Face Recognition System Security: Anti-spoofing and Template Protection

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Outline

1. Background and Motivations
2. Face Anti-spoofing
3. Face Template Protection
4. Conclusions

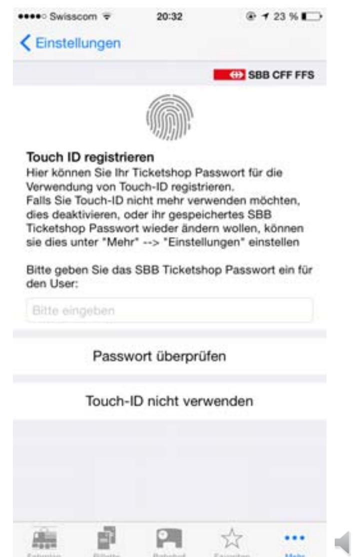
Biometrics

- Deployed practical applications

Border Control

Door Access Control

Touch ID (iPhone)



SBB for buying ticket

Face Biometrics

- Face Recognition Technology

Jack Ma's first unmanned supermarket

Today, on a street in Hangzhou (Zhejiang province), Jack Ma's first unmanned supermarket officially opened for business. Because there are no costs for manpower, the expenses for running the unmanned supermarket only add up to about a quarter of those of traditional supermarkets. The shop owner just needs to replenish the inventories every morning - nothing else needs to be done.

Entrance to the unmanned supermarket

face-recognition payment Alipay

'World's first' facial recognition ATM unveiled in China

PUBLISHED : Sunday, 31 May, 2015, 6:38am
UPDATED : Monday, 01 June, 2015, 11:31am
COMMENTS:

Source: china.com and iomniscient.com

Face Biometrics

FaceID in iPhone X

Announced on 12 September 2017

"With a simple glance, Face ID securely unlocks your iPhone X. You can use it to ***authorize purchases from the iTunes Store, App Store, iBooks Store, and payments with Apple Pay***. Developers can also allow you to use Face ID to sign into their apps. …."

3D Face Recognition:

Employed Structured-light 3D technology

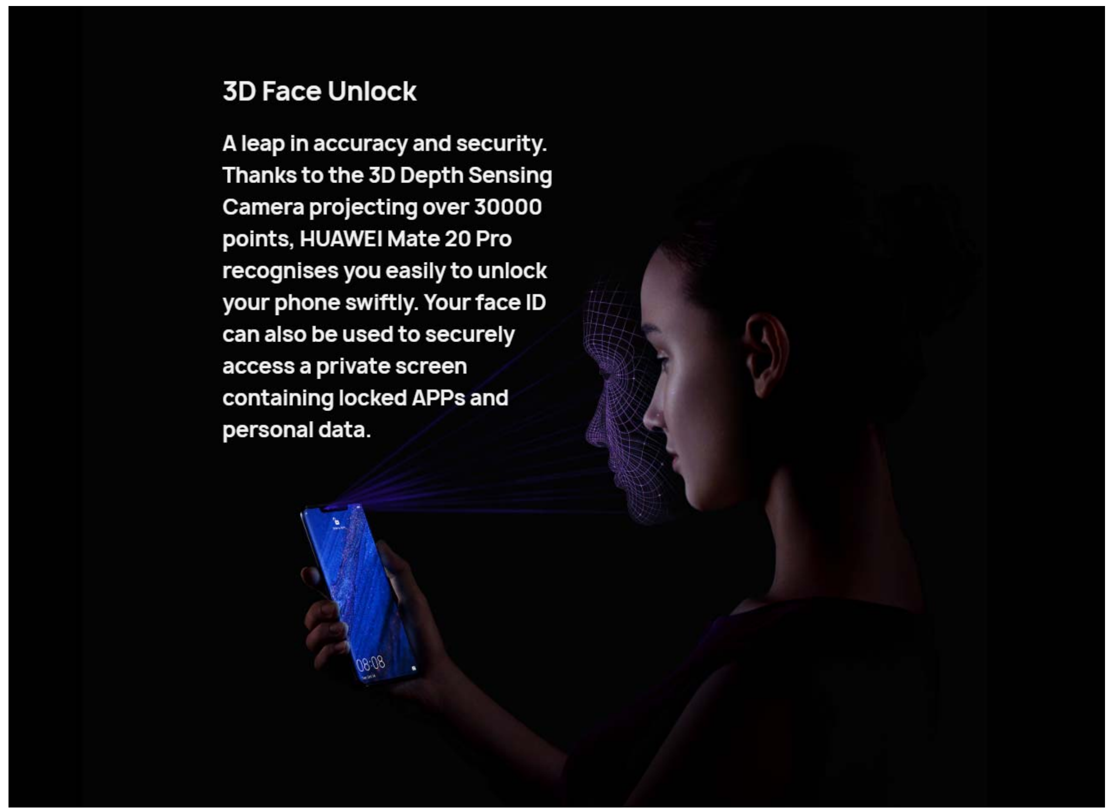
Face Biometrics

HUAWEI Mate 20 Pro

Nov 2018

Biometric Technology

Unlock Life's Possibilities

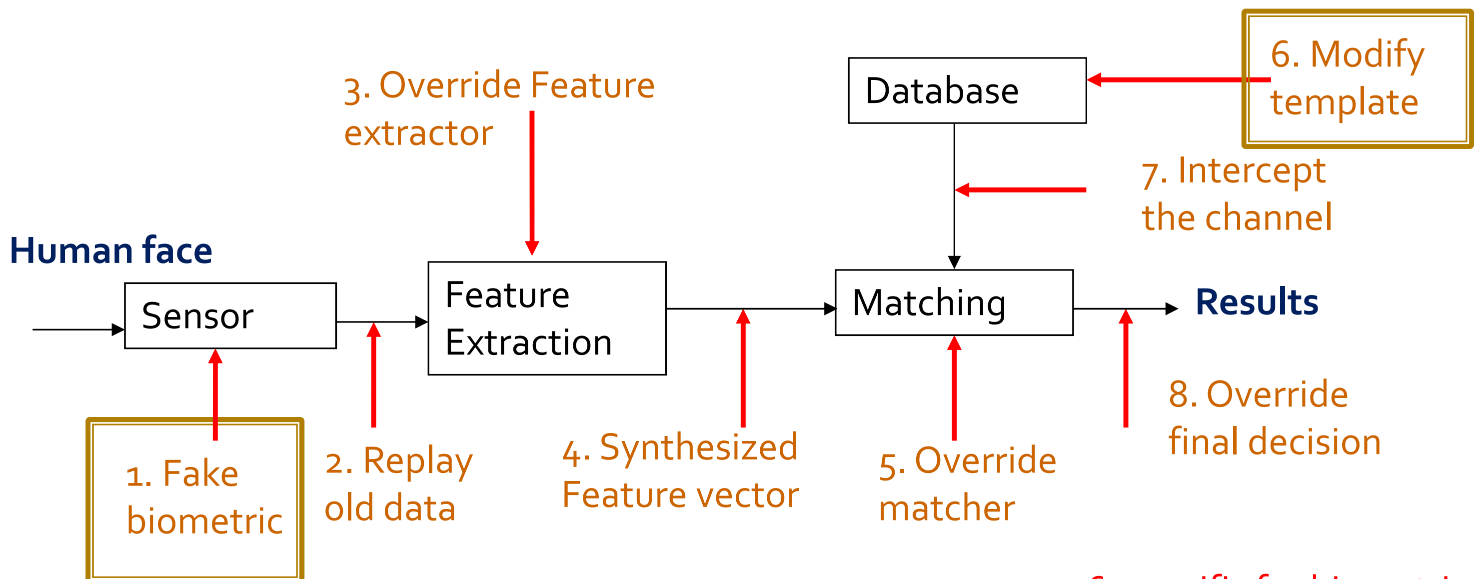


https://consumer.huawei.com/en/phones/mate20-pro/

What happens if
a face recognition system is NOT secure?

Background and Motivations

- Vulnerabilities: Ratha *et al.* [IBM Sys J 2001] pointed out eight possible attacks on biometric systems



1, 6: specific for biometric systems

Part I:
Face Anti-Spoofing

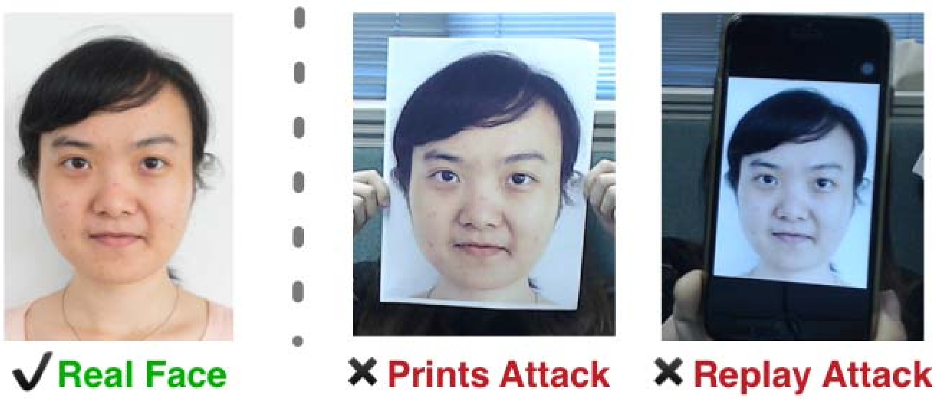
Mission Impossible - Rogue Nation (2015): Biometric Spoofing

