A Novel Technique to Enhance Performance of Multibiometric Framework using Bin based Classifier Based on Multi-algorithm Score Level Fusion

Sandip Kumar Singh Modak, Vijay Kumar Jha

Abstract**:** ***This work shows a multibiometric framework to upgrade the recognition rate and reduce the error rate using Bin based classifier based on score level (multi-algorithm) fusion. In this work Bin based classifier is used as the combination rule which integrate the matching scores from two distinct modalities namely iris and face. An optimization technique, PSO is utilized to minimize the unwanted information after combination of the feature sets of the iris and face using different feature extraction algorithms like PCA, LDA and LBP. The test results demonstrate that the multibiometric system as a Bin based classifier employing multi-algorithm score level fusion provides better outcomes than the other fusion rule like Likelihood Ratio based fusion, Linear Discriminant Analysis (LDA) and support vector machine (SVM). The experimental result on Face (ORL, BANCA,FERET) and iris (CASIA, UBIRIS) shows that the proposed multimodal system derived from CBBC (continuous bin based classifier) with PSO as an optimization technique achieve EER=0.012 , which outperform than the other fusion technique with EER=0.018 for SVM (RBF) and EER=0.02 for SVM linear.***

Index Terms: Multibiometric, Multi-algorithm, Face, Iris, Score Level Fusion, Support Vector Machine, Particle Swarm Optimization, and Continuous Bin Based Classifier.

I. INTRODUCTION

Biometric systems considered to be more convenient to use because users need not have to carry any token or remember any password and this advantage of biometric enable to replace the existing token and password based technology used in several applications such as electronic data security and access control [1].In this paper, we consider both iris and face modalities because of numerous comparable attributes. However, the information obtained from biometric data is vulnerable and uncertain to many environmental, technical and human related factors, such as, noise in the data, illumination, occlusions, pose, image capturing, camera movements, operator training, and so on [2]. These factors reduce interclass difference of biometric samples and increase intraclass variability. Recent research on biometric prove that the fusion of multimodal biometrics can be able to overcome this problem by using the proper fusion rule [3].

The unimodal based system has several limitations like noise, intra-class variability, failure-to-enroll and low acceptance rate. So as to overcome the shortcoming of unimodal system we are floating towards a multimodal biometric framework which combined the information from various sources so as to affirm or determine the distinctive character of a claimed user. Data from different biometric sources can be incorporated at the sensor level (combined raw data from the different sensors), feature level (features of different biometrics combined), score level (consolidating the match score of genuine and imposter), decision level (integrate the decision generated by different classifier) and rank level (consolidate the rank output by individual matcher).Feature set which is obtained from the various biometric traits are having a large amount of data, yet because of the enormous dimensionality of feature vectors, it might produce redundant and irrelevant information which can influence the performance of the entire system. Because of the huge accessibility of the data, researchers prefer to use score level fusion which can be utilized to easily differentiate between the genuine and imposter user. Fusion at the decision level is not so easy because the information at this stage is not so enough when as compared to score level fusion [4].

Multibiometric is based on fusion approach, where the multiple evidence of feature sets is integrated in a proper manner to enhance the performance and minimize the shortcoming faced by the unimodal system. Score normalization is needed in the score level fusion on the grounds that the data acquired from different biometric sources are heterogeneous in nature, so before to consolidating them into a single score it required to convert these scores into a similar range. The most well-known normalization strategies are z-score, tanh and min-max schemes. In a multibiometric system the information integrates at the early stage of processing is viewed more powerful than those frameworks which perform incorporation at the later stage [5]. Score level combination strategy can be classified as: a) Classifier based (train a classifier using the score from multiple matchers) like a support vector machine (SVM),

Revised Manuscript Received on January 06, 2020.
***** Correspondence Author
Sandip Kumar Singh Modak*, Department of Computer Science and Engineering, Birla Institute of Technology, Mesra, Ranchi 835215, India. Email: modaknit@gmail.com
Vijay Kumar Jha, Department of Computer Science and Engineering, Birla Institute of Technology, Mesra, Ranchi 835215,India.Email: vkjha@bitmesra.ac.in

(b) transformation-based score fusion (match score first converts to a common domain and afterward consolidated) like product rule, weighted sum rule and sum rule and c) density based fusion like likelihood ratio test [6]. Further, the existing score level fusion technique can be classified as: evolutionary-based fusion method, belief function theory based, learning based and transformation based. The score level fusion based on evolutionary technique is a more applicable in fusion method which generates a set of pertinent solutions. The primary objective of any evolutionary technique is to find the optimum solution among the population through looking and refreshing the previous history of the particle of the population. A score level fusion based on belief function is mostly accomplished by the different match score, which form a belief assignment and then finally combine them. The best example of belief function is Dempster-Shafer (DS) and Dezert-Smarandache (DSm). In the case of learning method, to train the fusion algorithm different kernel technique is used. The most well-known example of the kernel based technique is SVM (Support vector machine) and neural network where the different kernel is used for classification. In transformation based fusion rule, using a different normalization technique the matching score of various classifiers are first transformed into a similar range and afterward to produce a final score the normalized score are combined with the help of simple sum, max, min, product or weighted sum rule [7].The overall fusion technique can be arranged into two classifications: pre-matching and post-matching fusion scheme. Pre-matching fusion scheme generally consists of Sensor level and feature level fusion, whereas score, decision and rank level fusion come under the category of post-matching [8]. In multibiometric the fusion strategy should be selected on the basis of biometric traits, level of combination and the type of application. The rank level fusion scheme is relatively new and understudied problems as compared to the other fusion scheme [9].The problems of higher dimensionality of the feature set and redundant data can we minimize by a feature selection process where the optimal subset of the original features set is selected based on certain objective function. For optimization of feature sets in a multibiometric system several feature selection methods like Ant Colony Optimization (ACO) , Genetic Algorithm (GA) and Particle Swarm Optimization (PSO) have been implemented [10].The three different feature extraction algorithm like PCA,LDA and LBP are utilized in this paper to extract the features from two different modality face and iris. An evolutionary approach like PSO is utilized as a feature selection method to minimize the irrelevant data and reduce the dimensionality of the resultant feature sets of iris and face. The resultant iris and face score vectors are concatenated, which produce a single score vector and then Bin-based classifier is used to distinguish the claimed user as a genuine or an imposter. LBP feature extraction technique achieved better performance and high recognition rate Compared to other feature extraction technique. In the feature level fusion scheme, the extracted features of face-iris by the all feature extraction methods are combined together to form a concatenated face-iris feature set. In this investigation, we utilized global (PCA, LDA) and local (LBP) feature extraction methods on iris and face to enhance the recognition rate and performance of the system.

The hidden information in matching score is not fully discovered in most of the score level fusion technique as the distinctiveness of several biometric traits could not be effectively reflected by just one weight variable. To manage this sort of trouble we utilized bin based classifier as a combination rule which can improve the performance of the systems by using the hidden information of match score [11]. In Bin-based classifier fusion at first the scores of face-iris are divided into small unit called bin and for each bin a classifier is assigned which discovered distinctive and details information from the matching scores. The rest of this paper is summarized as follows: in section 2 related works are displayed; section 3 gives insights about Bin based classifier; section 4 features about the proposed work; section 5 concerns about experimental result; section 6 for discussion and finally concludes the papers in section 7.

