Latent Palm Fused with Fingerprint to Improve Authentication Performance

Karthikeyani. K
Student
Department of Computer Science and Engineering
Kumaraguru College of Technology, India

Thangasamy. S, Ph.D
Dean (R & D)
Department of Computer Science and Engineering
Kumaraguru College of Technology, India

Latha. L
Associate Professor
Department of Computer Science and Engineering
Kumaraguru College of Technology, India

ABSTRACT
Biometric Authentication systems adopt a suitable image processing technique to manipulate the biometric images. It refers to verifying a person using their biometric traits that includes physiological, biological and/or behavioral traits like iris, face, fingerprint, voice, hand writing etc., A biometric characteristic should be unique, universal, permanent and acceptable. In this work, the texture feature of palm and finger print extracted using Gabor filter and fusion is done by concatenation. The high dimensionality of fused features are reduced using ant colony optimization(ACO) algorithm and finally only the most significant features are used for classification of genuine and imposter users. Any two-class classifier can be used for classification. Three classifiers namely a SVM classifier with Linear and RBF kernels and NC (Normalized Correlation) are used for classification and the results were compared. A classification accuracy of 98.6% is discussed in literature for high resolution scanner images. The least Total Error ever reported in literature is 7.94% [12] This work aims at improving the accuracy of classification of the authentication system with noisy samples, while reducing the Total Error (TE), False Acceptance Rate (FAR), False Rejection Rate (FRR) and Equal Error Rate (EER). For evaluation of the system a real time database was constructed with a finger and palm print scanner. The database consists of four samples each for an individual.

General Terms
Security, Biometric Authentication, User Verification, Ant colony optimization, SVM.

Keywords
Multi biometric fusion, palm and fingerprint, Ant Colony Optimization, SVM classifier, Gabor filter, Texture features.

1. INTRODUCTION
The fusion of more than one biometric trait improves the performance of the system by increasing the accuracy of authentication as multiple biometric traits provide robustness to the system. Though the biometric systems provide at most security, a uni modal system where a single biometric trait is used for authentication can be forged easily. For example, fingerprints can be easily forged with silicon or gelatin masks which are made artificially. This is the reason why multimodal biometric systems started gaining popularity. Multimodal biometric system that uses more than one biometric character together to authenticate a person is more secure than uni modal systems. Multimodal systems not only increase the accuracy of the system but also make it difficult for the imposter to gain unauthenticated access to the system. There are many multimodal systems that are discussed in the literature like finger and palm [1], face and palm print [2] and so on. This work uses palm print and fingerprint for authentication.

Image Processing

Image processing is any form of signal processing for which the input is an image such as a photograph or an image from a scanner; the output of image processing may be either an image or a set of characteristics or parameters related to the image. Most image processing techniques involve treating the image as a two-dimensional signal and applying standard signal-processing techniques to it. Image processing usually refers to digital image processing but also optical and analog image processing are possible.

1.1 Biometrics

Biometrics deals with identification or authentication of individuals based on their physiological or behavioral characteristics. Biometrics has lately been receiving attention in popular media. It is widely believed that biometrics has become a significant component of identification technology because (i) the prices of biometric sensors continue to fall, (ii) the underlying technology becomes more advanced and (iii) the public has become aware of the strengths and limitations of biometrics.

2. REVIEW OF SOME EXISTING SYSTEMS

Lu *et al. [3]* discussed a palm print recognition system based on Eigen space technique where the original palm print images were transformed by KL transformation with the obtained Eigen palm features used for palm print recognition. But such a system works well only for face and palm features. Authors in [4] also discussed that among the fusion rules min-max normalization and sum- rule are effective for open population applications with unknown population densities. Meanwhile, for a closed population application, where repeated user samples and their statistics can be accumulated, the fusion methods like QLQ adaptive normalization and user weighting fusion methods are effective.

