

Research Article

Optimized Radial Basis Function Classifier for Multi Modal Biometrics

¹Anand Viswanathan and ²S. Chitra

¹Department of Information Technology, V.S.B. Engineering College, Karur, India

²Department of Computer Science Engineering, Er. Perumal Manimekalai College of Engineering, India

Abstract: Biometric systems can be used for the identification or verification of humans based on their physiological or behavioral features. In these systems the biometric characteristics such as fingerprints, palm-print, iris or speech can be recorded and are compared with the samples for the identification or verification. Multimodal biometrics is more accurate and solves spoof attacks than the single modal biometrics systems. In this study, a multimodal biometric system using fingerprint images and finger-vein patterns is proposed and also an optimized Radial Basis Function (RBF) kernel classifier is proposed to identify the authorized users. The extracted features from these modalities are selected by PCA and kernel PCA and combined to classify by RBF classifier. The parameters of RBF classifier is optimized by using BAT algorithm with local search. The performance of the proposed classifier is compared with the KNN classifier, Naïve Bayesian classifier and non-optimized RBF classifier.

Keywords: BAT optimization, fingerprint, finger vein, local search, multimodal biometrics, Radial Basis Function (RBF) classifier

INTRODUCTION

In recent years, the biometric systems are used widely to recognize the humans by using either the physiological or the behavioral characteristics. Systems which use bio metric measures are more secure, because it does not recognize a person by the things carried such as smart cards which are used in the conventional authorization systems. These conventional systems use some of the possession-based and knowledge-based recognition methods. The advantages of the biometric identifiers are, they cannot be mislaid, forgotten, guessed, or easily copied. Even though, there are many inherent advantages in the bio metric based recognition systems, there are some limitations if they are used in wider scale, because of the following reasons. The accuracy of the identification is very less in some domains. For example, recognition of human faces, because the accuracy of recognition depends on the illumination of the light, pose and the expressions of the face (Monrose and Rubin, 2000). It is very difficult to avoid the spoof attacks. In case of illness or some disabilities, some people cannot give the needed measurement for the biometric system (Feng *et al.*, 2004).

Biometric systems can be used in two modes for the recognition of a person. They are verification and identification. During the verification process, an identity of a person is claimed and the comparison step

crosschecks to confirm the identity. For the identification mode, there is no claim needed for the identity and the system checks its reference in the data store to determine whether a stored reference matches the recorded biometric characteristics.

When comparing many characteristics or traits of the humans, the hands are very easier and convenient to represent and be imaged. They also can show different kinds of features which can be captured with variety of illuminations and ranging imaging resolutions. The illumination ranges are visible, near infra-red, thermal infrared. The metrics such as palm-print, finger knuckle and hand geometry can be acquired in the visible illumination to get fingerprint features and palm-vein features can be acquired using the near infrared and far infrared imaging. These made a lot of research works and developments in the last decade (Venkataramani *et al.*, 2005).

Fingerprint Identification uses the impressions created by the minute ridge formations or patterns available on the fingertips to identify the persons. Because two persons do not have perfectly matched patterns of ridge and these patterns of a person does not change in the entire life of the person. So the fingerprints can be used for the personal identification. Usually, Fingerprints can be acquired by using a standard fingerprint card or it can be recorded digitally and transmitted electronically for comparison. For example, for crime investigations, fingerprint recorded

Corresponding Author: Anand Viswanathan, Department of Information Technology, V.S.B. Engineering College, Karur, India

This work is licensed under a Creative Commons Attribution 4.0 International License (URL: <http://creativecommons.org/licenses/by/4.0/>).

at the place of the crime is compared with the suspected person's fingerprints and used as a proof to identify the criminals.

The traditional fingerprint identification is very strong, because a high resolution (over 400 dpi) imaging can be obtained and used. The finger images captured by using the webcams attached in the desktops, laptops or in mobile phones are low-resolution images that have less than 75 dpi needs more processing efforts to utilize in civilian and forensic applications to identify persons (Arandjelovic and Cipolla, 2007).

Multimodal biometrics means that the use of a combination of more than one biometric modalities for the verification/identification system. Recognition based on the multiple biometrics is an emerging trend in all the fields:

- The strong reason for combining different modalities in the identification is to enhance the recognition rate. This can be achieved when different statistically independent biometric features are combined or fused.
- Different biometric modalities strength different applications appropriately.
- Customer may prefer some modalities in the identification/verification.