II. RELATED WORK

There are various related works have been proposed in the domain of multibiometric systems based on face and iris. Wang et al. [12] in 2013 address a multimodal system of iris and face based on RBFNN for verification purpose and used two different strategies, namely un-weighted sum approach and the weighted sum approach for fusion the features of the iris and face. Experimental analysis shows that the proposed fusion strategy (RBFNN) has achieved a higher recognition rate of 0.973. Chen et al. [17] in 2006 developed a multibiometric system of face and iris based on Wavelet probabilistic neural network (WPNN), the experiment result reveals the verification of multimodal system is more precise and reliable than single biometric models. In the proposed framework a 2-D face image is changed into a 1-D energy profile signal and to localize the pupil position and to obtain a lower resolution image of the iris, the 2-D wavelet transform is used. For classification purposes, WPNN classifier is used where features of face and iris are feed to make the final decision of whether the claimed user is truly accepted or rejected.

A score level fusion of near infrared face and iris was addressed by Zhang et al. [18] in 2007 the proposed framework was tested using different combination rule and it is found that on a close set the genuine accept rate (GAR) of face and two irises increase from 97.35% to 99.75% and on an open set it is increased from 83.31% to 98.12% when FAR is at 0.001.In 2008, Morizet et al. [24] present a novel approach for face and iris based on a precise statistical analysis of bootstrapped match scores generated from similarity matrices. The overall performance of the biometric system depends on the separation between genuine and imposter distribution, to boost the exhibition of the framework the separation must be expanded. The separation distance, skewness and kurtosis are three parameters which are used in the formation of cost function. The analyses are carried out on CASIA iris and FERET face dataset and results demonstrate that the proposed framework achieved a GAR (genuine acceptance rate) equal to 100% at a FAR (false acceptance rate) of 0.0007%.

In 2009, Wang and Han [13] proposed an SVM (Support vector machine) based score level fusion of iris and face. The proposed framework utilized two matching scores, one for Phase information based iris verifier and other from Laplacian face based face verifier. Experimental results shows that the proposed fusion strategy (SVM) brings clear improvement contrasted with the unimodal based biometric identification framework. A score level fusion based multimodal framework using iris and NIR (near-infrared) face was addressed by Wang et al. [31] in 2010. This work consists of several fusion methods, including combination approach (sum, max, and min) and classification approach like LDA and PSM-based method. The test results demonstrate that the learning based technique such as PSM and LDA are comparatively superior to the other conventional combination rule. In 2011, Liau et al. [15] proposed an SVM based face-iris multimodal system, discrete cosine transform (DCT) is employed as extraction of facial features and to obtain an optimal subset of those features, PSO is utilized as an optimization technique. The test result demonstrates that the classification accuracy of the proposed framework can improved by the PSO based feature selection technique. An efficient feature level fusion scheme for iris and face was addressed by Wang et al. [32] in 2011, the proposed work consist of a normalization technique (z-score) which converts the both iris and facial features into a common format and later as a combination technique serial rule was employed. The proposed framework was tested on two face database (ORL, YALE) and CASIA iris database and the results demonstrate the adequacy of the proposed technique. The EER of the proposed method using weighted sum rules is 5.54 whereas it is 1.67 using the proposed technique. In 2012, Eskandari et al. [25] developed a multibiometric framework of the iris and face with the help of global and local feature extraction technique. In this investigation, the author uses subspace Linear Discrimination Analysis (sLDA) as a global feature extractor and Linear Discrimination Analysis (LDA) as a local feature extractor for iris and face image individually, tan-h normalization technique is used to get the resultant scores of face and iris. The test are done on various subsets of iris and face image database, including two iris datasets (CASIA, UBIRIS) and ORL face dataset, obtained recognition rate of 99.0% using three feature extractor algorithm (PCA, mPCA and LBP) when weighted sum rule based on tan-h normalization were used in dataset1 consisting of CASIA and ORL, whereas a recognition rate of 95.5% achieved for dataset2 consisting of UBIRIS and ORL using LBP feature extractor based on tan-h normalization method. A minimum total error rate (TER) of 0.0100 achieved by the proposed framework when dataset comprises of CASIA iris and ORL face, the best recognition rate of the proposed system was recorded as 97.00% at 0.01% of the FAR. Kim et al. in [26] proposed a score level fusion of face and both irises based on SVM classifier, to capture the face image and both irises of each individual proper image capture device were used, which consists of near infrared (NIR) illuminator, face camera, cold mirror and two iris cameras. In this study eye regions and face are captured by eye detection and AdaBoost technique, Retinex algorithm is used to normalize illumination and normalization of size were carried out to eliminate variation in the detected facial image. Distinguish between genuine and imposter user is accomplished by SVM classifier. The investigation is carried out on database comprises of 3450 images collected from 30 people, of which 1150 images of face, 1150 of left iris images and 1150 of right iris images. Proposed system achieved EER of 0.131 using score level fusion based on SVM classifier. In 2012, a novel multimodal biometric system based on feature level fusion using iris and face was addressed by Wang et al.[30], in this proposed work author focus on minimizing the difficulties like device variation , signal noise and background noise and how overall system performance can be maximized. They perform the concatenate features of face and iris in the series using feature level fusion, to improve the performance of the system fisher discriminant analysis is used which select the best features of the face and iris. Two face database (ORL and Yale) and CASIA iris database are used to validate the proposed algorithm. The test result shows the multimodal verification is much more robust and accurate than unimodal system. In 2013, Eskandari et al. [20] address a novel technique using score level fusion for face-iris multimodal recognition framework, the author applied several local and global feature extraction techniques such as PCA, subspace LDA, spPCA, mPCA and LBP which extracts the distinctive features of the face and iris. Transformation based and Classifier based score combination technique, and then applied to get the concatenated score which classifies the matching scores. To distinguish the claimed user as a genuine or an imposter Nearest Neighbor Classifier is used. An EER of 1.02% is achieved by the proposed scheme of face and iris multimodal system.

In 2013, Wang et al. [27] developed a multibiometric system of dual iris, visible and thermal face images based on the hybrid combination method, in this work Complex Gabor Jet Descriptor (CGJD) is utilized to enhance the image quality of thermal and visible face and serial feature vector is formed of 1D log-Gabor dual iris code. Aczel-Alsina triangular norm (AA t-norms) based score level fusions were proposed. The performance is validated on the virtual multibiometric database consist of NVIE face dataset with visible and thermal face and CASIA-IRIS dual iris dataset. The proposed framework accomplished EER with 2.89×10^{-4}, which outperform the other unimodal system. In 2014, Eskandari et al. [14] addressed score and feature level based Multi-algorithm framework for face and iris. The proposed approach applies feature level combination rule and to select the best feature, an optimization technique PSO is utilized to generate the scores of face and iris. The results, based on two CASIA, UBIRIS iris dataset and three datasets using ORL, BANCA, FERET face databases show that proposed framework performed well using SVM classifier based on t-norm normalization. A weighted score level fusion system based on face and non-ideal iris were introduced by Sim et al in [19].The experiment is carried out using a dataset of ORL face databases and Malaysia iris-Face Multimodal Datasets (UTMIFM).The proposed framework improved the recognition rate and achieves higher accuracy of the system.

A fusion of the iris and face biometrics using weak classifier based on Bin-based was introduced by Miao et al. [11] in 2015, in this proposed work different bins are produced using the matching scores of face and iris image so that distinctive and detailed information from the matching scores can be easily obtained from bins learned by the weak classifiers.

