [5]		68%
Hossain et al [17]		65%
Proposed Results		93.45%

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