ISSN (Print) : 0974-6846
ISSN (Online) : 0974-5645
Indian Journal of Science and Technology, *Vol 10(34), DOI: 10.17485/ijst/2017/v10i34/118307, September 2017*

Features Subset Selection using Improved Teaching Learning based Optimisation (ITLBO) Algorithms for Iris Recognition

C. Raghavendra[1], A. Kumaravel[1] and S. Sivasuramanyan[2]

[1]Depatment of CSE, Bharath University, Chennai – 600073, Tamil Nadu, India
[2]Depatment of CSE, Dhanalakshmi engineering College, Chennai – 601301, Tamil Nadu, India

Abstract

Objective: Iris recognition is one of the emerging areas as the demand for security in social and personal areas is increasing day by day. The most challenging step in the process of iris recognition is accurate iris localization. **Methods/Statistical Analysis:** In this paper, we propose an iris recognition method in light of Teaching Learning Based Optimisation (ITLBO) to choose the ideal components subset. The iris information, for the most part, contains a tremendous number of textural elements and a similarly modest number of tests per subject, which make the accurate iris pattern classification challenging. **Findings**: Feature selection scheme is used to identify the most important and irrelevant features from extracted features set of a relatively high dimension based on some selection criterions. It is not generally handy to gather an extensive number of tests because of some security issues. In this paper, we propose ITLBO to enhance the feature subset determination by consolidating important results from different component choice strategies. **Application/Improvements:** The principle target of ITLBO is to accomplish an adjust the Recognition Rate (RR), the False Acceptance Rate (FAR), the False Reject Rate (FRR) and they chose feature subset measure. The proposed method is computationally successful with the RR of 97.97 % on the CASIA iris datasets.

Keywords: Biometrics, CASIA, Feature Subset, ITLBO, Log Gabor Filter

1. Introduction

A biometric conspire gives the computerised recognition of an individual, in light or something to that effect of exceptional Feature or qualities controlled by the person. A biometric framework has been created in light of the unique mark, facial components, voice, hand geometry, handwriting, retina and the iris. The recognition of the iris biometric has grown considerably in the course of the last three to four years. Biometric confirmation has gained abundant retention to both the Research Community and Government associations as of late. Planning commission of India framed UIDAI (Unique Identification Authority of India) department to collect bio samples from 120 billion Indian people for various application.

*Author for correspondence

This demonstrates the significance of biometric in future period. There are a few critical components are affected the expanded interest for iris biometric are as per the following:

1. Structure uniqueness of iris
2. Stability of iris
3. Open Acceptance
4. User-friendly hardware
5. Wide scope of use.

Iris-based recognition framework can be non-intrusive to the clients since the iris is an inside organ and in addition remotely visible, which is of extraordinary significance for the real-time applications. Feature extraction and a feature optimisation is a basic area of research in the field of iris recognition framework. The extraction of a feature from iris image is a very difficult task because of a lower substance of the feature. In image processing concept, the iris is essentially separated of three sorts, for example, colour, texture and shape and these are considered as components of iris. There are different algorithms which can be applied to remove the feature in feature extraction process and pattern matching processes. Proposed algorithm uses texture features of the iris.

In the iris recognition framework, the fractal measurement can be used to look at the texture of iris image productively and it has been accepted to represent the Gabor filtered images. The optimal feature set determination from a feature arrangement with a relatively high measurement has turned into a critical calculate the field of iris recognition. The conventional feature selection techniques (e.g., Principal components analysis, Independent components analysis, Singular valued decomposition etc.) require sufficient number of samples per subject to select the most representative features sequence. Choice of a feature on different theoretical strategies may deliver diverse outcomes in simulation for the same dataset.[15] This makes choosing the optimal feature subset for an informational collection troublesome. In this paper, we underscore on the usage of the valuable data from various feature choice strategies to choose the most imperative feature subset and furthermore to enhance the classification accuracy. We propose Teaching Learning Based Optimization (ITLBO) to choose the significant features subset by combing the multiple feature determination criteria. The proposed approach gives the advantageous method for choosing a better feature subset in view of the execution of the component using ITLBO. This algorithm takes out redundant feature amid choice by employing a progressive Teacher Best values. The number of features selected reduces significantly, while still keeping the average recognition rate higher.