The experimental results based on CASIA-Iris databases demonstrated the advantage of the proposed method over other multibiometric combination rules. A hybrid combination rule based on a feature and score level using face and iris was addressed by Azom et al. in [23], this work consists of a combination of three classifiers based on a feature and score level fusion based on decision level fusion rule also known as hybridized fusion scheme. For each of the faces and iris modality five different feature extraction algorithms, namely local methods like Linear Discrimination Analysis (LDA) and Principal Component Analysis (PCA) and global methods like modular Principal Component Analysis (mPCA), sub-pattern Principal Component Analysis (sp-PCA) and Local Binary Pattern Histogram (LBPH) are utilized. The features obtained from the five different feature extraction algorithms are undergone into the feature level fusion and fusion of scores generated by the features of the face and iris using LDA method are done by weighted score level fusion. The final selection of genuine or imposter user is determined by using a decision level fusion of both feature and score level combination rule, in decision level fusion the majority voting strategy is utilized to make the final decision. An accuracy rate of 98.75% is achieved using the proposed method based on ORL face and CASIA iris datasets which are shown improvement compared to unimodal framework. A feature level fusion using face and iris was addressed by Huo et al. [28] in 2015, in this paper author extract the feature sets from face and iris through a two-dimensional Gabor filter bank and finally the identification is accomplished through a fusion strategy of PCA and SVM.

In 2016, Connaughton et al. [16] proposed a match score fusion based face and iris multimodal system where the features of face and iris are captured through a single sensor. For data acquisition Iris on the Move (IOM) sensor was selected where to handle a large range of subject heights the presence of multiple cameras are used. To combine corresponding frames the three videos from each IOM acquisition are “stitched” together. The experiment result shows that the match score combination scheme using face and iris biometric produce a 5.4% increase in recognition rate compared to single-modality approach that was examined. In 2016, Sharifi et al. [22] developed an optimal face and iris based multimodal approach using feature, score and the decision as combination scheme. In this study, the author applied different fusion strategy at each level of fusion to improve the recognition performance, to examine the robustness of all unimodal and multimodal schemes CASIA Iris database is used. To select the best features to improve the performance of the system and to reduce the number of features Backtracking Search Algorithm (BSA) is applied in this study. A GAR of 98.03% and TER of 0.27% is reported trough the experimental result based on the proposed study.

An optimum scheme selection for face and iris biometric was proposed by Eskandari and Sharifi [29] in 2016; in this study, they investigate the performance of various combination rules (feature level, score level and decision level) on face and iris modality. In this study threshold optimizes decision is utilized to combine the face and iris biometrics optimal decision. The experiment is performed on CASIA-Iris-Database with 142 individuals with a total number of 2567 images, score fusion using weighted sum rule achieves GAR about 95.03% at 0.01% of the FAR and decision fusion using threshold-optimized AND rule achieve GAR about 96.23% at 0.01% of FAR when Log-Gabor algorithm used as feature extraction methods. The proposed schemes achieve GAR about 98.87 % at 0.01% of the FAR.

In 2017, Miao et al. [21] introduce Bin based classifier for the combination of face and iris biometric, in this work bin-based classifier is utilized to convert the matching scores into higher dimensional space. The test outcome based on the CASIA-Iris Distance database exhibit the predominance of the proposed combination strategy. Bouzouina et al. in [33] developed a multimodal system using score level fusion based on face and iris, in this study two feature extractors, namely Zernike moment and Gabor filter are used in order to combine the properties of global and local methods. Later they explore the combination at the scores level, of the face and iris modalities in the wake of being normalized by using an SVM classification strategy. The outcome of the proposed framework is tried utilizing the CASIA-IrisV3- Interval database, the recognition rate accomplished with this database is 98.8.In 2018, Larbi and Taleb [34] introduce a matching score level based face-iris multimodal biometric system. In this proposed framework several score normalization and fusion techniques are utilized to combine the scores from the iris and. To test the proposed methodology, ORL face database and CASIA iris database are utilized and the results demonstrate that the proposed multimodal biometric framework accomplishes higher precision than both single biometric approaches and the other existing multi-biometric framework based on a combination of iris and face.

III. BIN-BASED CLASSIFIER FUSION

In Bin-based classifier fusion at first the scores of face-iris are divided into small unit called bin and for each bin a classifier is assigned which discovered distinctive and detailed source of data from the matching scores. In most of the score level fusion technique the main problem is the unavailability of the hidden information on matching score as the only one weight variable is not enough to distinctiveness of several biometric traits. To deal with this type of difficulty we used bin based classifier as a fusion rule which can easily utilize the hidden information of match score and can help in the recognition process and improved the performance of the systems. Overall working procedure of Bin-based classifier (BBC) is shown in Fig. 1. In Bin-based classifier the concatenated score vectors of face and iris is used as an input parameter and feature of the BBC is formed by using the each element of the score. For each element, the BBC partitions its domain into various bins and a linear classifier is assigned for each bin which best fits the training data in the bin. For each feature a piecewise linear classifier is formed by concatenate multiple linear classifier. To select the best performed piecewise classifier Bipartite Rankboost algorithm is used. Bin based classifier can be subdivided into three categories; these are Pairwise Continuous Bin-based classifier (PCBBC), Discontinuous Bin-based classifier (DBBC) and Continuous Bin-based classifier (CBBC).CBBC is most suitable for those situations where noise can influence the system performance, DBBC perform well for those situations where noise is in clustered in nature and located some area of the feature domain, such as an occlusion in face image and iris image have with spot of light. Among all three PCBBC is more accurate, but it is complex to implement and so it achieved more accurate and reliable fusion result.

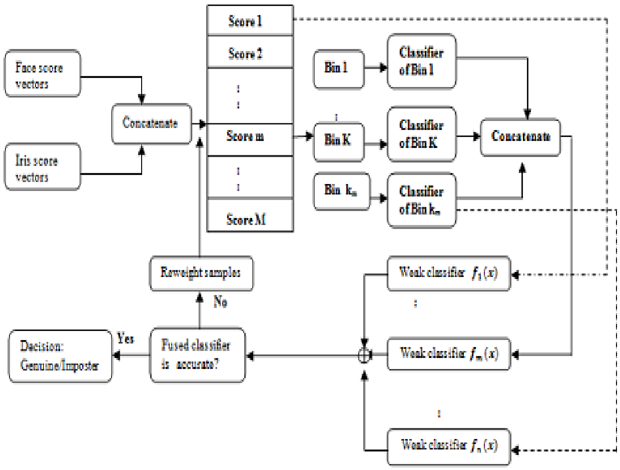

Fig.1. Bin-based classifier fusion

IV. PROPOSED WORK

This paper presents a multibiometric framework utilizing Bin-based classifier based on score level combination scheme to upgrade the performance of the system. This work consists of extraction of distinctions features from face and iris biometric modalities. On the enrollment stage a respective database of face and iris is formed by using the features of two different biometric modalities face and iris. A multi-algorithm approach is utilized to fuse the features of the face and iris. Different feature extraction algorithms like PCA (Principle Component Analysis), LDA (Linear Discriminant Analysis) and LBP (Local Binary Pattern) are used in this proposed work to extract the features of the face and iris.

4.1 Face Recognition using Principle Component Analysis (PCA)

The PCA (Principle Component Analysis) is one of the most prominent methods that have been utilized in image compression and recognition. The main concept of PCA for recognition of face is to represent the enormous 1-D vector of pixels developed from the 2-D facial image into the reduce principal components of the feature space, known as eigenspace projection. We use the circular Gabor filter which has the following general form:

$$G(x,y,\theta,u,\sigma) = \frac{1}{2\pi\sigma^2}\exp\left\{-\frac{x^2+y^2}{2\sigma^2}\right\} \times \exp\{2\pi i(ux\cos\theta + uy\sin\theta)\}$$

-------- (1)

Where σ is set as $\{2,4,6,8\}, u = \frac{1}{\sigma}$, and θ is set as $\{0,1,2,3,4,5,6,7\} \times (\frac{\pi}{8})$ .Gabor transforms have four scales and eight orientations. Finally, we combine the Gabor and PCA transform to extract the discriminant features as follows: (i) let x_{face} represent the face image sample sets. We preprocesses it using Gabor transform technique and obtained 32 transformed images and rename as $x_{gabor-face}$ (ii) Use PCA transform to extract discriminant features form $x_{gabor-face}$ and we get the corresponding face discriminant feature as y_{face}.

