MULTIMODAL BIOMETRIC SYSTEM COMBINING MATCHING SCORE LEVEL AND FEATURE LEVEL FUSION

Vinay Kumar. M. S[1], Dr. R. Srikantaswamy[2]

[1]PG Scholar, [2]Professor, Dept of ECE, Siddaganga Institute of Technology, Tumakuru, Karnataka, (India)

ABSTRACT

Nowadays, Multimodal biometrics has created a substantial interest in the field of identification management due to higher recognition performance. This paper combines the matching score level and feature level fusion in order to develop a multimodal biometric system for face and fingerprint biometrics. Histogram of Oriented Gradients (HOG) descriptor has been used for fingerprint recognition, Viola-Jones algorithm for face detection and Linear Discriminant analysis (LDA) along with Principal component analysis (PCA) for face recognition. The features extracted from the fingerprint and face biometrics are combined at matching score level and feature level. We have combined matching score level fusion and feature level fusion for verification and identification respectively. And the system yields good verification and recognition performance when compared to other multimodal and unimodal biometric systems.

Keywords: Face detection & recognition, Fingerprint recognition, Multimodal biometrics, Feature level, Score level.

I. INTRODUCTİON

Biometric Technology is an automatic technique of recognizing a person based of one (Unimodal) or more (Multimodal) behavioral or physiological characteristics. An authentication system is now a part of almost every major information technology. Biometric technology has become the foundation for highly secure person verification and identification. The global-state of information security survey reveals that the security breaches are on rise. Unimodal biometric systems can be hacked easily and it suffers from the problems like noisy sensor data, non-universality, intra-class variation, lack of individuality and spoofing attacks. Multimodal biometrics [1][2] has additional information regarding various discreet modalities which in turn increases the recognition performance in terms of accuracy and also to overcome the drawbacks associated with unimodal biometrics. A combination technique is necessary which fuses information from diverse modalities so as to have a multimodal biometric system. There are four levels of fusion techniques viz., fusion at sensor level, fusion at feature level, fusion at matching score level and fusion at decision level[3][4][5]. But the fusion at sensor level is used very rarely and also not compatible in most of the applications.

Many fusion strategies has been proposed by several authors [6-9][10-12]. In this paper, a robust multimodal biometric system using face and fingerprint modalities (as each of the modalities are unique and consistent over time) which are combined at feature level fusion and matching score level fusion is proposed.

In this paper, we have used pattern based fingerprint recognition using the Histogram of Oriented Gradient (HOG) descriptors which was used in computer vision for object recognition purpose and for face we have used a robust face recognition method called Linear Discriminant Analysis (LDA). In order to ensure better recognition, we have cropped the face region from the background using the Viola-Jones face detection method. Later, features and scores are computed from each of the modalities. The individual scores are normalized and combined using min-max normalization technique and weighted sum rule respectively. If the query face and fingerprint are verified then the features extracted from those modalities are passed to feature level fusion for recognition. Features extracted are combined using feature concatenation method and these features are combined in such a way that even though the imposter gains the access in the verification stage still we can comprehensively identify the imposter in the identification stage, thus making the proposed system more robust to illegal access. These combined features are given to multi-class Support Vector Machine (SVM) for classification.

The rest of the paper is organized as follows, Chapter 2 discusses a feature extraction method for both face and fingerprint. Chapter 3 describes the matching score level fusion and feature level fusion is discussed in Chapter 4. Proposed structural flow of the methodology is explained in Chapter 5. Experimental results are given in Chapter 6 and Chapter 7 provides the conclusion.

II. PROPOSED FEATURE EXTRACTION TECHNIQUES FOR FINGERPRINT AND FACE

2.1 Fingerprint Recognition

HOG methodology is mainly based on evaluating well-normalized local histograms of image gradient orientation in a dense grid with 50% overlapping blocks. HOG features are calculated by taking orientation histograms of edge intensity in local region. The basic thought is that local object appearance and shape can often be characterized rather well by the distribution of local intensity gradients or edge directions, even without precise knowledge of the corresponding gradient or edge positions. The Structural flow for fingerprint recognition is as shown in Fig 1.