Organization of the paper is as follows: Section II presents Literature Review about recent methodology. Section III shows proposed iris recognition system. Experimental results are discussed in Section IV and finally section V gives conclusion.

2. Literature Review

F. He*et al.* have provided multiple local feature representations and their fusion scheme based on a Support Vector Regression (SVR) model for iris recognition by utilizing optimized Gabor filters.[1] In this proposed method a Particle Swarm Optimization (PSO)-and a Boolean Particle Swarm Optimization (BPSO)-based algorithm was proposed to provide suitable Gabor filters for each involved test dataset without predefinition or manual modulation. Several comparative experiments on JLUBR-IRIS, CASIA-I, and CASIA-V4-Interval iris datasets were conducted. The outcomes showed that their work can generate improved local Gabor features by using optimized Gabor filters for each dataset. Additionally, the proposed SVR fusion method might make full use of their discriminative ability to improve accuracy and reliability. Other comparative experiments showed that their approach may beat other popular existing iris systems.

A. Bansal *et al.* have proposed and implemented a statistical feature extraction technique based on correlation between adjacent pixels.[2] Hamming distance based metric was used for matching. Performance of the proposed Iris Recognition System (IRS) was measured by recording False Acceptance Rate (FAR) and False Rejection Rate (FRR) at different thresholds in the distance metric. System performance was assessed by computing statistical features along two directions, namely, radial direction of circular iris region and angular direction extending from pupil to sclera. Experiments were carried out to study the effect of number of statistical parameters on FAR and FRR. The outcomes showed that there was a significant improvement in Equal Error Rate (EER) when number of statistical parameters for feature extraction was increased from three to six. Additionally, it was found that increasing radial/angular resolution, with normalization in place, improved EER for proposed iris recognition system.

P. R. Nalla*et al.* have developed a domain adaptation framework and introduced a new algorithm by utilizing Markovrandom Fields (MRF) model to significantly enhance cross-domain iris recognition. The proposed domain adaptation framework based on the naive Bayes nearest neighbour classification utilized a real-valued feature representation which was capable of learning domain knowledge. Their method to estimate corresponding visible iris patterns from the synthesis of iris patches in the near infrared iris images achieved outstanding results for the cross spectral iris recognition. Additionally, a new class of bi-spectral iris recognition system that can simultaneously acquire visible and near infra-red images with pixel-to-pixel correspondences was proposed and assessed. They presented reproducible experimental results from three publicly available databases; PolyUcross spectral iris image database, IIITD CLI and UND database, and achieved outstanding results for the cross-sensor and cross spectral iris matching.

H. Hofbauer*et al.* have investigated the detection and segmentation of the iris and its influence on the overall performance of the iris-biometric tool chain.[4] The authors examined whether the segmentation accuracy, based on conformance with a ground truth, can serve as a predictor for the overall performance of the iris-biometric tool chain. Furthermore, the authors systematically evaluated the influence of segmentation parameters, pupillary and limbic boundary and normalisation centre (based on Daugman's rubber sheet model), on the rest of the iris-biometric tool chain. They showed that for ascertaining segmentation accuracy the choice of measure does not really matter since the differences were small, means, the F-measure seems to be the better choice. Also, the segmentation accuracy was not a reliable predictor of overall iris tool chain performance, and the combination of database, segmentation and feature extraction behave non-uniformly. A feature extraction method can produce better overall results with a worse, based on segmentation accuracy, segmentation algorithm. Regarding segmentation accuracy, they found that it was not necessary to extract the whole iris image as long as the extracted region was consistent.

