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GAIT RECOGNITION BASED ON GEI & GABOR FILTER

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ABSTRACT

The field of Human Gait Recognition is one of the active research fields. The number of studies has increased which indicates that this area is important. The present study has many benefits as it enables us to recognize a person through his gait in front of a camera even if the gait picture is taken from a long distance with a low-quality camera. Moreover, many other biometrics require special equipment; and some of them require taking the picture from a short distance. This study aims at finding a solution with high quality and efficiency in the process of recognizing human gait. This is achieved by providing a strong training set. For this purpose, we created two training sets. The first depends on figuring out human features by using Gait Energy Image (GEI). The second set depends upon figuring out human features by using Gait Energy Image (GEI), and then filtering it by using Gabor Filter. This study was conducted as an experimental research to gain ideal parameter values for Gabor Filter that contributes to enhancing the training sets samples that leads to increasing the system performance efficiency, and we found the best values for Gabor filter parameters for our system is kernel =3 ,theta = 225 , γ=1.25, ψ=0, λ=3.5, and a bandwidth =2.8. The training and testing were conducted by using (SVM) Algorithm, the study uses the gait database (CASIA-B) to evaluate our system, Then, we used (CCR) for Performance measurement . The study reached good ratios for all views with an average of 76.50% for (GEI+GABOR FILTER) and 76.42 for (GEI). Moreover, the study achieved an ideal percentage of 78.10% for (GEI+GABOR FILTER) and 77.66 for (GEI), as compared to previous studies of the positions of normal-walking, wearing-coat, and carrying-bags at a view of 90.

Keywords: *biometrics ، Human Gait Recognition، (GEI) Gait Energy Image، Gabor filter، Support Vector Machine, the correct classification، rate (CCR).*

1. INTRODUCTION

Gait recognition is a brand-new biometric technology that tries to recognise people at a distance by the way they walk (i.e. the behaviour of moving on foot). Human gait recognition works from the perception that a person's walking style is individual and can be handled for human identification [1].

Gait recognition has always been a challenging problem. It is shown in medical and physiological studies that human gait is a unique identifier. Unlike other biometrical indices such as fingerprints, face, or iris recognition, it has a very important advantage: it can be measured at a large distance without any interaction with the human. This feature makes gait recognition applicable to intelligent video surveillance problems used, for example, in the security field [2]. Compared with the first generational biometrics such as face, fingerprints, and iris which are widely applied in some commercial and low applications, gait has great prominent advantages of being non-contact, non-invasive, unobvious, low resolution requirement and it is the only perceivable biometric feature for human identification at a distance till now though it is also affected by some factors such as drunkenness, pregnancy, and injuries involving joints. Unlike face, gait is also difficult to conceal

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and has great potential applications in many situations especially for human identification at a distance[2][3]. However, There are many factors that may negatively impact the efficiency of the biometric gait identification system, which can assort into two classes: (i) outside factors such as viewing angles, lighting conditions, walking surface conditions, shoe types, and object carrying; clothing, and (ii) inside factors, such factors cause variations of the normal gait due to illness or other physiological changes in the body, medical conditions, etc Due to these factors, gait recognition became a difficult problem of computer vision . Moreover, gait recognition is immediately associated with quality of segmentation of the walking person. Gait recognition approaches manipulate both static (above the waist) and dynamics feature (below the waist e.g. foot) for recognition. It is inferred that dynamic parts of the body carry rich information about the gait. Most of the existing methods adopt both the features and some methods adopt a dynamic feature only. A major challenge in gait recognition is to generate robust recognition algorithms that can select gait features that are invariant to the presence of various conditions, which affect people appearance [1]. Also, Human gait recognition techniques can be split into two or three types of approaches: model-based approaches and model-free approaches and multi-information fusion. Model-based approaches in which gait signatures are constructed by modeling. Within the model-free approaches, ignored the human body structure in favor of silhouette that based on representations and varied information fusion approach in order to reproduce human vision perception through utilizing the biometrics or double, face for instance [4][5]. A considerable amount of literature published on gait recognition is based on model-free approaches where the gait features are obtained from the moving shape of the individual [5]. Furthermore, these gait features are derived from spatio-temporal patterns of an individual gait [7], 2D optical flowfield [10], skeleton variance image [8], binary silhouettes [9], variations of area within a particular region or Gait energy image (GEI) [11] which is a spatio-temporal gait representation. GEI is the human silhouette image obtained by determining the skeleton from the body segments. Several studies in the field of gait recognition have focused on the model-free approaches to make them robust against covariate factors such as clothing and carrying conditions. Among the approaches that have been proposed recently, one can cite, for example, gait representation using flow fields, gait entropy image and gait recognition based on local binary pattern (LBP) descriptors. On the other hand, model-based approaches aim to extract the characteristics of the human body's movement using the torso and the legs. Methods of these approaches use static body parameters for identification, such as stride lengths. Although these approaches focus on person recognition using walking only, Yam et al. extended the concept to enable the recognition not only by the walking gait but also by the running gait by analysis of leg motion and the angles between the limbs [5].

