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Research Article

GAIT based Automatic Human Gender Prediction

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Abstract

As automatic gender prediction of a person is important in many social activities, a study and analysis of human gait for automatically predicting the gender of a person is presented in this paper. The main objective of this work is to develop a system to identify the gender of individuals derived from a video sequence of their walking (GAIT). Unlike other human traits such as finger print, face, palm etc., acquiring the GAIT of a person does not require his cooperation and hence GAIT is used in this study to predict gender. People belonging to same age but different genders have different gait appearance and in this work, appearance-based gait feature namely gait energy image (GEI) is chosen for predicting the gender. The GEI image is partitioned into five regions such as head & neck, chest & back, waist &buttocks, leg and foot from which features are extracted. Different weights are assigned to different body components according to their gender discriminating power. Since gender classification is a two-class problem, equal number of subjects belonging to male and female class is taken from the CASIA Gait Database (Dataset B) to avoid bias. The gait data for the 62 subjects consists of 31 male and 31 female subjects. Out of 31 male subjects 21 samples is used for training and 10 is used for testing. Similarly, it is done for training and testing the female subjects too. Three -fold cross-validation is employed to evaluate the performance of the SVM classifier and the overall accuracy, specificity and sensitivity of the proposed gender detection system are 91.537%, 91.38% and 91.11% respectively.

Keywords: Gait analysis, gender recognition, silhouettes, GEI, SVM classifier.

1. Introduction

Automatic detection of human gender without needing their close physical presence or interaction and cooperation plays a very important role in many social applications. If a system could automatically detect gender, for example if robots could perceive gender it'll be terribly useful in several applications. Automatic gender classification will improve police work systems, intelligence, help in analysing gender-based choice and liking of customers etc. Compared to different biometric traits the foremost distinctive characteristics of GAIT is that it does not need the subject's attention and cooperation in order to capture ones GAIT image as, human gait is captured from a distance and does not require physical data from subjects [1].This feature is quite useful especially where capturing once face image or finger print is not feasible or considered confidential. Moreover, gait recognition offers nice potential for recognition of low-resolution videos.

Model based and appearance-based features are the most widely used features in most of the Gait based recognition systems. Model based methods utilize mathematical models whereas appearance-based features are easy to capture and have low computational cost. This work uses appearance-based GEI features to model the classifier.

The authors in [2] carried out experiments to analyse how humans recognize the gender of a person subjectively. They investigated the upper body features that convey information on the body shape which is static in nature and the lower body features that convey information on the movement of hips, leg and arms which is dynamic in nature. The authors further investigated the contribution made by the various body components in predicting gender by dividing the body into head & neck, chest & back, waist &buttocks, leg and foot. Volunteers were asked to subjectively analyse each body component and they have to provide a score between zero and five where score 0 means no help on gender classification, and 5 mean this option is very important. The average scores are listed in Table 1 which indicates that humans are more sensitive to static body shape information than to dynamic information. This average score is used in our work to derive different weights to different body components for achieving better gender prediction.

Table 1: Average Scores of various body parts in detecting gender

Body Part	Component	Score
Static	head & neck	4.71
	chest & back	3.93
Moving	waist &buttocks	2.07
	leg	1.86
	foot	2.57

The few work on gender prediction based on gait analysis could be seen in the literature. The authors have described a gait-based gender identification system in [3] which consists of four steps: silhouette object is detected using morphological operations. Gait features were extracted using 2D discrete wavelet transform and KNN classifier is used for classification. In paper [4] the author proposed a novel gait appreciation method on feature fusion of GEI images. Gait contour images were detected, GEI and Gabor features were extracted at different angles and KPCA is used to scale down feature space dimension. Finally, multiclass SVM is used for classification. The work in [5] tries to identify the gender prediction from GEI and GII. SVM is used as a data classifier. The empirical outcome attained was 55% with GEI and 60% with GII, whereas GII with SVM had the best accuracy in gender classification. The author proposed [6] multi-model approach for gender prediction based on gait analysis. The dataset contains 10 subjects collected at Raman Lab, MNIT Jaipur and cross validation were also done with standard gait database CASIA B. The author implemented multi-model machine algorithm such as RF and LDA as Model1 and Model2 as PCA. Then SVM with RBF Kernel was enforced to get final prediction results. Gender identification method based on gait study is proposed in [7]. Feature extraction system uses time series deviations in the scene location and gender prediction is done with SVM classifier. The database consists of six males and six females at the age of twenties and the results obtained were appreciable. The main aim of this proposed work is to develop a system to predict human gender based on walking style (GAIT). The paper is formulated into the following sections. Section 2 describes the methodology of the proposed work. Experimental results and discussion are provided in Section 4 and finally Section 5 concludes the paper.

