International Journal of Current Advanced Research
ISSN: O: 2319-6475, ISSN: P: 2319-6505, Impact Factor: SJIF: 5.995
Available Online at www.journalijcar.org
Volume 7; Issue 3(E); March 2018; Page No. 10736-10742
DOI: http://dx.doi.org/10.24327/ijcar.2018.10742.1834

Research Article

EFFICIENT IRIS RECOGNITION SYSTEM BASED ON CONTOURLET AND GABOR FEATURES

Susitha N.[1] and Ravi Subban[2]

[1]Mother Teresa Women's University, Kodaikanal, Tamilnadu, India
[2]Department of Computer Science, School of Engineering and Technology, Pondicherry University, Pondicherry, India

A R T I C L E I N F O

Article History:

Received 9th December, 2017
Received in revised form 6th January, 2018 Accepted 20th February, 2018
Published online 28th March, 2018

Key words:

Iris recognition, biometrics, feature extraction.

A B S T R A C T

Biometrics based security applications are one of the evergreen research areas. Irrespective of the presence of several biometrics, iris sets mark owing to its permanence and constancy. Understanding this fact, this work proposes to employ iris as the barricade to access services. When a iris image is passed on to the proposed iris recognition system, the iris image is segmented by integro-differential operator and the contrast of the image is enhanced by histogram equalization technique. The contrast enhanced image is then normalised by Daugman's rubber sheet model and the contourlet, gabor features are extracted. Finally, Extreme Learning Machine (ELM) is employed to match the test iris image with the trained feature set. When the images match with each other, the access is granted else denied. The performance of the proposed approach is tested in terms of accuracy, sensitivity, specificity and time consumption over four iris databases. However, the performance of the proposed approach is stable and consistent.

INTRODUCTION

Due to advancement of technology, the usage of digital data is exponentially increasing. Hence, most of the mid and small scale industries find it difficult to manage the complete database, as it incurs heavy expense. For instance, there is a strong requirement for getting voluminous expensive data storage equipments, in order to store huge data. Besides this, the process of data management gets tougher and is directly proportional to the data growth. This point makes the industries to opt for data outsourcing in which the data is transferred to the external cloud storage, which in turn overthrows the need to upgrade storage equipments. However as the data is outsourced, several security threats such as data steal, data tamper come into picture.

In order to sustain these security attacks, strong security mechanisms are needed to be incorporated. For this sake, several security mechanisms are presented in the existing literature. Out of all these techniques, biometric enforced security mechanisms are quite efficient, as they are unique and reliable. Biometrics based security attempts to provide security to an application by taking the biological characteristic features of an individual. Some of the notable biological traits are face, fingerprint, palmprint, voice, signature and so on. The major advantage of a biometric based security application is that the biological trait of a person cannot be duplicated and is static for lifetime.

Corresponding author:* **Susitha N.
Mother Teresa Women's University, Kodaikanal, Tamilnadu, India

This article intends to enforce an iris based security mechanism, as features of iris remain static unlike other biometrics. For instance, the human face may get changed due to some accidental issues, the signature may change over time and voice may sound different due to illness or emotions. Unlike other biometrics, iris is observed to be the constant at all times. This increases the reliability of the system, yet there are plenty of challenges placed in front of iris based security mechanism. The major challenges involved are extracting iris from the complicated eye structure is a crucial challenge and the iris recognition rates may be affected by illumination conditions.

Taking all these factors into account, an iris based security mechanism which recognizes the identity of the individual and provides access to the data. To achieve this goal, the proposed work segregates the complete work into five phases, which are iris image acquisition, segmentation, normalization, enhancement, feature extraction and classification. All these phases have a preset goal and unitedly work towards achieving the central goal of the work. The highlighting points of this work are listed below.

- Iris is the most reliable biometric, as it never changes over time.
- The iris is segmented by employing integro-differential operator and the contrast of the iris is enhanced by histogram equalization techniques.
- The contourlet and gabor features are extracted from the normalized and contrast enhanced image.
- This feature vector acts as the key part of recognition phase and the Extreme Learning Machine (ELM)

classifier is employed to distinguish between different iris images.

- The performance of the proposed approach is tested over four different iris datasets and the efficiency of the proposed work is justified.

The remainder of the paper is organised as follows. Section 2 presents the related review of literature with respect to iris recognition. The proposed iris recognition approach is elaborated in section 3. The performance of the proposed approach is evaluated against several existing techniques and the results are presented in section 4. The concluding remarks of the paper are presented in section 5.

REVIEW OF LITERATURE

This section presents the state-of-the-art review of related literature with respect to iris recognition.

In [1], an algorithm is proposed to recognize iris by employing phase based mapping technique. The mapping technique utilizes the phase components over two dimensional Discrete Fourier Transform (DFT). The experimental procedure is carried out on CASIA iris image dataset and the results prove that the phase components of iris images work better in improving the recognition rates. However, the performance of the proposed approach is tested on a single dataset. An edge map based iris recognition system is proposed in [2]. This work computes Hausdorff distance between the binary edge maps of the iris images. The performance of this work is justified by carrying out experiments on UPOL iris images by varying the size of image blocks.