3. Proposed Methodology

The texture patterns of the iris image contain numerous moment and fine edges which should be removed deliberately keeping in mind the end goal to enhance the recognition. A few features which are ignored or not legitimately isolated may decrease the recognition or give a false recognition rate. Furthermore, some irrelevant feature subset might be chosen amid highlight determination, along these lines pointlessly expanding the complexity. The utilization of Gabor filters is proposed to fundamentally segregate and isolate the fine feature in the image which may somehow or another be ignored. Gabor filter used with reasonable introductions and a particular number of filters gives a decent feature portrayal and

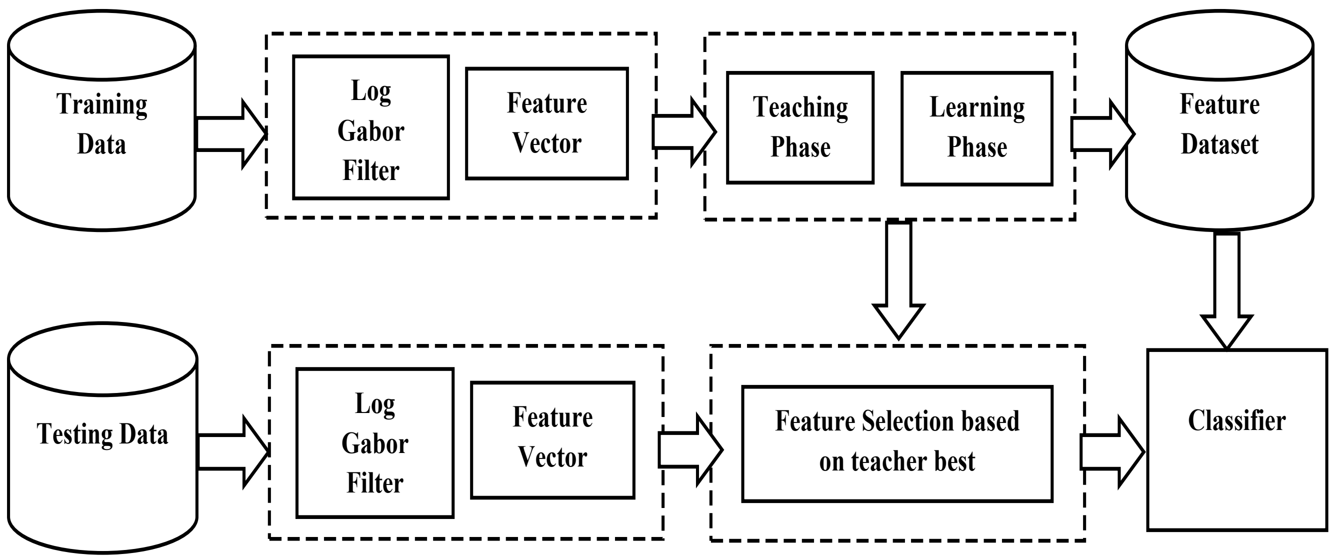

Figure 1. Block Diagram.

establishes the framework for a superior feature extraction.

3.1 Database Collection and Preprocessing

We direct the experimentation on CASIA (Chinese Academy of Science Institute of Automation) iris dataset. The CASIA dataset comprises of left and right iris pictures for experimentation. CASIA Iris Image Database Version 3.0 incorporates 756 iris pictures from 108 eyes. For each eye, 7 pictures are caught in two sessions with self-created gadget CASIA shut close up iris camera. All pictures are stored as BMP arrangement with resolution 320*280.

The iris is encompassed by different non-important locales, for example, the pupil, the sclera, the eyelids, and furthermore has some noise that incorporates the eyelashes, the eyebrows, the reflections and the encompassing Skin.Noisy regions are required to wiped out and additionally inward and external boundary likewise should be distinguished utilising unwrapping strategies. Pupil also get eliminated using masking after the normalisation. Figure 2 indicates actual transformations of the image required in preprocessing.

