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Gender Recognition Based on Computer Vision System

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ABSTRACT
Detecting human gender from complex background, illumination variations and objects under computer vision system is very difficult but important for an adaptive information service. In this paper, a preliminary design and some experimental results of gender recognition will be presented from the walking movement that utilizes the gait-energy image (GEI) with denoised energy image (DEI) pre-processing as a machine learning support vector machine (SVM) classifier to train and extract its characteristics. The results show that the proposed method can adopt some characteristic values and the accuracy can reach up to 100% gender recognition rate under combining the horizontal added vertical feature and using a normal image size and test data when people are walking at a fixed angle. Meanwhile, it will be able to achieve over 80% rate within some allowed fault-tolerant angle range.

KEYWORDS
Computer vision system; gait-energy image; denoised energy image; machine learning; support vector machine; fault-tolerant angle

1. Introduction

The digital product development has made many of benefits for human life and convenient in information technology. If the recognition system in a department store or convenience store entrance can accurately distinguish for people gender and age, it will be able to provide customers with more convenient and friendly service. When the service system can identify the customer's gender and age, then provides personal service for the different gender customer, which can reduce the time when customer searches for products, on the other hand, it will also make the customer feel very intimate and accelerate to service their guests, finally increase the company's performance. Gender recognition system (Golomb, Lawrence, & Sejnowski, 1990; Jain & Huang, 2004) can also be useful for the security monitor system, because today social security let people panic, more public toilets are located in a corner place, and the security is a big consideration. If the computer vision system can be stalled in outside toilet or locker room, when some specific strangers wander out, the recognition system can notify guards or the related people to handle it, so it can reduce guarding 24 h patrol and also has a protection on the social security aspects.

Gender recognition is an important research topic (Huang, Harris, & Nixon, 1999; Sarkar et al., 2005; Xue, Ming, Song, Wan, & Jin, 2010; Wang, Tan, Ning, & Hu, 2003) at present. In the past, the gender studies mostly focused on face or the profile feature, but the face image on the monitor system has had a low resolution or other factors lead to a lower recognition rate. Meanwhile someone being to commit crimes would deliberately wear secret and hide face feature that will result in the difficult of gender recognition. In addition, the face image is limited to help gender recognition in a long-distance monitoring, which will lead to these methods of facial feature not applied to our application. A number of key features detection of modern humans—face, race, body shape and age will be very difficult when somebody wears a hat, a sun glass or loose dressing. Therefore, it is found that the people walking footsteps and the body swing exist some gender differences; male usually has the larger swing and shoulder size than female. The female has the difference in the hair length and chest; these will help for the gender recognition according to their characteristics. In this study, the CASIA gait data-set B (http://www.cbsr.ia.ac.cn/english/Gait%20Databases.asp) and data-set (http://www.csie.ntu.edu.tw/cjlin/libsvm/index.html) were used as the experimental bases, and then SVM classifier was used as a gender recognition source.

Many researches (Golomb et al., 1990; Jain & Huang, 2004) adapted the facial features as the gender recognition in the past, now the gait recognition is used for the gender recognition, such as Kozlowski & Cutting (1997) proposed a method based on gait to distinguish the gender which used the point lights to link the joints and via observers to observe the gender, the accuracy rate can be up to 63%, although this method can be for the gender recognition but its accuracy is quite low. The other studies (Davis & Gao, 2004; Troje, 2002) also used the point lights for the gender classification, Davis & Gao (2004) used an adaptive three-points model to extract the features, and their testing database contains 40 objects with 20 males and 20 females respectively, its accuracy rate can be up to 95.5%, this method's accuracy is higher than those of Kozlowski & Cutting (1997) but its test data volume is small.

