CHAPTER 5

FACE RECOGNITION SYSTEM

Human face is a powerful means of communication. It is used not only to identify one from another constantly, naturally and effortlessly, but also to transmit information about the human feelings (Colmenarez et al 2004). All faces are similar in features and structure, yet they are very much different from each other. In most face recognition approaches, the goal of the system is to find a similarity measure invariant to facial expressions head pose, and illumination changes so that images of faces can be successfully matched in spite of these variations.

5.1 PROPOSED FACE RECOGNITION SYSTEM

The proposed face recognition system exploits the extraction of global features from the given query face image and local discriminative features from the transformed query face image (Su et al 2009). Here, the global features are extracted from the whole face image by extracting the standard deviation features from the Gabor transformed output images, which encodes the holistic facial information, such as facial contour. Local features are extracted by applying multi-resolution transforms to the selected local patches such as eyes, nose and mouth of the query face image. Both these global and local features are combined to form the final feature vector, which is used for recognition.
Figure 5.1 (a) depicts the enrollment phase and Figure 5.1 (b) depicts the recognition phase of the proposed face recognition system by performing matching of face images using Manhattan distance (Md) measures.

![Block Diagram of the Proposed Face Recognition System](image_url)

**Figure 5.1** Block Diagram of the Proposed Face Recognition System
(a) Enrollment Phase and (b) Recognition Phase
5.2 EXTRACTION OF GLOBAL FEATURES

The 2-D Gabor Wavelet Transform (GWT) is adopted for global feature extraction. The Gabor Wavelet Transform (GWT) is a discretized version of a continuous function for which, continuous derivations can be calculated. Each input face image is decomposed using Gabor Wavelet Transform with five scales and eight orientations, in order to extract the global facial features from the forty Gabor sub-band images. To compute the local facial features, the four local patches namely, left eye, right eye, nose and mouth regions have to be selected from the input facial image.

5.3 SELECTION OF LOCAL PATCHES

The four local patches such as left and right eyes, nose and mouth are selected from the input face image. For the eye patches selection, a point on the left pupil region is to be found first by scanning all the pixels from bottom to top (in order to avoid eyebrows and forehead hairs) and right to left (in order to avoid sideburn, if any) in the left upper half of the face image ‘I’ as follows:

- For each pixel in the input face image $I(i, j)$, five neighborhood pixels are considered in all the four directions (resembling a plus sign) and the average value of all the twenty one pixels is calculated.
- If the average value falls within the specified threshold, then the pixel is marked as white pixel; otherwise proceed to the next pixel.
- This procedure is followed for all the pixels in the range specified. The point of intersection of both rows and columns containing maximum white pixels is marked as estimated pupil region of the left eye.
- Now, a patch of desired dimension is selected around this pixel region, which is identified as the left eye patch.
Using similar procedure, another such patch is selected for the right eye from the input face image ‘I’. After computing the approximate midpoint from the centers of the two eyes patches, the nose patch is selected with the desired dimension. Again little down to the bottom of the selected nose patch, a patch for the mouth region is selected with appropriate size.

Figure 5.2 Locating Two Pupil Regions in the Eyes from (a) FERET (b) ORL and (c) Self-Built Face Images
Thus, four local patches (left eye, right eye, nose, mouth) are selected from each given input face images. For the ORL database, the left eye and right eye patches are of size 21 x 24 pixels. The size of the nose and mouth patches is 28 x 28 and 24 x 64 respectively. For the FERET and self-built database, size of the left eye and right eye patches are 32 x 32. The size of the nose and mouth patch is 48 x 48 and 32 x 72 respectively. The obtained outputs for approximately locating two pupil regions for the given input face image is shown in Figure 5.2 (a), (b) and (c) for FERET, ORL and self-built database respectively.

Figure 5.3 Selection of Four Local Patches from (a) FERET (b) ORL and (c) Self-Built Face Images
From the identified pupil regions, the local patches such as left eye, right eye, nose and mouth are selected as shown in Figure 5.3 (a), (b) and (c) for FERET, ORL and self-built database respectively.

5.4 MULTI-RESOLUTION TRANSFORM DECOMPOSITION OF FACE IMAGES

Gabor transform with five scales and eight orientations is applied to the input face image for global feature extraction and the obtained forty Gabor transformed sub-band images are shown in Figure 5.4.

Figure 5.4 Gabor Transformed Outputs for ORL Image
To these four individual local patches obtained from the ORL input image as shown in Figure 5.3 (b), Curvelet transform is applied with three scales and eight orientations. For the extraction of Ridgelet transformed features, all these four patches are resized to 64 x 64 pixels. The Curvelet and Ridgelet transformed outputs obtained for these four patches are shown respectively in Figure 5.5 (a) and (b).

**Figure 5.5**  (a) Curvelet Transformed and (b) Ridgelet Transformed Outputs from Four Local Patches of ORL Face Image
5.5 FEATURE EXTRACTION

Among the forty sub-bands of the Gabor transformed output, the standard deviation features are extracted empirically from the odd scales (i.e., 1, 3 & 5) and odd orientations (i.e., 1, 3, 5 & 7) of the sub-bands to form a global feature vector by summing the features obtained from each individual orientation. The feature vectors thus obtained are concatenated to form a global feature vector of size $1 \times 384$ for FERET and self-built face images and $1 \times 336$ for ORL images. For the four local patches of FERET and self-built face images, standard deviation features are extracted from the Curvelet and Ridgelet transformed outputs and the respective features are concatenated to form a local feature vector of size $1 \times 108$ and $1 \times 96$ respectively. For the four local patches of ORL face images, standard deviation features are extracted from the Curvelet and Ridgelet transformed outputs and the features are concatenated to form a local feature vector of size $1 \times 96$ for both the transforms.

