Jointly Learning Multiple Curvature Descriptor for 3D Palmprint Recognition

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Background

Palmprint recognition has becoming an increasing active biometrics.

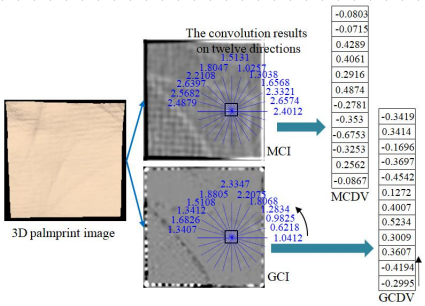
- ➢ rich characteristics
- ➢ high user-friendliness

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.



An example of how to calculate the MCDV and GCDV for a 3D palmprint image. We first recover the MCI and GCI from the original 3D palmprint image. Then, we calculate the convolution responses between Gabor templates and MCI/GCI on twelve directions. Finally, we concatenate the differences of the convolution responses between the neighboring directions to form the MCDV and DCDV.

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.

$$J=\sum_{p=1}^{P}(\sum_{v=1}^{V}(\alpha_v)(\sum_{i=1}^{N}\| c_{p,i}-b_{p,i}^{v}\|^2+\lambda_1\sum_{i=1}^{N}\sum_{j\in\Omega(i)}^{N}\|\tilde{b}_{p,i}^{v}\odot\tilde{b}_{p,j}^{v}\|^2-\lambda_2\sum_{i=1}^{N}\sum_{j\notin\Omega(i)}^{N}\|\tilde{b}_{p,i}^{v}\odot\tilde{b}_{p,j}^{v}\|^2)$$

$$=\sum_{p=1}^{P}\sum_{v=1}^{V}(\alpha_v)(\| C_p-0.5-(W^v)^T X_p^v\|^2+tr((W^v)^T X_p^v S(X_p^v)^T W^v))$$

$$=\sum_{p=1}^{P}(tr(\tilde{C}_p\tilde{C}_p^T)-2tr(W^T X_p\tilde{C}_p^T\tilde{I})+tr(W^T X_p X_p^T W)+tr(W^T X_p\bar{S}X_p^T W))$$

$$s.t.\ \ C_p\in\{0,1\}^{K\times N}, W^T W=I,$$

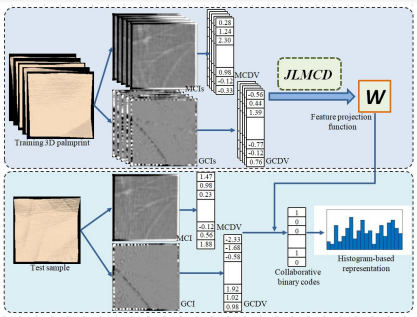
Algorithm 1 JLMCD

Input: Training data: $X_p^v=[x_{p,1}^v,x_{p,2}^v,...,x_{p,N}^v]$; Parameters $\alpha_1(\alpha_2$=1-$\alpha_1)$, λ_1 and λ_2; Convergence parameter ε; 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 (8);
5: if $((t>1)\&\&(\|W^{(t)}-W^{(t-1)}\|^2<\varepsilon))$ break;
6: **end**

Output: W.

Flowchart



The basic idea of the proposed method. For each training 3D palmprint, we first calculate its MCI and GCI and further form the Mean and Gaussian curvature data vectors. Then, we jointly learn a feature projection function. For a test sample, the Mean and Gaussian curvature data vectors are first calculated and then encoded into binary codes using the learned feature projection. Finally, we cluster the block-wise histograms of the binary feature codes as the 3D palmprint feature descriptor.

Experiments

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

TABLE I. THE IDENTIFICATION RESULTS (AVERAGE ACCURATE RATES ± STANDARD ERRORS) OF THE DIFFERENT METHODS.

Methods	#n=1	#n=2	#n=3	AVG
CompCode	89.6039±1.0842	96.9375±1.8363	97.9941±1.3963	94.8452±4.5697
OLOF	83.1513±1.4410	91.9333±3.6851	94.7941±3.2625	89.9596±6.0672
MCI_GCI_ST	82.5921±1.2386	92.1389±3.7216	95.5838±2.6280	90.1049±6.7304
LHST	93.7632±0.9376	97.4028±0.9740	98.2206±0.9822	96.4622±2,3729
CST_S	89.3763±1.8542	96.0389±2.3584	97.3250±2.1950	94.2467±4.2667
CBR	95.2724±1.1407	97.7692±1.0223	99.2642±0.6236	97.4353±2.0167
JLMCD	***96.1500±0.5478***	***98.8222±0.9211***	***99.3897±0.5928***	***98.1206±1.7300***

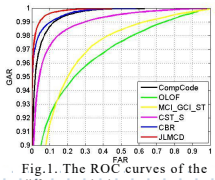


Fig.1. The ROC curves of the different methods.

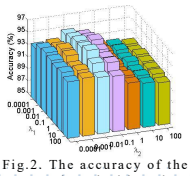


Fig.2. The accuracy of the proposed method based on different parameters.

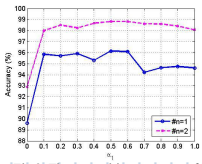


Fig.3. The recognition accuracy of the proposed method with different weight values of α1.

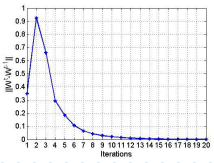


Fig.4. The norm differences of the feature projection matrix between the neighboring iterations versus different iteration steps.