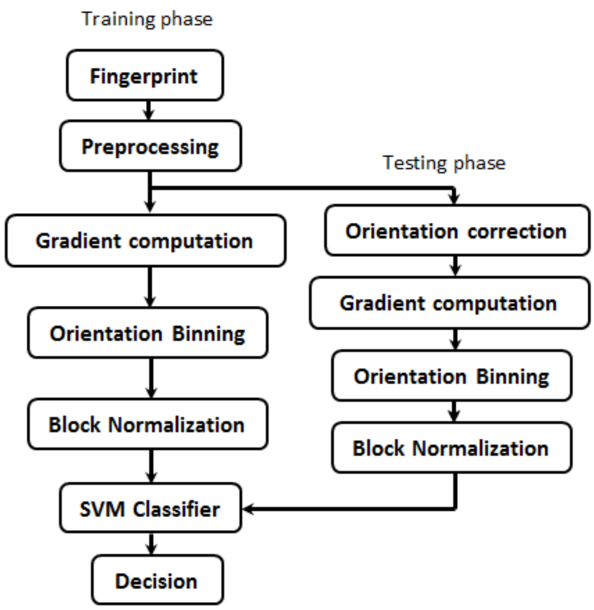

Figure 1. Flow for Fingerprint Recognition

In preprocessing stage, the fingerprints acquired are subjected to sharpening into order to enhance the ridge details as this method is mainly based on ridges and the sharpened image is converted into binary. The fingerprint image is divided into 3×3 blocks. For each block, gradients along X and Y directions are calculated (I_x and I_y) using 1-D Gaussian kernels d_x=[-1,0,1], d_y=[-1,0,1]^T. The magnitude and gradient orientations are computed using (1) and (2):

$$I_{mag} = \sqrt{I_x^2 + I_y^2} \tag{1}$$

$$\theta = \arctan(\frac{I_y}{I_x}) \tag{2}$$

The gradient orientations are quantized into 9 bins. Each pixel within the cell casts a weighted vote for an orientation based histogram channels and the histogram channels are evenly spread over 0 to 360 degrees. The gradient magnitude calculated for each pixel gives the weighted vote. In order to take care of illumination (in this case, pressure variation), each blocks are locally normalized using L-1 norm using (3):

$$f = \frac{v}{\|v\|_1 + e} \tag{3}$$

HOG features extracted from the fingerprints are given to SVM for training. During the testing phase, an ellipse is fitted on to the query fingerprint in order to find the orientation of the fingerprint. The orientation of the fingerprint is found out by calculating the orientation of major axis for the ellipse that has been fitted earlier. If the orientation angle is within the acceptable range then no action will be taken, if it exceeds the acceptable range (shown in Fig.2) then the fingerprint image has to be rotated with same angle but in opposite direction to that of the inclination angle. After orientation correction, the region of interest is extracted and image is resized to actual dimension of the fingerprint image.

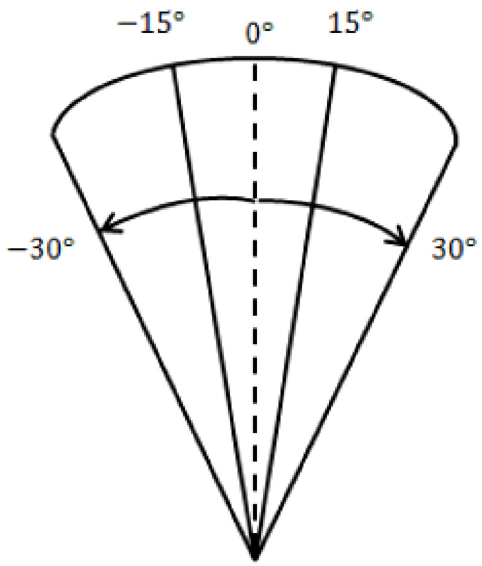

Figure 2. Maximum Acceptance Angle

Fingerprint will be corrected if the inclination of major axis is in between $\pm 15^\circ$ and $\pm 30^\circ$. A feature extracted from the corrected fingerprint is given to the SVM for classification. Brief description of HOG descriptor on fingerprint is as shown in Fig. 3.

