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Research Article

Feature Level Fusion using Multi-wavelet Based Iris Feature Extraction

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Abstract

A new approach for the iris recognition based on feature level fusion using multi-wavelet transform is presented in this paper. It specifically uses the combined wavelet transform with multi-wavelet on the unique features obtained from the grey level iris images. It is composed of iris image acquisition, preprocessing, feature extraction and classifier design for matching process. The algorithm for iris feature extraction is based on texture analysis by using combination of wavelets and multi-wavelets transform. Multi-wavelet is extremely effective to analyze mutational and singular signals. It selects spatial directions and the energy is basically concentrated in low frequency section. Compared with existing methods, our method extracts 2-dementional information of iris which is scale, translation and rotation invariant. The fused iris image with combination of wavelets and multi-wavelets provide better accuracy and iris recognition rate.

Keywords: *Biometrics, Iris Feature Extraction, Iris Recognition, Fusion process, Wavelet, Multi-wavelet, Matching Process.*

1. Introduction

Security scenario in 21st century has caused research communities to explore novel and innovative methods for automated person authentication. Iris recognition plays a very important role in identifying and verifying a person automatically from the given database (Wend *et al*, 2010). Among all the biometrics reported such as finger print, palm print, retina, face, ear, vein, signature, voice, gait etc., iris is the unique organ in human being. Iris recognition offers the highest accuracy in identifying individuals. From the survey it has been reported that no two irises are alike- not between the identical twins, or even between the left and right eye of the same person. The iris pattern is fully formed by ten months of age and remains stable throughout the life-time (Sung *et al*, 2004). Iris recognition relies on unique patterns of the human iris to identify or verify an individual which remains stable throughout life (Wildes, 1997), (Daugman, 2004). Thus iris recognition has received extensive attention and is reputed to be most reliable and accurate person identification system in last decade. An iris has various features such as pigment frill, collarette, crypts, concentric area etc. Figure 1 shows different features on iris (Meng and Xu, 2006).

The concept of image fusion is used in various applications now a day's such as medical science, remote sensing, biometrics and so on. Due to calibration problem in camera or sensor; sometimes it is not possible to get complete information from an image. Image fusion is the technique to merge or combine such images to get the complete information.

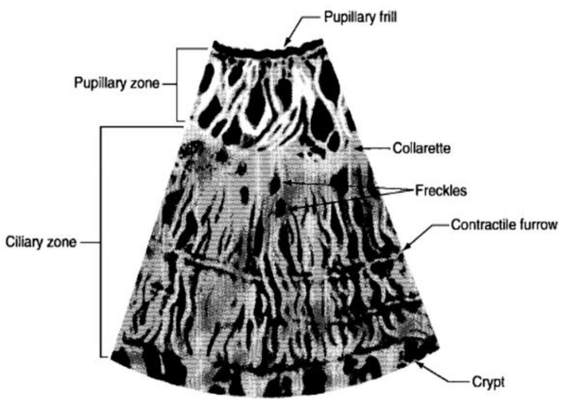

Fig.1 Structure of iris (Source: Meng and Xu, 2006)

The main objective of image fusion is to combine multi sensor, multi temporal or multi view data into a new image to reveal complete information. The actual fusion process can take place in different levels of information and it is shown in figure 2.

The lowest level in fusion process is pixel level fusion. It is a non-linear method where the pixel intensities were used to merge two images. The highest level of fusion is decision level where the symbolic representation of the images is considered. Basically the matching score is combined to fuse the image in decision level fusion. Middle level is feature level of fusion which operates on the characteristics such as size, edge, shape etc (Maruthi *et al*, 2007).

