Multi Model based Biometric Image Retrieval for Enhancing Security

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Abstract

Objective: Biometric image retrieval becomes the most popular application scenario in the real world where the many application are started to use bio metric authentication. It plays a key role in the security management system of the real world application to prevent the malicious user access. Storage and management of the bio metric details of multiple users are the biggest issue which may lead to inefficient performance. In our previous work, two model bio metric based human recognition is introduced where the iris and finger prints are considered. But it may not recognize the human system in case of missing information and the corruption of extracted features. To overcome this problem in this work multi model based human recognition is introduced. Methodology: The four models considered in this work are: Iris, finger print, face and the palm print. The unique methodology is used for extracting the features from these models. In the previous research work, Speeded Up Robust Features (SURF) algorithm is used for iris feature extraction and Improved Locality-Sensitive Hashing (ILSH) indexing method is used for finger print feature extraction. In our proposed methodology, weighted attributes sparse code words indexing is proposed for face image retrieval where the attribute scores are selected optimally by using the BAT algorithm and a Novel hierarchical Indexing approach is proposed for Palm Print Image Retrieval. Finally these extracted features are fused together to generate a single model from the multiple models by using the approach called uni-model indexing scheme. Findings: The experimental tests conducted prove that the proposed methodology provides better result than the existing approach in terms of improved retrieval accuracy. This simulation evaluation is done in the MATLAB simulation environment for the both existing and proposed approach which is then compared with each other to obtain the performance improvement. Applications: The findings of this work prove that the proposed approach provides better result than the existing approach in terms of improved accuracy. This approach can be applied in the many research field where the security is required for preventing from the intruders attack like military, hospital management etc.

Keywords: Face, Finger Print, Fusion, Iris, Multi-Model Retrieval, Palm Print

1. Introduction

Multi-biometric model utilize several sources of biometric datato ascertain the identity of a personal. By adopting multi-biometric models the popularity performance may be improved. The use of multiple sources of knowledge additionally ensures that the system is more durable to forge and also the failure to enrolis a smaller amount probable.

The possibility of using biometric models causes the creation of biggest multi-biometric sources. Existing programs that use massive multi-biometric databases embody the US-VISIT program for border security supported the face and finger print modalities, and therefore the FBI’s fingerprint information that presentlystores the ten-print info of over eighty million distinct people. The United Kingdom National Identity theme, once enacted, can produce information storing the face, iris, and fingerprint knowledge of each ID card holder within the UK.

The issue that may occur in the bio metric sources are: 1. Searching the information to retrieve an identity will be
slow as a result of the information has got to be compared (matched) against the biometric data of each identity within the info, and 2. Error rate may increase⁵. (So far, solely iris recognition systems are uncontested to own no false match errors below bound conditions⁶). Therefore, filtering the info so as to scale back the quantity of potential candidates (i.e., identities) for matching could be a fascinating element of any large-scale biometric system.

Filtering biometric information will be accomplished exploitation two distinct schemes: Classification and categorization. A classification scheme partitions the information into many categories. The class of the input file is initial calculable and, afterward, the input is compared solely against those identities within the info happiness there to category. The main limitation of classifying biometric information is that the unbalanced distribution of the identities across the assorted categories. This drawback exists within the ancient Henry fingerprint organisation⁷ similarly as techniques for face⁸, palm print⁹, and iris classification¹⁰.

Filtering methods, on the opposite hand, fix an index priceto each biometric model. However, the indices of two biometric pictures referring to constant identity area unit unlikely to be constant as a result of the method of information acquisition and process are subject to noise. Therefore, categorization systems retrieve those identities whose indices are kind of like the index price of the input file. The input image is compared solely against the retrieved identities thereby minimizing the finding time and, doubtless, the false error rate. Most of the ways for categorization fingerprint pictures are supported image options like trivialitie striplets and ridge curvature. Indexing of iris pictures is commonly supported iris codes.

Multiple biometric traits are often wont to speed-up the filtering method and additionally to boost its hardness. Robustness is achieved once the modest performance of one modality is remunerated by the nice performance of another modality. Thus, the chance of discarding the right identity throughout filtering is reduced. The final identification is then performed within the reduced search house by employing a completely different modality that incorporates a higher matching accuracy.