3.2 Feature Extraction

Gabor filter based strategies have been broadly utilized as feature extractor in computer vision, particularly for the texture examination. Nonetheless, one shortcoming of the Gabor filter in which the even symmetric filter will have a DC components whenever the data transfer capacity is bigger than one octave. To conquer this weakness, a kind of Gabor filter known as log-Gabor filter, which is Gaussian on a logarithmic scale, can be utilized to deliver zero DC segments for any band width. The log-Gabor function more nearly mirrors the frequency response for the assignment of dissecting regular images and is reliable with the estimation of the mammalian visual framework. The log-Gabor channels are acquired by multiplying the radial and the angular segments together where each even

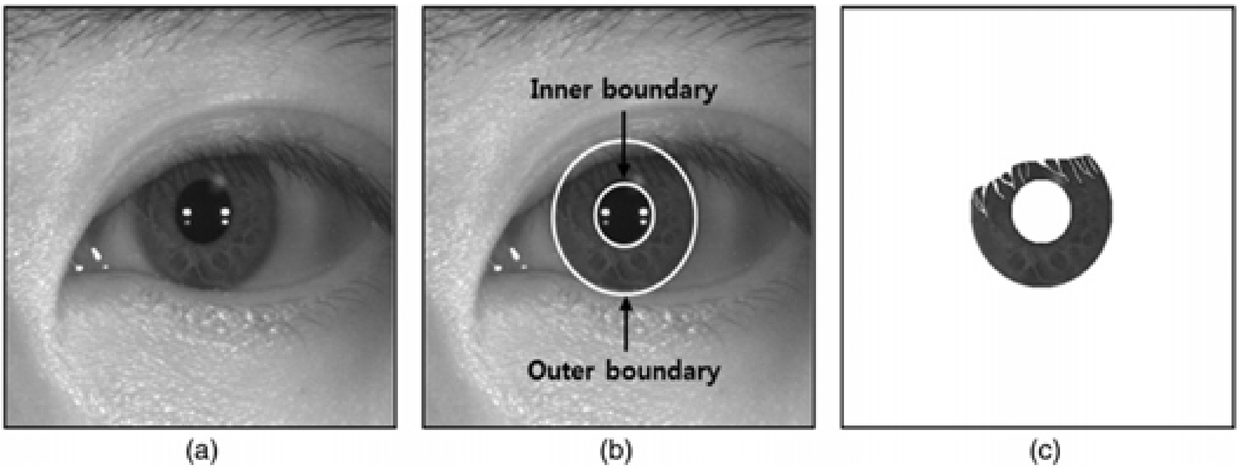

Figure 2. Iris localization and detection of noise factors: (a) original iris image; (b) detection of inner and outer boundaries of iris; (c) the pre-processed.

and odd symmetric combine of log-Gabor filters includes a complex log-Gabor filter at one scale. The frequency response of a log-Gabor filter is given in condition (1)

$$G(f) = \exp\left(-\left(\log\left(f/f_0\right)\right)^2 / 2\left(\log\left(\sigma/f_0\right)\right)\right) \tag{1}$$

Where f_0 is the centre frequency, and σ provides the bandwidth of the filter. Keeping in mind the end goal to remove the discriminating features from the standardized collarette range, the standardized example is convolved with 1D log-Gabor filter.[9]

The Teaching advancement is guided utilising the proposed fitness basis, the nature of a given learning is relative to the information gain measure figured using the dataset records recovered from the training dataset. The outcome is finally approved using another test dataset. ITLBO acquired three advantages over previous methods, the first that computational complexity is decreased as there is a smaller number of information sources regularly, an optional advantage found is that the accuracy of the classifier increments and the last one is to expel the additional elements (i.e like noise, obscuring other features from the learning algorithm) from a feature set, as unnecessary data appeared in Figure 3.