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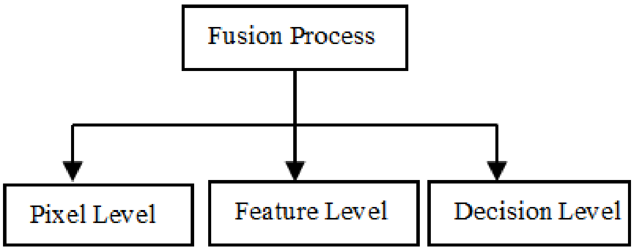

Fig.2 Different Levels of Fusion Process

In this study we investigate the best technique of iris feature extraction using wavelet and multi-wavelets and best feature level fusion technique. The rest of this paper is organized as follows. Section 2 summarizes the previous work in feature extraction and image fusion. Section 3 describes how we have selected and pre-processed iris images for our experiment. Our experimental method is outlined in Section 4. Section 5 presents the analysis done. Finally, Section 6 presents a summary of our findings, a discussion of the implications of our experiment. It also includes the recommendations for future work.

2. Related literature

The iris recognition work can be classified in two categories. The first category includes different methods for image fusion and second category includes recent research on different feature extraction algorithms.

2.1 Image Fusion Techniques

(B. R. Reddy *et a,l* 2013) has used a pixel based image fusion method on MRI [Magnetic Resonance Imaging] and CT [Computer Tomography] scan images to combine two images and extract more and more information. Principal Component Analysis [PCA] and wavelet transform has been used for feature extraction by them. The performance measure used is mean, variance, co-variance, entropy, co-relation coefficient etc. (Rani *et al,* 2012) has proposed a feature level fusion on SAR images taken from different sensors and used contourlet transform for feature extraction. (Gan *et al,* 2006) proposed a method of feature level fusion to combine iris (CASIA database) and face (ORL database) features and claimed that they achieved 98%, 93% and 90.5% results. (Krishnamoorthy *et al,* 2010) has applied eleven different pixel level image fusion techniques with multi-wavelets and observed that DWT with Haar gives 63.33% result. They also suggested that multi-wavelets based fusion can be used in future to improve image quality. (Gayathri *et al,* 2012) applied feature level image fusion using Gabor wavelet and achieved 99.2% accuracy on IITK iris database and PolyU palm-print database combined together and observed that the combination of different features of different biometric traits or modalities can provide greater security in any system.

2.2 Feature Extraction Techniques

Different algorithms were available for iris feature extraction and recognition to improve the accuracy and iris recognition rate. (Masood *et al* 2007) used 2D Haar, Symlet, Bi-orthogonal and Mexican hat at level 1 to extract the iris image features and average absolute matching difference is calculated for iris recognition on MMU database. (Lin *et al,* 2009) applied Marr wavelet transform for feature extraction and they achieved very good recognition rate. But they claimed that the time complexity is not superior. (Wend *et al,* 2010) applied 4^{th} level decomposition of Haar wavelet on CASIA 3 (Interval) database. The iris code is reduced and they achieved better results. (Yongjun *et al,* 2011) applied DB4 wavelet on fractal images and observed that reconstructed image is similar to the original iris image. But they found that the database is having numeric precision error.

3. Iris Data and preprocessing

In this work, we have considered two different databases for testing and analysis. The first database is CASIA V1 which have 756 images of 108 subjects. The resolution of each iris image is 380 X 230. There are two different illumination conditions in which the 7 images of each subject were captured and the classification is done on the basis of these illumination conditions. Out of 108 classes, we have selected 13 classes of each illumination conditions as training and testing dataset.

The second database is KVKIris database having about 1760 images of 88 subjects from which only 4 classes and then 15 classes were used for training and testing to prove our results. The iris images were captured through IScan2, a dual iris capture scanner. This database consists of left and right iris images for each subject with resolution 480 X 480. The classification is done on the basis of right and left iris. Both the databases include gray scale iris images. The third database used is Palaky iris database from which about 48 images of 8 subjects were selected. The iris images were scanned with TOPCON TRC50IA optical device connected with SONY DXC-950P 3CCD camera. File format is PNG and resolution is 576 X 768.

The first difference between our work and above mentioned papers is iris localization technique. For both databases, Daugman's integro-differential operator (Sung *et al,* 2004), (Daugman, 2004), (Daugman, 2003), (He *et al,* 2008), (Bolle *et al,* 2004) and our localization technique (Khobragade *et al,* 2014) named "KKLocal" is applied to find inner and outer boundaries of iris. The basic advantage of KKLocal technique is segmenting iris as fast as possible by selecting the correct region of interest and by avoiding noise such as eyelid, eyelashes, reflection etc. Another difference is that we have applied various combinations of wavelets and multi-wavelets to extract features from both these databases.

