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Two-Modal Biometrics Based Content-Based Image Retrieval Approach (TMB-CBIR) for Biometric Authentication

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Abstract: Biometric-based systems are used for human recognition in real-time applications. Due to the huge size of biometric database in current methodologies, more time is required for image search in the database. In this study, an innovative technique is introduced called Two-Modal Biometrics based Content-Based Image Retrieval approach (TMB-CBIR) for biometric authentication. In the two-modal biometrics, iris and fingerprint images are considered. In the iris image, both color and texture features are extracted where color feature is used for indexing and text feature is used to find the similarity of images extracted by using Speeded Up Robust Features (SURF) algorithm. In the fingerprint images, the Improved Locality-Sensitive Hashing (ILSH) indexing method is used that considers the locality of points so that the nearby points remain closer instead of recognize perfect match. In this method, the data is disseminated and every data point is uniformly hashed. Union of Candidate Lists fusion method is used to merge both lists of candidate identities output. Finally, the set of reference images are chosen from convex hull of feature space in order to reduce the estimation time. Experimental results show that TMB-CBIR achieves high accuracy and less response time.

Key words: Biometrics, image retrieval, feature extraction, fingerprint recognition, iris recognition

INTRODUCTION

Biometric system is basically a pattern recognition system that acquires a biometric data from the persons, extract the features and compare the feature set with the template in the database. Based on the application, a biometric system may work either in authentication mode or recognition mode. The physical and behavioral qualities of the humans are considered for identifying the human beings. The physical qualities such as fingerprints, DNA and behavioral qualities such as voice, gait and typing rhythm including digital signature are considered for biometric security. Now-a-days biometric security is highly investigated and it is used in various applications. The main intent of the applications is to detect and recognize a human for achieving security as said by Jain *et al*. (2004). But, accurate detection and performance in terms of response time is highly important for the human recognition system. The main intent of this research is to integrate content-based image retrieval approach in order to improve the biometric security.

In the content-based image retrieval method, a user gives a query that is used by the system to get the visual features from the images. The visual features such as shape, color and texture are extorted that is based on the image retrieval system. The extracted features are processed and compared with the images accumulated in the database. Because of the large size of the database, it requires more time to find the image stored in the database. So, it is essential to improve the detection accuracy and less detection time in the human identification system. Existing feature selection methods such as Gray-Level Run-Length Method (GLRLM) by Radhakrishnan *et al*. (2012) feature selection method that is used extract the texture features for the texture analysis. Local Binary Pattern (LBP) by Shams *et al*. (2011) is another feature selection method that is an effectual method for feature extraction and texture classification. Gabor filters by Liang (2015) is an efficient method for feature selection that decomposes the iris image by using the multi-scale and multi-orientation Gabor filters and then separates the images into blocks and obtain the mean and variance of Gabor coefficients can be acquired by statistical techniques.

Various indexing methods of iris images are suggested that is based on the iris texture. Zhang suggested a coarse iris classification method that utilizes fractals that categories iris images into four types. The iris image is divided into sixteen blocks in that eight blocks belong to upper group and remaining eight blocks comes under the lower group. From the image blocks, the fractal dimension is computed and the mean value is computed

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for the upper and lower group fractal dimensions. Mehrotra *et al.* (2010) suggested geometric hashing based indexing method for iris images by using SIFT feature selection method. The identified key points of the iris images are used for indexing. Then, the key points are hashed into a suitable bin of the hash table by utilizing a geometric hashing.

In the proposed research, Two-Modal Biometrics based Content-Based Image Retrieval approach (TMB-CBIR) is introduced for biometric authentication. This two-modal biometrics considers the iris and fingerprint images. This method considers both iris and texture features. Iris color is used for indexing and according to this the images are recovered from the database. An index is decided from the color of the iris images and compare with the images in the databases and filter the images that are not same as the input image. In addition to that, the texture features are extracted from the iris images and find the similar image in the database. The color information of the iris images is used to design an effectual indexing method based on the color indices.

