CHAPTER VI

FACE RECOGNITION USING OLTP

To evaluate the performance of the proposed texture model OLTP in addition to texture analysis, this chapter is included in this thesis. In this chapter, proposed texture model OLTP was used in the face representation and recognition applications.

6.1 FACE RECOGNITION-AN OVERVIEW

Automatic face recognition system plays a vital role in computer vision and pattern recognition applications. In the present world, biometric identification is unavoidable in various security applications such as surveillance, computer-human interactions, video conference, airport security, etc. As face is one of the most important biometrics, automatic face analysis is a necessary step in the field of security applications and research fields. Though many commercial application systems for face recognition are available in market, face recognition system is still an active and challenging topic because commercial applications will not deliver the correct result under uncontrolled environments like variations of pose, expression, illumination, etc. As texture feature is an important factor in recognizing face images, for the last 25 years, many face representation approaches based on the texture features have been developed. Turk and Pentland [130] used Eigen faces for face recognition and another new technique called Elastic Bunch Graph Matching (EBGM) approach was initiated by Wiskott et al., [131] in which a face can be represented as a graph
by connecting many selected points in a face. A face authentication system based on Linear Discriminant Analysis (LDA) was developed by Kittler et al., [132]. Hidden Markov Models (HMM) and Gaussian Mixture Models (GMM) were successfully used for face authentication by Cardinaux et al., [133]. The local intensity distributions are combined with the spatial information in the name of multi-resolution spatial histogram for face recognition and this idea was developed by Hadjidemetriou et al., [134]. The LBP operator, a well recognized texture feature has also been acting as a major role in face recognition application [135]-[136]. Texture features combined with geometrical feature were proved to be successful in enhancing the quality of face recognition [137]. Likewise, Al-Osaimi et al., [138] combined texture feature with shape feature for face recognition.

Face recognition methods can be classified into features based methods and holistic methods [139]. Feature-based approaches identify and extract geometric relationships among the distinctive facial features such as the eyes, mouth, nose, etc. and then any pattern recognition techniques are employed to match faces using these measurements [140]. Holistic approaches identify faces using global representations, i.e., descriptions based on the entire image rather than on local features of the face. LDA and PCA are some well known methods that are applied in the holistic approaches for face recognition. The method that was used in this research, which is based on the proposed texture model OLTP falls into the category of feature based method.
6.2 FACE IMAGE DATASETS

This study selects publicly available and well recognized face databases namely Yale B and AR face databases for these experiments. These two selected face databases (Yale B and AR) are very much suitable for testing any face representation and face recognition experiments because these databases contain face images which were captured under different lighting conditions with different poses. Yale B face database consists of 38 subjects with 9 different poses and 64 different illuminations for every pose whereas the AR face database consists of 4,000 frontal images for 135 individuals (subjects). For each subject, up to 26 face images are available which are taken under different variations in illuminations, expressions, and occlusions. This research considered only frontal face images without any occlusions for this study.

6.3 FACE DESCRIPTION AND RECOGNITION ALGORITHM

This section discusses about the face recognition algorithm which was used in this experiment. Generally all the face recognition system consists of two major phases namely training phase and testing phase. The following algorithm illustrates the processing chain in the face recognition algorithm used for this study,

**Training Phase**

1. The input training image is selected.
2. Preprocessing is done. Preprocessing involves the process of cropping the face regions from the unwanted background regions by using an elliptical mask. Cropping was done with the help of eye coordinates that is based on the general assumption that the distance between two eyes is calculated and
the width of the face is roughly two times of the distance and the height of the face is three times of this distance.

3. The selected training image is divided into 8x8 non overlapped sub blocks which is shown in the Figure 6.1.

4. The selected texture model is applied over the sub blocks.

5. A one dimensional histogram is generated for each sub blocks.

6. A pattern spectrum is formed by concatenating all the one dimensional histograms derived for all the sub blocks. This pattern spectrum is the global face description of the given input training image.

7. This pattern spectrum is stored as the training feature in the database.

8. Steps 1 to 7 are performed repeatedly for all the training images and all the resulting features are stored in the database.