4.2 Face Recognition using Local Binary Patterns (LBP)

LBP (Local Binary Pattern LBP) is one of the most accurate feature extraction strategies utilized in face modality, this is accomplished by extraction of features by dividing the face image into several small regions shown in (Fig.2.) [35].The surroundings of pixels in the regions can be described by the binary pattern of the feature sets. A feature histogram is constructed with the concatenated features set obtained from features from the regions, which structures an image representation. The similarity between their histogram Images can be used to compare the image. This strategy likely to be more robust against face images with different lightening conditions, aging of persons, different facial expressions, and image rotation.

Fig.2. Face image divided into 64 regions

The LBP operator is based on the eights neighbors of a pixel. The fundamental idea is that if compared to the central incentive value a neighbor pixel has a higher or same gray value, then one is relegate to the pixel otherwise zero is relegated to the pixel. The binary code obtained from the concatenating the eight ones or zeros will decide the LBP code for the central pixel shown in (Fig.3) [35].

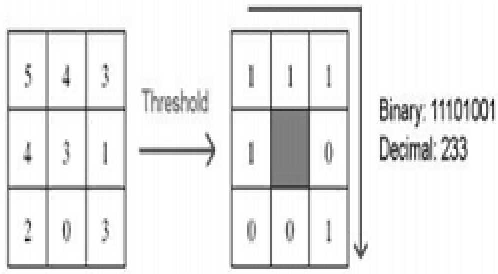

Fig.3.The original LBP operator

4.3 Iris Recognition using Local Binary Patterns (LBP)

In this proposed work, the extraction of the iris pattern is accomplished by LBP operator. The LBP code is evaluated by measuring the similarity of a pixel of an image with its neighbor pixels. For texture description the original LBP operator is considered to be a powerful tool. The neighboring pixels g_0-g7 is converted to 0 on the basis of the center pixel as a threshold, if their intensity level is smaller than that of the center g_c, or to 1 in another scenario. Then an LBP code for the center pixel g_c, is generated by multiplying weights 2^n given to the corresponding pixels with the converted neighbourhood pixel values. The LBP operator working model is shown in Fig. 4.

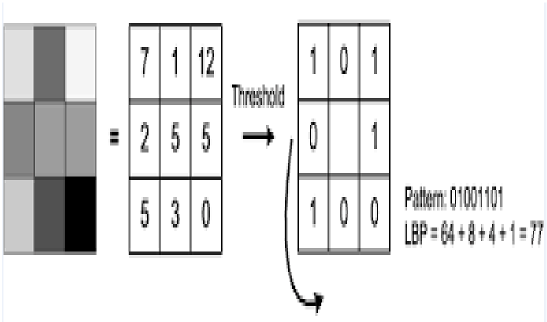

Fig.4.The basic LBP operator

Utilizing condition (2), LBP operator of 16-neighbourhood gets LBP images whose range are 0~$(2^{16}-1)$.

$$LBP_{P,R}=\sum_{p=0}^{p-1} r(g_p-g_c)2^p, r(x)=\begin{cases}1, x\geq 0\\ 0, x<0\end{cases}$$

----------- (2)

Where g_c represents the center pixel intensity level, gray value of the neighboring pixel is denoted by g_p, p and R denotes the total numbers of the neighboring pixels and radius of the neighborhood respectively. The LBP pattern is evaluated for each pixel of that image from the images of m*n , and to represent the iris texture histogram is generated .

$$Hist(k)=\sum_{i=1}^{l}\sum_{j=1}^{l} f(LBP_{p,R}(i,j),k), k\in[0,k],$$

$$f(x,y)=\begin{cases}1, x=y\\ 0, otherwise\end{cases}$$ --------- (3)

4.4 Iris Recognition using Principle Component Analysis (PCA)

PCA (Principal Component Analysis) is a numerical method that utilizations direct Transformations outline data from a higher dimensional space to lower dimensional space. The two-dimensional matrixes of iris region are captured by preprocess, localize the iris regions and normalize.PCA involves the following steps.

- An Iris region is utilized to obtain the data.
- Find difference of mean from each dimension of the data.
- Covariance matrix is further evaluated.
- Eigenvalue and eigenvectors of the covariance matrix is evaluated.
- Forming a feature vector by selecting component.
- The new data set is generated.

In the final step of PCA a feature vector is formed by choosing the appropriate eigenvectors that we want to keep in our data. The working procedure of the proposed framework is shown in Fig. 5.

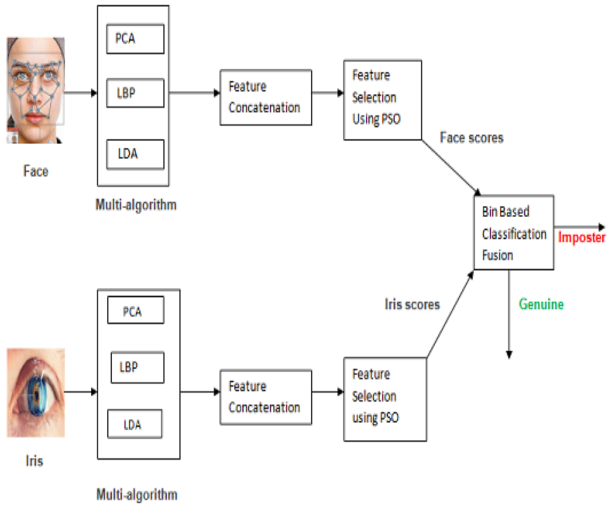

Fig.5. Block diagram of the proposed framework.

4.5 Feature selection using PSO

Pso is a stochastic based optimization technique, having population called swarm with a candidate solution called particles. Each particle in feature space of n-dimensional is considered as a point and ith particle is represented as $x_i=(x_{i1},x_{i2},\dots\dots\dots x_{in})$ .In this representation particle number is expressed by the first subscript and dimension by the second subscript. In PSO, two parameters (velocity and position) play an important role, first each particle in n-dimensional space has some velocity according to which it moves in and the position according to which every particle changes its own position. Hence the performance of PSO is affected by two factors: the local best solution causes by itself and the due to the each particle involved in the solution space called global best solution. The particle velocity is represented by the N-dimensional vector, $V_i=(v_{i1},v_{i2},v_{i3},\dots\dots.v_{in})$. An N-dimensional vector, $pos_i=(p_{i1},p_{i2}\dots\dots,p_{in})$ is used to represent the previous best position of the particle and N-dimensional vector, $pos_g=(g_{i1},g_{i2},\dots\dots,g_{in})$ is utilized to represent the global best position of the particle.

An updating of particle velocity at kth iteration is accomplished by:

$$V^{k+1}{}_{id}=\omega V^{k}{}_{id}+r_1\alpha(pos_{id}-x^{k}{}_{id})+r_2\beta(pos_{gd}-x^{k}{}_{id}) \quad (4)$$

An updating of particle position is done by:

$$x^{k+1}{}_{id}=x^{k}{}_{id}+V^{k+1}{}_{id} \quad (5)$$

Where α and β are positive constant known as cognitive and social parameter respectively, the two random number r_1 and r_2 have the value between 0 and 1. ω is called inertia weight, k=1,2,3 ... is the iteration steps. A complete PSO pseudo code is shown in Fig. 6.

