Jointly Learning Multiple Curvature Descriptor for 3D Palmprint Recognition
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Palmprint recognition has becoming an increasing active biometrics.
- rich characteristics
- high user-friendliness

3D Palmprint Category
- 2D feature representation
- 3D feature representation

Motivation
There is still no work that investigates the discriminative feature learning and extraction from 3D palmprint. Therefore, we aim to leverage multiple curvature descriptor, such as MCDV and GCDV, for improved 3D palmprint recognition.

Model
We first obtain the multi-curvature information of a 3D palmprint, then learn the collaborative feature representation of the multiple data vectors for 3D palmprint recognition.

Algorithm 1 JLMCD
Input: Training data $X = [x_1, x_2, ..., x_n]$: Parameters $\alpha, \beta, \lambda_1, \lambda_2$; Convergence parameter $\varepsilon$; Maximum iteration number $T$;
1. Initialization: Initialize $W$ to the $K$ eigenvectors corresponding to the $K$ smallest eigen-values of $Y$.
2. for $t = 1$ to $T$
3. Fix $C$ and Update $W$ using (4); 4. Fix $W$ and Update $C$ using (5);
5. if $(t \geq 1) \& (\|\|W(t) - W(t-1)\||| < \varepsilon)$ break;
6. end
Output: $W$.

Table I. The Identification Results (Average Accurate Rates ± Standard Errors) of the Different Methods.

<table>
<thead>
<tr>
<th>Method</th>
<th>m=1</th>
<th>m=2</th>
<th>m=3</th>
<th>AVG</th>
</tr>
</thead>
<tbody>
<tr>
<td>CompCode</td>
<td>89.0394±1.0842</td>
<td>96.9753±1.363</td>
<td>97.394±1.3853</td>
<td>94.0452±4.5697</td>
</tr>
<tr>
<td>GLOF</td>
<td>83.1513±1.4410</td>
<td>91.933±3.4851</td>
<td>94.7041±2.2625</td>
<td>89.0556±6.0872</td>
</tr>
<tr>
<td>MCI/GCI ST</td>
<td>82.9221±1.3396</td>
<td>92.7039±1.7316</td>
<td>93.5838±1.6280</td>
<td>90.0494±6.7304</td>
</tr>
<tr>
<td>LHT</td>
<td>85.3632±0.9736</td>
<td>97.4528±0.9740</td>
<td>98.2206±0.9822</td>
<td>96.4622±2.3729</td>
</tr>
<tr>
<td>CST S</td>
<td>89.1763±1.8542</td>
<td>96.0199±2.1384</td>
<td>97.3205±1.9309</td>
<td>94.2467±4.2067</td>
</tr>
<tr>
<td>CBR</td>
<td>95.2724±1.4107</td>
<td>97.7601±1.0233</td>
<td>99.2642±2.6236</td>
<td>97.4353±4.0116</td>
</tr>
<tr>
<td>JLMCD</td>
<td>96.1650±0.5478</td>
<td>98.8229±0.9211</td>
<td>98.1978±0.5928</td>
<td>98.1206±1.7300</td>
</tr>
</tbody>
</table>

We conduct experiments on the widely used PolyU 3D palmprint database to evaluate the proposed method.

Experiments

Fig.1. The ROC curves of the different methods.
Fig.2. The accuracy of the proposed method based on different parameters.
Fig.3. The recognition accuracy of the proposed method with different weight values of $\alpha$.
Fig.4. The norm difference of the feature projection matrix between the neighboring iterations versus different iteration steps.