AN EFFICIENT METHOD FOR PERSON IDENTIFICATION USING WAVELET TRANSFORM WITH PALM PRINT FEATURES

Sumathi S[1], RaniHema Malini R.[2]

[1]Research Scholar, Sathyabama University, Rajiv Gandhi Road, Chennai
[2]Dept of E&I, St.Peter's University, Chennai-54, Chennai.
[1]sumathi_ba@rediff mail.com
[2]ranihema@yahoo.com

ABSTRACT

Biometric system is designed to identify the people accurately, based on human physiological features. The palm print is regarded as one of the most unique, reliable, stable personal charecterstics and performs effectively as a biometric. This paper proposes a new efficient method for the purpose of individual identification using palm print based on Discrete Wavelet Transform (DWT). The wavelet coefficients are used as features for identifying the individual and given to the Support Vector Machine (SVM) classifier for the classification purpose. The wavelet coefficients for palm print are reduced by using specified window size placed at center of the image. Experiments are conducted for various window sizes and the best window size which gives better success rate is chosen. Here using selected window size instead of complete palm print which gives good recognition rate and better result in substantial savings in storage and computation time. Experimental results show promising performance with the proposed methods from IIT palm print database.

Key words: Biometrics, Identification, Palm print, Discrete Wavelet Transform, Support Vector Machine.

I. INTRODUCTION

Biometrics be the most secure and convenient method to satisfy the need for identity recognition of individual in the society. For that physiological or behavioral characteristics of person are used for automatic identification of an individual Palm prints are potentially a good choice for biometric applications because they're invariant with a person, easy to capture, and difficult to duplicate. They offer greater security than fingerprints because palm veins are more complex than finger veins. Compared with the fingerprint, the palm provides a larger surface area so that more features can be extracted. The line features of a palm are stable throughout one's lifetime. Since palm print uses much lower resolution imaging sensor compared with fingerprints, the computation is much faster in both preprocessing and feature extraction stages.

Iris scanning biometric system can provides a high accuracy biometric system but the cost of iris scanning devices is high. Palm print biometric system is user-friendly because users can grant the access frequently by only presenting their hand in front of the camera. In face recognition system, users are required to remove their accessories such as spectacles or ear pendant during acquisition. Palm print biometric system achieves higher accuracy than hand geometry biometric system because the geometry or shape of the hand for most of the adults is relatively similar. Palm print contains geometry features, line features, point features, statistical features and texture features.

An online personal verification system by fusing palm print and palm vein information is presented in [1] based on GLMC entropy. A novel palm print and knuckle print tracking approach to automatically detect and capture these features from low resolution video stream is proposed in [2] and no constraint is imposed and the subject can place his/her hand naturally on top of the sensor without touching any device. A method of feature extraction of palm print using real- Gabor transform (RGT) is proposed [3], which converts the spatial domain information of palm print to joint spatial frequency domain. In critical sampling case, by calculating the compactly distributed coefficients of RGT, the sub-block energy distribution of palm print in spatial-frequency domain are extracted as recognition features.

A frequency domain feature extraction algorithm for palm-print recognition is proposed [4], which efficiently exploits the local spatial variations in a palm print image based on extracting dominant spectral features from each of these bands using two dimensional discrete cosine transform (2D-DCT). A novel approach is proposed, [5] to computing hand geometry measurements from frontal views of freely posed hands. These approaches offer advantages in hygiene, comfort and reliability. A novel fusion approach at the lowest level, i.e. the image pixel level is proposed [6]. It performs the Gabor transform on face and palm print images and combines them at the pixel level. A scanner-based personal authentication system by using the palm print features is proposed in [7]. The authentication system consists of enrollment and verification stages. In the enrollment stage, the training samples are collected and processed to generate the matching templates. In the verification stage, a query sample is matched with the reference templates to decide whether it is a genuine sample or not.