The average value is taken for the entire red and blue color pixels for acquiring color indices. The SURF algorithm is used to extract texture features of the iris images. The extorted features are used to judge against the query image with the images stored in the database. The ILSH indexing method is used for the fingerprint images that considers the locality of the points so that the nearby points remain closer instead of distinguish perfect match. In order to reduce the detection time, the data is disseminated and every data point is uniformly hashed in the ILSH method. Then the iris and fingerprint images are fused by using the Union of Candidate Lists fusion method that is used to merge both the lists of candidate identities output. Then, the group of reference images is selected from the convex hull of the feature space in order to reduce the estimation time. The contribution of this research is as follows:

- Firstly, the iris color and texture features are extracted. The color features of iris are used in indexing and texture features are extracted by using SURF algorithm
- Secondly, the fingerprint features are extracted by using ILSH method that every data point is uniformly hashed in this method
- Thirdly, Union of Candidate Lists fusion method is used to combine the iris and texture features. The features are compared with images stored in the database. The experiments are evaluated for the TMB-CBIR method for analyzing the performance

Literature review: In this study, various methods are analyzed for biometric security. Alami (2011) presented a content-based image retrieval system that is based on three methods like feature extraction, image mining and rule based. In the feature extraction process, the color and texture features are extracted from the images and transform the images. These transformed images are used for object identification. Then, the image mining method is used to get the internal knowledge from the images. Finally, the rules are determined according to the significance feedback given by experts to purify the results by enhancing clusters.

Gonzalez-Quevedo and coauthors suggested presented a Content-Based Image Retrieval (CBIR) system called Blob world. In this method, the segmentation process is executed to divide the image into various sections and these sections are used as image query. According to the region, the system finds the images which have same relation with other regions in the image query. This method utilizes the color and texture features for the retrieval of images.

Iqbal *et al.* (2012) developed CIRES (Content-Based Image Retrieval System) for extracting helpful features from the images like structural, textural and color features. For the color features, the color histogram method is used to compare the images. To extract the texture features the Gabor filter is used. Finally, image structure like line junction and line crossing are taken for illustrates the structural image. The image retrieval procedure is takes place by using the weighted linear combination of the structural, texture and color histogram values.

Iqbal *et al.* (2012) and Yu *et al.* (2005) suggested a novel content-based image retrieval method for biometric security. This method considers the features like color, texture and shape features and it can be proscribed by using fuzzy heuristics. This method uses the algorithms such as color histogram, texture and moment invariants. By using this method, the highly pertinent images are retrieved for the query image. The Euclidean measure is used as similarity distance measure in this method.

MATERIALS AND METHODS

Two-Modal Biometrics based Content-Based Image Retrieval approach (TMB-CBIR): Figure 1 shows the architecture for the TMB-CBIR approach. The input images such as iris and fingerprint are taken for the human recognition system. The searching and recovery of the images is achieved by extracting the visual contents. The significant visual contents are color feature and texture

