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Using skeleton model to recognize human gait gender

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ABSTRACT

Biometrics became fairly important to help people identifications persons by their individualities or features. In this paper, gait recognition has been based on a skeleton model as an important indicator in prevalent activities. Using the reliable dataset for the Chinese Academy of Sciences (CASIA) of silhouettes class C database. Each video has been discredited to 75 frames for each (20 persons (10 males and 10 females)) as (1.0), the result will be 1,500 frames. After Pre-processing the images, many features are extracted from human silhouette images. For gender classification, the human walking skeleton used in this study. The model proposed is based on morphological processes on the silhouette images. The common angle has been computed for the two legs. Later, principal components analysis (PCA) was applied to reduce data using feature selection technology to get the most useful information in gait analysis. Applying two classifiers artificial neural network (ANN) and Gaussian Bayes to distinguish male or female for each classifier. The experimental results for the suggested method provided significant accomplishing about (95.5%), and accuracy of (75%). Gender classification using ANN is more efficient from the Gaussian Bayes technique by (20%), where ANN technique has given a superior performance in recognition.

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1. INTRODUCTION

Now, growing interest in identifying individuals effective to prevent terrorist attacks led to proposed biometrics techniques. These techniques have appeared to identify and verify individuals such that concern: face, palm print, fingerprint, iris, deoxyribo nucleic acid (DNA), walking, or a mixture of these characteristics [1], [2]. It is worth mentioning, people can be classified using most biometrics, like gender classification by analysing voice, face, and gait [3]–[7]. Generally, gender classification plays an important and big role in many fields of life. Gait recognition is defined as an ability that existing for most people. When a computer can recognize gender, it will increase work robustness, such as, gender classification which can analyses clients for administrators, employ people with proper works, and so on [4]. Unlike current recognition methods, like facial, iris, and fingerprint recognition are physical information that requires characteristics or traits for people, therefore there challenging to distinguish individuals use remote methods. Nevertheless, walking as a feature of people does not have these limitations. In recent times, gait is a good biometric feature. As many researchers have increasingly interested in this topic. So, walking has become a serious issue in advanced computer technologies [8]–[10]. Additionally, gait classifications have many effective parameters such as age, pregnancy, and sick. Human gender gait recognition has become an important topic for researchers [11], [12]. In 2001 Tanawongsuwan and Bobick studied learning to walk via the bottom parts of the human body [13]. Some researchers provided a clear process for estimating the place of compensation in flat form between signs.

The given displacements that researchers used to calculate common angle pathways aimed at compensating for systematic time differences. This study recognition was applied in databases of 18 people who performed further than 150 places of walking by the adjacent neighbor procedure and Euclidean space as assessment procedures [13]. In 2009 Ming *et al.* discussed the descriptor-based silhouette and explained the area of the border was suggested in a way that describes the shape of the walk [14]. The wavelet transformation was applied on the boundary area and extracted the parallel descriptors concurrently. Xiao *et al*. [15], proposed a strategy in 2010 based on the use of skeletons to determine walking. This skeletal structure allows us to express every gait. Consequently, a recognition rate of 96.21% was reached. In the same year, Li and Yang, [16] introduced a recognition system based on the legs and ankles. These two types of optimal characteristics were addressed by using the feature incorporation strategies, where the test outputs in the gait database were showed reasonable results [16]. In April 2013 Arai and Andrie described a method for extract features from the skeleton human body using support vector machine (SVM) that estimates average foot angle, where reached classification accuracy is about 85.33% [5]. In 2020, suggested analysis in the time domain of many features using classifier [17], [18].

2. PROPOSED METHODOLOGY

Basically, this paper has proposed a method for gender classification based on the skeleton model. It depends on trusty Chinese Academy of Sciences (CASIA) database gait, class C, with kinds of walking views of images and many changes for silhouette pictures [19]. Figure 1 explain the framework of the proposed method that used in this paper.