A new bimodal biometric system using feature-level fusion of hand shape and palm texture is presented in [8]. The combination is of significance since both the palm print and hand-shape images are proposed to be extracted from the single hand image acquired from a digital camera. A new method to authenticate individuals based on palm print identification and verification is described in [9] via multiple feature extraction. Palm print authentication based on intra-model feature fusion using wavelet is presented in [10].

II. METHODOLOGY

The proposed system is built based on Discrete Wavelet Transform of the image and by applying multiclass SVM for building the classifiers. In this section the theoretical background of both the approaches are introduced.

2.1 Discrete Wavelet Transform

Nowadays, wavelets have been used quite frequently in image processing. They have been used for feature extraction, de-noising, compression, face recognition, and image super-resolution. The decomposition of images into different frequency ranges permits the isolation of the frequency components introduced by "intrinsic deformations" or "extrinsic factors" into certain sub-bands. This process results in isolating small changes in an image mainly in high frequency sub-band images. Hence, discrete wavelet transform (DWT) is a suitable tool to be used for designing a classification system.

The 2-D wavelet decomposition of an image is performed by applying 1-D DWT along the rows of the image first, and, then, the results are decomposed along the columns. This operation results in four decomposed sub-band images referred to as low–low (LL), low–high (LH), high–low (HL), and high–high (HH). The frequency components of those sub-band images cover the frequency components of the original image as shown in Figure 1.

LL	HL
LH	HH

Figure.1.The result of 2-D DWT decomposition

2.2 Support Vector Machine

Support vector machines (SVMs) are a set of related supervised learning methods that analyze data and recognize patterns, used for classification and regression analysis. The standard SVM is a non-probabilistic binary linear classifier, i.e. it predicts, for each given input, which of two possible classes the input is a member of. A classification task usually involves with training and testing data which consists of some data instances. Each instance in the training set contains one "target value" (class labels) and several "attributes" (features). SVM has an extra advantage of automatic model selection in the sense that both the optimal number and locations of the basis functions are automatically obtained during training. The performance of SVM largely depends on the kernel [11].

SVM is essentially a linear learning machine. For the input training sample set

$$(x_i, y_i),\ i = 1 \dots n,\ x \in R^n,\ y \in \{-1, +1\} \qquad (1)$$

the classification hyper plane equation is let to be

$$(\omega \cdot x) + b = 0 \qquad (2)$$

thus the classification margin is $2/|\omega|$. To maximize the margin, that is to minimize $|\omega|$, the optimal hyper plane problem is transformed to quadratic programming problem as follows,

$$\begin{cases} \min \phi(\omega) = \frac{1}{2}(\omega, \omega) \\ s \cdot t \cdot y_i((\omega, x) + b) \geq 1, i = 1, 2 \dots l \end{cases} \tag{3}$$

After introduction of Lagrange multiplier, the dual problem is given by,

$$\begin{cases} \max Q(\alpha) = \sum_{i=1}^{n} a_i - \frac{1}{2} \sum_{i=1}^{n} \int_{j=1}^{n} y_i y_j \alpha_i \alpha_j K(x_i, x_j) \\ s, t \sum_{i=1}^{n} y_i \alpha_i = 0, \alpha_i \geq 0, i = 1, 2 \dots, n \end{cases} \tag{4}$$

According to Kuhn-Tucker rules, the optimal solution must satisfy

$$\alpha_i (y_i (w \cdot x_i) + b) - 1 = 0, i = 1, 2, \dots n \tag{5}$$

That is to say if the option solution is

$$\alpha' = (\alpha_1{}^*, \alpha_2{}^*, \dots, \alpha_i^*)^T, \quad i = 1, 2, \dots n \tag{6}$$

Then

$$w^* = \sum_{i=1}^{n} \alpha_i^* y_i x_i$$

$$b^* = y_i - \sum_{i=1}^{n} y_i \alpha_i^* (x_i \cdot x_j), j \in \{ j / \alpha_i^* > 0 \} \tag{7}$$