The outcome of any biometric system is either genuine user or imposter user. The outcome of any biometric framework can be measured by its false acceptance rate (FAR), which is the probability of acceptance of non-authorized people incorrectly and it's false rejection rate (FRR), which is the probability of rejection of authorized person.

By changing the threshold value from 0 to 1 in normalization, case, the FRR demonstrate an expanding pattern while the FAR shows diminishing pattern. The FAR vs. FRR curve is shown in Fig. 7[15]. The main objective is to reduce the Total error rate (TER) which is the sum of FAR and FRR by selecting an optimal feature. Let the total numbers of genuine user's biometric samples be denoted as m^+ and total number of imposter user's biometric samples by m^-. The formulation of FAR and FRR having a threshold value of τ can be expressed as follows:

$$FAR = \frac{1}{m^-} \int_{i=1}^{m^-} I_{g(x^-_i) \geq \tau} \qquad (6)$$

$$FRR = \frac{1}{m^+} \int_{i=1}^{m^+} I_{g(x^+_i) < \tau} \qquad (7)$$

Where $g\ (x)$ represents the biometric decision function. Eq. (8). Represent a trapezium rule which denote the area under the DET (Detection Error Tradeoff curve) .The Eq. (8) act as the fitness function that utilized to estimate the each particle performance in PSO algorithm.

$$DET = \sum_{FAR=0}^{FAR=1} \frac{1}{2} \times (FAR(\tau+1) + FRR(\tau+1) - FAR(\tau) \times FRR(\tau))$$
--------- (8)

Algorithm: **PSO**
For every particle j
  For every dimension m
    Randomly initialize velocity v_{jm}
    Randomly initialize position x_{jm}
  End for
End for
K←1
Do
  For each particles i
   Calculate fitness function
    If the fitness value is superior than the p_best_{im} then
     Set present fitness value as p_best_{im}
    End if
  End for
 Choose the particle with the best fitness value as g_best_{im}
 For every particle i
  For very dimension m
   Calculate velocity as
   $v_{im}(k+1) = wv_{im}(k) + c1rand_1(p_{im} - x_{im}) + c2rand_2(p_{gm} - x_{im})$
   Particle position is updated as
   $x_{im}(k+1) = x_{im}(k) + v_{im}(k+1)$
  End for
 End for
 K←K+1
While maximum iteration is not attained

Fig.6. Pseudo code of PSO

4.6 Fusion Using BBC (Bin Based Classifier)

In this segment we investigate how easily the information extracted from BBCs can be efficiently combined together. A decision made by each BBC's is not heterogeneous in nature and so it is possible with the rule of linear combination fused into a powerful 'committee'. In this proposed work ensemble learning methods such as Boosting is used to learn and combine each of BBCs, to extract considerable relevant information. A machine learning technique, Boosting is a method in which combination of weak classifier (produce by a weak learner) can generate the best result and can be considered as a simple classifier. The main strategy of boosting is to learn different weak classifiers and finally combine them in some way. In classification problem, it is very easy to train single complex classifier than various simple classifiers and finally combining them into a more complex classifier. In other word boosting technique can be considered as a process of regularly applying differently weighted version of training data for the weak learning algorithm [36]. The boosting algorithm can be classified as: AdaBoost algorithm, GBA (Generic Boosting algorithm), XGBoost (Extreme gradient Boosting), stochastic gradient boosting and Bipartite Rankboost. The best BBC performing is selected during the each iteration by the Bipartite Rankboost rule and then the training samples are reweighted. In Bipartite Rankboost algorithm a highly accurate single ranker is formed by using the combination of weak learner and bipartite feedback is used when there are two sets of instances and we have to rank all instances of one set over another set. The complete pseudo code for the Bipartite Rankboost algorithm is shown in Fig. 8.

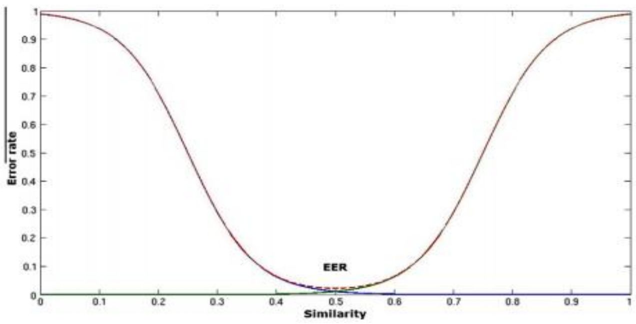

Fig.7. FAR Vs. FRR Curve

Algorithm: Bipartite Rankboost
Given: disjoint subset of X_1 and X_2 of X.
Initialize:

$$V_1(x) = \begin{cases} \frac{1}{|X_1|} & if\ x \in x_1 \\ \frac{1}{|X_0|} & if\ x \in x_0 \end{cases}$$

For z= 1… Z:

- Weak learner training using Distribution
  $D_z = v_z(x_0)\ v_z(x_1)$
- Obtain weak ranking $h_z : X \in R$
- Select $\alpha_z \in R$
- Update :

$$v_{z+1}(x) = \begin{cases} \frac{v_z(x)\exp(-\alpha_z(x))}{Q^1_z} & if\ x \in x_1 \\ \frac{v_z(x)\exp(\alpha_z(x))}{Q^0_z} & if\ x \in x_0 \end{cases}$$

Where Q^0_z and Q^1_z normalize v_z over x_0 and x_1 :

$$Q^0_z = \sum_{x\in x_0} v_z(x)\exp(-\alpha_z h_z(x))$$
$$Q^1_z = \sum_{x\in x_0} v_z(x)\exp(\alpha_z h_z(x))$$

Output the final ranking: $H(x) = \sum_{z=1}^{Z} \alpha_z h_z(x)$

Fig. 8. Pseudo code of Bipartite Rankboost Algorithm

In this work we utilized weak learning algorithm which generates weak learner h_z with output $\{0,1\}$. For computing $\propto$ we assume $h(x)$has the range of $0,1$, with $b \in \{-1,0,1\}$.

Let: $W_b = \sum_{x_0,x_1} D_z(x_0 x_1) I(h_z(x_0) - h_z(x_1) = b)$ (9)

By replacing W_{-1}, $W_{+1}$with W_- and W_+, we get

$$Z = W_0 + W_- e^{-\propto} + W_+ e^{\propto} \quad (10)$$

By taking the derivative of Z with respect to $\propto$, we get

$$\frac{dz}{d\propto} = \frac{d(W_0 + W_- e^{-\propto} + W_+ e^{\propto})}{d\propto}$$
$$0 = 0 - W_- e^{-\propto} + W_+ e^{\propto}$$

The final value of $\propto$ can be computed as:

$$\propto = \frac{1}{2}\ln\left(\frac{W_-}{W_+}\right) \quad (11)$$

To determine the weak learner, we should minimize Z using the equation (12) and value of $\propto$ can be computed using (11)

$$Z = W_0 + 2\sqrt{W_0 W_1} \quad (12)$$

The way to choosing the best performing BBCs is processed until it achieved the maximum level of iteration or the accuracy is sufficiently high. The sum of all the selected BBCs is finally producing the fusion classifier, which is expressed as follow:

$$F(x) = \sum_{m=1}^{M} f_m \quad (13)$$

An ultimate choice of recognition is made upon the indication of the combination classifier $F(x)$ .A client is treated as genuine if $F(x) > 0$ and an imposter otherwise.

