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Score and Feature Level Fusion Approaches for Evaluation of Multi-Features of Fingerprint Modality for Person Recognition System

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Abstract

In the biometrics, the technologies grow day by day and the security also increased related to that technologies. The fingerprint was the most intensively researched in the field of biometrics system due to permanence and uniqueness features which made varies of different peoples. The paper addressing many stages, in addition to the primary stages of any biometrics system the fusion of unimodal system was used in order to improve the performance of the system. The double enhancement techniques were used to make the images very clear by Histogram Equalization and Fast Fourier Transformation (FFT). The feature extraction was conducted using three techniques which called Zernike Moment (ZM), Hu-Moments (Hu) and Gray-Level Co-occurrence Matrix (GLCM) that categorized to statistical and texture features. The matching between these features was performed using the Euclidean distance to find the scores matrix. Additionally, the fusion as the most modern technique was used to improve the performance of the biometrics system which performed in this work by feature level and score level fusions. The feature level fusion by using concatenation and score level fusion by using Weight sum rule strategy led to improve the performance of the system. The system was evaluated by False Accepted Rate (FAR), False Rejected Rate (FRR), Equal Error Rate (EER) and Genuine Accept Rate (GAR). The results show that, the fusion gave the most efficiency results compared with individual system. The work was tested on four datasets such as Fingerprint Verification Competition (FVC2000), (FVC2002), (FVC2004) and our department datasets which called KVK dataset. The best results were achieved by FVC2002 with maximum GAR reached to 98.45% and minimum EER of 1.54% as compared with other datasets and existing works.

***Keywords**: Analysis; Fingerprint; Fusion; GLCM ; Hu-moments; Zernike moment.*

1. Introduction

The Identification system is the active and widely used in our life specially by using biometrics traits like fingerprint, palmprint, face, iris etc. which have uniqueness and permanence features and different characteristics for each modality [1]. Nowadays Biometrics identification system is one of the most important and famous systems with more secure and with excellent performance of the system depend on the types of modalities, the selected features and the implemented procedures. The goal of any biometrics system is to reduce at least one of the performance parameter like False Accept Rate (FAR), False Reject Rate (FRR) and Error Equal Rate(EER), which give highest accuracy. In addition, the time is very important for any biometrics system. However, the biometrics system has many problems like noise sensor, inter-class, intra class and universality [2], which can be made the biometrics application un-sufficient or unacceptable). These problems can be solve by using the multimodal or information fusion with various platform like multi-algorithm, multi-sensor, multi-feature, multi-traits and so on. The pattern recognition field is used to obtain the biometrics data from different source and extract the most important features.

The remainder of this research work was organized by different sections as follows. Section 2 briefly the related works; Section 3 describes the proposed system of fingerprint multi-features and, their fusion. Section 4 presents experimental Results and this section divided into different sub-section to explain the results more clearly; Section 5. Conducted with summarizes overall Performance of the system and Comparisons with own and existing work. In the final, the conclusion was addressing of this work with the future works describes in section 6.

2. Related Work

The moment invariant is the most important in pattern recognition and computer vision field to descriptors of a shape which categories into two classes namely contour-based and region based. The contour-based descriptor was based on Hu- moment which is the popular techniques and by mean goal of moment invariants to extract the features from images by primary steps done prior of extract like rotation, translation, etc. Yong and park, 2008 [3] proposed the fingerprint verification using invariant moment and an neural network. And they used STFT for preprocessing and LMS algorithm for orientation and invariant moment analysis on ROI. The matching stage implemented by similarity measures using absolute distance and BPNN. They are resulted the fast matching speed and high matching accuracy compare with other methods. Chaorong LI et al., [4] proposed a verification methods based on combination of (DFB) directional filter banks and Hu-moment. The fingerprint preprocessing conducted by using STFT for enhancement and ROI divided into blocks and extracts the feature from each block by DFB, then the Hu-moment. The suggested the enhanced the performance of verification system. G. Aguilar-Torres et al.,[5] proposed fingerprint recognition by using local feature and Hu-moment for verification purpose. The combination of FFT and Gabor filter was used to enhancement the fingerprint images, and they test their methods on FVC2002 dataset and the local feature used such as minutiae feature by using Crossing number (CN) to detect the type of minutiae feature. They solve the problem of rotation and translation movement which handled by scanner and they obtained high recognition rate with FAR=0.8 % with accuracy =95.3%. Mohammed et al.,[6] proposed fingerprint identification by using global feature. They used geometrics moment invariant (GMI) as feature extraction. To find the similarity they used mean absolute error (MAE). They found that GMI gave highest degree of individually compare with minutiae technique for identification purpose. Leon-Garcia et al.,[7] work on fingerprint recognition based on invariant moments which tested on 500 images for both cases good and poor quality and they used FFT and Gabor filter to enhance the clarity of fingerprint images. They used crossing number to extract the minutiae feature. They resulted that FFT=76.85% and Gabor=80.55% while by using both of them the accuracy reached to 85.75%. Chen and Li [8] proposed comparative study of analysis and combining different types of features by using different fusion schemes like Neyman Pearson rule and SVM. The feature was used such as Minutiae, Minutia Descriptor, Ridge Feature Map, Orientation and Ridge Density Map. They said that results improve the recognition performance by apply different combination. Qiongxiu Li et al.,[9] proposed the multi-feature of fingerprint with score fusion and got 97.05% accuracy.

3. Proposed System

In this system the fingerprint identification was implemented and discussed by different stages and each stage has effective to another by sequential procedures which include acquisition, preprocessing, feature extraction, matching and decision. Figure 1 depicts the proposed system and the next section will explains the systematic of the identification system step by step.

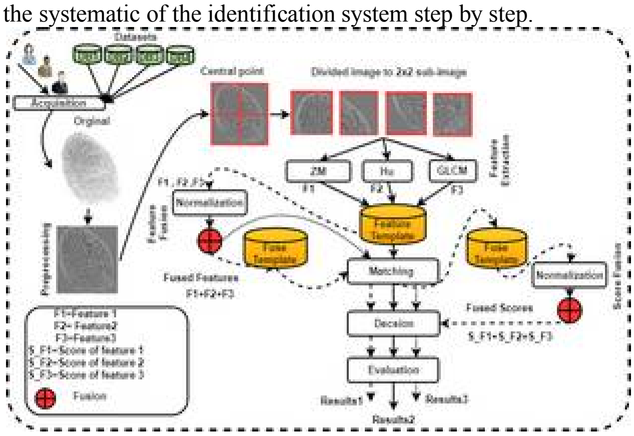


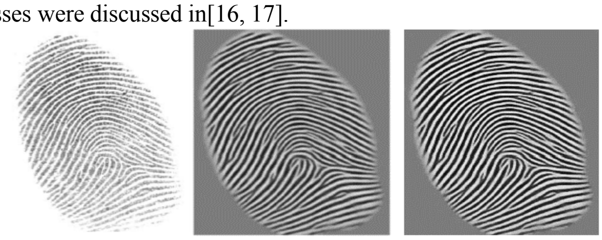
Fig.1 Proposed system of fingerprint identification using feature and score level fusion

3.1. Acquisition

This stage focuses on fingerprint acquisition which represents the answer of different types of questions such as what are the characteristics, images type in addition to size of image and dataset etc. and the details of fingerprint datasets was discussed in [10]. In this work, the methods were tested on four types of datasets. Three of them are public which called (FVC2000 [11], FVC2002 [12], and FVC2004 [13], and the fourth dataset is of our department which called KVK dataset [14]. The details of all the datasets were discussed in section 4.1.