Authors in [5] discuss about the optimal feature selection for hand geometry based authentication system. This work inspired in working on optimal feature selection based authentication. Authors in [6] describes about the feature extraction using Gabor filters and the feature vectors were classified using Momentum optimized Genetic Partial

Recurrent Neural Network. The work optimizes MSE (Mean Squared Error).

Qian Tao *et al. [7]* discussed about the matching score calculation based on likelihood ratio of the feature vectors in feature space. The thresholds used to make authentication decision are not prefixed .Instead, it is optimally chosen based on the classifier used. The threshold varies based on the classifiers because of their varying performance. Yanmin Gong *et al. [8]* formulated score fusion for face into a linear model. An assumption that weighted similarity scores of different features are normally distributed was made. The matching scores were assigned based on QOM (Quasi convex Optimization Metrics). The QOM has unique property that it has no local minimum that are not global.

3. PRELIMINARIES

3.1 Image capture and Pre processing

The main reason for the degradation of performance in image based authentication systems is the poor quality of the biometric samples. To overcome that problem a proper image capturing device based on the application requirement should be chosen. This work concentrated on that by using a powerful scanner for palm and finger print capture. The image database for evaluation of the results was a real time database constructed in out institute. The preprocessing stage included the removal of unwanted noise from the image samples. The image was represented for manipulation as a 128× 128 matrix. If more samples needed to be used in training the classifier, then the image can be represented as 64× 64 matrix.

3.2. Gabor Wavelet Filters

Basically, 2D Gabor filter [6, 10, 11] can be defined as a linear filter whose impulse response function is the multiplication of harmonic function and Gaussian function in which Gaussian function is modulated by a complex sinusoid. In this regard, the convolution theorem states that the Fourier transform of a Gabor filter's impulse response is the convolution of the Fourier transform of the harmonic function and the Fourier transform of the Gaussian function .Gaussian function is a non-orthogonal wavelet and it can be specified by the frequency of the sinusoid $\omega = 2\pi f$ and the standard deviations of σ_x and σ_y.The 2D Gabor wavelet Filter can be defined using

$$g(x, y: f, \theta) = \exp\left[-\frac{1}{2}\left[\frac{m^2}{\sigma_x^2} + \frac{n^2}{\sigma_y^2}\right]\cos(2\pi f m)\right]$$

(1)

$$m = x\sin\theta + y\cos\theta; \ \mathrm{n} = \cos\theta - y\sin\theta \ ;$$

Here f is frequency of the sinusoidal plane wave along the direction θ from the x-axis and specify the Gaussian envelop along x-axis and along y-axis respectively. This can be used to determine the bandwidth of the Gabor filter.

4. FEATURE EXTRACTION AND FUSION

This work uses a gray scale palm and finger print images fused with size of 128×128 and a resolution of 200 dpi. It uses spatial frequencies that can be represented as $f = \pi/2^i$ (*i*=1, 2... 5) The parameter $\theta = k\pi/8$, (k= 1, 2... 8). For Gabor palm and finger print representation fused images are convolved with Gabor filter bank with five frequencies and eight orientations are used for generation of 40 spatial frequencies and for Gabor feature extraction.

In order to compute the Gabor responses of the images Gabor filter is convolved with the fused image. Let $f(x, y)$ be the intensity of the point (x, y) in the fused image and its conventional with Gabor filter$G(x, y: f, \theta)$ can be given as

$$GR(x, y: f, \theta) = f(x, y) \emptyset G(x, y: f, \theta)$$

(2)

Here $\emptyset$ represents the convolution operator. The response to each Gabor kernel representation is a complex function with a real and imaginary part.

5. ACO BASED OPTIMAL FEATURE SELECTION

The learning based classifiers require a high quality feature vector for more accurate classification. For such a classifier based authentication system, the feature quality can be improved using two main techniques. The first method is to select the relevant and distinct features and the second method is to assign more weights to distinct features. This work adopts the first approach. The high dimensionality of the feature vector obtained from the Gabor responses is reduced using a swarm intelligence based algorithm called Ant Colony Optimization algorithm. Thus only relevant and distinct features are selected from the Gabor space. This high dimensionality reduction is based of the classification accuracy and the length of the feature vector. In contrast to other feature dimensionality techniques like projection (Principal component analysis) or data compression (Information analysis) , ACO based feature selection technique does not alter the original representation of the features but selects a subset of features from the feature space. It preserves the original feature semantics and offers the advantage of interpretability of a domain expert.

