

One-Shot Representational Learning for Joint Biometric and Device Authentication

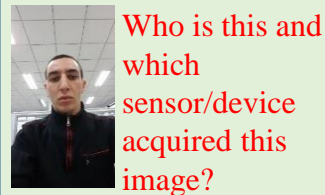
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Paper ID: 1640

Introduction

Question: Given a biometric image, can we tell...



Solution: Joint biometric and sensor recognition
Application:

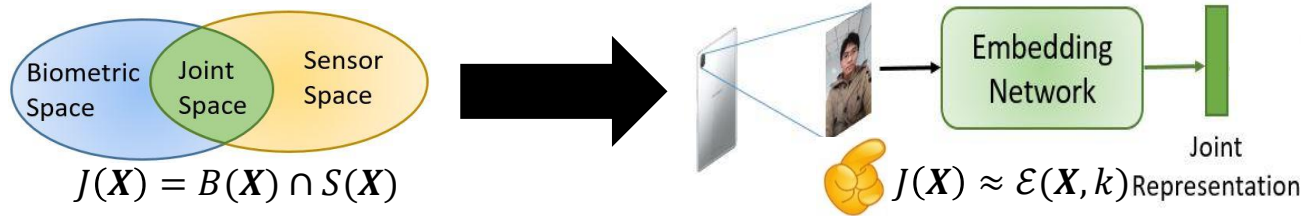
Remote banking on smartphones (2-FA)

Motivation

Surge in biometrics-based smartphone verification (iPhone X) and remote banking (expected 2.3 B users by 2023)
Existing methods use **separate** routines – **Limited** performance and generalizability

Proposed Method

Objective: Capture biometric-specific and sensor-specific details **simultaneously** from a biometric image to create a **joint representation** – **Joint biometric-device authentication**



Properties of joint representation:

- Can be used for the tasks of **joint identification** and **joint verification** – Both subject and device (sensor) identities should yield correct matches
- Implicitly **privacy** preserving – joint template cannot be trivially de-coupled
- **Lower dimensional** embedding compared to biometric and sensor templates
- Will generalize to different biometric **modalities** and **sensors** (Iris-NIR & Face-VIS)

Learns the joint representation in one-shot!

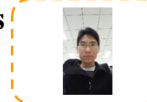
Results

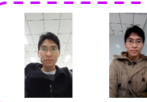
Siamese network with single-margin contrastive loss **outperformed** other training routines

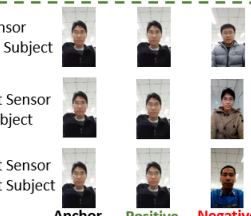
Best performance on face images with joint identification accuracy **99.81%** @ Rank 1 (Baseline 83.13%); joint verification accuracy **100%** @ 1% FMR

Experiments

	Modality	#Subjects, #Sensors
Dataset	Iris (CASIA Iris V2)	60, 2
	Periocular (MICHE-I)	75, 7
	Face (OULU-NPU)	55, 6
Total no. of images = 14,451		
Loss	Cross-entropy loss, Contrastive loss, Triplet loss (offline and online triplet mining), Multi-class N-pair	
Analysis	Used Classical , Siamese and Triplet training paradigms. Analyzed varying input resolution, distance metrics and embedding dimensionality	







SWITCHING CIRCUIT

Classical

Siamese

Triplet

EMBEDDING NETWORK

INPUT: 5 x 5 @ 128

Conv-2D

Max-pooling

Conv-2D

Max-pooling

Linear @ 512

Linear @ 128

Linear @ 8

OUTPUT

Baselines

Enhanced PRNU (sensor)
COTS and ResNet-101 (biometric)

Summary

Performed **one-shot** learning of **joint biometric-sensor template** for 3 modalities with **promising results**

Marsico et al., PR 2018
Boulkenafet et al., FG 2017
Li, T-IFS 2010
Bromley et al., NeurIPS 1993