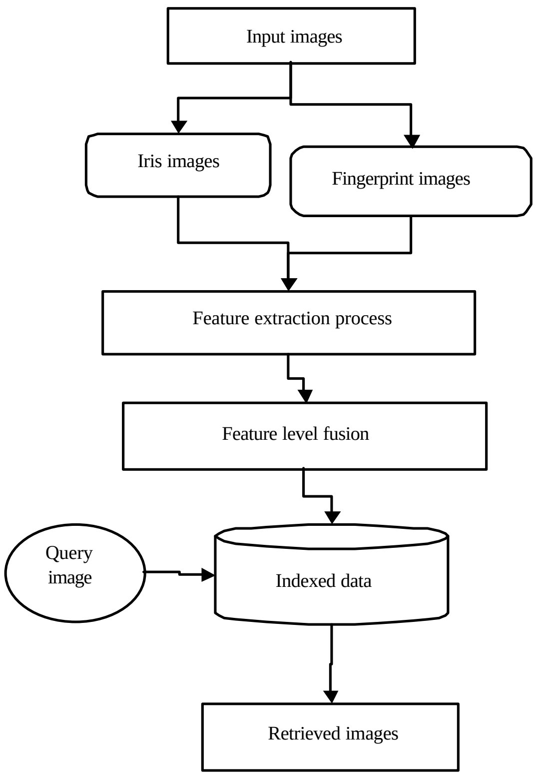

Fig. 1: Architecture for TMB-CBIR approach

feature. In the iris images, color feature is used for indexing and filter out the images and stored in the indexed iris database. Then, the iris texture features are extracted by using the SURF algorithm. For the fingerprint images, the ILSH method is used that considers the locality of the points so that the nearby points remain nearer as an alternative of distinguish perfect match. To reduce the estimation time, the data is disseminated and every data is independently hashed. Then, these features are fused by using The Union of Candidate Lists fusion method that joins both the lists of candidate identities output. Then, the images are compared with the stored images in the database and retrieve the images (Fig. 1).

Iris image retrieval technique using SIFT feature extraction method

Iris color indexing: The features are extracted from the iris image in the iris biometric recognition system. These features are mapped into a feature space and defined as a point (f_1, f_n) in the space. A metric is defined on the space and recognition is achieved by identifying the k nearest points in the given point for a given query. The features points are indexed so that, it is not necessary to compare all the feature points during the searching process. For the color indexing of the iris image, Kd-tree based indexing method is presented for iris database. 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 is calculated under YC_bC_r color space. Let us consider I is the segmented iris region for a given input iris image. The iris region I is initially in RGB color space is transformed into YC_bC_r color space:

$$Y(x,y) = 16 + \frac{1}{256}.\begin{pmatrix} 65.7.R(x,y) + 129.0.G \\ (x,y) + 25.0.B(x,y) \end{pmatrix}$$

$$C_b(x,y) = 128 + \frac{1}{256}.\begin{pmatrix} -37.9.R(x,y) - 74.4.G \\ (x,y) + 112.4.B(x,y) \end{pmatrix} \quad (1)$$

$$C_r(x,y) = 128 + \frac{1}{256}.\begin{pmatrix} 112.4.R(x,y) - 94.1.G \\ (x,y) + 182.2.B(x,y) \end{pmatrix}$$

In this equation, R (x, y), G (x, y) and B (x, y) are red, green and blue pixel values of (x, y) in the RGB color space. After that, these blue and red indices of I under YC_bC_rcolor space is acquired by:

$$b_1 = \frac{1}{|I|} \sum_{\forall(x,y)\in I} C_b(x,y) \quad (2)$$

$$r_1 = \frac{1}{|I|} \sum_{\forall(x,y)\in I} C_r(x,y) \quad (3)$$

In this equation, C_b (x, y) and C_r (x, y) represents the chrominance of the blue and red color correspondingly for the pixel (x, y). The YC_bC_r color space separate illumination from the color so that it operates high efficient in the varying light levels. The color indices are computed as follows.

Let us consider DB = {D_1, D_2, ..., D_N} denotes the database of N iris images in which D_L, = L 1, 2, ..., N denotes a 2-tuple including blue and red indices of the iris region I in the YC_bC_r color space, i.e., $D_L = (b_L, r_L)$. 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_bC_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):

$$\|q - i\| \leq \|q - n\|, \ \forall n \in (DB - K) \quad (4)$$

In this equation, ‖.‖ denotes a distance measure.

Texture feature extraction of iris images: In this study the texture features are extracted to find the similarity of the images for a given query image. 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 4×4 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_x) for every sub-region is added to identify the polarity o f the intensity values of the image. Therefore, the feature vector in every sub-region is given by:

$$f = \left(\sum d_x, \sum d_y, \sum \left|d_y\right|\right) \quad (5)$$

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.