3.2. Pre-processing

To extract the proper feature from any fingerprint images, these images have to be under clarity and quality measures, this measure can be achieved under the pre-processing stage which leads to remove the noise and unwanted data by using enhancement techniques. In this work, the double enhancement techniques were used to give the fingerprint images more clarity. In the beginning, the histogram equalization was used then the Fast Fourier Transformation (FFT) was applied which was derived from [15]. The image was divided to overlapping blocks and gradient was computed for each block to determine ridge orientation of an image and obtained the FFT values, afterward the smoothing was used to generate a coherence images, finally the region mask was generated by threshold the images. For each overlapping block the angular and radial filter were generated on orientation and frequency images respectively. The image enhancement was reconstructed by filter the block in FFT and composing each block and finally the region mask was applied to fingerprint image for enhancement. Figure 2 shows the pre-processing with first and second enhancements. The details of fingerprint processes were discussed in[16, 17].



(a) (b) (c)

Fig.2 Fingerprint preprocessing (a) original (b) 1st enhancement(c) 2nd enhancement

The central point of fingerprint images was determined and the images divided into 4 partitions (sub-images) to reduce the noise and each sub-image was passed to feature extraction stage to extract the feature from that images. The figure 3 shows the process of divided the images to 4 equal portions.

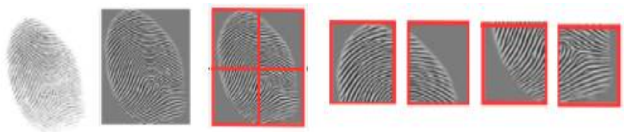


Fig.3. Divided fingerprint images to 4 partitions (sub-images)

3.3. Feature Extraction

In this stage three feature extraction techniques known as Zernike moment, Hu-moment and Gray level co-occurrence matrix (GLCM) were used to extract the feature from fingerprint images. All feature techniques were combined at feature and score level fusion. Algorithm 1 demonstrates the feature extraction process of Zernike moment, Hu-moment and GLCM in brief. The explanation of each technique separately was given in the next section.

Algorithm 1*: Feature Extraction*

1: **Input** : Fingerprint images after preprocessing
2: **Output**: Hu Features vector, ZM Features vector and GLCM Features vector.
3: **Begin**
4: Divided fingerprint images to(2x2) block as 4 partition sub-images
5: **For** (for every sub-images of fingerprint) **do**
6: Compute the *Hu moment* of 7 moments for each sub-image as :

$$FV_{Hu} = \bigcup_{i=1}^{4}\left[\bigcup_{j=1}^{moment 7} (F_{Hu1}, F_{Hu2}, F_{Hu3}, F_{Hu4}, F_{Hu5}, F_{Hu6}, F_{H}\right.$$

7: Compute the *Zernike moment* of order 10 for each sub-image as

$$FV_{ZM} = \bigcup_{i=1}^{4}\left[\bigcup_{j=1}^{order=10} (F_{ZM1}, \ldots, F_{ZM26})\right]$$

8: Compute the *GLCM* for each sub-image as

$$FV_{GLCM} = \bigcup_{i=1}^{4}\left[\bigcup_{j=1}^{13} (F_{GLCM1}, \ldots, F_{GLCM13})\right]$$

9: Apply Feature selection for FV_{Hu}, FV_{ZM} and FV_{GLCM} by *F-ratio* as $F_i = \frac{\mu^2}{\delta^2}$

10: Store features in database as templates for matching purpose

11: **End**

12: **End**

3.3.1. Hu- Moments Feature

The theory of Hu- moments was used first by (Hu, 1962) as mathematical for 2D moment and it was firstly used on shape recognition to aircraft shapes [18] with different operations like translation, scale and rotation. In the case of fingerprint images $f(x,y)$ the moment defined as

$$M_{pq} = \int_{-\infty}^{\infty}\int_{-\infty}^{\infty} x^p y^q f(x,y)\,dx\,dy \qquad (1)$$

For p,q=0,1,2,…

This raw moment for fingerprint image is not invariant to translation rotation and scaling. Central moments based on these raw moment defined based on centroid as given below

$$M_{pq} = \int_{-\infty}^{\infty}\int_{-\infty}^{\infty} (x-\bar{x})^p (y-\bar{y})^q f(x,y)\,dx\,dy \qquad (2)$$

Where , $\bar{x}=\frac{M_{10}}{M_{00}}$ $\bar{y}=\frac{M_{01}}{M_{00}}$

are components of centroid.

Hu has normalized these moments and defined six orthogonal moments and one skew orthogonal moment. These new moments are independent of position size and orientation and also parallel projection. These moments are invariant for translation, rotation and scaling. Normalized central moments are defined as

$$\eta_{pq} = \frac{\mu_{pq}}{\mu_{00}^{\gamma}} \qquad (3)$$

Where $\gamma=1+(p+q)/2$ and $(p+q)=2,3,\ldots$..

