INTRODUCTION

This work concerns the face recognition task and, in particular, the distortion of face images by partial occlusions and various expressions. The subspace-based technique is the one of most popular for finding low-dimensional representation subspaces that are embedded in a high-dimensional face space. Motivated by the work on Euler representation, we propose a locality-preserving complex-valued Gaussian process latent variable model (LP-CGPLVM) to learn a complex-valued representation of face image.

MAIN CONTRIBUTIONS

1. The learned complex-valued representation supports facial recognition that is robust against partial occlusion and various expressions.
2. A locality-preserving based complex prior distribution over complex-valued low-dimensional representations is developed. The MAP estimation of representation preserves not only global structure but also locality structure of face data.

CONCLUSION

• The potential of using complex-valued representation for occluded face images was studied.
• The results for visualizations of face images revealed that the introduced complex prior distribution makes the complex-valued representations more discriminative.
• Experimental results showed that the proposed method is more robust than baselines for facial images with simulated occlusions and practical occlusions.

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PROPOSED METHOD

I. Robust Transformation

The cosine-based dissimilarity measure yields a shorter distance between face image and its associated occluded image than does the Euclidean norm. It can be equivalently computed using the Euler formula which maps pixel value $y_i$ of image into complex data $z_i$,

$$z_i = \frac{1}{\sqrt{2}} (e^{i\alpha}y_{i1}, \ldots, e^{i\alpha}y_{in})$$

where $\alpha$ is a constant.

II. Complex-valued Facial Representation

With the robust transformation, the CGPLVM [1] is utilized to learn a complex-valued low-dimensional representation $W$ of image in complex domain. The objective of CGPLVM is

$$\ln p(Z|W) = -DN \ln \pi - D \ln |T_c| - \text{tr}(T_c^{-1}Z^H)Z$$

where $T_c$ is a kernel matrix.

III. Locality-preserving Training

To incorporate the locality-preserving term into the CGPLVM, the complex prior distribution over low-dimensional representation $W$ is introduced.

$$p(W) = \frac{1}{Z_d} \exp \left( - \frac{1}{2\sigma^2} \text{tr}(WLW^H) \right)$$

where $L = E - S$ is a Laplacian matrix and $E_{nm} = \sum_m S_{mn}$ with $S$ is computed as

$$S_{mn} = \begin{cases} 
\exp(-\|y_n - y_m\|^2/\rho) & : \epsilon(y_n, y_m) = 1 \\
0 & : \epsilon(y_n, y_m) = 0 
\end{cases} \quad \epsilon(y_n, y_m) = \begin{cases} 
1 & : y_n, y_m \text{ belong to the same subject and } \rho \text{ is a constant.}
\end{cases}$$

IV. Prediction

For a new test image $x'$, the low-dimensional representation $w'$ can be estimated by optimizing the objective $L$ with an uninformative prior of $w'$,

$$L(w') = -\ln |\sigma^2(w')L| - \frac{1}{2\sigma^2} \text{tr}(w'L^{-1}w) - \frac{1}{2} \|w'\|^2$$

where

$$\mu(w') = Z^H T_c^{-1}$$

$$\sigma^2(w') = k_c(w', w') - k_c^H T_c^{-1} k$$

$$k = [k_c(w, w'), \ldots, k_c(w, w')]^T$$

VISUALIZATION

- Database: MHMC [2] and YaleFace database
- Size of random block: 60 × 65 to 85 × 85 pixels
- Baselines: PCA, NMF, GSNMF, GPLVM, and CGPLVM
- In YaleFace database, M non-occluded images were randomly selected and masked using a block of size 55 × 85. An occluded image (glasses) and M artificially occluded images ($M = 3, 4, 5$) from each subject are used for testing. The remaining $N$ images are used for training ($N = 5, 6, 7$).

EXPERIMENTAL RESULTS

Table 1: Recognition rates for various numbers of training samples ($N$) on YaleFace.

<table>
<thead>
<tr>
<th>$N$</th>
<th>5</th>
<th>6</th>
<th>7</th>
</tr>
</thead>
<tbody>
<tr>
<td>PCA</td>
<td>86.67</td>
<td>89.33</td>
<td>93.33</td>
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<tr>
<td>NMF</td>
<td>87.78</td>
<td>92.00</td>
<td>90.00</td>
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<td>GSNMF</td>
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<tr>
<td>GPLVM</td>
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<tr>
<td>CGPLVM</td>
<td>90.00</td>
<td>94.67</td>
<td>96.67</td>
</tr>
<tr>
<td>LP-CGPLVM</td>
<td>91.11</td>
<td>96.00</td>
<td>98.33</td>
</tr>
</tbody>
</table>

- Recognition rate of the proposed robust complex-valued representation exceeds those of the other real-valued representation methods on all occlusion block sizes.
- Comparison between the CGPLVM and the LP-CGPLVM confirmed the power of the locality-preserving term.

REFERENCES