CHAPTER 7

RESULTS AND DISCUSSION

7.1  INTRODUCTION

This chapter discusses the results of various modules of the proposed ear biometric recognition system depicted in Chapter 3 by extracting RUSH features (Robust UMRT Shape and Histogram Features) from the acquired ear biometric images as illustrated in Chapter 4. The dimensionality of the proposed RUSH features is reduced by feature selection algorithm based on Genetic Algorithm (GA) and information theory. The results of GA based feature selection are presented. The probe ear biometric images are recognised with the help of nearest neighbour (KNN and Cityblock distance) classifiers. In order to evaluate the performance of the proposed ear biometric recognition system, performance measures such as Recognition Rate, Verification Rate, Error rate etc. are evaluated and performance curves such as Receiver Operating Characteristic (ROC), Cumulative Match Characteristic (CMC), Expected Performance Characteristic (EPC) curves are plotted. The proposed ear recognition framework is coded using MATLAB (R2013a) version 8.1 on Intel Core i7 CPU@ Clock 2.5GHz.

7.2  EAR BIOMETRIC DATABASES TESTED

The effectiveness of the proposed ear biometric recognition methodology is tested using one of the benchmark ear databases, IIT Delhi ear images database and also using an internal ear database. In both cases, the
ear images are preprocessed and the proposed RUSH (Robust UMRT Shape and Histogram) features are extracted.

7.2.1 IIT Delhi Ear database

The proposed methodology is tested on IIT Delhi ear image database consisting of ear images acquired from students and staffs at Indian Institute of Technology (IIT) Delhi. The database consists of 471 ear images of 121 different subjects with at least three ear images per subject. All these images are sequentially numbered by assigning unique integer identification to each subject. The spatial resolution of these images is 272 x 204 pixels.

![Sample ear images from IIT Delhi Ear database](image)

**Figure 7.1 Sample ear images from IIT Delhi Ear database**

Few sample ear images from the IIT-Delhi database are shown in Figure 7.1. Out of the four images shown above, Figures 7.1 (a) and (b) corresponds to ear images of same person whereas Figures 7.1 (c) and (d)
correspond to the ear images of different persons. The IIT-D ear images are resized to a size of 256 x 256 pixels in order to facilitate the computation of UMRT features which constitute the texture component of the proposed RUSH features.

7.2.2 Internal Ear database

An internal ear database is prepared for this research work, which consists of 25 ear images acquired from men and women using Nikon D90 digital camera with a resolution of 800 x 1200 pixels. Both right and left ears of each person are captured. These RGB colour images are converted into grayscale and are resized to a uniform size of 256 x 256 pixels so as to facilitate the computation of UMRT texture features (Rajesh Cherian R et al. 2009), Shape features and Histogram features.

![Sample ear images from Internal Ear database](image)

Figure 7.2 Sample ear images from Internal Ear database

Few sample images from the internal database are shown in Figure 7.2. In the above ear images, Figure 7.2 (a) correspond to the ear image of a person A whereas Figures 7.2 (b) and (c) correspond to the left and right images of another person, B.
7.3 PREPROCESSING

Ear images in the training, test and evaluation datasets are preprocessed before extracting texture features from them. The size of ear images in the IIT Delhi ear database (Version 1.0) is 272 x 204 pixels. As the manipulation of UMRT coefficients and hence UMRT texture features is suggested for sub image blocks of size as powers of 2 (Rajesh Cherian R et al. 2009), all these images are resized to 256 x 256 pixels. The preprocessing steps are carried out on the ear images in all three datasets of both ear databases after resizing are illustrated in Figure 7.3.

![Preprocessing steps on IIT Delhi ear database images](image)

(a) Sample IIT Delhi database image; (b) CLAHE & Median filtered of (a); (c) Constrained Delaunay Segmented image of (b)

The various preprocessing steps applied on IIT Delhi ear database images are illustrated in Figure 7.3.

7.4 PROPOSED FEATURE EXTRACTION METHODOLOGY

Robust and computationally efficient features are extracted from the preprocessed ear modalities during enrolment phase as well as recognition phase by composing a proposed feature space called RUSH space (Robust UMRT Shape and Histogram Features).
7.4.1 Testing robustness of RUSH Features

In order to make our investigation to be a potentially viable biometric recognition methodology, the extracted features should be robust against illumination variations, rotational changes and also be computationally efficient. The proposed RUSH features are obtained by combining UMRT texture features (of length 22 for a sub image size of 8 x 8), histogram and seven shape features (of length 263) so that the dimensionality of an extracted RUSH feature vector is 285.