Hu's seven moments [19] are defined as given in following.

$$\varnothing_1 = \eta_{20} + \eta_{02} \qquad (4)$$

$$\varnothing_2 = (\eta_{20}-\eta_{02})^2 + 4\eta_{11} \qquad (5)$$

$$\varnothing_3 = (\eta_{30}-3\eta_{12})^2 + (3\eta_{21}-\eta_{03})^2 \qquad (6)$$

$$\varnothing_4 = (\eta_{30}+\eta_{12})^2 + (\eta_{21}+\eta_{03})^2 \qquad (7)$$

$$\varnothing_5 = (\eta_{30}-3\eta_{12})(\eta_{30}+\eta_{12})[(\eta_{30}+\eta_{12})^2 - 3(\eta_{21}+\eta_{03})^2] + (3\eta_{21}-\eta_{03})(\eta_{21}+\eta_{03})[3(\eta_{30}+\eta_{12})^2) - (\eta_{21}+\eta_{03})^2] \qquad (8)$$

$$\varnothing_6 = (\eta_{20}-\eta_{02})\ [(\eta_{30}+\eta_{12})^2 - (\eta_{21}+\eta_{03})^2] + 4\eta_{11}(\eta_{30}+\eta_{12})(\eta_{21}+\eta_{03}) \qquad (9)$$

$$\varnothing_7 = (3\eta_{21}-\eta_{03})(\eta_{30}+\eta_{12})\left[(\eta_{30}+\eta_{12})^2 - 3(\eta_{21}+\eta_{03})^2\right] + (3\eta_{12}-\eta_{30})(\eta_{21}+\eta_{03})[3(\eta_{30}+\eta_{12}) - (\eta_{21}+\eta_{03})^2)^2] \qquad (10)$$

These seven Hu's moment invariant features were extracted from four fingerprint sub-images as (7 x 4=28) and combined as features points which represent the particular fingerprint image and these features were not independence, so related to that reason the F-ratio was applied to each feature set to selected the optimal features. The idea behind the F-ratio mean and variance was taken for each feature. F-ratio can be calculated by Eq.(11):

$$F_i = \frac{\mu^2}{\delta^2} \qquad (11)$$

Where μ^2 is Means and δ^2 is Variance. After applied F-ratio the optimal features was (5 x4 = 20) independence features points for each fingerprint images. Those features points were stored as feature vector in the database template for matching stage.

3.3.2. Zernike Moment Feature

This technique was used to extract and describe the numeric quantities of some distance from reference point and projected of an image onto these orthogonal basis functions. It was created to solve the problems of compute the higher order of Hu's moment invariants [20] because it is complex and very difficult to reconstruct the images from Hu's moment invariants, thus, the Mukundan and Ramakrishnan [21] proposed the Zernike moment by the orthogonal basis function and it has characteristics like rotation, scaling and translation which is useful for matching propose. In this paper the Zernike moment was applied for fingerprint as statistical feature. The advantages of Zernike moments are translation, rotation, and scaling invariant. The Zernike moments for an image f(x,y) is the ability to change from one coordinate to other coordinate f(r,θ) where the r is radius and θ is azimuth. The transformation of the images is done by the following:

$$r = \sqrt{x^2+y^2} \quad \mathit{and} \quad \theta = \arctan\left(\frac{y}{x}\right) \qquad (12)$$

The image is specified on the unit circle with r⩽1 and the compute orthogonal basic function of unit circle [22,23] are given by Eq.(13).

$$V_{nm}(x,y) = V_{nm}(r,\theta) = R_{nm}(r)e^{im\theta} \qquad (13)$$

Where n is a non-negative , m is a non-zero integer subject to the constraint that $n-|m|$ is even, and |m|⩽n , r= √ (x^2+y^2) is the length of the vector from the origin to the pixel (x,y); θ =arctan(y/x) is the angle between the vector r and x-axis, and is the Zernike radial polynomial which is defined as:

$$R_{nm}(r)=\sum_{k=0}^{(n-|m|)/2}\frac{(-1)^k(n-k)!}{k!\left[\frac{n+|m|}{2}-k\right]!\left[\frac{n-|m|}{2}-k\right]!}r^{n-2k} \quad (14)$$

$$R_{nm}(r)=\sum_{k=0}^{(n-|m|)/2}\beta_{nm}r^{n-2k} \quad (15)$$

The 2D Zernike Moment with order n and repetition m for function f(x,y) is calculated by using Eq.(16)

$$Z_{nm}(r)=\frac{n+1}{\pi}\int\int_{x^2+y^2\le 1}f(x,y)V_{nm}^*(x,y)\,dx\,dy \quad (16)$$

$$Z_{nm}=\delta_{np}\;\delta_{mq} \quad (17)$$

Where, $\delta_{ab}=\begin{cases}1 & if\ a=b\\ 0 & otherwise\end{cases}$ (18)

For calculate Zernike Moment of digital image there are change with summations[24]:

$$M_{nm}(r)=\frac{n+1}{\pi}\sum\sum_{x^2+y^2\le 1}f(x,y)V_{nm}^*(x,y) \quad (19)$$

$Where\ V_{nm}^*(x,y)=V_{n-m}(x,y)$ is the complex conjugate of $V_{nm}(x,y)$ Finally, the compute the Zernike Moment by determine the center of an image and taken to be origin, then the magnitude of Zernike Moment is rotation ,and translation and scale invariance of the image is scale inside the unit circle by $f(x,y)$ to, $f(x+\bar{x},y+\bar{y})$ where, $\bar{x}=m_{10}/m_{00}$ and $\bar{y}=m_{10}/m_{00}$.

From the advantages of Zernike Moment if the origin image $f(x,y)$ was rotated by angle, the Zernike Moment can be obtained by $Z_{nm}=Z'_{nm}e^{-ima}$ (20)

In this study the Zernike Moment was applied on order 10 and 36 features points from each sub-image were obtained which represented the fingerprint image. These features were not independence, so related to that reason the F-ratio was applied to each feature set to selected the optimal features. The idea behind the F-ratio mean and variance was taken for each feature. F-ratio can be calculate by Eq.(11). After applied F-ratio the optimal features was (15 x4=60) independence features points for each fingerprint images. Those features points were stored as feature vector in the database template for matching stage.

3.3.3. Gray-Level Co-Occurrence Matrix (GLCM) Feature

Gray level co-occurrence matrix (GLCM) is one of the famous and common applied extraction methods for texture feature [25]. The characteristics of the images are appreciated by using this method. In addition, this method, support valuable knowledge related to the place of two near pixels in an image. This method plays an important rule in texture analysis and subsequently in recognition application [26]. It includes two dimensional histogram where each element (m,n) represent the frequency of event m co-occurrence with event n. the relative frequencies P(m, n , d, θ) were utilized to assign the co-occurrence matrix where d is the distance between two pixels and θ is the angle of their direction , gray scales values (m, n), one of the pixels has gray level m and other has gray level n. For this reason, the co-occurrence matrix is considered as a function of gray scales values (m,n), separated as distance d and angle θ. Suppose an image I has a size N x N, the co-occurrence matrix can be illustrated by according to the following Eq.(21) and the more details of GLCM can be found in [27,28].

$$G(m,n)=\sum_{x=1}^{N}\sum_{y=1}^{N}\begin{cases}1, & if\ I(x,y)=m\ \&\ I(x+\Delta x,y+\Delta y)=n\\ 0, & \text{Otherwise}\end{cases} \quad (21)$$

Where Δx and Δy are the offset and assign the distance between the pixel-of-interest and its neighbor. Multiple GLCMs are evaluated for various orientations of θ at 0°, 45°, 90°, and 135° which has the ability to explain the spatial relation between close pixels and lead to dependable texture features of fingerprint images. After the GLCMs are calculated for every sub-image, it is used to compute the statistical descriptors which unrivaled illustrated the fingerprint images. Harlick defined some statistical measures to extract textual properties [28]. In this paper 13 features can effectively depict the statistical disposal. Some of these features are Contrast, Correlation, Energy, Homogeneity, Mean, Standard Deviation, Entropy, Root Mean Square (RMS), Variance, Smoothness, Kurtosis, Skewness and etc.