3.3 Feature Subset Selection using ITLBO

Iris feature optimization is an arduous assignment in the field of iris recognition. Now, optimization processes of iris image need a feature subset of iris image data. In current years, different methodologies are accessible for iris feature subset optimisation, for example, artificial neural network, genetic algorithm, particle swarm

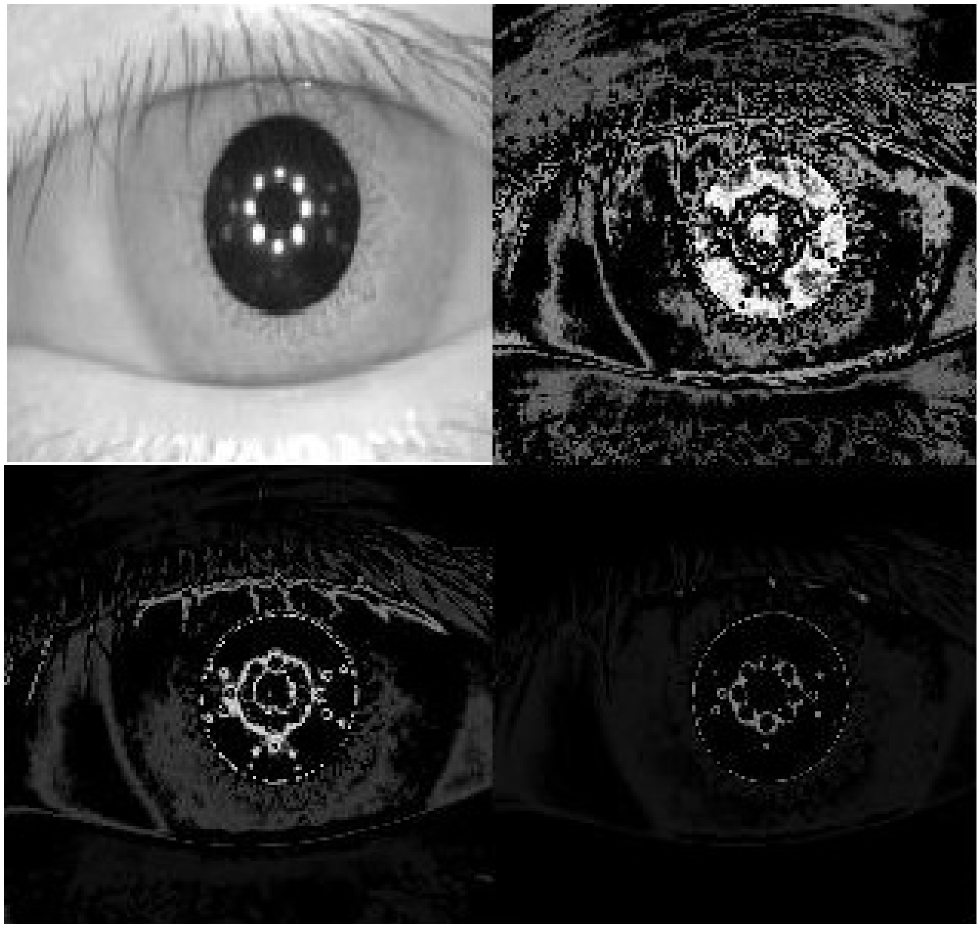

Figure 3. Illustration of the effects of Gabor in different orientation and wavelength based iris representation.

optimisation and so forth. Proposed ITLBO based architecture for iris recognition system as shown below,

Extricate the feature subset from iris dataset and appointed these values to feature matrix. Change feature information to the format of a feature space, i.e. change feature matrix to feature space which is given by: $X_i \in R^d$

where X is an original feature, R is transform feature space and d is a dimension of data. Initiate scaling operation in feature subset and the scaling factor α defined as follows in Equation (2),

$$\alpha = \sum_{i=1}^{m} \sum_{j=1}^{n} sim(X_i, X_j) / m * k \tag{2}$$

Where m total data is point, k is the total number of instance and sim is the similarity function which finds the similarity between data. The resultant data of past stride is considered as input or population for ITLBO calculation. These components are practically equivalent to a number of students in ITLBO.