For every training sample point x_i, there is a corresponding Lagrange multiplier. And the sample points that are corresponding to $\alpha_i = 0$ don't contribute to solve the classification hyper plane while the other points that are corresponding to $\alpha_i > 0$ do, so it is called support vectors. Hence the optimal hyper plane equation is given by,

$$\sum_{x_i \in SV} a_i y_i (x_i \cdot x_j) + b = 0 \tag{8}$$

The hard classifier is then,

$$y = sgn\left[\sum_{x_i \in SV} \alpha_i y_i (x_1 \cdot x_j) + b \right] \tag{9}$$

For nonlinear situation, SVM constructs an optimal separating hyper plane in the high dimensional space by introducing kernel function $K(x \cdot y) = \phi(x) \cdot \phi(y)$, hence the nonlinear SVM is given by,

$$\begin{cases} \min \phi(\omega) = \frac{1}{2}(\omega, \omega) \\ s \cdot t \cdot y_i((\omega \cdot \phi(x_i)) \geq 1, l = 1, 2 \dots l \end{cases} \tag{10}$$

And its dual problem is given by,

$$\begin{cases} \max L(\alpha) = \sum_{i=1}^{l} \alpha_i - \frac{1}{2} \sum_{i=1}^{l} \sum_{j=1}^{l} y_i y_j \alpha_i \alpha_j K(x_i, x_j) \\ s, t, \sum_{i=1}^{n} y_i \alpha_i = 0, \ 0 \leq \alpha_i \leq c, l = 1, 2, \dots, l \end{cases} \tag{11}$$

Thus the optimal hyper plane equation is determined by the solution to the optimal problem. A SVM classifier can predict or classify input data belonging to two distinct classes. However, SVMs can be used as multiclass classifiers by treating a K-class classification problem as K two-class problems. This is known as one vs. rest or one vs. all classification.

The SVM classifier implementation is standard implementation. In the MATLAB environment the LIBSVM software is used. LIBSVM is integrated software for support vector classification, regression and distribution estimation. It supports multi-class classification.

III. PROPOSED METHOD

3.1 Palm print Identification Phase

The proposed PIP consists of two stages. They are feature extraction stage and classification stage.

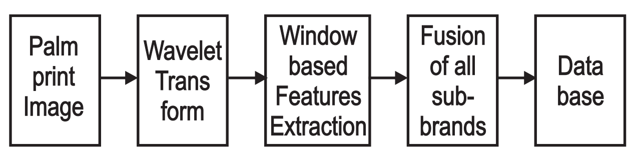

Fig. 2 Feature Extraction Stage in PIP

3.1.1 Feature Extraction Stage

The feature extraction stage in PIP is shown in Figure 2. First, the given palm print image is decomposed by using Haar wavelet transform. From 3-Level wavelet decomposition, 10 sub-bands are obtained. The selection of wavelet coefficients as features depends on the size of the window placed over the center of each sub-bands as shown in Figure 3.

The selected features from the 10 sub-bands are fused together in a serial manner starting from the detailed coefficients to approximate wavelet coefficients. For training purpose, window based wavelet features are extracted for 4 images from each object, totally 152 images and stored in a vector called as Feature Vector for training purpose.