Daugman's rubber sheet model is used for normalizing segmented iris. Multi-wavelet works on square matrix that is why normalization is done on 64 X 64 matrixes.

4. Proposed feature level fusion method

In this paper the best combination of coefficients are extracted using wavelets and Multi-wavelets. The features are extracted from an iris image by applying different multi-wavelets namely DD2, GHM, IGHM, GHMAP and

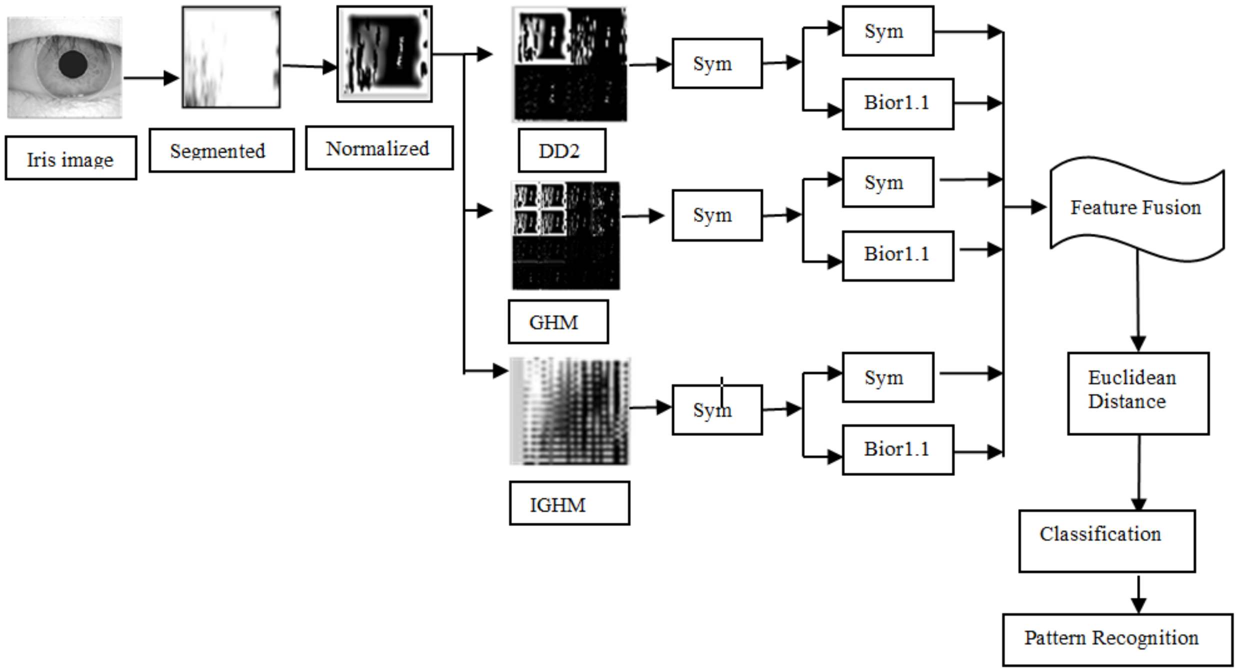

Fig.3 Feature Level Fusion

GHMAP2 etc. On these resultant coefficients different wavelets are applied such as bi-orthogonal Bior1.1, Symlet Sym4, Coiflet Coif1 Daubechies Db2, Haar, Sym4 + Sym4, Sym4+Bior1.1 etc. Figure 3 shows the feature level fusion process on CASIA V1. Euclidean distance is used to classify the data.