Multi-biometric indicates may use more than one biometric aspect in some way of combined use to do a specific biometric verification/identification decision (Ko, 2005). The goal of multi-biometrics may be one or more of the following:

- Minimizing False Accept Rate (FAR)
- Reduction False Reject Rate (FRR)
- Reducing Failure to Enroll rate (FTE)
- Reducing the Susceptibility to artifacts or mimics

Some of the limitations of multimodal biometric systems are.

Interpretability: Different types of systems which use multimodal features should follow uniform set of rules for the classification, but these rules are not yet standardized.

Implementation cost: As different modalities to be recorded, these systems use more types of hardware and computational resources. This increased the setup cost.

Reduced matching levels: Better decision and fusion algorithms should be used to get the higher level of matching when combining different biometric traits rather than the individual matching level (Mishra, 2010).

Usually, the multimodal biometric fusion is used to combine the measurements recorded from the different

biometric traits to improve the strengths and eliminate the limitations or the weaknesses of the individual measurements. The various levels of fusions used are sensor level, feature level, matching score level and decision level.

In this study, the features of finger vein and the features from the fingerprint images are extracted and fused after the normalization procedure. Then top ranked features are selected by the principle component analysis. RBF classifier is used to classify the authorized and unauthorized user. Radial Basis Function (RBF) based Neural Network classifier is used for identifying the authorized user. The norm that takes input from the input layer to the hidden layer is the Euclidean distance. The parameters of the RBF activation functions are optimized by the combined BAT algorithm and the local search.

LITERATURE REVIEW

Kumar and Zhou (2012) presented a new approach to enhance the performance of the finger-vein identification systems. In the proposed system, both the finger-vein and low-resolution fingerprint images were recorded simultaneously and they were combined by using a score-level combination strategy. The fingerprint images were recorded from a webcam and the utility of these images was examined to ascertain the matching performance from these low resolution images. Two new types of score-level combinations like holistic and nonlinear fusion were developed and evaluated to ascertain their effectiveness in the proposed system. Results proved that combination of finger-vein and low resolution fingerprint images improved the identification significantly.

Kim *et al.* (2012) proposed a new type of multimodal biometric system by using score level fusion to recognize by using face and irises images. The unimodal biometric systems suffered from the problems because of the variations in the illuminations and devices, condition of the skin and the environment. Therefore to overcome those limitations, the author proposed a multimodal bio metric system by combining both the face and the iris images. The proposed device captured both of the images simultaneously. The experimental results proved that the proposed one performed better than face or iris recognition individually and also than other combination methods.

Moganeshwaran *et al.* (2012) discussed the System-On-Chip (SOC) Field Programmable Gate Array (FPGA) based implementation in the multimodal biometric systems for authentication. The proposed authentication system was embedded in the environment which was resource constrained. The traits such as Fingerprint and finger vein were used in biometric system and all the steps of authentication check were implemented in SOC FPGA. An embedded

processor was used for the execution and information fusion was done by the matching at the score level. Experiments were conducted with the proposed system and the results showed that the accuracy was good with 0.33% of Error Equal Rate (EER).

Hariprasath and Prabakar (2012) proposed a multi-resolution approach to recognize humans by using patterns of iris and palm-print. Wavelet Packet Transform (WPT) was used for texture analysis. An adaptive threshold was used and the coefficients of the WPT sub images were quantized into 1, 0 or -1 as iris signature. This signature showed the local information of different irises. The biometric signature of code's size was obtained 960 bits when wavelet packets were used. Then the new pattern in the signature was computed and matched against the stored patterns.

Wang and Sun (2012) proposed a new approach to improve the distinctive ability of texture features to recognize the humans by using the palm prints. Riemannian geometry outcomes were used to get the details of palm lines and then direction fields of palm lines were constructed. Because the direction fields are one of the portions of the textural features of the palm-print image and can be used to improve the distinctive ability of the texture features. Then, a Dual-Tree Complex Wavelet Transform-based Local Binary Patterns are Weighted by Histogram method (DT-CWT based LBPWH) was used to get the improved texture features. Experiments were conducted with the proposed method and the experimental results were evaluated to study the effectiveness of the method.