An iris recognition system for video frame is proposed in [3], which fuses at the signal level. This work forms a single iris image from different frames of iris video. The performance of the proposed approach is compared with the standard score level fusion techniques such as Ma, Krichen and Schmid. However, this work is meant for iris image video. In [4], an iris recognition system based on random projections and sparse representation is proposed. This work undergoes a real time iris image acquisition and processes them. As this work acquires images in a live fashion, the process of segmentation is handled by itself. However, this work suffers from computational complexity.

Most of the iris recognition systems utilize texture feature of iris for effective recognition and the texture features are represented by binary iris codes. Many techniques exclude the fragile bits from consideration but, this work extracts some useful information from it. The fragile bit distance is proposed and the consistency of fragile bits is measured in [5]. Finally, the combination of fragile bit distance and hamming distance is utilized and score level fusion takes place. In [6], an iris recognition system is proposed for ensuring user authentication. This work detects the eyelashes by means of directional filters and the edge effect of wavelets is reduced by combining the multiscale and multidirectional transform. The iris indexing technique is presented by considering the eye corner. However, this work suffers from time and computational complexity.

The dynamic features of iris are detected in [7], which captures the pupil of an eye image with near infra-red radiation and the next pupil with visible light pulse. Hence, dynamic features of the iris image can be extracted and this work can be used to analyse the response of human eye to different illumination and for security purposes as well. A kernel based iris recognition system is proposed in [8], which exploits multiclass kernel fisher analysis based features. The SVM classifier is employed for grouping related features together. The final classification is attained by Hidden Markov Model (HMM). However, this work can prove its efficiency provided a large set of features are utilized, which in turn increases the space and computational complexity.

In [9], an iris recognition technique based on local consistency and global weight map of the iris bits is proposed. The iris features are represented by zernike moment based phase encoding technique. The zernike features are computed from the normalized iris images. The performance of this approach is tested over three different databases. The iris image normalization model is proposed in [10], which performs normalization by radial strips. CASIA V3 dataset is utilised for testing the functional efficiency of the proposed approach. An iris detection system based on local binary descriptors is proposed in [11]. This work three different local binary descriptors such as BRIEF, ORB and BRISK and the performance of these descriptors are compared in terms of efficiency, memory and time consumption.

In [12], an iris recognition system based on pupil dilation between the template and the test images. This work claims that the accuracy of an iris recognition system is improved, when the pupil dilation is taken into account. Several images are captured and the median dilated image is chosen as the template. The performance of this approach is observed to be optimal. In [13], an iris recognition system based on optimized iris codes is presented. The iris codes are optimized by introducing two different objective terms. The first objective term utilizes the spatial relationship between the bits in various positions of the iris. The second objective term reduces the influence of the fragile bits. These objective terms can be utilized in single or combined.

An iris recognition system based on geometric key is proposed in [14]. The geometric keys are produced in a random fashion and allotted to each and every template of the system. It is claimed that the scaling and rotation changes does not affect the quality of the system. The similarity computation is attained by hamming distance. The performance of this approach is tested over three public iris databases.

In [15], an iris recognition approach that combines both hardware and software is presented. In the hardware perspective, this work utilizes wavefront coding and the software aspect of the system employs super-resolution technique for good image quality. In [16], a automatic recognition system of iris images is presented. The proposed protocol is applied in two different approaches, where one employs SVM and the other utilizes Convolutional Neural Networks (CNN). This work concludes that the performance of SVM is better than CNN.

After thorough study, it is observed that most of the existing approaches suffer from computational, time and space complexity. In addition, the performances of most of the works are tested upon limited databases. Motivated by these works, the proposed approach intends to present a reliable and promising iris recognition system that can assure better accuracy rates. The proposed approach is elaborated in the coming section.

Proposed Iris Recognition System

This section describes the working nature of the proposed iris recognition approach along with the overall flow of the work.

Overall flow of the work

The central goal of this work is to present a reliable iris recognition system with better accuracy rates. In order to achieve the goal, the proposed approach is subdivided into several individual phases and they are iris image acquisition, segmentation, enhancement, feature extraction and iris matching. The iris images are acquired from different iris databases, where the nature and quality of an iris database differ from each other. The acquired iris images are segmented by means of integro-differential operator and the contrast of the segmented images is enhanced by histogram equalization technique. The reason for the choice of integro-differential operator to perform segmentation is its simplicity and effectiveness.

The segmented image is normalized, so as to standardize the view of the segmented portion. The contrast of the segmented images is then enhanced by means of histogram equalization technique. The histogram equalization technique is known for its simplicity and efficiency. The histogram equalization technique preserves the edge, while enhancing the contrast of the iris images. The contourlet and the gabor features are then extracted from the contrast enhanced iris images. The overall flow of the work is depicted in figure 1.