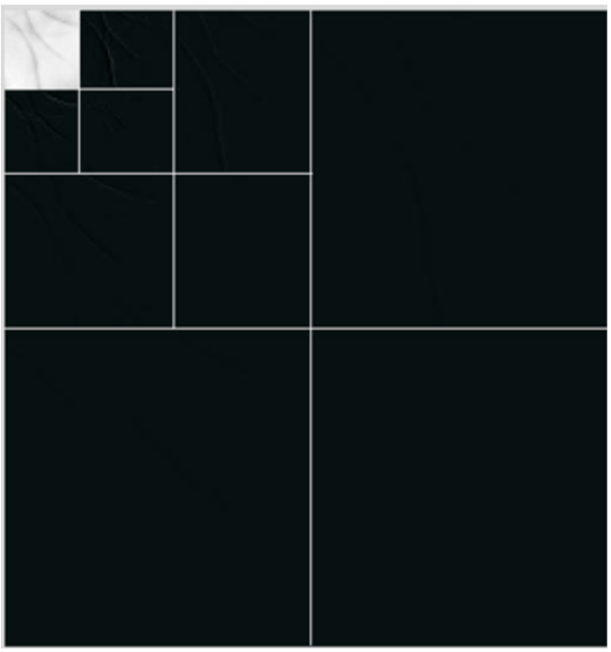

Figure 3 Selection of Wavelet coefficients in PIP

3.1.2 Classification Stage

In the classification stage, the multi class SVM classifier with linear kernel is trained with the Feature vector calculated in the feature extraction stage. To recognize the user, the same wavelet features explained in the feature extraction stage are extracted from the user and tested with the SVM classifier. The classifier gives the class i.e. index of the retrieved image. Specifically, a threshold value is chosen, the correlation value between the user and the training images in the retrieved index whose absolute value exceeds the threshold are recognized while others are unrecognized. The correlation value is defined by

$$r = \frac{\Sigma_m \Sigma_n (A_{mn} - \bar{A})(B_{mn} - \bar{B})}{\sqrt{(\Sigma_m \Sigma_n (A_{mn} - \bar{A})^2)(\Sigma_m \Sigma_n (B_{mn} - \bar{B})^2)}}$$

where $\bar{A}$ = mean 2 (A) and $\bar{B}$ = mean 2 (B). The moderate correlation value 0.5 is used for classification purpose.

IV. EXPERIMENTAL RESULTS

In order to execute the proposed method in the previous section we performed by using new data set with palm image from IIT Delhi Palm Print database [12].

It consists of the hand images collected from the students and staff at IIT Delhi. This database has been acquired using a simple and touch less imaging setup. All the images are collected in the indoor environment and employ circular fluorescent illumination around the camera lens. 7 images from 235 users, from each of the left and right hand, are acquired in varying hand pose variations. In addition to the original images, 150×150 pixels automatically cropped and normalized palm print images are also available. The normalized right hand palm print images of 40 individual are used for palm print identification system. Among the 7 images from each user, 4 images are taken for training and the remaining 3 images for testing. The sample IIT palm print images are shown in Figure 4.

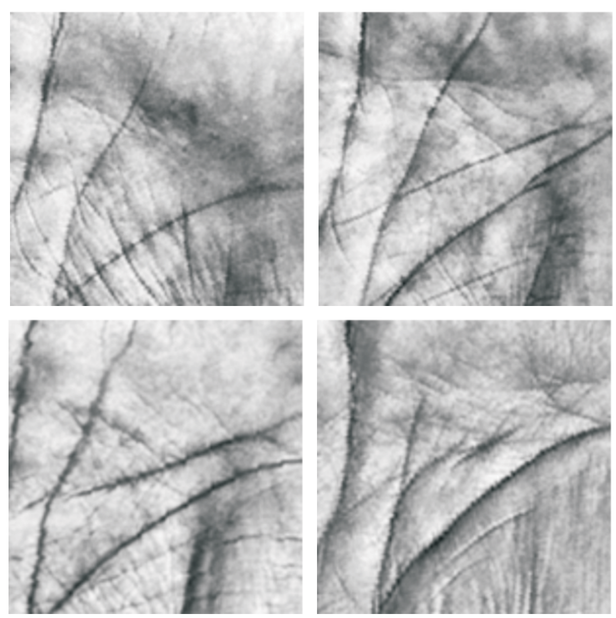

Figure 4 Sample IIT Palm print Images

To show the effectiveness of the proposed system, many computer simulations and experiments conducted with IIT database. The performance measures False Acceptance Rate (FAR) and False Rejection Rate (FRR) are calculated. The system is implemented in MATLAB version 7.6. FRR and FAR values of palmprint identification phase are shown in Table 1 and 2 respectively and the graphical representations are shown in Figure 5 and 6 respectively. Table 3 shows the FAR and FRR values of selected parameters for FRP and PIP.