Kumar *et al.* (2012) investigated the integration of two modalities such as facial thermograms and ear and both were extracted from the same face simultaneously. The rank level fusion was used to combine characteristic of both of these modalities. Facial thermogram was infrared thermal faces that were captured by using an infrared camera and the second modality was the point features of the ear which was recorded by using an ordinary digital camera. Both the facial thermograms and images of ear were normalized after locating ROI and then features were extracted by using the Haar wavelets and SHIFT (Scale Invariant Feature Transform), respectively. The proposed authentication system was experimented with 500 facial thermograms and ear images and 98% of Genuine Acceptance Rates (GAR) at 0.1% of False Acceptance Rate (FAR) was achieved.

Mohamed *et al.* (2012) introduced a method to enhance the accuracy of the finger vein biometric system by using the multiple finger vein patterns for each person. Totally four fingers such as 2 fingers in the right hand and two fingers in the left hand were used a single identity. From the recorded modality, the finger region was segmented and vein tree for each finger was constructed by using the maximum

curvature points in image profiles. The pattern of binary vein from each single finger was matched by using the Phase Only Correlation (POC) method. To fuse the multiple finger vein patterns of a single identity score level fusion methods were used.

Sangeetha and Radha (2013) provided an authentication system based on Fingerprint-Iris patterns to study the performance of Support Vector Machine (SVM) and extreme learning machine. Score-level fusion methods were used to combine the characteristics of fingerprint and iris. Experiments proved that, when using score-level fusion ELM performed better when compared to the SVM by means of accuracy. But SVM had reduced time for classification.

Awang *et al.* (2013) proposed a feature level fusion of features extracted from the faces. But the fusion gives high dimensional combined features and this is solved by using Linear Discriminant Analysis (LDA) for the extraction of the features. Then feature selection was performed using Genetic Algorithm (GA) with a novel fitness function. Experimental results ensured that usage of concatenated features and optimization gave an accuracy of 97.50%.

Tharwat *et al.* (2012) proposed two multimodal biometric authentication methods with using ear and Finger Knuckle (FK) images. These two images were fused before the extracting the features to eliminate the loss of information. Multi-level fusion methods in the image and stage of classification were proposed. Then the set of features were extracted in the fused images with various classifiers and the outcomes of the classifiers were combined in the abstract, rank and score levels of fusion. Experimental results proved that the proposed authentication techniques enhance the rate of recognition when compared to any of the state-of-the-art methods.

Kaur (2013) used a fuzzy vault framework by using iris, retina and finger vein templates for security aspects. The proposed method proves as stable and had template longevity so that their combination could be used applications which need high security. The proposed multimodal fuzzy vault used the fusion of feature points extracted from the three traits like iris, retina and finger vein. The security level of the proposed vault was measured by using min-entropy.

Hamad *et al.* (2012) proposed multimodal biometric prototype which captured a palm vein and three fingerprints simultaneously. These modalities were evaluated whether or not their combination was statistically independent. In many studies, multimodal biometrics gave high recognition accuracy and population coverage by merging different biometric sources. The results were evaluated by the false acceptance.

METHODOLOGY

In this study, feature level fusion is used to combine the finger vein and finger image features. The data recorded from the different biometric devices are first preprocessed, feature vectors are extracted separately and the feature vectors are normalized. Then Principle Component Analysis is used to select best set of features and using a specific fusion algorithm, these feature vectors are concatenated forming a composite feature vector which is then used for classification process. The proposed classification steps are shown in the following Fig. 1.

Feature extraction by the Gabor filter: In image processing, a Gabor filter was introduced by Dennis Gabor (Kumar and Pang, 2002). This filter is a linear filter and used for detecting edges in the images. The representations of the frequency and orientation used in the Gabor filters are very similar to the frequency and orientations of the Human Visual System (HVS). Therefore, these filters are much appropriate for the texture representation and discrimination. The set of Gabor filters with different frequencies and orientations will be useful to extract the useful features from an image. Usually, the two dimensional Gabor filter is applied to the image with different scales and frequencies. The filtered image is obtained from convoluting the real and the imaginary parts of the image. The Gabor wavelet function is given by the following equation:

$$f(x, y) = \frac{1}{2\pi\sigma_x\sigma_y} \exp\left[-\frac{1}{2}\left(\frac{x^2}{\sigma_x^2} + \frac{y^2}{\sigma_y^2}\right)\right] \exp(2\pi ju_0x) \tag{1}$$

where,

u_0 : The radial frequency of the Gabor function
 σ_x and σ_y : The space constants and define the Gaussian envelope along the x and y axes

Energy coefficients from wavelet transform: Wavelet is an appropriate basis to separate the noisy signals

from the image signal. The main aim of usage of the wavelet transform for images is, it is good at energy compaction and the small coefficients are more likely due to noise and large coefficients are due to important signal features. These small coefficients are used as threshold without disturbing the significant features of the image. Thresholding based on wavelet theory provides an improved approach for eliminating the sources of noise and ensure getting images with better quality.