Contourlet is a multidirectional technique that minimizes the redundancy and increases the processing speed. Gabor filter can work effectively in not only in spatial domain, but also in frequency domain. Gabor filters end up with richer texture features as well.

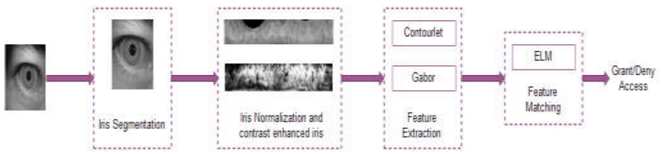


Fig 1 Overall flow of the proposed approach

The classifier ELM is trained with the so formed feature vector and is capable of differentiating between different iris images. The performance of the proposed approach is tested over different iris databases and the proposed iris recognition system proves its efficacy in all cases. The following sections present the detailed description of the proposed approach.

Iris image acquisition

The iris images are acquired from the standard datasets such as CASIA V1, V2, V3, Ubiris V2 datasets. The CASIA V1 dataset contains 756 images of iris extracted from 108 eyes. Seven different images are captured for every eye and the image resolution is about 320×280. The CASIA V2 dataset is comprised of about 2400 iris images with resolution 640×480. The CASIA V3 dataset possesses three subclasses such as Iris-interval, Iris-lamp and Iris-twins. The proposed work is tested on Iris-interval and Iris-lamp versions of the dataset. The iris-interval images and iris-lamp images are captured by a short distance camera and hand-held iris sensor respectively. All these datasets are downloaded from the link [17]. The Ubiris V2 dataset can be downloaded from [18], which contains about 522 iris images.

Iris image segmentation

As soon as the images are acquired, the aim is to localize iris and to segment it. The iris images are segmented by integro-differential operator, which can locate the boundary of pupil and iris regions effectively. The integro-differential operator works in a circular fashion by means of gradients over a particular centre point and radius. The gradients of the iris image are computed by considering the circumference of all possible circles that can be formed in the image. The circumference with greater value is recognized as the outer border of the iris region. The partial derivatives are maximized by considering the radius of the circle and it increases with the amplitude. Initially, the boundaries of pupil, limbic and eyelids are located by means of

$$ID_o = max_{rad,p_0,q_0} \left| GS_\sigma(rad) \times \frac{\partial}{\partial_{rad}} \oint_{rad,p_0,q_0} \frac{GI(p,q)}{2\pi rad} ds \right| \quad (1)$$

In the above equation, rad is the radius, $GI(p,q)$ is the greyscale image, $GS_\sigma(rad)$ is the Gaussian smoothening function with σ as scale and p_0, q_0 is the centroid of the circle. The integro-differential operator performs well for the images with good contrast.

Contrast enhancement and normalization

The contrast of the segmented iris images is enhanced by histogram equalization technique. This process results in the improvisation of the final results. When the image contrast is enhanced, several minute details of the images can be observed easily. The image contrast is enhanced by means of adjusting the gray levels of the pixels, such that uniformity is attained. When this process is repeated for all pixels, the image contrast is increased. The histogram is computed by considering different gray level intensities of an image from 0 and 255. Each and every pixel is treated for enhancing the contrast and is achieved by

$$HE = \sum_{pi=1}^{l} \frac{s_p}{T_p} \quad (2)$$

In the above equation, s_p is the total number of pixels with the intensity kp_i and T_p is the total count of pixels in an image. This operation uniformly distributes the gray level and enhances the image contrast. These contrast enhanced iris images are then normalized by Daugman's rubber sheet model [19].

Contourlet and Gabor feature extraction

Contourlet is superior to curvelets, as it can deal with both continuous and discrete kinds of images. Contourlet is a multidirectional, multiresolution transformation that operates over the discrete domain. Multiresolution is a special ability of a transformation, which makes it possible to process all the digital images, irrespective of its resolution. Multidirectionality is another important characteristic feature of a transformation, which can function over different directions of a particular scale. The contourlet is multidirectional, as it supports iterated filter banks and it satisfies multiresolution as well.

The functionality of contourlet relies on Laplacian Pyramid (LP) and Directional Filter Bank (DFB). The DFB is focuses on high frequency components and hence, the components with low frequency are excluded from consideration. When a sample image $a_0[n]$ is fed to LP, R different bandpass images are obtained as follows.

$$b_r\,[n]; r = (1,2,3,\dots,R) and\ a_r[n] \quad (3)$$

In the above equation, r denotes the image with different textures right from coarseness to fine images and $a_r[n]$ is the lowpass image. This makes sense that the image $a_{r-1}[n]$ is divided into coarse and fine images as represented by $a_r[n]$ and $b_r[n]$. All the bandpass images are again decomposed with the degree d_r to 2^{d_r} directional images, as represented as

$$a_r^{(d_r)}[n]; k = (0,1,\dots,2^{d_r} - 1) \quad (4)$$

By this way, the contourlet is applied over the iris images and the features are extracted.

