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Research Article

Multimodal Biometrics Based on Fingerprint and Finger Vein

[1]Anand Viswanathan and [2]S. Chitra
[1]Department of Information Technology, V. S. B. Engineering College, Karur, India
[2]Department of Computer Science Engineering, Er. Perumal Manimekalai College of Engineering, India

Abstract: Biometric systems identify a person through physical traits or verify his/her identity through automatic processes. Various systems were used over years including systems like fingerprint, iris, facial images, hand geometry and speaker recognition. For biometric systems successful implementation, it has to address issues like efficiency, accuracy, applicability, robustness and universality. Single modality based recognition verifications are not robust while combining information from different biometric modalities ensures better performance. Multimodal biometric systems use multiple biometrics and integrate information for identification. It compensates unimodal biometric systems limitations. This study considers multimodal biometrics based on fingerprint and finger veins. Gabor features are extracted from finger vein using Gabor filter with orientation of 0, 15, 45, 60 and 75°, respectively. For fingerprint images, energy coefficients are attained using wavelet packet tree. Both features are normalized using min max normalization and fused with concatenation. Feature selection is through PCA and kernel PCA. Classification is achieved through KNN, Naïve Bayes and RBF Neural Network Classifiers.

Keywords: Biometric systems, Gabor filter, K-Nearest Neighbors (KNN), naïve bayes and Radial Basis Function (RBF) neural network classifier, Principal Component Analysis (PCA)

INTRODUCTION

Biometric technologies are automatic means to verify/recognize a person's identity based on physiological and behavioural characteristics (Jain and Verma, 2012). Biometrics use characteristics like fingerprint, hand shape, facial characteristics, voice or iris. Biometrics also uses learned/acquired characteristics including behavioural traits like signatures and speech (Wayman *et al*., 2005). A biometric system based on application, operates in verification and identification modes. In the former mode, a system confirms a person's identity through comparison of captured biometric data with biometric template in a database. During authentication, a person claims his/her identity through Personal Identification Number (PIN), user name or smart card. The system does a one-to-one comparison to decide whether the claim is true. In the latter mode, a system recognizes persons by searching templates of database users for correct match. Biometric systems carry out a one-to-many comparison to establish individual identity without individuals claiming an identity (Fierrez-Aguilar *et al*., 2005).

Biometric authentication/verification systems are pattern recognition systems of 4 modules (Jain *et al*., 2004):

- Data acquisition module which captures an individual's biometric sample, e.g., fingerprint image, palm print, or face.
- Feature extraction module where representative features are extracted from acquired biometric samples.
- Matching and decision making module which compares computed feature set with a template, (containing extracted feature sets during enrolment) and putting out a similarity score which decides identity validity claimed by an individual.
- System's database module used by verification systems to store user templates.

Multimodal systems reduce failure to enrol and resist spoofing as multiple biometric sources cannot be spoofed simultaneously. Multimodal systems search large databases quickly through a less accurate modality to narrow down database options before applying complex and accurate modality on remaining data for final identification. Multimodal systems disadvantages are its cost and the need for additional resources to compute and store information compared to unimodal systems. Multimodal systems need more time to enrol/verify thereby inconveniencing users. Finally system accuracy degrades compared to unimodal systems when improper techniques are followed when combining evidence from differing

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

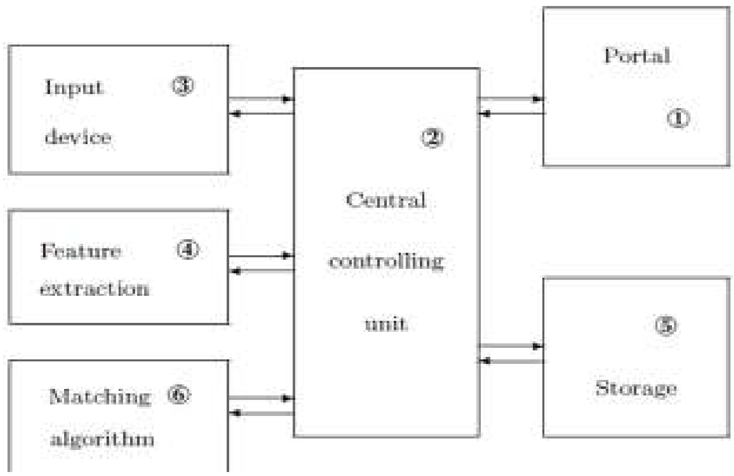

Fig. 1: Model of a biometric system

modalities, but advantages outweigh limitations and so they are deployed in security related applications (Snelick *et al*., 2005; Shukla *et al*., 2010).

More data is collected by multimodal systems from subjects which is fused or data processing results are fused for authentication. Biometric fusion is use of multiple biometric data/processing methods to improve system performance. Combining modalities assures robustness and adaptability to circumstances. Many approaches combine different modalities, but two major approaches are feature fusion and decision fusion, also known as early and late fusion (Ross and Jain, 2003).