The two dimensional Discrete Wavelet Transform (DWT-2D) (Mallat, 1989) is used for multi-resolution approximation expressions. Usually, the multi-resolution analysis is done by using 4 channel filter banks. Each filter bank corresponds to each level of decomposition. The filter bank is composed of a low-pass and a high-pass filter. Each one is then sampled at a half rate of the previous frequency. By applying this procedure repeatedly, another wavelet transform of any order is done.

The down sampling procedure maintains the scaling parameter constant De-noising and Compression in Wavelet Domain through successive wavelet transforms. The benefit is simplifying the implementation in computers. When it is applied for the images, the filtering is done in a separable way, by filtering the lines and columns. The DWT of an image has four frequency channels for each level of decomposition.

Min-max normalization: Normalization is a procedure used to scale the values of an attribute data within a small specified range, for example the range (-1.0 to 1.0) or (0.0 to 1.0). For the distance-based methods, normalization is useful to prevent the attributes with initially large ranges from out-weighting attributes with initially smaller ranges.

Min Max Normalization does a linear transformation on the actual data. For example assume, the attribute name is A and min_A and max_A are the minimum and maximum values of an attribute A. then, Min-max normalization maps an actual value, v, of

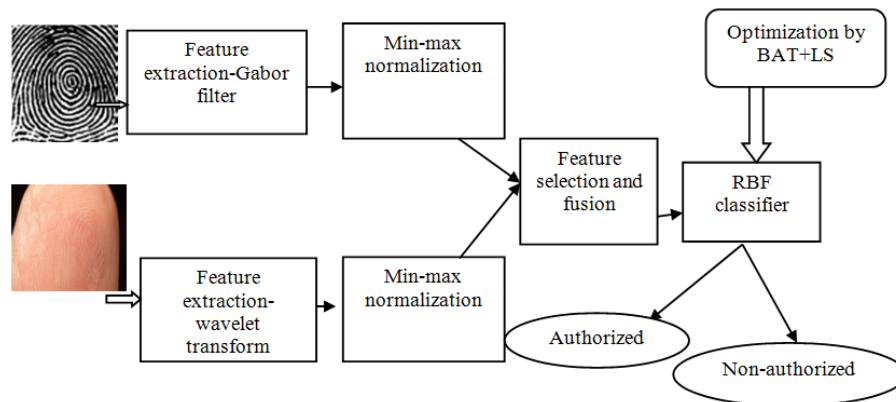


Fig. 1: Proposed classifier steps

A into new value v' in the range (new_min_A , new_max_A) by using the following formula (Manikandan *et al.*, 2013):

$$v' = \frac{v - min_A}{max_A - min_A} (new_max_A - new_min_A) + new_min_A \quad (2)$$

Feature selection by PCA and kernel PCA: Principal Components Analysis (PCA) is used for reducing the dimensionality or selecting the subsets. Let, a set of data on n dimensions, PCA is used to find a linear subspace of dimension d lower than n with the data points scattered on the linear subspace. This reduced subspace tries to maintain most of the variability of the data. The most common definition of PCA, (Hotelling, 1933) is that, “for a given set of data vectors x_i , $I = 1, \dots, t$, the d principal axes are those orthonormal axes onto which the variance retained under projection is maximal”.