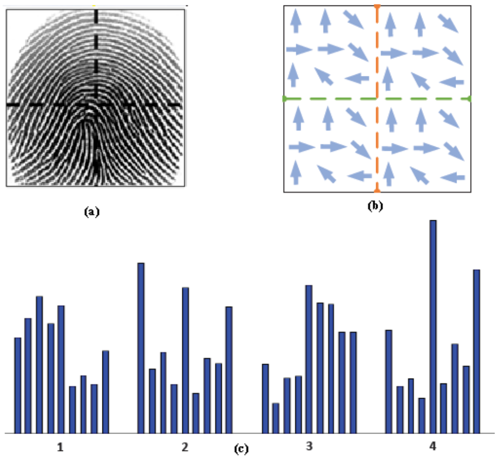

Figure 3. Brief Description of HOG Descriptor (A) Fingerprint İmage Divided into 4 Blocks (B) Gradient Orientation of Each Block (C) Histogram of Oriented Gradients

2.2 Face Recognition

The facial features are extracted from the face images using Fisher's linear discriminant analysis (FLDA) technique. FLDA gives importance to those vectors in the underlying space that best describe the best discriminate among classes rather than best describing the data. It makes the projection from high dimensional image space to a low-dimensional image space and tries to maximize the ratio of between-class scatter matrix and the within-class scatter matrix as shown in Fig 4.

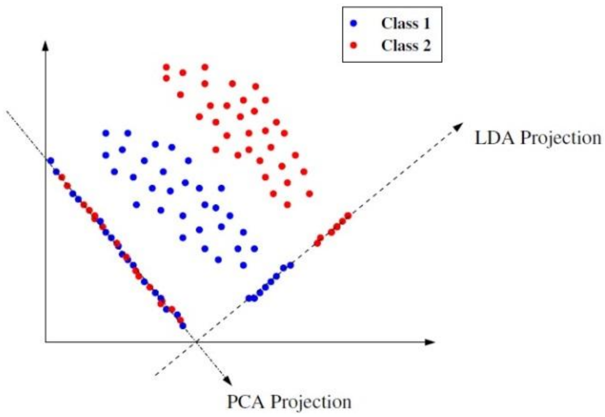

Figure 4. PCA and LDA Projection or Two Class Problem

Fisher's face method has been used for face recognition which is robust to illumination and poses variation. As a preprocessing step we have used Viola-Jones face detection algorithm[13] which detects the face and the detected face is cropped from the background region. This cropped face is used for feature extraction and it is given to Euclidean distance classifier. It calculates the Euclidean distance between the query image and the templates that is stored in the database and assigns the query image to the template which ever yields the minimum distance. The flow for face recognition is as shown in Fig 5.

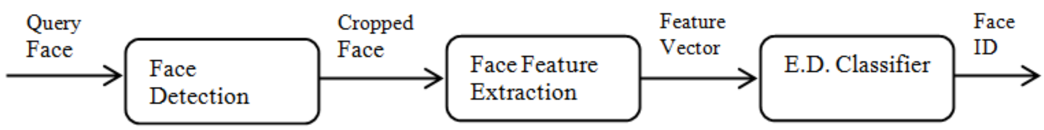

Figure 5. Flow for Face Recognition

Let us consider R face images of C individuals (classes) in the training set and each image X_i is a 2-D array of size $m \times n$ of intensity values. An image X_i is transformed into a vector of D (D=m*n). Defining the training set of R images by $X = (X_1, X_2 ..., X_R) \subset \Re^{D \times R}$. The between-class scatter matrix is defined as follows:

$$C_B = \sum_{c}^{C} N_c (\mu_c - \overline{X})(\mu_c - \overline{X})^T \quad (4)$$

