

Gender Classification Using Scaled Conjugate Gradient Back Propagation

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Abstract:

In this paper, we design an automated system that classifies gender by utilizing a set of human gait data. The gender classification system consists of four stages: in this method, firstly binary silhouette of a walking person is detected from each frame by using Eigen background method. Secondly, gait cycle is detected by using aspect ratio method. Thirdly, features from each frame in gait cycle are extracted by using: model free method. Finally, neural network are used for training and testing purposes. The experimental results on CASIA B database (12 males, 12 females) show that the proposed approach achieves a high accuracy in automatic gender classification. Project is designed by Matlab.

Keywords: Gender classification, Gait, Eigen Background, Neural Network.

I. INTRODUCTION

Gait recognition is the process of identifying an individual by a particular way or manner in which they walk [1]. Without any co-operation or interaction from the subject, gait gives the possibility to recognize people at a distance in less unobtrusive biometric technique. This is the most important property, which makes it so attractive. Human gait recognition as a new biometric tried to recognize person via the manner of people walking, which contain the physiological or behavioural characteristics of human. Gait-based gender classification is still unripe because of its unique advantages of being noncontact, non-invasive, and easily acquired at a distance; it is gaining increasing interest from researchers. Human Gait classification and recognition giving some advantage compared to other recognition system. Gait classification system does not require observed subject's attention and assistance. It can also capture gait at a far distance without requiring physical information from subjects [1-3]. There is a major difference between human gait and other biometrics classification. In human gait, we should use video data instead of using image data as other biometrics system used widely. In video data, we can utilize spatial data as well as temporal data compare to image data. Most of the gait classification and or

recognition system created are using spatial data only [4-11]. Gender classification system will be very helpful in many applications. For example, gender classification can improve surveillance systems, intelligence, analyse customers for store managers, allow robots to perceive gender, etc. Gait gender classification system divide to three steps, preprocessing to extract human body to the person walking, feature extraction to extract useful feature to the person walking and the last step is classification by using one or more of the classification methods like support vector machine, neural network, etc. this paper present gender classification system depended on walking style by extracted tamura feature from gait energy image and classification by using neural network. The rest of the paper is organized as follows. Section II describes the proposed method in which silhouette extraction, feature extraction process is explained and classification. Section III explains the overall implementation and experiment of gender classification system. Finally, we conclude in section IV.

II. THE PROPOSED ALGORITHMS

This section gives a general view of the proposed algorithm for gender classification. The structure of the proposed system is shown in Figure (1).