Fingerprint image retrieval technique 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_o) ridge frequency, (r_f) ridge count, (r_c) ridge length (r_l) are extracted. The Ridge orientation is defined as a point (x, y) that denotes the angle θ_{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 ∇ (x, y) at the point of P that is a two-dimensional vector [∇_x (x, y), ∇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. The ridge frequency is computed according to the average number of pixels between the two successive peaks. Then the minutiae points are extracted from the skeletonized image. Every minutia is defined as set of x and y coordinates and the angle between the tangent to the ridge line at the minutia location and the horizontal axis. In order to determine the minutia type, the end point of each ridge is decided as follows:

- End point: if a ridge line finishes at any point
- Bifurcation: if a ridge line deviates into two branches at any point
- Trifurcation: if a ridge line deviates into three branches at any point
- Crossover: if a two ridge lines interconnects at any point and maintain to flow

According to the fingerprint features extracted the indexing feature vector is decided as ridge orientation, ridge frequency, ridge count, ridge length and ridge curvature direction, minutiae and minutiae category. Pore points are smaller points in which the diameter is small than the width of the ridge which originate perspiration. The pore points are in the ridge line. According to the position of the pore it is categorized as open and close pores. The close pore is inside the ridge line and some of the open pores are on the ridge and remaining of them is on the valley. There is more difference between the position of the pore and density of the pore. There is closer distance between the successive two pores.

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 $(\vec{v}) = \vec{v}\vec{x}$ and it is defined as:

$$h^{x,b}(\vec{v}) = \left|\frac{\vec{x}.\vec{v} + b}{w}\right| \quad (6)$$

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:

$$P_H\left[h(p)=h(q)\right]\geq P_1 \text{ for} \|p-q\|\leq R_1 \quad (7)$$

For any point x and y in R_d which are farther away from each other then, the probability is $P_2<P_1$ and it is fall into the same bucket so that:

$$P_H\left[h(p)=h(q)\right]\geq P_2 \text{ for} \|p-q\|\geq cR_1=R_2 \quad (8)$$

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 f $H_k(v)$ of every hash table H_k for k = 1 to n
- For every query vector, a similarity search is performed and the nearby vectors are recovered as list of matches from the consequent buckets
- The hamming distance is used to compute the similarity score

Union of candidate lists based fusion method and finding similarity: In this section, the fingerprint and iris features are fused by using Union of Candidate Lists based Fusion Method. In this method, firstly the index code of the images is fused. Let $S_x(R^i) = \{S\ x, r^i_1), S(x, r^i_2), .., s(x, r^i_n)\}$ is the index code of the image x from modality i. The fused index code is denoted as is acquired by combining all the index codes from different modalities. $F_x = \{s(x, r^1_1)$,.., $s(x, r^1_n)$, $s(x, r^2_1)$, ..$s(x, r^2_n)$ Let us consider C^i is the set of retrieved identities based on the modality i. The final set of identities C is recovered from the indexing will be $C = U\ r^k_{i=1} C^i$. This fusion method is capable to remove errors in the candidate list by individual modalities. Finally, the set of reference images are chosen from the convex hull of the feature space in order to reduce the estimation time.

The index codes can also viewed as points in a Euclidean space and the similarity between the index codes is measured by their spatial proximity:

$$l_2(S_x, S_y)=\left(\sum_{i=1}^{n}\left(S_{xi}-S_{yi}\right)^2\right)^{\frac{1}{2}} \quad (9)$$

The association between two index codes can be measured by using the similarity measure.

Algorithm:

Two-Modal Biometrics based Content-Based Image Retrieval (TMB-CBIR) algorithm:

Input: Query image QI and Images $C = I_1, .. I_N$ in database (Image: face and fingerprint)

Output: Retrieval of similar images.