Mather and Murdoch (1994) proposed the method for the male and female walking with a body swing, the differences of lumbar and hip proportion and the differences of shoulder proportion, they found that the male in walking, his shoulder swing range is higher than female, but female in walking, her hip swing range is higher than male, usually male shoulder is wider than female, most female lumbar part is thinner. This research will use gait-energy image to extract the people feet feature when walking, then use the denoised energy image to remove image noise to acquire the walking physical change

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variance between the male and female, and then use the extracted feature as the gender recognition information. The experimental test will prove that the accuracy of our proposed method is higher than the other methods. The challenge for gait recognition is the different perspective of the marching gait which affects the correctness of the recognition. So in the paper, it will adopt the walking people in a store as object of the gait and use a single camera within the allowed fault-tolerant angle range to identify its gender, therefore it will take a series of experiments to verify their accuracy and finally make some comparisons with other similar methods in the experiment tests. But because the face, race, body shape and age detections are the total different research methods with ours and have some invalidated flaws, here we will not make a cross-comparison of these approaches.

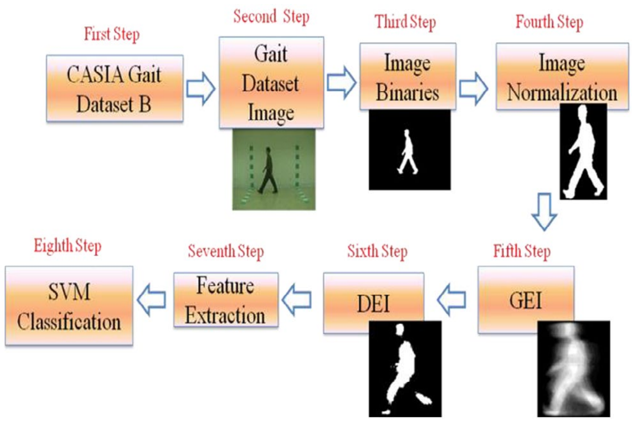

Figure 1. Flowchart for the proposed procedure of image classification.

2. The Procedure of the Image Processing Technique

In this research, the gait-energy image(GEI) and the denoised energy image(DEI) were used as a pre-process for the gait features extraction, and then based on the horizontal and vertical features extraction between male and female as an important characteristic reference for the gender recognition.

2.1. Procedure

In this paper, it used the people-walking gait image as the gender recognition and the procedure includes eight steps, Figure 1 shows its flowchart. The first step is to use “CASIA gait data-setB” database image for the experimental data source. The second step is to extract the image lattice by gait sequence in the capture all shadow lattice of image. The third step is to use a threshold value (Xue et al., 2010) or background subtraction (Huang et al., 1999; Sarkar et al., 2005; Wang et al., 2003) then binaries and separates them from the object and background segmentation. The fourth step is to make erosion and dilation process to smooth image and removes noise as formula (1) and (2) (Xue et al., 2010), then normalize them.

$$E(x,y) = AND_{i,j=0}^{m}\left[f\left(x+i,y+j\right)\&T\left(i,j\right)\right] \quad (1)$$

$$D(x,y) = OR_{i,j=0}^{m}[f\left(x+i,y+j\right)\&T(i,j)] \quad (2)$$

Where $E(x,y)$ is the erosion image, $f(x,y)$ is the binary image, $T(i,j)$ is the structure element, and $D(x,y)$ is the expanding image. Here m represents the image length and width, which are equal to each other. The fifth step is to use these normalized serial images for GEI (Lam, Cheung, & Liu, 2011) processing. The sixth step is the GEI image processing to remove noise (Chen, Liang, Zhao, Hu, & Tian, 2009). The seventh step is for features extraction. The eighth step is to use the support vector machine (SVM) for gender recognition. Steps fifth step through eighth are the significant process in this research that will be explained in detail in the following section.

2.2. System Schema

Figure 2 is the system schema figure for this proposed method. The schema is divided into two parts respectively for training data and test data. The proposed method is to extract the gait sequence image from movie then binaries and subtracts background to acquire the prospect image. Furthermore, the image will be normalized and run GEI processing to acquire the serial giant variance, and then uses DEI method to remove noise, finally extracts the features from DEI image and uses SVM classifier to train male and female samples to acquire the best SVM model. The ultimate goal is to use the best trained model for further testing and acquires the gender recognition.