In order to obtain much of the variability as possible, the first principal component which is represented as U_1 should have the maximum variance. If all the centered observations are stacked into the columns of an $n \times t$ in the input matrix X , where each column corresponds to an n -dimensional observation and there are t observations. Let the first principal component be a linear combination of X defined by coefficients/weights $w = [w_1 : \dots : w_n]$. In matrix form:

$$U_1 = w^T X \quad (3)$$

$$\text{var}(U_1) = \text{var}(w^T X) = w^T S w \quad (4)$$

PCA algorithm:

- Recover basis:
- Calculate $XX^T = \sum_{i=1}^t x_i x_i^T$ and let $U =$ eigenvectors of XX^T corresponding to the top d eigenvectors
- Encode training data:
- $Y = U^T X$ where Y is a $d \times t$ matrix of encoding of the original data.
- Re construct training data:
- $\hat{X} = UY = UU^T X$
- Encode test examples:
- $y = U^T x$ where y is a d -dimensional encoding of x
- Re construct test example:
- $\hat{x} = Uy = UU^T x$

Kernel PCA: Simple PCA models efficiently for the linear variabilities in high-dimensional data. But many high dimensional data sets have a nonlinear nature. In these cases the high-dimensional data lie on or near a nonlinear manifold. Thus, PCA cannot be used to model the variability of the data. Kernel PCA finds principal components that are nonlinearly related to the

input space by performing PCA in the space produced by the nonlinear mapping, where the low-dimensional latent structure is easily found.

Consider a feature space H such that:

$$\phi : x \rightarrow H \quad (5)$$

$$x \mapsto \phi(x) \quad (6)$$

The objective of kernel PCA is:

$$\min \sum_i^t \|\phi(x_i) - U_q U_q^T \phi(x_i)\| \quad (7)$$

The solution can be found by SVD:

$$\phi(X) = U \sum V^T \quad (8)$$

RBF classifier: The RBF network is a neural network with one hidden layer and many forms of radial basis activation functions (Thomaz *et al.*, 1998). The widely used one is the Gaussian function and defined by:

$$f_j(x) = \exp\left(-\frac{\|x - \mu_j\|^2}{2\sigma_j^2}\right) \quad (9)$$

- where,
- σ = The width parameter
- μ = The vector determining the center of basis function f
- x = The d dimensional input vector

In this RBF network, one neuron in the hidden layer is activated whenever the input vector is close enough to its center vector m . There are many methods and heuristics are available to optimize the parameters in the radial basis function or finding the number of hidden neurons required for the best classification.

The next layer of the hidden layer in the RBF network is the output layer which consists of one neuron to each individual. Their output are linear functions of the outputs of the neurons in the hidden layer and is equivalent of OR operator. The final result of the classification is taken from the output neuron which gives the highest output. If total number of clusters in the RBF network is n , output from the hidden layer neuron k is k_m and weight from k^{th} hidden layer neuron to output neuron t is as w_m , then the expected output is:

$$y(t) = \sum_{i=1}^n w_m k_m \quad (10)$$

The center of the cluster is found by:

$$c_j = \frac{\sum_{i=1}^N u_{ij}^m x_i}{\sum_{i=1}^N u_{ij}^m} \quad (11)$$

where, u_{ij} represents the degree of input i belongs to the cluster j :

$$u_{ij}^m(x) = 1 / \sum_{k=1}^c \left[\frac{\|x_i - c_j\|^2}{\|x_i - c_k\|^2} \right]^{\frac{2}{m-1}} \quad (12)$$

The norm is specified as $\| \cdot \|$. Here, for the non linear hidden layer Euclidean distance is used.

For tuning the centres and spreads of the Gaussian activation, clustering methods such as k-means (local search) or Fuzzy c-means can be used. The weight of the links between the nodes in RBF is also tunable parameter (Guerra and dos Coelho, 2006).

Parameter optimization: In our study, the parameters of the RBF activation functions are classified by the BAT algorithm.

Bat Algorithm (BA) (Yang, 2008) was a recently introduced nature inspired algorithm. It was introduced by Yang (2008) based on the inspiration by the behaviours of Bats. Bat is a mammal that has wings and a very good feature of generating echolocation. Yang (2008) used these characteristics of bat to develop an algorithm. BA uses three major. The rules are given in the following:

- To sense the distance, bat uses the capacity of the echolocation. Based on the echolocation, it differentiates the food and prey and barriers even in the darkness.
- Bats can fly randomly and the fly has some characteristics such as velocity, fixed frequency and loudness to find the prey.
- Its loudness varies from a large loudness to minimum loudness.

Normally, all the bats fly randomly in a velocity, position and fixed frequency but the wavelength and loudness will vary to find the prey. Based on the proximity of the target, the bats will adjust automatically the frequency of pulses emitted and pulse rate. The loudness varies from a large value to a smaller value based on the distance to the target.