Outline: Face Anti-spoofing: 3D Mask Attack

1. Background and Motivations
2. Related Work
3. rPPG Approach
4. Deep Learning Approach
5. Conclusions

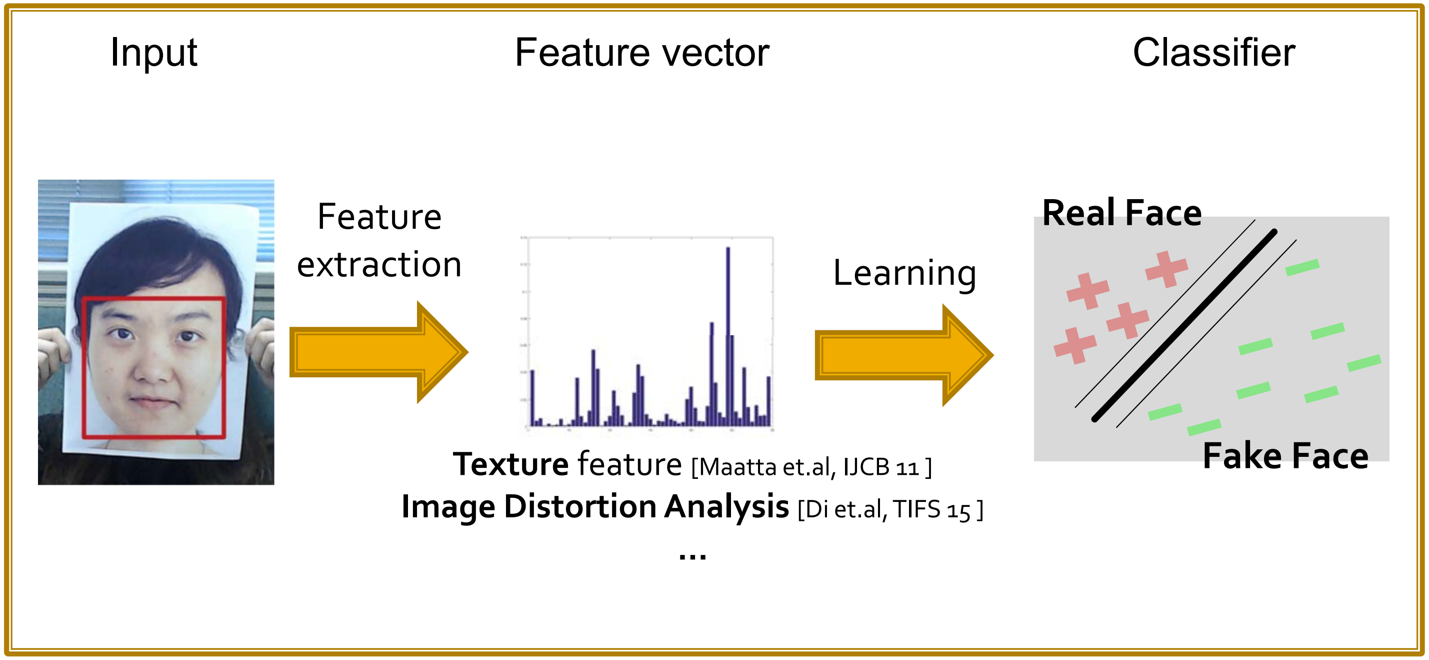
Background and Motivations

- Face Spoofing Attack
  - With rapid development of social network such as Facebook and Twitter, face information can be easily acquired (facebook, twitter) and abused



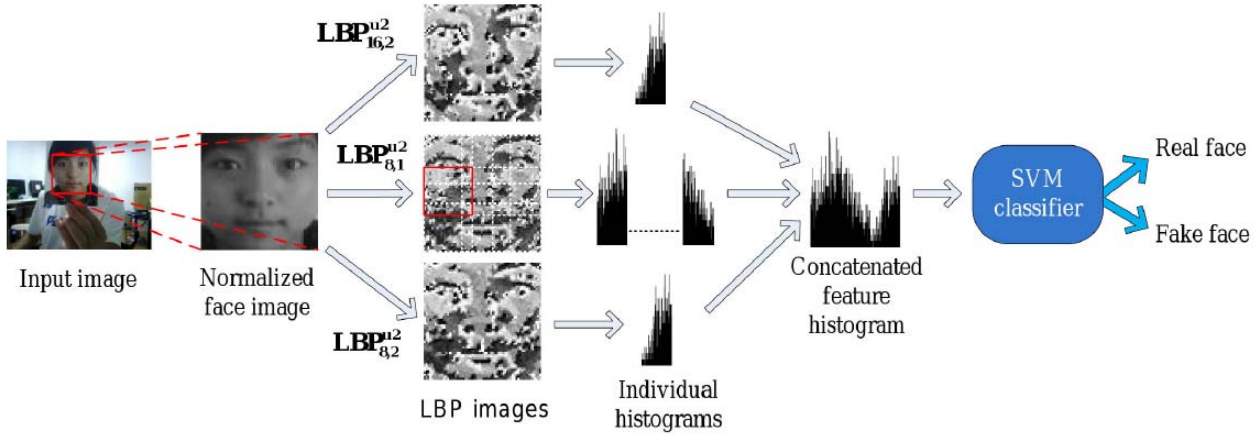
Background and Motivations

- Anti-spoofing approach: Appearance-based
  - Spoof media (print and screen) and genuine face has different appearance



Background and Motivations

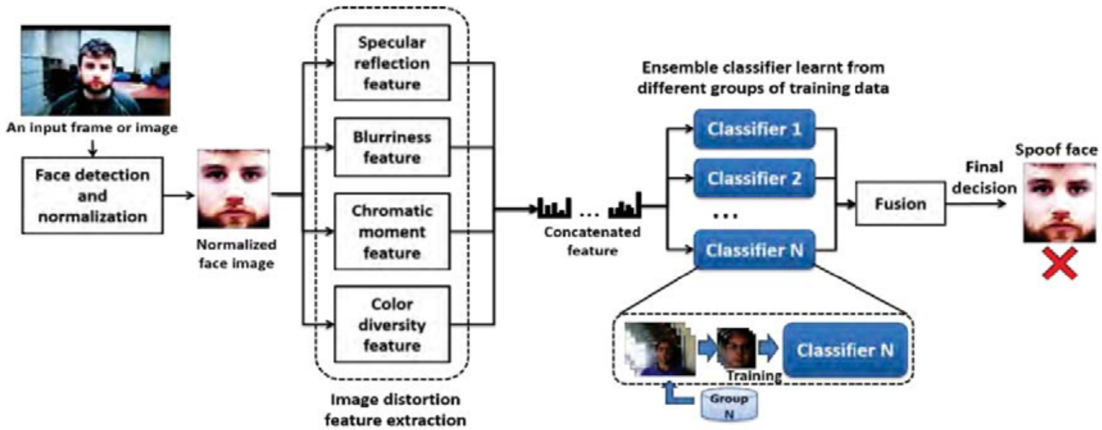
- Anti-spoofing approach: Appearance-based
  - Spoof media (Prints and screen) has different texture, comparing with genuine face



Source: Jukka Maatta, Abdenour Hadid, Matti Pietikainen, "Face Spoofing Detection From Single Images Using Micro-Texture Analysis", *IJCB* 2011

Background and Motivations

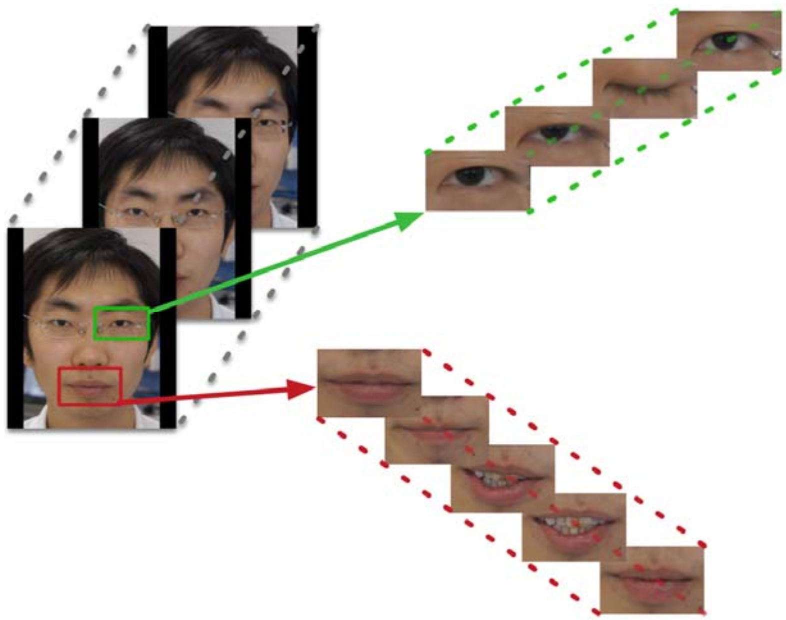
- Anti-spoofing approach: Appearance-based
  - Spoof media (prints and screen) has specific quality defects



Source: Di Wen, Hu Han, Anil K. Jain, "Face Spoof Detection with Image Distortion Analysis", *TIFS* 2015

Background and Motivations

- Anti-spoofing approach: Motion-based
  - 2D spoofing medium cannot move, or has different motion pattern compare with real face