The proposed methodology of ear recognition is tested using both the IIT-D ear database and also an internal ear database. For the IIT-D database, three datasets namely training, test and evaluation datasets are prepared by taking 75 ear images from 25 persons with 3 instances per person. Similarly, for testing the internal ear database, the training dataset contains 36 ear images from 18 persons with 2 images per person. For both these databases, the evaluation and the test datasets are taken to be mutually exclusive.

For testing the robustness of the proposed features against rotations, the test and evaluation datasets in our investigation consists of rotated versions of actual images. Also, robustness against illumination variations is tested by varying brightness and contrast of actual images in training dataset and including them in the test as well as evaluation datasets of IIT-D and internal ear databases and commendable recognition rate is obtained with such test and evaluation datasets. Various performance curves to evaluate the performance of the proposed model are discussed in detail in this chapter (7.6).
Figures 7.4 (b) and (c) show two rotated instances of the image shown in Figure 7.4 (a). Figure 7.4 (b) is obtained by rotating the ear image of Figure 7.4 (a) by +5 degrees and ear image in Figure 7.4 (c) is obtained by rotating it by -5 degrees. These two rotated versions are included in the test dataset of IIT-D ear database in our present investigation.

To test the robustness of the proposed RUSH features against illumination variations, the actual ear image shown in Figure 7.4(a) is blurred
with 3 x 3 and 5 x 5 averaging low pass filter masks and the resultant blurred images are shown in Figure 7.5.

The ear images resulting after blurring are included in the test and evaluation datasets of IIT-D database in our present investigation. Performance measures such as rank one recognition rate, False Acceptance Rate (FAR), False Reject Rate (FRR) and performance curves such as Receiver Operating Characteristic (ROC) curve and other curves for such training, test and evaluation datasets are illustrated in this chapter.

### 7.4.2 Extraction of RUSH features

The ear images in training, test and evaluation datasets are preprocessed and the desired ear region is segmented out. For extracting RUSH features as a serial fusion of UMRT texture features and Shape & Histogram features, the segmented ear region is resized to 256 x 256 pixels and is divided into non-overlapping sub image blocks of size 8 x 8. UMRT coefficients are calculated as in Equation 3.11 and are placed according to the placement algorithm depicted in Table 3.1. Thus, UMRT coefficients are computed as a spatial filtering operation carried out on every 8 x 8 sub image blocks. Finally, the UMRT texture features of dimensionality 22 are calculated as per Table 3.2.

Seven shape features namely Area, Perimeter, Convex, Solidity, Minor axis length, Major axis length and Eccentricity are then computed. Colour information based Histogram features are then computed for the preprocessed ear image. Finally, the computed UMRT texture features, Shape features and Histogram features of dimensionality 22, 7 and 256 respectively are combined in a serial fashion to generate the proposed features called RUSH (Robust UMRT Shape and Histogram) features. In our present investigation, the size of the sub image block is taken to be 8 x 8 pixels. So
the dimensionality of UMRT texture features is 22 as calculated from 3N-2, N is the size of sub image block (Manju B et al. 2015). This generates RUSH features of dimensionality 285. The dimensionality of RUSH features for different sizes of sub image blocks is shown in Table 7.1.

Table 7.1  Dimensionality of RUSH features for various sizes of sub image blocks

<table>
<thead>
<tr>
<th>Sl.No.</th>
<th>Size of sub image block</th>
<th>Dimensionality of UMRT texture features</th>
<th>Dimensionality of RUSH features</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>8</td>
<td>22</td>
<td>285</td>
</tr>
<tr>
<td>2</td>
<td>16</td>
<td>46</td>
<td>309</td>
</tr>
<tr>
<td>3</td>
<td>32</td>
<td>94</td>
<td>357</td>
</tr>
</tbody>
</table>

UMRT texture features are calculated for various sizes of sub image blocks say 8, 16 and 32 and hence RUSH features of respective dimensionality (Table 7.1) are extracted. Our present investigation on ear recognition is carried out with only UMRT texture features of dimensionality 22 (i.e. sub image block size of 8 x 8) and hence with RUSH features of dimensionality 285, due to the increased complexity of high dimensional feature vectors with respect to storage space requirements, curse of dimensionality and computational time (Tan F et al. 2008).