3.4. Matching and Decision

The Euclidean distance used to measure the similarity between two feature vectors of query image and with feature vectors of template stores in database and the result of this stage was score matrix.

$let\ fv1=\{a_1,a_2,\ldots\ldots,a_n\}$ and $fv2=\{b_1,b_2,\ldots.\,b_n\}$

fv1 and fv2 denote the feature vectors of the two fingerprints to match and the Eq.(22) show the formula of Euclidean distance.

$$dist(f_{v1},f_{v2})=\sqrt{\sum_{n=1}^{N}\left(fv_{n1}-fv_{n2}\right)^2} \quad (22)$$

Where, N is determining the number of feature in fv1 and fv2. Then the final stage of identification system was the decisions of matching results which determined by accept or reject depend on threshold values.

$$D_0=\begin{cases}Accepted & if\ S\le T_0\\ \text{Rejected} & otherwise\end{cases} \quad (23)$$

The thresholds values T_0 generated from matching score with the following Eq. (24):

$$\Delta=\frac{\max(T_0)-\min(T_0)}{\beta} \quad (24)$$

β is a constant pre-determined which is used to divide threshold value into N parts. Then, N values threshold will be tested to obtain the optimal values of FAR and FRR by Eq. (25)

$$\begin{aligned}\theta_1 &= min(T_0)+\Delta\\ \theta_2 &= min(T_0)+2\Delta\\ \theta_N &= min(T_0)+N\Delta\end{aligned} \quad (25)$$

θi (i = 1, 2,…,N) is selected when the values of FRR or FAR are very small[29] depending on the specifications required.

3.5. Feature Level Fusion of Fingerprint

The feature fusion indicates the combination of three types of feature techniques from unimodal system to improve its performance for fingerprint identification. The feature level fusion is used by simple feature fusion techniques which called concatenation. The two feature vector can be concatenated directly if they were from same numerical range (homogeneous). However, if they were not from the same numerical range (heterogeneous), they should be normalized by using Z-score to transform the feature vector into common domain prior to concatenate them. The results of inner fusion using Zernike moment, Hu-Moment and GLCM show the improvement of unimodal system with all datasets. Afterward, the matching stage was conducted with the help of threshold values to make decision of each system [30]. The mathematical formula of feature level fusion is shown in Eq.(26). Suppose there are three feature sets of fingerprint (FZM) with size (1 x m), (FHu) with size (1 x n) and (FGCLM) with size (1 x g), the combination of them can be performed as:

$$FV_{fuse} = \bigcup_{i=1}^{3} \left[FV_{ZM(1\ ,\ m)}, FV_{Hu(1\ ,\ n)}, FV_{GLCM(1\ ,\ g)} \right] \quad (26)$$

$$FV_{fuse} = FV_{1X\ (m+n+g)} \quad (27)$$

Where, m , n and g are the size variables of three feature vectors. In this case, the features of Zernike moment, Hu-moment and GLCM with the sizes (1x60), (1x 20) and (1x21) respectively were combined and the fuse feature vector found to be (1x101) feature points to represent each sample.

Algorithm 2 describes the feature level fusion step by step.

Algorithm 2: *Feature level Fusion*

1: **Input** Feature vector of ZM, Hu and GLCM
2: **Output**: Fuse features vector
3: **Begin**
4: Load feature vector of ZM, Hu and GLCM
5: **IF** $(FV_{ZM(1\ ,\ m)}, FV_{Hu(1\ ,\ n)}, FV_{GLCM(1\ ,\ g)})$ same domain **do**
6: Fused feature vector of ZM, Hu and GLCM by concatenation as Equation(26,27)
7: **Else**
8: Normalized feature vectors by Z-score techniques as

$$S' = \frac{S-\mu}{\sigma}$$

9: Fused feature vector return to Steps 6
10: Store fused feature in database as template for matching purpose.
11: Matching query with template to generated score matrix
12: Decision with help of threshold values.
13: Evaluation of the system (FAR,FRR,EER and GAR)
14: **End**

3.6. Score Level Fusion of Fingerprint

The fuse at score level fusion of Zernike moment, Hu moment and GLCM features were conducted after each score was generated from each technique individually. A single score was generated and with the help of threshold values the decision either accepted or rejected. The score fusion rule used was weight sum rules as shown in Eq. (28).

$$FV_i = \sum_{m=1}^{3} w_m \cdot F_{S\ ZM_i}, w_m \cdot F_{S\ Hu_i}, w_m \cdot F_{S\ GLCM_i}, \quad \forall_i \quad (28)$$

Where w_m is the weight associated with each individual score and this weight can be generated by the following Eq.(29).

$$w_i = \frac{1-(FAR_i+FRR_i)}{2-(FAR_j+FRR_j+FAR_i+FRR_i)} \quad (29)$$

Where i=1,2,j=1,2 and i≠j. and the FAR and FRR values depend on threshold values. Algorithm 3 illustrates the procedure of score level fusion for different feature techniques as below.

Algorithm 3: *Score level Fusion*

1: **Input :** Genuine Scores vectors and Impostor Scores vectors of ZM, Hu and GLCM
2: **Output**: Fuse scores
3: **Begin**
4: Load scores vectors of ZM, Hu and GLCM
5: **IF** $(F_{S\ ZM_i}, F_{S\ Hu_i}, F_{S\ GLCM_i})$ same domain **do**
6: Fused scores from ZM, Hu and GLCM by Weight sum rule as **Equation** (28,29)
7: **Else**
8: Normalized scores vectors by Z-score techniques as

$$S' = \frac{S-\mu}{\sigma}$$

9: Fused scores vector by return to **Steps 6**
10: **End IF**
11: Store fused scores in database as template for Decision purpose.
12: Decision with help of threshold values.
13: Evaluation of the system (FAR,FRR,EER and GAR)
14: **End**

4. Experimental Results

This section was conducted by several implementations for each technique individually and each technique was tested on several datasets which gives in brief in section 4.1. The evaluation of parameter is described in section 4.2. Section 4.3 discusses the results obtained by Zernike moment, section 4.4 describes the results obtained by Hu-moments and the section 4.5 discusses the results obtained by GLCM, finally the section 4.6 gives the brief of results obtained by fusing Zernike moment, Hu- moment and GLCM at feature level and score level fusion.