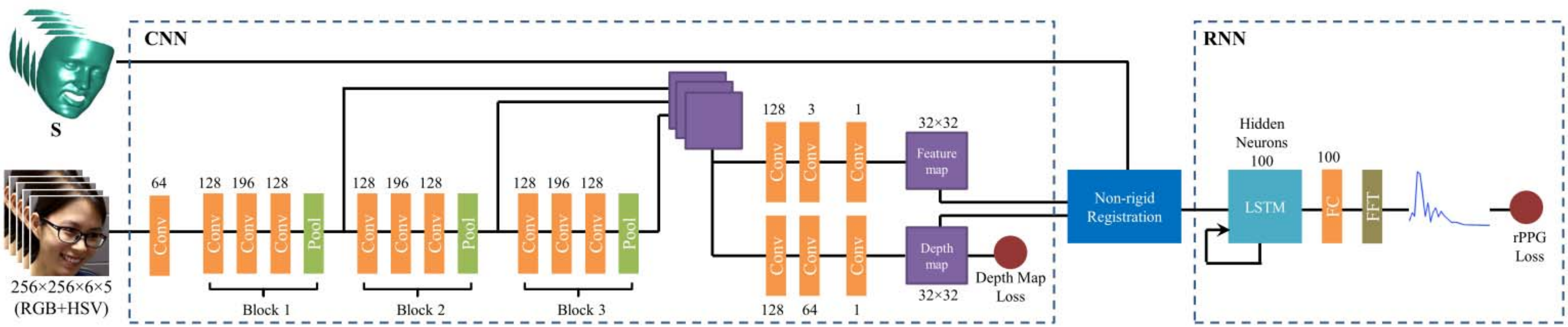


Background and Motivations

- Anti-spoofing approach: Motion-based
  - **Eyeblink-based** anti-spoofing in face recognition from a generic web-camera (G.Pan et al., ICCV'07)
  - Real-time face detection and **motion analysis** with application in liveness assessment. (K. Kollreider et al., TIFS'07)
  - A liveness detection method for face recognition based on **optical flow field** (W. Bao et al., IASP'09)
  - Face liveness detection using **dynamic texture** (Pereira et al., JIVP'14)
  - Detection of face spoofing using **visual dynamics** (S. Tirunagari et al., TIFS'15)

Background and Motivations

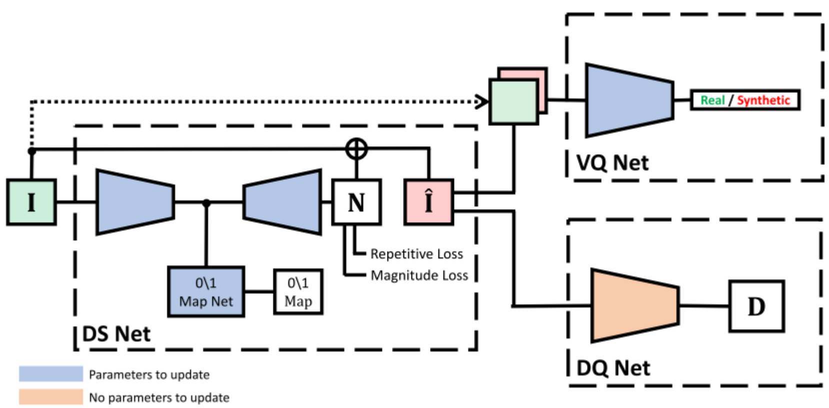
- Multiple modality approach
  - CNN: Learn different **face depth maps** at pixel-wise level +
  - RNN: Learn different **rPPG signals** with sequence-wise



Y. Liu, A. Jourabloo, and X. Liu. Learning deep models for face anti-spoofing: Binary or auxiliary supervision, CVPR 2018

Background and Motivations

- Face de-spoofing approach
  - Inversely decompose a spoofed face into a spoof noise and a live face, and then utilizing the spoof noise for classification.
  - Real face: no spoof noise vs. Fake face: clear spoof noise



Y. Liu, A. Jourabloo, and X. Liu. Face De-Spoofing: Anti-Spoofing via Noise Modeling, ECCV 2018

Background and Motivations

- Performance on traditional face spoofing attack

	Replay Attack		Print attack	
Pipelines	***Dev***	***Test***	***Dev***	***Test***
DMD+SVM (face region)	8.50	7.50	0.00	0.00
DMD+LBP+SVM (face region)	5.33	3.75	0.00	0.00
PCA+SVM (face region)	20.00	21.50	16.25	15.11
PCA+LBP (face region)	11.67	17.50	9.50	5.11
DMD+LBP+SVM (entire video)	0.50	0.00	0.00	0.00
PCA+LBP+SVM (entire video)	21.75	20.50	11.50	9.50

[S. Tirunagari et al., TIFS'15]

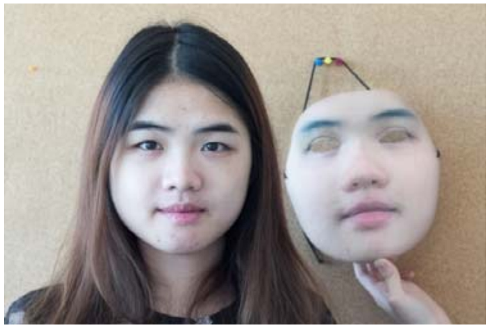
Promising results are achieved on tradition face spoofing attack

Background and Motivations

Problem solved?

Background and Motivations

- **New Challenge**: 3D Mask Attack
  - With the advanced development on 3D reconstruction and 3D printing technology, 3D face model can easily be constructed and used to spoof recognition systems



Source: idiap.ch

Mask is made from ThatsMyFace.com

Background and Motivations

- **New Challenge**: Super-realistic 3D Mask
  - 3D mask can be so real that we can hardly differentiate them from appearance

(a) Life face

(b) Real-F hyper real mask

Source: real-f.jp

Background and Motivations

Asia Pacific (../../asia) | Hong Kong SAR (../) Hong Kong (../)

Hong Kong airport security fooled by these hyper-real silicon masks

Masks like the one that transformed a Chinese kid into a U.S. grandpa are now available online

By Zoe Li (../../author/zoe-li-hong-kong-editor) 8 November, 2010

Suspicious old folks: the Elder Mask from SPFX Masks is so real.

Before...

That Chinese guy who disguised himself as an old white man to slip by Hong Kong airport security and board an Air Canada flight might have ordered his old man mask from SPFX Masks (http://www.spfxmasks.com) .

This is the stuff that entered popular imagination with the Mission Impossible television series (http://www.youtube.com/watch?v=b6golhLE3c&NR=1) and is used by the CIA (http://abcnews.go.com/Health/Cosmetic/story?id=1354130) and as prosthetics for medical conditions (http://www.prosthesis.com/services.htm) .

Now we can order our own so-real-its-creepy mask online.

Silicon masks from SPFX adhere to facial features such that the mask is able to move with the musculature of the wearer, like a second skin. The mask is attached to a neck flap and some come with silicon gloves to disguise the hands and forearms as well.

is attached to a neck flap and some come with silicon gloves to disguise the hands and forearms as well.

Check out the video above of a demonstration of the Elder Mask (http://www.spfxmasks.com/maskelder.html) from SPFX, which resembles the one that Chinese stowaway was caught with in Canada. Priced at US$689, the mask is aimed at Halloween revelers and haunted house actors.

... and after.

But the passenger who breached Hong Kong airport security on October 29 used his mask to smuggle himself into Canada.

The Chinese man who appeared to be in his early 20s disguised himself as an elderly Caucasian man, obtained a boarding pass from a U.S. citizen while in transit in Hong Kong, and boarded the Air Canada flight using an Aeroplan card for identification.

Read more details about the case from the confidential alert obtained by CNN (http://articles.cnn.com/2010-11-04/world/canada.disguised.passenger_1_flight-crew-hong-kong-regional-communications-officer?_s=PM:WORLD) .

Source: http://travel.cnn.com/hong-kong/visit/hong-kong-airport-security-fooled-these-hyper-real-silicon-masks-743923/

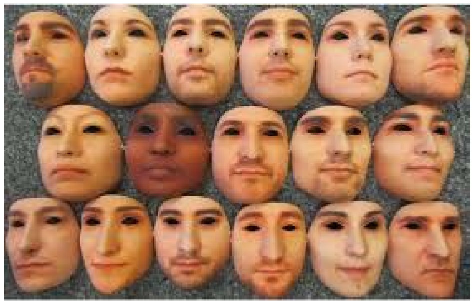
Related Work

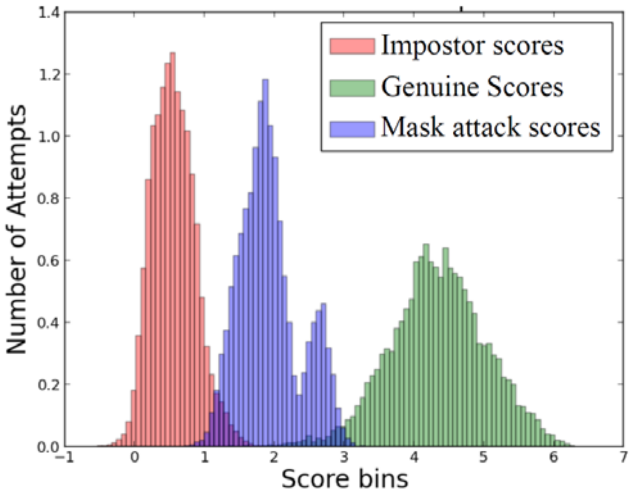
- Existing works on 3D Mask Spoofing Attack
  - The 3DMAD dataset [Erdogmus et al., BTAS'13]
  - LBP-based solution [Erdogmus et al., TIFS'14]

RESEARCH INSTITUTE

Related Work

- The 3DMAD dataset
  - Score distributions of genuine, impostor, and mask attack scores of 3DMAD using ISV for 2D face verification

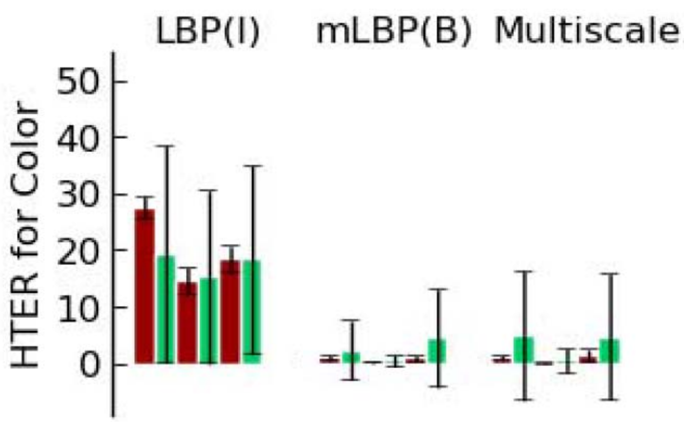


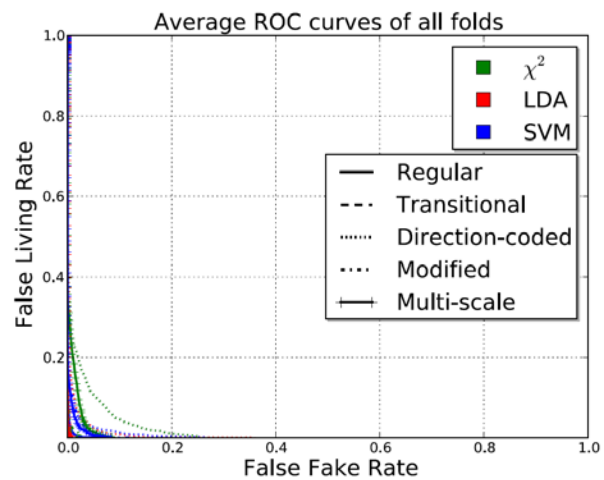


[Erdogmus et al., BTAS'13]