The total population X is randomly distributed in total dimensions of matrix. Objective function $F(X)$ is the maximum value of feature vector. Teacher phase: Measure the mean (column wise) in population stated in Equation (3)

$$M_{D^r} = [m_1, m_2, \ldots\ldots\ldots\ldots, m_D] \tag{3}$$

The best solution which acts as teacher in ITLBO for that iteration is the maximum value in feature matrix as follows in Equation (4)

$$X_{Teacher^r} = X_F(x) = \max imum \tag{4}$$

The teacher is try to shift this mean from M_{D^r} to $X_{Teacher^r}$ therefore the difference is calculated between $X_{Teacher^r}$ and M_{D^r} which is given as in Equation (5)

$$difference = \left(r\left(X_{Teacher^r} - T_F M_{D^r}\right)\right) \tag{5}$$

Use the best value of T_F to select the optimal feature. The value of T_F is selected as 1 or 2. The difference obtained is added to the current value to update it. It is calculated in Equation (6)

$$X_{new} = X_{old} + difference \tag{6}$$

Now, if X_{new} gives maximum value then accept.

3.3.1 Learner Phase

Learners increase their knowledge with mutual iteration. Therefore for feature optimization select any two value from above step and update the smallest value corresponding to the largest one. The selection of students are random in iterative process. This step is applied for all data calculated in above step. It is given as:

$$X_{new_i}^{\;g} = \begin{cases} x_i^g + rand \times \left(-X_r^g\right) if \;\; f\left(x_i^g\right) < f\left(X_r^g\right) \\ x_i^g + rand \times \left(X_r^g - x_i^g\right) otherwise \end{cases} \tag{7}$$

In Equation (7) g the current iteration and $rand$ is a constant. ITLBO gets terminated either optimized feature matrix is obtained or maximum number of iterations are reached otherwise Equation (6) need to process iteratively. The resultant optimized features generated by the above mentioned algorithm is then used for selection and identification. During selection process the low rated feature subset get eliminated and best solution subsets are move to feature dataset. The tested data's are regulated by the teacher's best from the Equation (6).

Optimal subsets are moved through the Chebychev Distance Classifier to anticipate the iris classes. Ordinarily hamming or Euclidian distance measure is utilised to discover the distinction amongst training and testing contributions, in our proposed replace hamming into Chebychev Distance which is working effectively in clustering. Distance function chebyshev represent in Equation (8), for a cluster.

$$Dist_{chebyshev}(x, y) = \max_i \left(\left| x_i - y_i \right| \right) \quad (8)$$

Here x_i, y_i are feature coordinate points or vector.

4. Experimental Setup

The performance of the proposed method for the Iris verification system is evaluated by performing some experimental task using MATLAB 8.1 on CASIA Iris Image Database, which contains different types of iris and the results have been calculated on the basis of Execution time, FAR, FRR and Recognition Rate (RR) parameters.

$$FAR = \frac{Number\ of\ Accepted\ verification\ attempts\ for\ an\ imposter\ N}{Number\ of\ all\ verification\ Attempts\ for\ the\ same\ imposter\ N}$$

$$FRR = \frac{Number\ of\ rejected\ verification\ attempts\ for\ a\ genuine\ user\ N}{Number\ of\ all\ verification\ Attempts\ for\ the\ same\ genuine\ user\ N}$$

$$RR = \frac{Number\ of\ succuess\ verification\ for\ all\ user}{Number\ of\ all\ verified\ user\ (N)}$$

5. Results and Discussion

The experiments have been performed on CASIA database and all experimental results have been tabulated as shown in Table 1.[18] The size of each image is 320×280, and the images are resized to 80x80. The pre-processed images given as input to the extraction stage Gabor filtering. Among the various templates used, the best recognition rate is observed for ITLBO. Both left side 7 images and right 7 images are taken for consideration to evaluate identification. We test the performance of the features under the same training and testing condition followed

Table 1. Comparative RR of existing and Proposed System.