4.1. Datasets

The this section the experiments performed on four fingerprint datasets of fingerprint verification competitions FVC2000, FVC2002, FVC2004 and KVK datasets with same size of 100 subjects with eight impressions. Table 1 shows the characterizations of each datasets.

Table 1 Fingerprint datasets characterization

Dataset	Type	Subject/sample	Image size	Resolution	Sensor
FVC2000	DB1 _B	110 x8 = 880	300x300	500 dpi	Optical
FVC2002	DB1 _B	110 x8 = 880	388x374	500 dpi	Optical
FVC2004	DB1 _A	110 x8 = 880	640x480 pixels	500 dpi	Optical
KVK	-------	100/8= 800	480 x 480 pixels	500 dpi	L scan 500P

4.2. Evaluation of parameters

To evaluate any biometric system related to specific application there are different parameters namely False Accepted Rate (FAR), False Rejected Rate (FRR) and Equal Error Rate

(EER). These parameters should be the lowest values to achieve the better performance of the system. The FAR is the ratio of imposter score which exceeds the threshold values divided by all the imposter score generated by the system whereas the FRR is the ratio of genuine score which falls below the threshold values divided by all the genuine score generated by the system. The EER is the intersection between FAR and FRR. The Genuine Accept Rate (GAR) determines the relation between the FAR and (1-FRR). The EER and the GAR determine the performance of the system. These parameters can be calculated as given in Eq. (30-33). In this work the genuine for all the datasets can be $N \text{ x } C_m^2$ matches the N and m denotes to number of fingers, the impressions respectively. The total genuine scores were $100 \text{ x } C_8^2 = 2800$ genuine scores. The impostor scores were C_N^2. The total impostor scores were $100 \text{ x } 99 \div 2 = 4950$ impostor scores.

$$FAR = \frac{\text{Impostor Score exceeding thershold}}{\text{All Impostor Score}} \times 100 \quad (30)$$

$$FRR = \frac{\text{Genuine Scores falling below thershold}}{\text{All Genuine Scores}} \times 100 \quad (31)$$

$$EER = \frac{FAR + FRR}{2}, \ if \ \text{FAR=FRR} \quad (32)$$

$$GAR = (1 - FRR) \quad (33)$$

Algorithm 4 investigates the details of the evaluations of the system by using different evaluation matrix such as genuine score, impostor score, threshold generator, FAR, FRR, EER and GAR step by step by sequentially.

Algorithm 4: *Evaluations of the system*

```
Input : score matrix, Subject_Id , T0
Output: Genuine Score ,Impostor Score, FAR,FRR,EER,GAR
Begin
Step 1: load Score matrix
Step 2: Generate the threshold values for each subject by
/*  Configuring the threshold for calculating the FAR and FRR */
Step 3: Initialization of parametr
        minscore = min(min(Score)); /* minimum score */
        maxscore = max(max(Score)); /* maximum score */
        gta = 100;      /* size of threshold score */
        delta = (maxscore - minscore) / gta;
        const = 1:1:gta;       /* threshold matrix
        FAR = [ ];   FRR = [ ];   P= Size(score) ;
      Total_No_of_gen=0; Total_No_of_imp=0;
      /* For all the scores matrix S  do
Step 4: For  g = 1  to   length(const)  do   /* loop for the check
      the scores */
     th = minscore + const(g) * delta;
       For  i =1 to  P        do   /* for all subject in dataset*/
            For  j=1 to  P        do
                  IF score(i,j) > th(g)
                        IF (Subject_Id (j) ~= Subject_Id (i)
   Impostors(i)= score(i,j)    /* Add the score to impostor matrix
          Total_No_of_imp= Total_No_of_imp + 1
                              Else
 genuine(i)= score(i,j)  /* Add the score to Genuine matrix*/
     Total_No_of_gen = Total_No_of_gen  + 1
                              End if
                         End if
                  End for j
            End for i    End for g
Step 5: /* Estimation of thresholds used to calculate FAR and FRR
   num_ genuines = length (genuine); /* size of client vector*/
   num_ impostors = length (impostors); /* size of impostor vector*/
```

Algorithm 4: *Evaluations of the system*

```
      T1 = (max (genuine) - min (impostors))/T0;
      x = [min (impostors): T1: max (genuine)]';
      num = length (x);
Step 6: /* calculation of FAR and FRR*/
   For i=1:num
            fr=0;    fa=0;
         For j=1:num_ genuine
               IF genuine(j)< x(i)
                     fr=fr+1;
               End if
         End for j
      For k=1:num_impostors
            IF impostors(k)>= x(i)
                  fa=fa+1;
            End if
      End for k
     FRR(i)=100*fr/num_ genuine;  /*  False Reject Rate /
     FAR(i)=100*fa/num_ impostors; /*   False Accept Rate /
End for i
 Step 7: /*  calculation of EER value where the FAR=FRR */
tmp1=find (FRR-FAR<=0);
tmps=length(tmp1);
IF ((FAR(tmps)-FRR(tmps))<=(FRR(tmps+1)-FAR(tmps+1)))
          EER=(FAR(tmps)+FRR(tmps))/2;
          tmpEER=tmps;
     Else
          EER=(FRR(tmps+1)+FAR(tmps+1))/2;
          tmpEER=tmps+1;
     End if
 Step 8: Calculate  GAR( i) = 100-FRR(i)
Step 9: Plot the ROCs for FAR,FRR,EER and GAR of the system
End
```