**Testing Phase**

1. The input testing image is selected.

2. Steps 1 to 7 of training phase are performed to extract the feature of this testing image.

3. The resultant pattern spectrum will represent the face description of the given input testing image. This feature is compared with all the training features in the database by using a similarity measurement called ‘Weighted Chi-square distance’ ($\chi^2$), which is defined in the equation 6.1.

$$\chi^2 (x, y) = \sum_{i,j} w_j \frac{(x_{i,j} - y_{i,j})^2}{x_{i,j} + y_{i,j}}$$  \hspace{1cm} \ldots (6.1)

![Figure 6.1](image)

**Figure 6.1** An example for the division of a face image into 8x8 non overlapped sub-blocks
where $x$ is the pattern spectrum of the testing image sample and $y$ is the pattern spectrum of the training image sample, $x_{i,j}$ is the frequency at bin $i$ of the sub block $j$ of the testing image pattern spectrum and $y_{i,j}$ is the frequency at bin $i$ of the sub block $j$ of the training image pattern spectrum. $w_j$ is the weight for sub block region $j$. Each region in the sub blocks of the selected image is assigned with a weight based on the important of the information it contains. The larger a weight is more important is the region. The Figure 6.2 shows the weights set for weighted dissimilarity measure. The black coloured sub blocks in the Figure 6.2 are given weight 2 because they contain useful information than other sub block regions and all other sub blocks are given weight 1.

4. Choose the correct match from the trained pattern spectrum database for which the given testing pattern spectrum is having a value of minimum weighted Chi-square distance ($\chi_w^2$).

### 6.4 COMPARATIVE RESULT ANALYSIS

This section is included for the comparative face recognition performance of four texture descriptors TS, LBP, LTP and OLTP. This study analyses the performance of selected texture models on face representation and face recognition application through the following assessment factors:

![Figure 6.2](image)

**Figure 6.2** An example for the weights set for the selected regions-black coloured region was given more weight than other sub-blocks
1. Face Recognition Rate
2. False Acceptance Rate (FAR), False Rejection Rate (FRR) and Equal Error Rate (EER)
3. False Acceptance Rate versus Genuine Acceptance Rate (GAR)
4. Processing Time Analysis

6.4.1 Face Recognition Rate

First the experiments are conducted on Yale B face database. This study uses only frontal face images and 15 subjects are taken for research. Four frontal images with controlled illumination variation from each selected subject are randomly selected for training and 16 frontal images from the remaining images of the same selected subjects are used for testing. All the selected images for this experiment are down sampled into 64x64 size and are converted into grey scale images before experiments. Using nearest neighbour classifier method the high similarity match of the testing sample with any one of the training sample is identified and such match is validated as either correct or incorrect based on the supervised knowledge. The Recognition Rate is calculated by,

\[
\text{Recognition Rate} \% = \frac{\text{No. of correct matches}}{\text{No. of test images}} \times 100.
\]

Figure 6.3 shows some sample images which are selected for this experiment. This experiment compares the face recognition performance of four texture descriptors TS, LBP, LTP and OLTP in the form of Recognition Rate. The comparison results of this experiment are shown in Table 6.1. From the above results on face recognition, it is noted that LBP performs better than TS whereas LTP performs superior to LBP. OLTP performs best over all the other texture methods namely, TS, LBP and LTP.
Secondly, another experiment was conducted on AR face database for finding the adaptability of this proposed face recognition system for various face databases. The AR face database consists of 4,000 frontal images for 135 individuals (subjects). For each subject, upto 26 face images are available which are taken under different variations in illuminations, expressions, and occlusions. For this experiment also, only frontal face images without any occlusions are considered. Twenty individuals (subjects) are selected first and then 20 frontal images that is one frontal image from each selected subject are used for training. One hundred frontal images from the remaining images of the
same selected subjects which include both gallery images as well as non gallery images are used for testing. All the selected images for face recognition are down sampled into 64x64 size and are converted into grey scale images before experiments. Figure 6.4 shows the sample images selected for this experiment. This experiment also compares the face recognition performance of texture descriptors TS, LBP, LTP and OLTP. The results obtained for this experiment is shown in Table 6.2 and from the results, it is clear that, OLTP was the best among all texture models used.