Bat Algorithm initializes a set of bats as population; individuals are assigned a position for starting and called as a initial solution, pulse rate, loudness and a find frequency. In our study, the rate of pulse and loudness are used randomly. Each bat will shift from the initial solutions towards the global best

solution at each iteration. The emission of Pulse and loudness will be updated, when any bat finds a better solution after moving. During the iteration of flying, the best so far solution is updated. This search process is repeated continuously until the termination conditions are satisfied. The best solution found by the BAT algorithm is considered as final best solution (Sureja, 2012).

Pseudocode for BAT optimization:

1. define objective function
2. initialize the population of the bats
3. define and initialize parameters
4. while (Termination criterion not met)
 - {
 - generate the new solutions randomly
 - if (Pulse rate (rand) >current)
 - select a solution among the best solution
 - generate the local solution around the selected best ones.
 - end if
 - generate a new solution by flying randomly
 - if (Pulse rate (rand) >current)
 - select a solution among the best solution generate the local solution around the selected best ones.
 - end if
 - generate a new solution by flying randomly
 - if (loudness and pulse frequency (rand) <current)
 - accept the new solutions increase pulse rate and reduce loudness
 - end if
 - rank the bats and find the current best
 - }

To find the best values of parameters and further improve the convergence speed towards the global best solution, local search algorithm is combined with BAT algorithm. Different solutions given by the BAT algorithm are evaluated by the local search algorithm.

RESULTS AND DISCUSSION

Gabor features are extracted from fingervein using Gabor filter with orientation of 0, 15, 45, 60 and 75°, respectively. For the fingerprint images, energy coefficients are obtained using wavelet packet tree. Both the obtained features are normalized using min max normalization and fused using concatenation. Feature selection is achieved using PCA and kernel PCA. The classification is achieved using RBF Classifier and Euclidean distance. It is proposed to optimize the RBF kernel using BAT algorithm and BAT with local search. Recognition rate is used to evaluate the performance of the proposed classifier. Recognition rate with PCA and kernel PCA features in various classifiers are compared in the following Fig. 2 and 3. The ROC of the classifiers in the classifiers with PCA and Kernel PCA are shown in the Fig. 4 and 5.

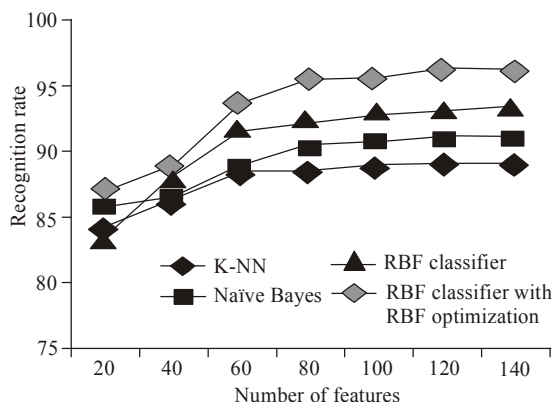


Fig. 2: Recognition rate by PCA based feature selection

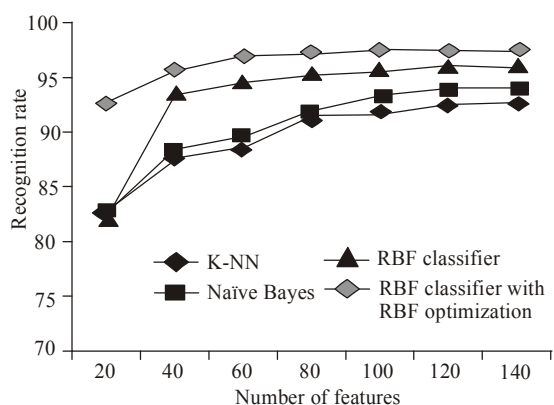


Fig. 3: Recognition rate by kernel PCA based feature selection

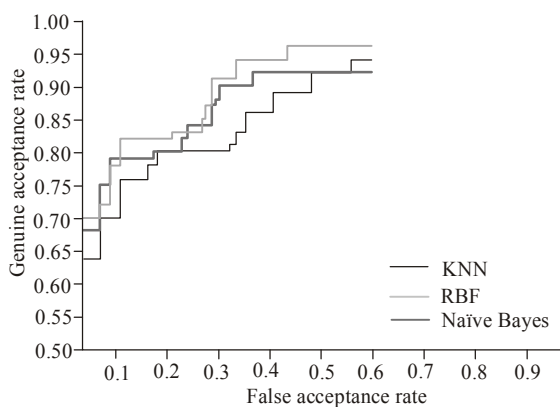


Fig. 4: ROC PCA

From the figure, it is observed that the recognition rate of the optimized RBF classifier was improved by 6.5, 4.5 and 3.82% when comparing to the KNN, Naive Bayesian classifier and simple RBF classifier respectively with feature selection by PCA.

