Jointly Learning Multiple Curvature Descriptor for 3D Palmprint Recognition

Lunke Fei, Jianyang Qin, Peng Liu
School of Computer Science and Technology,
Guangdong University of Technology,
Guangzhou, 510006, China

Jie Wen, Chunwei Tian
The Bio-Computing Research Center,
Harbin Institute of Technology(Shenzhen),
Shenzhen, 518055, China

Bob Zhang, Shuping Zhao
Department of Computer and Information Science,
University of Macau, Taipa,
Macau, 999078, China

2021.1.13

Palmprint recognition

Palmprint recognition has becoming an increasing active biometrics area due to its rich characteristics and high user-friendliness. It can be mainly classified into two groups

- ***Two-dimensional (2D) palmprint recognition***
- ***Three-dimensional (3D) palmprint recognition***

3D Palmprint recognition

The **3D palmprint recognition** consists of two learning step.

- ***Learning Curvature images of 3D palmprints***
  - Mean curvature
  - Gaussian curvature

- ***Extracting Curvature-based feature***
  - Binary feature method
  - Direction feature-based method

Related Work

Two category of **3D palmprint recognition**

- ***2D feature representation methods*** mainly first convert the original 3D palmprint data into 2D gray-level images and then extract 2D features for 3D palmprint recognition
- ***3D feature representation methods*** mainly extract the palm surface characteristics from 3D palmprint for personal recognition

The Proposed Method

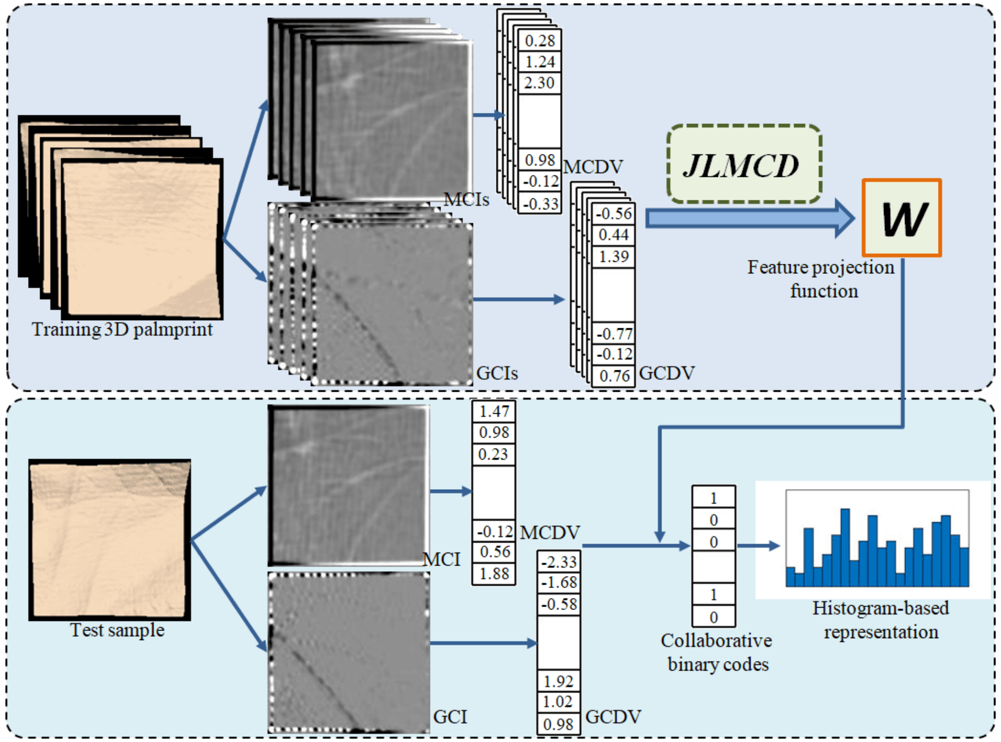

Fig. 1. The basic idea of the proposed method.

For each training 3D palmprint learning, there are two step:

1. Learn Multiple curvature data vectors

   We first calculate its MCI and GCI and further form the Mean and Gaussian curvature data vectors.

2. Jointly learn multiple curvature binary codes

   Then, we jointly learn a feature projection function.

For a test sample encoding

1. We first calculate their Mean and Gaussian curvature data vectors
2. Then we encode them into binary codes by the learned feature projection.
3. Finally, we cluster the block-wise histograms of the binary feature codes as the 3D palmprint feature descriptor.