2. Methodology

The framework of the proposed gender prediction system and is shown in Fig. 1 and it consists of the following steps.

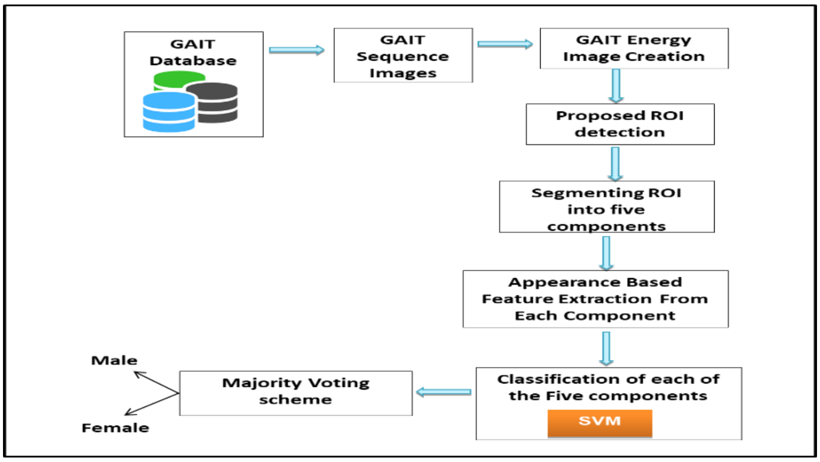

Fig. 1 Framework of the proposed Gender Prediction System

GEI creation, automatic ROI detection, segmenting GEI into five components, feature extraction, classification and prediction based on majority voting scheme.

First gait energy image (GEI) [8] is obtained from the binary Gait silhouette images using the following equation.

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

where $B_t(x,y)$ - Binary silhouette image at time *t* in a sequence

N_T- Number of the frames in the silhouette sequence

Fig. 2(a-e) shows the binary silhouette images in a gait sequence and corresponding GEI image of the gait sequence is shown in Fig. 2(f).

Fig.2. (a-e) Binary silhouette images in a gait sequence, (f) Corresponding GEI Image

From the GEI image obtained the following newly proposed algorithm to automatically crop the ROI is carried out to prevent unnecessary processing of the background pixels which could bias the prediction results.

1.Scan the image *I (x, y)* from left to right

2. If *I (x, y) = 255*

ROI = Crop *I (j-50, i-20 j+60, i+110)*

The values of the rectangular coordinates for cropping were found out empirically after experimenting with the silhouette images present in the CASIA B database. The output from the automatic ROI cropping is further partitioned into five regions such as head & neck, chest & back, waist &buttocks, leg and foot, which is shown in the Fig. 3.

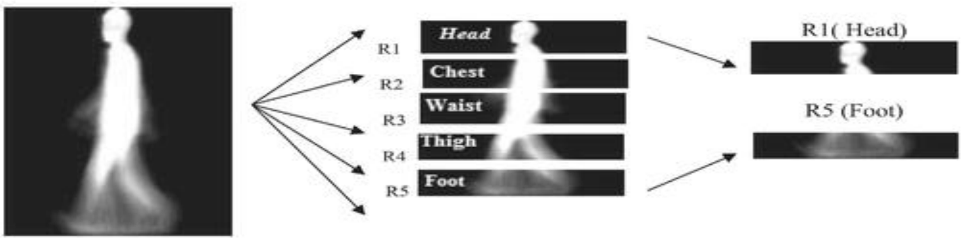

Fig. 3. Output for partitioned image

Next the GEI values are obtained from each component and weighted feature vector of each of the components are created. In accordance with the discriminative effectiveness of each body component different weights are assigned to each of them. . The weights [w_1, w_2, ……, w_5] are the scores shown in Table 1.

The component scores are normalized as follows to make the average of w_i' be 1.

$$w_i' = \frac{5 \, . \, w_i}{\sum_{j=1}^{5} w_j}$$

So the weighted feature vectors can be *[w_1'. V_1,], [w_2'. V_2,], [w_3'. V3,]* , *[w_4'. V4,], [w_5'. V_5]* where *Vi* is the feature of the *i^th^* component [9].