The multi-wavelets were basically used for image compression (Stella *et al, 1998).*

GHM (Geronimo, Hardin and Messopust) is a single level 2-D multi-wavelet transform and it performs the decomposition with four multi-filters. The resultant matrix is 128 X 128 with detail coefficients [LL, LH; HL, HH]. HH represents diagonal features and HL represents horizontal features. Whereas LH represents vertical features and LL represents the approximation order features on which next level of decomposition can be applied. The H{k} and G{k} are the matrix filters. GHMAP and GHMAP2 are based on GHM Multiwavelet and use the same coefficients. But the resultant matrix is 64 X 64. These coefficients are initialized as follows:

$$H_0=\begin{bmatrix}\frac{3}{5\sqrt{2}} & \frac{4}{5}\\ -\frac{1}{20} & -\frac{3}{10\sqrt{2}}\end{bmatrix}\quad H_1=\begin{bmatrix}\frac{3}{5\sqrt{2}} & 0\\ \frac{9}{20} & \frac{1}{\sqrt{2}}\end{bmatrix}\qquad (1)$$

$$H_2=\begin{bmatrix}0 & 0\\ \frac{9}{20} & -\frac{3}{10\sqrt{2}}\end{bmatrix}\quad H_3=\begin{bmatrix}0 & 0\\ -\frac{1}{20} & 0\end{bmatrix}\qquad (2)$$

$$G_0=\begin{bmatrix}-\frac{1}{20} & -\frac{3}{10\sqrt{2}}\\ \frac{1}{10\sqrt{2}} & \frac{3}{10}\end{bmatrix}\quad G_1=\begin{bmatrix}-\frac{9}{20} & \frac{1}{\sqrt{2}}\\ \frac{9}{10\sqrt{2}} & 0\end{bmatrix}\qquad (3)$$

$$G_2=\begin{bmatrix}\frac{9}{20} & -\frac{3}{10\sqrt{2}}\\ \frac{9}{10\sqrt{2}} & -\frac{3}{10}\end{bmatrix}\quad G_3=\begin{bmatrix}-\frac{1}{20} & 0\\ -\frac{1}{10\sqrt{2}} & 0\end{bmatrix}\qquad (4)$$

IGHM is inverse of GHM which is used for reconstruction of an image but we have applied it for feature extraction. IGHM provides detailed coefficients as 128 X 128 matrixes. The IGHM coefficients are initialized as follows:

$$H_0=\begin{bmatrix}\frac{3}{5\sqrt{2}} & \frac{4}{5}\\ -\frac{1}{20} & -\frac{3}{10\sqrt{2}}\end{bmatrix}\quad H_1=\begin{bmatrix}\frac{3}{5\sqrt{2}} & 0\\ \frac{9}{20} & \frac{1}{\sqrt{2}}\end{bmatrix}\qquad (5)$$

$$H_2=\begin{bmatrix}0 & 0\\ \frac{9}{20} & -\frac{3}{10\sqrt{2}}\end{bmatrix}\quad H_3=\begin{bmatrix}0 & 0\\ -\frac{1}{20} & 0\end{bmatrix}\qquad (6)$$

$$G_0=\begin{bmatrix}-\frac{1}{20} & -\frac{3}{10\sqrt{2}}\\ \frac{1}{10\sqrt{2}} & \frac{3}{10}\end{bmatrix}\quad G_1=\begin{bmatrix}-\frac{9}{20} & \frac{1}{\sqrt{2}}\\ \frac{9}{10\sqrt{2}} & 0\end{bmatrix}\qquad (7)$$

$$G_2=\begin{bmatrix}\frac{9}{20} & -\frac{3}{10\sqrt{2}}\\ \frac{9}{10\sqrt{2}} & -\frac{3}{10}\end{bmatrix}\quad G_3=\begin{bmatrix}-\frac{1}{20} & 0\\ -\frac{1}{10\sqrt{2}} & 0\end{bmatrix}\qquad (8)$$

DD2 is single level 2-D multi-wavelet transform with Daubechies wavelet with four coefficients which are as follows:

$$C_0=\frac{1+\sqrt{3}}{4\sqrt{2}}\quad C_1=\frac{3+\sqrt{3}}{4\sqrt{2}}\quad C_2=\frac{3-\sqrt{3}}{4\sqrt{2}}\quad C_3=\frac{1-\sqrt{3}}{4\sqrt{2}}\qquad (9)$$

5. Result and Discussion

We have performed different set of experiments to evaluate the results. After acquiring and preprocessing iris image, features are extracted by using GHM, DD2, GHMAP, GHMAP2 and IGHM. To get the compact detail coefficient for these features the wavelets (Ym4, Coif1, Bior1.1, Db2 and Haar were applied. Euclidean distance is calculated on these coefficients.