7.4.3  Significance of RUSH features

The proposed RUSH features are obtained by combining UMRT texture features of dimensionality 22, Shape features of dimensionality 7 and Histogram features of dimensionality 256 in a serial fashion, resulting in a dimensionality of 285. Unique Mapped Real Transform (UMRT) features extract texture information pertaining to Region-Of-Interest (ROI) i.e.
segmented ear region. The texture classification ability of UMRT (Manju B et al. 2015) is being utilised in our investigation to classify features extracted from segmented ear region. These texture features are regarded as the resultant of spatial filtering performed as a neighbourhood operation on sub image blocks each of size 8 x 8. The first term in the UMRT texture feature for each ear image has the highest magnitude and it is called the Pattern strength indicator related to the strength of the pattern along dominant direction which in the case of ear corresponds to the features labelled ‘1’, ‘5’, ‘9’ and ‘12’ as in Iannerelli measurements (Iannarelli A 1989) shown in Figure 7.6.

Figure 7.6 Ianneralli measurement of 12 ear features

Histogram features and 7 Shape features based on mathematical morphology are extracted from the ROI ear region. UMRT texture features are local texture features whereas histogram and shape features are computed as global features of an image. UMRT texture features, Shape and Histogram features are combined in a serial fashion to generate a set of robust features named RUSH features.
7.5 OPTIMISATION OF RUSH FEATURES

It is evident from Table 7.1 that the dimensionality of proposed RUSH features increases as the size of sub image block in the spatial filtering carried out as a neighbourhood operation for the computation of UMRT texture features increases. This leads to several disadvantages which are listed below.

- Requirement of more storage space
- Increase in training time and recognition time of RUSH features
- Possibility of noise accumulation during serial fusion
- Degradation of recognition performance

Optimum RUSH features are selected by feature selection algorithm based on Genetic Algorithm and information theory (Ludwig O et al. 2010). In our investigation, 200 out of 285 features are selected based on GA and mutual information. The discriminative nature of selected optimum RUSH features for ear images of 15 persons with 2 images per person are visualised with the help of glyphplots plotted using MATLAB and are shown in Figure 7.7.

![Glyphplots for GA optimised RUSH features](image)

**Figure 7.7** Glyphplots for GA optimised RUSH features (a) 200 (b) 17
Glyphplots are useful tools for visualising multidimensional data and are constructed as extended scatter plots by representing additional variables using glyph symbols (Carr DB 1998). Each variable in this multidimensional scatter plot corresponds to each RUSH feature in the GA optimised RUSH feature vector corresponding to individual ear biometric modality. If the dimensionality of each optimised RUSH feature vector is $N$, glyphplots are plotted by plotting the multidimensional scatter plot with $N$ variables, one variable corresponding to each RUSH feature.

Figure 7.7 (a) & (b) correspond to glyphplots of GA optimised RUSH feature space with 200 and 17 features respectively. In both the figures, every pair of glyph symbols corresponds to the GA optimised RUSH features of a person. For example, the glyph symbols numbered 1 & 2 look identical and they correspond to the proposed RUSH features of an individual ear biometric. They are also unique from the remaining glyph symbols in both Figure 7.7(a) and 7.7(b). This is applicable to all pairs of glyph symbols with every pair belonging to an individual. Thus, it is visually evident that both the GA optimised RUSH features are highly discriminative and can very well be used for pattern recognition.

7.6 PERFORMANCE MEASURES AND PERFORMANCE CURVES

The performance of proposed ear recognition system using extracted RUSH features is tested using simple distance based classifiers as well as $K$-nearest neighbour classifiers. The proposed recognition methodology is tested using both IIT Delhi ear image database as well as internal ear database images. Few case studies are performed to evaluate the performance of the investigated ear recognition system.
7.6.1 Case 1: Test and Evaluation datasets with untrained ear instances of enrolled persons

In order to test the performance of the system, the training dataset is prepared from IIT-D database consisting of ear images of 25 persons with 2 instances per person. Both test and evaluation data sets consist of trained as well as untrained instances of these 25 persons. So, train dataset consists of 50 ear images with 2 images per person. Test and Evaluation datasets are taken to be mutually exclusive and they have 39 ear images and 36 ear images respectively. Both test and evaluation datasets contain ear images rotated to an angle of 5° as well as blurred versions of ear images in training dataset as shown in Figures 7.4 (b) - (c) and Figure 7.5 respectively. This is done to ensure the robustness of the proposed ear recognition algorithm against rotations (up to 5°) and also invariance against illumination.