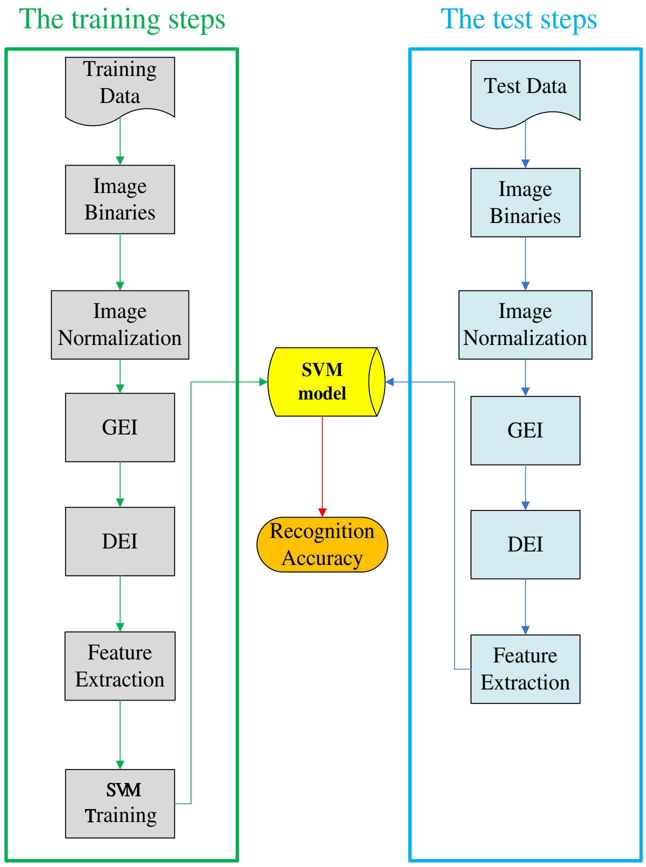

Figure 2. The training and test schema.

2.3. Gait-energy Image (GEI)

The gait is the people is unique characteristics, and its gender can be judged from pedestrian walking by using cameras shooting. In this research, GEI was used to calculate the gait which can dedicate the change variance between pre-process and post-process giant images. Figure 3 shows the image lattice from camera shooting, after background subtraction

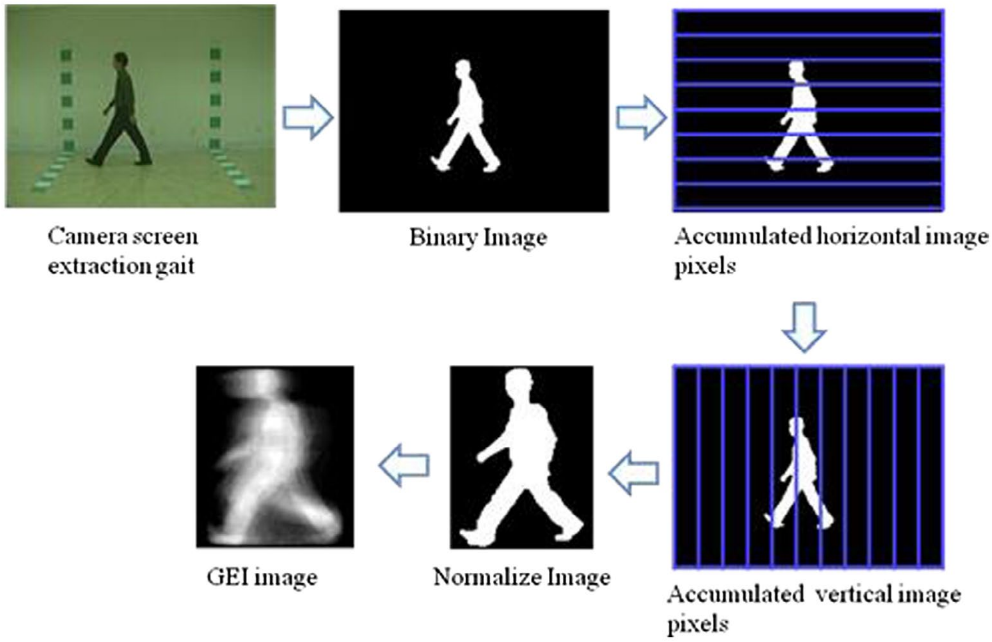

Figure 3. Gait-energy image processing.