Ant colony optimization [11] is inspired by ant's social behavior in the search for shortest paths to reach food sources. The main intention behind applying feature selection technique is select the optimal features that help in well discriminating the users of authentication system. This algorithm avoids over fitting problem and improves classification performance, provide faster and cost-effective models. Also the algorithm easily scales the very high dimensional feature space into intrinsic and low dimensional feature space and it is independent of classification algorithms.

The ACO algorithm technique [12] is that initially artificial ants are placed randomly on the co-efficient features of Gabor responses. In each iteration all the ants computes the probability of moving to a new not yet visited feature point, not yet visited using a pseudo-random proportional rule that is a trade-off between exploration and exploitation. An ant either with probability q_0 exploits the available information about previous good solutions or with probability $(1 - q_0)$ explores new areas of solution space focusing on shorter distance with high pheromone rate. An ant k located at node j chooses the new feature point j to move according to

$$j = \begin{cases} \arg \max_{l \epsilon N_i^k} \left\{ P_{il} H_{il}^{\beta} \right\} & if\ q \le q_0 \\ S & otherwise \end{cases}$$
(3)

Where P_{ij} is the pheromone trail between trail on connection between feature point *i* and *j*, H_{ij} is the problem dependent heuristic. In this work the accuracy of the classifier and the length of the feature vector are the heuristics.β is the parameter that determines the relative importance of pheromone versus heuristics, *q* is a random variable distributed in [0, 1], q_0 is a parameter such that $0 \le q_0 \le 1$ and S is a random variable selected according to the probabilistic rule.

$$S = \begin{cases} \frac{P_{il} H_{il}^{\beta}}{\sum_{l \epsilon N_j^k} P_{il} H_{il}^{\beta}} & if\ j \epsilon N_j^k \\ 0\ otherwise \end{cases}$$
(4)

After all the ants have completed their tours, only the ant that finds the global best tour (the so far best tour obtained from the beginning of the algorithm's execution) reinforces the pheromone trails on the distance belong to its tour. This is called *global pheromone update* given by,

$$P_{ij} = (1-\sigma)P_{ij} + \sigma \Delta P_{ij}^{bs}$$
(5)

Here ΔP_{ij}^{bs} is the pheromone quantity added to the connection (i,j) that belongs to the best solution L^{bs}.The following expression represents ΔP_{ij}^{bs} as,

$$\Delta P_{ij}^{bs} = \begin{cases} \frac{1}{L^{bs}} & if\ (i,j)\, belongs\ to\ the\ best\ tour \\ 0 & otherwise \end{cases} \quad (6)$$

Here σ is the trail evaporation such that $(1-\sigma)$ represents the pheromone persistence. This parameter is used to avoid unlimited accumulation of pheromone trails and allows the algorithm to forget previously done bad choices.

The global pheromone updating increases the probability for other ants to use the short distance that have greater amount of pheromone trail and in turn increases the probability to build better solution. The pheromone evaporation mechanism is applied only on the edges that have been used by an ant. Every time an ant uses a distance, it decreases the pheromone intensity on that distance. This is called *local pheromone update* given by,

$$P_{ij} = (1-\gamma)P_{ij} + \gamma P_0$$
(7)

Here γ is another evaporation parameter and P_0 is the initial pheromone value. Updating the local pheromone encourages the exploration of new areas of the search space by reducing the importance of visited edges while modification of global pheromone encourages the exploitation of previously good solution by giving an extra weight to the distance of global best solution.

