Low-Shot Palmprint Recognition Based On Meta-Siamese Network

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Outline

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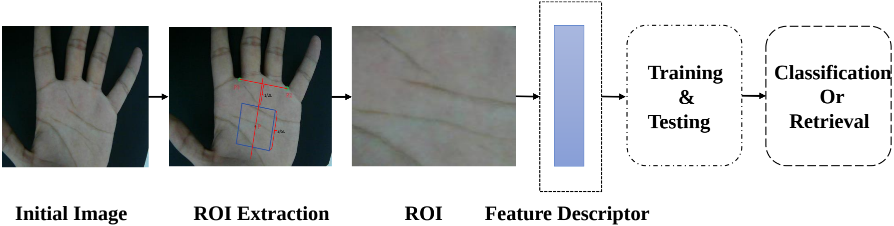
Palmprint Recognition

- Palmprint Recognition for Personal Identification, Security Check and Forensic Applications.
- Palmprint Recognition Pipeline
  - Image Acquisition, Preprocessing, **Feature Extraction**, Matching



Traditional vs DNN-based Palmprint Recognition

- Traditional Palmprint Recognition
  - Encoding-based algorithms(PalmCode [5], Competitive code [16], ...)
  - Structure-based methods(Ridge-based [4], Line-based [15], Point-based [14])
  - Statistics-based methods(Discrete Curvelet Transform [1], Wavelet Transform [20])
  - Subspace methods(LDA [3], ICA [6])
- DNN-based Recognition
  - Vanilla CNN plus Softmax [7]
  - Deep Hash Network for Palmprint Retrieval [18]
  - Deep Scattering Network [8]
  - Siamese Network [19]
  - ...

Outline

Few-shot Palmprint Recognition

- Problem of DNN-based Palmprint Recognition
  - Large amount paired training data.
  - Heavy ROI extraction and labelling work.
  - Complex palmprint data acquired which makes the neural net suffer from poor generalization capacity when faced with fewer training data, possibly one image per people.
  - Upon practical deployment, it is not user-friendly to collect multiply palmprint images for each user.
  - Benchmark datasets are not sufficient to test the robustness of the algorithms for practical palmprint recognition.

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Few-shot Learning in Literature

- Metric-based Method.(Learn a discriminative metric space for downstream classification)
  - Prototypical Network [13]
  - Matching Network [11]
- Meta-Learning (Learn to update parameters on unseen data)
  - Model-Agnostic Meta-Learning (MAML) [2]
  - Reptile [9]
- Memory-based Methods (Store Discriminative Information adapted along with different episodes)
  - Memory Augmented Neural Network (MANN) [10]

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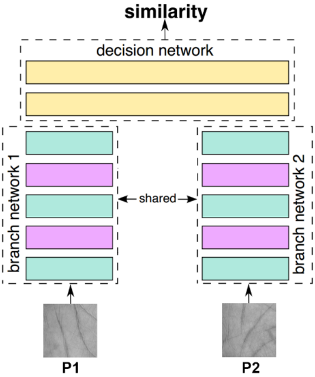
Meta-Siamese Network

- Backbone Network: Siamese Network for Palmprint Recognition [19].