Gabor filters are efficient in extracting texture features from the images and it minimizes the joint ambiguity in spatial and frequency domains. The gabor filter is generated by

$$gf(a,b) = \frac{1}{2\pi\sigma_a\sigma_y}\ exp\left[-\frac{1}{2}\left[\frac{a^2}{\sigma_a^2} + \frac{b^2}{\sigma_b^2}\right] + 2\pi M_a\right] \quad (5)$$

M_a is the modulation frequency. The gabor filters are created in different angles and is denoted by

$$g_{st}(a,b) = x^{-sc} g(a', b') \quad (6)$$

Where $a' = x^{-sc}(a\ cos\theta + b\ sin\theta)$ and $b' = x^{-sc}(-a \sin\theta + b\cos\theta); x > 1$. The θ is given by $\theta = \frac{ont\pi}{ONT}; ont = 0,1,2,\dots,ONT - 1$ and $sc = 0,1,2,\dots,SC - 1$.

In the above equations, $ont\ and\ sc$ are the orientation and scale of the gabor respectively. This work considers the gabor with varying sizes such as 3×3, 5×5, 7×7, 9×9 and value of θ is varied as 15°, 45°, 75°, 135° and 180°. The contourlet and gabor features are extracted and the feature vector is formed. The ELM classifier is trained with the extracted features and the classifier can distinguish between different irises.

ELM classification

ELM is one of the promising classifiers with quicker learning capability [20]. The classifier can perform its function, when it undergoes two significant phases such as training and testing. The training phase involves the process of learning and knowledge gaining through feature vectors. With the gained knowledge, the classifier is equipped to differentiate between the iris images in the testing phase.

Let there be A_{TS} training samples as denoted by (s_i, t_i), where $s_i = [s_{i1}, s_{i2}, s_{i3}, \dots, s_{in}]^T \in D^n$, where s_i is the i^{th} training entity having n dimensions. $tk_i = [tk_{i1}, tk_{i2}, tk_{i3}, \dots, tk_{im}]^T \in D^m$. that represents the i^{th} training label with m dimensions. Here, 'm' is the number of classes. This is followed by the construction of a Single hidden Layer Feed-Forward Neural Network (SLFN) with an activation function $act(x)$ having NR neurons. The following equation represents the same by

$$\sum_{i=1}^{NR} \mu_i (wt_i . s_i + c) = r_j; j = 1,2,\dots,n \quad (7)$$

In the above equation, wt_i is the weights as given by $wt_i = [wt_{i1}, wt_{i2}, \dots, wt_{in}]^T$ and it interconnects the i^{th} hidden neuron with the input neurons and i ranges from $[i1, i2, \dots, im]^T$. The weight vector is responsible for linking the i^{th} hidden neuron to the output neurons through the bias $(bias_i)$ of the i^{th} hidden neuron. The following equation represents the SLFN.

$$\sum_{i=1}^{NR} \mu_i act(wt_i . s_i + bias_i) = tk_i; i = 1,2,\dots,n \quad (8)$$

Consider HDL as the hidden layer output matrix of the classifier, so the i^{th} column of HDL contains the i^{th} hidden neurons output vector with respect to the input $s_{i1}, s_{i2}, \dots, s_{in}$.

$$HDL = \begin{bmatrix} act(wt_1 . s_1 + bias_i) & \dots & act(wt_{NR} . s_1 + bias_G) \\ \vdots & \vdots & \vdots \\ act(wt_1 . s_n + bias_i) & \dots & act(wt_{NR} . s_n + bias_G) \end{bmatrix} \quad (9)$$

$$\mu = \begin{bmatrix} \mu_1^T \\ \vdots \\ \mu_{NR}^T \end{bmatrix} \quad (10)$$

$$TK = \begin{bmatrix} tk_1^T \\ \vdots \\ tk_n^T \end{bmatrix} \quad (11)$$

This can be written in matrix format as

$$HDL\mu = TK \quad (12)$$

The output weights are calculated by the norm least-square solution by

$$\mu = HDL^{\dagger} TK \quad (13)$$

In the above equation, the Moore-Penrose generalized inverse of HDL is represented by $HDL^{\dagger}$. The pre-requirements of ELM training includes class count m, activation function $act(x)$, NR hidden neurons. During the knowledge gaining phase, the ELM is provided with a training set $Tr_{set} = \{(s_i, t_i) | s_i \in D^n, t_i \in D^m; i = 1,2,\dots,N\}$. The training process is done by performing the operation as in equation 13.

During the process of testing, the test image is carried out with all the preliminary processes, as discussed earlier. The feature vector of the test image is matched against the templates stored in the train set and based on the similarity, the user is provided or denied with the service.

Hence, the objective of the work is attained by incorporating rich features and thereby discriminating between the iris images. This work consumes lesser period of time, as there is no complex computations are involved in the entire process. However, the proposed approach ensures the reliability and accuracy and the performance of this work is analysed in the forthcoming section.