Figure 4. The post-process image from a series of gait-energy image processing.

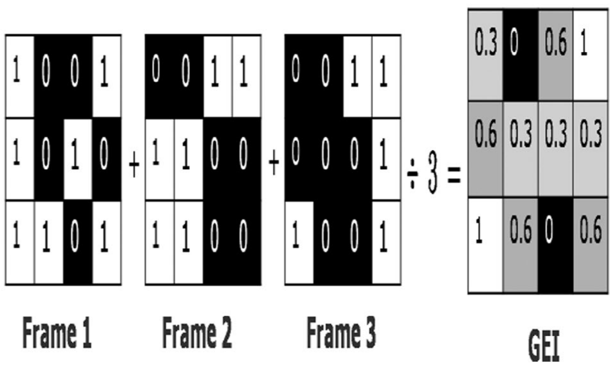

Figure 5. The gait-energy image processing example.

processing and binarization processing acquire the foreground image and normalize it, then the same serial normalized giant image lattice can use the formula (3) (Chen et al., 2009) evaluation to acquire the GEI image as shown in Figure 4.

$$G_c(x,y) = \frac{1}{N_c} \sum_{t \in Ac} B(x,y,t), \tag{3}$$

where $G_c(x,y)$ is GEI image, N_c is the total gait image serial numbers, Ac is the giant serial length, and t represents the time in the image $B(x,y,t)$, where x and y are the coordinates of the image pixel.

Figure 5 shows one GEI image processing example, here it is supposed two 4×4 normalized images, white block is for the gait foreground image and the black block is for the background image, and then gets the average image from the two images addition. If the GEI pixel value in the example image is equal to 1, it means that among the first, the second and the third image have no change. If the pixel value is 0.3 or 0.6, it means that among the first, the second and the third image have some change, so the people walking characteristics can be identified.

2.4. Denoised Energy Image (DEI)

Basically, DEI is used to remove out GEI noise, meanwhile the giant variance between male and female can be acquired. Following the formula in Chen et al. (2009) the DEI rule is the following

$$D_c(x,y) = \begin{cases} 1, \text{if } G_c(x,y) \geq T, \\ 0, \text{ otherwise}, \end{cases} \tag{4}$$

Where $D_c(x,y)$ is the image after noise removal, $G_c(x,y)$ is the GEI image, and T is a threshold value.

Figure 6. The denoised energy image processing example.

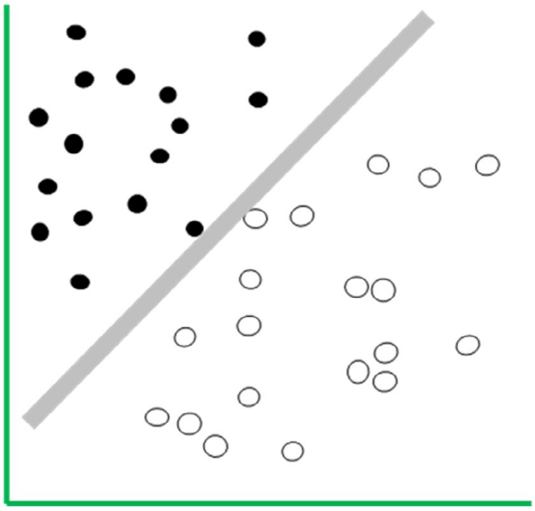

Figure 7. The two dimension support vector machine classification figure (y label is y direction location, and x label is x direction location).

Figure 6 is the example for the GEI image making DEI processing, one 3 × 3 GEI image, the threshold value is the maximum pixel value of the GEI image (the example is 1) and multiplies 0.8 (Chen et al., 2009) to get the threshold value T, then each pixel value of GEI image compares with T, if it is greater than or equal to T, then DEI image value is equal to 1, otherwise it is equal to 0. As Figure 6 left-hand side shows, after the left images of the GEI making the denoising processing can become the right-hand side DEI images as Figure 6 right-hand shows, the processed DEI image only retains the most important part of the original GEI.