Where, N_C is number of images in class c, μ_c, and $\overline{X}$ are the mean images of the *c* class and training images, respectively. They are defined as follows:

$$\mu_c = \frac{1}{N_c} \sum_{i \in c}^{R} X_i \quad (5)$$

$$\overline{X} = \frac{1}{R} \sum_{i}^{R} X_i \quad (6)$$

The within-class scatter matrix is defined as follows:

$$C_W = \sum_{c}^{C} \sum_{i \in c}^{R} (X_i - \mu_c)(X_i - \mu_c)^T \quad (7)$$

The Fisher's criterion is defined as follows:

$$F(W) = \frac{\left|W C_B W^T\right|}{\left|W C_W W^T\right|} \quad (8)$$

If C_W is a non-singular matrix then this ratio is maximized when the column vectors of the projection matrix W, are eigenvectors of $C_B C_W^{-1}$. The optimal projection matrix W_{opt} is defined as follows:

$$W_{opt} = \underset{W}{\operatorname{argmax}} \left|C_B C_W^{-1}\right| \quad (9)$$

$$= [w_1, w_2 ..., w_m]$$

Where $\{w_i \mid i = 1,2,.., m\}$ is the set of normalized eigenvectors of $C_B C_W^{-1}$ corresponding to m largest eigenvalues $\{\lambda_i \mid i = 1,2,.., m\}$. Each of the m eigenvectors is called Fisherface.

If C_W is a singular matrix, then the projection has to be made to a lower dimensional space so that resulting within-class scatter matrix C_W is non-singular. This is achieved by using PCA to reduce the dimension of the feature space to R-C and then applying the standard FLD to reduce the dimension to C-1. After calculating the optimal weights, these weights are given to Euclidean distance classifier. W_{opt} is given by:

$$W_{opt} = W_{fld} W_{pca} \quad (10)$$

Where, $W_{fld} = \operatorname{argmax} \frac{\left|W^T W_{pca}^T C_B W_{pca} W\right|}{\left|W^T W_{pca}^T C_S W_{pca} W\right|}$

$$W_{pca} = \underset{W}{\operatorname{argmax}} \left|W^T C_T W\right|$$

III. MATCHING SCORE-LEVEL FUSION

In our methodology, matching score level fusion is used to address the problem of verification. The scores of fingerprint image is obtained using the concept of feature matching i.e., given a feature of one image, finding out the best matching feature in one or more images. Absolute difference is computed between the feature extracted from the query image and the features of the training images stored in the database which results in a single vector. Summing up all the rows in the difference vector to get a single scalar score. Continuing this process for all the training features and score for each query fingerprint are calculated using the best feature match (smallest score) and the second best feature match (2nd smallest score).

$$\text{Score} = \frac{\text{Score of best feature match}}{\text{Score of second best feature match}} \quad (11)$$

The scores for query face can be obtained easily by finding the minimum Euclidean distance between each query face and the face template which is stored in database. The minimum Euclidean distance is itself taken as distance score.

In the context of verification, there are two approaches for consolidating the scores obtained from different matchers. One approach is to formulate it as a classification problem, while the other approach is to treat it as a combination problem. In classification approach, a feature vector is constructed using matching scores output by individual matchers; this feature vector is then classified into one of two classes: “Accept” or “Reject”. In combination approach, the individual matching scores are combined to generate a single scalar score which is then used to make the final decision. In order to ensure meaningful combination, all the scores must be transformed into common domain using any of the normalization techniques.

We have used a combination approach for the score level fusion. Before combining the scores, scores has to be normalized in order to transform the scores into same numerical range as the scores obtained from the fingerprint and face are similarity scores, dissimilarity scores respectively. Here we have used min-max normalization technique as this method is best suitable for the case where the bounds (minimum and maximum values) of the scores produced by the matcher are known. The normalization procedure shifts the scores between {0,1}. Let s_{ik} be a vector which contains the score of individual modality. Let s_{ik} and s_{ik}' be the un-normalized test score and normalized test score calculated using (11):

$$s_{ik}' = \frac{s_{ik} - \min(\{s_i\})}{\max(\{s_i\}) - \min(\{s_i\})} \quad (12)$$

The scores of both fingerprint and face are normalized using min-max normalization technique. And these normalized scores are combined using weighted sum fusion rule with equal weights ($\alpha = \beta = 0.5$).

$$\text{Final Score} = \alpha * \text{normalized face score} + \beta * \text{normalized finger score} \quad (13)$$

In order to make decision, threshold has been set which well discriminates the genuine and imposter scores. If final score < threshold, that score is characterized as imposter and if final score > threshold, that score is characterized as genuine.