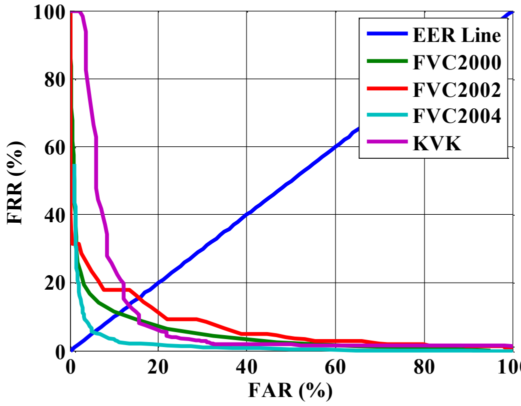
4.3. Results of Zernike moment feature

This technique was implemented on several datasets. In which Zernike moment of order 10 was applied on 4 sub-images partitions with feature vector size of 36 for each partition and the total feature vector of all partition was (1x144) and after applied feature selection by using F-ratio the optimal features was (1x 60) which store in the database for matching purpose. Afterward, the matching was conducted and the score matrix was generated for all the samples in datasets. From the score matrix, the genuine score and impostor score were generated. By the help of these scores and the FAR, FRR and EER were calculated with the help of thresholds values (T_0). The results obtained from FVC2000 gave EER=10.6483% with GAR reached to 89.35% , in similar case the FVC2002 achieved EER and GAR equals to 16.5536% and 83.45% respectively. In the case of FVC2004, the result showed EER=5.2318% with GAR=92.07% which considered as the lowest error rate compared with the previous dataset. The KVK dataset achieved GAR=87.41% with EER =12.5889%. Finally, from all the experimental work, it was concluded that FVC2004 gave the best result compared with other datasets. Table 2 shows the results of Zernike moment for all the datasets while the figure 4 (a) represent the ROC curve of EER for all datasets. Figure 4 (b) depict the ROC curve of performance of the system by plotting GAR against the FAR at different T_0 values.

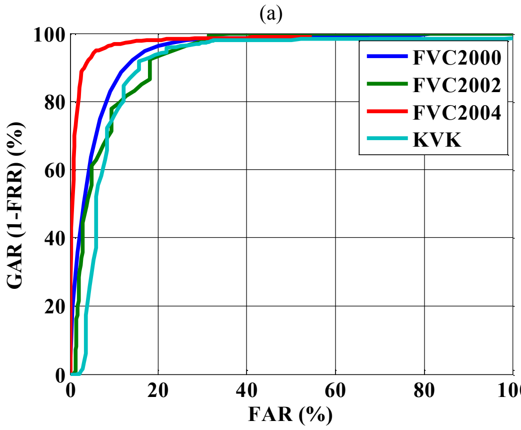
Table 2 Results of Zernike moment feature for all datasets

Dataset	T_0	FAR(%)	FRR(%)	EER(%)	GAR(%)
FVC2000	0.07	9.93939	11.3571	10.6483	89.35
FVC2002	0.24	15.1071	18	16.5536	83.45
FVC2004	**0.34**	**5.3929**	**5.0707**	**5.2318**	**92.07**

KVK	0.41	12.1071	13.0707	12.5889	87.41



(a)



(b)

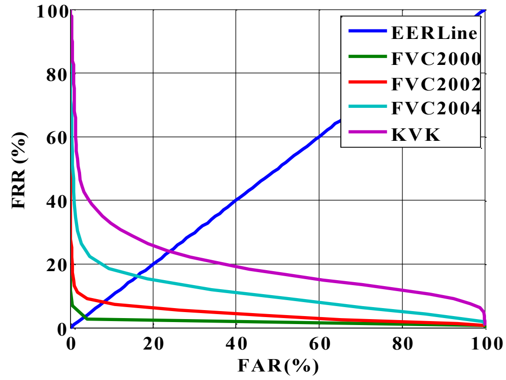
Fig. 4 Performance of Zernike moment on all the datasets (a) ROC of EER curve (b) GAR curve.

4.4. Results of Hu-moment feature

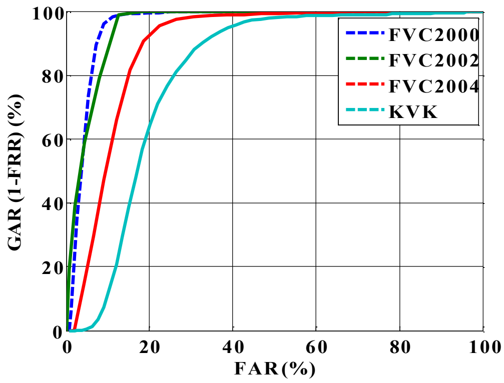
It is similar to the Zernike moment by evaluation with different that the seven moment was calculate as discussed in section 3.3.1 and the feature point from each sub-image 7 feature point with 4 sub-image. The total feature point after combining of all moments of 4 sub-images is 28 feature points (7 x4=28) and after applied feature selection by using F-ratio the optimal features was (1x 20) which store in the database for matching purpose. The results obtained from FVC2000 gave EER=3.4720% with GAR reached to 96.53% whereas, FVC2002 achieved EER and GAR equals to 9.06% and 94.47% respectively. In case of FVC2004, the results showed EER=20.996% and GAR=86.56% which considered as the highest error rate compared with the previous datasets. The KVK dataset achieved minimum GAR=76.58% and the highest EER =35.5100%. Finally, from all the experimental work it was concluded that FVC2000 gave the best result compared with other datasets. Table 3 shows the results of Hu-moment with all the datasets while the figure 5 (a) represent the ROC curve of EER for all datasets. Figure 5(b) depict the ROC curve of performance of the system by plotting GAR against the FAR at different T_0 values.

Table 3 Results of Hu-moment feature for all datasets

Dataset	T_0	FAR (%)	FRR (%)	EER (%)	GAR(%)
FVC2000	0.11	3.9798	2.9643	3.4720	96.53
FVC2002	0.05	3.9587	7.0714	9.0613	94.47
FVC2004	0.06	11.7778	15.1071	20.996	86.56
KVK	0.17	22.4849	24.3571	35.5100	76.58



(a)



(b)

Fig. 5 Performance of Hu-moment on all datasets (a) ROC of EER curve (b) GAR curve

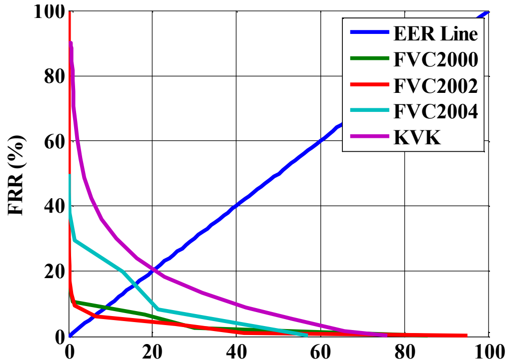
4.5. Results of Gray-Level Co-Occurrence Matrix (GLCM)

The evaluation of GLCM with 13 feature points was calculated for each sub-images partition with feature vector size (4x13=52) feature points and after applied feature selection by using F-ratio the optimal features was (1x 21) which store in the database for matching purpose. Afterward, the matching was conducted and the score matrix was generated for all the samples in datasets. From the score matrix, the genuine score and impostor score were generated. By the help of these scores and the FAR, FRR and EER were calculated with the help of thresholds values (T_0). The results obtained from FVC2000 gave EER=5.1957% and GAR reached to 94.80%, in similar case the FVC2002 achieved EER and GAR equals to 3.2671% and 96.73% respectively. Whereas FVC2004, EER=11.6858% with GAR=88.31% which considered as the highest EER compared with the previous dataset. The KVK dataset achieved minimum GAR=77.27% with highest EER =22.7267%. Finally, from all the experimental work, it was concluded that FVC2000 gave the best result compared with other datasets. Table 4 shows the results of GLCM for all the datasets while the figure 6 (a) represent the ROC curve of EER for all datasets. Figure 6(b) depict the ROC curve of performance of the system by plotting GAR against the FAR at different T_0 values.