Feature level fusion is performed with various combinations of wavelets and multi-wavelets. Classification is done on the basis of subclass 1 and 2 on CASIA V 1 database and right and left iris on KVKIris and Palaky database. Euclidean distance is used for classification. The iris images from these databases are shown in figure 4.

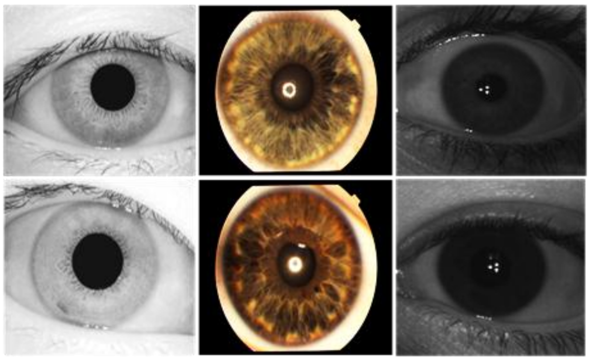

Fig.4 (a) Casia V1 (b) Palaky (c) KVKIris Databases

The iris recognition analyses iris patterns found in an iris and gives better results in verification and/or identification. The statistical feature mean is used for classification. All the features should enter into a comparison process to verify whose iris image had been taken. This comparison is supposed to be made with the templates stored and the comparison algorithm is used for this. We have applied a hard threshold for finding falsely accepted and falsely rejected iris images. On this FAR and FRR data we have drawn ROC to find equal error rate [EER] and correct recognition rate [CRR]. The result of KVKIris database is shown in table 1, 2, 3 and 4 respectively.

Table 1 Result of GHM Sym4 Sym4 on KVKIris (Left)

	100	101	102	104	min
100	0.742	5.633	7.818	7.351	0.742
101	5.365	1.165	5.931	4.179	1.165
102	7.092	4.788	0.643	5.718	0.643
104	7.208	4.039	4.792	1.263	1.263

The ROC curve of all the above tables is shown in figure 5. From the figure it has been observed that the EER is 0.06% with 0.053 and 0.16 threshold for left iris images where as EER is 0.06 with hard threshold 0.053 and 0.19 for right iris images. This result is shown in table V.

Table 2 Result of GHM Sym4 Bior1 on KVKIris (Left)

	100	101	102	104	min
100	2.402	8.730	13.238	16.907	2.402
101	6.189	4.867	13.344	17.266	4.867
102	15.915	15.041	9.013	21.774	9.013
104	19.453	20.377	22.062	4.780	4.780

Table 3 Result of GHM Sym4 Sym4 on KVKIris (Right)

	100	101	102	104	min
100	1.399	2.886	4.963	7.060	1.399
101	3.076	1.088	3.136	6.893	1.088
102	5.189	2.304	1.366	7.387	1.366
104	5.894	6.648	5.553	0.797	0.797

Table 4 Result of GHM Sym4 Bior1 on KVKIris (Right)

	100	101	102	104	Min
100	5.548	13.256	25.466	20.817	5.548
101	11.879	3.068	26.419	22.925	3.068
102	14.443	9.329	27.739	22.357	9.329
104	18.564	21.565	8.339	5.363	5.363

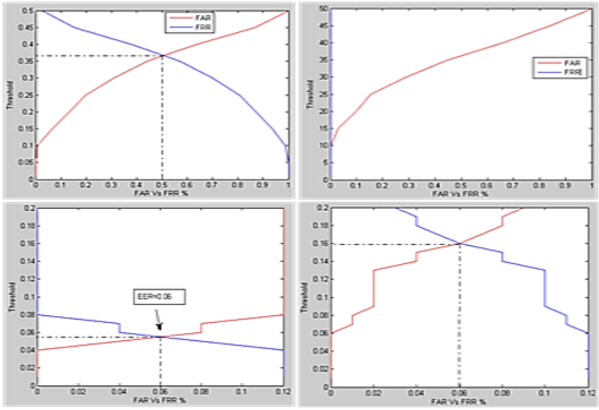

Fig.5 (a) Table 1 (b) Table 2 (c) Table 3 (d) Table 4

Table 5 Result of KVKIris

Multiwavelet	GHM			
	Sym4 + Sym4		Sym4 + Bior1.1	
KVKIris DB	Threshold	EER	Threshold	EER
Left	0.053	0.06	0.16	0.06
Right	0.053	0.06	0.19	0.06