A subset of only important features is used for classification. If S is the original set of x features representing Gabor responses then say, T is the reduced set of y features (where $x < y$). In the process of searching a feature subset of y features, each ant randomly chooses a feature subset of y features. Initially the best k subsets (k<number of ants) are used to update the pheromone trail and influence the feature subsets in the next iteration. During next subsequent iterations, each of the ants start with $y - p$ (where p is an integer ranging from 1 to $y - 1$) features that are randomly chosen from the previously selected k-best subsets. Thus in the next iteration the features that constitute the best k subset will be present with more probability. For any ant i those features will be the best compromise between local importance and pheromone trails with respect to S_i, where S_i is the subset of features already selected by ant i.Thus only the best features are selected at the end of the last iteration.

6. CLASSIFIERS USED FOR CLASSIFICATION

The best subset of features that proves to be the best compromise between the pheromone trails and the local importance is obtained by applying ACO algorithm on Gabor response feature space. Now, a two class classifier is required to make a discrimination of genuine and imposter user. So Support Vector Machine (SVM) [13] is used for the decision making. SVM is used for classification of test samples with respect to training samples. Therefore SVM is popularly known as statistical learning theory and are built based on the principle if minimization of structural risk. The minimization of upper bound on expected or actual risk can defined as,

$$R(\alpha) = \int \frac{1}{2} |z - f(x,\alpha)| dP(x,z)$$
(8)

Here α is a set of parameters that can be used to define the trained machine and z is a class label which is associated with the training sample x. The function $f(x,\alpha)$ is used to map the training samples to class label. The term $P(x,z)$ is an unknown probability distribution which associates a class label with each of the training sample. Let k denote the number of training samples and from k choose η such that $0 \le \eta \le 1$. For expected risk with probability $1-\eta$ the following bound holds,

$$R(\alpha) \le R_{emp}(\alpha) + \sqrt{\frac{h\left(\left(\log\left(\frac{2k}{h}\right)+1\right)-\log(\eta/4)\right)}{k}}$$
(9)

Here h is Vapnik Charvonenkis (VC) dimension [14] which is a non-negative integer. It gives the measure of complexity of the decision function. The R. H. S term is called VC bound. To minimize the overall risk one need to minimize the empirical risk as well as VC dimension.

An optimal hyper plane should be chosen from a set of hyper planes to separate a given training sample. Such a hyper plane will minimize the VC confidence that in turn will provide the best generalization capabilities. To minimize the sum, known as the margin of the separating hyper plane, of the distances to the closest positive and negative training samples, the optimal hyper plane is used. The optimal hyper plane $wx + b$ can be obtained by the minimization of $\|w\|^2$ which is considered as a quadratic optimization problem. This can be applied for non-separable and non-linear cases. Adding a suitable term to the previously mentioned expression, the separability problem can be solved. The sum is weighted to control the cost of misclassification. To solve the problem of non-linear decision boundaries, mapping of training samples to a high dimensional feature space is done. The decision boundary is set using kernel functions.

7. EXPERIMENTAL EVALUATION

This work is based on the results discussed in [12] for CASIA palm print database. It is obvious from the results that the dimensionality reduction will account for better performance of the system. The experimental set up, here, consists of two thumbs and right palm samples of 100 people, as shown in Fig.1. Four samples for each individual were taken using a real time scanner.