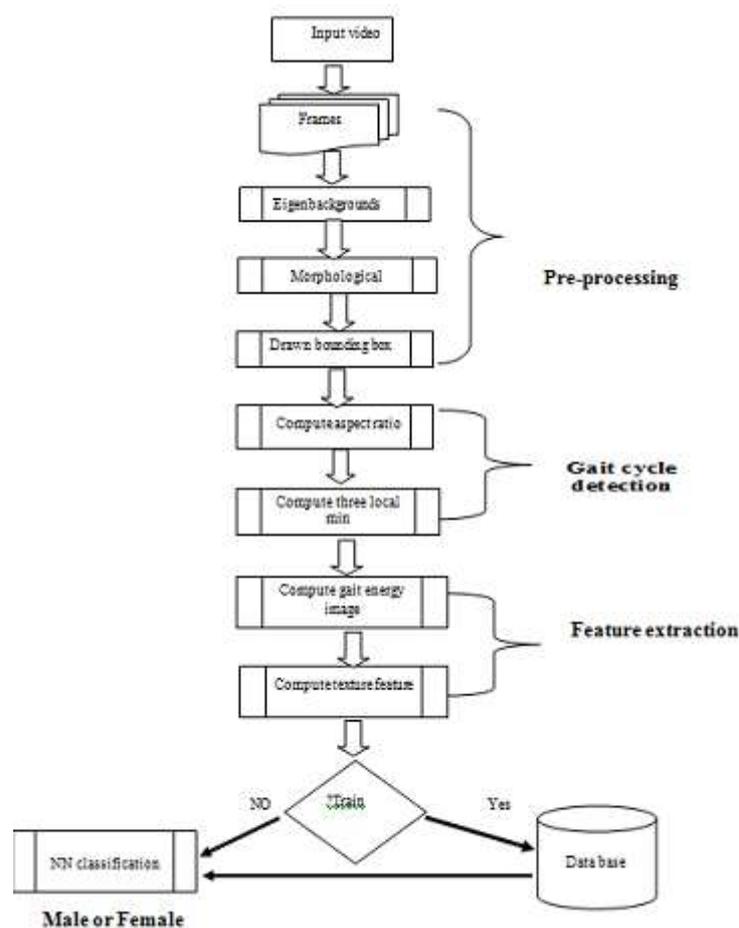


Fig. 1 The essential steps of the proposed system.

The proposed gender classification algorithm could be divided into the following four steps:

1. Background subtraction.
2. Gait cycle detection.
3. Feature extraction.
4. Gender classification.

1) Background subtraction

To get silhouettes, we employed an effective subtraction method to separate foreground from background and morphological filtering to reduce noise after separation. Eigen background method proposed in [12] is the method that used to get silhouettes, **Algorithm (1)**: describes the main steps of Eigen background Algorithm.

Input: All color images (frames), threshold=25.

Output: Cell array contain gray level images.

Step1: All the images are of the size (240*320), determine the number of train image is 50 images and convert them to gray level images and stored all them in three dimensions matrix, see Figure (2).

Step2: Compute the mean to the 3D matrix ,the result is matrix with size (240*320).

Step3: Compute the covariance to the result of the step2, the result is matrix with size (320*320).

Step4: Compute the Eigen value to the results of the step3, and sort the result in descend order, the result is vector with size (1*320).

Step5: Create matrix with size (240*240) and implying the values at the result in step4 at diagonal (only 240 values) and the remain is zeros.

Step6: Read new image and convert it into gray level image called *Img*.

Step7: Find projected image to the image *Img* by using the equation (1)

$$\hat{I} = \Phi_{mb}(I - \mu_b) \dots\dots\dots (1)$$

where Φ_{mb} is eigenvector matrix result of step5, *I* is new image *Img*, μ_b is the mean matrix result of step2.

Step8: Find reference image to the image *Img* by using the equation (2)

$$\hat{I}'' = \Phi_{mb}^t \hat{I} + \mu_b \dots\dots\dots (2)$$

where Φ_{mb}^t is the Transpose matrix of Eigen vector matrix.

Step9: Compute the different between reference image and *Img* (new image) using the equation (3).

$$|I - \hat{I}''| > T \dots\dots\dots (3)$$

Step10: The pixel is considered foreground pixel if the result of step9 large than threshold as the equation (3) else consider background pixel, see Figure (3), the result is cell array of gray level images. Repeat step6-step10 until the video is end.

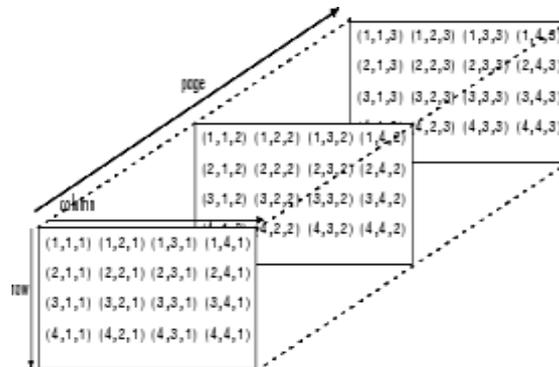


Fig. 2 Step one of Eigen background.

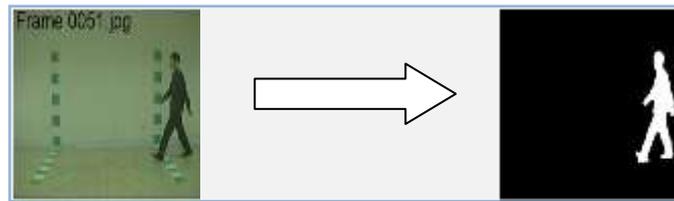


Fig. 3 An example on background subtraction.