We have applied similar experiment on 15 subjects of KVKIris database. The feature level fusion is done with DD2, GHM, GHMAP and GHMAP2. The ROC obtained from fusion DD2 with other wavelets and GHM with other wavelets is shown in figure 6 and 7 respectively.

From the ROC it has been observed clearly that wavelet db2, haar with DD2 and db2, haar with GHM gave better results of EER 1.1% as they need minimum threshold i.e. 0.065; whereas other combinations needs threshold of 0.082, 0.129 and so on.

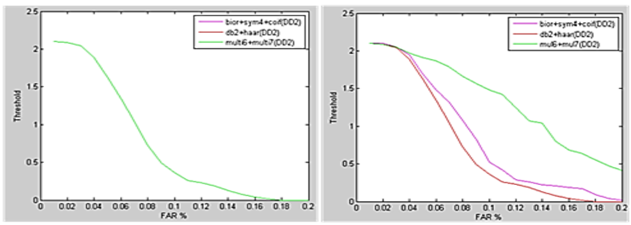

Fig.6 DD2 (a) Right Iris (b) Left Iris

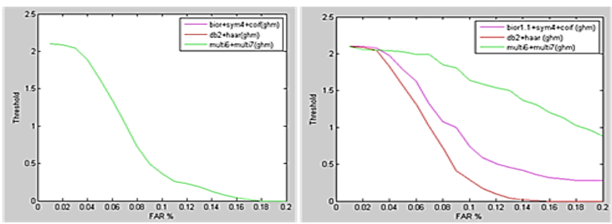

Fig.7 GHM (a) Right Iris (b) Left Iris

Table 6 Result of GHM, Sym4 Sym4 Bior1 on Casia 1 Subclass 1Database

	1	8	14	16	24	45	65	66	74	75	83	87	93
1	4.23	11.06	11.94	11.89	15.16	14.97	15.82	20.85	12.13	15.95	19.35	24.23	24.37
8	11.64	2.72	15.88	14.7	17.51	14.79	17	20.01	13.45	18.77	22.01	25.2	25.45
14	20.28	22.47	9.84	15.91	24.97	24.09	18.51	19.82	18.46	21.22	24.3	27.27	25.54
16	13.62	10.25	8.93	9.73	18.32	14.73	12.19	14.25	11.04	15.98	20	23.38	22.81
24	21.24	23.2	23.91	23.23	9.82	18.21	21.24	28.38	23.08	23.16	22.39	26.29	25.48
45	12.54	12.73	16.58	12.13	6.63	5.81	10.23	18.93	12.76	12.89	14.94	20.89	21.06
65	15.14	15.99	15.87	9.13	13.88	7.65	6.53	17.07	13.05	8.54	13.06	20.82	20.88
66	17.15	16.99	13.99	11.16	20.19	15.67	10.45	7.59	8.44	11.24	13.12	15.54	15.38
74	12.5	13.39	12.79	10.23	17.87	14.23	11.12	9.99	3.55	8.87	10.54	13.55	13.81
75	13.92	16.06	14.31	9.39	16.95	12.51	8.5	10.76	6.08	5.16	7.47	13.32	13.79
83	18.37	20.36	19.76	14.12	18.46	13.98	11.51	14.92	12.13	5.86	5.06	12.9	13.69
87	21.86	23.04	22.02	19.31	21.24	19.59	16.74	13.37	12.94	12.8	7.12	3.84	4.73
93	26.04	26.99	25.31	23.95	25.51	24.73	21.66	16.08	17.11	17.84	12.13	4.3	3.52