Related Work

- LBP-based solution
  - The multi-scale LBP features yield to very good results on 3DMAD [Erdogmus et al., TIFS'14]





[Erdogmus et al., TIFS'14]

Analysis of Existing Methods

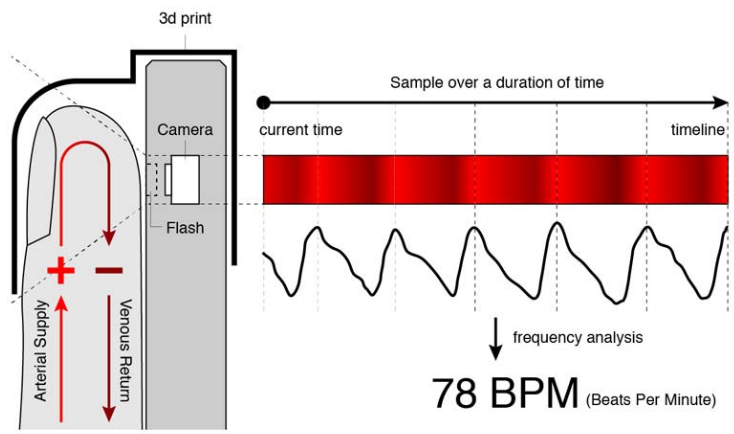
- Pros and Cons

  + Achieve high performance in 3DMAD dataset

  - **Hyperreal 3D mask may not have quality defects**
  - **LBP-based solution may not have good generalization ability across databases**

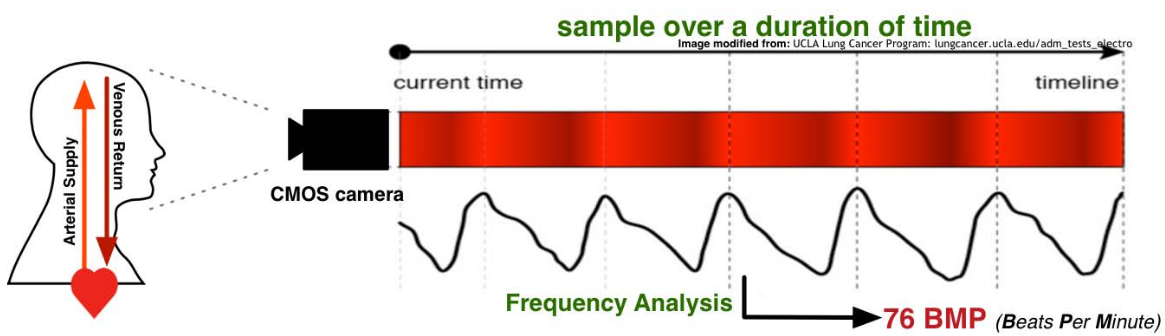
rPPG Approach for 3D Face Anti-spoofing

PhotoPlethysmoGraphy (PPG)

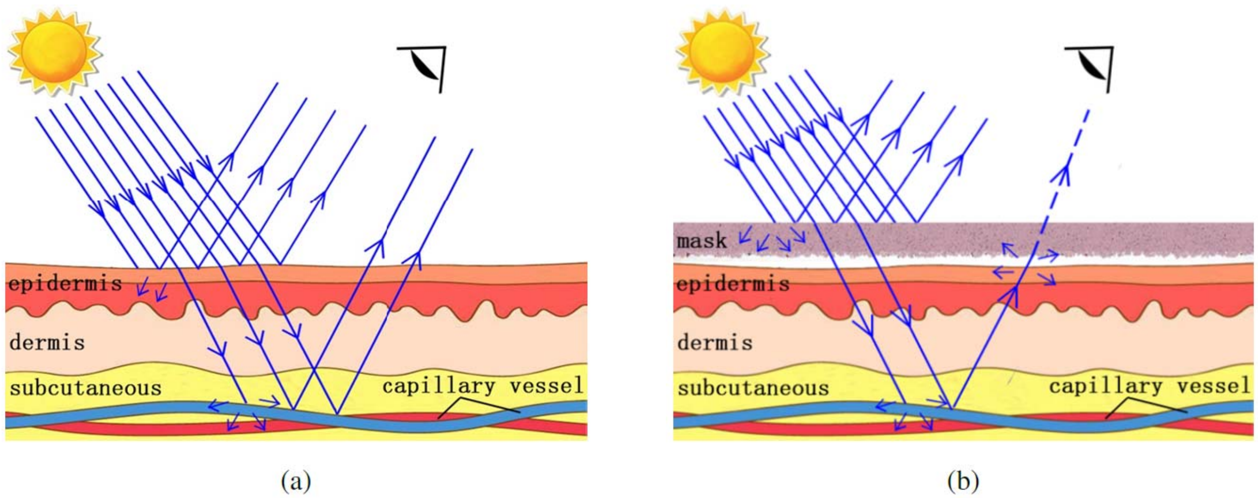


Pic. from UCLA Lung Cancer Program http://lungcancer.ucla.edu/adm_tests_electro.html

remote PhotoPlethysmoGraphy (rPPG)



Principle of rPPG Based Face Anti-Spoofing



(a) rPPG signal can be extracted from genuine face skin.

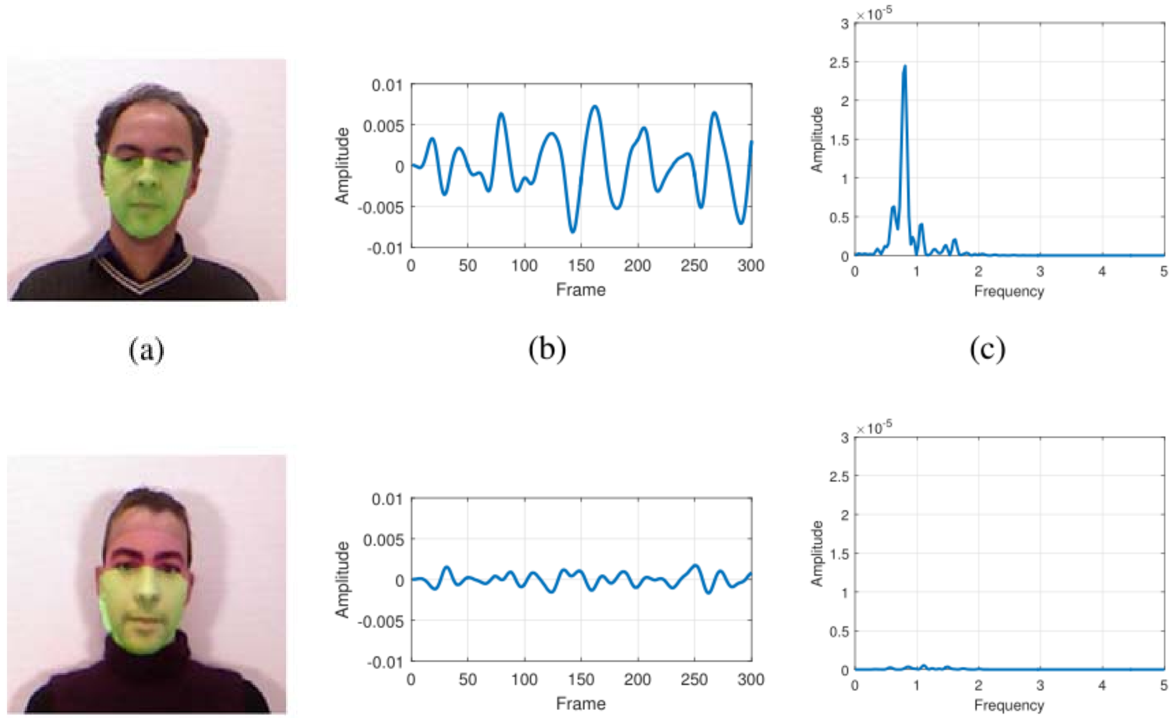
(b) rPPG signals will be **too weak** to be detected from a masked face.