RESULTS AND DISCUSSION

The performance of the proposed iris recognition system is evaluated over four different datasets and the proposed approach works in a consistent fashion on all datasets. Hence, this work is claimed to be promising and reliable. The experimental procedure is carried out in MATLAB environment on a stand alone computer with 8 GB RAM and i7 Processor. The performance of the proposed approach is tested in terms of recognition accuracy, sensitivity and specificity.

$$Seg_{acc} = \frac{TP+TN}{TP+TN+FP+FN} \times 100 \quad (14)$$

The sensitivity and the specificity of the proposed segmentation algorithm are measured by

$$Seg_{sen} = \frac{T_p}{T_p+F_n} \times 100 \quad (15)$$

$$Seg_{spe} = \frac{T_n}{F_p+T_n} \times 100 \quad (16)$$

The greater the sensitivity rate, the lesser is the false negatives. Similarly, the greater the specificity rate, the lesser is the false positives. Attaining maximum accuracy rates is a bit easier than to achieve greater sensitivity and specificity rates. When an iris recognition algorithm proves maximum sensitivity and specificity rates, then that algorithm is proven to be reliable. The experimental procedure of this work is carried out in three different aspects. The segmentation, feature extraction and classification techniques are varied and the performance of the proposed approach is tested. Additionally, the performance of the proposed iris recognition system is compared against the existing techniques.

Results attained by the proposed approach

This section presents the visual results of the proposed approach with respect to iris image segmentation and normalization.

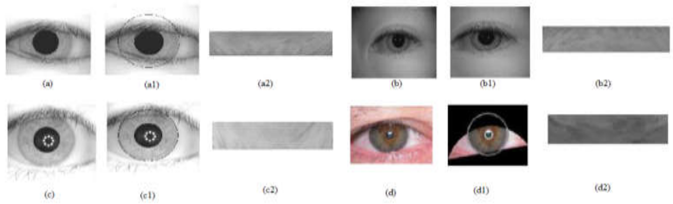


Fig 2 (a-d) Original iris images from CASIA V1, V2, V3, Ubiris V2, (a1-d1) Iris segmented images (a2-d2) Normalized iris

Fig 3 Decision of the system

Figure 3 presents the final decision of the system in granting or denying the service.

The visual results of the proposed approach are shown in figure 2. The following section presents the detailed comparative analysis of the proposed approach in terms of accuracy, sensitivity, specificity and time consumption.

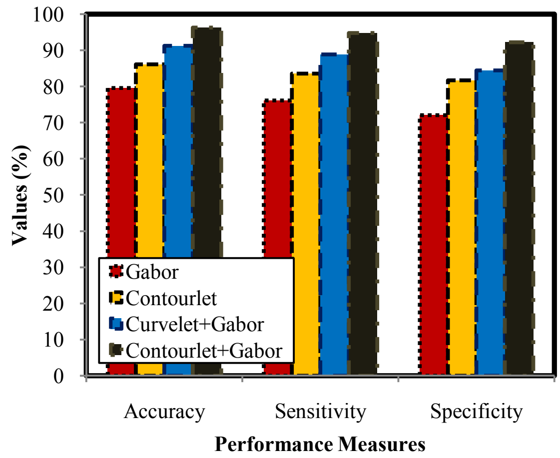
Performance evaluation by varying segmentation techniques

Segmentation is the most important process, as it forms the foundation for the future processes such as feature extraction and recognition. In order to check the efficiency of the segmentation, this work compares the performance of segmentation techniques such as segmentation algorithm presented in [21] and integro differential operator based segmentation. The performance of these segmentation techniques are compared in terms of performance metrics such as segmentation accuracy, sensitivity, specificity and time consumption. The experimental results attained by different segmentation techniques are tabulated in table 1. The experimental evaluation is carried out by incorporating the previously proposed morphological operation based segmentation [21] and the integro differential based segmentation into the proposed contourlet + gabor feature extraction technique and ELM based classification.

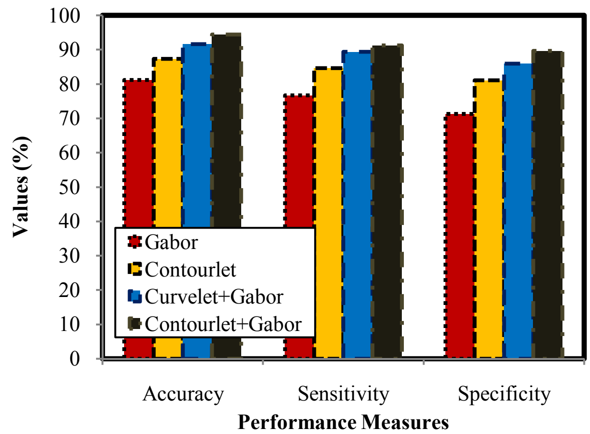
Table 1 Experimental Results w.r.t. different segmentation techniques