Table 7 Result of GHM, Sym4 Sym4 Bior1 on Casia 1 Subclass 2 Database

	1	8	14	16	24	45	65	66	74	75	83	87	93
1	4.23	11.06	11.94	11.89	15.16	14.97	15.82	20.85	12.13	15.95	19.35	24.23	24.37
8	11.64	2.72	15.88	14.7	17.51	14.79	17	20.01	13.45	18.77	22.01	25.2	25.45
14	20.28	22.47	9.84	15.91	24.97	24.09	18.51	19.82	18.46	21.22	24.3	27.27	25.54
16	13.62	10.25	8.93	9.73	18.32	14.73	12.19	14.25	11.04	15.98	20	23.38	22.81
24	21.24	23.2	23.91	23.23	9.82	18.21	21.24	28.38	23.08	23.16	22.39	26.29	25.48
45	12.54	12.73	16.58	12.13	6.63	5.81	10.23	18.93	12.76	12.89	14.94	20.89	21.06
65	15.14	15.99	15.87	9.13	13.88	7.65	6.53	17.07	13.05	8.54	13.06	20.82	20.88
66	17.15	16.99	13.99	11.16	20.19	15.67	10.45	7.59	8.44	11.24	13.12	15.54	15.38
74	12.5	13.39	12.79	10.23	17.87	14.23	11.12	9.99	3.55	8.87	10.54	13.55	13.81
75	13.92	16.06	14.31	9.39	16.95	12.51	8.5	10.76	6.08	5.16	7.47	13.32	13.79
83	18.37	20.36	19.76	14.12	18.46	13.98	11.51	14.92	12.13	5.86	5.06	12.9	13.69
87	21.86	23.04	22.02	19.31	21.24	19.59	16.74	13.37	12.94	12.8	7.12	3.84	4.73
93	26.04	26.99	25.31	23.95	25.51	24.73	21.66	16.08	17.11	17.84	12.13	4.3	3.52

Table 8 Threshold required for different database

Database	DD2	GHM	GHMAP	GHMAP2
CASIA subclass 1	0.023	0.020	0.005	0.030
KVKIris Left	0.015	0.015	-	0.021
Palaky Right	0.024	0.024	-	0.033

Table 9 Comparison with existing system

Recognition Methods	Database Name	Total No of Subjects	Images	EER (%)	CRR (%)
(Peng Zou et al,)	-	-	-	-	44.51
Proposed Approach	CASIA 1	13	subclass 1	-	92.31
			Subclass 2	-	100
		108	Subclass 1	0.5	99.5
			Subclass 2	0.5	99.5
	KVKIris	4	Right	0.06	99.94
			Left	0.06	99.94
		13	Right	1.1	98.9
			Left	1.1	98.9
	Palaky	8	Right	0.28	99.72
			Left	0.28	99.72

The result of feature level fusion of CASIA V 1 is shown in table VI and VIII respectively. The Euclidian distance score with hard threshold is shown in figure 8 and 9 respectively.

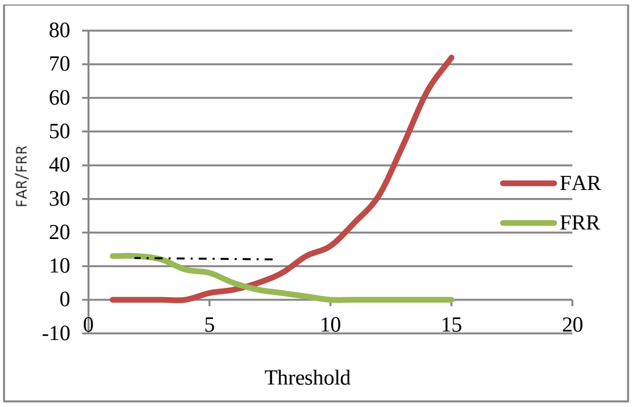

Fig.8 ROC curve of Table 6

The result is on the basis of comparison and statistical analysis and is 92.30% for subclass1 and 100% for subclass 2 of Casia 1 database.