Multimodal biometric systems use more than one physiological/behavioural characteristic to enrol, verify or identify. NIST report recommends a system using many biometrics in a layered approach. Combining different modalities improves recognition rate. Multi biometrics aim to reduce one or more of the following:

- False Accept Rate (FAR)
- False Reject Rate (FRR)
- Failure to enrol rate (FTE)
- Susceptibility to artefacts or mimics

For multimodal biometric systems inputs are taken from single/multiple sensors measuring two or more different biometric characteristic modalities. For example, a system with face recognition and fingerprint is "multimodal" even if "OR" rule was applied, allowing users to be verified using any one modality (Indovina *et al*., 2003).

Multi algorithmic biometric systems: Multi algorithmic biometric systems use one sample from a sensor and process it with two or more algorithms.

Multi-instance biometric systems: Multi-instance biometric systems use one or more sensors to acquire samples of two or more diverse instances of similar biometric characteristics. An example is capturing images from different fingers.

Multi-sensorial biometric systems: Multi-sensorial biometric systems sample a biometric trait's same instance with two or more different sensors. Multiple samples processing is with one algorithm or a combination of algorithms. Examples are face recognition application use both visible light camera and infrared camera coupled with specific frequency (Sasidhar *et al*., 2010) (Fig. 1).

Feature is a function of one or more measurements, each specifying an object's some quantifiable property and computed so that it quantifies the object's some significant characteristics. Currently used features are classified as follows.

General features: Application independent features like color, texture and shape. Based on abstraction level, they are further divided into.

Pixel-level features: Features calculated at each pixel, e.g., color, location.

Local features: Features calculated over results of image band subdivision on image segmentation or edge detection.

Global features: Features calculated over entire image or an image's regular sub-area.

Domain-specific features: Application dependent features like human faces, fingerprints and conceptual features. These are often domain specific synthesis of low-level features.

All features are classified as low-level and high-level features. Low-level features are extracted directly from original images, whereas high-level feature extraction is based on low-level features (Choras, 2010).

Extraction transforms rich images content into various content features. Feature extraction generates features for use in selection/classification tasks. Feature selection reduces features number provided for classification. Those features likely to assist in discrimination are selected and used in classification. Un-selected features are discarded.

This study considers multimodal biometrics based on fingerprint and finger vein. Gabor features are extracted from finger vein using Gabor filter with orientation of 0, 15, 45, 60 and 75°, respectively. For fingerprint images, energy coefficients are obtained using wavelet packet tree. Both features are normalized using min max normalization and fused through concatenation. Feature selection is got by using PCA and kernel PCA. Classification is through KNN, Naïve Bayes and RBF Neural Network Classifiers.

LITERATURE REVIEW

Enhancing off-line biometric signature verification using fingerprint assessment was proposed by Guest and Miguel-Hurtado (2011) who designed it to match biometric fingerprint images applicable to static/image-based "off-line" human signature modality. Through a publically available signature dataset, verification performance was compared to three current static methods. Also, verification was assessed using the four methods in a multi-classifier system. Results showed that fingerprint method application lead to comparable performance with current methods and great improvement was achieved in multi-classifier configuration.

Feature extraction using Gabor filter and recursive fisher linear discriminant with application in fingerprint identification was proposed by Dadgostar *et al*. (2009), that presented a Gabor filter and RFLD algorithm based new feature extraction method used for fingerprint identification. The new method was assessed on images from bio-lab database. Experiments revealed that applying RFLD to a Gabor filter in four orientations compared to Gabor filter and PCA transform, increased identification accuracy from 85.2 to 95.2% by nearest cluster centre point classifier with leave-one-out method. The new method had lower computational complexity and high accuracy rates compared to texture features based traditional methods.

Score level fusion based multimodal biometric identification was suggested by Elmir *et al*. (2012), which addressed two issues related to score level fusion. Performance of score level fusion based multimodal biometric system against various mono-modal voice, fingerprint modalities based biometric system and a feature level fusion of the same modalities based bimodal biometric system. These were evaluated regarding efficiency and identification rate on a close group from test data. Results were shown using cumulative match characteristic curve.

A frequency-based approach for feature fusion in fingerprint and iris multimodal biometric identification systems was proposed by Conti *et al*. (2010) where the aim was to discriminate automatically between subjects reliably and dependably, according to target specific application. An innovative iris and fingerprint traits multimodal biometric identification system was proposed. It was a state-of-the-art multi-biometrics advancement, offering innovative perspective on features fusion. A frequency-based method results in a consistent biometric vector, integrating fingerprint and iris data while a hamming-distance-based matching algorithm deals with unified homogenous biometric vector.