### 1.1 Iris Indexing

In² author conducted iris classification techniques. The first technique relies on Iris Codes (post encoding) it’s supported an analysis of Iris Codes extracted from an individual’s iris. And performs unattended cluster on index vectors extracted from the Iris Code. The second technique supported raw texture analysis. Pre-encoding, examines the textural content of the image victimisation the Signed Picture Element Level Distinction bar Graph (SPLDH) of the raw picture element intensities. Result square measure PCA-based categorisation of Iris Code the common penetration for a eightieth hit rate is terrorist organization. However, once categorisation relies on the block-based statistics of the Iris Code (8x8 blocks), the common penetration for a eightieth hit rate is merelyV-day. The second technique supported raw texture analysis ends up in successful rate of 84 for a median penetration rate of half-hour. Since a success rate of 100 percent wasn’t earned mistreatment these techniques.

### 1.2 Fingerprint Indexing

If the practicing samples won’t to style a classifier are labelled by their class membership, the partitioning technique is named supervised agglomeration. However if a group of untagged samples ought to be divided, the partitioning technique is termed unsupervised clustering¹¹. K-means algorithmic rule is an unsupervised clump procedure to cluster objects into K partitions supported their attributes. The goal is to see the K-means of knowledge generated from Gaussian distributions-means rule tries to attenuate the full intra category variance or the square error operate E, wherever there are K clusters Ci, i=1,2……..k and μi is that the centre of mass of all the points X in cluster G.

### 1.3 Face Indexing

Indexing strategies for face databases typically concentrate on a particular recognition rule. The approach of Maya Lin et al., proposes an economical classification structure for looking an individual’s face in very massive information¹². The approach is predicated on the classical eigen face methodology and uses the coefficients of projection to rank the information pictures with relevancy every eigen face.

The probe is hierarchical within the same approach and a neighborhood search is performed for every eigen face to search out the information image that’s highest to the probe. Takacs introduces a face similarity live derived as a different of the Hausdorff distance by introducing the notion of a locality perform (N) and associated penalties (P)⁵. Torralba et al., proposed machine learning
approaches to change the Gist descriptor (a real valued vector that describes orientation energies at completely different scales associated orientations inside an image) to a compact computer code, with a couple of hundred bits per image.\(^{13}\)

### 1.4 Indexing using Match Scores

Reducing the spatial property of the biometric template by employing a set of distance (or similarity) scores to a set of templates has been utilized in speaker recognition. Sturim et al.,\(^{14}\) compared every listed speaker against a hard and fast set of speaker models (called anchor models). The ensuing set of scores was used as a projection of the speaker within the area outlined by the anchor models. Retrieval was supported the distances between the probe and therefore the registered speakers within a projection house. The calculation of those distances is way quicker compared to standard speaker matching schemes that utilize mathematician mixture models. This technique light-emitting diode to a serious improvement in machine price with solely tony low decrease in identification rate once accustomed scale back the dimensions of the info before identification.

More recent studies improved the strategy of anchor models by imposing constraints on the set of anchor models so as to de-rive an optimum projection space\(^{15}\) and applicable distance measures. Sakata et al.,\(^{16}\) used an analogous method to form a secure fingerprint finding system.

## 2. Multi Model Bio Metric based Image Retrieval System

Human recognition is the most important process in many fields where the security is achieved by recognizing the humans based on their bio metric fields. In our previous work, human recognition is done by using the two model bio metrics where the iris and the finger prints are taken as two models. The retrieval accuracy is not well as expected in the previous work where there is more missing information. In this work multi model bio metrics are introduced for recognizing the humans where the bio metric models considered are iris, finger print, face and the palm print.

The features are extracted from this input images and then the final obtained multi model is combined together to generate a unique model. This is done to make ease of similarity matching process where it will be more difficult by comparing with multiple models. The feature extraction in different model is done by using different approaches and then finally extracted features are combined together using fusion approach. At last this uni model value will be used for similarity matching to recognize the human. The overall flow of this work is given as follows:

- Iris image retrieval using SIFT feature extraction method.
- Finger print image retrieval using improved LSH method.
- Face image retrieval using weighted attribute sparse code word scheme.
- Palm print image retrieval using Novel hierarchical Indexing approach.
- Integrating feature set using fusion methodology.

This is overall flow of the work which is followed to recognize the human with improved accuracy and success rate which is discussed detailed in the following sub sections.

### 2.1 Iris Image Retrieval using SIFT Feature Extraction Method

Iris image retrieval is done in two steps. Those are indexing and the feature extraction. Indexing is done by using the methodology called the color feature which is used to eliminate the unwanted images from the database. Iris color indexing is done by using the kd-tree based indexing method.