Image Database	Accuracy (%)		Sensitivity (%)		Specificity (%)		Time (ms)	
	IDO	**[21]**	**IDO**	**[21]**	**IDO**	**[21]**	**IDO**	**[21]**
CASIA Iris V1	96.3	99.6	94.8	96.2	92.3	94.8	1298	1083
CASIA Iris V2	94.4	97.3	91.2	93.6	89.6	92.6	1876	1464
CASIA Iris V3	96.1	98.2	90.2	93.7	89.9	94.3	1767	1383
Ubiris V2	93.8	96.4	90.4	92.4	88.7	91.7	1683	1329
Average	94.9	97.87	86.47	93.97	83.95	93.35	1656	1314

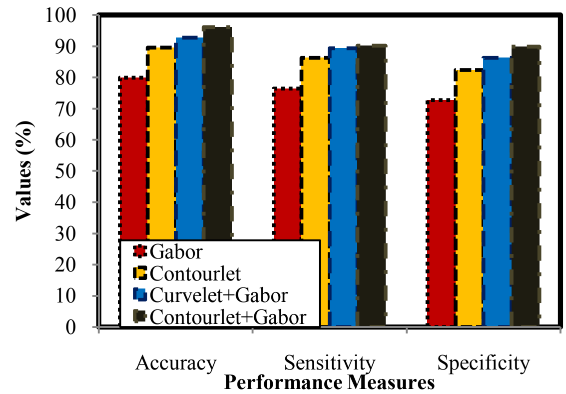
On analysis, it is observed that the previously proposed segmentation technique in [21] proves its efficiency, when compared to the Integro Differential Operator segmentation technique. The proposed feature extraction and classification techniques are utilized in the segmentation algorithms presented in the previous work and the IDO based segmentation. The experimental results show that the performance of recognition system is better, when the proposed segmentation technique is employed in the place of IDO segmentation technique. The accuracy, sensitivity and specificity of the proposed approach with the segmentation technique as in [21] are greater, when compared to the recognition system with IDO segmentation technique. Additionally, the time consumption of the proposed system is lesser, as the segmentation operation is carried out by means of simple morphological operations.



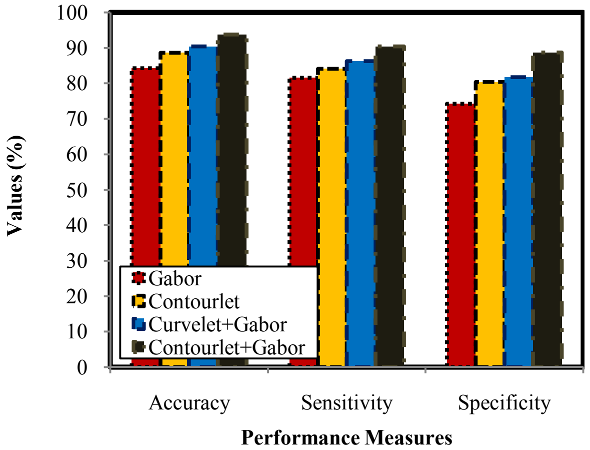
a



b



c



d

Figure 3 (a) Performance analysis on CASIA Iris V1 (b) Performance analysis on CASIA Iris V2, (c) Performance analysis on CASIA Iris V3, (d) Performance analysis on Ubiris V2.

Performance Evaluation W.R.T Feature Extraction Techniques

This section intends to justify the choice of contourlet and gabor features by comparing the performance against gabor, contourlet, curvelet+gabor, contourlet+gabor. Curvelet is also a multidirectional and multiresolution based analytic tool, but it is not suitable for all kinds of images. Contourlet overcomes all the drawbacks being faced by curvelet. In order to prove the efficiency of contourlet, this work compares the performance of contourlet against curvelet.

The combination of contourlet and gabor features serves well, rather than employing a single technique. However, the combination of curvelet and gabor features shows better results with maximum accuracy, sensitivity and specificity rates. The time consumption of various feature extraction techniques are presented as follows.

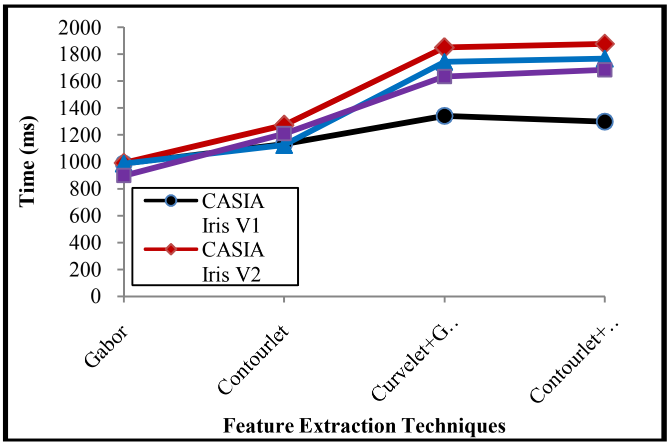


Fig 4 Time consumption analysis by varying feature extraction techniques

On observation, it is obvious that the time consumption of single feature extraction techniques such as gabor and contourlet are relatively low, when compared to the combination of feature extraction techniques. However, the other important performance metrics such as accuracy, sensitivity and specificity rates are greater for combined feature extractors rather than the single feature extractor. Though the time consumption is a bit greater, it is tolerable.