Otherwise, the performance of the proposed gait recognition methods depends mainly on the quality of the extracted gait features. The inclusion of shape information in gait features can introduce variations that will hinder the recognition performance especially in the cases where the same person wears different clothes and has different carrying conditions.[5] In this paper, we propose gait recognition based on GEI & gabor filter system for human identification under variations of side views in order to test the positions of normal-walking, wearing-coat, and carrying-bags, in order to overcome the above limitations.

The proposed approach is based on a supervised feature extraction method capable of selecting discriminating features by using two techniques. The first one is Gait Energy Image (GEI) and the second one is Gait Energy Image (GEI), and then filtering it by using Gabor Filter , and the system that can work under varying clothing and carrying conditions , and when we use features extracted GIE+GABOR FILTER, we try to find best parameter for Gabor Filter that works to improve the recognition performance . The evaluation of the performances including a comparative analysis against a few recent and similar techniques is carried out using B-CASIA gait database.

The organization of the rest of this paper is as follows: Section 2 provides a review of related works, while Section 3 introduces the principle of gait recognition approach. The proposed approach is described in details in Section 4, and we present experimental results and their analysis using CASIA database. Finally, the paper presents discussions and conclusion.

2. RELATED WORK

The overwhelming majority of the state-of-the-art approaches to gait recognition are based on hand-crafted features of body motion: pose estimations or just silhouettes. One of the most

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popular descriptors based on silhouette is Gait Energy Image (GEI) (Han and Bhanu, 2006), the average image of the binary silhouette masks of the subject over the gait cycle. After the GEI was invented many authors began proposing computation various popular descriptors from these images, for example, HOG descriptor in (Liu et al., 2012). In (Chen and Liu, 2014) the modification of GEI is proposed – frame difference energy image (FDEI). Instead of averaging all normalized silhouettes over the gait cycle, they take the difference between every pair of consecutive frames and combine it with ”denoised” GEI. Due to their report, such modification improves the metrics of quality. Zheng in (Zheng et al., 2011) applies a special feature selection algorithm called Partial Least Square regression to GEI in order to learn optimal vectors representing gait. One more approach is based on the inner model of gait computed using various measurements of the human body and motion. (Yang et al., 2016) proposes to measure relative distances between joints, their mean and standard deviation, make a feature selection and then train a classifier based on selected descriptors [2]

Ali Saadoon et al., 2015[4] proposed a method based on joint angle estimation of body motion for gait recognition is. The representation of gait feature for the motion angles of upper and lower of the body part is investigated and the joint angle is calculated using Fourier, radon and Gabor features. Based on the joint angles estimation, we build a histogram of the feature individually. In the measurement stage of distance, function is used to measure the similarity between these histograms. After that, a classifier is built to implement the stage of classification. Experiments were tested on CASIA (B) Database.

Saad M. Darwish et al., 2015 [1] proposed design of an intelligent gait recognition system that tackles the problems mentioned above. This system is based on spatial-domain energy deviation image as a gait signature by adopting a clustering technique to estimate the gait period in the gait sequence with arbitrary walking directions. To further improve the performance of the proposed system, interval type-2 fuzzy K-nearest neighbor classifier is used to diminish the effect of uncertainty formed by variations in gait signature extraction. Interval type-2 fuzzy set is involved in extending the membership values of each gait signature by using several initial K in order to handle and manage uncertainty that exists in choosing the initial value K. The proposed method realises the reduction in the dimensions of the gait feature and over-fitting. The comprehensive analyses reveal that the proposed algorithm can significantly enhance the multiple view gait recognition performance when being matched to the similar methods in the literature.

(Sokolovaa, A.Konushina 2017 [2]) work they investigate the problem of people recognition by their gait. For this task, they implement deep learning approach using the optical flow as the main source of motion information and combine neural feature extraction with the additional embedding of descriptors for representation improvement. In order to find the best heuristics, they compare several deep neural network architectures, learning and classification strategies. The experiments were made on two popular datasets for gait recognition, so they investigate their advantages and disadvantages and the transferability of considered methods .

3. RESEARCH METHOD

3.1 Proposed Scheme

The proposed work uses the gait energy image (GEI) to extract features from each frame and compose a feature sequence for the human walking sequence and also uses 2D Gabor filter method In order to compare the results in the case of use of Gabor filter or not, and uses (SVM) algorithms for the purpose of human gait recognition . Figure (1) show that .