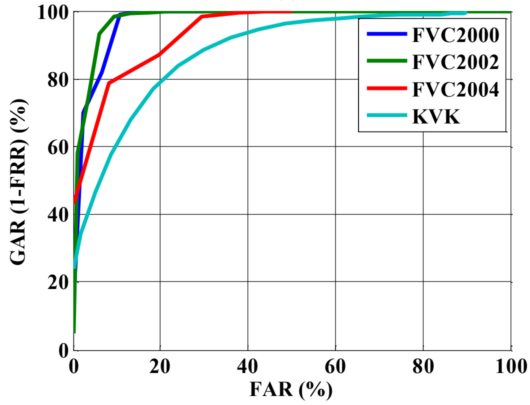
Table 4 Results of GLCM feature for all datasets

Dataset	T_0	FAR (%)	FRR (%)	EER(%)	GAR(%)
FVC2000	0.01	4.1434	6.25	5.1957	94.80
FVC2002	0.02	4.1554	2.3929	3.2671	96.73
FVC2004	0.01	10.5859	12.7857	11.6858	88.31

KVK	0.05	26.0606	19.3929	22.7267	77.27



(a)



(b)

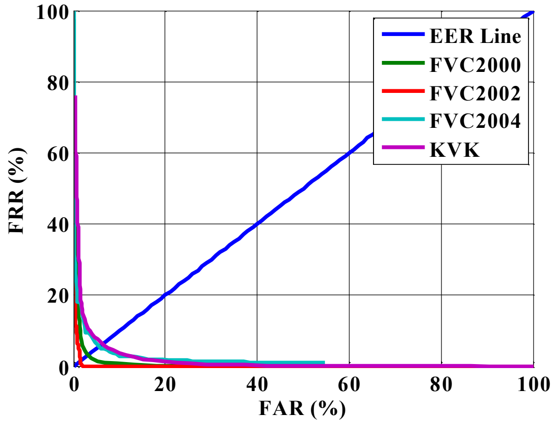
Fig.6 Performance of GLCM feature on all datasets (a) ROC of EER curve (b) GAR curve

4.6. Results of feature level fusion of Zernike moment, Hu-moment and GLCM

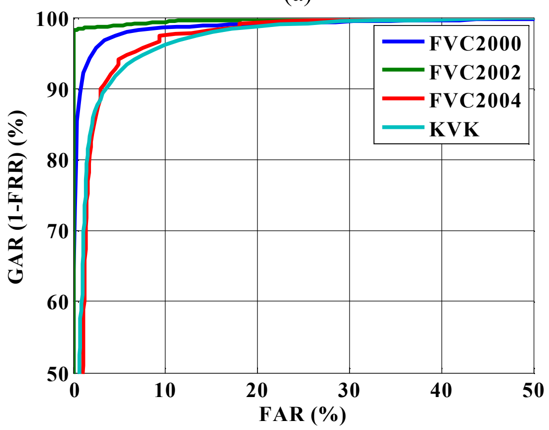
In this experiment, the features generated from ZM, Hu and GLCM were concatenated and stored in database as template for all the fingerprint images of all the datasets, then the matching process was performed by matching the query with all the templates, this stage leads to generate the matching scores, from which the genuine and impostor scores were created with the help of threshold values. Afterward with help of these scores the system was determined by evaluation matrix like FAR, FRR, EER and GAR. The results of this experiment show that, FVC2000 gave the best results compared with other datasets combination with minimum EER of 3.0465% and maximum GAR of 96.95% on the threshold value T_0 of 0.36. Whereas FVC2002 gave the more efficiency results compared with the other datasets with EER of 1.5464% and highest GAR of 98.45% on the threshold value T0 of 0.25. Furthermore, the FVC2004 was attained EER of 5.2403% and GAR of 94.76% by the threshold value T_0 of 0.35. Finally, the KVK dataset acquired the least results with highest EER of 6.2626% and GAR of 93.74% on the threshold value T_0 of 0.34. Table 5 shows the comparison study of feature level fusion results on all the datasets. Figure 7 (a) represent the ROC curve of EER for all datasets. Figure 7 (b) depict the ROC curve of performance of the system by plotting GAR against the FAR at different T0 values.

Table 5 performance of feature level fusion by fuse ZM_Hu_GLCM for all Datasets.

Dataset	T_0	FAR %	FRR%	EER%	GAR%
FVC2000	0.36	3.8788	2.2143	3.0465	96.95
FVC2002	0.25	1.4141	1.6786	1.5464	98.45
FVC2004	0.35	5.5714	4.9091	5.2403	94.76
KVK	0.34	6.5253	6	6.2626	93.74



(a)



(b)

Fig. 7 Comparison of Feature fusion on all datasets (a) ROC curve of EER (b) GAR curve

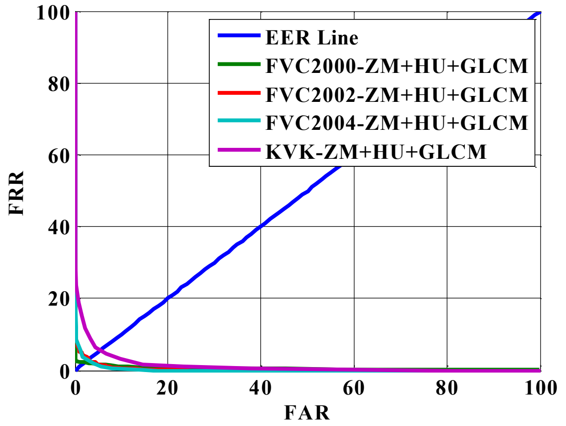
4.7. Results of score level fusion of Zernike moment, Hu-moment and GLCM

The information fusion was used in this work to achieve the best performance compared with individual implementation. In this experiment the fusion at score level was used, and the scores was calculated from individual feature techniques. Thus, the system combined three scores vector of ZM, Hu and GLCM after normalize each score by using z-score techniques to generate the single score vector which was useful for identification system. The combination was conducted by weight sum rule by added weight to each scores system. The results show that FVC2000 gave the best efficiency with minimum EER of 2.1375% and GAR of 97.86% on the threshold value T_0 of 0.26 while the FVC2002 achieved on the threshold value T_0 of 0.63 with EER of 3.1153% and GAR of 96.89%. Furthermore, the FVC2004 attain on the threshold value T_0 of 0.23 with the minimum EER of 3.0761% and highest GAR of 96.92%. Finally, the KVK dataset acquired on T_0 of 0.15 the EER of 5.6618% and GAR of 94.34%. Table 6 shows the results of score fusion of all the datasets. Figure 8 (a) represent the ROC curve of EER for all datasets. Figure 8 (b) depict the ROC curve of performance of the system by plotting GAR against the FAR.