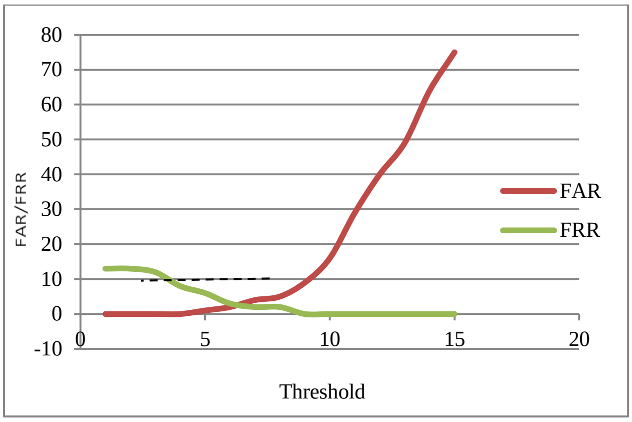

Fig.9 ROC of Table 7

The comparison of all three databases with DD2, GHM, GHMAP and GHMAP2 is performed and the ROC's are shown in figure 10, 11, 12 and 13 respectively.

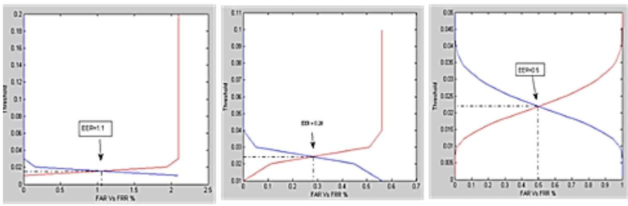

Fig. 10 DD2 (a) KVKIris (b) Palaky (c) Casia 1

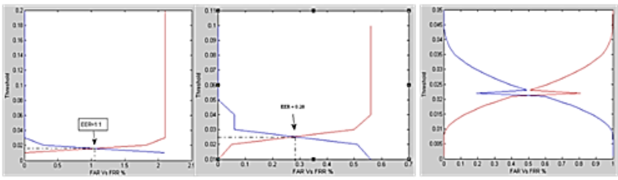

Fig.11 GHM (a) KVKIris (b) Palaky (c) Casia 1

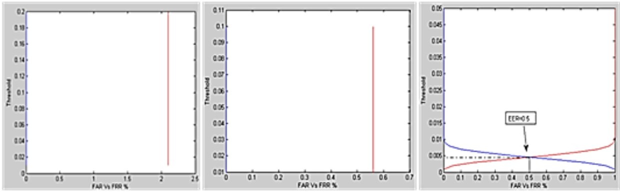

Fig.12 GHMAP (a) KVKIris (b) Palaky (c) Casia 1

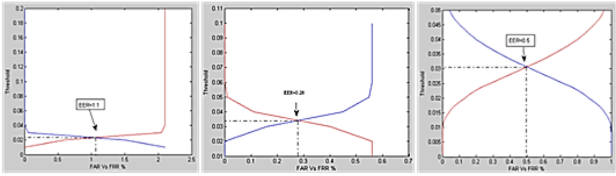

Fig.13 GHMAP2 (a) KVKIris (b) Palaky (c) Casia 1

We have applied hard threshold on the Euclidean distance scores and it has been observed that GHMAP provides the better accuracy of 99.50% for cassia 1 database with threshold 0.005. DD2, GHM and GHMAP2 provide the similar result with the threshold of 0.023, 0.020 and 0.030 respectively. KVKIris database gives accuracy of 98.90% and threshold is 0.015 with DD2 and GHM whereas Palaky required 0.024 as minimum threshold. This is shown in Table 8.

The results were compared with the existing system and we have observed that our results are much better than the existing system. This is shown in table 9.

Conclusions

The present work considers three databases and uses wavelet and multi-wavelets for feature extraction. The main aim of this work is to extract features and then perform feature level fusion to get most compact coefficients. Based on the experimental work carried out with GHM, IGHM, GHMAP, GHMAP2 and DD2 multi-wavelets, the result achieved is 92.31% and 100% with 13 subjects and 99.50% with 108 subjects for CASIA V1. The accuracy of 99.94% with 4 subjects and 98.90% with 13 subjects is achieved for KVKIris database. Similarly 99.72% accuracy is achieved by Palaky database. In future we would like to extend this work for larger and multiple datasets and different multi-wavelets.

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