In this work, SVM is use to model the five different body components based on GEI features. Generally, SVM fares well in two class problems and since gender prediction is a two-class problem, SVM is proposed in this work. The SVM algorithm plots the features in a n-dimensional feature space where n is the number of features. Then classification is performed by finding the hyperplane that is capable of discriminating the two classes very well [10].

Classification for each of the five components is done using the RBF kernel of the Support Vector Machine (SVM) classifier where each component gets classified into either male or female. The finally the prediction is done based on the majority voting scheme. If more than two components are classified as male then the gender prediction is male else female. If more than two components are classified as female then the prediction is female else male.

3. Results and Discussions

Classification for each body component is done using Support Vector Machine (SVM) classifier where each region gets classified into either of the class namely male or female. Since gender classification is a two-class problem, equal numbers of subjects belonging to male and female class are taken from the CASIA Gait Database (Dataset B) [11-12] to avoid bias. The gait data for the 62 subjects consists of 31 male and 31 female subjects. Out of 31 male subjects 21 samples is used for training and 10 is used for testing. Similarly, it is done for training and testing the female subjects too.

The performance of the proposed gender estimation method is calculated using the confusion matrix shown in Table 2. Three-fold cross-validation is employed to evaluate the performance of the SVM classifier without bias.

Table 2: Confusion matrix of the SVM classifier for the various body components.

Cross Fold	**True Positive**	**False Negative**	**True Negative**	**False Positive**
Confusion matrix for Head & Neck region				
1	9	1	10	0
2	10	0	9	1
3	10	0	10	0
Confusion matrix for Chest & Back region				
1	9	1	9	1
2	9	1	10	0
3	0	0	10	0
Confusion matrix for Waist & Buttocks region				
1	9	1	7	3
2	8	2	7	3
3	8	2	9	1
Confusion matrix for Leg region				
1	10	0	9	1

2	9	1	9	1
3	9	1	10	0
Confusion matrix for Foot region				
1	8	2	9	1
2	9	1	9	1
3	9	1	8	2

Table 3 shows the average performance obtained from doing 3-fold cross validation of each body component and the average overall performance of the system when static body parts and moving body parts are considered separately is also depicted in the table.

Table 3: Overall performance measures when static and moving body parts are considered

Body Part	Body component	Accuracy (%)	Sensitivity (%)	Specificity (%)
Static	Head & Neck	96.67	96.67	96.67
	Chest & Back	95	93.33	96.67
Static Overall (%)		**95.84**	**95**	**96.67**
Moving	Waist & Buttocks	80	83.33	76.67
	Leg	93.33	93.33	93.33
	Foot	88.33	86.67	86.67
Moving Overall (%)		**87.22**	**87.77**	**85.56**

The results indicate that the static body parts comparatively help in classifying the gender better than the moving body parts. The same was also the case with the human observers as could be seen in Table 1. The overall accuracy of the proposed system taking all the body components or in other words when the whole body is considered is 91.53% and is shown in Table 4. In this work from the classification results obtained from each of the five components a majority voting scheme is used to give the gender prediction. If more than two components classify a person to be a male the person is predicted as male else female and vice versa. The results obtained are quite promising and the proposed system can be effectively used to predict gender from GAIT images.

Table 4: Overall performance measures when the whole body is considered

Overall Performance (%)	**Accuracy (%)**	**Sensitivity (%)**	**Specificity (%)**
Static Body Parts	95.84	95	96.67
Moving Body Parts	87.22	87.77	85.56
Whole Body	91.53	91.38	91.11

4. Conclusion

In this work a new algorithm to automatically crop the silhouette image from a video sequence is proposed. The output from the automatic ROI cropping is further partitioned into five regions such as head & neck, chest & back, waist &buttocks, leg and foot from which GEI features are extracted. This is done to analyse of the contributions of different human components, which shows that head and hair, back, chest and thigh are more discriminative than other components. Different weights are assigned to different body components according to their gender discriminating power. The experiments were done using SVM classifier and 3-fold cross validation was done to evaluate the performance of the proposed GAIT based gender detection system. The results indicate that the static body parts comparatively help in classifying the gender better than the moving body parts. The performance measures obtained are promising and could be employed in systems where automatic gender detection is needed.

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