2.5. Characteristic Value Extraction

The trunk shape or hairstyle appearance in DEI images is also an important characteristics to distinguish the differences between male and female. Here we introduce how to extract the characteristic value from each DEI image, first let X_i represents the ith column characteristic value and Yj represents the jth row characteristic value in the DEI extracted image, the characteristic extraction formulas are as follow:

$$X_i = \sum_{k=1}^{9} c_{ik} \tag{5}$$

When $k = 18$, then c_{ik} is as follows:

$$c_{ik} = \left\{ b_{i((k-1)\times 18+l)} | l = 1 \sim 18 \right\} \tag{6}$$

When $k = 9$, then c_{ik} is as follows:

$$c_{ik} = \left\{ b_{i((k-1)\times 18+l)} | l = 1 \sim 6 \right\} \tag{7}$$

$$Y_j = \sum_{k=1}^{9} d_{kj} \tag{8}$$

When $k = 18$, then d_{kj} is as follows:

$$d_{kj} = \left\{ b_{((k-1)\times 18+l)j} | l = 1 \sim 18 \right\} \tag{9}$$

When $k = 9$, then d_{kj} is as follows:

$$d_{kj} = \left\{ b_{((k-1)\times 18+l)j} | l = 1 \sim 6 \right\} \tag{10}$$

Where i is for the ith image column, j is for the jth image row, k is the block number, X_i is the calculated feature of each column, Y_i is the characteristic value of each row, c_{ik} is the split block of each column, d_{kj} is the split block of each row, and b_{ij} is the image pixel location.

X_i is calculated from the ith column pixel of DEI image, where the DEI image size is 150 × 150 pixels, so $1 \le i \le 150$, X_i is acquired from the 150 pixels of the ith column and the 150 pixels of the jth row in the DEI image. Each column and row pixels are divided into 9 blocks which are the best optimum segmented block numbers for 150 × 150 to get the minimal characteristic parameters and avoid complicated calculations and lose its originality, c_{i1} to c_{i8} to and d_{1j} to d_{8j} are codified as 18 bits, c_{i9} and c_{9j} are codified as the remained 6 bits, then the characteristic values in the 9 blocks will be totally added for the column X_i and row Yj values respectively. Therefore, one DEI image will have 300 characteristic parameters for its classification processing as the following.

2.6. Gender Recognition

Nowadays exists a lot of classifiers (Huang & Wang, 2007; Lee & Grimson, 2002; Xue et al., 2010; Yu, Tan, Huang, Ia, & Wu, 2009); however support vector machines (SVM) (Gunn, 1998) always was used for the classification. SVM was proposed by Vapnik in AT&T LAB team in 1995. Its main concept comes from the structural risk minimization (SRM) errors in the statistical learning theory method (Gunn, 1998). SVM operation is to identify an optimal hyperplane which can separate two different collections, hyperplane means a high-dimensional plane assumed the used data belonging to high dimension. Taking linear core functions for its illustration, it is hoped to identify a line to separate two different sets and also want this line to enlarge the margin more and more in between the two groups, so it can precisely identify the category belonging to which collection and also its calculation accuracy is better. Figure 7 shows SVM's two-dimensional classification graph, if the data is belonged to a high-dimensional data-set, then it can be projected onto the two-dimensional plane, for example, the diagram data is divided into two groups, the blue circle is considered as a group and the red circle is considered as another group, the grey part is the best line to separate the two groups. The SVM classification core functions include Linear, Polynomial, and Radial Basis Function (http://www.csie.ntu.edu.tw/cjlin/libsvm/index.html), (Gunn, 1998), which formulae is given by equation (11)-(13) (Xue et al., 2010)

(a) Linear:

$$K(x, x_i) = x \cdot x_i \tag{11}$$

(b) Polynomial:

$$K(x, x_i) = [1 + x \cdot x_i]^q \tag{12}$$

(c) Radial Basis Function:

$$K(x, x_i) = exp\{-|x - x_i|^2 / 2\delta^2\} \tag{13}$$

Each core function has different parameters, the parameter value also affects the classification accuracy, and user can test multiple-core functions to allow the best classification accuracy reaching the highest. In this research, polynomial function was used for the classification recognition, which has the higher gender classification accuracy than other functions according to our test experiment.