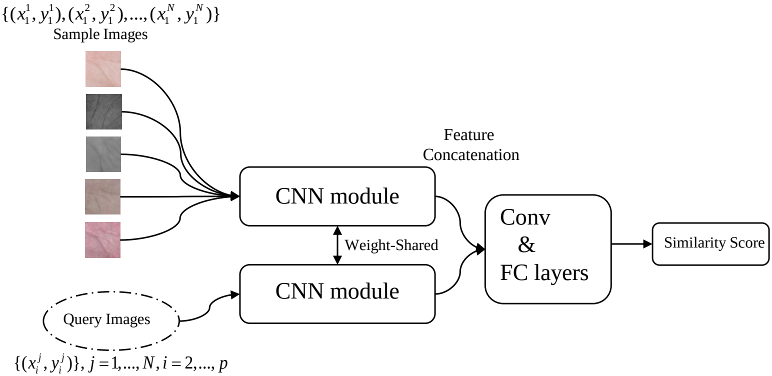


Episode Training for Few-shot Learning

- Episode Training (N way, k shot)
  - Split the dataset into mete-train set and meta-test set with non-overlapping classes.
  - Sample (N way, k shot) classification tasks in meta-train set.
  - Split it into sample set $(x_i^j, y_i^j), i = 1, ..., k, j = 1, ..., N$ and query set $(x_i^j, y_i^j), i = k + 1, ..., p, j = 1, ..., N$. Suppose p images in total per class.
  - Split the meta-test set to support/testing set which are in the same form of the splitting in the meta-train set.

One-shot Palmprint Recognition

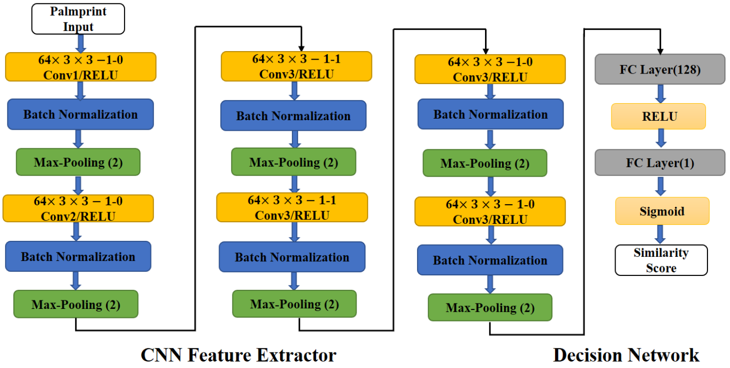
- One palmprint image per class.



- Compare $N \times N \times (p - 1)$ times.

Detailed Architecture

Structure of used CNN feature extractor and the comparison module.



One-shot Palmprint Recognition

- Loss function
  - Obtain the ground truth label for every comparison. 0 denotes genuine match. 1 denotes imposter match.
  - Obtain a $N \times N \times (p-1)$ dimensional vector.
  - L2 loss function between the predicted similarity and the label.
- Advantages
  - Obtain convolutional features in order to improve the flexibility of the features.
  - The convolutional modules for calculating the similarity between two palmprint images are easy to adapt than pure fully connected layers.
  - Adaptive and Transferable Comparison Metric.
- Meta-test Stage
  - Apply the learned modules to the support and testing set and obtain the similarity.
  - Compare with the label and then calculate the accuracy.

k-shot Palmprint Recognition

- Similar to the one-shot palmprint recognition, but with k known samples per class.
- During feature concatenation, average the feature maps of the sample set and then concatenate it with the image from the query set.

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Zero-shot Palmprint Recognition

- Zero-shot palmprint recognition doesn't need images for a particular class but uses semantic attributes to recognize a certain identity.
- We apply three different zero-shot palmprint recognition scenarios to test the performance of the Meta-Siamese Network, which is similar to [12].
    - Pure Zero-shot Palmprint Recognition. (Meta-train set has different classes from the meta-train set)
    - Generalized zero-shot Palmprint recognition with unseen classes. (Support set has semantic attributes of all classes, testing set has images from unseen classes)
    - Generalized zero-shot Palmprint recognition with seen classes. (Support set has semantic attributes from all classes, testing set has semantic attributes of all seen classes)
- How to learn the semantic attributes?

Learn the Semantic Attributes

- Deep Hash Network (DHN)
  - Encode each palmprint image as a binary vector consisting of -1 and 1.
  - The hash code has a high inter-class variance and a low intra-class variance, which semantically connect the palmprint images.
- Loss Function
  - Hash loss

    U_i denotes the binary output of the $i-th$ image. T_{ij} denotes the relationship between different images such that if the $i-th$ and $j-th$ image belong to the same class, $T_{ij}=1$. $D_h(\cdot)$ is Euclidean distance operation.