Query image and images in database are taken as input.

For all i = 1 to N and QI

Extract the features for QI and images in database

// Color feature extraction of iris images

Iris region I is initially in RGB color space is transformed into YC_bC_r color space:

$$Y(x,y)=16+\frac{1}{256}\begin{pmatrix}65.7.R(x,y)+129.0.G\\(x,y)+25.0.B(x,y)\end{pmatrix}$$

$$C_b(x,y)=128+\frac{1}{256}\begin{pmatrix}-37.9.R(x,y)-74.4.G\\(x,y)+112.4.B(x,y)\end{pmatrix}$$

$$C_r(x,y)=128+\frac{1}{256}\begin{pmatrix}-112.4.R(x,y)-94.1.G\\(x,y)+18.2.B(x,y)\end{pmatrix}$$

where, R (x, y) and C_r (x, y) are red, green and blue pixel values of in the RGB color space.

Blue and red indices of I under YC_bC_r color space is acquired by:

$$b_I=\frac{1}{|I|}\sum_{\forall(x,y)\in I}C_b(x,y)$$

$$r_I=\frac{1}{|I|}\sum_{\forall(x,y)\in I}C_r(x,y)$$

where, C_b (x, y) and C_r (x, y) represents the chrominance of the blue and red color correspondingly for the pixel (x, y)

// Texture feature extraction of iris images using SURF method

Feature vector in each sub-region is given by:

$$f=\left(\sum d_x, \sum d_y, \sum |d_x|, \sum |d_y|\right)$$

where, F_J the feature of the jth iris image in the subset K is is formed by taking descriptor vector of all key points, d_x and d_y are the horizontal and vertical directions.

// Fingerprint feature extraction

In the fingerprint images, ridge features, minutiae points and pores points are extracted.

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 f $H_k(v)$ of every hash table H_k for k = 1 to n.

For every query vector, a similarity search is performed and the nearby vectors are recovered as list of matches from the consequent buckets.

The hamming distance is used to compute the similarity score.

// Fusion of fingerprint and iris features.

The index code of the image x is defined as $S_x (R^i) = \{S(x, r^i_1), S (x, r^i_2), .. , s (x, r^i_n)\}$

Fused index code is denoted as F_x and it is denoted as $S (x\ r^1_1) = \{S\ x, r^1_n), S (x, r^2_1), .. , s (x, r^2_n)\}$.

// Similarity between the images

Index codes can also viewed as points in a Euclidean space

For every image the variance is computed $v_i = Var(s(i_n, i_{n+1}$

Sort the images in the descending order of the v_i values.

RESULTS AND DISCUSSION

In this study, 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° Field of View (FOV). Every image was acquired by using 8 bits per color plane at 768 by 584 pixels. The FOV of each image is circular with a diameter of approximately 540 pixels.

The numerical results are evaluated for the existing and the proposed method. In the existing method, Image retrieval using GLRLM feature extraction, SIFT feature extraction methods are used. In the proposed method, Two-Modal Biometrics based Content-Based Image Retrieval Approach (TMB-CBIR) is presented for biometric authentication. The performance is evaluated in terms of precision, Recall, F-measure and retrieval accuracy.

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

$$\text{Precision} = \frac{\text{True positive}}{(\text{True positive} + \text{False positive})}$$

Figure 2 shows the precision rate for the existing and proposed system. In the X-axis subset size is taken. In the Y-axis precision is taken. In the existing method, image retrieval using GLRLM feature extraction, SIFT feature extraction methods are used. In the proposed method, Two-Modal Biometrics based Content-Based Image Retrieval Approach (TMB-CBIR) is presented for biometric authentication. When compared to the existing system, there is high precision rate in the proposed system.