Learn Multiple curvature data vectors

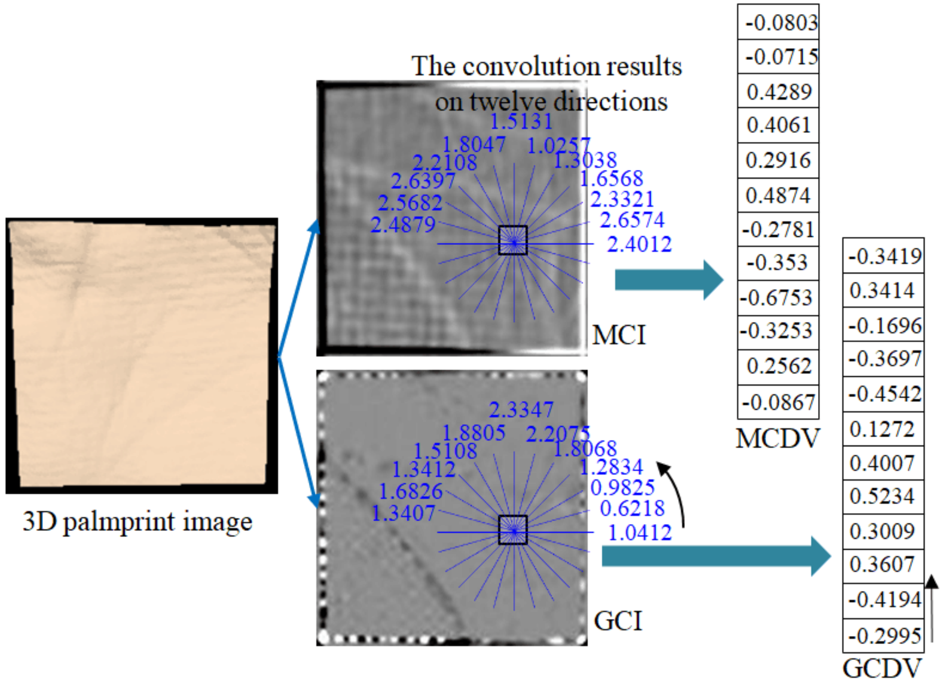

Fig. 2. An example of how to calculate the MCDV and GCDV for a 3D palmprint image.

- 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.

Jointly learn multiple curvature binary codes

The **objective function** of jointly learning multiple curvature binary codes can be formulated as follows, which consists of three constraints:

$$\min J = \sum_{p=1}^{P} \sum_{v=1}^{V=2} (\alpha_v) \Big(\underbrace{\sum_{i=1}^{N} \| c_{p,i} - b_{p,i}^{v} \|^2}_{\textit{collaborative learning}} + \underbrace{\lambda_1 \sum_{i=1}^{N} \sum_{j \in \Omega^{+}(i)}^{N} \| b_{p,i}^{v} - b_{p,j}^{v} \|^2}_{\textit{intra similarity preserving}} - \underbrace{\lambda_2 \sum_{i=1}^{N} \sum_{j \in \Omega^{-}(i)}^{N} \| b_{p,i}^{v} - b_{p,j}^{v} \|^2}_{\textit{inter similarity preserving}} \Big)$$

The first term is to learn the collaborative binary codes of the multiple curvature features.

The second term makes the intra class distance of the learned feature codes minimum on each curvature domain

The third term ensures that the feature codes have the maximizing inter-class distances.

Experiments

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

- ***Palmprint verification***
- ***Palmprint identification***

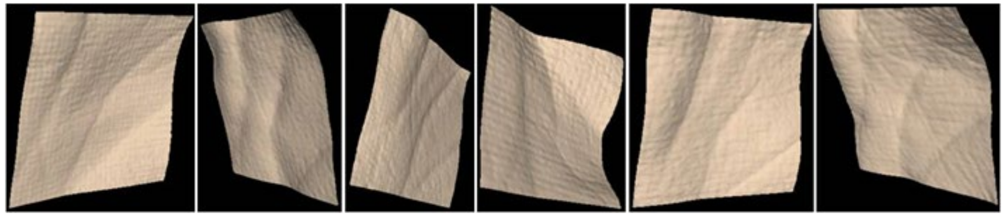

Fig. 3. Six typical 3D palmprint ROI samples selected from the PolyU database.

Palmprint verification

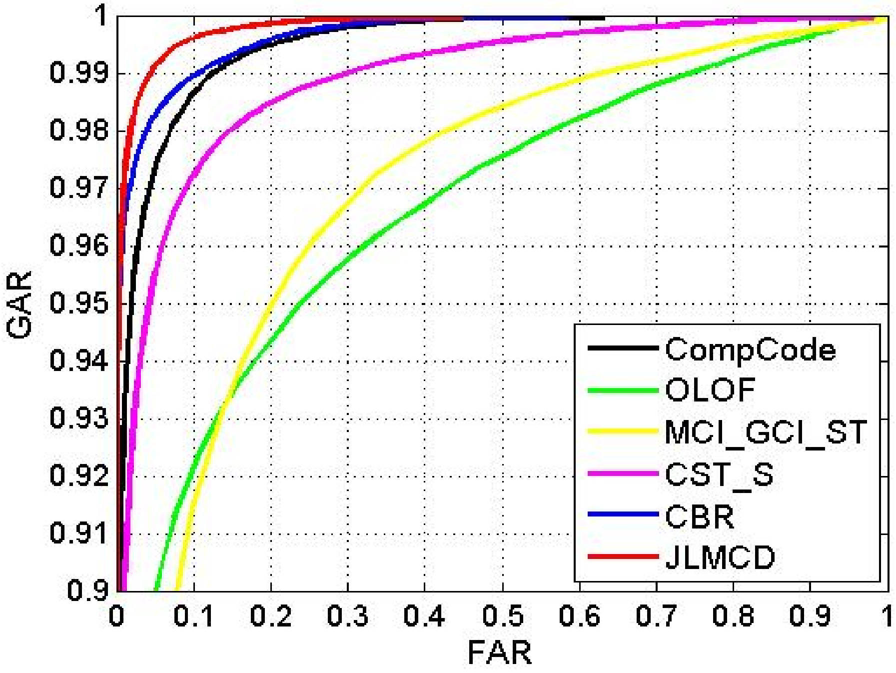

Fig. 4. The ROC curves of the different methods.

In the verification experiments, we compared each pair of two 3D palmprints in the PolyU database and calculated the False acceptance rate (FAR) and Genuine acceptance rate (GAR).

Palmprint identification

In identification experiments, we first randomly selected n(n=1,2,3) images for each palm as the training samples and used the remaining images as the query samples.

Table 1. The identification accuracies of different methods on the TJU, CASIA and IITD databases.

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***

Thank You!