3. Experimental Tests

In this research, we used a CASI gait data-set B image and data-set (http://www.csie.ntu.edu.tw/cjlin/libsvm/index.html) for the experiment tests which have a total of 63 test gait serial of images including 36 males and 27 females and adapt Chen et al. (2009) proposed LIBSVM software with polynomial core functions for the gender training and testing. The training image will train a SVM model for subsequent testing from the 18 males and 14 females and use two image sizes 75×75 and 150×150 for SVM model classification test. Table 1 shows results for the image size 75×75 in the vertical feature extraction which accuracy is 74.19%, the horizontal feature extraction accuracy is 90.32%, and the horizontal added vertical feature extraction accuracy is 93.55%. Table 2 shows results for the image size 150×150, the vertical feature extraction accuracy is 77.42%, the horizontal feature extraction accuracy is 96.77%, and the horizontal added vertical feature extraction accuracy is 100%, the result is reasonable due to combining the horizontal + vertical feature and using a normal image size and test data. The experimental results show that the 150×150 is the best image size, the vertical feature extraction accuracy is better than the vertical feature extraction, so the 150×150 image is adapted for the horizontal and vertical feature extraction. Table 3 shows the comparison for the other four methods (Huang & Wang, 2007; Lee & Grimson, 2002; Li, Maybank, Yan, Tao, & Xu, 2008; Yu et al., 2009) with our proposed method. To compare with Lee & Grimson's (2002) method, our proposed method has more experimental data and the accuracy is higher, then comparing with Huang & Wang (2007) methods, our proposed method still has much more experimental data and higher accuracy. Furthermore with Li et al's (2008) method comparison, our recognition accuracy rate is also higher, and with Yu et al's (2009) method comparison, which used 31 male and 31 females for the gait serial image test, then used SVM linear core function for the training with test, the feature amount will effect SVM on the processing time and speed, but they used whole image

Table 1. The experiment results for the first image data.

Image size	Characteristic extraction	CASIA Data-set	Accuracy
75×75	Vertical characteristics	36 males 27females	74.19%
75×75	Horizontal characteristics	36 males 27females	90.32%
75×75	Horizontal+ vertical characteristics	36 males 27femals	93.55%

Table 2. The experiment results for the second image data.

Image size	Characteristic extraction	CASIA Data-set	Accuracy
150×150	Vertical characteristics	36 males 27females	77.42%
150×150	Horizontal characteristics	36 males 27females	96.77%
150×150	Horizontal + vertical characteristics	36 males 27femals	100%

Table 3. The experiment results for the third image data.

Methodology	CASIA Data-set	Accuracy
(Lee & Grimson, 2002)	25 males 25females	85.0%
(Huang & Wang, 2007)	25 males 25females	85.0%
(Li et al., 2008)	31 males 31females	93.28%
(Yu et al., 2009)	31males 31females	95.97%
Our method	36 males 27females	100%

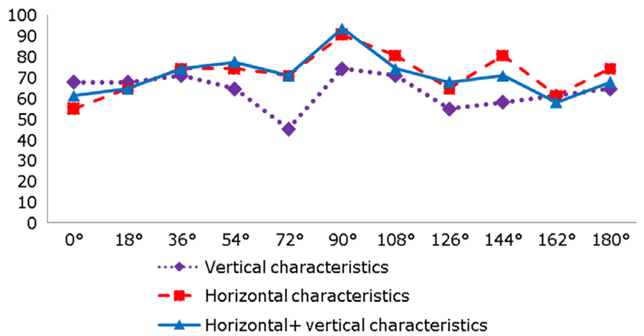

Figure 8. The feature extraction accuracy (y label) for the DEI 75×75 image size under the different captured angles (x label).

as the gender features, and assumed the image size 150×150 for the test example, Yu et al's (2009) extracted 22,500 feature values, however our method only extracted 300 feature values, apparently it is less than Yu et al. (2009) and our accuracy is higher than the previous method.