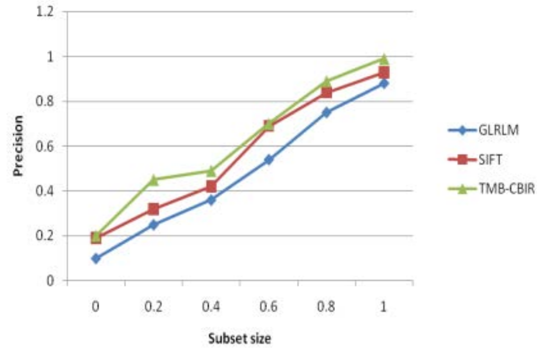

Fig. 2: Precision

Table 1: Precision

Subset size	GLRM	SIFT	TMB-CBIR
0	0.10	0.19	0.2
0.2	0.25	0.32	0.45
0.4	0.36	0.42	0.49
0.6	0.54	0.69	0.7
0.8	0.75	0.84	0.89
1	0.88	0.93	0.99

Table 1 shows the precision rate comparison for the existing and proposed system. If the subset size is 1, the precision rate in the existing GLRLM feature extraction is 0.88 for SIFT feature extraction method is 0.93 and for TMB-CBIR method is 0.99.

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

$$\text{Recall} = \frac{\text{True positive}}{(\text{True positive} + \text{False negative})}$$

Figure 3 shows the recall for the existing and proposed system. In the x-axis subset size is taken. In the y-axis recall is taken. In the existing method, image retrieval using GLRLM feature extraction, SIFT feature extraction methods are used. In the proposed method, Two-Modal Biometrics based Content-Based Image Retrieval Approach (TMB-CBIR) is presented for biometric authentication. When compared to the existing system, there is high recall rate in the proposed system.

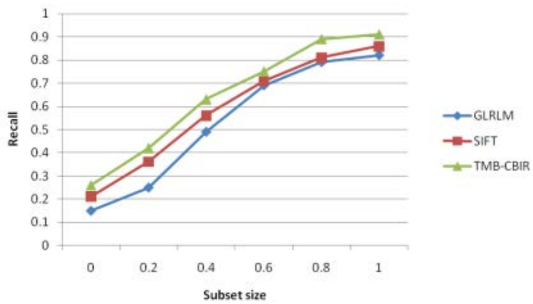

Fig. 3: Recall

Table 2: Recall

Recall			
Subset size	GLRM	SIFT	TMB-CBIR
0	0.15	0.21	0.26
0.2	0.25	0.36	0.42
0.4	0.49	0.56	0.63
0.6	0.69	0.71	0.75
0.8	0.79	0.81	0.89
1	0.82	0.86	0.91

Table 2 shows the recall rate comparison for the existing and proposed system. If the subset size is 1, the recall rate in the existing GLRLM feature extraction is 0.82, for SIFT feature extraction method is 0.86 and for TMB-CBIR method is 0.91.

F-measure: F-measure is a measure of a test's accuracy. It considers both the precision p and the recall r of the test to compute the score: p is the number of correct results divided by the number of all returned results and r is the number of correct results divided by the number of results that should have been returned.

The F-measure score can be interpreted as a weighted average of the precision and recall, where an F_1 score reaches its best value at 1 and worst score at 0:

$$\text{F-measure} = 2.\text{Precision.recall} / (\text{precision} + \text{recall})$$

Figure 4 shows the F-measure for the existing and proposed system. In the X-axis subset size is taken. In the y-axis F-measure is taken. In the existing method, Image retrieval using GLRLM feature extraction, SIFT feature extraction methods are used. In the proposed method, Two-Modal Biometrics based Content-Based Image Retrieval Approach (TMB-CBIR) is presented for biometric authentication. When compared to the existing system, there is high F-measure in the proposed system.

Table 3 shows the F-Measure comparison for the existing and proposed system. If the subset size is 1, the F-measure in the existing GLRLM feature extraction is 0.87, for SIFT feature extraction method is 0.92 and for TMB-CBIR method is 0.99.