IV. EXPERIMENT AND RESULTS

In this paper the presentation of the unimodal and multimodal framework is completed utilizing four sets of face and iris database. In most of face-iris fusion methods [12, 14, 32], analyses are done out on autonomous face and iris database. There is no open database is accessible which incorporates same personality both traits of the face and iris. In the first dataset named "Dataset1" we utilized a consolidated virtual database with ORL and BANCA face database together with UBIRIS and CASIA iris database. This database incorporates 222 individuals' with 1776 face-iris images, validation set contains 222 subjects with 2 samples for each having 444 images in total, and verification set contains 222 subjects with 6 samples for each having 1332 images in total. In the second dataset named "Dataset2" consists FERET face database and CASIA iris database. In the ORL face dataset, 40 different subjects with 10 samples are available. The third dataset named "Dataset3" consist of a collection of FERET face and UBIRIS iris database. The different feature extraction technique (PCA, LDA and LBP) is utilized to obtain the feature sets of face and iris and combined together to form a feature vector and then Euclidean distance measurement is used to compare the image. The test results are reported in Table 1 where the LBP technique on face produces the best accuracy, whereas LDA technique on iris gives the best accuracy. On account of the multimodal framework by using the feature concatenation method the performance of the system will be improved. The presentation of the individual framework can be boosted by shaping a multimodal framework utilizing face and iris based on score combination approach. The proposed work uses PSO as an optimization technique which minimize the unwanted data and select only the best features set which can maximize the execution of the framework as far as higher recognition rate and minimum error rate, the exhibition of multimodal framework is also evaluated using weighted sum rule. The concatenations of face and iris feature sets and combination technique based on score level can improve the recognition rate and at the same time diminish the error rate. The equal error rate (EER) of the multimodal system observed in experimental result (shown in Fig. 9) is 0.028, which achieve better result as compared to the unimodal system having EER=0.045 for iris and EER=0.0675 for the face. The ROC curve in Fig.10 demonstrates that feature concatenation of face and iris based on PSO optimization technique with EER=0.03 outperform than the score level fusion method using a weighted sum rule with EER=0.032 and feature concatenation process without PSO with EER=0.035.The ROC curve in Fig 11 demonstrates that the multimodal system using PSO based on continuous bin based classifier (CBBC) with EER=0.012 outperform than the system without PSO with EER=0.015.From Fig. 12 it is clear that the proposed multimodal framework of face and iris based on CBBC with PSO as an optimization technique with EER=0.012 outperform than the other fusion technique with EER=0.018 for SVM (RBF) and EER=0.02 for SVM linear. Some sample images of face and iris is shown in Fig. 13.

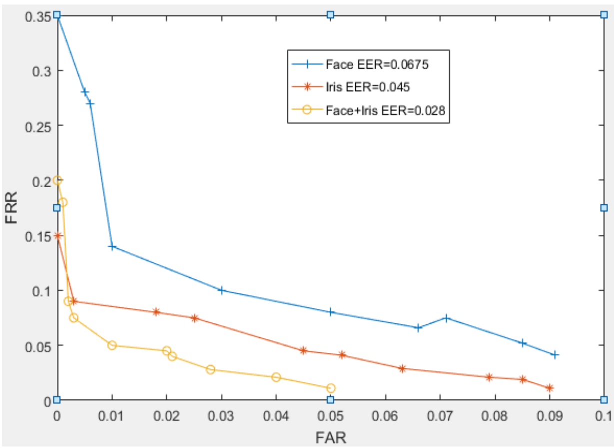

Fig.9.Roc curve for unimodal and multimodal system for face and iris

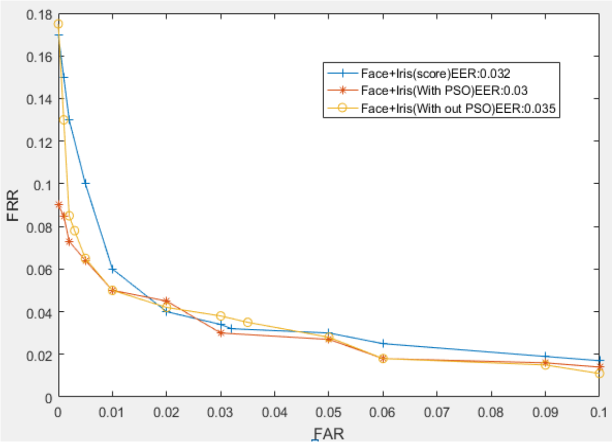

Fig.10. ROC curve for a multimodal system using PSO and without PSO

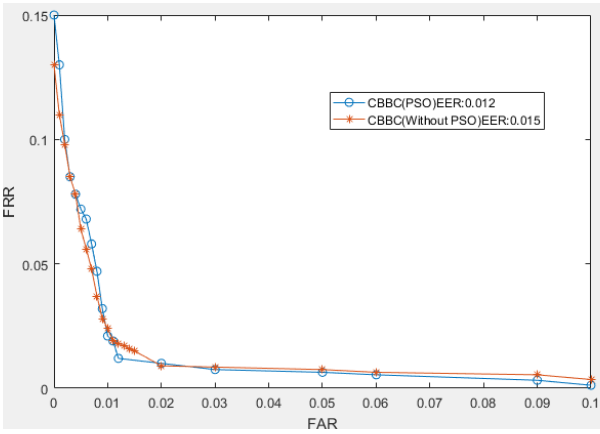

Fig.11. ROC curve for CBBC using PSO and without PSO

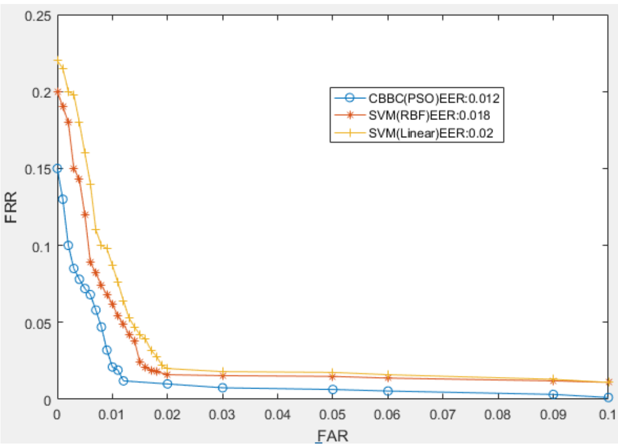

Fig.12. ROC SVM using RBF and linear methods

Table 1: Performance (Recognition rate) on unimodal systems

Dataset	Unimodal system	PCA	LDA	LBP
Dataset1	Face(BANCA, ORL)	71.5	77.8	80.7
	Iris (UBIRIS, CASIA)	87.2	92.5	84.0
Dataset2	Face (FERET)	77.8	85.9	88.7
	Iris (CASIA)	80.7	93.4	78.6
Dataset3	Face (FERET)	77.8	85.9	88.7
	Iris (UBIRIS)	78.12	83.7	75.8