Kd-tree method is used to index the two dimensional data in an effective manner. If the data has higher dimension, there is high difficult to obtain the color histogram. So, a simple technique called color indices that are computed by taking the average for the intensity values for all blue and red color pixels. In this indexing method, two-dimensional data are blue and red indices of iris images that are calculated under $YC_b,C_r$ color space.

Let us consider $DB = \{D_1,D_2,...,D_N\}$ denotes the database of $N$ iris images in which $D_i, 1 \leq i \leq N$ denotes a 2-tuple including blue and red indices of the iris region $I$ in the $YC_b,C_r$ color space. i.e., $D_i = (b_l,r_l)$. The blue and red indices are created for the $N$ images in the database by using the Insert procedure. If the query image is given, blue and red indices are calculated over $YC_b,C_r$ and the k-NN search method is used to acquire the
subset K of size k images that is closer to a query image. The subset includes the entire iris images that is satisfying \( \forall i \in K \), \[ \| q - i \| \leq \| q - n \|, \forall n \in (DB - K) \] (4)

In this equation, \( \| \| \) denotes a distance measure.

After indexing, texture feature extraction is done to find the dissimilarity present among the input images that are reside in the database. The texture feature is used to retrieve the top best match from a subset K according to the iris texture patterns. There is highly related information in the iris region I that is used to enhance the matching performance. The matching performance is enhanced is due to the combination of a local feature descriptor, Speeded-Up Robust Features (SURF). The extraction of local features is accomplished by identifying the key points in an image and the descriptor vector is formed around every identified key point. The SURF method approximates the second order Gaussian derivatives with box filters. For every pixel \((x, y)\) in the iris region, Hessian matrix at scale \(r\) is acquired. This matrix is used to choose location and scale. By using the approximated Hessian matrix determinant, the local maxima are interposed in the scale and image space.

The descriptors of the SURF method are acquired by taking a rectangular window around every perceived key point. The rectangular window is separated into \(4 \times 4\) sub-regions. In every sub-region, the Haar wavelet response is extracted. The polarity of the intensity values is identified by taking wavelet response in the horizontal \(d_x\) and vertical \(d_y\) directions and the accurate values of the wavelet responses \(d_x\) and \(d_y\) for every sub-region is added to identify the polarity of the intensity values of the image. Therefore, the feature vector in every sub-region is given by,

\[
f = (\sum d_x, \sum d_y, \sum |d_x|, \sum |d_y|) \]

(5)

In this equation, the feature vector \(F_j\) of the jth iris image in the subset K is formed by taking descriptor vector of all key points. Lastly, the given input image is compared with the entire images in the subset K by using the descriptor vectors. Then, the best match image is acquired and retrieval of images is achieved.

### 2.2 Finger Print Image Retrieval using Improved LSH Method

In this fingerprint based image retrieval system, the ridge features, minutiae points and pores points are extracted. In the ridge feature extraction process, the features like ridge orientation \(r\), ridge frequency \(f\), ridge count \(c\), ridge length \(l\) are extracted. The Ridge orientation is defined as a point \((x, y)\) that denotes the angle \(\theta_{xy}\) at the fingerprint ridges. To extract the local ridge orientation features, the gradient based method is used. The gradient is denoted by the symbol \(\nabla (x, y)\) at the point \(x, y\) of P that is a two-dimensional vector \([\nabla_x(x, y), \nabla_y(x, y)]\) and the components are the derivatives of P at \(x, y\) in x and y direction. The local ridge frequency is defined as the number of ridges for a unit length beside a hypothetical section orthogonal to the local ridge orientation.

#### 2.2.1 Indexing of Fingerprint

In order to index the fingerprint, the fingerprint biometric data is allocated with an index value that is produced according to the features take out from the fingerprint and this can be used to find an imposter. The Improved Locality-Sensitive Hashing (ILSH) method is used that considers the locality of the points so the closer points remain nearer instead of identifying exact match when compared to other traditional methods. ILSH is used to reduce the dimension in a high-dimensional data. The ILSH is a scalar projection represented by \(h(\vec{v}) = \vec{v}x\) and it is defined as,

\[
h^{x,b}(\vec{v}) = \frac{\vec{x} \cdot \vec{v} + b}{w} \]

(6)