Performance evaluation w.r.t recognition techniques

The recognition technique is meant for making the final decision. Hence, the recognition technique must be accurate with reduced false positive and false negative rates. The performance of the proposed approach is tested by varying the recognition techniques also. This employs ELM for making decision about the iris recognition. However, the performances of various classifiers such as SVM and k-NN are also utilized for analysing the recognition performance. The experimental results of this analysis are presented as follows.

Table 2 Experimental results by varying recognition techniques

Image category	Accuracy (%)			Sensitivity (%)			Specificity (%)			Time (ms)		
	k-NN	SVM	ELM	k-NN	SVM	ELM	k-NN	SVM	ELM	k-NN	SVM	ELM
CASIA Iris V1	86.9	91.6	96.3	81.8	88.6	94.8	76.7	86.7	92.3	1932	1462	1298
CASIA Iris V2	88.3	90.8	94.4	84.7	86.4	91.2	80.3	83.9	89.6	2698	2127	1876
CASIA Iris V3	84.2	92.3	96.1	81.4	89.7	90.2	74.3	85.8	89.9	2349	2089	1767
Ubiris V2	86.4	90.7	93.8	82.3	87.3	90.4	78.5	84.6	88.7	2378	1993	1683
Average	86.45	91.35	95.15	82.55	88	91.65	77.45	85.25	90.12	2339	1917	1656

The above presented table justifies the choice of ELM classifier for the purpose of recognizing iris. The ELM classifier shows the greatest accuracy, sensitivity and specificity rates, when compared to the k-NN and SVM classifier. Additionally, the time consumption for recognizing iris is minimal for ELM, when compared to k-NN and SVM.

Experimental results w.r.t state-of-the-art techniques

In order to prove the capability of the proposed work, the performance of the proposed approach is tested against several recent research works [1, 2]. The performance of the works is evaluated in terms of accuracy, sensitivity and specificity rates and the experimental results are presented as follows.

Table 3 Comparative analysis with the existing techniques

Image category	Accuracy (%)			Sensitivity (%)			Specificity (%)			Time (ms)		
	[2]	[1]	Prop	[2]	[1]	Prop	[2]	[1]	Prop	[2]	[1]	Prop
CASIA Iris V1	86.8	90.89	96.3	82.3	84.6	94.8	74.9	86.4	92.3	1690	1598	1298
CASIA Iris V2	82.1	88.9	94.4	78.3	80.1	91.2	75.3	84.3	89.6	2096	1896	1876
CASIA Iris V3	90.7	93.6	96.1	83.2	87.6	90.2	80.1	82.6	89.9	1984	1821	1767
Ubiris V2	89.3	90.6	93.8	84.2	87.9	90.4	82.6	83.6	88.7	1987	1862	1683
Average	87.22	90.99	95.15	82	85.05	91.65	78.22	84.22	90.12	1939	1794	1656

The phase based technique [1] recognizes iris with the help of phase based mapping technique and is based on the phase components. The computational complexity of this work is high and the experimental analysis of this work is carried out over a single dataset. The edge map based technique [2] is based on the computation of Hausdorff distance between the binary edge map of iris images. The binary edge map computation is not reliable and the results are not satisfactory. The proposed approach overcomes the shortcomings of the existing approaches and improves the performance by means of IDO based segmentation, combination of contourlet and gabor features and ELM based iris recognition. From the experimental results, the efficacy of the proposed approach is proven with maximum accuracy, sensitivity, specificity rates with minimal time consumption.

CONCLUSION

This article proposes a promising and reliable iris recognition system based on contourlet and gabor. The objective of this work is attained by different phases such as image acquisition, segmentation, enhancement, feature extraction and recognition. The iris images are acquired from four different datasets and the images are segmented by means of integro-differential operator. The quality of the segmented images is enhanced by means of histogram equalization technique and normalised by Daugman's rubber sheet model. The quality enhanced images are passed to the feature extraction phase, which is achieved by contourlet and gabor features. The classifier ELM is trained with the extracted features and the feature vectors are stored for future references. In the testing stage, whenever a test image is passed, the feature vector of the test image is compared against the feature vectors of the trained set. The data access is provided only when the images are matched with one another. The performance of the proposed approach is satisfactory in terms of accuracy, sensitivity and specificity. In future, this work is planned to be extended with real time image acquisition in a live experimental setup.