Table 1a FRR for various thresholds and window sizes in 10% - 50%

	10	20	30	40	50
0.1	0	0	0	0	0
0.2	0	0	0	0	0
0.3	0	0.0038	0.0038	0.0075	0.0075
0.4	0.0075	0.0075	0.0075	0.0113	0.0113
0.5	0.0113	0.0150	0.0150	0.0188	0.0188
0.6	0.0301	0.0489	0.0414	0.0489	0.0526
0.7	0.0451	0.0865	0.1053	0.1241	0.1316
0.8	0.0902	0.1429	0.1767	0.1955	0.2030
0.9	0.1541	0.2105	0.2519	0.2707	0.2782
1	0.1692	0.2256	0.2669	0.2857	0.2932

Table 1b FRR for various thresholds and window sizes in 60% - 100%

	60	70	80	90	100
0.1	0	0	0	0	0
0.2	0	0	0	0	0
0.3	0.0038	0.0075	0.0075	0.0075	0.0075
0.4	0.0075	0.0113	0.0113	0.0113	0.0113
0.5	0.0150	0.0188	0.0188	0.0188	0.0188
0.6	0.0489	0.0564	0.0564	0.0564	0.0564
0.7	0.1278	0.1429	0.1391	0.1391	0.1429
0.8	0.2030	0.2181	0.2181	0.2181	0.2218
0.9	0.2782	0.2932	0.2932	0.2932	0.2970
1	0.2932	0.3083	0.3083	0.3083	0.3120

Table 2a FAR for various thresholds and window sizes in 10% - 50%

	10	20	30	40	50
0.1	0.0046	0.0030	0.0019	0.0014	0.0012
0.2	0.0033	0.0024	0.0017	0.0013	0.0012
0.3	0.0024	0.0019	0.0011	0.0011	0.0010
0.4	0.0011	0.0007	0.0001	0.0002	0.0001
0.5	0.0003	0.0002	0	0	0
0.6	0	0	0	0	0
0.7	0	0	0	0	0
0.8	0	0	0	0	0
0.9	0	0	0	0	0
1	0	0	0	0	0

Table 2b FAR for various thresholds and window sizes in 60% - 100%

	60	70	80	90	100
0.1	0.0011	0.0008	0.0008	0.0008	0.0007
0.2	0.0010	0.0008	0.0008	0.0008	0.0007
0.3	0.0008	0.0007	0.0007	0.0007	0.0006
0.4	0.0003	0.0003	0.0004	0.0004	0.0003
0.5	0.0001	0.0001	0.0003	0.0003	0.0002
0.6	0	0	0	0	0
0.7	0	0	0	0	0
0.8	0	0	0	0	0
0.9	0	0	0	0	0
1	0	0	0	0	0

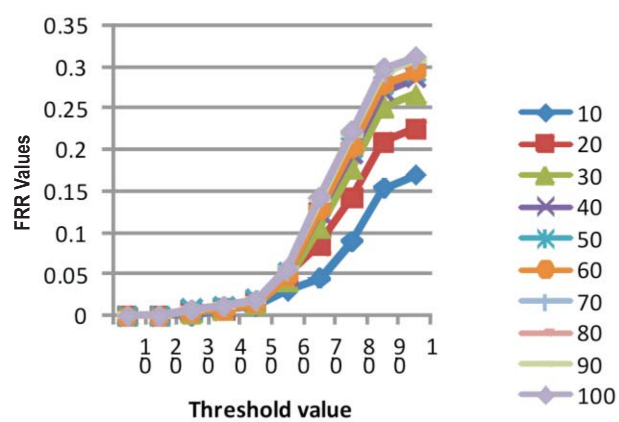

Figure 5 Graphical representations of FRR for various thresholds and window sizes in the PIP