Database	Umer [15]	Umer [15]	Umer [15]	Umer [15]	Umer [15]	Proposed
CASIA V3	78.43	82.86	48.75	74.57	99.71	99.80
CASIA Syn	55.36	60.22	56.12	63.14	95.26	96.15
CASIA - Combined	66.89	71.54	52.43	68.85	97.48	97.97

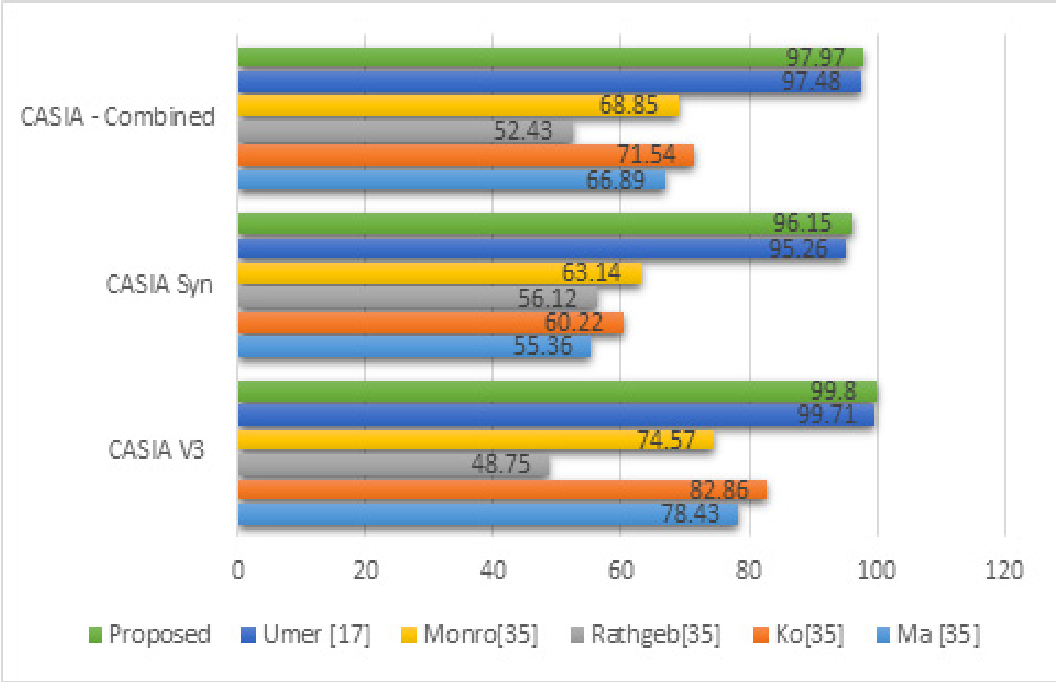

Figure 4. Iris Recognition rate Comparison.

Table 2. Performance comparison of proposed system for different type of datasets

Database		Average Recognition (%)	Peak Recognition (%)	Training Time (ms)	Testing Time (ms)	Distance (m)	FAR (%)	FRR(%)
Umer [15]	CASIA V3	97.42	99.71	1.05	0.03	0.18	0.0229	4.45
	CASIA Syn	94.22	95.26	1.41	0.05	0.17	0.0474	2.16
Proposed	CASIA V3	97.64	99.80	0.90	0.03	0.08	0.002	3.65
	CASIA Syn	95.16	96.15	1.33	0.05	0.07	0.0385	1.49

by.[15] Feature subset selection done for i^{th} subject at time t.

The experiment is conducted for CASIA V3 and CASIA Syn database and combined results are evaluated in terms of accuracy. Different number of possible combinations are taken for consideration to evaluate the results. CASIA Syn gives less recognition rate, because database contains half closed or fully closed pupil. It's directly affect segmentation.