After suitable preprocessing, the proposed RUSH features are extracted from the segmented ear regions and 200 features out of 285 features are selected using GA based feature selection algorithm. These optimum RUSH features are used for recognition using the K-Nearest Neighbour distance based classifier with city block distance measure and K<=3. Figure 7.8 shows recognition rates for actual RUSH features plotted against various values of K in K-nearest neighbour classifier constructed with squared Euclidean distance measure and City block distance measure. Similar performance is obtained for GA optimised features with different values of K in K-NN classifier.

It is evident from our experiments that the performance of the proposed ear recognition is equally good with and without GA optimisation. City block distance measure has an excellent recognition rate of 94.87% with both GA optimised RUSH features and actual RUSH features for K-NN classifier with K<=3. However the advantages of GA based feature selection in the present investigation are better explained with the help of performance curves.
The performance of the investigated ear biometric recognition system is evaluated by plotting various performance curves such as Receiver Operating Characteristic (ROC) curve, Cumulative Match Characteristic (CMC) curve and Expected Performance Characteristic (EPC) curve.

Figure 7.8 Recognition rate (%) Vs Number of nearest neighbours

Figure 7.9 Receiver Operating Characteristic curve for RUSH features
These performance curves are plotted for feature extraction using GA optimised RUSH features and that using actual RUSH features in the proposed ear recognition model. ROC curve is plotted in two ways – either by plotting False Accept Rate (FAR) Vs False Reject Rate (FRR) or by plotting Verification Rate Vs False Accept Rate (FAR). Both such ROC curves are obtained as shown in Figures 7.9 and 7.10 respectively by varying the decision threshold while calculating the distance between the feature vectors belonging to test / evaluation dataset and training dataset.

It is obvious from Figure 7.9 that the False Accept Rate (FAR) is lower for GA optimised RUSH features than for actual RUSH features. FAR is closely related to inter class similarity and False Rejection Rate (FRR) is closely related to intra class variance (Liu H et al. 2011). The scenario of imposters incorrectly accepted by the biometric system leads to False Accept and the rate at which imposters are accepted is called False Accept Rate (FAR). The important reason for False Accept is the existence of interclass similarity between features belonging to different classes. On the other hand, the scenario of genuine users being rejected leads to False Reject and the rate at which genuine users are rejected is called False Reject Rate (FRR). The major reason for False Reject is the existence of intra class variance between features belonging to different instances of a particular class.

Optimum RUSH features with a fair interclass variance and negligible intra class variance are selected using GA and mutual information to achieve FAR of 15.7%.
Also, it is evident from the second type of ROC curve plotted in Figure 7.10 that the Verification Rate is improved by 6% in the case of GA optimised RUSH features.

ROC curves are of significance in a biometric verification system, a biometric system executing Enrolment and Verification phases. For a biometric identification system executing Enrolment and Identification phases, Cumulative Match Characteristic (CMC) curves are of important. The CMC curve for the proposed ear biometric system in identification mode is plotted as shown in Figure 7.11.
Figure 7.11  Cumulative Match Characteristic curve of an Identification system for RUSH features

Figure 7.11 shows the Cumulative Match Characteristic (CMC) curve of the proposed ear biometric system in identification mode, which is obtained by plotting Recognition Rate against various rank values. Here, rank refers to the number of top matches from the training dataset with the probe (test or query) ear image.

Rank one refers to the topmost match from training dataset with the probe image. It is evident from above figure that the CMC characteristic curve is equally good for GA optimised RUSH features and actual RUSH features. The Rank one Recognition rate (corresponding to the topmost match) is obtained to be 94.87 % which is also obtained using K-NN classifier with city block distance as shown in Figure 7.8.
Figure 7.12 Expected Performance Characteristic curve for RUSH features

Figure 7.12 shows the Expected Performance Characteristic (EPC) curve obtained by plotting Half Total Error Rate (HTER) against various values of the cost parameter, \( \alpha \) (Alpha). This cost parameter corresponds to a weighting factor which controls the relative importance of False Accept Rate (FAR) and False Reject Rate (FRR) (P Peer et al. 2014, Galbally J et al. 2013) by minimising the Weighted Error for various values of cost parameter \( \alpha \), as given in Equation 7.1. So, the EPC curve reflects the expected performance of the investigated ear biometric system for verification applications.