From the Fig. 3, it is observed that the recognition rate of the optimized RBF classifier was improved by 7.54, 6.39 and 3.25% when comparing to the KNN,

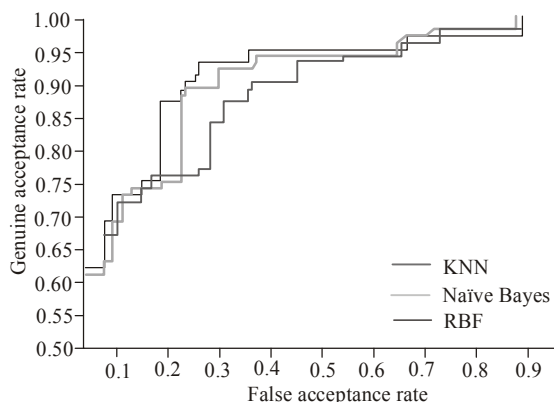


Fig. 5: ROC kernel PCA

Table 1: Improvement of recognition rate in KPCA

Number of features	Percentage of improvement of recognition rate of optimized RBF classifier with KPCA features over PCA features
20	6.45
40	7.43
60	3.12
80	1.57
100	1.89
120	1.04
140	1.04

Naive Bayesian classifier and simple RBF classifier respectively with feature selection by kernel PCA.

The Receiver Operating Characteristic (ROC) curve for PCA and kernel PCA is given in Fig. 4 and 5.

Discussion: When comparing the recognition rate of the proposed classifier with respect to the number of features, the improvement obtained by KPCA selected features is given by the following Table 1.

Also, it is observed the improvement of recognition rate by using KPCA selected features over PCA selected features ranges from 0 to 3.82% for KNN classifier. The improvement of recognition rate by using KPCA selected features over PCA selected features ranges from 0.68 to 3.08% for Naives Bayesian classifier. The improvement of recognition rate by using KPCA selected features over PCA selected features ranges from 2.57 to 6.14% for None optimized RBF classifier.

CONCLUSION

In this study, an optimized RBF classifier is proposed in the multimodal biometric system to identify the authorized users by using the fingerprint images and finger-vein patterns. Features from each modality was extracted, normalized and fused before applying into the classifier. To improve the recognition rate the parameters of the RBF classifier was optimized by the BAT algorithm and local search. Results proved that the recognition rate of the optimized RBF classifier

was improved by 6.5, 4.5 and 3.82% when comparing to the KNN, Naive Bayesian classifier and simple RBF classifier respectively with feature selection by PCA. Also the recognition rate of the optimized RBF classifier was improved by 7.54, 6.39 and 3.25% when comparing to the KNN, Naive Bayesian classifier and simple RBF classifier respectively with feature selection by kernel PCA.