A new human identification centred on fusion fingerprints and face biometrics using LBP and GWN descriptors was proposed by Gargouri Ben Ayed *et al*. (2011) which developed a multimodal biometric recognition system combining face and fingerprint modalities. Face trait builds GWNs based features while LBP was used for finger print trait. Experiments affirmed that a weighted sum based fusion achieved excellent recognition performances, outperforming both single biometric systems.

Low cost multimodal hand geometry, palm and finger print texture based biometric identification system were proposed by Ferrer *et al*. (2007) that presented a combination of palm, finger print and geometrical features of the human hand based multimodal biometric identification system. Right hand images were acquired through a commercial scanner with a 150 dpi resolution and geometrical features through binaries images and consisted of 15 measures. A SVM was the verifier.

A new approach to finger-knuckle-print recognition based on GABOR feature fusion was suggested by Shariatmadar and Faez (2011), which presented a method for personal identification and identity verification that included GABOR filter bank, combining PCA and LDA algorithms and Euclidean distance measure. These steps were used for feature extraction, dimensionality reduction and classification. Results of identification and verification experiments combining features of four fingers were obtained, 98.79 and 91.8%, respectively demonstrating the efficiency and effectiveness of the new biometric characteristic.

Finger-vein identification using pattern map and PCA was proposed by Beng and Rosdi (2011). The authors suggested a new approach for finger-vein recognition using PPBTF and PC based pattern map. Instead of obtaining finger-vein features from multi-filtered images, it got features from pattern map images. Experiments showed that the new algorithm had higher identification rates compared to current method with only 40 features and revealed that pattern map could represent finger-vein pattern effectively.

Comparison of iris recognition using PCA, ICA and Gabor wavelets was proposed by Shi and Gu (2010). It compared PCA, ICA and Gabor wavelets based feature extraction algorithm for a compact iris code, using the methods to generate optimal basis elements which represent iris signals efficiently. In practice these methods coefficient was used as feature vectors. Then an iris feature vector was encoded into iris code to store and compare an individual's iris patterns.

A framework for fingerprint and iris recognition using SVM and Extreme Learning Machine (ELM) based on score level fusion was proposed by Sangeetha and Radha (2013) where a comparison of SVM and ELM based on score-level fusion methods was obtained. ELM provided better performance in score-level fusion as compared to SVM. It reduced system classification time. This study was accurate in such applications and could be used for person identification in many applications.

Feature level fusion of fingerprint and face modalities using Gabor filter bank was proposed by Deshmukh *et al*. (2013) where a biometric authentication system was based on face and fingerprint modalities feature level fusion. The new method used Gabor filter bank with two scales and eight orientations, for extraction of directional features from source data. Use of a small set of Gabor filters reduced system processing time. Experiments were carried out on ORL face database and FVC2002 fingerprint database.

Fingerprint verification using Gabor co-occurrence features was suggested by Arivazhagan *et al*. (2007), which presented an efficient GWT based algorithm for finger print verification for personal identification. The GWT based method provided local and global information in a fixed length finger code. Finger print matching was by means of finding Euclidean distance between two corresponding finger codes with matching being very fast.

Human authentication using face and fingerprint biometrics was suggested by Darwish *et al*. (2010), which employed product rule in the investigation. Final identification was performed using a nearest neighbour classifier that was fast and effective. Experiment results confirmed that the approach achieved excellent recognition and that fusion approach outperformed single modalities based biometric identification.

METHODOLOGY

This study considers fingerprint and finger vein based multimodal biometrics. Gabor features are extracted from finger vein by using Gabor filter with orientation of 0, 15, 45, 60 and 75°, respectively. For fingerprint images, energy coefficients are obtained using wavelet packet tree. Both features are normalized using min max normalization and fused through concatenation. Feature selection is through use of PCA and kernel PCA. Classification is through using KNN, Naïve Bayes and RBF Neural Network Classifiers.

Dataset-5 finger vein images of left index finger from 100 subjects and 5 fingerprint images of left index finger from 100 subjects were used in experiment.

Feature extraction:

Gabor filter: Gabor filter was introduced by Dennis Gabor. One-dimensional Gabor filter is the multiplication of a cosine/sine wave with Gaussian windows as follows:

$$g_e(x) = \frac{1}{\sqrt{2\pi\sigma}} e^{\frac{x^2}{2\sigma^2}} \text{Cos}\ (2\pi w_o x) \quad (1)$$

$$g_o(x) = \frac{1}{\sqrt{2\pi\sigma}} e^{\frac{x^2}{2\sigma^2}} \text{Sin}\ (2\pi w_o x) \quad (2)$$

where w_o defines centre frequency (frequency where filter yields greatest response) and σ spread of Gaussian window (Derpanis, 2007).