In this equation, \(\vec{v}\) represents a point in the high dimensional space that is a vector component at random from Gaussian distribution, \(w\) denotes the width of every quantization bin and \(b\) represents an arbitrary variable uniformly disseminated between 0 and \(w\). The scalar projection is quantized into a group of hash bins to make the entire nearby points to fall into the similar bin. The points which are close together should have the following properties:

For any point \(x\) and \(y\) in \(R_d\) which are near to each other then there is a probability that \(P_1\) fall to the similar bucket so that,

\[
P_H \left[ h(p) = h(q) \right] \geq P_1 \text{for} \| p - q \| \leq R_1 \]

(7)

For any point \(x\) and \(y\) in which are farther away from each other then, the probability is and it is fall into the same bucket so that,

\[
P_H \left[ h(p) = h(q) \right] \leq P_2 \text{for} \| p - q \| \geq cR_1 = R_2 \]

(8)
The procedure in the LHS is as follows:

- The data point is distributed so that each data point is uniformly hashed.
- A family of hash function is defined as $S(g)$ and $H = \{i_1, i_2, ..., i_n\} \subseteq \{1, 2, ..., n\}$.
- The n hash function is constructed randomly so that n subsets are selected such as $H_1, H_2, ..., H_n$, and a index table includes n hash table $H_1, H_2, ..., H_n$.
- Every vector v is located into bucket $fH_k(v)$ of every hash table for $k = 1$ to $n$.
- For every query vector, a similarity search is performed and the nearby vectors are recovered as a list of matches from the consequent buckets.
- The hamming distance is used to compute the similarity score.

### 2.3 Face Image Retrieval using Weighted Attribute Sparse Code Word Scheme

After finding and indexing the local features of iris and the fingerprint images, face images are indexed to retrieve the contents efficiently and accurately. In this work, face image feature extraction and indexing is done by using the methodology called the weighted attribute sparse code word scheme through which one can authenticate the process successfully by finding similarity score. This sparse coding scheme is used to represent the image with meaningful information where the image patches are converted into code words which are integrated together to represent the entire image. In this attribute based sparse representation is introduced through which an image can be represented with the help of human definable attributes. In this work, 70 human attributes are considered for indexing the face images. The face images will be classified into two classes based on the attribute values through which one can recognize the human. The attributes that are considered for recognizing the human are listed in Table 1.

These are all the features which are considered to classify and index the images.

The attribute based sparse coding is used to index the images with different code words which are consists of attributes with different values. After indexing the images with different code words those will be classified based on the similarity level. To differentiate the images that are having the different attributes values in this work similarity score calculation is introduced based in which images patches will be assigned with weight values. The weight

| Sl. No. | Attribute       | Sl. No.       | Attribute          |
|--------|----------------|--------------|--------------------|
| 1      | Gender         | 36           | Youth              |
| 2      | Asian          | 37           | Middle aged        |
| 3      | Caucasian      | 38           | Senior             |
| 4      | African American | 39         | Black hair         |
| 5      | Indian         | 40           | Blond hair         |
| 6      | Baby           | 41           | Brown hair         |
| 7      | Child          | 42           | Gray hair          |
| 8      | Bald           | 43           | Wearing hat        |
| 9      | Curly hair     | 44           | Wavy hair          |
| 10     | Straight hair  | 45           | Receding hairline  |
| 11     | Bangs          | 46           | Visible hairline   |
| 12     | Obscured forehead | 47         | Blocked forehead   |
| 13     | Eyebrow thickness | 48         | Eyebrow shape      |
| 14     | Eye shape      | 49           | Eyes open          |
| 15     | Eye colour     | 50           | No eye wear        |
| 16     | Eye glasses    | 51           | Sun glasses        |
| 17     | Bags under eyes | 52         | Wearing earrings   |
| 18     | Side burns     | 53           | High cheek bones   |
| 19     | Rosy cheeks    | 54           | Nose size          |
| 20     | Nose shape     | 55           | Nose-mouth lines   |
| 21     | Moustache      | 56           | Mouth closed       |
| 22     | Mouth open     | 57           | Mouth wide open    |
| 23     | Lip thickness  | 58           | Wearing lipstick   |
| 24     | Teeth visible  | 59           | 5 o clock shadow   |
| 25     | Beard          | 60           | Goatee             |
| 26     | Double chin    | 61           | Jaw shape          |
| 27     | Chubby face    | 62           | Oval face          |
| 28     | Square face    | 63           | Round face         |
| 29     | Heavy makeup   | 64           | Shiny skin         |
| 30     | Pale skin      | 65           | Flushed face       |
| 31     | Smiling        | 66           | Frowning           |
| 32     | Wearing neck tie | 67         | Wearing necklace   |
| 33     | Blurry image   | 68           | Harsh lighting     |
| 34     | Flash lighting | 69           | Soft lighting      |
| 35     | Environment    | 70           | Color photo        |
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The sparse coding is done by using the following equation:

$$\min \sum_{i=1}^{n} \left\| x^{(i)} - D v^{(i)} \right\|_2^2 + \| x^{(i)} - v^{(i)T} \|_1$$

where,

- $h(i, j)$ = hamming distance.
- $T$ = threshold.

