2.5D Face Recognition Using Gabor Discrete Cosine Transform

Ali Cheraghian, Farshid Hajati, Soheila Gheisari, Yongsheng Gao

Abstract—In this paper, we present a novel 2.5D face recognition method based on Gabor Discrete Cosine Transform (GDCT). In the proposed method, the Gabor filter is applied to extract feature vectors from the texture and the depth information. Then, Discrete Cosine Transform (DCT) is used for dimensionality and redundancy reduction to improve computational efficiency. The system is combined texture and depth information in the decision level, which presents higher performance compared to methods, which use texture and depth information, separately. The proposed algorithm is examined on publicly available Bosphorus database including models with pose variation. The experimental results show that the proposed method has a higher performance compared to the benchmark.

Keywords—Gabor filter, discrete cosine transform, 2.5D face recognition, pose.

I. INTRODUCTION

Face recognition has been an active area of research for many decades. It still remains a challenging problem due to the complexity and variability of human face images. One of the challenges in the face recognition is pose variation. Algorithms presented for pose variation are divided in two main categories depends on the type of gallery images [1]. The first category consists of multi-view face recognition systems, which require several poses for each subject in the gallery. The second category identifies probe faces, which have different poses compared to the gallery. In real applications, a frontal face is in the gallery while probe faces have unpredicted pose variations. Therefore, the system should be robust to these pose variations.

Local Binary Pattern (LBP) [2] is applied for feature extraction. Compared to holistic approaches, LBP is more robust to pose changes because it does not require exact locations of patterns but relies just on the histogram of the pattern in a region. Recently, a high-order local pattern descriptor, local derivative pattern (LDP) [3], is proposed for robust face recognition. LDP is a micro-pattern representation, which can also be modeled by histogram. Liu and Chen [4] proposed a Probabilistic Geometry Assisted (PGA) face recognition algorithm to handle pose variations. In their algorithm, human heads are approximated as an ellipsoid whose radiiuses, locations, and orientations are estimated based on a universal mosaic model.

II. PROPOSED GABOR DISCRETE COSINE TRANSFORM (GDCT)

The overall scheme of the proposed method is shown in Fig. 1. The proposed method consists of four steps: Preprocessing, Gabor filter, Discrete Cosine Transform, and Classifier. The detail of each step will be described in the following:
where \( z = \left( z_x, z_y \right) \), \( k_{u,v} = \left( k_{u}, k_{v} \right) = \left( k_{u} \cos \phi_{u}, k_{v} \sin \phi_{v} \right) \), \( k_{v} = \frac{\pi}{2\sqrt{m^2+n^2}}, \phi_{v} = u(\pi/8), v = 0, \ldots, v_{\text{max}} - 1 \), \( u = 0, \ldots, u_{\text{max}} - 1 \), \( v \) is the frequency, \( u \) is the orientation, \( v_{\text{max}} = 5 \), \( u_{\text{max}} = 8 \) and \( z = 2\pi r \).

In this paper, five different scales and eight different orientations are used. Each image has two Gabor parts: amplitude and phase. Here, we just use the amplitude part for face recognition. For each pixel of the image, we have totally 40 Gabor magnitude coefficients, so we can obtain 40 Gabor magnitude and 40 Gabor face images from a single input face image.

C. Discrete Cosine Transform (DCT)

In this study, Discrete Cosine Transform (DCT) is applied to reduce the dimensionality and redundancy of the Gabor images for face recognition. DCT transforms images from the spatial domain to the frequency domain, where an image is decomposed into a combination of various and uncorrelated frequency components. DCT is able to extract the features in the frequency domain to encode different facial details that are not directly accessible in the spatial domain. Due to the specific properties, DCT has been successfully applied in face recognition systems [13].

The two-dimensional DCT of an image \( A \) with size \( M \times N \) is defined as,

\[
B_{pq} = a_p d_{pq} \sum_{m=0}^{M-1} \sum_{n=0}^{N-1} A_{mn} \cos \left( \frac{\pi (2m+1)p}{2M} \right) \cos \left( \frac{\pi (2n+1)q}{2N} \right)
\]

\[
a_p = \begin{cases} \frac{1}{\sqrt{M}}, & p = 0 \\ \frac{2}{\sqrt{M}}, & 1 \leq p \leq M - 1 \\ 0, & p > M - 1 \end{cases}
\]

\[
a_q = \begin{cases} \frac{1}{\sqrt{N}}, & q = 0 \\ \frac{2}{\sqrt{N}}, & 1 \leq q \leq N - 1 \\ 0, & q > N - 1 \end{cases}
\]

To obtain the feature vector representing a face, its DCT is computed, and only a subset of the obtained coefficients is retained. Different DCT coefficients are corresponding to different spatial information. The upper-left subset in the DCT domain encodes most of the energy in a face image. Based on this assumption, a sub-image with size 20x20 is selected starting from the upper-left region.

D. Classifier

In this paper, k-Nearest Neighbor method [14] is used for classification. In this method, we classify \( x \) by assigning it to the class label \( \hat{c} \) (most frequently represented among the k-nearest neighbors) which has the minimum distance among all the classes,

\[
d(x, x_{c_i}) = \min_{1 \leq c_i \leq \text{class}} d(x, x_{c_i})
\]

where, \( d(x, x_{c_i}) = ||x - x_{c_i}|| \) is the Euclidean norm of the vector.