\[
\text{WER}(T, \alpha) = \alpha \text{FAR}(T) + (1-\alpha) \text{FRR}(T)
\] (7.1)

For the present case study, the training set consists of 50 ear images of 25 persons with 2 images per person. The test and evaluation datasets consist of 36 images and 39 images respectively. The training dataset is used to find the decision threshold \( T \) by minimising Equation 7.1. The estimated
threshold, $T$ is applied on the test dataset and Half Total Error Rate (HTER) is calculated for various values of $\alpha$ and for the estimated decision threshold say, $T$. Finally EPC curve is plotted for the calculated values of HTER on the Test dataset against various values of cost parameter, $\alpha$. It is evident from Figure 7.12 that the Half Total Error Rate (HTER) for various values of $\alpha$, is lower for GA optimised RUSH features than that for actual RUSH features.

7.6.2 Case 2: Effect of left and right ear symmetries on ear recognition

The purpose of this case study is to analyse the effect of degree of symmetry (or asymmetry) of human left and ear images on ear recognition by conducting two experiments. The internal ear database is used for this study and it consists of 36 ear images of 18 persons with 2 images per person. The sample ear images from this internal ear database are shown in Figure 7.2. For experiment 1, the training dataset is prepared from actual left images and right ear images. Test and evaluation datasets consist of actual left & right ear images. Test and evaluation datasets consist of actual left & right ear images.

For experiment 2, the training dataset is prepared from actual left images and the flipped versions of the corresponding left images. Test and evaluation datasets consist of actual left and right ear images. Table 7.2 illustrates the specifications taken for two experiments to study the effect of degree of ear symmetry on recognition. The proposed RUSH features are extracted from ear images in all three datasets during enrolment and recognition phases.
Table 7.2 Specifications of internal ear database for extraction of RUSH features

<table>
<thead>
<tr>
<th>Specifications</th>
<th>Experiment 1</th>
<th>Experiment 2</th>
</tr>
</thead>
<tbody>
<tr>
<td>Training dataset</td>
<td>Actual Right and Left ear images (36)</td>
<td>Actual Left ear images and flipped Left ear images (36)</td>
</tr>
<tr>
<td>Test and Evaluation datasets</td>
<td>Actual Right and Left ear images (36)</td>
<td>Actual Right and Left ear images (36)</td>
</tr>
<tr>
<td>Sub image block size (pixels)</td>
<td>8 x 8</td>
<td>8 x 8</td>
</tr>
<tr>
<td>Dimensionality (features)</td>
<td>285</td>
<td>285</td>
</tr>
</tbody>
</table>

Person recognition is carried out using simple distance based classifiers and K-NN classifiers with City block distance measure. The following inferences are obtained during both the experiments and are tabulated in Table 7.3.

Table 7.3 Inferences about ear recognition on internal ear database

<table>
<thead>
<tr>
<th>Inferences</th>
<th>Experiment 1</th>
<th>Experiment 2</th>
</tr>
</thead>
<tbody>
<tr>
<td>Rank one Recognition Rate (%)</td>
<td>95</td>
<td>72.22</td>
</tr>
<tr>
<td>Verification rate at 1% FAR (%)</td>
<td>61.11</td>
<td>61.11</td>
</tr>
<tr>
<td>Verification rate at 0.1% FAR (%)</td>
<td>55.56</td>
<td>55.56</td>
</tr>
<tr>
<td>Minimal HTER on Evaluation dataset (%)</td>
<td>14.87</td>
<td>14.05</td>
</tr>
</tbody>
</table>

It is evident from the above experiments that the Rank one recognition rate using RUSH features when the biometric system is trained with actual left and flipped ear images, is found to be 72.22% (based on city block distance measure) which is about 23% less than that obtained for training set with actual left and right ear images. This is in agreement with the experimental results of study of symmetry in human ears done on WVU Ear
Database by constructing 2.5D models of ears called Shape From Shading (SFS) approach (Abaza A et al. 2013). Using SFS approach, Rank 1 recognition rate was obtained to be 49.06% by including flipped ear images in the test dataset and 84.87% by including actual ear images in the test dataset.