Gabor filter is got by modulating a sinusoid with a Gaussian. For one Dimensional (1D) signals, a 1D sinusoid is modulated with Gaussian. This will respond to some frequency, but only in the signal’s localized part. Let g (x, y, θ, φ) be function defining a Gabor filter cantered at origin with θ as spatial frequency and φ as orientation. Gabor filter is defined as:

$$g(x, y, \theta, \phi) = \exp\left(-\frac{x^2+y^2}{\sigma^2}\right) \exp\left(2\pi\theta i(x\cos\phi + y\sin\phi)\right) \quad (3)$$

It was shown that σ, standard deviation of Gaussian kernel depends on spatial frequency to measured, i.e., θ.

Wavelet packet tree: Wavelet packet method is a wavelet decomposition generalization offering wide signal analysis possibilities. A signal is split into approximation and detail in wavelet analysis. Approximation is split into a second-level approximation and details the repeated process. There are n+1 possible ways to decompose/encode a signal for n-level decomposition. Details and approximations in wavelet packet analysis are split yielding more ways to encode a signal. For e.g., wavelet packet analysis allows signal S to be represented as A1+A6+D6+D3. This example of representation is impossible with ordinary wavelet analysis (Amiri and Asadi, 2009). Wavelet decomposition tree is a part of a binary tree. Wavelet packet analysis is similar to DWT, the difference being that in addition to wavelet approximation component decomposition at every level, wavelet detail component decomposes to get own approximation and detail components as in Fig. 2.

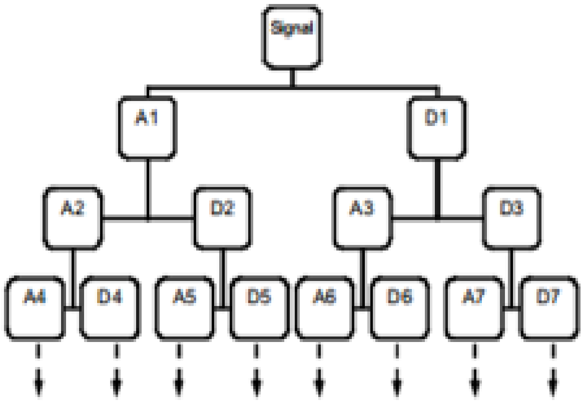

Fig. 2: Wavelet packet decomposition tree

Wavelet packet tree's components are viewed as filtered components with filter bandwidth decreasing with increased decomposition. The entire tree is viewed as a filter bank. Wavelet packet components time resolution is good at tree top, but it is at the expense of poor frequency resolution while at the bottom wavelet packet analysis ensures frequency resolution of decomposed component with high frequency, content increases. So, wavelet packet analysis ensures better frequency resolution control in signal decomposition (Shinde, 2004). Wavelet packet is represented as a function, ψ where 'i' is modulation parameter, 'j' dilation parameter and 'k' translation parameter:

$$\psi_{j,k}^{i}(t) = 2^{-\frac{j}{2}}\psi^{i}(2^{-j}t - k) \tag{4}$$

where, i = 1, 2…j_n and 'n' is wavelet packet tree decomposition level.

Feature selection:

PCA: PCA is a widely held technique for dimensionality reduction and feature extraction. PCA tries to locate a lower dimensionality linear subspace of original feature space where new features have largest variance. This is called dimensionality reduction, as a vector $\bar{x}$ containing original data and N-dimensional is reduced to compressed vector $\bar{c}$ which is M-dimensional, where M<N. A vector $\bar{x}$ is coded to vector $\bar{c}$ with reduced dimension. Vector $\bar{c}$ is stored, transmitted or processed, resulting in vector $\bar{c}'$, which is decoded back to vector $\tilde{\bar{x}}'$. The last vector is a result approximation which can be attained by storing, transmitting or processing vector $\bar{x}$ (Jolliffe, 2005) (Fig. 3).

The diagram's encoder should perform a linear operation, using a matrix $\bar{\bar{Q}}$:

$$\bar{c} = \bar{\bar{Q}}\bar{x} \tag{5}$$

The diagram's encoder should perform a linear operation, using a of $\bar{c}$ multiplied by the columns of matrix:

$$\bar{\bar{Q}}: \tilde{\tilde{x}} = \bar{c}^{T}\bar{\bar{Q}}^{T} \rightarrow \tilde{\tilde{x}} = \sum_{i=1}^{M} c_i \bar{q}_i \tag{6}$$

Kernel PCA: Traditional PCA allows only linear dimensionality reduction, but, if data has more complicated structures impossible to be simplified in linear subspace, traditional PCA becomes invalid. Fortunately, kernel PCA permits traditional PCA generalization to nonlinear dimensionality reduction.

Kernel PCA was introduced (Honkela *et al*., 2004) as a nonlinear generalization of PCA the idea being to map given data points from input space $\mathbb{R}^n$ to high-dimensional (possibly infinite-dimensional) feature space $\mathcal{F}$:

$$\Phi = \mathbb{R}^n \rightarrow \mathcal{F} \tag{7}$$

and to perform PCA in F. Space F and therewith also mapping Φ can be complicated. Employing so-called kernel trick, kernel PCA avoids using Φ: PCA in F is formulated so that only inner product in F is needed. This can be seen as a nonlinear function called kernel function:

$$\mathbb{R}^n \times \mathbb{R}^n \rightarrow \mathbb{R} \tag{8}$$

$$(x, y) \rightarrow k(x, y) \tag{9}$$

This calculates real number for every vectors pair from input space.