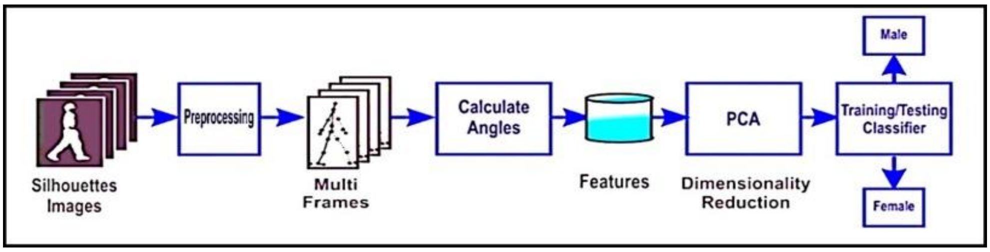


Figure 1. The framework of the proposed method

In the proposed method skeleton model have been used on reliable silhouette image CASIA database that depends on the following steps:

a. Applied several morphological operations.
b. Create three lines to get a triangle.
c. Determine gait cycle.
d. Distinguished between two legs.
e. Estimated points between two legs of the body.

2.1. Pre-processing

The proposed human gait model is a specific feature of the proposed model using many operations. At first, silhouette images have been converted to a binary image. Then applied morphological operations for the creation of a skeleton. By using close operation (dilation, erosion), and removes (prunes) all branches shorter that specified length [20].

2.2. Hinge points for a single image

Figure 2 illustrate the overview of the manner of the individual's gait model. In the human skeleton model can be found 20 joint points from head to toe see Figure 2. They provide many features which that play role to obtain gait properties exactly for each person or to give the ability for classification between men and women [21], [22].

2.2.1. Gait cycle estimation

Human gait is considered as a cyclic motion for all individual gait cycle. Can be computed from heel strike to heel strike of a single leg and can be viewed as the time between two similar events during a walking person. In the gait cycle, there are two basic phases called stance and swing as Figure 3 [23].

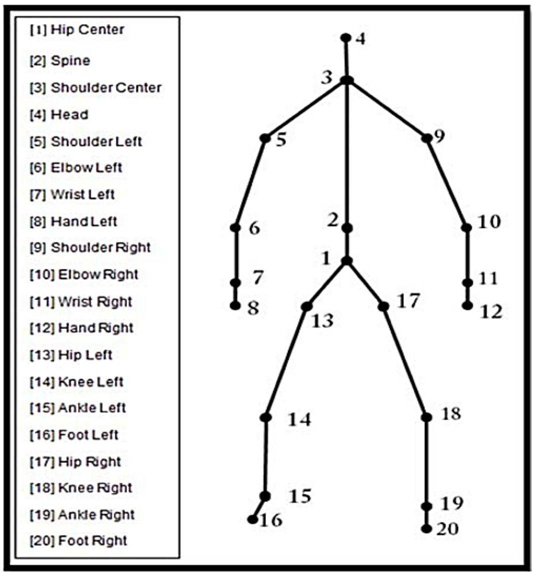


Figure 2. Skeleton joint points

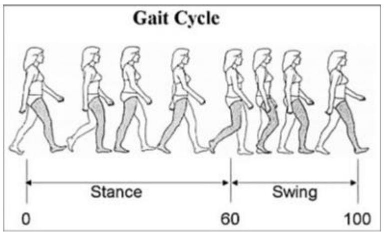


Figure 3. Gait cycle of individual

2.4. Angle estimations method

Using a simple trigonometry formula, compute the angles of each point: a and b represent a vector as Figure 4 [24].

$$\vec{a}.\vec{b} = |a|.|b| \cos\theta \tag{1}$$

$$\cos(\theta)=\frac{\vec{a}.\vec{b}}{|a|.|b|} \tag{2}$$

Therefore, the angle of θ is calculated as shown,

$$\theta = \cos^{-1}\left(\frac{\vec{a}.\vec{b}}{|a|.|b|}\right) \tag{3}$$

principal component analysis (PCA's) purpose is to minimize the data's dimensionality while keeping as feasible in the original huge data. It's a technique for discovering patterns in data and explaining them in a way that emphasizes their resemblances and differences in fact, PCA is extremely closely related to means Figure 5.