After separation foreground from background the detection operation is done by connect compound operation and down bounded box to the blob by using connect component labelling, see figure (4).



Fig. 4 An example of bounding box surrounding person moving.

2) Gait cycle detection

Gait cycle represent the time interval between two repetitive events. It represents three local minimum in aspect ratio curve, where aspect ratio represent the ratio between height to width of bounding box surrounding person moving, see

figure(5), which represent the frame in one gait cycle, from heel strike reference limb to heel strike reference limb.

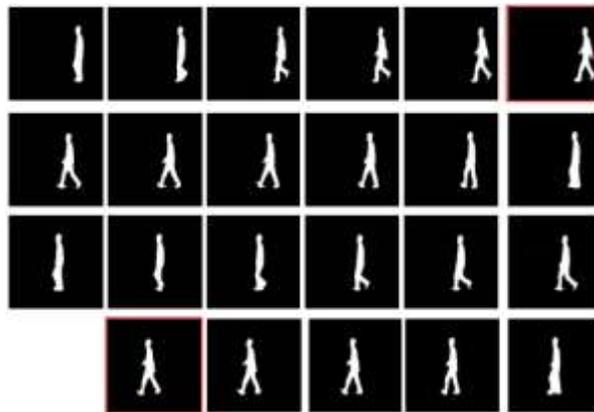


Fig.5 one gait cycle person walking from right to left.

3) Feature extraction

The third step in our work is feature extraction. Feature extraction is the process of defining a set of features or person characteristics, which will most efficiently or meaningfully represent the information that is important for analysis and classification, as describe before, you can extract silhouette from video sequence to the person walking and extract feature from it. Gait energy image represent the mean to the images in one gait cycle after make size normalization and alignment to this images. In this work tamura features from gait energy image are considered as signature to the person walking and used in gender classification method.

A) Tamura's Features

The texture of an image region is determined by the way the gray levels are distributed over the pixels in the region. Texture features extract from gray level gait energy image. In this paper, tamura method is used to extract texture features.

Tamura method is an approach of devising texture features that correspond to human visual perception [13]. It defined six textural features (coarseness, contrast, directionality, line-likeness, regularity and roughness) and compared them with psychological measurements for human subjects. The first three features are achieved very successful results and are used in our evaluation, both separately and as joint values.

Coarseness has a direct relationship to scale and repetition rates. Coarseness aims to identify the largest size at which a texture exists, even where a smaller micro texture exists. Computationally one first takes average at every point over neighbourhoods the linear size of which are powers of two. The average A over the neighbourhood of size $2k \times 2k$ at the point (x, y) , where $k = 0, 1, \dots, 5$ is

$$A_k(x, y) = \sum_{i=x-2^{k-1}}^{x+2^{k-1}-1} \sum_{j=y-2^{k-1}}^{y+2^{k-1}-1} f(i, j) / 2^{2k} \dots\dots\dots (4)$$

Then at each pixel, compute the difference (Ek(x, y)) between pairs of non-overlapping moving averages in the horizontal and vertical directions. At each pixel, the value of k that maximizes Ek(x, y) in either direction is used to set the best size (Sbest): Sbest(x, y) = 2k. The coarseness measure (Fcrs) is then computed by averaging Sbest(x, y) over the entire image.

Contrast aims to capture the dynamic range of grey levels in an image, together with the polarization of the distribution of black and white. The first is measured using the standard deviation of grey levels and the second the kurtosis α_4 . The contrast measure defined as is therefore

$$F_{con} = \frac{\sigma}{(\alpha_4)^n} \quad \text{Where} \quad \alpha_4 = \mu_4 / \sigma^4 \dots\dots\dots (5)$$

μ_4 is the fourth moment about the mean, σ is the variance, and n is a positive number.

Directionality is a global texture property. Patterns can be highly directional (e.g., a brick wall) or may be non-directional, as in the case of a picture of a cloud. The degree of directionality, measured on a scale of 0 to 1, can be used as a descriptor.