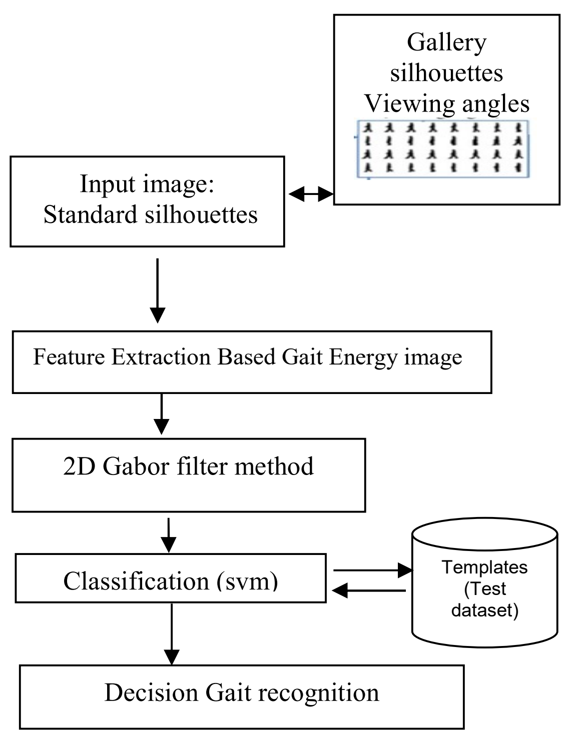

Figure 1. Human gait recognition system diagram

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3.2 Gait Energy Image (GEI)

We only consider individual recognition by activityspecific human motion, i.e., regular human walking, which is used in most current approaches of individual recognition by gait. Regular human walking can be considered as cyclic motion where human motion repeats at a stable frequency. While some gait recognition approaches extract features from the correlation of all the frames in a walking sequence without considering their order, other approaches extract features from each frame and compose a feature sequence for the human walking sequence. During the recognition procedure, these approaches either match the statistics collected from the feature sequence or match the features between the corresponding pairs of frames in two sequences that are time-normalized with respect to their cycle lengths. The fundamental assumptions made here are: 1) the order of poses in human walking cycles is the same, i.e., limbs move forward and backward in a similar way among normal people, and 2) differences exist in the phase of poses in a walking cycle, the extend of limbs, and the shape of the torso, etc. Under these assumptions, it is possible to represent the spatio-temporal information in a single 2D gait template instead of an ordered image sequence. [12]

3.2.1 Representation Construction

We assume that silhouettes have been extracted from original human walking sequences. A silhouette preprocessing procedure [5] is then applied on the extracted silhouette sequences. It includes size normalization (proportionally resizing each silhouette image so that all silhouettes have the same height) and horizontal alignment (centering the upper half silhouette part with respect to its horizontal centroid). In a preprocessed silhouette sequence, the time series signal of lower half silhouette size from each frame

indicates the gait frequency and phase information. We estimate the gait frequency and phase by maximum entropy spectrum estimation from the time series signal. Given the preprocessed binary gait silhouette images Btðx; yÞ at time t in a sequence, the gray-level gait energy image (GEI) is defined as follows:

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

where N is the number of frames in the complete cycle(s) of a silhouette sequence, t is the frame number in the sequence (moment of time), and x and y are values in the 2D image coordinate. Fig. 1 shows the sample silhouette images in a gait cycle from two people and the right most image is the corresponding GEI. As expected, GEI reflects major shapes of silhouettes and their changes over the gait cycle. We refer to it as gait energy image because: 1) each silhouette image is the space-normalized energy image of human walking at this moment, 2) GEI is the time-normalized accumulative energy image of human walking in the complete cycle(s), and 3) a pixel with higher intensity value in GEI means that human walking occurs more frequently at this position (i.e., with higher energy). Bobick and Davis propose motion-energy image (MEI) and motion-history image (MHI) for human movement type representation and recognition. Both MEI and MHI are vector-images where the vector value at each pixel is a function of the motion properties at this location in an image sequence. As compared to MEI and MHI, GEI targets specific normal human walking representation and we use GEI as the gait template for individual recognition. [12]

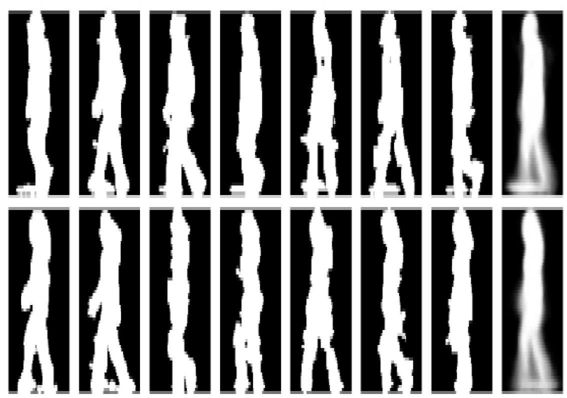

Figure 2 Examples of normalized and aligned silhouette frames in different human walking sequences. The rightmost image in each row is the corresponding gait energy [12]

3.3 Feature Extraction Based 2D Gabor filter method

The characteristics of the Gabor wavelets (filters), especially for frequency and orientation representations, are similar to those of the human visual system and are particularly appropriate for human perceptive representation and discrimination. The Gabor filters-based features, directly extracted from gray-level images, have

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been successfully and widely applied to gait recognition. However, the dimension of the Gabor feature vector is very high when multiple scales and orientations are adopted. For example, if the size of an image is 64×64, and 3 scales and 8 orientations are selected, the dimension of the Gabor feature vector will reach 98,304 (64×64×3×8). It is difficult to calculate such a high dimension feature vector [13] [14]. Therefore, in this paper, we propose an improved scheme for the feature extraction of gait images. The improved methods use 2D Gabor filter method of [15].