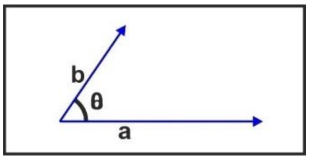


Figure 4. the angle between two vectors

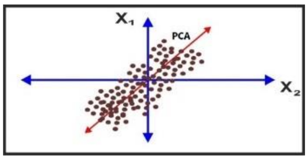


Figure 5. Dimensionality reduction

2.5. Feature extraction

One of the difficulties that researchers confront while analyzing data is the problematic of expressing data owing to the large amount that is difficult to obtain. principal component analysis is a well-known as dimension reduction method used in pattern recognition. PCA technique is mostly used to pick important data and eliminate irrelevant. The feature selection strategy used to determine which data provides the most relevant information in gait analysis. PCA primarily computes variances function by transforming information into orthogonal linear space. The variances are then sorted by the magnitude of the differences, with the largest variance value are calculated [25]. PCA's purpose is to reduce data dimensionality while maintaining as much diversity as possible in the original large data set.

2.6. PCA algorithm execution steps

Suppose x_1, x_2, x_M are Nx1 vectors,
Step 1: Calculate the average,

$$\bar{X} = \frac{1}{M}\sum_{i=1}^{M} x_i \tag{4}$$

Step 2: Mean normalization,

$$\Phi i = xi-\bar{x} \tag{5}$$

Step 3: From the matrix $A = [\Phi_1\Phi_2 \ldots \Phi_M]$ (N *M matrix), then compute,

$$C = \frac{1}{M}\sum_{N=1}^{M} \Phi_n {\Phi_n}^T = AA^T \tag{6}$$

(Sample covariance matrix, N*N, characterizes the scatter of the data)
Step 4: Compute the eigenvalues and sort the eigen vectors according to the eigen value of C,

$$\lambda_1 > \lambda_2 > \cdots \lambda_N \tag{7}$$

where: C represent covariance matrix.
Step 5: Compute the eigenvectors of C: u_1, $u_2 \ldots u_N$
Step 6: Dimensions reduction step (keep only the terms corresponding to the K largest eigen values),
Select K, and use the following criterion,
$\frac{\sum_{i=1}^{K} \lambda i}{\sum_{i=1}^{N} \lambda i}$ >= Threshold, Threshold= 0.99 then stop, use the value of K [26], [27].

The variance matrix will be rebuilt from the highest variance values from step (4), whom arrange descending. PCA is used to identify patterns and measures the range of combination and different in data. The data cannot be represented graphically, due to elevate dimensional space due to elevate dimensional space as Figure 6. The calculation process of (k) value based on the understanding of decision-making mechanism [26]–[28].

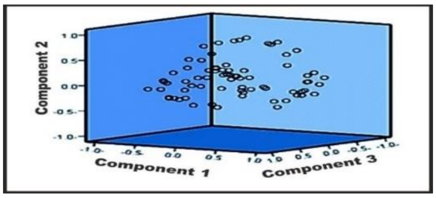


Figure 6. Component plot in related space

A confusion matrix can be used to evaluate models for binary (male and female) classification in overall. In the confusion matrix, the percentage value of accuracy, sensitivity, specificity, and precision must be considered. With true positive (TP), true negative (TN), false positive (FP), and false negative (FN), the calculation in the confusion matrix is (8)-(10).

$$\text{Accuracy} = \frac{\text{TP+TN}}{\text{TP+FP+TN+FN}} \tag{8}$$

$$\text{Precision} = \frac{\text{TP}}{\text{TP+FP}} \tag{9}$$

$$\text{Sensitivity} = \frac{\text{TP}}{\text{FN+TP}} \tag{10}$$

2.7. ANN classifier

Artificial neural network ANN has a higher classification accuracy in comparison to other classifier models. Due to the consume training time for big database the training is inadequate. Hence many features selection techniques are used with ANN classifiers to give an accurate result for human gait gender classification for gait [29]–[31].