Classifier:

Naive bayes classifier: Naïve Bayes classifiers are statistical classifiers based on Bayes theorem (McCallum and Nigam, 1998) using a probabilistic approach to predict a given data's class, by matching given data to class with highest posterior probability. Following are algorithms used in Naïve Bayes:

$$P(C_i|V) = \frac{P(V|C_i)P(C_i)}{P(V)} \tag{10}$$

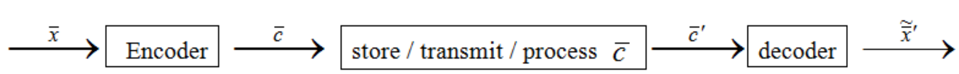

Fig. 3: Process of PCA

where, $V = (v_1, \ldots, v_n)$ is document represented in n-dimensional attribute vector and $C_1, \ldots, C_m$ represents m class. But is it computationally expensive to compute $P(V|C_i)$ to reduce computation, naïve assumption of class conditional independence is made. Thus:

$$P(V|C_i) = \prod_{k=1}^{n} P(x_k|C_i) \tag{11}$$

K-nearest neighbour classification: k-NN classifier is based on the premise that vector space model is similar for similar documents. Training documents are indexed and each is associated with corresponding label. When a test document is submitted, it is treated as a query and retrieves documents from the training set similar to test document. The test document class label is assigned based on distribution of k-NN. Class label is further refined by adding weights. Thus, higher accuracy is obtained by tuning. k-NN method is simple to understand and easy to implement (Kulkarni *et al*., 1998; Timofeev, 2004):

$$p(x) \cong \frac{k}{NV} \tag{12}$$

Similarly probability density function $p(x|Hi)$ of observation x conditioned to hypothesis H_i can be approximated. Let's now assume N_i is number of patterns associated to hypothesis $H_i, i = 1 \ldots C$, so that $N1 + \cdots + NC = N$.

Radial Basis Function Neural network (RBFN): A RBFN is a three layer feed-forward network consisting of an input layer, one middle layer and an output layer. Every input neuron corresponds to an input vector x component. The middle layer has n neurons and one biased neuron. Each input neuron is connected to middle layer neurons except the one biased. Every middle layer neuron computes a kernel function (activation function) usually the following Gaussian function:

$$y_i = \begin{cases} \exp\left(-\frac{\|x-c_j\|}{2\sigma_i^2}\right) & i = 1,2 \ldots \ldots, n \\ 1 & i = 0 \quad (bias\ neuron) \end{cases} \tag{13}$$

where c*i* and s*i* the center and the width of the $i-th$ neuron in middle layer, respectively. k denotes the Euclidean distance (Hwang and Bang, 1997). Weight vector between input layer and i-th middle layer neuron corresponds to the center c*i* in Eq. (1). And in an RBFN net input to the $i-th$ middle layer neuron is $\|x - cj$ rather than x . ci the kernel function decreases rapidly if width s*i* is small and slowly if large. Output layer consists of *m* neurons which correspond to possible classes of problem and is connected to middle layer. Each output layer neuron computes a linear weighted sum of outputs of middle layer as follows:

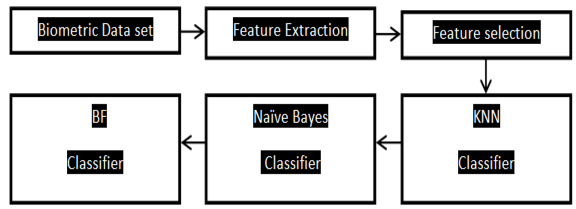

Fig. 4: Flowchart of the proposed framework

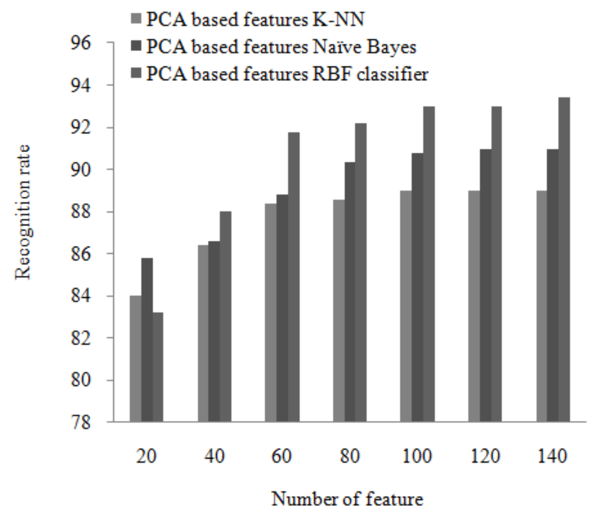

Fig. 5: PCA based feature

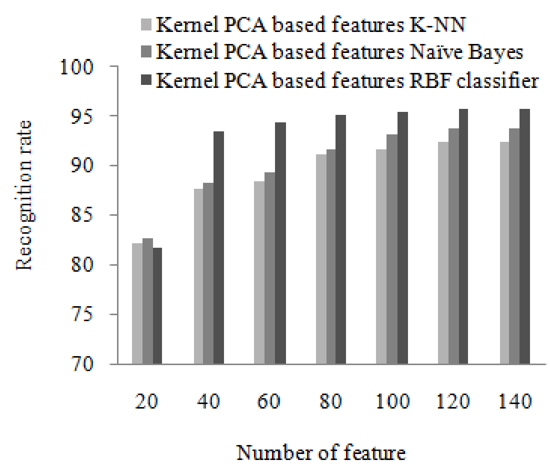

Fig. 6: Kernel PCA based feature

$$Z_j = \sum_{i=0}^{n} y_i w_{ij}, \quad j = 1,2 \ldots \ldots, m \tag{14}$$

where, w_{ij} is weight between the *i*-th middle layer neuron and *j*-th output layer neuron (Fig. 4).

RESULTS AND DISCUSSION

In this study multimodal biometrics based on fingerprint and finger vein are considered. Gabor features are extracted from finger vein using Gabor filter with orientation of 0, 15, 45, 60 and 75°,