Figure 6.4   Sample images-from AR face database

Table 6.2: Face recognition accuracy results on AR face database

<table>
<thead>
<tr>
<th>No.of Training Images</th>
<th>No.of Testing Images</th>
<th>Texture Model</th>
<th>Recognition Rate(%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>20</td>
<td>100</td>
<td>TS</td>
<td>60.07</td>
</tr>
<tr>
<td></td>
<td></td>
<td>LBP</td>
<td>82.35</td>
</tr>
<tr>
<td></td>
<td></td>
<td>LTP</td>
<td>86.91</td>
</tr>
<tr>
<td></td>
<td></td>
<td>OLTP</td>
<td>90.88</td>
</tr>
</tbody>
</table>
6.4.2 False Acceptance Rate (FAR), False Rejection Rate (FRR) and Equal Error Rate (EER)

Generally a face recognition system is prone to two kinds of errors, namely False Acceptance Rate and False Rejection Rate. FAR is a measurement tool to calculate how many impostors are falsely recognized as authentic users whereas FRR is a measurement tool that tells how many genuine users are falsely recognized as imposters by the face recognition system. Figure 6.5 shows the relationship between FAR and FRR of a biometric authentication system and in this case, it is a face recognition system. The FAR and FRR of any biometric system depends on the reference threshold. If the reference threshold is low, then FAR of the system is very high and consequently false acceptance happens which means the system is prone to attack. When the reference threshold value is raised, FAR decreases but at the same time FRR increases. Therefore the aim of any biometric system should be to keep both FAR and FRR as small as possible.

Figure 6.5 The relationship of FAR, FRR with the reference threshold
FAR and FRR are calculated as follows

\[
\text{FAR (\%)} = 100 - \text{Recognition Rate}
\]

\[
\text{FRR (\%)} = 100 - \text{Rejection Rate}
\]

where

\[
\text{Recognition Rate(\%)} = \frac{\text{No. of correct matches}}{\text{No. of test images}} \times 100
\]

\[
\text{Rejection Rate(\%)} = \frac{\text{No. of correct rejection}}{\text{No. of test images}} \times 100
\]

For the evaluation of these error rates FAR & FRR of the proposed OLTP based face recognition algorithm, 15 selected subjects with 20 face images from each subject of the Yale B face database were selected and then they were divided into two groups such as 9 known subjects and 6 unknown subjects. The system is trained with 45 images of known subjects that are 5 face images from each subject. Testing is done with balance 255 images of both known and unknown subjects. Figure 6.6 shows the FAR and FRR produced by the proposed texture model OLTP based face recognition method, for the various thresholds of similarity measurements for the Yale B face database.

Assuming that the threshold of the systems is adjustable, there is no reasonable way to decide if a system with a higher FAR and a lower FRR performs better than a system with a lower FAR and a higher FRR value. The EER of a system can be used to give a threshold independent performance measure. From these two error rates FAR & FRR, another important technical value called EER can be derived.
Figure 6.6  FAR and FRR for various thresholds used in the face recognition system on Yale B face database

EER is the intersection point at which FAR and FRR are equal which is shown in the following Figure 6.7. The lower the EER value is, better is the system’s performance as the total error rate which is the sum of the FAR and FRR at the point of the EER decreases. So, it is understood that, the lower the EER value is, the better is the verification or recognition accuracy. Figure 6.8 depicts the value of EER when the proposed texture model Optimized Local Ternary Patterns was used with the face recognition method on Yale B face database.
Figure 6.7  The relationship of FAR, FRR with EER

Figure 6.8  The value of EER when OLTP texture model was used in the face recognition system on Yale B face database
Table 6.3 summarizes the EER values achieved by various texture models (TS, LBP, LTP and OLTP) for Yale B face database. So, from the details of Table 6.3, it can be concluded that among all the texture models considered for this experiment (TS, LBP, LTP and OLTP), the EER value for the newly proposed texture model OLTP is the lowest (4%). So, the newly proposed texture model OLTP can be used as a good face recognition tool also in addition to texture analysis applications.