- light source needs to penetrate the mask before interacting with the blood vessel.
- rPPG signal need to penetrate the mask before capturing by camera

Principle of rPPG Based Face Anti-Spoofing

genuine face

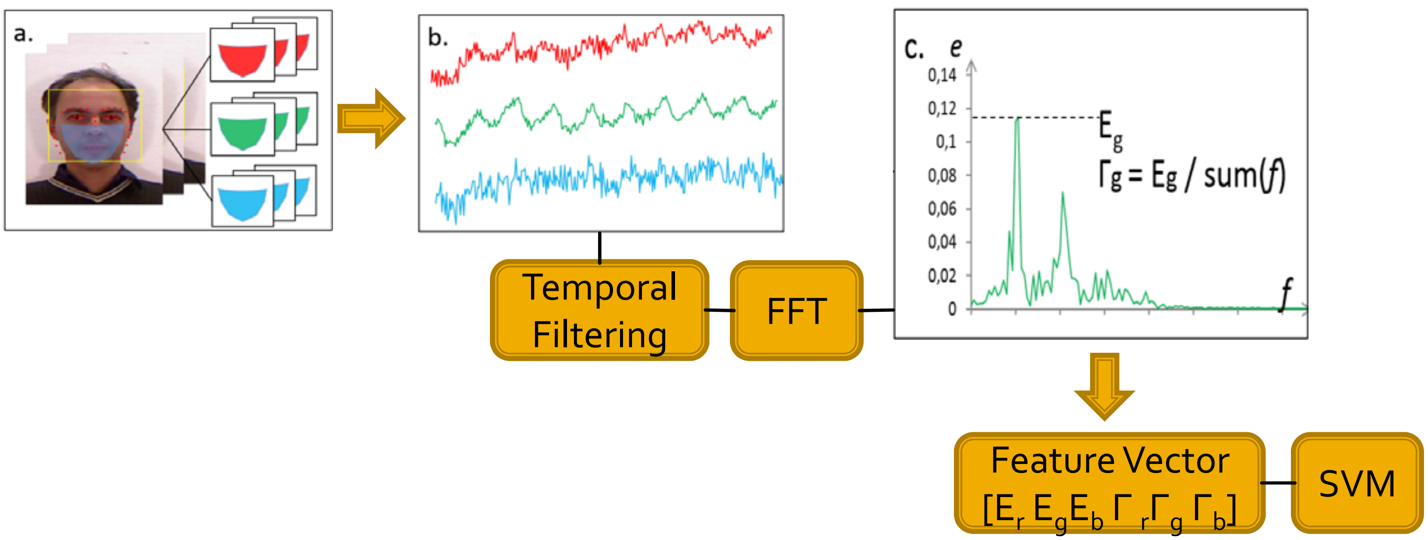
masked face



(a) (b) (c)

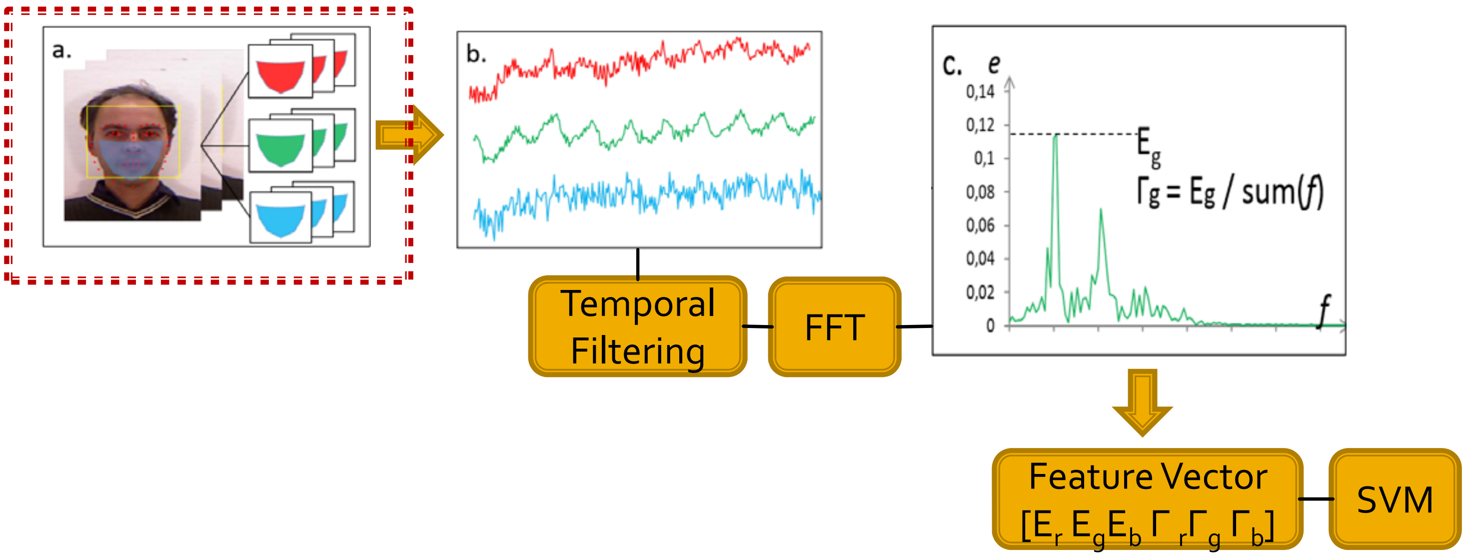
(d) (e) (f)

Global rPPG-based Face Anti-Spoofing [ICPR 2016]



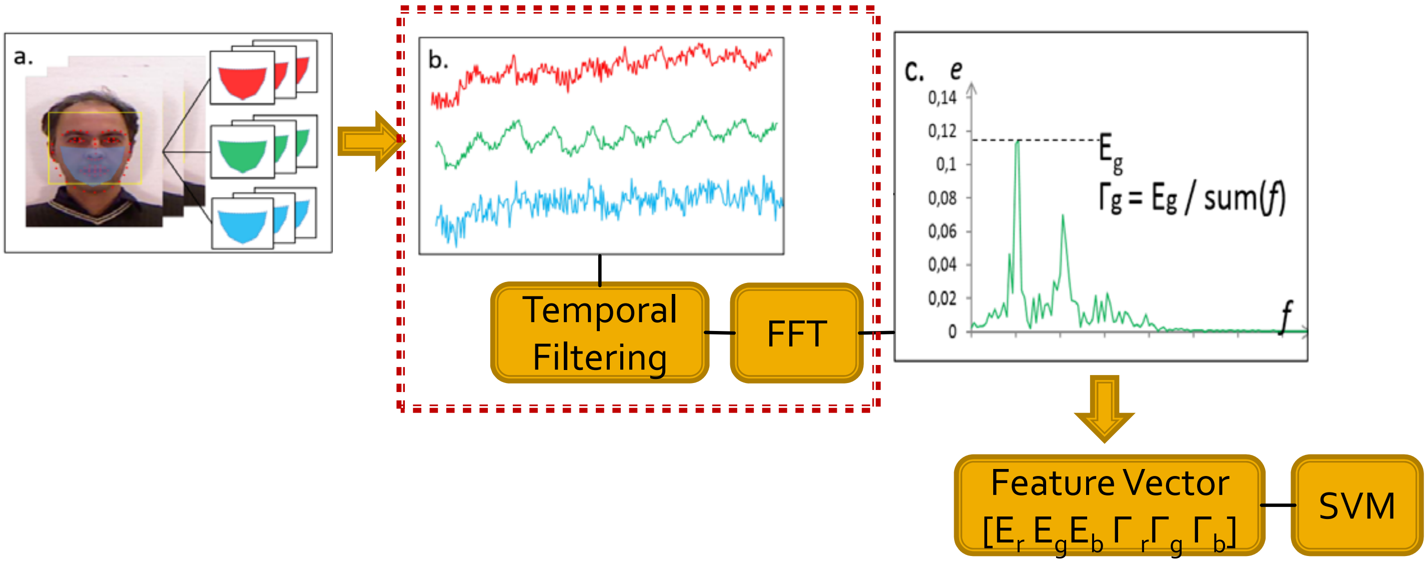
X Li, J Komulainen, G Zhao, P C Yuen and M Pietikainen,
"**Generalized face anti-spoofing by detecting pulse from face videos**"
ICPR 2016

Global rPPG-based Face Anti-Spoofing



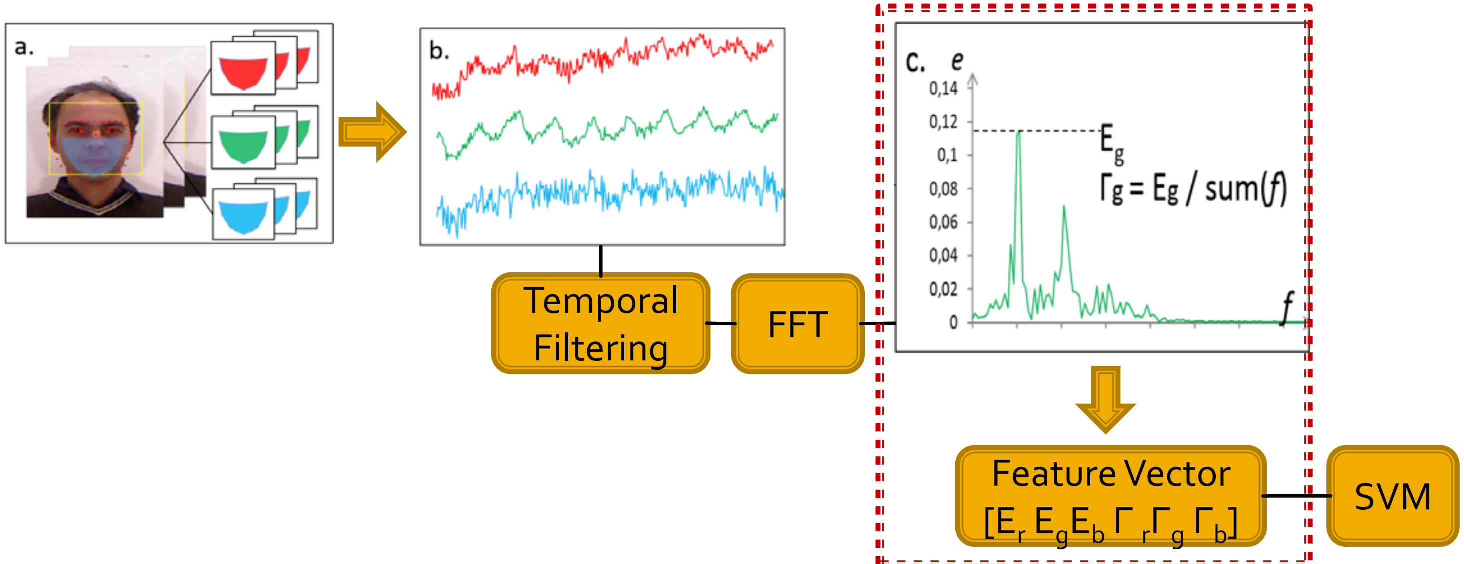
a. Face Detection and ROI tracking
- Use Viola-Jones face detector on the first frame
- Find 66 facial landmarks [CVPR'13 Asthana et.al] within the face bounding box. Use 9 of them to define the ROI
- ROI is tracked through all frames using KLT