In this Table 2, it can be seen that the proposed algorithm significantly reduces the FRR. However, the rejection rate cannot be reduced if a closed eye image or an eye image with limited information is present for matching. We next evaluated the effectiveness of the proposed iris image quality enhancement algorithm and compared with existing enhancement algorithms, used in Umer.et al.[15] The proposed ITLBO algorithm gives 3.65% FRR at 0.002% FAR. The performance improves by 2.16% when the proposed ITLBO feature subset selection algorithm is used. Similarly the average runtime time of proposed system gets reduced after using ITLBO.

5.1 Recognition Characteristics Calculation

A number of iterations are performed for the proposed ITLBO and it is noticed that the number of features subset selected significantly decreases with each iteration, with the average recognition rate being fairly similar for less number of iterations but showing a slight decrease up to 16% as the number of iterations increase. Difference between traditional and proposed Recognition Characteristics is more than 74% averagely. Figure 5 represents the nature of the features subset selected and

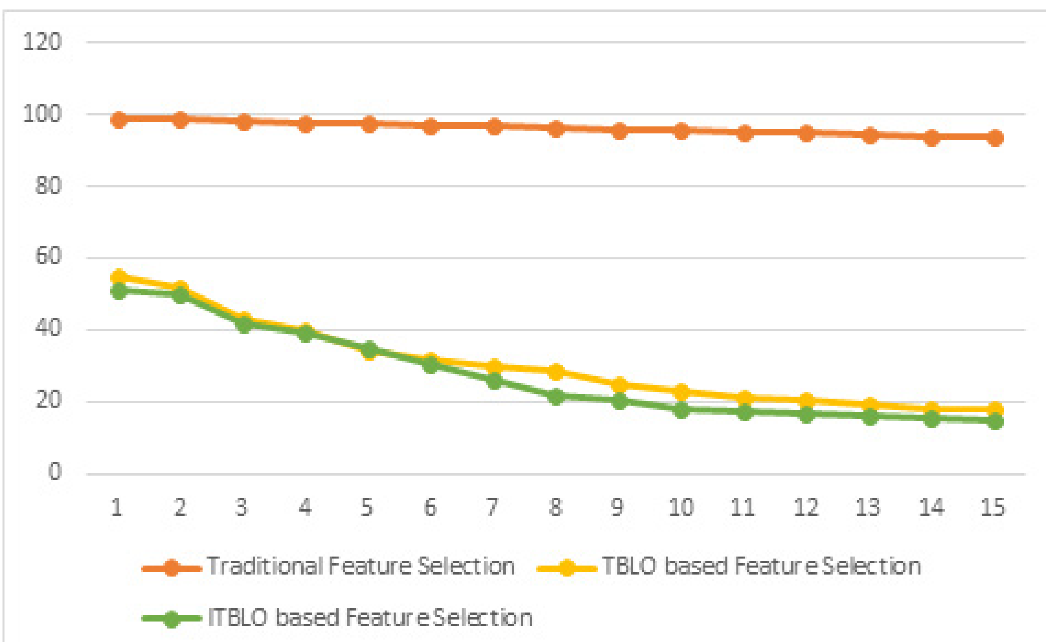

Figure 5. Recognition Characteristics Vs iteration.

the average recognition rate as the number of iterations increase.

6. Conclusion

Iris recognition framework is a novel approach of biometric validation framework which manages security issues. As of late, it is most secure and dependable framework among other biometric frameworks. Nowadays, feature extraction and optimisation is an open research territory in the field of iris recognition framework. ITLBO is one of the minimal cost and exceptionally reliable than swarm Intelligence based strategy for optimisation. This paper proposed a ITLBO based iris recognition framework for feature subset optimisation. This procedure is prepared on feature matrix extricated from feature extraction handle. Here, Log Gabor Filter is utilized for texture element extraction prepare. For eliminating unwanted subsets, ITLBO is used and upgraded feature framework is acquired. Templates are produced with this optimised matrix by Teachers best. The ITLBO based iris recognition framework gets 97.975 % recognition rate and diminishes the quantity of false dismissal proportion.

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