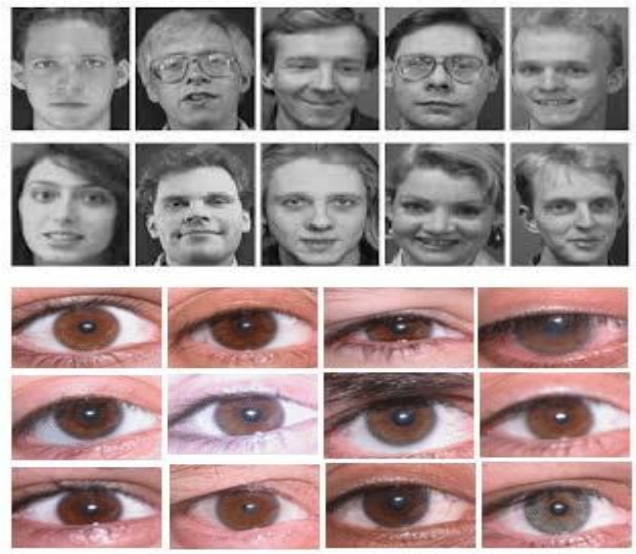

Fig.13. Images of face and iris from ORL, CASIA, BANCA and FERET databases

V. Discussion

These sections discuss about the related work on different fusion strategy based on face and iris.A weighted score level combination of iris and non-ideal face was addressed in [19]. Based on an UTMIFM dataset of multimodal framework the DI (decidability index) has increased to 2.9988.The test results based on an UTMIFM dataset show that DI for multimodal biometric fusion achieved 2.778 with total accuracy of 99.6%. As compared to results reported in [14] the proposed combination scheme has achieved better output in terms of DI and total accuracy. In 2015, biometric person identification framework based on face and iris using hybrid (feature and score) fusion technique was addressed in [23]. The test results demonstrate that based on ORL face dataset the recognition rate of 90.25% achieved using LDA method, whereas it was 92.83% based on CASIA iris dataset using LBP method. The proposed feature and score level based hybrid combination scheme produce a recognition rate with 98.75%, which show that there is enhanced as compared to a weighted score fusion with a rate of 97.50% as per as recognition rate is concerned. In 2016, BSA (Backtracking search algorithm) technique based multimodal framework using face and both irises was introduced in [22], this paper focused on the enhancement of the recognition rate based on different combination technique. The test outcomes based on hybrid combination technique reveal that the exhibition of the BSA based procedure is better than the schemes without the BSA feature selection rule. A GAR 95.00% and TER of 0.81% is achieved by the match score level combination scheme, whereas A GAR 96.87% and TER of 0.58% is achieved by the use of decision level fusion. As compared to the results reported in [23] it is found that the proposed hybrid fusion reported a recognition rate of 98.93%, which shows better enhancement in terms of recognition rate.

The exhibitions of the proposed strategies based on a feature and score level combination scheme are shown in Table 2.

The outcomes of the results based on FERET face and CASIA iris datasets show that at feature level fusion using PSO technique best recognition rate of 96.1% is achieved, whereas weighted sum rule based score level combination scheme achieved a recognition rate of 95.8%.The performance of the bin based classifier fusion with PSO and without PSO is shown in Table 3. The outcomes from the Table 3 exhibit that the CBBC approach dependent on PSO procedure beats the other combination strategies. The best recognition rate of 98.8% is achieved using CBBC with PSO in a multimodal system using FERET face and CASIA iris databases, DBBC approach based on PSO technique achieved a recognition rate of 97.2%.The comparative analysis of the proposed approach with the others fusion methods is reported in Table 4.

Table 2: Performance (Recognition rate) of multimodal framework based on feature and score level fusion

Dataset	Multimodal system	Score level Weighted sum	Feature level Without PSO	Feature level With PSO
Dataset1	Face (ORL, BANCA) Iris (CASIA, UBIRIS)	94.9	94.8	95.7
Dataset2	Face (FERET) Iris (CASIA)	95.8	95.2	96.1
Dataset3	Face (FERET) Iris (UBIRIS)	94.1	93.9	94.5

Table 3: Performance (Recognition rate) of proposed framework with PSO and without PSO

Dataset	Multimodal system	CBBC With PSO	CBBC Without PSO	DBBC With PSO
Dataset1	Face (ORL, BANCA) Iris (CASIA, UBIRIS)	96.5	95.8	96.1
Dataset2	Face (FERET) Iris (CASIA)	98.8	95.9	97.2
Dataset3	Face (FERET) Iris (UBIRIS)	97.6	94.9	95.7

Table 4: Comparison of performance of proposed approach with state-of-the-art fusion approach

Year	Authors	Recognition rate	Error rate
2014	Sim et al [19]	99.6	EER=0.055
2014	Eskandari et al [14]	98.53	EER=0.015
2015	Azom et al. [23]	98.75	Not Reported
2016	Sharifi et al. [22]	98.93	EER=0.135
2018	Larbi et al. [34]	99.2	EER=0.032
2019	Proposed approach	98.8	EER=0.012

VI. CONCLUSION

This work addressed a multimodal system using face and iris based on score level fusion to reduce the error rate and enhance the performance of the proposed framework, an optimization technique PSO (particle swarm optimization) is utilized to select the optimum feature sets. Genetic algorithm requires several complex evolution operations like crossover and mutation, but PSO avoids such complex operation and involve with different mathematical operations and this is the one of the primitive criteria for selecting a PSO as an optimization technique. In terms of speed and memory requirement PSO is more computationally inexpensive. The other purpose of selecting PSO is that it has a memory which helps to maintain the best solution for the particle which is not possible in the case of genetic algorithm. In most of the score level fusion technique the main problem is the hidden information in matching score is not fully identified, to deal with this type of difficulty we used bin based classifier as a combination rule which can easily utilize the hidden information of match score and can help in the recognition process and improved the performance of the proposed framework.The three algorithms, namely LBP (Local Binary Pattern), LDA (Linear Discriminant Analysis) and PCA (Principle component analysis) are utilized to extract the features of the face and iris.

The combined feature sets of face and iris have several disadvantages including large in dimension and large set of irrelevant data which influence the accuracy level of the system. To reduce the dimension of features set and minimize the irrelevant data, we utilized PSO (particle swarm optimization) as an optimization technique. At last the features of face and iris are combined together and feed into the Bin Based Classifier (BBC) combination technique which enable the system to differentiate between the genuine or imposter one.The test result demonstrates that among the several combination rules (CBBC, SVM-RBF, SVM-Linear, LDA), the performance of the CBBC method is outperform than the other combination rule with minimum error rate and high accuracy level.

REFERENCES

1. Chin, Yong Jian, Thian Song Ong, Andrew Beng Jin Teoh, and K. O. M. Goh. "Integrated biometrics template protection technique based on fingerprint and palmprint feature-level fusion." *Information Fusion*, 2014, vol.18, pp. 161-174.
2. Jain, Anil K., Ruud Bolle, and Sharath Pankanti, eds. “Biometrics: personal identification in networked society.” Springer Science & Business Media, 2006,479.
3. Paul, Padma Polash, Marina L. Gavrilova, and Reda Alhajj. "Decision fusion for multimodal biometrics using social network analysis." *IEEE transactions on systems, man, and cybernetics: systems*, 2014, vol.44, no.11, pp. 1522-1533.
4. Hanmandlu, Madasu, Jyotsana Grover, Ankit Gureja, and Hari Mohan Gupta. "Score level fusion of multimodal biometrics using triangular norms." *Pattern recognition letters*, 2011, vol.32, no.14, pp. 1843-1850.
5. Anil Jain,Karthik Nandakumar, Arun Ross,” Score Normalization in Multimodal Biometric System*”, journal of Pattern Recognition* ,2005,vol. 38,pp.2270.
6. He, Mingxing, et al. "Performance evaluation of score level fusion in multimodal biometric systems*." Pattern Recognition*, 2010, vol. 43, no.5, pp. 1789-1800.
7. Mezai, Lamia, and Fella Hachouf. "Score-level fusion of face and voice using particle swarm optimization and belief functions." *IEEE Transactions on Human-Machine Systems*, 2015, vol.45, no.6, pp. 761-772.
8. Dalila, Cherifi, Hafnaoui Imane, and Nait-Ali Amine. "Multimodal score-level fusion using hybrid ga-pso for multibiometric system." *Informatica*, 2015, vol.39, no.2.
9. Monwar, Md Maruf, and Marina L. Gavrilova. "Multimodal biometric system using rank-level fusion approach." *IEEE Transactions on Systems, Man, and Cybernetics, Part B (Cybernetics)*, 2009, vol.39, no.4, pp. 867-878.
10. Kumar, Amioy, Madasu Hanmandlu, Harsh Sanghvi, and H. M. Gupta. "Decision level biometric fusion using ant colony optimization." In *Image Processing (ICIP), 2010 17th IEEE International Conference on*, IEEE, 2010, pp. 3105-3108.
11. Miao, Di, et al. "Bin-based weak classifier fusion of iris and face biometrics." *Biometrics Theory, Applications and Systems (BTAS), 2015 IEEE 7th International Conference on*. IEEE, 2015.