IV. FEATURE LEVEL FUSION

Feature level fusion addresses the problem of both verification and identification. In our method, we are using this fusion level to solve the problem of identification. The features extracted from the face and fingerprint modalities using LDA and HOG are serially concatenated in order to combine them. The features are fused in such a way that, even though the imposter succeeds in verification stage he can be easily rejected in identification stage thus, making the proposed algorithm robust and dynamic. Let Y_{face} be the face feature vector extracted by LDA given by $[w_{face_1}, w_{face_2}, ..., w_{face_n}]$ and Y_{finger} be the feature vector of fingerprint extracted using HOG given by $[w_{finger_1}, w_{finger_2}, ..., w_{finger_n}]$ where n is the number of training samples or test samples. A new feature vector is generated by serially concatenating face feature, Y_{face} and its corresponding fingerprint feature, Y_{finger}. The combination of both feature vectors becomes $[w_{face_1}, w_{face_2}, ..., w_{face_n}, w_{finger_1}, w_{finger_2}, ..., w_{finger_n}]$. These combined features are given for SVM for classification.

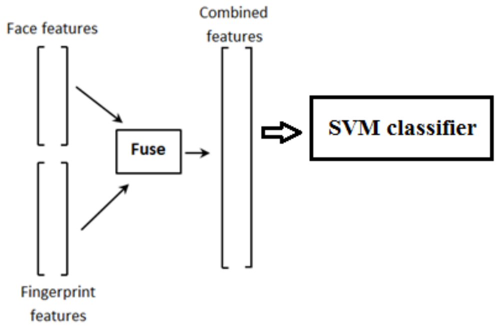

Figure 6. Feature Fusion Using Concatenation Method

V. PROPOSED STRUCTURE FOR COMBINING MATCHING SCORE LEVEL AND FEATURE LEVEL

A multimodal biometric system has been developed using face and fingerprint with the information fusion at matching score level and feature level. Matching score level fusion has been used for verification purpose and feature level fusion is used for recognition purpose. Whenever the query face and fingerprint comes for authentication, they are checked for their existence in the database, if they exists then the system proceeds for identification stage. The data flow in our proposed multimodal biometric system is shown in Fig. 7.

In order to authenticate a user, the scores of the query face and fingerprint images are computed. Fingerprint results in similarity scores and face results in distance scores. Hence the scores are transformed into common domain using min-max normalization technique which transforms the scores between {0,1}. Now the normalized face and fingerprint scores are fused using the combination approach where the weighted sum rule has been used for fusion. After calculating the final scores of face and fingerprint for both genuine and imposter, the threshold has been set which clearly discriminates the scores of the imposter and scores of genuine. If the query face and fingerprint are found to be genuine (i.e., found in the database) then the features extracted from the query face and fingerprint are subjected for fusion at feature level, if not, modalities are rejected by labeling them as unauthorized user. The multi-class support vector machine (SVM) has been used for classification, it takes the input data and labels each one of samples as either belonging to a given class or not.