$$J\left(U_i, U_j, T_{ij}\right)=\min\left[\frac{1}{2}T_{ij}D_h\left(U_i, U_j\right)+\frac{1}{2}\left(1-T_{ij}\right)\max\left(M-D_h\left(U_i, U_j\right), 0\right)\right] \tag{1}$$

$$J_H=\sum_{i=1}^{N}\sum_{j=1}^{N}J\left(U_i, U_j, T_{ij}\right) \tag{2}$$

  - Quantized Loss

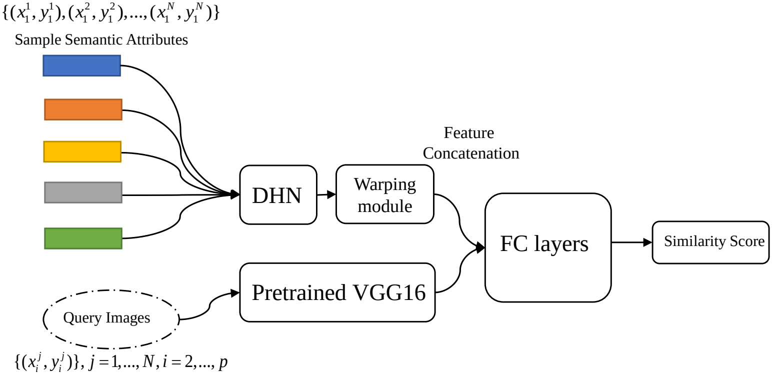
$$J_Q=\sum_{i=1}^{N}\frac{1}{2}\left(\|1-|U_i|\|_2\right) \tag{3}$$

  - Overall Loss

$$\min J=\alpha J_H+J_Q \tag{4}$$

Zero-shot Architecture

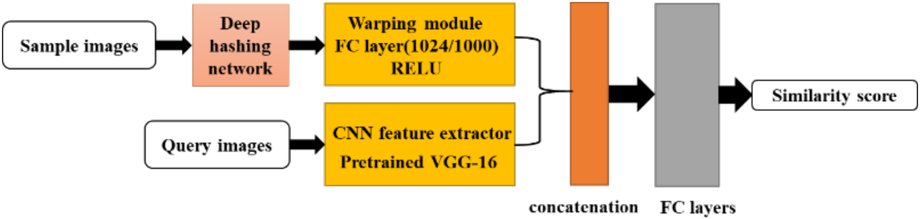
- Using semantic attributes instead of real images in the sample set.
- Learned features are 1000 dimensional vectors.
- Adding warping module to transform semantic attribute to features.



- The comparison stage is the same as the few-shot recognition.

Detailed Architecture

Structure of used CNN feature extractor and the comparison module.



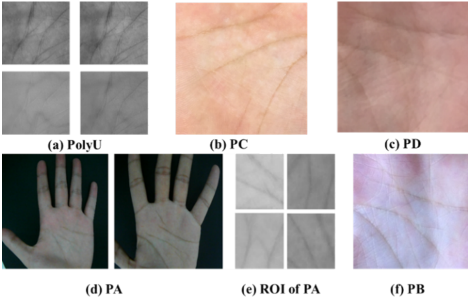
Outline

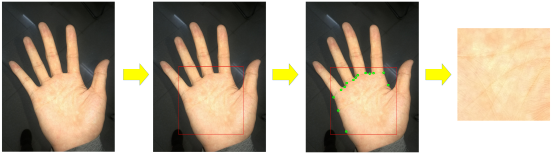
Dataset and Preprocessing

- Datasets
  - Benchmark Dataset
    - PolyU Multispectral Palmprint Dataset [17].
    - 6000 grayscale images from 500 different palms of 250 people. For each palm, 12 images are collected.
  - Self-collected Unconstrained Palmprint Dataset
    - PA: 570 grayscale images of both left and right palms from 57 different people are collected by CMOS camera.
    - PB: 1000 RGB images from 100 different people are collected by CMOS camera.
    - PC: 1960 images from 196 different people with flash light are collected by iPhone 6s.
    - PD: 1970 images from 197 different people without flashlight are collected by Samsung.