Algorithm (2): describes the steps of compute texture features.

Input: Gait period images.

Output: Texture features vector.

Step1: Resize all the image of gait cycle to size 240 * 240.

Step2: Align each image to make all the images have the same centre by shift rows and shift columns to each image in one gait cycle.

Step3: Compute gait energy image as the equation (6).

$$G(x, y) = 1/N \sum_{t=1}^N I(x, y, t) \dots (6)$$

Where N is the number of frames in a complete gait cycle, x and y are the image coordinates, and t is the frame number in the gait cycle. See figure (6) as an example on GEI.

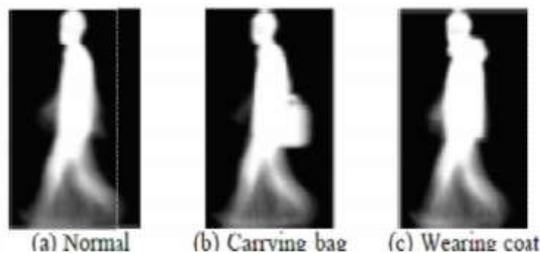


Fig.6 Gait energy image.

Step4: Resize gait energy image to size 128* 128.

Step5: Compute the tamura texture features to gait energy image coarseness, contrast and directionality as in the equations (4) and (5).

Step6: The result from this algorithm is a vector with three values. After that store all signature in database.

4)Gender classification

The last step in the propose system is gender classification, distinguish between male and female, after obtained feature vector and store it in mat file ,the classification step is followed, in our approach we use neural network(NN) as method to make classification ,algorithm (3) describe all those steps .

Algorithm (3): NN Classification

Input: A vector of features.

Output: Total accuracy from the NN.

Step1: Create feed forward neural network with three hidden layers, number of neuron in each hidden layer 170,160,170 respectively. Input layer for created neural network is determined by characteristics of inputs. We have three-attribute feature vector. Therefore, number of neuron in input layer is three, and output layer neuron determined by number of class we have two classes (male and female) therefore number of neuron in output layer are two.

Step2: Determined the important parameter, learning rate equal to one, epochs equal to 20000, maximum number of iterations, training time infinity, data division function (divide rand), transfer function of ith layer hyperbolic tangent sigmoid transfer function is used 'tansig', linear activation function is selected for output layer 'purelin' , performance function, default = 'mse 'and training function is back propagation function (Scaled conjugate gradient), weight and bias is generating randomly.

Step3: Train the network with train data and target matrix (target matrix is matrix with two rows and one hundred twenty columns each row consists of a vector of all zero values except for a 1 in element i, where i is the class they are to represent).

Step4: Simulates the neural network by taking the initialized net and network input matrix (train data), return the indices to the largest output as class predict.

Step5: Compute the network performance.

Step6: Simulates the neural network by taking the training net and test data return the indices to the largest output as class predict.

III. EXPERIMENT RESULTS

In this paper, we are using MATLAB environment to implement it, on i3 processor with the RAM of 2GB. To evaluate the proposed method, we used CASIA database (class B), we choose 24 person (12 is male and 12 is female) with normal gait each person have six sequences taken at different time at angle 90, the person walking from right to left, extracted features for them and stored in data base with size 144*3, where 144 refer to the number of sequence to twenty four person and 3 refer to the number of features in features vector. We used cross validation (holdout) to divide the database to train set and test set, the best sequence to test phase and the remain for training phase (five sequences used to training NN classifier and test with one sequence) . The total accuracy from the NN, it equal to the ratio between the correct predict class label on all sample that test.

$$\text{Total Accuracy} = \frac{\text{correct predict class label}}{\text{all sample that test}} \times 100\% \dots \dots \dots (7)$$

The network gives high accuracy when train and test equal to 98% with simple training time equal to (0.19seconds) at 302 epochs, with best training performance is 1.92e-008 at epoch 302, see figure (7).