In our proposed method, they are applied The 2-D Gabor function is described by the following equations:

$$g_{\lambda,\theta,\varphi,\sigma,\gamma}(x,y) = \exp\left(\frac{x'^2+\gamma^2 y'^2}{2\sigma^2}\right)\cos\left(\frac{2\pi x'}{\lambda}+\varphi\right), \quad (2)$$

$$x' = x\cos\Theta + y\sin\Theta,$$

$$y' = -x\sin\Theta + y\cos\Theta.$$

λ(which is set to 3.5) is the wavelength of the sinusoidal factor, Θ is the degrees of orientation of the filter, φ is the phase, σ is the standard deviation of the Gaussian envelope, and γ is the aspect ratio [9, 19].

A Gabor-based approach is widely used for the feature extraction in biometric applications, such as iris, face, fingerprint and palmprint recognition [16]. By applying the tuning process to a training set consisting of grey-level images,

The optimum parameters chosen for the Gabor filter in this study (determined by measurements of root mean square error (RMSE), standard deviation (SD), and entropy, are as follows: the filter is set to a 10x10 size with a given$ktype$ (a classification of type and range of values (0-255) at each position in the Gabor kernel). The orientation angles (θ), 0, 90, 180 and 270 degrees are considered, with γ=1.25, ψ=0, λ=3.5, and a bandwidth value of 2.8 (ratio of standard deviation of the Gaussian function and the preferred wavelength).[17]

3.4 Support Vector Classification

Originating from statistical learning theory (Vapnik and Vapnik, 1998), and first implemented in (Cortes and Vapnik, 1995), support vector machines (SVMs) are recognized as among the most efficient and powerful supervised machine learning algorithms (Byun and Lee, 2002). An SVM attempts to determine an optimal separating hyperplane between two sets of labeled training data.

An SVM is trained based on a set consisting of n samples, of the form ($\sim x_1$, y_1) ,..., ($\sim x_n$, y_n) where each vector $\sim x_i$ is m-dimensional, containing input features, and each yi is labeled either +1 or −1 according to the class to which the vector $\sim x_i$ belongs. If possible, the SVM will find a hyperplane that divides the set of $\sim x_i$ labeled y_i = +1 from those labeled yi = −1. The SVM-generated hyperplane will be optimal, in the sense that it will the maximize the margin, where "margin" is defined as the minimum distance between the hyperplane and any sample $\sim x_i$ in the training set. In general, the training data will not be linearly separable, that is, no separating hyperplane will exist in the input space. In such cases, we can use a nonlinear kernel function to transform the data to a higher dimensional feature space, where it is more likely to be linearly separable (or at least reduce the number of classification errors). The so-called kernel trick enables us to embed such a transformation within an SVM, without paying a significant penalty in terms of computational efficiency. In our case, each input sample consists of a 4- dimensional feature vector and its corresponding label, while the desired output value is a label of 0, 1, or 2, which specifies the subject. After feature regularization, an optimal hyperplane boundary is determined by training an SVM classifier. We use a one-vs-one scheme for this multi-class classification problem, in which each class is individually compared to every other class, as opposed to a one-vs-all scheme.2 Additional testing examples are classified to determine the accuracy of the resulting classification scheme [18]

3.5 Results and Analysis

The experiments are implemented on the publicly available CASIA gait database (dataset B) [19], which is a multi-view gait database. This database was constructed from 124 subjects (93 men and 31women) and 11 cameras around the left-hand side of the subject when they were walking. Thus, the data were captured from 11 different angles starting from 0◦ to 180◦ (i.e., the angle between two nearest view directions is 18◦ in the range of [0o, 180o]). Each subject has six normal walking sequences (Set A), two carrying-bag sequences (Set B) and two wearing-coat sequences (Set C). For our experiments, we have selected

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from this database the three first sequences from Set A and the first sequence from Set B and Set C to test the performance of the proposed method under the following three conditions: normal, carrying-bag and wearing-coat. The remaining sequences for all the 124 subject were assigned to the training set. Experiments are carried out under the following viewing angles: 0◦, 18◦, 36◦, 54◦, 72◦, 90◦, 108◦, 126◦, 144◦, 162 and 180◦.