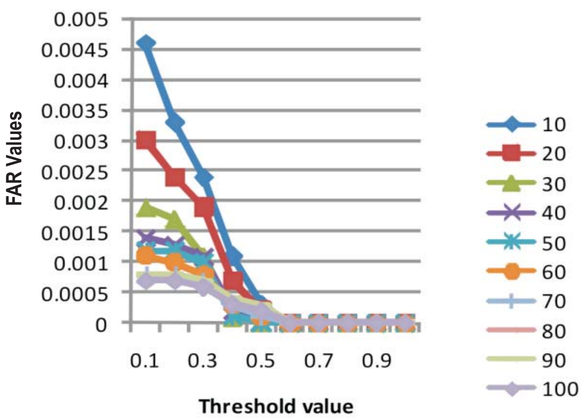

Figure 6 Graphical representations of FAR for various thresholds and window sizes in the PIP

Table 3 FAR and FRR values for FRP and PIP

	PIP
FRR	0.015
FAR	0.0001

To carefully analyze the table 1 and 2, a threshold of 0.5 with 60% window size is chosen for identification of individual. For security applications, the FAR is reduced to almost zero.

V. CONCLUSION

In this paper, a new efficient method is presented for the purpose of individual identification. The wavelet coefficients for palm print identification are reduced by using specified window size placed at center of the image. Experiments are conducted for various window sizes and the best window size of 60% which gives better success rate is chosen. Furthermore, the proposed approach considerably reduces the computation time and substantial savings in storage with 60% instead of 100%. The experimental results demonstrate that the proposed approach is an effective technique for individual identification with nearly zero false acceptance rates.

REFERENCES

[1] David Zhang and Zhenhua Guo, “Online joint palmprint and palmvein verification”, Journal of Expert Systems with Applications, MARCH 2001, pp 2626-2631.

[2] Goh Kah Ong Michael and Tee Connie, “Robust Palm Print and Knuckle Print Recognition System Using a Contactless Approach”, IEEE 5th Conference on Industrial Electronics and Applications, June 2010, pp 323-329.

[3] Yu ZHANG and Dequn ZHAO, “Palm Print Recognition Based on Sub-Block Energy Feature Extracted by Real 2D-Gabor Transform”, IEEE conference on Artificial Intelligence and Computational Intelligence, October 2010, pp 124-128.

[4] Hafiz Imtiaz and Shaikh Anowarul Fattah, “A DCT-based Feature Extraction Algorithm for Palm-print Recognition”, IEEE International Conference on Communication Control and Computing Technologies, October 2010, pp 657-660.

[5] Xiaoqian Jiang, Wanhong Xu, “New Directions In Contact Free Hand Recognition” IEEE International Conference on Image Processing, October 2007, pp 389-392.

[6] Xiao-Yuan Jing and Yong-Fang Yao, “Face and palmprint pixel level fusion and Kernel DCV-RBF classifier for small sample biometric recognition”, Journal of Pattern Recognition, January 2007, pp 3209 – 3224.

[7] Chin-Chuan Han and Hsu-Liang Cheng, “Personal Authentication Using Palm Print Features”, 5th Asian Conference on Computer Vision, January 2002, pp 1-6.

[8] Ajay Kumar and David Zhang, “Personal Recognition Using Hand Shape and Texture”, IEEE Transactions on Image Processing, August 2006, pp 2454-2461.

[9] Jane You and Wenxin Li, “Hierarchical palmprint identication via multiple feature extraction”, Journal of Pattern Recognition, April 2002, pp 847-859.

[10] K.Krishneswari and S.Arumugam, “Intramodal Feature Fusion Using Wavelet for Palmprint Authentication”, International Journal of Engineering Science and Technology, February 2011, pp 1597-1605.

[11] Smola A. J., Scholkopf B., and Muller K. R., “The connection between regularization operators and support vector kernels”, Neural Networks New York, vol.11, November 1998, pp 637-649.