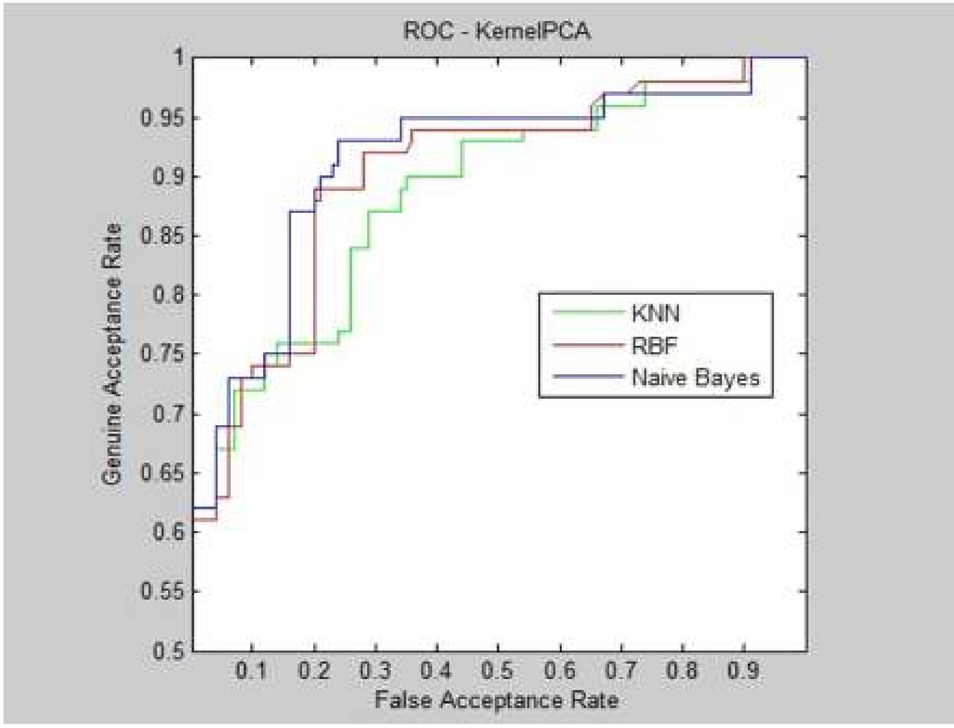

Fig. 7: Kernel PCA

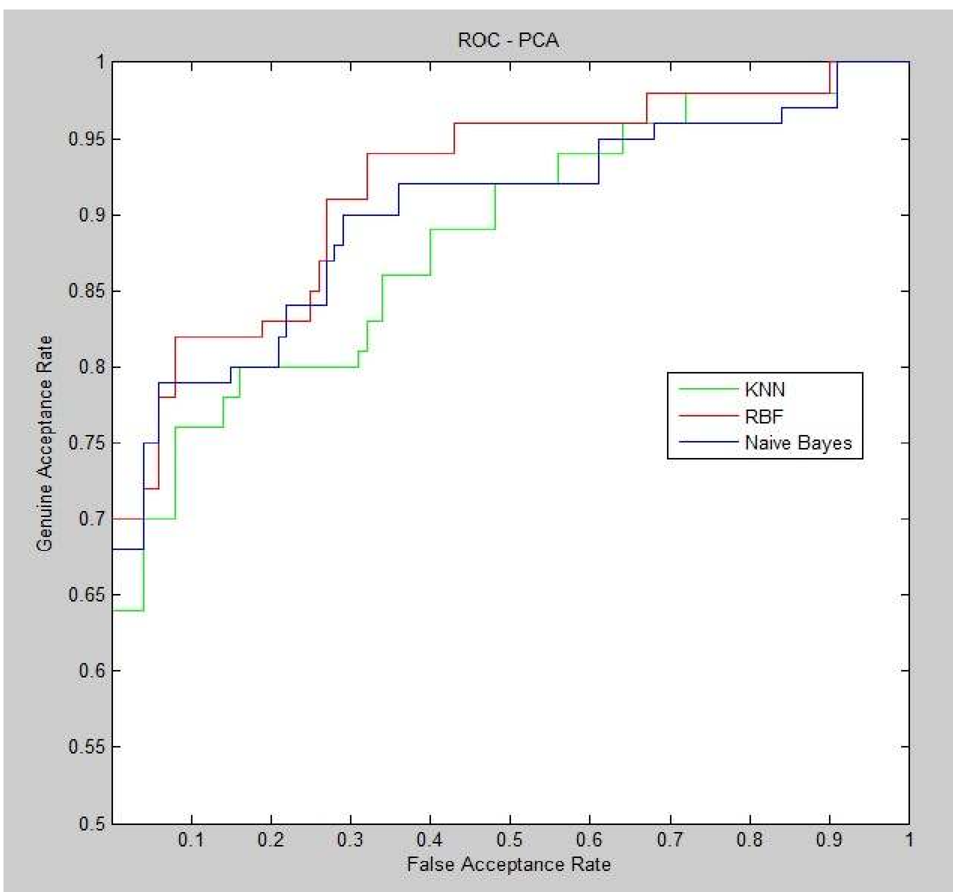

Fig. 8: PCA

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 KNN, Naïve Bayes and RBF Neural Network Classifier. The results obtained are shown from Fig. 5 to 8.

From Figure 5 it is shown that the proposed PCA based feature RBFNN classifier has higher recognition rate of 93.4%.

From Figure 6 it is shown that the proposed Kernel PCA based feature RBFNN classifier has higher recognition rate of 95.8%.

Figure 7 shows the false acceptance rate of ROC kernel- PCA.

Figure 8 shows the false acceptance rate of ROC-PCA.

CONCLUSION

Multimodal biometrics is popular due to its performance and advanced security. This study presents issues related to multimodal biometrics systems. Combining multiple biometric traits improves system performance. This study considers fingerprint and finger vein based multimodal biometrics. Gabor features are extracted from finger vein using Gabor filter with orientation of 0, 15, 45, 60 and 75°, respectively. For fingerprint images, energy coefficients are obtained using wavelet packet tree. Both features are normalized using min max normalization and fused through concatenation. Feature selection is by using PCA and kernel PCA. Classification is through use of KNN, Naïve Bayes and RBF Neural Network Classifiers. Results showed the proposed PCA based feature RBFNN classifier had higher recognition rates of 93.4% while Kernel PCA based feature RBFNN classifier had higher recognition rates of 95.8%.

REFERENCES

Amiri, G.G. and A. Asadi, 2009. Comparison of different methods of wavelet and wavelet packet transform in processing ground motion records. Int. J. Civ. Eng., 7(4): 248-257.

Arivazhagan, S., T.G. Flora and L. Ganesan, 2007. Fingerprint verification using Gabor co-occurrence features. Proceeding of International Conference on Computational Intelligence and Multimedia Applications, 2: 281-285.

Beng, T.S. and B.A. Rosdi, 2011. Finger-vein identification using pattern map and principal component analysis. Proceeding of IEEE International Conference on Signal and Image Processing Applications (ICSIPA), pp: 530-534.

Choras, R.S., 2007. Image feature extraction techniques and their applications for CBIR and biometrics systems. Int. J. Bio. Biomed. Eng., 1(1): 6-16.

Conti, V., C. Militello, F. Sorbello and S. Vitabile, 2010. A frequency-based approach for features fusion in fingerprint and iris multimodal biometric identification systems. IEEE T. Syst. Man Cybernetics, Part C: Appli. Rev., 40(4): 384-395.

Dadgostar, M., P.R. Tabrizi, E. Fatemizadeh and H. Soltanian-Zadeh, 2009. Feature extraction using gabor-filter and recursive fisher linear discriminant with application in fingerprint identification. Proceeding of 7th International Conference on Advances in Pattern Recognition (ICAPR'09), pp: 217-220.

Darwish, A.A., W.M. Zaki, O.M. Saad, N.M. Nassar and G. Schaefer, 2010. Human authentication using face and fingerprint biometrics. Proceeding of 2nd International Conference on Computational Intelligence, Communication Systems and Networks (CICSyN), pp: 274-278.