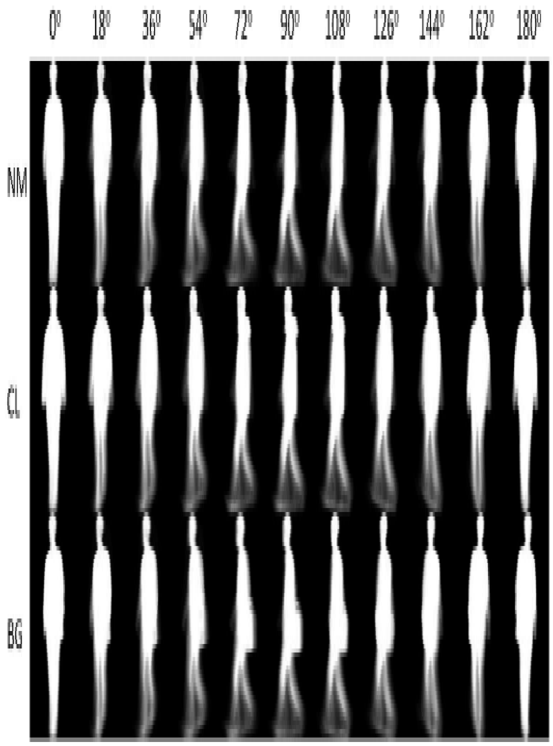

Figure 3 Examples for all views in CASIA gait database (dataset B) [19]

In order to compare the performance of different gait recognition algorithms, the correct classification rate (CCR) is used as an evaluation index [20]

in the first experiment, we created two training sets. The first is based on GEI, and the second is based on GEI that undergoes a data filtering process by Gabor Filter. Then, we chose the parameters of the transform according to study [17], Next, we tested the Algorithm according to the varied value of theta: 0, 90, 45, 270, 225, 180, and 135, to get the ideal values according to the application we are working on. This comparison is shown in Table (1), Figure 4, and it shows that the best values are when (θ)=225.

Table 1: the correct classification rate (CCR) for GEI + Gabor filter algorithm in CASIA database for side view 180◦, with Gabor filter parameter Kernel=2, γ=1.25, ψ=0, λ=3.5, and a bandwidth value of 2.8..

theta (Θ)	CCR (%)
0°	79.35
45°	78.79
90°	79.51
135°	79.35
180	78.54
225°	79.83
270°	79.35

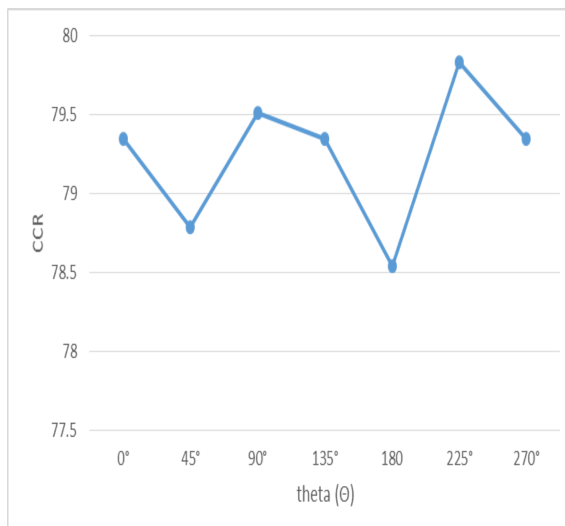

Figure 4: the correct classification rates (CCRS) for GEI + Gabor filter versus theta (Θ)

In the second experiment (GEI+Gabor filter), we tested the Kernel position on the values 1,2,3, 4,5,6.7,8, 9, and Kernel equals 3,2 was the ideal value as shown in Table (2), Figure 6, Figure 7.

We also note that there is a match between the performance ratios at the values of the kernel 2 with 3, 4 with 5, 6 with 7, 8 with 9, and at the value of the kernel equals 1, it gives the same performance (GEI) without the Gabor filter.

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TABLE 2: THE CORRECT CLASSIFICATION RATE (CCR) FOR GEI + GABOR FILTER ALGORITHM IN CASIA DATABASE (DATASET B), WITH GABOR FILTER PARAMETER THETA = 225, γ=1.25, ψ=0, λ=3.5, AND A BANDWIDTH VALUE OF 2.8 KERNEL VALUES

view	*kernel* **1**	*kernel* **2**	*kernel* **3**	*kernel* **4**	*kernel* **5**	*kernel* **6**	*kernel* **7**	*kernel* **8**	*kernel* **9**
0°	78.38	76.08	76.08	53.38	53.38	68.95	68.95	77.17	77.17
18°	73.95	73.9	73.9	51.20	51.20	60.00	60.00	70.64	70.64
36°	70.24	70.68	70.68	51.20	51.20	54.91	54.91	67.58	67.58
54°	75.08	76	76	50.96	50.96	57.17	57.17	72.09	72.09
72°	74.11	74.95	74.95	51.61	51.61	53.95	53.95	70.32	70.32
90°	77.66	78.1	78.1	56.04	56.04	59.67	59.67	72.74	72.74
108°	75.25	75.68	75.68	53.62	53.62	57.66	57.66	69.51	69.51
126°	76.45	77.13	77.13	51.69	51.69	54.35	54.35	68.87	68.87
144°	78.70	79.23	79.23	51.93	51.93	53.54	53.54	71.20	71.20
162°	79.19	79.79	79.79	52.82	52.82	57.58	57.58	73.70	73.70
180°	81.69	80.03	80.03	51.45	51.45	57.50	57.50	78.46	78.46
Mean	76.42	**76.50**	**76.50**	52.35	52.35	52.75	52.75	72.02	72.02