The optimal weight value is chosen in this work by using the BAT algorithm which is based on the foraging behaviour of BAT.

The procedure of face indexing and retrieval is given as follows:

1. Gather the different set of images.
2. Classify the images based on attribute values.
3. Calculate the attribute score.
4. Find the similarity distance between the same attribute values in the different classes.
5. Assign the weight values using the BAT.

The attribute with same weight value indicates the images to be similar mostly. Thus, images with similar weight values can be assigned with unique code words mostly. The attribute score is calculated by using the following equation:

$$a_j = \begin{cases} +1, & \text{if } j \geq \frac{K}{2} \\ -1, & \text{otherwise} \end{cases}$$

From this equation the masking vector can be calculated as like follows:

$$z_j^{(i)} = \exp \left( \frac{d(f_a(i), a_j)}{\sigma} \right)$$

where,

- $d(f_a(i), a_j) = $ distance between the images to be identified and the dictionary image.

Finally similarity score between the two images based on the indexed code word value is calculated as follows:

$$s(i, j) = \begin{cases} c^{(i)} \cap c^{(j)} & \text{if } h(i, j), b^{(i)} \leq T \\ 0 & \text{otherwise} \end{cases}$$

where,

- $h(i, j)$ = hamming distance.
- $T$ = threshold.

The optimal weight value is chosen in this work by using the BAT algorithm which is based on the foraging behaviour of BAT.

The procedure of face indexing and retrieval is given as follows:

- Gather the different set of images.
- Classify the images based on attribute values.
- Calculate the attribute score.
- The images with positive attribute score in to the $+1$ class.
- The images with negative attribute score in to the $-1$ class.
- Find the similarity distance between the same attribute values in the different classes.
- Assign the weight values using the BAT.

Objective function $f(x) = (x_1, ..., x_d)^T$

Initialize the bat population $x_i (i = 1, 2, ..., n)$ and $v_i$ Define pulse frequency $f_i$ at $x_i$

Initialize pulse rates $r_i$ and the loudness $A_i$

while ($t < \text{Max number of iterations}$)

Generate new solutions by adjusting frequency, and updating velocities and locations/solutions [equations (2) to (4)]

if ($r < r_i$)

Select a solution among the best solutions

Generate a local solution around the selected best solution

end if

Generate a new solution by flying randomly

if ($r < A_i \& f(x_i) < f(x_\_)$)

Accept the new solutions

Increase $r_i$ and reduce $A_i$

end if

Rank the bats and find the current best $x_\_$

end while
Postprocess results and visualization
}

- Index the image patches with code words based on attribute score

\[ z_j^{(i)} = \exp \left( \frac{d(f_i, a_j)}{\sigma} \right) \]

- Find the similarity score between images

\[ s(i, j) = \begin{cases} 1 & \text{if } h(b^{(i)}, b^{(j)}) \leq T \\ 0 & \text{otherwise} \end{cases} \]

2.4 Palm Print Image Retrieval using Novel Hierarchical Indexing Approach

The palm print model based recognition of human is introduced in this work with the finger print, face and the iris models. This palm print based recognition is the most time consuming process where there is an need to process more minute information which can differ in multiple images. In this palm indexing and retrieval is done by using the hierarchical methodology in which the palm print images that are not similar will be removed in each and every iteration. Palm print identification is the most complex process which needs to be done with more concern. To do so, minutiae extraction is done which attempts to extract the most small and precious information from the images.

Minutiae extractions in palm print are the most complex process due to presence of more minutiae, missing minutiae and large non linear distortions. This minutiae extraction needs to be done carefully to recognize the images more accurately.

In this work, set of palm print images are taken for training phase which is then will be used to match with the test image for final output. Hierarchical based methodology proposed in this work, will segment the entire palm print images into small portions which will be used for matching process through which computational cost will be reduced considerably.