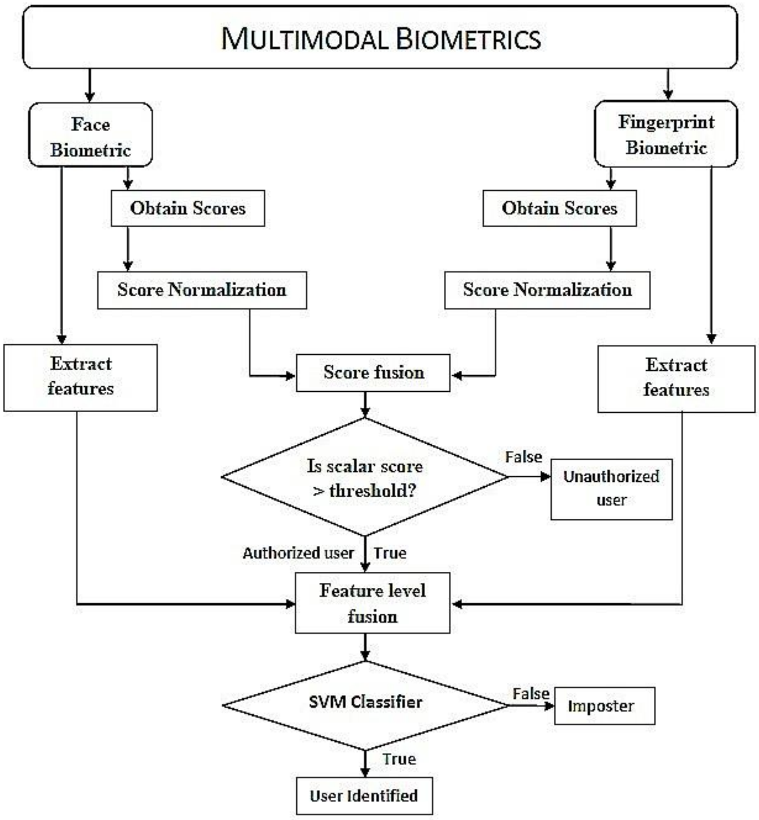

Figure 7. Data flow of the Proposed Multimodal Biometric System

IV. EXPERIMENTAL RESULTS

In this section, we have presented the experimental results of the proposed methodology. The algorithm is implemented using Matlab 2013. The proposed work has been carried out using PC Intel core i3 2nd generation CPU @ 2.2GHz processor and 4GB RAM. The database used for fingerprint consists of 10 images / subject for training and 5 images / subject for testing of 20 subjects. The database used for face consists of 15 images / subject for training with illumination and pose variation and 5 images / subject for testing of the same 20 subjects. The accuracy of individual biometric modality is low but the combination of modalities results in superior accuracy.

Table 1. Comparison of Accuracy of Different Modalities Using Score Level Fusion

Biometric Modalities	FRR	FAR	Accuracy
Face	23%	16%	80.5%
Fingerprint	8%	25%	83.5%
Face + Fingerprint using weighted sum rule	9%	19%	86%

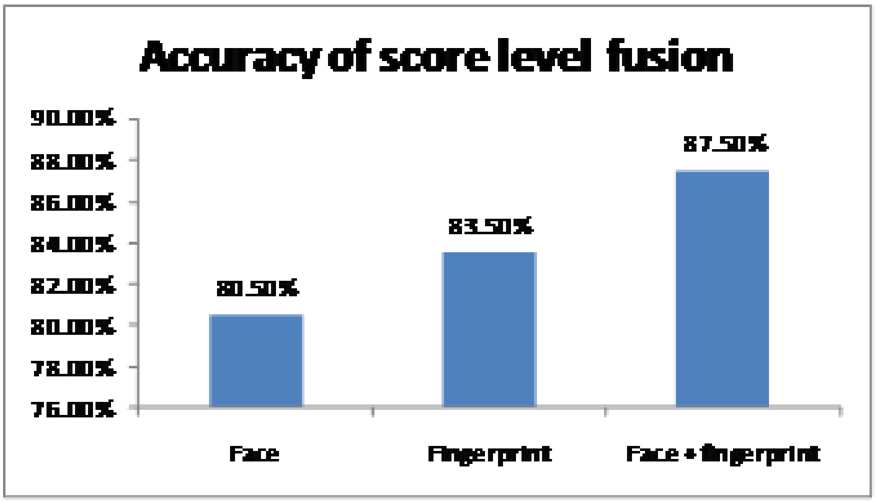

Figure 8. Comparison of Accuracy of Different Modalities Using Score Level Fusion

The individual accuracy of face with Euclidean distance classifier is 84.6% and accuracy of fingerprint with SVM classifier is 85%. The accuracy of fusion at feature level is 93.6%.

Table 2. Comparison of Accuracy of Different Modalities Using Feature Level Fusion

Biometric Modalities	Accuracy
Face	84.6%
Fingerprint	85%
Face + Fingerprint using concatenation method	93.6%