![Figure 7.13 Experiments for ear asymmetry on recognition](image)

The difference in matching scores using normalized city block distances between Experiments 1 & 2, say, $d_1$ is calculated. Also the difference in matching scores between Experiment 1 & Imposters, say $d_2$ is also calculated (Abaza A et al. 2010). Performing t-test over these distributions, it is found that the difference between $|d_1 - d_2|$ is significantly different with p value < 0.02.

It is evident from this study that ear biometric has uniqueness with an inherent asymmetry between a left ear image and its counterpart. This degree of asymmetry observed between both ears of a human makes it a viable biometric tool for human recognition.
7.7 PROPOSED EAR RECOGNITION METHODOLOGY Vs CONVENTIONAL TECHNIQUES

The proposed ear recognition methodology is compared with conventional ear recognition techniques such as Uniform Local Binary Pattern (ULBP), Principal Component Analysis (PCA), Local Phase Quantization (LPQ) and Binarized Statistical Image Features (BSIF) (Benzaoui A et al. 2014) on IIT Delhi ear database and the following inferences are obtained as in Table 7.4.

Table 7.4 Comparison of proposed and few existing ear recognition techniques

<table>
<thead>
<tr>
<th>Inferences</th>
<th>Proposed RUSH +GA +KNN</th>
<th>Proposed RUSH +KNN</th>
<th>PCA +KNN</th>
<th>ULBP +KNN</th>
<th>LPQ +KNN</th>
<th>BSIF +KNN</th>
</tr>
</thead>
<tbody>
<tr>
<td>Sub image block size</td>
<td>8 x 8</td>
<td>8 x 8</td>
<td>8 x 8</td>
<td>8 x 8</td>
<td>8 x 8</td>
<td>8 x 8</td>
</tr>
<tr>
<td>Feature vector length</td>
<td>200</td>
<td>285</td>
<td>100</td>
<td>59</td>
<td>256</td>
<td>256</td>
</tr>
<tr>
<td>Recognition time / feature vector (ms)</td>
<td>0.7</td>
<td>1.9</td>
<td>2.6</td>
<td>7</td>
<td>6.5</td>
<td>10</td>
</tr>
<tr>
<td>Rank one Recognition Rate (%)</td>
<td>94.27</td>
<td>94.27</td>
<td>84</td>
<td>73.33</td>
<td>93.33</td>
<td>86.66</td>
</tr>
</tbody>
</table>

It is observed that the Recognition time is decreased by 10 fold in the proposed RUSH+GA+KNN technique when compared to the ULBP+KNN technique and hence the proposed method is found to be
computationally efficient for human recognition as the UMRT can be computed very fast owing to its integer operations in texture computation.

7.8 SUMMARY

Thus this chapter has illustrated the results of various modules in the proposed ear recognition framework discussed in Chapter 4. Discriminative features which are robust against illumination variations and rotations are generated using the proposed Robust UMRT texture, Shape and Histogram features extraction methodology. The proposed methodology is tested on ear images from IIT Delhi and internal ear databases. The robustness against illumination changes and rotations (upto 5°) is verified by including the rotated and blurred images of actual ear images in the test and evaluation datasets. Further, to reduce the training time as well as recognition time of proposed RUSH features, optimum RUSH features are selected based on GA and mutual information in such a way that the interclass variance is maximised and intra class variance is minimised. The discriminative nature of both actual RUSH features and GA optimised RUSH features is visually studied with the help of glyphplots (multidimensional scatterplots) also.

Performance curves such as ROC, CMC and EPC curves are plotted for analysing the performance of the proposed framework. The proposed ear biometric recognition methodology works very well as an identification system and as a verification system with Rank-one Recognition rate of 94.27% and an appreciable Verification Rate under varying illumination conditions and in the presence of rotations which proves the robustness of the proposed system against rotations and noise. Further the recognition time of the order of 0.7 ms for a single feature vector suggests the practicability of the proposed RUSH features in a real time scenario. The impact due to asymmetry of human ear on ear recognition and the uniqueness of both ears of an individual are also studied using the internal ear database.
Finally, the proposed ear recognition methodology is compared with the conventional ear recognition techniques such as ULBP+KNN, PCA+KNN, LPQ+KNN and BSIF+KNN. It is evident that the proposed ear biometric recognition framework using RUSH features shows commendable performance with respect to recognition time, training time and recognition rate. This suggests the potential use of RUSH features in real life biometric systems using ear modality for a variety of commercial and defence applications.