Global rPPG-based Face Anti-Spoofing



b. Three raw pulse signals r_{raw} g_{raw} and b_{raw} are computed; one from each RGB channel, respectively.
   - FIR bandpass filter with a cutoff frequency range of [0.7; 4] Hz ([42; 240] beat-per-minute)
   - Use fast Fourier transform (FFT) to convert the pulse signals into frequency domain-> PSD curve: f

Global rPPG-based Face Anti-Spoofing

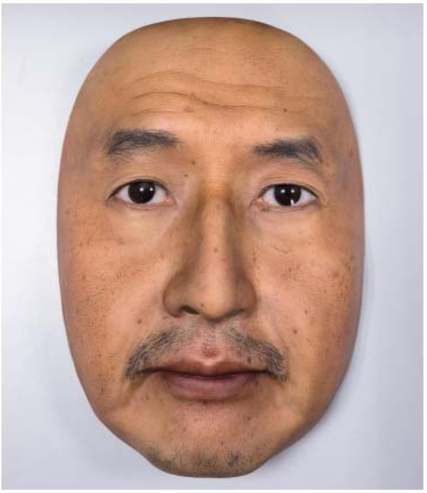


c. Feature Extraction $[E_r\ E_g E_b\ \Gamma_r \Gamma_g\ \Gamma_b]$

- $E = \max(e(f))$
- $\Gamma = \frac{E}{\sum_{\forall f \in [0.7,4]} e(f)}$

Experimental Results

- Data:
  - 3DMAD [Erdogmus et.al TIFS'14]
    - 255 videos recorded from 17 subjects
    - Masks made from *ThatsMyFace.com*
  - 2 REAL-F Masks
    - 24 videos recorded from 2 subjects
    - Hyper real masks from *REAL-F*



Experimental Results

- Results on 3DMAD
  - LOOCV protocol [Erdogmus *et.al* TIFS'14]

	3DMAD-dev	3DMAD-test	
Method	EER(%)	HTER(%)	EER(%)
Pulse (ours)	**2.31**	**7.94**	**4.17**
LBP-blk	0	0	0
LBP-blk-color	0	0	0
LBP-ms	0	0	0
LBP-ms-color	0	0	0

Note:
LBP-blk: $LBP_{8,1}$ extracted from 33 blocks of a gray-scale face
LBP-blk-color: LBP-blk extracted separately from each RGB color channel
LBP-ms: multi-scale LBP extracted from a whole gray-scale face image combining $LBP_{8,1}$, $LBP_{8,2}$, $LBP_{8,3}$, $LBP_{8,4}$, and $LBP_{16,2}$
LBP-ms-color: LBP-ms extracted separately from each RGB color channel

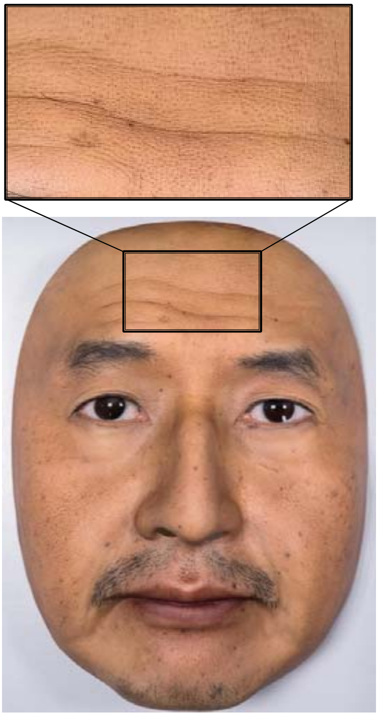
Experimental Results

- Results on REAL-F
  - Randomly select 8 subjects from 3DMAD for training and the other 8 subjects as the development set

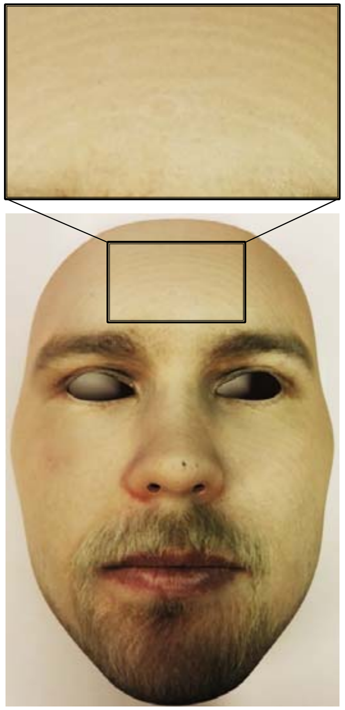
	REAL-F			
Method	HTER(%)	EER(%)	FPR (@FNR=0.1%)	FPR (@FNR=0.01%)
Pulse (ours)	**4.29**	**1.58**	**0.25**	**3.83**
LBP-blk	26.3	25.08	37.92	48.25
LBP-blk-color	25.92	20.42	31.5	48.67
LBP-ms	39.87	46.5	59.83	73.17
LBP-ms-color	47.38	46.08	86.5	95.08

Analysis of Results

- Observations:
  - LBP-based texture method gives *zero error for 3DMAD* dataset but very *large error in REAL-F*
  - Global rPPG method (pulse) provides *very small errors in both 3DMAD and REAL-F datasets*



REAL-F



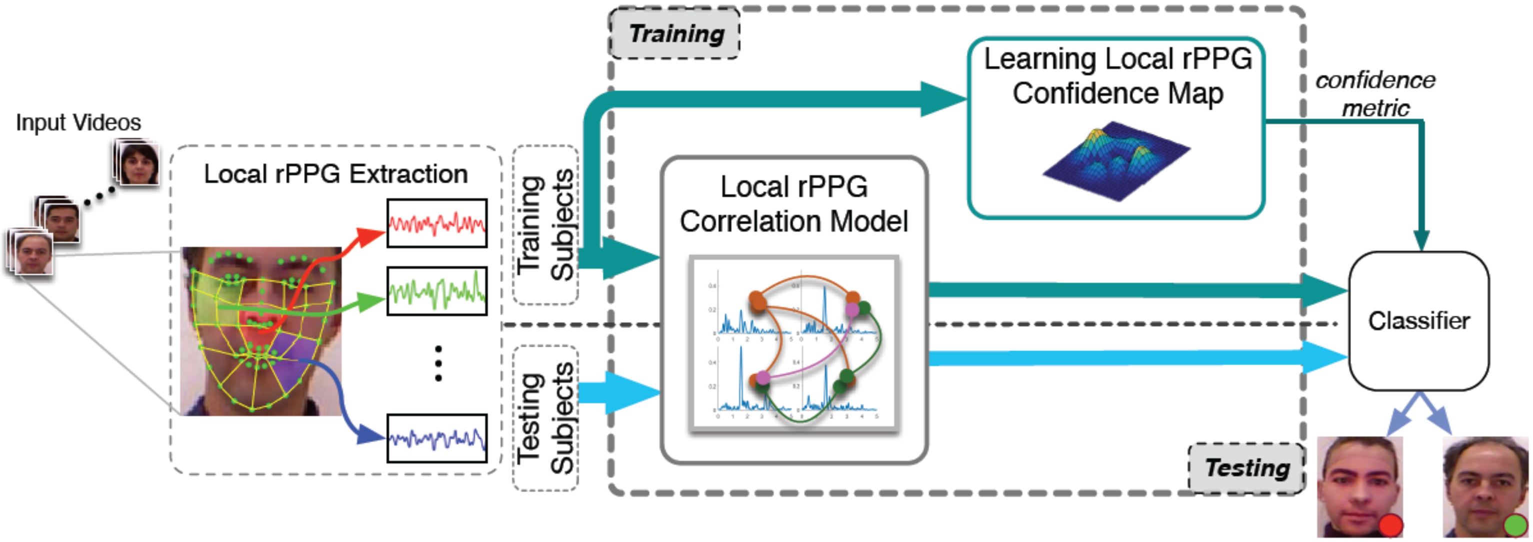
3DMAD

Limitations on Global rPPG method

- Global rPPG signal is sensitive to certain variations such as illuminations, head motion and video quality
- rPPG signal strength may vary with different subjects

How to increase the robustness of rPPG-based Face Anti-spoofing?