REFERENCES

- Arandjelovic, O. and R. Cipolla, 2007. A manifold approach to face recognition from low quality video across illumination and pose using implicit super-resolution. Proceeding of IEEE International Conference on Computer Vision, Vol. 2.
- Awang, S., R. Yusof, M.F. Zamzuri and R. Arfa, 2013. Feature level fusion of face and signature using a modified feature selection technique. Proceeding of IEEE International Conference on Signal-Image Technology and Internet-based Systems (SITIS, 2013), pp: 706-713.
- Feng, G., K. Dong, D. Hu and D. Zhang, 2004. When faces are combined with palmprints: A novel biometric fusion strategy. In: Zang, D. and A.K. Jain (Eds.), Proceeding of 1st International Conference on Biometric Authentication (ICBA, 2004), LNCS 3072, Springer-Verlag, Berlin, Heidelberg, pp: 701-707.
- Guerra, F.A. and L.S. dos Coelho, 2006. Multi-step ahead nonlinear identification of Lorenz's chaotic system using radial basis neural network with learning by clustering and particle swarm optimization. *Chaos Soliton. Fract.*, 35(5): 967-979.
- Hamad, A.M., R.S. Elhadary and A.O. Elkhateeb, 2012. Multimodal Biometric Personal Identification System Based on IRIS and Fingerprint.
- Hariprasath, S. and T.N. Prabakar, 2012. Multimodal biometric recognition using iris feature extraction and palmprint features. Proceeding of the IEEE International Conference on Advances in Engineering, Science and Management (ICAESM, 2012), pp: 174-179.
- Hotelling, H., 1933. Analysis of a complex of statistical variables into principal components. *J. Educ. Psychol.*, 24(6): 417.
- Kaur, M., 2013. Multimodal based fuzzy vault using iris retina and fingervein. Proceeding of the 4th IEEE International Conference on Computing, Communications and Networking Technologies (ICCCNT, 2013), pp: 1-5.
- Kim, Y.G., K.Y. Shin, E.C. Lee and K.R. Park, 2012. Multimodal biometric system based on the recognition of face and both irises. *Int. J. Adv. Robot. Syst.*, 9: 6.
- Ko, T., 2005. Multimodal biometric identification for large user population using fingerprint, face and iris recognition. Proceeding of the 34th IEEE Applied Imagery and Pattern Recognition Workshop, pp: 6.
- Kumar, A. and G.K. Pang, 2002. Defect detection in textured materials using Gabor filters. *IEEE T. Ind. Appl.*, 38(2): 425-440.
- Kumar, A. and Y. Zhou, 2012. Human identification using finger images. *IEEE T. Image Process.*, 21(4): 2228-2244.
- Kumar, A., M. Hanmandlu and S. Vasikarla, 2012. Rank level integration of face based biometrics. Proceeding of the 9th International Conference on Information Technology: New Generations (ITNG, 2012), pp: 36-41.
- Mallat, S.G., 1989. Multiresolution approximations and wavelet orthonormal bases of $L^2(R)$. *T. Am. Math. Soc.*, 315(1): 69-87.
- Manikandan, G., N. Sairam, C. Saranya and S. Jayashree, 2013. A hybrid privacy preserving approach in data mining. *Middle East J. Sci. Res.*, 15(4).
- Mishra, A., 2010. Multimodal biometrics it is: Need for future systems. *Int. J. Comput. Appl.*, 3(4): 28-33.
- Moganeshwaran, R., M. Khalil Hani and M. AnnuarSuhaini, 2012. Fingerprint-fingervein multimodal biometric authentication system in field programmable gate array. Proceeding of the IEEE International Conference on Circuits and Systems (ICCAS, 2012), pp: 237-242.
- Mohamed, H.N., E.A. El-Alamy and M.K. Shahin, 2012. Whole-hands multiple-instances finger vein biometric system. Proceeding of the 2012 Cairo International Biomedical Engineering Conference (CIBEC, 2012), pp: 68-72.
- Monrose, F. and A.D. Rubin, 2000. Keystroke dynamics as a biometric for authentication. *Future Gener. Comp. Sy.*, 16(4): 351-359.
- Sangeetha, S. and N. Radha, 2013. A new framework for IRIS and fingerprint recognition using SVM classification and extreme learning machine based on score level fusion. Proceeding of the 7th International Conference on Intelligent Systems and Control (ISCO, 2013), pp: 183-188.
- Sureja, N.M., 2012. New inspirations in nature: A survey. *Int. J. Comput. Appl. Inform. Technol.*, 1(3): 21-24.
- Tharwat, A., A.F. Ibrahim and H.A. Ali, 2012. Multimodal biometric authentication algorithm using ear and finger knuckle images. Proceeding of the 7th International Conference on Computer Engineering and Systems (ICCES, 2012), pp: 176-179.

- Thomaz, C.E., R.Q. Feitosa and A. Veiga, 1998. Design of radial basis function network as classifier in face recognition using eigenfaces. Proceeding of the 5th Brazilian Symposium on Neural Networks, pp: 118-123.
- Venkataramani, K., S. Qidwai and B. Vijayakumar, 2005. Face authentication from cell phone camera images with illumination and temporal variations. IEEE T. Syst. Man Cy. C, 35(3): 411-418.
- Wang, Y.X. and G.H. Sun, 2012. Palmprint recognition using Palm-line direction field texture feature. Proceeding of International Conference on Machine Learning and Cybernetics (ICMLC, 2012), pp: 1130-1134.
- Yang, X.S., 2008. Nature-inspired Metaheuristic Algorithms. 1st Edn., Luniver Press, Frome.