References

1. Kazuyuki Miyazawa; Koichi Ito; Takafumi Aoki; Koji Kobayashi; Hiroshi Nakajima, "An Effective Approach for Iris Recognition Using Phase-Based Image Matching", IEEE Transactions on Pattern Analysis and Machine Intelligence, Vol. 30, No. 10, pp. 1741-1756, 2008.
2. N. Sudha ; N.B. Puhan ; H. Xia ; X. Jiang, "Iris recognition on edge maps", IET Computer Vision, Vol.3, No.1, pp. 1-7, 2009.
3. Karen Hollingsworth ; Tanya Peters ; Kevin W. Bowyer ; Patrick J. Flynn, "Iris Recognition Using Signal-Level Fusion of Frames From Video", IEEE Transactions on Information Forensics and Security, Vol. 4, No.4, pp.837-848, 2009.
4. Jaishanker K. Pillai ; Vishal M. Patel ; Rama Chellappa ; Nalini K. Ratha, "Secure and Robust Iris Recognition Using Random Projections and Sparse Representations", IEEE Transactions on Pattern Analysis and Machine Intelligence, Vol.33, No.9, pp. 1877-1893, 2011.
5. Karen P. Hollingsworth ; Kevin W. Bowyer ; Patrick J. Flynn, "Improved Iris Recognition through Fusion of Hamming Distance and Fragile Bit Distance", IEEE Transactions on Pattern Analysis and Machine Intelligence, Vol. 33, No. 12, pp. 2465-2476, 2011.
6. Yulin Si; Jiangyuan Mei; Huijun Gao, "Novel Approaches to Improve Robustness, Accuracy and Rapidity of Iris Recognition Systems", IEEE Transactions on Industrial Informatics, Vol.8, No.1, pp. 110-117, 2012.
7. Ronaldo Martins da Costa; Adilson Gonzaga, "Dynamic Features for Iris Recognition", IEEE Transactions on Systems, Man, and Cybernetics, Part B (Cybernetics), Vo.42, No.4, pp.1072-1082, 2012.
8. V. V. S. Tallapragada; E. G. Rajan, "Improved kernel-based IRIS recognition system in the framework of support vector machine and hidden markov model", IET Image Processing, Vol.6, No.6, pp. 661-667, 2012.
9. Chun-Wei Tan; Ajay Kumar, "Accurate Iris Recognition at a Distance Using Stabilized Iris Encoding and Zernike Moments Phase Features", IEEE Transactions on Image Processing, Vol.23, No.9, pp.3962-3974, 2014.
10. Alaa Hilal; Pierre Beauseroy; Bassam Daya, "Elastic strips normalisation model for higher iris recognition performance", IET Biometrics, Vol.3, No.4, pp. 190-197, 2014.
11. Frances Albert Santos; Fabio Augusto Faria; Leandro Aparecido Villas, "Iris Recognition Based on Local Binary Descriptors", IEEE Latin America Transactions, Vol.13, No.8, pp.2770-2775, 2015.
12. Estefan Ortiz; Kevin W. Bowyer; Patrick J. Flynn, "Dilation-aware enrolment for iris recognition", IET Biometrics, Vol.5, No.2, pp.92-99, 2016.
13. Yang Hu; Konstantinos Sirlantzis; Gareth Howells, "Optimal Generation of Iris Codes for Iris Recognition", IEEE Transactions on Information Forensics and Security, Vol.12, No.1, pp.157-171, 2017.
14. Chun-Wei Tan; Ajay Kumar, "Efficient and Accurate At-a-Distance Iris Recognition Using Geometric Key-Based Iris Encoding", IEEE Transactions on Information Forensics and Security, Vol.9, No.9, pp.1518-1526, 2014.
15. Sheng-Hsun Hsieh; Yung-Hui Li ; Chung-Hao Tien ; Chin-Chen Chang, "Extending the Capture Volume of an Iris Recognition System Using Wavefront Coding and Super-Resolution", IEEE Transactions on Cybernetics, Vol.46, No.12, pp.3342-3350, 2016.
16. Adam Czajka ; Kevin W. Bowyer; Michael Krumdick; Rosaura G. VidalMata, "Recognition of Image-Orientation-Based Iris Spoofing", IEEE Transactions on Information Forensics and Security, Vol.12, No.9, pp.2184-2196, 2017.
17. http://biometrics.idealtest.org
18. http://iris.di.ubi.pt/ubiris2.html
19. John Daugman, "How iris recognition works", IEEE Trans. Circuit Systems & Video Technology, Vol.14, No.1, pp.21 30, 2004.
20. Guang-Bin Huang, Hongming Zhou, Xiaojian Ding, and Rui Zhang, Extreme Learning Machine for Regression and Multiclass Classification, IEEE Transactions on systems, Man and Cybernetics - Part B, Vol.42, No.2, pp.513-529, 2012.
21. Susitha N., Dr. Ravi Subban, "Reliable Pupil Detection and Iris Segmentation Algorithm based on SPS", Under Review, Sustainable Computing, 2018.

How to cite this article:

Susitha N. and Ravi Subban (2018) 'Efficient Iris Recognition System Based on Contourlet And Gabor Features', *International Journal of Current Advanced Research,* 07(3), pp. 10736-10742.
DOI: http://dx.doi.org/10.24327/ijcar.2018.10742.1831

****