2.8. Gaussian naive bayes classifier

This classifier was used to recognize human gender gait. As indicated in (11), it determines the mean and standard deviation from the training data to apply gaussian naïve bayes classifier [32], [33] gaussian naïve bayes selects the input features with the highest probability, to determine which input features have the maximum probability. Figure 7 shows the histogram comparison between two classifiers for human gait between the two genders [34], [35],

$$PDF(x, \mu, \sigma)=\frac{1}{\sqrt{2\pi\sigma^2}}e^{\frac{-(x-\mu)}{2\sigma^2}} \quad (11)$$

where:
PDF is probability density function
V is input feature vectors,
μ is mean of features.
σ is the standard deviation.

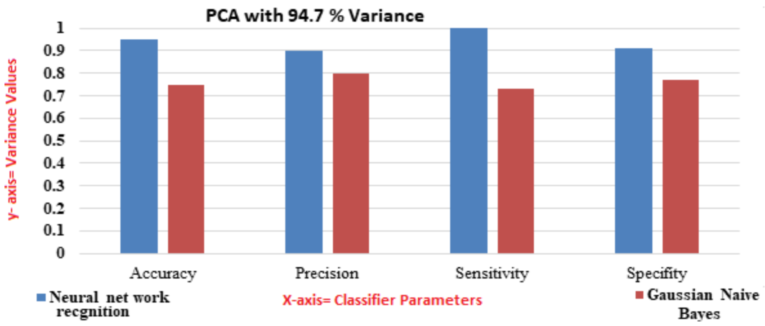


Figure 7. The histogram comparison between two classifier and all measures

The recognition for human gender has used two techniques neural network (NN, and Gaussian Bayes). The analysis of classify gender into one of two groups (male, female). It has reached amazing result in NN Table 1 for the measures.

Table 1. The performance comparison measures

Classifier	Performance measures(%)			
	Accuracy	Precision	Sensitivity	Specifity
ANN	95.5%	100%	90%	100%
Gaussian Naive Bayes	75%	80%	73%	78%

2.9. CASIA class c gait database

The CASIA Class C is additional huge gait database including the gait sequences of 153 subjects with (320,240) dimensions. The video sequences under different situations at night using a low-resolution thermal camera. The database contains walk sequences with four variations: Figure 8(a) normal walk, Figure 8(b) slow walking, Figure 8(c) fast walking, and walking with bag in Figure 8(d). Figure (8) shows the sample walking styles in Class-C database. Individually, each subject in the database has (10) sequences of gait, including (4) sequences of normal walking and (2) sequences for each of the rest walking styles. The proposed method is evaluated on Class-C gait database to illustrate its robustness related of carrying things, walking hurry and illumination conditions during the walk. After applying the morphological processing, including the skeleton model as Figure 9 [19]. The calculation process to create confusion matrix. The measurements rue positive (TP), true negative (TN), false positive (FP), and false negative (FN) as Figure 9 [28].

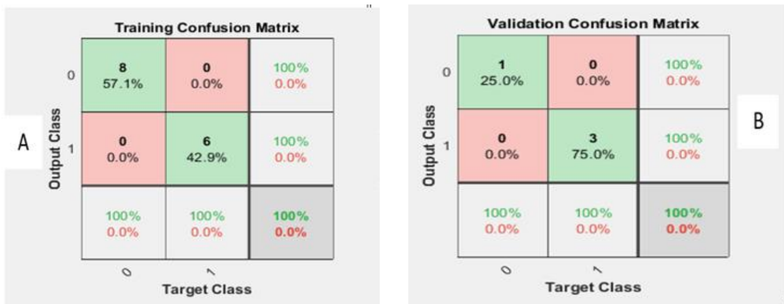
(a) (b) (c) (d)

Figure 8. Represent CASIA Class C images all movement (a) Normal walking, (b) slow walking, (c) fast walking and (d) walk with carried bag