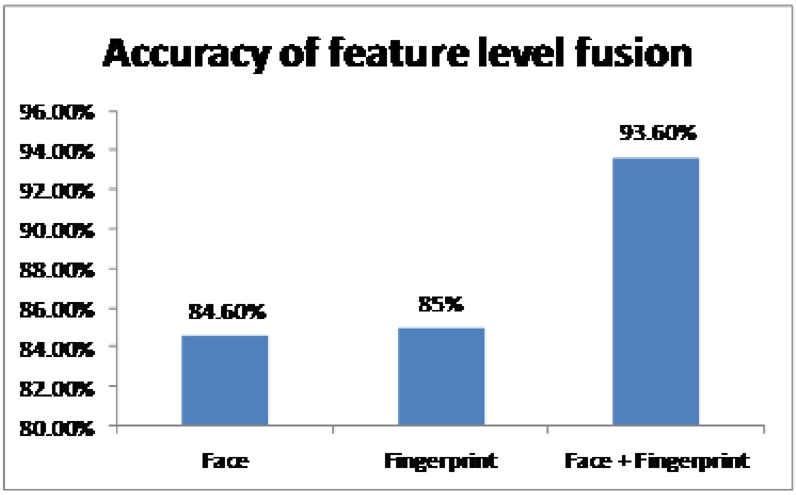

Figure 9. Comparison of Accuracy of Different Modalities Using Feature Level Fusion

VII. CONCLUSION

In this paper we have proposed a multimodal biometric system with fusion at score level and feature level for face and fingerprint. It is evident from the experimental results that multimodal biometric systems outperform unimodal biometric systems and also the recognition performance has improved when compared to individual biometric system. The main contribution of this paper is to develop a multimodal biometric system which reduces the FRR and FAR. This authentication system is robust to variations in illumination and posture. Also it can deal with noisy sensor data, non-universality and spoofing problems efficiently and effectively.

Further work of authentication can be improved significantly by integrating other biometrics into the system.

REFERENCES

[1] P. S. Sanjekar and J. B. Patil, "An Overview of Multimodal biometrics", Signal & Image Processing: An International Journal (SIPIJ), Vol.4, No.1, February 2013.

[2] L. Hong, A. K. Jain, and S. Pankanti, "Can Multibiometrics Improve Performance?" , In Proceedings of IEEE Workshop on Automatic Identification Advanced Technologies, pp: 59-64, New Jersey, U.S.A., October 1999.

[3] Arun Ross and Anil K. Jain, "Multimodal Biometrics: An Overview", Proc. Of 12th European Signal Processing Conference (EUSIPCO), (Vienna, Austria), pp. 1221-1224, September 2004.

[4] A. K. Jain and A. Ross, "Multibiometric Systems", Communications of the ACM, Special Issue on Multimodal Interfaces, 47(1), pp:34-40, January 2004.

[5] Arun Ross, Anil. K. Jain, "Information fusion in biometrics", Elsevier, Pattern Recognition Letters 24, pp: 2115-2125, March 2003.

[6] Hassan Soliman, "Feature level fusion of Palm veins and Signature Biometrics", International Journal of video & Image Processing and Network Security, IJVIPNS-IJENS, vol:12, no.01,2006

[7] Rattani.A, Kisku.D.R, Bicego.M, and Tistarelli.M, "Feature level fusion of face and fingerprint biometrics", In proc. Of 1st IEEE international conference on biometrics: Theory, applications and systems, pp. 1-6, Washington DC, USA.

[8] Sumeet Kaur, Priyanka Sharma, "Analysis of Multimodal Biometrics at Feature Level using face and palmprint", International Journal of Advanced Research in Computer Science and Software Engineering, Volume 3, Issue 7, July 2013.

[9] Maya V. Karki, Dr. S. Sethu Selvi,"Multimodal Biometrics at Feature Level Fusion using Texture Features", International Journal of Biometrics and Bio-informatics (IJBB), Volume (7) : Issue (1), 2013.

[10] Feifei Cui, Gongping Yang, "Score Level Fusion of Fingerprint and Finger Vein Recognition", Journal of Computational Information Systems 7: 16, pp: 5723-5731, 2011.

[11] Priyanka S. Patil, A. S. Abhyankar, "Multimodal Biometric Identification System Based On Iris & Fingerprint", IOSR Journal of VLSI and Signal Processing (IOSR-JVSP), Volume 1, Issue 6, PP 76-83, April 2013.

[12] Youssef Elmir, Zakaria Elberrichi, Reda Adjoudj, "Score level fusion based multimodal biometric system", Science of Electronics technologies of Information and Telecommunications (SETIT), March 2014,Tunisia.

[13] Paul Viola, Michael J. Jones, "Robust Real-Time Face detection"International Journal of Computer Vision 57(2), 137–154, 2004.