Now we consider the method accuracy for people walking in the different captured angles. Figure 8 shows feature extraction of the DEI 75×75 image size for the different captured angles, the results show that the vertical feature extraction which average accuracy is 63.64%, the horizontal feature extraction average accuracy is 72.21%, and the horizontal + vertical feature extraction average accuracy is 70.97%. Figure 9 shows feature extraction of the DEI 150×150 image size for the different captured angles, the results show that the vertical feature extraction which average accuracy is 72.43%, the horizontal feature extraction average accuracy is 82.11%, and the horizontal + vertical feature extraction average accuracy is 87.98%. Therefore, we can conclude the horizontal + vertical

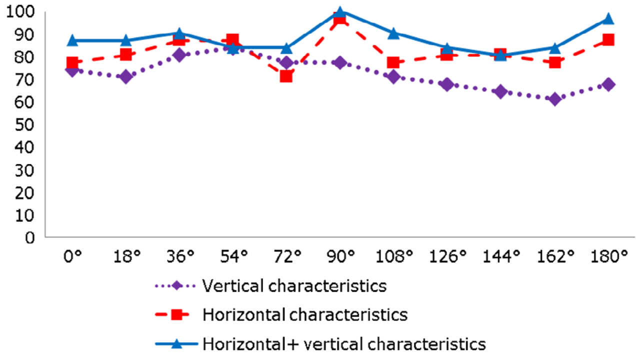

Figure 9. The feature extraction accuracy (y label) for the DEI 150 × 150 image size under the different captured angles (x label).

Table 4. The first set data accuracy for the three different shot angles.

Training data (18 males 14 females)	Test data (18 males 14 females)	Accuracy
90°	72°	80.65%
90°	108°	83.87%
0°	18°	80.65%
180°	162°	87.1%

Table 5. The second set data accuracy for the three different shot angles.

Training data (20 males 20females)	Test data (36 males 27 females)	Accuracy
90°	72°	84.12%
90°	108°	84.12%
0°	18°	82.54%
180°	162°	87.3%

feature extraction has the credible effect data. We also made another tests for the three kinds of camera captured angles, 90° (side), 0° (positive) and 180° (back). Table 4 lists the test using 18 males and 14 females for training data and meanwhile lists the test using 18 males and 14 females for people walking in 72°, 108°, 18° and 162°, and 90° is used as the shot giant, here has a 18° fault-tolerant angle range. The result shows 80.65% and 83.87% accuracy for 72° and 108° shot angle respectively. The test shot angle 18° has 80.65% accuracy in terms of 0° (positive) shot and the test shot angle 162° has 87.1% accuracy in terms of 180° (back) shot. Because the accuracy not yet achieves the idea condition, it needs to add more train data. Table 5 lists the training data using 20 males and 20 females and the test data using 36 males and 27 females, if 90° is for the training data, 72° and 108° are for the test data, and then the accuracy can be up to 84.12%. If 0° is for the training data, and 18° is for the test data, then the accuracy can be up to 82.54%. If 180° is for the training data, and 162° is for the test data, then the accuracy can be up to 87.3%. The proposed method can also be applied to cross-ethnicity gender recognition because it uses gait-energy image which is a general ground regardless ethnicity (Davis & Gao, 2004; Kozlowski & Cutting, 1997; Mather & Murdoch, 1994).

4. Conclusions

In this research, we proposed a realization of gender detection from walking movements using gait-energy image with denoised energy image pre-processing as support vector machine classifier. These evaluations on the image database show the encouraging results which accuracy has reached to 100% under combining the horizontal added the vertical feature and using a normal image size and test data. And the method accuracy for people walking in three kinds of different captured angles also can be above 80%. In the future, the proposed method for a holding object condition under variant filming condition will be extended.

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Disclosure statement

No potential conflict of interest was reported by the authors.

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