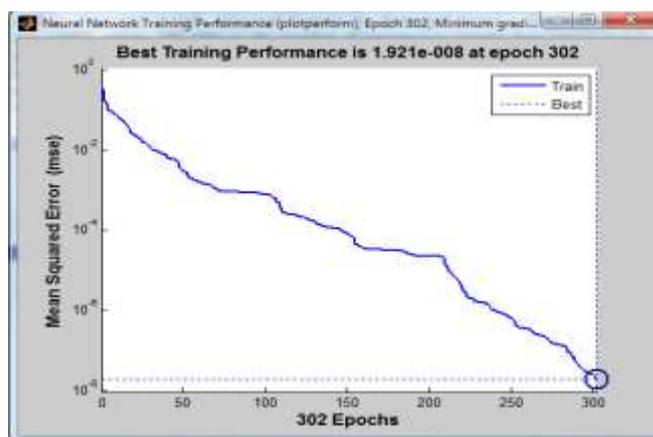


Fig.7 Neural network training performance at 302 epochs.

Figure (8) shows the actual design of our neural network, while figure (9) is the view of our network and figure (10) is the snapshot generated during the training neural network using back propagation algorithm.

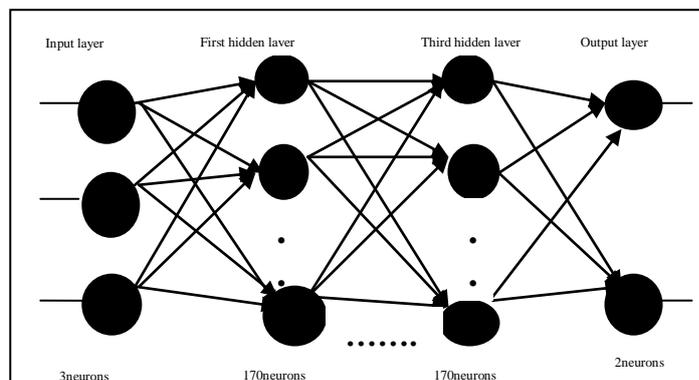


Fig. 8 Design neural network classify

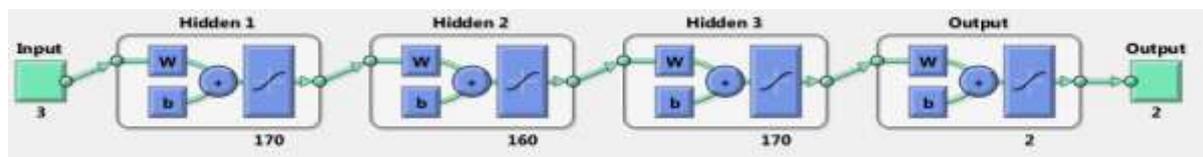


Fig.9 View of neural network.

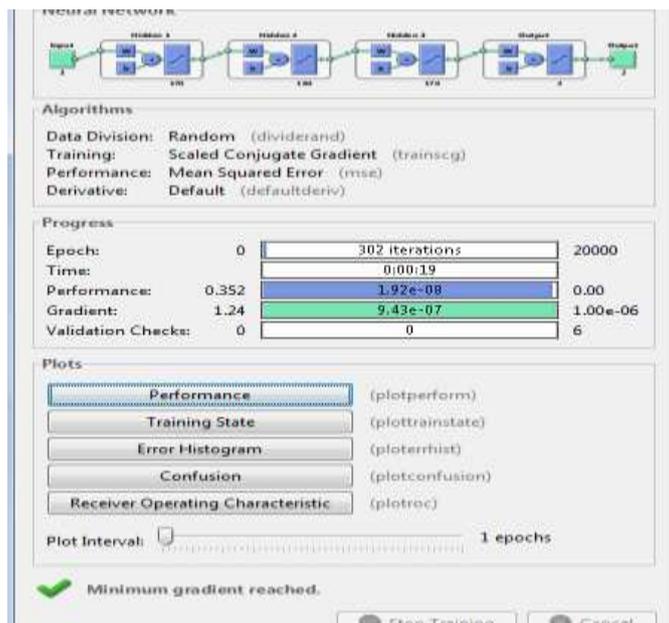


Fig.10 Neural network training.