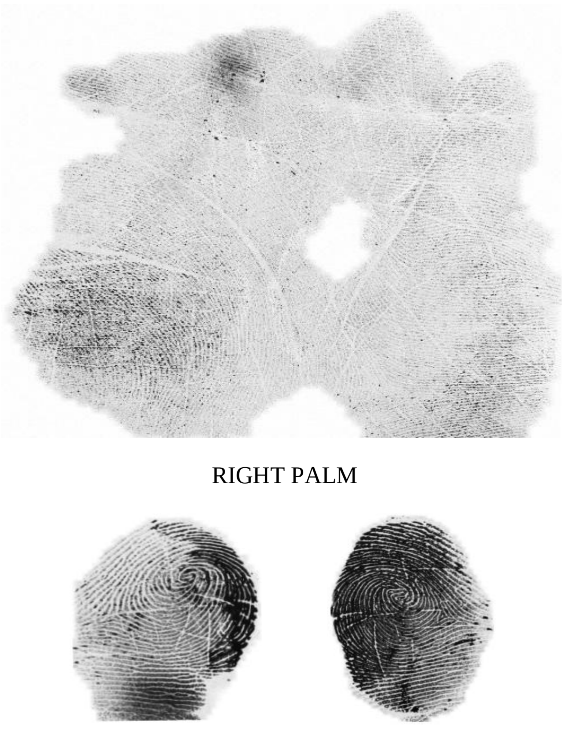

Fig 1: Biometric images of a single person used for fusion

Each image was represented as 64×64 matrix in MATLAB implementation. The Gabor response for three biometric traits was then obtained. The texture features thus obtained was represented as vectors. The features are then fused using simple concatenation.

$$Feature_{Total} = F_{Palm} + F_{L.Thumb} + F_{R.Thumb} \qquad (10)$$

The performance metrics considered here such as EER and TE were evaluated using confusion matrix. All the feature vectors were reduced in dimension using ACO algorithm. Now the performance metrics of interest were calculated. This is compared with the previous results. The compared results are shown in Table 1 and Table 2 in the next section.

8. EXPERIMENTAL RESULTS

The authentication system that is based on the above mentioned kind of biometric samples will give better classification accuracy with SVM Classifier using Linear Kernel. Table.1 shows the comparison of the results obtained with the high dimensionality features and the Table.2 depicts the results with the dimension of features reduced using ACO algorithm. It is obvious from the results that the SVM Linear Kernel is the suitable classifier for the real time scanner that we used. The EER of the system is found to be reduced from 6.34% to 4.30% when ACO optimization is applied. The TE has reduced from 12.68% to 8.60%. The other parameters like False acceptance Rate and False Rejection Rate were reduced from 12.698 % and 0.9911% to 4.3011% and 0.3241% respectively.

Table 1. Performance before applying ACO

Classifier / **Parameter**	**SVM Linear Kernel**	**SVM RBF Kernel**	**NC (normalized correlation)**
EER	6.34%	8.73%	11.11%
TE	12.68%	17.46%	22.22%
FAR	12.6984%	7.9365%	12.6984%
FRR	0.9911%	9.5238%	9.5238%

Since the TE of the system is 8.60%, the accuracy of the system is thus 91.4% .This is a high accuracy achieved for the noisy samples. This accuracy is more significant while we consider the challenging palm image as shown in Fig. 1. This kind of partial image is called palm print image.

The accuracy of authentication in latent palm print based authentication system is around 78%. Thus an idea to try fusion of this biometric trait with some other more reliable one was obtained. Here we chose finger print as one such trait that individually gave around 98% of authentication accuracy. Thus these two traits were fused together to obtain a higher accuracy with the palm prints that seems to be challenging images. Finally the desired higher accuracy was achieved as 91.4%. Another approach to deal with the latent palms is to fill the missed data appropriately with some correct data. It can also be dealt by purposely ignoring a particular portion from all the samples and consider only that for authentication purposes. This method will make the missing area in the palm print samples uniform in all the images.

Table 2. Performance after applying ACO

Classifier / Parameter	SVM Linear Kernel	SVM RBF Kernel	NC (normalized correlation)
EER	4.30%	6.45%	8.60%
TE	8.60%	12.90%	17.20%
FAR	4.3011%	8.6022%	8.6022%
FRR	0.3241%	6.4516%	4.3011%

9. CONCLUSION

The paper presents a system that effectively discriminates the genuine and imposter users. The selection of only optimal features helps not only in increasing accuracy of the system but also in reducing EER, TE and the burden of computation.

The high dimensionality of features can be reduced by adopting some other genetic or swarm intelligence based algorithms in future for improved results. Even a small increase in accuracy is much significant in these kind of security systems.

10. ACKNOWLEDGMENT

We would like to thank DRDO for funding this project Also, we would like to thank the reviewers for their valuable suggestions and comments which helped in improving the quality of this work.