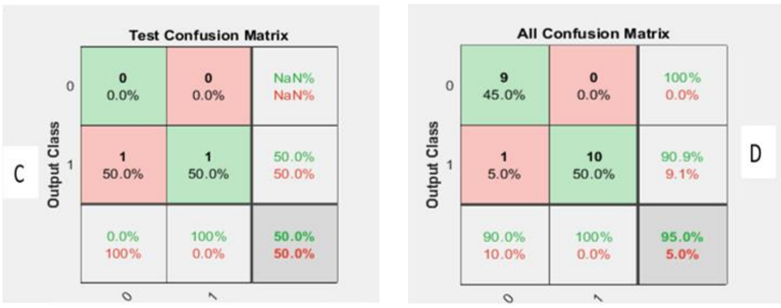
Figure 9. Skeleton images

3. RESULTS AND DISCUSSION

This paper has two classifiers to identify human gender gait based on (20 persons (10 males and 10 females)) with (1,500 frame). Each group have 750 frames for male and 750 frames for female from CASIA reliable database and comparison between them. In this paper, the features refer to the angles between two legs used as a good sign by determining three-points. Two points for ankle and other one between the legs to form triangle to specify the angle. All these data base have taken from CASIA class (C), The results were given by the skeleton model employed to develop human typical body. Usually, the hand and the foot are cancelled through the morphological processes. These factors were summarized using basic component analysis, and the percentage of data representation was (94.7%). Classification can be evaluated by using the confusion matrix as explained in Figure 10. The training confusion matrix are illustrated in Figure 10(a), and Figure 10(b) validation confusion matrix, Figure 10(c) test confusion matrix and Figure 10(d) explain a good summery for confusion matrix as the percentage value of accuracy, precision, sensitivity, and specificity. Figure 10 shows how to calculate the TP, TN, FP, and FN values in a confusion matrix. The recognition in ANN gave better accuracy than the classification technique compared with gaussian naïve bayes is (95.5%). Another classifier, gaussian naïve bayes was used to recognize human gender.



(a) (b) =



(c) (d)

Figure 10. Neural network confusion matrix for gender classification; (a) training confusion matrix, (b) validation confusion matrix, (c) test confusion matrix, and (d) explain a good summery for confusion matrix

This classifier has been evaluated by using the confusion matrix according to Figures 11 and 12, were the percentage of accuracy being (75%). Rock curve (ROC) as shown, depicting the performance of a classification model. Table 2 involve of a 2×2 Confusion Matrix combinations of expected and real values. It is usefully and importantly to use the ratios: Precision, sensitivity, specificity and accuracy.
True positive rate (TPR),

$$= \frac{\Sigma\, True\ positive}{\Sigma\, Condition\ Positive} = \frac{TP}{TP+FN} \tag{12}$$

False positive rate (FPR),

$$= \frac{\Sigma\, False\ positive}{\Sigma\, Condition\ Negative} = \frac{FP}{FP+TN} \tag{13}$$

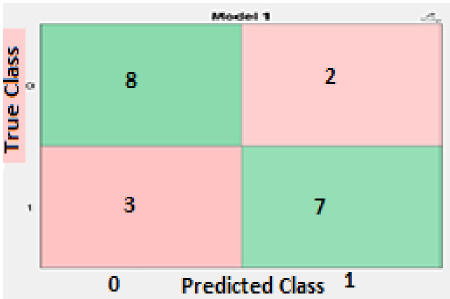


Figure 11. Gaussian Naive Bayes confusion matrix

Table 2. The four results can be found in 2×2 confusion matrix [36]–[43]

	Total population	Predicted condition positive	Predicted condition negative
True Condition	Condition positive	True positive TP	False positive FP (Type I error)
	Condition negative	False negative FN (Type II error)	True negative TN

The confusion matrix as Figure 12 and Roc. curve as shown in a graph depicting the performance of a classification model is Figure 13 which indicates the performance measurement for Gaussian Naive Bayes confusion matrix. Table 2 involves a 2×2 confusion matrix combination of expected and real values. It is useful and important to use the ratios: precision, sensitivity, specificity, and accuracy.