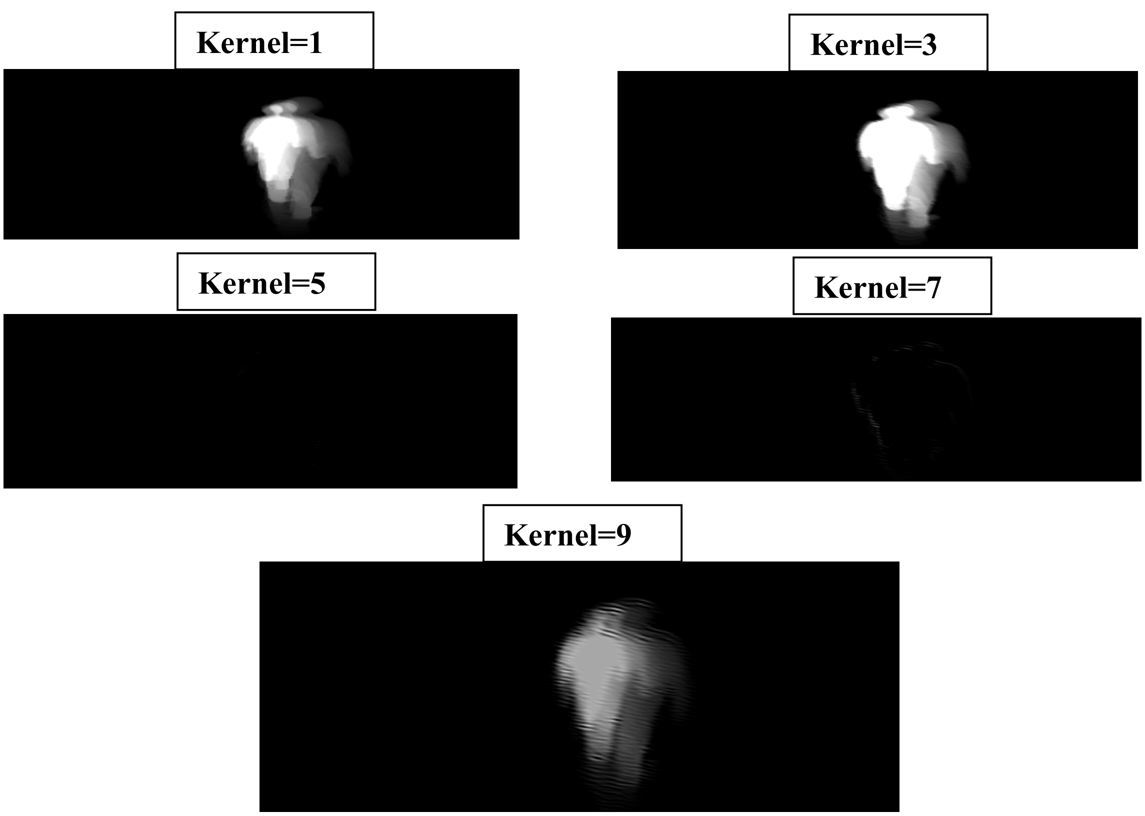

Figure 5: image example Gabor filter versus kernel values

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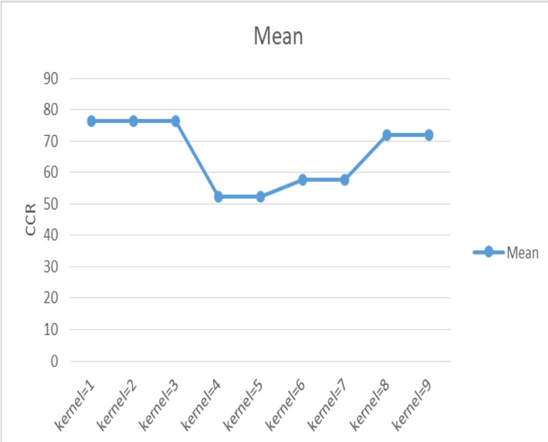

Figure 6: the means for the correct classification rates (CCRS) for GEI + Gabor filter versus kernel values

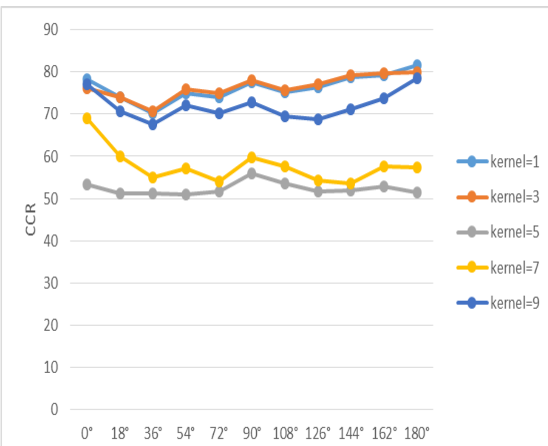

Figure 7: the correct classification rates (CCRS) for GEI + Gabor filter versus kernel values for all views