Local rPPG based Face Anti-Spoofing Method [ECCV 2016]



S Q Liu, P C Yuen, S P Zhang and G Y Zhao

3D Mask Face Anti-spoofing with Remote Photoplethysmography

ECCV 2016

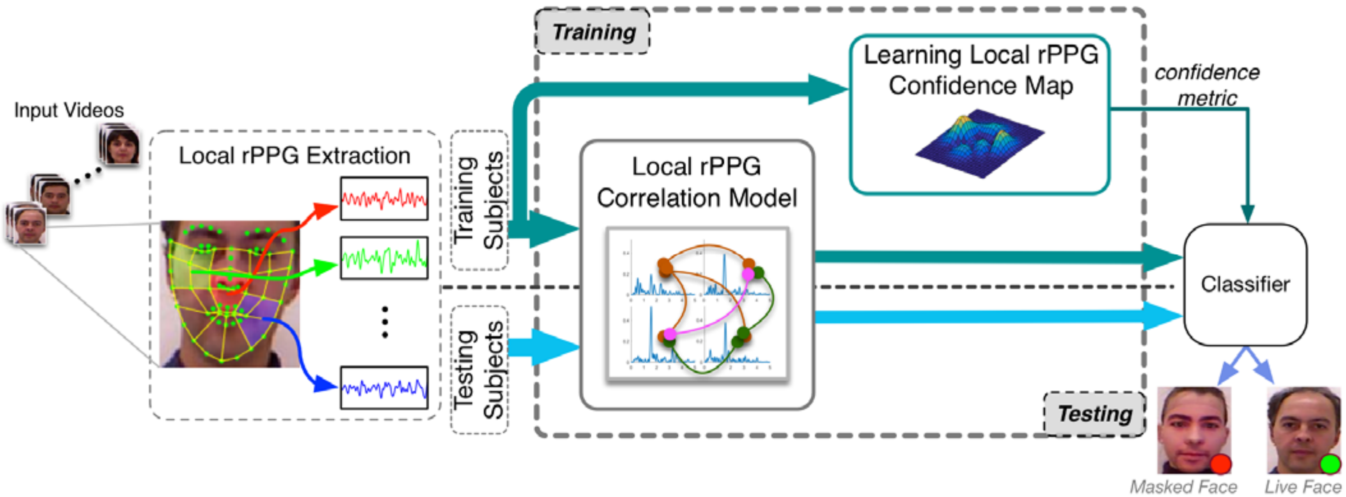
Rationale

- Correlation of local regions could remove noise
- For different subjects, the patterns of facial blood vessels are similar

Generic map of blood vessels on the face

SNR map of local rPPG signals for different subjects

Local rPPG based Face Anti-Spoofing Method

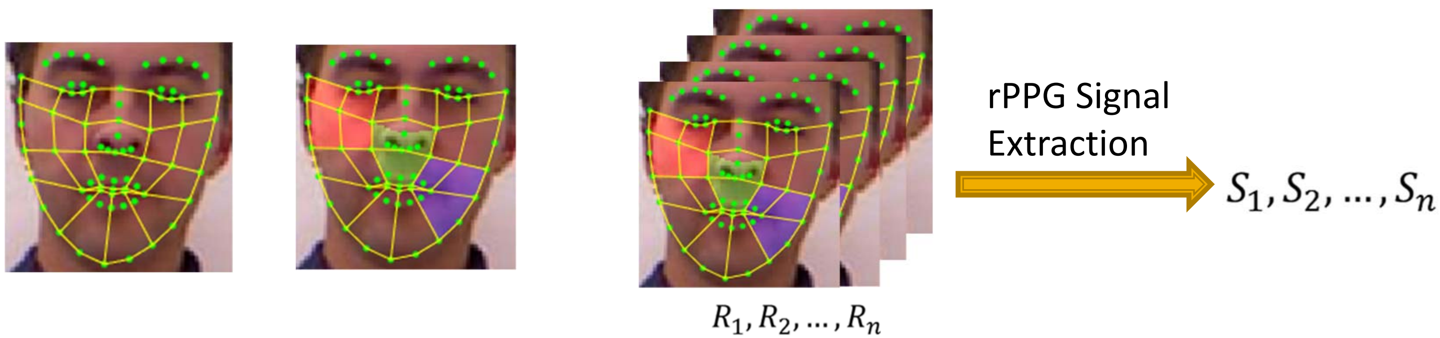


(a) Local ROIs are pre-defined based on the facial landmarks. Local rPPG signals are extracted from these local face regions.
(b) Extract Local rPPG patterns through the proposed **local rPPG correlation model**.
(c) Training stage: local rPPG confidence map is learned, and then transformed into distance metric for classification.
(d) Classifier: SVM

1. Local rPPG Signal Extraction

- (i) ROI detection and tracking
  - Landmark detection and tracking
  - Local ROIs are pre-defined based on the facial landmarks

- (ii) rPPG Signal Extraction
  - We adopt (Haan et.al., TBE, 2013) method to extract rPPG signals.

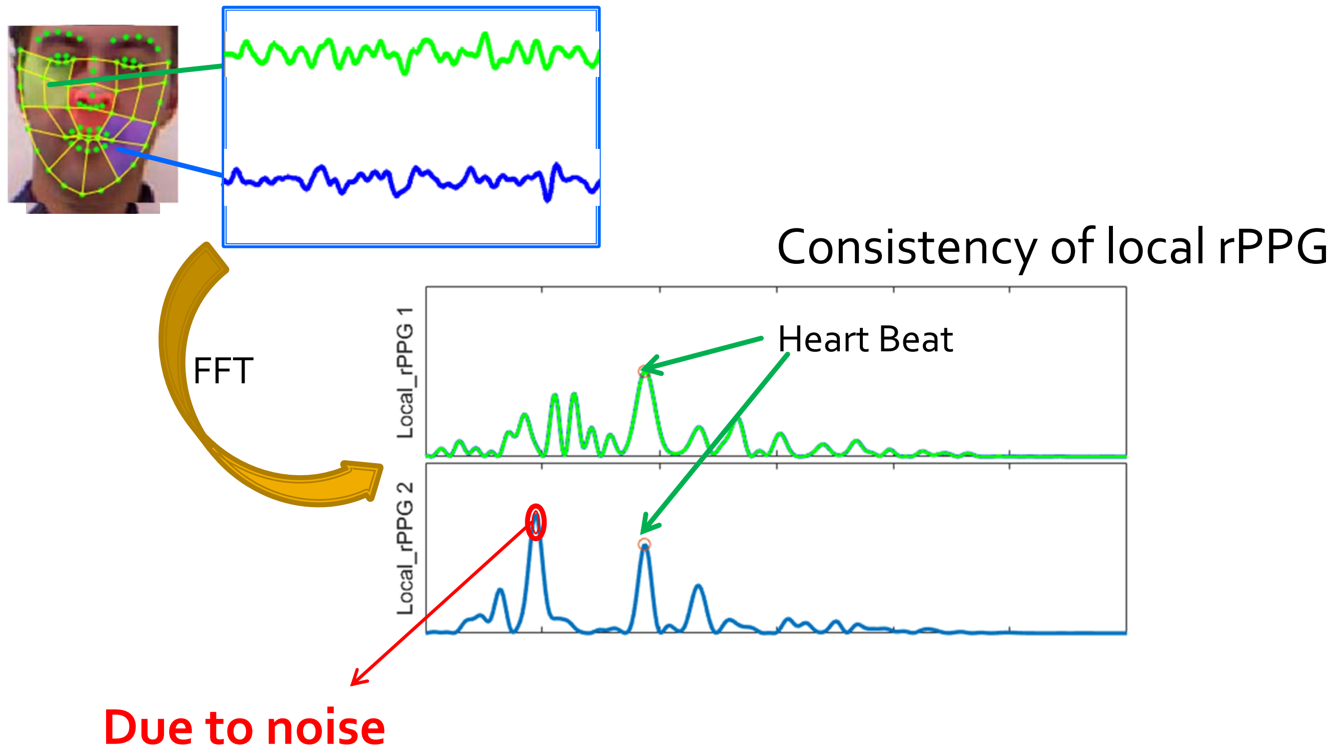


2. Local rPPG Correlation Model

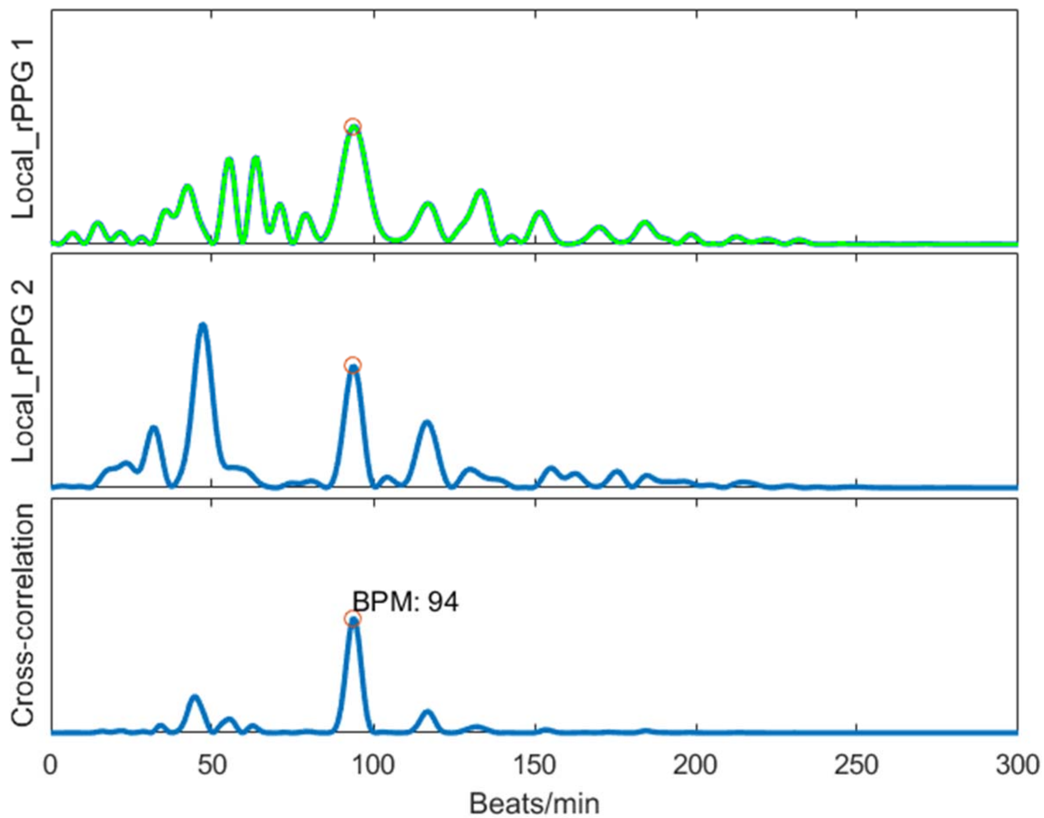
- To handle noise introduced in rPPG signal due to different variations, such as illuminations, head motion, …
- For genuine face, local rPPG signals should have high consistency
- For masked face, local rPPG signals should have a small frequency similarity and periodicity