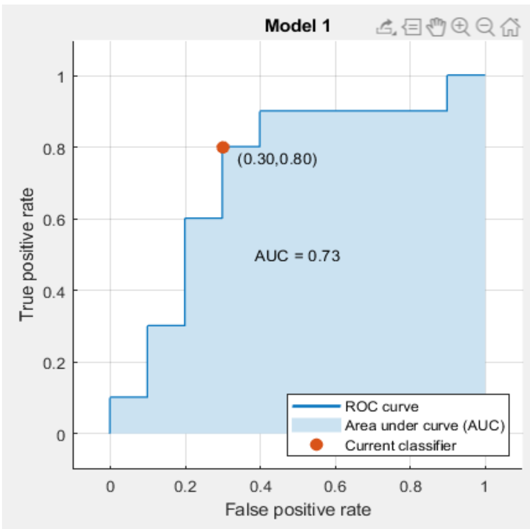


Figure 12. Rock curve for Gaussian Naive Bayes

The rock of curve (ROC) is designed with TPR as y-axis against the FPR and x-axis represent threshold value, according to (12) and (13). ROC explains the capacity of presentation for grouping difficulties at several thresholds (1,0) is represented (male, female) respectively as mentioned before. Figure 13 is the optimal case, at a point when two arches don't intersect, the model has an ideal of distinguishable. It is quite capable of recognizing positive and negative classes. Figure 14 shows the overlapping between the two classes, it presents mistakes. At the point when the area under the curve (AUC) is 0.7, it implies that there is a 70% possibility that the model will be isolated between positive and negative classes. Figure 15 shows the most extremely terrible states, at the point when AUC reach to 0.5, so the model has no ability to separate between positive and negative classes.

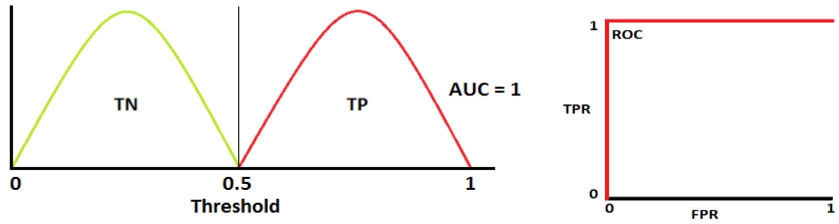


Figure 13. Distribution case1 probability of roc curve

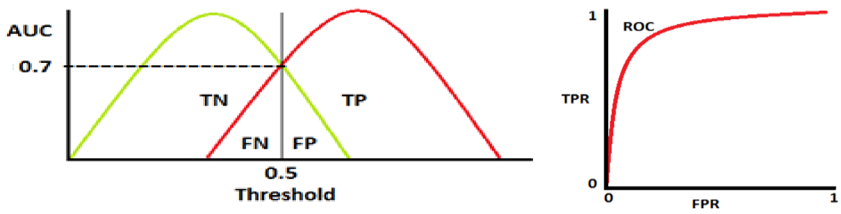


Figure 14. Distribution case2 probability of roc curve

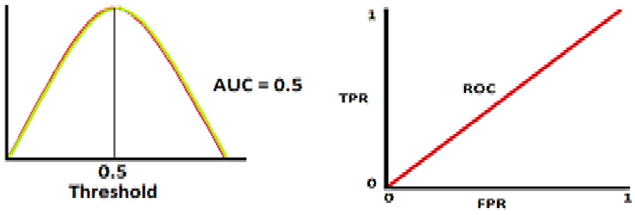


Figure 15. Distribution case3 probability of roc curve

4. CONCLUSION

Gender classification based on the gait features are very important subject. The proposed method satisfies a proficient result under the effects of many conditions such as carrying bag, slow gait, fast gait, and normal gait. By applying a few morphological operations and skeletons in 20 videos that opened as frames in each one, the reliable database CASIA class C have been got angles between two legs. The gaits for each video have been discreated to seventy-five frames for each 20-person (10 male and 10 female) that have values of (1,0) respectively, so the result will be 1500 frame, and applying PCA on these angles, it is given ideal linear dimensionality reduction. Successful two classifier gaussian bayes, ANN is accuracies 75%, 95.5% were achieved respectively. The latest results in ANN for gender classification in human gait is more remarkable and superior. ANN have a very good result more than gaussian bayes by an amount of (20%).

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