After choosing the ideal values when (θ)=225 and Kernel =3, we made a comparison between the performance of recognition algorism on both training sets. The first is based on GEI, and the second is based on GEI that undergoes a data filtering process by Gabor Filter as shown in Table (3) , Figure 8. The analysis of comparison results shows that the best performance of Set 1 based on GEI when (θ)=0, 180, and 18, whereas the performance of Set 2 base on GEI+Gabor Filter when (θ)=16, 144, 126, 108, 90, 72, 54, and 36. By comparing of the performance average, the GEI is optimum; and GEI+Gabor Filter has better performance when the number of angles (θ) is more.

Also, the performance of the proposed systems is compared with other methods shown in table 4.

TABLE 3: COMPARING THE CORRECT CLASSIFICATION RATE (CCR) FOR PROPOSED METHODS ON CASIA DATABASE (DATASET B) FOR ALL SIDE VIEW THE CORRECT CLASSIFICATION RATE (CCR)

view	Gait energy image (GEI)	GEI + Gabor filter
0°	78.38	76.08
18°	73.95	73.9
36°	70.24	70.68
54°	75.08	76
72°	74.11	74.95
90°	77.66	78.1
108°	75.25	75.68
126°	76.45	77.13
144°	78.70	79.23
162°	79.19	79.79
180°	81.69	80.03
Mean	76.42	**76.50**

TABLE 4: CORRECT CLASSIFICATION RATE (CCR) FOR VARIOUS OTHER METHODS AND PROPOSED METHOD

Approaches	CCR (%)
Bouchrika, et al. [27]	73.4
Khalid Bashir [22]	55.0
Proposed methods	
Gait Energy Image (GEI)	76.42
GEI + Gabor filter	**76.50**

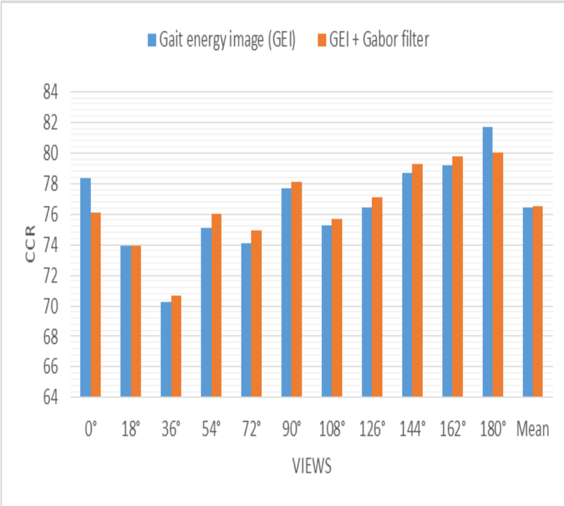

Figure 8: Comparing the correct classification rate (CCR) for proposed methods on CASIA database (dataset B) for all side view

In the third experiment, we made a performance comparison on a group of previous studies in the same field according to CASIA database (dataset B) for side view 90 in order to test the positions of normal-walking, wearing-coat, and carrying-bags, as shown in Table (5), Figure 9. This shows that the algorithm performance achieved 78.10%, which is better than the concerned previous studies ratios. This indicates the optimum of the present system with noticeable quality and efficiency on the ideal training sets samples, which had a great impact on reaching this good percentage.

We also compared the performance of our proposed methods to the positions of normal walking, wearing-coat, and carrying-bags, as shown in Figure10.

TABLE 5: COMPARING THE PROPOSED METHODS WITH DIFFERENT STATE-OF-THE-ART METHODS ON CASIA DATABASE (DATASET B) FOR SIDE VIEW 90◦

Variable	Normal walking	Carrying-bag	Wearing-coat	Mean
Bashir et al. [21]	97.50	83.60	48.80	76.60
Bashir et al. [22]	100	78.30	44.00	74.10
Hu et al. [23]	94.00	45.20	42.90	60.70
Ait et al (RELIEF/V)[5]	78.50	69.35	67.00	71.67
Dupuis et al. [24]	97.60	73.80	62.50	77.96
Yu et al [25]	97.60	52.0	32.7	60.76
Han et al.[26]	99.4	60.2	30.0	63.2
Proposed methods				
Gait Energy image (GEI)	79.36	79.03	74.59	77.66
GEI + Gabor filter	79.83	78.67	75.80	**78.10**