TABLE I
CLASSIFICATION RESULT FROM NN FOR GENDER CLASSIFICATION

Data type	Feature type	Classification Accuracy %	
		Train Data	Test Data
Male	Tamura texture Features	100	98
Female	Tamura texture Features	100	98
Total accuracy from the NN		98%	

IV. CONCLUSIONS AND FUTURE WORK

Gender classification system depended on tamura texture feature is more effective because it depended on gait energy image. This image avoid synchronization difficulties and prevent noises from individual images. This image consider model free gait approach , the model free gait recognition methods or appearance based methods work directly on the gait sequences. They are not considered as a model for the human body to rebuild human walking steps. They have the advantage of low computational cost in compare with model-based approaches and tamura feature considered third ordered texture feature, this type of feature not depended on only pixel but it depended on pixel neighborhoods and this fact give tamura feature strongest to effect by noise for all these reason the system give more robust solution to gender classification in future work suggest deal with multi view person walking.

References

- [1] N. V. Boulgouris, D. Hatzinakos, and K. N. Plataniotis, "Gait recognition: a challenging signal processing technology for biometric identification,"*IEEE Signal Processing Magazine*, vol. 22, pp. 78-90, 2005.
- [2] M. S. Nixon and J. N. Carter, "Automatic Recognition by Gait, "Proceedings of the IEEE, vol. 94, pp. 2013-2024, 2006.
- [3] Y. Jang-Hee, H. Doosung, M. Ki-Young, and M. S. Nixon, "Automated Human Recognition by Gait using Neural Network, "First Workshops on Image Processing Theory, Tools and Applications, 2008, pp. 1-6.
- [4] J. Wang, M. She, S.Nahavandi, and A.Kouzani, "A Review of Vision-based Gait Recognition Methods for Human Identification," *IEEE Computer Society, 2010 International Conference on Digital Image Computing: Techniques and Applications*, pp. 320 - 327, 2010 .
- [5] B. Pogorelc and M. Gams, "Medically Driven Data Mining Application: Recognition of Health Problems from Gait Patterns of Elderly, "IEEE International Conference on Data Mining Workshops, 2010.
- [6] S. Ha, Y. Han and H. Hahn, "Adaptive Gait Pattern Generation of Biped Robot based on Human's Gait Pattern Analysis, "World Academy of Science, Engineering and Technology, 34, 2007.
- [7] M. Hu, Y. Wang, Z. Zhang and Y. Wang, "Combining Spatial and Temporal Information for Gait Based Gender Classification," *International Conference on Pattern Recognition 2010*.

- [8] X. Li, J. Stephen, M. S. Yan, D. Tao and D.Xu, "Gait Components and Their Application to Gender Recognition, IEEE Transactions On Systems, Man, And Cybernetics "Part C: Applications And Reviews, 38(2),2008.
- [9] S. Yu, T. Tan, Kaiqi Huang, KuiJiaand Xinyu Wu, —A Study on Gait-Based Gender Classification," IEEE Transactions On Image Processing, 18(8), 2009.
- [10] M.Hanmandlu, R.Bhupesh Gupta, F. Sayeed and A.Q. Ansari"An Experimental Study of different Features for Face Recognition,"International Conference on Communication Systems and Network Technologies, 2011.
- [11] R. Asmara, A.Basuki and K. Arai, "A Review of Chinese Academy of Sciences (CASIA) Gait Database As a Human Gait Recognition Dataset," Industrial Electronics Seminar, 2011, Surabaya Indonesia.
- [12] Nuria M. Oliver, Barbara Rosario, and Alex P. Pentland," A Bayesian Computer Vision System for Modeling Human Interactions", IEEE Transactions on Pattern Analysis and Machine Intelligence, Vol. 22, No. 8, August 2000.
- [13] Peter Howarth and Stefan R"uger," Evaluation of Texture Features for Content-Based Image Retrieval", Department of Computing, Imperial College London, South Kensington Campus, London, 2004.
- [14]CASIA GAIT DATABASE Available:
<http://www.cbsr.ia.ac.cn/english/Gait%20Databases.asp>.