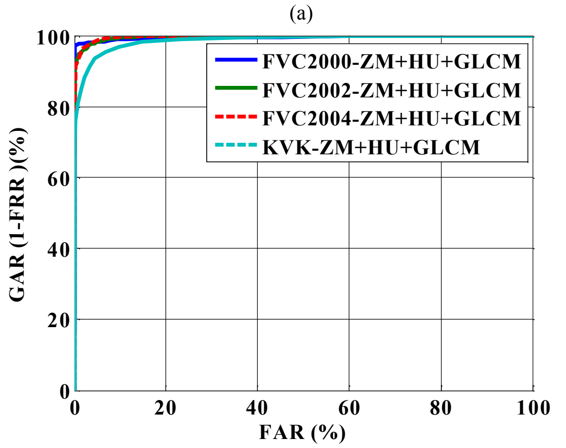
Table 6 Comparison of score fusion of (ZM_Hu_GLCM) fingerprint on all Datasets.

Dataset	T_0	FAR %	FRR%	EER%	GAR%
FVC2000	0.26	2.0606	2.2143	2.1375	97.86

FVC2002	0.63	2.9091	3.3214	3.1153	96.89
FVC2004	0.23	4.0808	2.0714	3.0761	96.92
KVK	0.15	6.7879	4.5357	5.6618	94.34



(a)



(b)

Fig. 8 Comparison of score fusion on all datasets (a) ROC curve of EER (b) GAR curve

5. Overall Performance and Comparisons

Finally, the overall results can be summarized in this section. As shown in the previous tables (2-6) of each feature techniques demonstrated individually on four datasets and the fusion by feature and score was the new concept which was added in this work by combining different types of features in order to give remarkable effect on the performance of the system. The comparison of the performance can be illustrated by EER and GAR as shown in the table 7 for all datasets. The feature fusion of ZM, Hu and GLCM improved the performance on all the datasets and the best results achieved by feature level fusion on FVC2002 with minimum EER=1.546% and highest GAR reached to 98.45%. Similarly the score level fusion denote the fused score using weight sum rule gave nearby results with EER=2.1375% and GAR= 97.86%. The performance of each feature techniques individually and fusions were illustrated to check the effectiveness and distinctiveness of individual and fuse of proposed system and compared with other techniques of the same field. The comparisons of the performance of the proposed system with existing work can be illustrated by EER as shown in the table 8.

Table 7 Comparisons of the performance of the individual system and fusion system on all datasets.

Feature techniques	Datasets							
	FVC2000		FVC2002		FVC2004		KVK	
	EER	GAR	EER	GAR	EER	GAR	EER	GAR
	%	%	%	%	%	%	%	%
ZM	10.6	89.3	16.6	83.5	5.23	92.1	12.6	87.4
Hu	3.47	96.5	9.06	94.5	20.9	86.6	35.6	76.6
GLCM	5.20	94.8	3.27	96.7	11.7	88.3	22.7	77.3
Fusion1	3.05	96.1	**1.55**	**98.5**	5.24	94.8	6.27	93.7
Fusion2	**2.14**	**97.9**	3.12	96.9	**3.08**	**96.9**	**5.66**	**94.3**

***Fusion1=feature level fusion,*Fusion2=Score level fusion**

Table 8 Comparisons of different system by EER

Ref.	Dataset	Fusion level	EER(%)
Li, Qiongxiu et al. [31]	FVC 2000	Score fusion	2.37
Li, Qiongxiu et al. [31]	FVC 2002	Score fusion	2.34
Li, Qiongxiu et al. [31]	FVC 2004	Score fusion	6.18
Li, Qiongxiu et al. [9]	FVC2000	Score fusion	4.57
Proposed	FVC 2000	Feature level(concatenate)	3.0465
Proposed	FVC 2002	Feature level(concatenate)	1.5464
Proposed	FVC 2004	Feature level(concatenate)	5.2403
Proposed	FVC 2000	Score(weight sum rule)	2.1375
Proposed	FVC 2002	Score(weight sum rule)	3.1153
Proposed	FVC 2004	Score(weight sum rule)	3.0761

6. Conclusion

In this work, the multi-feature of fingerprint was performed and evaluated on different datasets. The efficiency of two scenarios was examined. In the first scenario, the individual system was conducted whereas in the other scenario the fusion system was performed. This paper covers different concepts for computing and analyzing the biometric system by using different evaluation matrix such as generated the threshold values, genuine score, impostor score, FAR, FRR and EER which help to determine the performance of the system. Two types of fusion were studied in this work which called feature level fusion and score level fusion based on different feature techniques like Zernike Moment, Hu moment and GLCM, from the experimental work it was concluded that the fusion system generally showed the best performance on all the datasets used. However, the performance of feature level fusion and score level fusion differed from one dataset to another. In case of FVC2000, the results showed GAR of 96.95% and GAR of 97.86% for feature level fusion and score level fusion respectively which indicated that the efficiency of the system was improved with 0.91% by applying the score level fusion. Similarly, in case of FVC2004 the score level fusion give the best performance of the system with GAR of 96.42% compared with feature level fusion with GAR of 94.76% which indicated that the efficiency of the system was increased with 2.16% by using score level fusion. Additionally, in case of KVK dataset the score level fusion raised the efficiency of the system by 0.6% since it achieved GAR of 94.34% compared with feature level fusion which gave GAR of 93.74%. However, in case of FVC2002 the feature level fusion showed the best performance with GAR of 98.45% compared with the score level fusion which gave GAR of 96.88% that means, the efficiency of the system was improved by 1.57%. Therefore, the score level fusion showed noticeable effect on the performance of system on most of the datasets used. The future work may extend by using different types of feature such as Minutiae, Minutia Descriptor, Ridge Feature Map, Orientation and Ridge Density Map and combination by different types of fusion with neural network to check either the performance improved.

Data Availability

The data which were used to support this study were collected from Fingerprint Verification Competition (FVC) FVC2000, FVC2002, FVC2004 and KVK datasets .

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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