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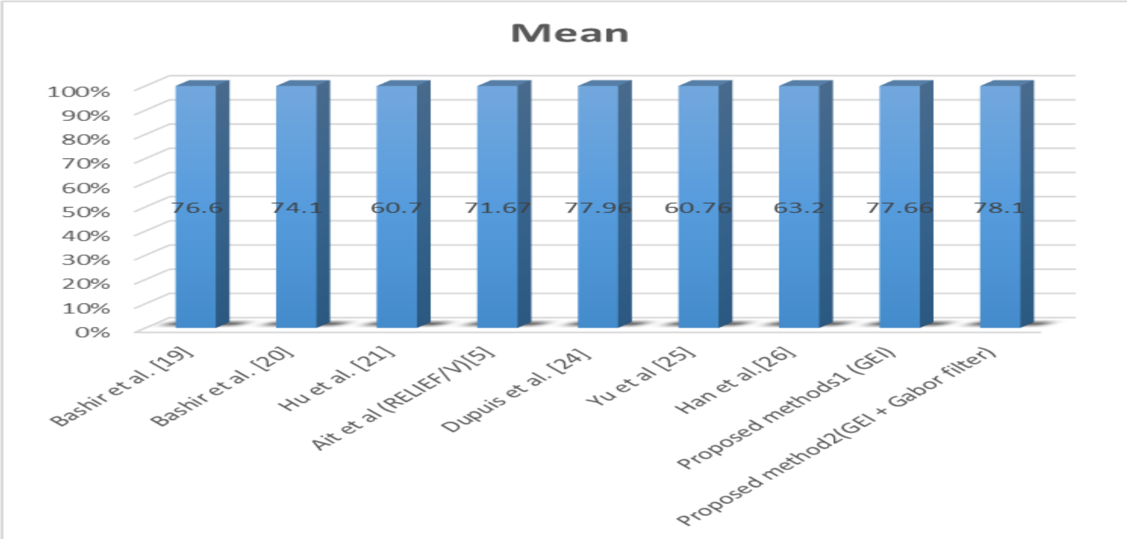

Figure 9: Comparing the proposed methods with different state-of-the-art methods on CASIA database (dataset B) for side view 90

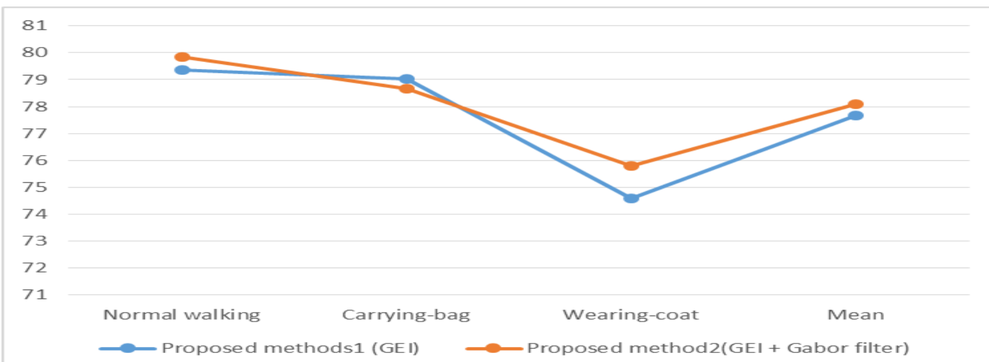

Figure 10: Comparing the stats (normal walking, carrying bag, wearing coat)for proposed methods on CASIA database (dataset B) for side view 90◦

4. DISCUSSIONS AND CONCLUSIONS:

Many research studies concentrated recently on the process of human gait recognition due to the need for this kind of recognition, which is considered as the solution to many recognition cases in which there are difficulty and inability to use the other biometrics. Therefore, we built a human gait recognition system based on the distinguishing features of personal human gait series, using (GEI)+Gabor Filter to get a good enhancing for the training sets samples and to develop the algorism performance. This method is considered very good for getting a better recognition of human gait.

Through this paper, we made comparisons to the two training groups , first whose features were extracted using the (GEI) method, the second using (GIE + GABOR FILTER). The results showed that the (GIE + GABOR FILTER) method gave better results than the first. This was done by calculating the average performance at all side view on the dataset (B-CASIA database) which reached 76.50% while (GEI) achieved 76.42% and can be seen in Table 3, Figure 8. This ratio is considered to be the best performance compared to previous studies (see Table 4).

And also we made a performance comparison on a group of previous studies in the same field according to B-CASIA database for side view 90 in order to test the positions of normal-walking, wearing-coat, and carrying-bags, as shown in Table 5, Figure 9 , Figure 10. This shows that the (GIE + GABOR) algorithm performance achieved 78.10%, which is better than the previous studies ratios

At the beginning of the results, the paper worked on the search for the ideal values Gabor filter, which increases the efficiency of the performance of the system, where the comparisons of a set of values of theta 'and kernel values were search to values gave the results were better than the first way. This was done at for Gabor filter parameters for our system is kernel =3 ,theta = 225 , γ=1.25, ψ=0, λ=3.5, and a bandwidth =2.8 (see Table 1, Table 2 , Figure 4, Figure 6).

Through these results we can point to the importance of using the gabor filter for researchers, which can provide an improvement in the quality of the image, which contributes to the improvement of the quality of performance, and the process of selecting gabor filter parameter very carefully, according to the application used because the results indicate that Optimizing values may vary from one application to another.

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