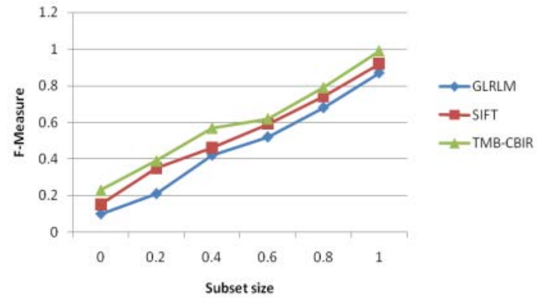

Fig. 4: F-measure

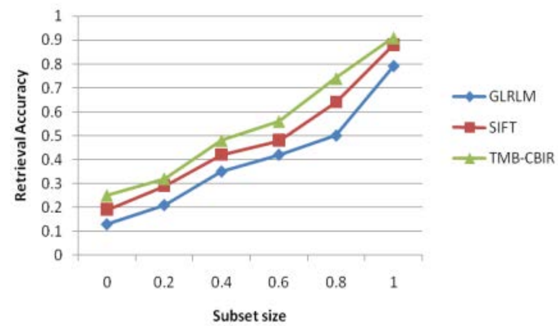

Fig. 5: Retrieval accuracy

Table 3: F-measure

F-Measure			
Subset size	GLRM	SIFT	TMB-CBIR
0	0.1	0.15	0.23
0.2	0.21	0.35	0.39
0.4	0.42	0.46	0.57
0.6	0.52	0.59	0.62
0.8	0.68	0.74	0.79
1	0.87	0.92	0.99

Retrieval accuracy: Retrieval accuracy is defined as the accurate retrieval of images. Retrieval accuracy is evaluated as:

$$\text{Accuracy} = \frac{\text{True positive} + \text{Ture negative}}{\begin{pmatrix}\text{True positive} + \text{False negative} + \\ @\text{False positive} + \text{False negative}\end{pmatrix}}$$

Figure 5 shows the retrieval accuracy for the existing and proposed system. In the x-axis subset size is taken. In the y-axis retrieval accuracy is taken. In the existing method, Image retrieval using GLRLM feature extraction, SIFT feature extraction methods are used. In the proposed method, Two-Modal Biometrics based Content-Based Image Retrieval Approach (TMB-CBIR) is presented for biometric authentication. When compared to the existing system, there is high retrieval accuracy in the proposed system.

Table 4: Retrieval accuracy

	Retrieval accuracy		
Subset size	GLRM	SIFT	TMB-CBIR
0	0.13	0.19	0.25
0.2	0.21	0.29	0.32
0.4	0.35	0.42	0.48
0.6	0.42	0.48	0.56
0.8	0.5	0.64	0.74
1	0.79	0.88	0.91

Table 4 shows the retrieval accuracy for the existing and proposed system. If the subset size is 1, the retrieval accuracy in the existing GLRLM feature extraction is 0.87, for SIFT feature extraction method is 0.92 and for TMB-CBIR method is 0.99.

CONCLUSION

In this research, Two-Modal Biometrics based Content-Based Image Retrieval Approach (TMB-CBIR) is introduced for efficient biometric authentication. In the two-modal biometrics, iris and fingerprint images are taken for the authentication process. The color and texture features are extracted from the iris images in which the color feature is used for indexing and texture features are extracted by using Speeded Up Robust Features (SURF) algorithm. For the fingerprint images, the Improved Locality-Sensitive Hashing (ILSH) indexing method is used to find the locality of the points. Finally, both features are combined by using Union of Candidate Lists fusion method and find the similarity by using the Euclidean measure. The simulation results show that the proposed method achieves high retrieval accuracy and less time consumption when compared to the existing system. But it has two main issues for encoding the human attributes into the sparse representation. First, it is not robust to possible attribute detection errors. Since, the human attributes are automatically identified, they are not error-free. So, this can be considered in future research.

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