After segmentation, the similarity score of two same segments of the palm print image will be compared with each other using fuzzy c means clustering algorithm. This similarity score will calculated between the minutiae of the two images segment portions. FCM will cluster the similar set of segments into one cluster through which one can obtain the matching sequences easily. At this clustering stage, dissimilar image segments will be omitted to reduce the computational cost where it eliminates the need to process those dissimilar images again.

The similar segments images portion will be aligned in the segment level to match with the entire view of palm print model to find the most similar image. The hierarchical matching process will set the threshold value during training phase, through which this approach can eliminate the most of dissimilar segment of images in the first level itself.

The procedure of palm print identification is given as follows:

Training phase

- Gather the training images.
- Segment the images into sub segments.
- For each segment.
  a. Extract minutiae from the images.
     i. Generate 5*5 square mask in the images.
     ii. Calculate the average of pixels.
     iii. If (Avg pixel value <0.25) then
         It is ridge termination minutiae.
     iv. If (Avg pixel value > 0.75) then
         It is bifurcation minutiae.
     v. label the minutiae in the image.
     vi. Store it in training database.

Testing phase

- Segment the test input image.
- Extract the minutiae from the images.
- Compute the similarity between the segmented image minutiae in the database.
- Cluster the similar set of segmented portion using fuzzy c means clustering approach.
  a. Initialize \( U = \left[ u_{ij} \right] \) matrix, \( U^{(0)} \).
  b. At k-step: calculate the centers vectors \( C^{(k)} = \left[ c_j \right] \) with \( U^{(k)} \)

\[ c_j = \frac{\sum_{i=1}^{N} u_{ij}^{(k)} \cdot x_i}{\sum_{i=1}^{N} u_{ij}^{(k)}} \]
pixels. The FOV of each image is circular with a diameter of approximately 540 pixels.

The comparison of Two Model Bio Metrics System (TMBS) and the Multi Model Bio Metric System (MMBS) is made using the parameters called the precision, recall, f-measure and retrieval accuracy.

3.1 Precision

Precision value is evaluated according to the retrieval of images at true positive prediction, false positive.

\[
\text{Precision} = \frac{\text{True Positive}}{\text{True Positive + False Positive}}
\]

In the Figure 1, comparison of precision values is made between the existing and proposed methodology from which it can be proved that the precision is improved in the proposed methodology. In the x axis subset size is taken in the range of 0 to 1 and the y axis denotes the precision values.

3.2 Recall

Recall value is evaluated according to the retrieval of images at true positive prediction, false negative.

\[
\text{Recall} = \frac{\text{True Positive}}{\text{True positive + False negative}}
\]

In the Figure 2, comparison of recall values is made between the existing and proposed methodology from which it can be proved that the recall is improved in the proposed methodology. In the x axis subset size is taken in the range of 0 to 1 and the y axis denotes the recall values.

The above pseudo code is used to recognize the human with the help of palm print.

2.5 Integrating Feature Set using Fusion Methodology

Finally, all the extracted feature values from the multi model (iris, finger print, face and the palm print) will be fused together to recognize the human accurately. The multi model fusion based methodology aims to retrieve the contents by taking the hash values of extracted information together and then similarity will be calculated with the human generated input data.

The final output of this scheme proves that the multi model based human recognition leads to the better and accurate output than the existing approaches. The performance evaluation that are conducted over the human generated input data are discussed detailed in the following section.

3. Experimental Results

In this section, the experiments are conducted by using the FVC2000 fingerprint data set and the DRIVE database. In the FVC2000 database, at the end of the collection, we gathered for each database a total of 120 fingers and 12 impressions per finger (1440 impressions) using 30 volunteers. DRIVE (Digital Retinal Images for Vessel Extraction) database contains the set of 40 images that has been separated into training and testing data set. Both of them contain 20 images. By using a Canon CR5 non-mydriatic 3CCD camera, the images are captured with a 45 degree Field of View (FOV). Every image was acquired by using 8 bits per color plane at 768 by 584
4. Conclusion

Human recognition plays an important role in the biometric authentication field. In our previous research work, authentication is done with the consideration of the two model biometric recognition where the accuracy may tempt to reduces in case of large volume data presence. To over come this problem in this work, multi model biometric based authentication is introduced through which one recognize the human with the consideration of four model called iris, finger print, face and palm print. The experimental tests conducted were proves that the proposed methodology provides better result than the existing approach in terms of improves accuracy, precision, recall and f-measure values.
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