Derpanis, K.G., 2007. Gabor filter. York University.

Deshmukh, A., S. Pawar and M. Joshi, 2013. Feature level fusion of face and fingerprint modalities using Gabor filter bank. Proceeding of IEEE International Conference on Signal Processing, Computing and Control (ISPCC), pp: 1-5.

Elmir, Y., Z. Elberrichi and R. Adjoudj, 2012. Score level fusion based multimodal biometric identification (Fingerprint and voice). Proceeding of 6th International Conference on Sciences of Electronics, Technologies of Information and Telecommunications (SETIT), pp: 146-150.

Ferrer, M.A., A. Morales, C.M. Travieso and J.B. Alonso, 2007. Low cost multimodal biometric identification system based on hand geometry, palm and finger print texture. Proceeding of 41st Annual IEEE International Carnahan Conference on Security Technology, pp: 52-58.

Fierrez-Aguilar, J., J. Ortega-Garcia, J. Gonzalez-Rodriguez and J. Bigun, 2005. Discriminative multimodal biometric authentication based on quality measures. Pattern Recogn., 38(5): 777-779.

Gargouri Ben Ayed, N., A.D. Masmoudi and D.S. Masmoudi, 2011. A new human identification based on fusion fingerprints and faces biometrics using LBP and GWN descriptors. Proceeding of 8th International Multi-Conference on Systems, Signals and Devices (SSD), pp: 1-7.

Guest, R. and O. Miguel-Hurtado, 2011. Enhancing off-line biometric signature verification using a fingerprint assessment approach. Proceeding of IEEE International Carnahan Conference on Security Technology (ICCST), pp: 1-4.

Honkela, A., S. Harmeling, L. Lundqvist and H. Valpola, 2004. Using kernel PCA for initialisation of variational Bayesian nonlinear blind source separation method. Proceedings of the 5th International Conference on Independent Component Analysis and Blind Signal Separation (ICA 2004) pp: 790-797.

Hwang, Y.S. and S.Y. Bang, 1997. An efficient method to construct a radial basis function neural network classifier. Neural Networks, 10(8): 1495-1503.

Indovina, M., U. Uludag, R. Snelick, A. Mink and A. Jain, 2003. Multimodal biometric authentication methods: a COTS approach. Proceeding of MMUA, pp: 99-106.

Jain, A. and C.K. Verma, 2012. A framework based on hybrid biometrics for personal verification systems. Int. J. Appl., 1(1): 55-58.

Jain, A.K., A. Ross and S. Prabhakar, 2004. An introduction to biometric recognition. IEEE T. Circuits Syst. Video Technol., 14: 4-20.

Jolliffe, I., 2005. Principal Component Analysis. John Wiley and Sons, Ltd, New York.

Kulkarni, S., G. Lugosi and S. Venkatesh, 1998. Learning pattern classification: A survey. IEEE T. Inform. Theor., 44(6).

McCallum, A. and K. Nigam, 1998. A comparison of event models for naive bayes text classification. Proceedings of AAAI-98 Workshop on Learning for Text Categorization, 752: 41-48.

Ross, A. and A. Jain, 2003. Information fusion in biometrics. Pattern Recogn. Lett., 24(13): 2115-2125.

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. Proceedings of 7th International Conference on Intelligent Systems and Control (ISCO), pp: 183-188.

Sasidhar, K., V.L. Kakulapati, K. Ramakrishna and K. KailasaRao, 2010. Multimodal biometric systems-study to improve accuracy and performance. arXiv Preprint arXiv: 1011.6220.

Shariatmadar, Z.S. and K. Faez, 2011. A novel approach for Finger-Knuckle-Print recognition based on Gabor feature fusion. Proceedings of 4th International Congress on Image and Signal Processing (CISP), 3: 1480-1484.

Shi, J.X. and X.F. Gu, 2010. The comparison of iris recognition using principal component analysis, independent component analysis and Gabor wavelets. Proceedings of 3rd IEEE International Conference on Computer Science and Information Technology (ICCSIT), 1: 61-64.

Shinde, A.D., 2004. A wavelet packet based sifting process and its application for structural health monitoring. M.A. Thesis, Faculty of Worcester Polytechnic Institute.

Shukla, A., R. Tiwari and R. Kala, 2010. Multimodal biometric systems. Towards Hybrid and Adaptive Computing, pp: 401-418.

Snelick, R., U. Uludag, A. Mink, M. Indovina and A. Jain, 2005. Large-scale evaluation of multimodal biometric authentication using state-of-the-art systems. IEEE T. Pattern Anal. Mach. Intell., 27(3): 450-455.

Timofeev, R., 2004. Classification and regression trees (cart) theory and applications. Humboldt University, Berlin.

Wayman, J., A. Jain, D. Maltoni and D. Maio, 2005. An introduction to biometric authentication systems. Biometric Syst., pp: 1-20.