12. Wang, Yunhong, Tieniu Tan, and Anil K. Jain. "Combining face and iris biometrics for identity verification." *International Conference on Audio-and Video-Based Biometric Person Authentication*. Springer, Berlin, Heidelberg, 2003.
13. Wang, F., and J. Han. "Multimodal biometric authentication based on score level fusion using support vector machine." *Opto-electronics review*, 2009, vol.17, no.1, pp.59-64.
14. Eskandari, Maryam, Önsen Toygar, and Hasan Demirel. "Feature extractor selection for face–iris multimodal recognition." *Signal, image and video processing*, 2014, vol.8, no.6, pp.1189-1198.
15. Liau, Heng Fui, and Dino Isa. "Feature selection for support vector machine-based face-iris multimodal biometric system." *Expert Systems with Applications*, 2011, vol.38, no.9, pp. 11105-11111.
16. Connaughton, Ryan, Kevin W. Bowyer, and Patrick J. Flynn. "Fusion of face and iris biometrics." *Handbook of Iris Recognition*. Springer, London, 2016, pp. 397-415.
17. Chen, Ching-Han, and Chia Te Chu. "Fusion of face and iris features for multimodal biometrics." *International Conference on Biometrics*. Springer, Berlin, Heidelberg, 2006
18. Zhang, Zhijian, et al. "Fusion of near infrared face and iris biometrics." *International Conference on Biometrics*. Springer, Berlin, Heidelberg, 2007.
19. Sim, Hiew Moi, et al. "Multimodal biometrics: Weighted score level fusion based on non-ideal iris and face images." *Expert Systems with Applications*, 2014, vol.41, no.11, pp. 5390-5404.
20. Eskandari, Maryam, Önsen Toygar, and Hasan Demirel. "A new approach for face-iris multimodal biometric recognition using score fusion." *International Journal of Pattern Recognition and Artificial Intelligence*, 2013, vol.27, no.3, pp.1356004.
21. Miao, Di, et al. "Bin-based classifier fusion of iris and face biometrics." Neurocomputing, 2017,224, pp. 105-118.
22. Sharifi, Omid, and Maryam Eskandari."Optimal Face-Iris Multimodal Fusion Scheme." Symmetry, 2016, vol.8, no.6.
23. Azom, Valentine, Aderemi Adewumi, and Jules-Raymond Tapamo. "Face and Iris biometrics person identification using hybrid fusion at feature and score-level." *Pattern Recognition Association of South Africa and Robotics and Mechatronics International Conference (PRASA-RobMech), 2015*. IEEE, 2015.
24. Morizet, Nicolas, and Jérôme Gilles. "A new adaptive combination approach to score level fusion for face and iris biometrics combining wavelets and statistical moments." *Advances in Visual Computing*, 2008, pp. 661-671.
25. Eskandari, Maryam, and Önsen Toygar. "Fusion of face and iris biometrics using local and global feature extraction methods." *Signal, image and video processing*, 2012, vol.8, no.6, pp. 995-1006.
26. Kim, Yeong Gon, et al. "Multimodal biometric system based on the recognition of face and both irises." *International Journal of Advanced Robotic Systems*, 2012, vol.9, no.3.
27. Wang, Ning, et al. "A novel hybrid multibiometrics based on the fusion of dual iris, visible and thermal face images." *Biometrics and Security Technologies (ISBAST), 2013 International Symposium on*. IEEE, 2013, pp. 217-223.
28. Huo, Guang, Yuanning Liu, Xiaodong Zhu, Hongxing Dong, and Fei He. "Face–iris multimodal biometric scheme based on feature level fusion." *Journal of Electronic Imaging*, 2015, vol.24, no.6, pp. 063020.
29. Eskandari, Maryam, and Omid Sharifi. "Optimum scheme selection for face–iris biometric." *IET Biometrics,* 2016, vol.6, no.5, pp. 334-341.
30. Wang, Zhifang, Jie Yang, Erfu Wang, Yong Liu, and Qun Ding. "A novel multimodal biometric system based on iris and face." *International Journal of Digital Content Technology and its Applications (JDCTA),* 2012, vol.6, no.2.
31. Wang, Rui, Shengcai Liao, Zhen Lei, and Stan Z. Li. "Multimodal Biometrics Based on Near-Infrared Face Recognition." *Biometrics: Theory, Methods, and Applications. Edited by Boulgouris, Plataniotis and Micheli-Tzanakou. IEEE, Inc* (2010).
32. Wang, Zhifang, Erfu Wang, Shuangshuang Wang, and Qun Ding. "Multimodal Biometric System Using Face-Iris Fusion Feature." *JC*, 2011, vol.6, no.5, pp.931-938.
33. Bouzouina, Yacine, and Latifa Hamami. "Multimodal biometric: Iris and face recognition based on feature selection of iris with GA and scores level fusion with SVM." In *2017 2nd International Conference on Bio-engineering for Smart Technologies (BioSMART)*, IEEE, 2017, pp. 1-7.
34. Larbi, Nouar, and Nasreddine Taleb. "A Robust Multi-Biometric System with Compact Code for Iris and Face." *International Journal on Electrical Engineering & Informatics*, 2018, vol.10, no.1.
35. Rahim, Md Abdur, Md Shafiul Azam, Nazmul Hossain, and Md Rashedul Islam. "Face recognition using local binary patterns (LBP)." *Global Journal of Computer Science and Technology*, 2013.
36. Ferreira, Artur J., and Mário AT Figueiredo. "Boosting algorithms: A review of methods, theory, and applications." In *Ensemble machine learning*, Springer, Boston, MA, 2012, pp. 35-85.

AUTHORS PROFILE

Sandip Kumar Singh Modak, MCA from NIT Jamshedpur and pursuing P.hd from BIT Mesra Ranchi, Currently working as Assistant Professor in Comp. Sc. Deptt. Of Mrs KMPM. Vocational college, Jamshedpur, having 06 years of teaching experience and 03 year of research experience, published various papers in national and international journals. His area of interest is Network security, Multibiometric, Machine learning etc.

Dr. Vijay Kumar Jha, Presently working as Associate professor in Comp. Sc. & Engg. Deptt.of BIT Mesra Ranchi, INDIA, Ph. D. Engg, M. Sc Engg., B. E. having 20 years of teaching experience and 10 year of research experience, Under his supervision 06 P.hd scholars currently enrolled,06 P.hd degree awarded, 26 M.Tech thesis guided, Published various papers in national and international journals. His area of interest is Data Mining, Network security, Big Data Analysis etc.