LOW-SHOT PALMPRINT RECOGNITION BASED ON META-SIAMESE NETWORK

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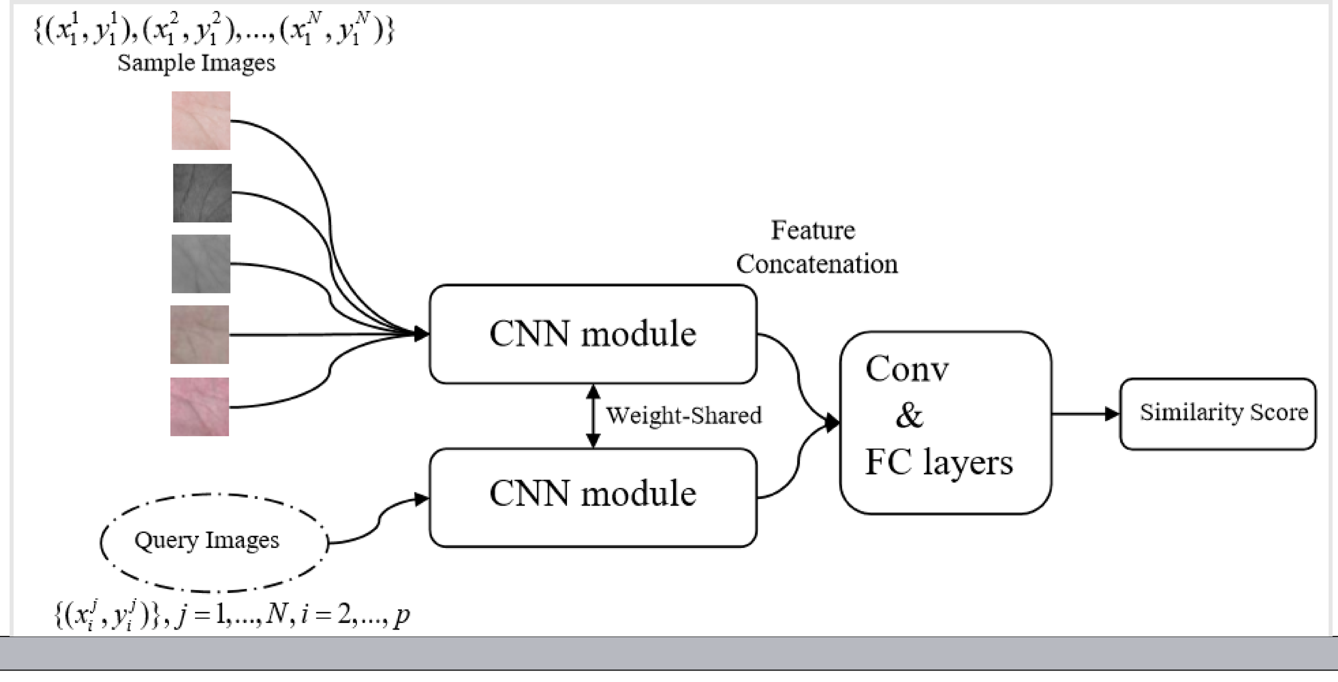
Introduction

Palmprint is one of the discriminant biometrical features of humans. Recognizing palmprints in complex environments is a significant multimedia task, which is highly suitable for applications in information security and forensics. Recently, deep learning-based recognition methods have improved the accuracy and robustness of recognition results to a new level. However, obtaining the required large amount of training data and labels is impracticable in practical scenarios. Therefore, in this paper, we exploit few-shot learning for palmprint recognition. We propose Meta-Siamese network based on Siamese network. Specifically, we train this network episodically with a more flexible framework to learn both the feature embedding and the deep similarity metric function. Moreover, we extend our model to zero-shot recognition tasks based on deep hashing network. Experiment result shows competitive improvements compared to baseline methods in eight different datasets.

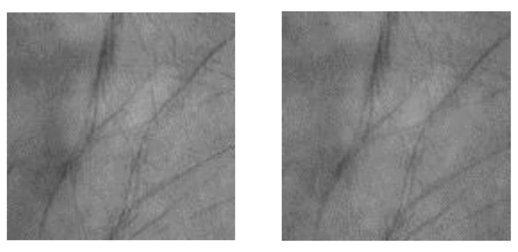
Methods

The low-shot palmprint recognition can be formulated as training a classifier to recognize the remaining images given a few training images in each category. Suppose we have M image samples in total. We denote the small support set as $(x_i, y_i), i = 1, .., N * k$ for training, where we have N classes and k samples in each class. The testing set with the same label space is denoted as $(x_i, y_i), i = N * k + 1, .., M$. Therefore, if directly trained, the model will suffer from overfitting. Hence, we introduce the meta-train set which is separated to sample set and query set to simulate the low-shot recognition setting in the meta-test set. Note that the label space of the sample /query set is different from that of support/testing set. We randomly sample N-way, k-shot tasks into the sample set and test on the query set. The losses we obtain on the sample/query set are backpropagated to make the system easier to adapt to new tasks. Therefore, after the episode-based training in the meta-train set, we apply our model to the meta-test set for low-shot palmprint recognition.



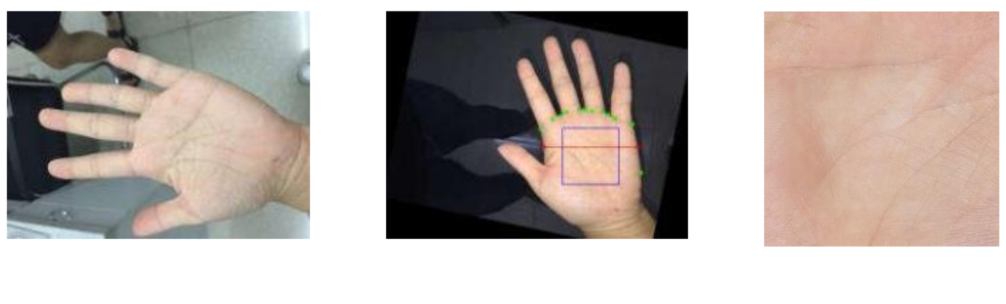
Databases

PolyU multispectral database



Semi-uncontrolled database

Uncontrolled database (captured by mobile phones)



Experiments and Results

Implementation details: we randomly split the dataset into the meta-train set and meta-test set with the ratio of 4:1. In the training stage, we test our model using 8 different datasets on different task setting, which are 5-way/1-shot, 5-way/3-shot, 5-way/5-shot, 15-way/1-shot, 15-way/3-shot and 15-way/5-shot recognition tasks. For episode-based training, we first train Meta-Siamese network by sampling tasks in sample/query set. Every 5000 episodes, we start testing on the support/testing set for 600 episodes and calculate the mean recognition accuracy with the confidence level to be 0.95. .

Few-shot Palmprint Recognition Results:

Table 1. Few-shot recognition results

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%

Table 2. Comparative results of few-shot recognition

Dataset/	S-Net	Maml	P-Net	**Ours**	M-Net	DHN
Shot	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 Results

Table 3. Zero-shot recognition results

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%

Conclusions

In this paper, we propose a low-shot model for palmprint recognition using a few labelled images. We build on the classical Siamese network and introduce meta episode training for better generalization performance. We also modify the initial model to compare two palmprint images flexibly Furthermore, we extend our model to zero-shot recognition by obtaining the semantic hash codes using Deep Hash Net. Our model is suitable practical personal when only a small part of the palmprints are labelled in the acquisition stage.

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