Texture and depth data are combined in the decision level. Combination of the 2D and 3D systems has been performed by the weight factor \( w \) as in (4).

\[
D = \frac{1}{2} d^2 + w \times d^2
\]
where \( d_T \) is the distance from the gallery set of the texture image and \( d_D \) is the distance from the gallery set of the depth image. The weight factor \( w \) is determined in a training process.

### III. EXPERIMENTAL RESULTS

In this section, we evaluate the robustness of the proposed method under different face rotations. In this experiment, we used the publically available Bosphorus database [15], which contains 2.5D face images in different rotations. This database has 105 subjects. Facial data are acquired using a structured-light based 3D system. Acquisitions are single view, and subjects were made to sit at a distance of about 1.5 meters away from the 3D digitizer. The sensor resolution in x, y, and z (depth) dimensions are 0.3mm, 0.3mm, and 0.4mm respectively, and color texture images are high resolution (1600x1200 pixels). We use faces with 10º, 20º, and 30º pose rotation in this study. Fig. 3 illustrates an arbitrary subject from the database in different pose rotations.

At first, we should find the value of the weight factor in the proposed algorithm. 105 subjects with 10, 20 and 30 degrees pose rotations were selected randomly, and the rank-1 recognition rate of the system was obtained for various values of weight factor and considering the \( w \) corresponding to the maximum recognition rate. For those values of \( w \) which are close to zero and for very large amounts of \( w \), the performance of the proposed method approaches to the performance of the system which is based just on the texture data and depth data, respectively. For some specific values of \( w \), the performance of the proposed method becomes the maximum.

Fig. 3 Some examples of Bosphorus database: (a) Frontal, (b) Right-turn 10º (respect to Y axis), (c) Right-turn 20º (respect to Y axis), (d) Right-turn 30º (respect to Y axis)

In this study, for those values of \( w \) between 5 and 20, the optimum state of the system efficiency is achieved. For these values of \( w \), the system performance reaches 95%. The results of this experiment are shown in Fig. 4. As can be seen, the recognition rate of the system for \( w=5,\ldots, 20 \) is the maximum. Therefore, we set \( w=12.5 \) in the following experiments.

![Fig. 4 Recognition rate versus w](image)

![Fig. 5 Cumulative Match Characteristics](image)

Since our goal is to recognize faces with pose variation from one sample per person, one frontal face with neutral expression of each person is utilized for the gallery and other faces are used as the probe. In this experiment, system is examined by faces, which have pose rotation in right directions (10º, 20º and 30º). Comparison of the recognition rates for the proposed method with 2D and 3D systems in term of Commutative Match Characteristics (CMC) is depicted in Fig. 5. As can be seen, the recognition accuracy of the proposed method is considerably improved when the depth and the texture information are combined. For 10º pose rotation, the performance of the proposed system (97%) is improved 2% and 8% compared to the texture and the depth data, respectively. For 20º pose rotation, the performance...
(95%) improved 5% and 10% compared to the texture and the depth data, respectively. Finally, for the 30° pose rotation, the system accuracy (85%) gained 5% and 15% improvement compared to the texture and the depth data, respectively. As a result, the texture data has better performance compared to the depth data and is more robust to pose variations. After the fusion of the depth and the texture data in the decision level, the proposed method has a better performance.

The proposed method is also compared with multimodal PCA as a benchmark. In the multimodal PCA algorithm [7], the PCA is used for feature extraction and combination of 2D and 3D information. The results of the comparison are tabulated in Table I. It is clear that the proposed method has a better performance. For the faces with 10° pose rotation, the performance of the proposed method improved 5.6% compared to the benchmark. In addition, for faces with 20° and 30° pose rotation, around 5.5% and 16.5% improvement is observed. It is obvious that for the faces with large pose rotation, the efficiency of the proposed method is much higher than the performance of the b.

TABLE I

<table>
<thead>
<tr>
<th>Considered Rotation</th>
<th>Multimodal PCA</th>
<th>Proposed Method</th>
</tr>
</thead>
<tbody>
<tr>
<td>10° right</td>
<td>91.4%</td>
<td>97%</td>
</tr>
<tr>
<td>20° right</td>
<td>89.5%</td>
<td>95%</td>
</tr>
<tr>
<td>30° right</td>
<td>68.5%</td>
<td>85%</td>
</tr>
<tr>
<td>Average</td>
<td>83.1%</td>
<td>92.3%</td>
</tr>
</tbody>
</table>

IV. CONCLUSION

In this paper, a 2.5D face recognition method based on Gabor Discrete Cosine Transform (GDCT) feature was presented. This method combined 2D and 3D information in the decision level, which was shown a higher performance than systems use separate information. A sufficient investigation was considered on the pose variation problem in the face recognition. The results of the experiments demonstrated significant accuracy improvement compared to the benchmark. According to the obtained experimental results, the proposed method achieved the overall recognition rate of 92.3% on faces with pose variation compared to 83.1% for the benchmark.

REFERENCES