Dataset and Preprocessing

- Dataset and ROI Extraction





Few-shot Palmprint Recognition

- Setup
  - 5-way (1-shot, 3-shot, 5-shot)
  - 15-way (1-shot, 3-shot, 5-shot)
- Baselines
  - Siamese Network, MAML, Prototypical Network, Matching Network, DHN

Dataset	5-way			15-way		
	1-shot	3-shot	5-shot	1-shot	3-shot	5-shot
PolyU-B	97.2%	99.2%	99.4%	96.8%	97.9%	97.3%
PolyU-R	96.9%	98.9%	99.3%	96.1%	96.2%	95.6%
PolyU-G	95.4%	97.3%	98.7%	94.7%	95.8%	95.9%
PolyU-N	94.3%	95.6%	99.7%	94.1%	93.9%	95.3%
PA	93.5%	94.6%	95.3%	91.6%	95.4%	94.8%
PB	87.8%	88.8%	93.4%	84.2%	86.9%	92.7%
PC	97.3%	96.3%	98.8%	95.6%	96.6%	98.3%
PD	94.2%	95.8%	96.4%	91.5%	91.9%	94.7%

Few-Shot Palmprint Recognition

Comparative Results

Dataset/Shot	Siamese-Net	MAML	Prototypical Net	Ours	Matching Net	DHN
	1	1	1	1	1	1
PolyU-B	66.7%	94.1%	94.3%	97.2%	83.6%	54.3%
PolyU-R	64.6%	93.8%	92.8%	96.9%	85.9%	62.4%
PolyU-G	69.5%	93.5%	91.7%	95.4%	88.0%	66.5%
PolyU-N	70.1%	96.7%	90.5%	94.3%	87.7%	64.1%
PA	71.5%	94.5%	88.5%	93.5%	91.2%	62.9%
PB	50.0%	84.5%	86.0%	87.8%	89.3%	43.8%
PC	61.2%	94.4%	93.7%	97.3%	88.5%	59.9%
PD	58.9%	98.9%	90.3%	94.2%	90.2%	47.3%

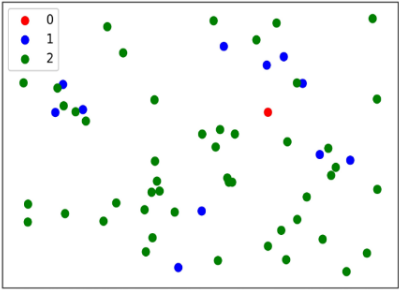
Zero-Shot Palmprint Recognition

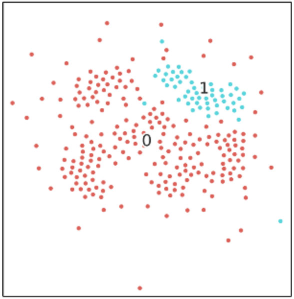
- Pure Zero-shor Palmprint Recognition: The support/testing set contains different identities from sample/query set.
- Generalized Zero-Shot Palmprint Recognition with Unseen Classes: The support set contains semantic attributes of all classes and the testing set only contains the feature maps from unseen classes.
- Generalized Zero-Shot Palmprint Recognition with Seen Classes: The testing set contains all the seen classes while the support set consists of semantic attributes of all classes.

Dataset	Pure zero-shot	Generalized zero-shot	
		Unseen	Seen
PolyU-B	65.9%	45.9%	90.4%
PolyU-R	71.3%	54.6%	89.4%
PolyU-G	69.7%	33.7%	92.1%
PolyU-N	71.4%	49.5%	88.1%
PA	35.1%	24.9%	79.3%
PB	36.8%	21.1%	58.9%
PC	42.9%	41.5%	79.4%
PD	48.2%	39.9%	81.6%

Visualization

- Visualization of the effect of episodic training on learned features
  - Palmprint data directly projected into 2D space.
  - Same data at the learned feature space.





Conclusion

- Few-shot Palmprint Recognition
- Zero-shot Palmprint Recognition
- Meta-Siamese Network
- Unconstrained palmprint dataset collected by CMOS camera and mobile phones.
- A flexible framework for learning a transferable comparison metric.

Thanks!

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