6.4.3 False Acceptance Rate (FAR) versus Genuine Acceptance Rate (GAR)

This section deals with one more assessment factor, namely Genuine Acceptance Rate for biometric authentication system. Genuine Acceptance Rate is another important measurement for finding the overall accuracy of any biometric system. GAR is calculated as follows:

\[
\text{Genuine Acceptance Rate} = 1 - \text{False Rejection Rate (FRR)}
\]

Table 6.3: Comparative analysis of EER values for various texture models on Face Recognition

<table>
<thead>
<tr>
<th>S. No</th>
<th>Texture Model</th>
<th>Equal Error Rate (EER)%</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>TS</td>
<td>8.1</td>
</tr>
<tr>
<td>2</td>
<td>LBP</td>
<td>6.2</td>
</tr>
<tr>
<td>3</td>
<td>LTP</td>
<td>5.3</td>
</tr>
<tr>
<td>4</td>
<td>OLTP (proposed)</td>
<td>4</td>
</tr>
</tbody>
</table>
To compare any biometric system, the GAR of that system with the specific FAR, should be compared with any other biometric systems and the system with the highest GAR rate is considered to be the most accurate. To prove the efficiency of the proposed texture model OLTP on face recognition system in a comprehensive way, this research finds the GAR values for the varying FAR values for all the texture models that are used in this comparative study.

For this evaluation study, 15 selected subjects with 20 face images from each subject of the Yale B face database are selected and then divided into two groups such as 8 known subjects and 7 unknown subjects. The system is trained with 40 images of known subjects that are 5 face images from each subject. Testing is done with balance 260 images of both known and unknown subjects. Generally, FAR and GAR are mapped against each other on a graph called Receiver Operating Characteristic (ROC). Receiver Operating Characteristic curve is used for measuring the accuracy of any biometric system at a particular confidence level, in this case it is FAR (False Acceptance Rate). The texture model with highest GAR at a particular level of FAR is always considered as the best biometric matcher.

Figure 6.9 shows the results of this experiment in the form of a Receiver Operating Characteristic curve. From the Figure 6.9, it can be easily concluded that, for all the FAR values, the corresponding GAR values for the proposed texture model OLTP are relatively higher than all other texture models considered in this comparative study. The result of this comparative study once again proves that, the proposed texture model OLTP can be a perfect tool for the face recognition method also in addition to texture analysis applications.
6.4.4 Processing Time Analysis

In order to evaluate the performance of the selected four texture models for the benchmark of execution time, a set of 4 different frontal face images from 10 different subjects are randomly selected from the frontal face images of Yale B face image database.

Figure 6.10 illustrates the average computational cost for the selected subjects, taken by the four texture methods for face recognition. As TS model is using very large number of bins in the pattern histogram (6561), it took more execution time for giving the result. In the case of LBP, since this texture model uses 256 patterns it took less time than LTP and TS for giving the output. LTP performs better than TS but less than OLTP. OLTP gives the
Figure 6.10  Computational cost analysis for the face recognition experiments on Yale B face database

results in the minimum time. This experiment is conducted on AR face database also for finding the adaptability of this proposed face recognition system for various face databases. To study the performance evaluation of various texture models based upon the execution time for face recognition problem on AR database face images, 40 frontal face images are randomly selected from 8 individuals that is in the manner of 5 from each subject.

Figure 6.11 shows the average computational cost for the selected four texture models for the face recognition over each subject. Obviously as TS model is using large number of bins in the pattern histogram (6561), it took
more execution time for giving the result. As expected, in the case of LBP, since this texture model uses 256 patterns it took less time than LTP and TS, for giving the output. Though LTP gave the result in less time compared to TS, its time complexity is high when compared with OLTP and LBP. Moreover, it is clearly observed that OLTP outperforms all other selected texture models in this experiment of time complexity analysis on face recognition. It can be observed that, OLTP outperforms all other texture models in the process of face recognition because it gave best performance in all assessment factors.