[12] IIT Database: http://www4.comp.polyu.edu.hk/~csajaykr/IITD/Database_Palm.htm

S.Sumathi, Research Scholar Sathyabama University. Graduated B.Sc, Physics, Madurai Kamarajar University, B.Tech Electronics, Madras Institute of Technology, Anna University, ME Applied Electronics, Sathyabama University. She has 15 years of experience in Teaching. She is presently serving as a Assistant Professor in Sri Sai Ram Engineering College, Chennai, Tamilnadu. Her area of interest includes Biometrics, Image Processing, Pattern Recognition, Embedded system. She is a life member of ISTE, IETE, and BES.

Figure 6 Graphical representations of FAR for various thresholds and window sizes in the PIP

Table 3 FAR and FRR values for FRP and PIP

	PIP
FRR	0.015
FAR	0.0001

To carefully analyze the table 1 and 2, a threshold of 0.5 with 60% window size is chosen for identification of individual. For security applications, the FAR is reduced to almost zero.

V. CONCLUSION

In this paper, a new efficient method is presented for the purpose of individual identification. The wavelet coefficients for palm print identification are reduced by using specified window size placed at center of the image. Experiments are conducted for various window sizes and the best window size of 60% which gives better success rate is chosen. Furthermore, the proposed approach considerably reduces the computation time and substantial savings in storage with 60% instead of 100%. The experimental results demonstrate that the proposed approach is an effective technique for individual identification with nearly zero false acceptance rates.

[3] Yu ZHANG and Dequn ZHAO, "Palm Print Recognition Based on Sub-Block Energy Feature Extracted by Real 2D-Gabor Transform", IEEE conference on Artificial Intelligence and Computational Intelligence, October 2010, pp 124-128.

[4] Hafiz Imtiaz and Shaikh Anowarul Fattah, "A DCT-based Feature Extraction Algorithm for Palm-print Recognition", IEEE International Conference on Communication Control and Computing Technologies, October 2010, pp 657-660.

[5] Xiaoqian Jiang, Wanhong Xu, "New Directions In Contact Free Hand Recognition" IEEE International Conference on Image Processing, October 2007, pp 389-392.

[6] Xiao-Yuan Jing and Yong-Fang Yao, "Face and palmprint pixel level fusion and Kernel DCV-RBF classifier for small sample biometric recognition", Journal of Pattern Recognition, January 2007, pp 3209 – 3224.

[7] Chin-Chuan Han and Hsu-Liang Cheng, "Personal Authentication Using Palm Print Features", 5th Asian Conference on Computer Vision, January 2002, pp 1-6.

[8] Ajay Kumar and David Zhang, "Personal Recognition Using Hand Shape and Texture", IEEE Transactions on Image Processing, August 2006, pp 2454-2461.

[9] Jane You and Wenxin Li, "Hierarchical palmprint identication via multiple feature extraction", Journal of Pattern Recognition, April 2002, pp 847-859.

[10] K.Krishneswari and S.Arumugam, "Intramodal Feature Fusion Using Wavelet for Palmprint Authentication", International Journal of Engineering Science and Technology, February 2011, pp 1597-1605.

[11] Smola A. J., Scholkopf B., and Muller K. R., "The connection between regularization operators and support vector kernels", Neural Networks New York, vol.11, November 1998, pp 637-649.

[12] IIT Database: http://www4.comp.polyu.edu.hk/~csajaykr/IITD/Database_Palm.htm

S.Sumathi, Research Scholar Sathyabama University. Graduated B.Sc, Physics, Madurai Kamarajar University, B.Tech Electronics, Madras Institute of Technology, Anna University, ME Applied Electronics, Sathyabama University. She has 15 years of experience in Teaching. She is presently serving as a Assistant Professor in Sri Sai Ram Engineering College, Chennai, Tamilnadu. Her area of interest includes Biometrics, Image Processing, Pattern Recognition, Embedded system. She is a life member of ISTE, IETE, and BES.