These global and local feature vectors are concatenated to form the final feature vector from the Curvelet transformed images whose dimensions are $1 \times 492$ for FERET and self-built face images; and for the Ridgelet transformed image, it is $1 \times 480$. For the ORL face images, the final feature vector size is $1 \times 444$ and $1 \times 432$ for the Curvelet and Ridgelet transformed images respectively.

5.6 EXPERIMENTAL RESULTS AND DISCUSSION

The frontal view of the face images with different expressions and light illumination variations are considered for recognition from the self-built face database. For FERET database, all the 100 subjects are considered for training and testing phase. Two samples per subject and one sample per
subject are randomly chosen for training and testing purpose from the FERET database, resulting in 200 images for training and 100 images for testing. For ORL and self-built face database, six samples per individual and four samples per individual are randomly chosen for training and testing respectively. As ORL database contains a maximum of 40 subjects, 240 images and 160 subjects are considered for training and testing respectively.

In the case of self-built Face database, 100 subjects are considered which leads to 600 images and 400 images for training and testing purpose. The experimental results obtained from the developed face recognition system using Gabor, Curvelet and Ridgelet transforms is shown in Table 5.1. The overall recognition rate is much higher for the Curvelet transformed features than the Ridgelet transformed features for all the three database considered for experimentation.

### Table 5.1 Face Recognition Rate using Curvelet Transform and Ridgelet Transform Features

<table>
<thead>
<tr>
<th>Database</th>
<th>No. of subjects used</th>
<th>No. of images used for</th>
<th>CT Features</th>
<th>RT Features</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>training</td>
<td>testing</td>
<td>TP</td>
</tr>
<tr>
<td>FERET</td>
<td>100</td>
<td>200</td>
<td>100</td>
<td>74</td>
</tr>
<tr>
<td>ORL</td>
<td>40</td>
<td>240</td>
<td>160</td>
<td>157</td>
</tr>
<tr>
<td>Self-built</td>
<td>100</td>
<td>600</td>
<td>400</td>
<td>396</td>
</tr>
</tbody>
</table>

The graphical outputs of FAR versus FRR curve and the ROC curve for these three database are shown in Figure 5.6 through Figure 5.8. From these graphs, it is clearly seen that the False Acceptance and False Rejection Rates are more for the Ridgelet transforms features than the Curvelet transformed features.
Figure 5.6 Graphical Outputs of (a) FAR Versus FRR Curve and (b) ROC Curve for FERET Face Database
Figure 5.7 Graphical Outputs of (a) FAR Versus FRR Curve and (b) ROC Curve for ORL Face Database
Figure 5.8 Graphical Outputs of (a) FAR Versus FRR Curve and (b) ROC Curve for Self-Built Face Database
It is clearly seen from the graphical outputs of Figure 5.6 through Figure 5.8 that the Curvelet transformed features have higher recognition rate when compared to Ridgelet transformed features for all the three face database.

Yan et al (2011) work conducted experiments on the ORL database for 40 subjects with three training and seven testing samples and stated that the overall recognition rate was 97.3 %. Xianwei & Guolong (2012) experimental results showed that the recognition rate for the ORL database was 85 %. From Table 5.1, it is clear that the recognition rate for Curvelet transformed features is 98.13 % which is higher than the Ridgelet transformed features for the ORL database. The comparative results with the previously done works are shown in Table 5.2.

**Table 5.2 Performance Comparison with Yan et al (2011) and Xianwei & Guolong (2012)**

<table>
<thead>
<tr>
<th>Methodologies</th>
<th>Recognition Rate (in %)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Yan et al (2011)</td>
<td>97.30</td>
</tr>
<tr>
<td>Xianwei &amp; Guolong (2012)</td>
<td>85.00</td>
</tr>
<tr>
<td>Proposed method [For ORL database]</td>
<td><strong>98.13</strong></td>
</tr>
<tr>
<td>Proposed method [For FERET database]</td>
<td><strong>80.00</strong></td>
</tr>
<tr>
<td>Proposed method [For Self-built Face database]</td>
<td><strong>99.38</strong></td>
</tr>
</tbody>
</table>

For the FERET database, 40 subjects are considered with two training and one testing samples for experimentation. The recognition rate is 80 % and 22.5 % respectively for Curvelet and Ridgelet transformed features. For the self-built database, 40 subjects are considered with three training,
seven testing samples and recognition rates are respectively 99.38 % and 91.25 % for Curvelet and Ridgelet transformed features.

5.7 SUMMARY

From the exhaustive experiments conducted with the face recognition system, it is observed that the Curvelet transformed features improves the overall recognition rates for all the three face database under consideration. Hence, among the two transforms, Curvelet transform performs better than Ridgelet transform for the proposed face recognition system.

The next chapter describes the multimodal biometric recognition system that combines/fuses the scores of the best features extracted from the experiments conducted so far on the three biometric modalities namely iris, fingerprint and face images. By using different score normalization and score fusion techniques, the performance of the multimodal biometric recognition system is studied by assigning different weights to these three modalities.