11. REFERENCES

[1] K.Krishneswari, S. Arumugam, "*An improved Genetic Optimized neural network for multimodal biometrics*", In JSIR, Vol.72, pp.23-30 (2013).

[2] R. Ragavendra, B. Dorizzi, Ashok Rao, G. Hemantha Kumar, "*Designing efficient fusion schemes for multimodal biometric systems using face and palm print*", Pattern Recognition, Elsevier, Vol.44, pp. 1076-1088 (2011).

[3] G. M. *Lu*, D. Zhang, K. Q. Wang, "*Palm print recognition using Eigen palms features*", Pattern Recognition Letters,24(9-10) ,pp.1463-1467, 2002

[4]. Mink .A, R.Snelick, U. Uludag, M. Indovina, and A.Jain, "*Large scale evaluation of Multimodal Authentication Using State-of-the –Art Systems*", IEEE Transactions on Pattern Analysis and Machine Intelligence, 2005, Vol.27, No.3, pp. 450-455

[5] M.Hemandhalu et.al,"*Fusion of hand based biometrics using Particle Swarm Optimization*" Proc. IEEE, 2008. The IEEE website. [Online]. Available: http://www.ieee.org/

[6]. Krishneswari,S.Arumugam,"*An Improved Genetic Optimized Neural network for multimodal Biometrics* ", In JSIR, Vol.72,2013. pp-23-30.

[7] Qian Tao et.al,"*Threshold optimized decision-level fusion and its applications to biometrics*", Pattern Recognition in Elsevier, Vol.42,2009. pp.823-836.

[8] Yanmin Gong et.al,"*Quasi-convex optimization of Metrics in Biometric Score Fusion*",Sixth International Conference on Image and Graphics,IEEE 2011.

[9] Norman Poh and Josef Kittler,"*On Using Error Bounds to Optimize Cost-Sensitive Multimodal Biometric Authentication*",IEEE,2008.The IEEE website. [Online]. Available: http://www.ieee.org/

[10] Tobias Scheidat , "*Parameter Optimization for Biometric Fingerprint Recognition using Genetic algorithm*",In International conference on MM&Sec,Geneva,Switzerland.ACM,2006.

[11] Z.Guo, D.Zhang and W.Li , "*Palmprint verification using Binary orientation co-occurrence Vector*", Pattern Recognition Letters, vol.30, No.13, 2009. pp.1219-1227.

[12] Dakshina Ranjan Kisku ," *Human Identity Verification Using Multispectral Palm print Fusion*",JSIP,vol.3 ,2012.pp. 263-273 pp.1076-1088.

[13] C. J. C. Burges, "*A Tutorial on Support Vector Machines for Pattern Recognition*", Data Mining and knowledge Discovery, Vol.2, No.2, 1998, pp.121-167.

[14] Chang-Chun Lin, Lu-Chan Tseng, Website reorganization using an ant colony system, *Expert System with Applications, Vol.37, 2010, pp.7598-7605,*

[15] Prabhakar. S, Pankanti. S, A. K. Jain, Biometric Recognition: Security and Privacy Concerns, *IEEE Security & Privacy*, 2003, pp. 33-42.

[16] Kittler.J, Hatef.M, Diun.R, Maatas.J, "*On combining classifiers*", IEEE Trans on Pattern Analysis and Machine Intelligence.vol.20, 1998.

[17] Jain A.K, S.Prabhakr, A. Ross,"*An Introduction to biometric Recognition"*, IEEE Trans. Circuits' System Video Technol., Vol.14, 2004, pp.4-20 (A special on video and image-based biometric systems).

[18]. C. Bergamini, "*Combining different biometric traits with one-class classification*", Signal Processing, Vol.89, 2009, pp.2117- 2127.

[19]CASIA Palm print database, (2007). Available on: http://www.sinobiometrics.com

[20]BIT Finger print database , (2011) . Available on: http://www.biometrics.idealtest.org.