2. Local rPPG Correlation Model

- Local rPPG on genuine face

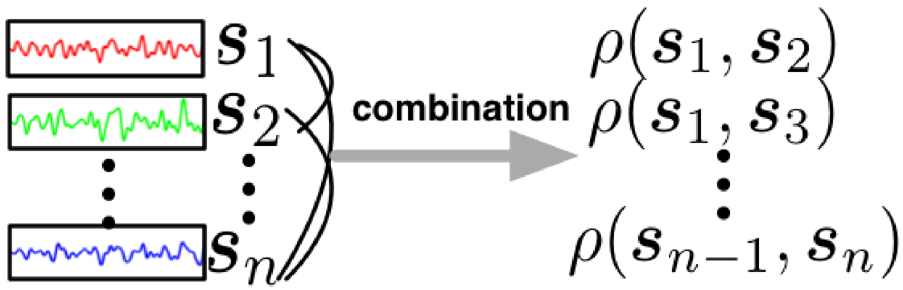


2. Local rPPG Correlation Model



2. Local rPPG Correlation Model

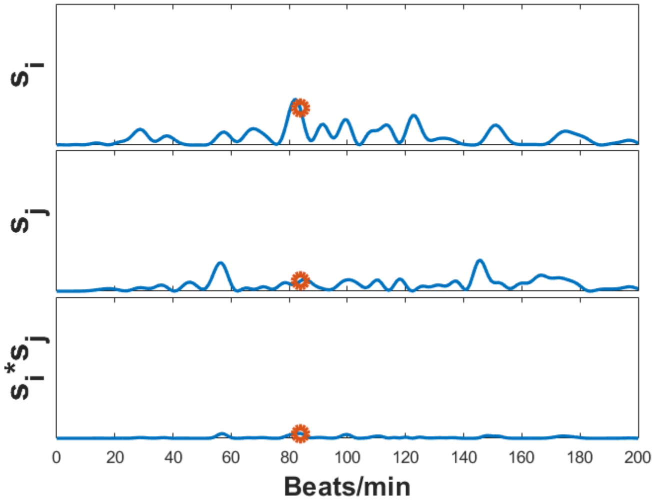
Similarity of all possible combinations of local rPPG signals



$$\rho(\boldsymbol{s}_i, \boldsymbol{s}_j) = \max \left| \mathcal{F}\{\boldsymbol{s}_i \star \boldsymbol{s}_j\} \right|$$

3. Learning Local rPPG Confidence Map

- Local rPPG correlation pattern may not be sufficient to handle noise in some cases
  - rPPG signals may be too weak in low quality video



3. Learning Local rPPG Confidence Map

- Local rPPG correlation pattern may not be sufficient to handle noise in some cases
  - rPPG signals may be too weak in low quality video and concealed by noise

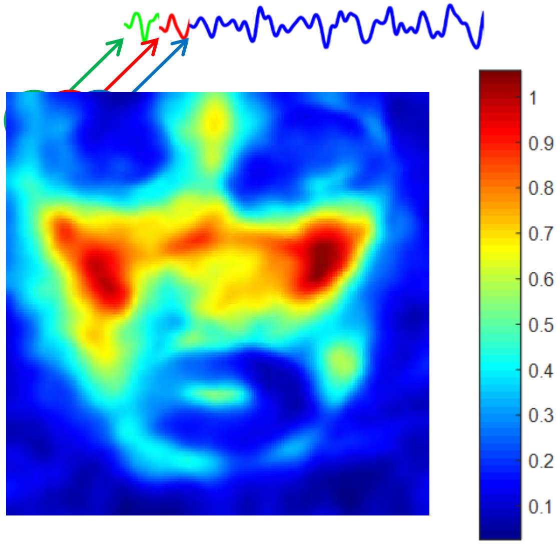
- rPPG signal strength varies with different local face regions

We propose to learn a ***local rPPG confidence map***

1. emphasizing the region with strong HR signal, and
2. weaken the unreliable region with pale HR signal.

3. Learning Local rPPG Confidence Map

Generic map of blood vessels on the face



The distribution of local rPPG signals should be considered

3. Learning Local rPPG Confidence Map

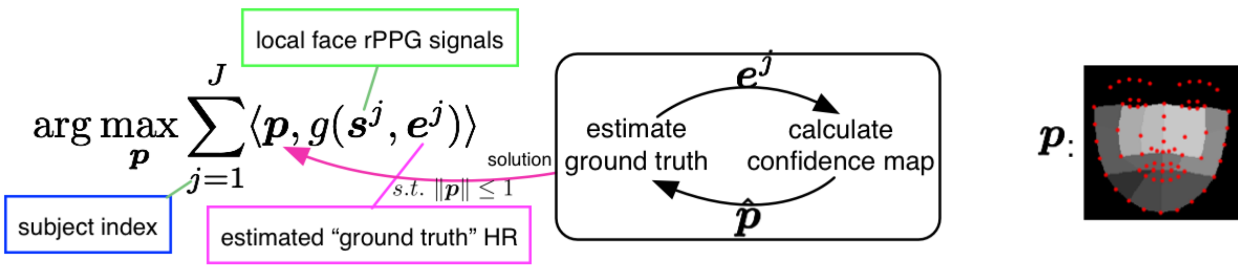
- How to measure the strength of HR signal?
- Signal to Noise Ratio (SNR)

$$\frac{\sum_{f_{HR-r}}^{f_{HR}+r} \hat{\mathbf{s}}^{j}(f)}{\sum \hat{\mathbf{s}}^{j}(f) - \sum_{f_{HR-r}}^{f_{HR}+r} \hat{\mathbf{s}}^{j}(f)}$$

- How to find the estimated ground truth HR signal?

3. Learning Local rPPG Confidence Map

- An iterative algorithm: Given ***J*** training subjects, learn the local rPPG confidence map ***p*** which reflects the reliability of local face regions:

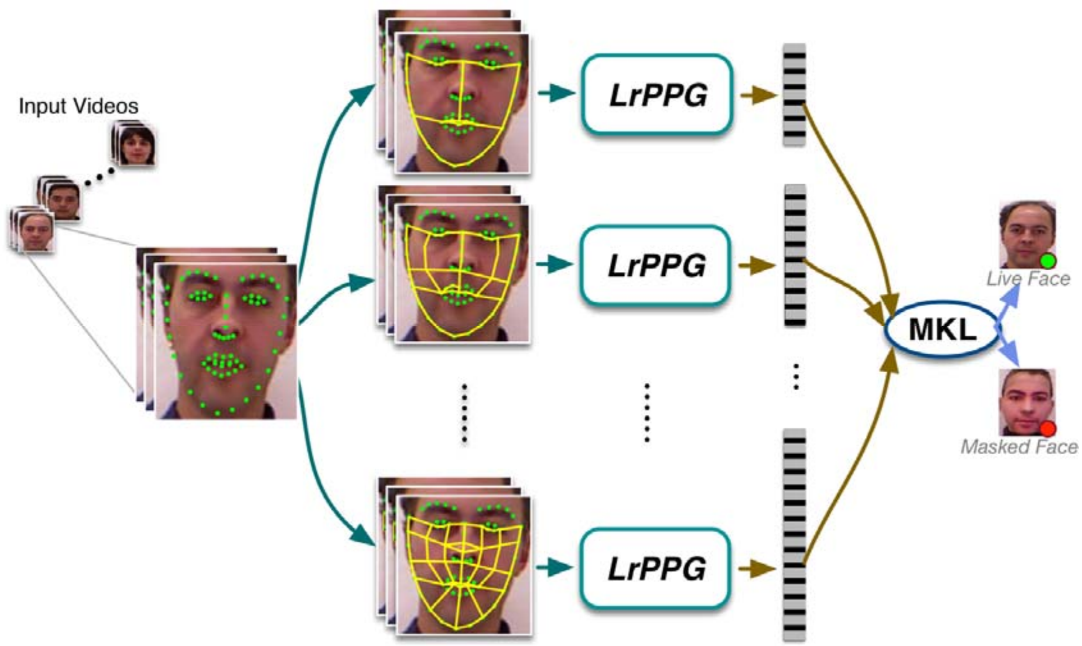


- Using local rPPG confidence map ***p*** to weight the distance metric in classifier

Limitations on Local rPPG Method

- rPPG quality (Discriminability) highly depends on the local regions size:
  - Smaller region: Signal quality ↓, spatial information ↑
  - Larger region: Signal quality ↑, spatial information ↓
- Large real environment variations (lighting condition & camera settings)
- Multi-scale ROI strategy can better adapt different application environment in practice

Multi-Scale Local rPPG Method



$$K_{\mathcal{MS}}(\boldsymbol{x}, \boldsymbol{x'}) = \sum_{m \in M} d_m K(\boldsymbol{x}_m, \boldsymbol{x'}_m)$$
$$s.t., d_m \geq 0, \sum_{m \in M} d_m = 1$$

M : number of scales
x_m: LrPPG feature extracted from of scale *m*
d_m: weight of scale *m*

Experimental Results

- **Datasets**
- 3DMAD [TIFS'14 Erdogmus et.al]
  - 255 videos recorded from 17 subjects
  - Masks made from ThatsMyFace.com

- HKBU MARs V2 Dataset:
  - 2 Mask types: **12** subjects: ThatsMyFace (6), REAL-F (**6**)
  - Captured by WebCam Logitech C920 (1280*720 RGB)

More details can be found: http://rds.comp.hkbu.edu.hk/mars/

Experimental Results

- Intra-Database Experiment (***LOOCV***)
  - 3DMAD, HKBU MARs V2, and Combined Dataset
    (3DMAD+HKBU MARs V2)
- Cross-Database Experiment
  - Training on 3DMAD, Test on HKBU MARs V2 dataset
  - Training on HKBU MARs V2 , Test on 3DMAD dataset
- Cross-Mask Experiment
  - Training and test using different mask types

Experimental Results

- Intra-database experiments (***LOOCV***)

Combined

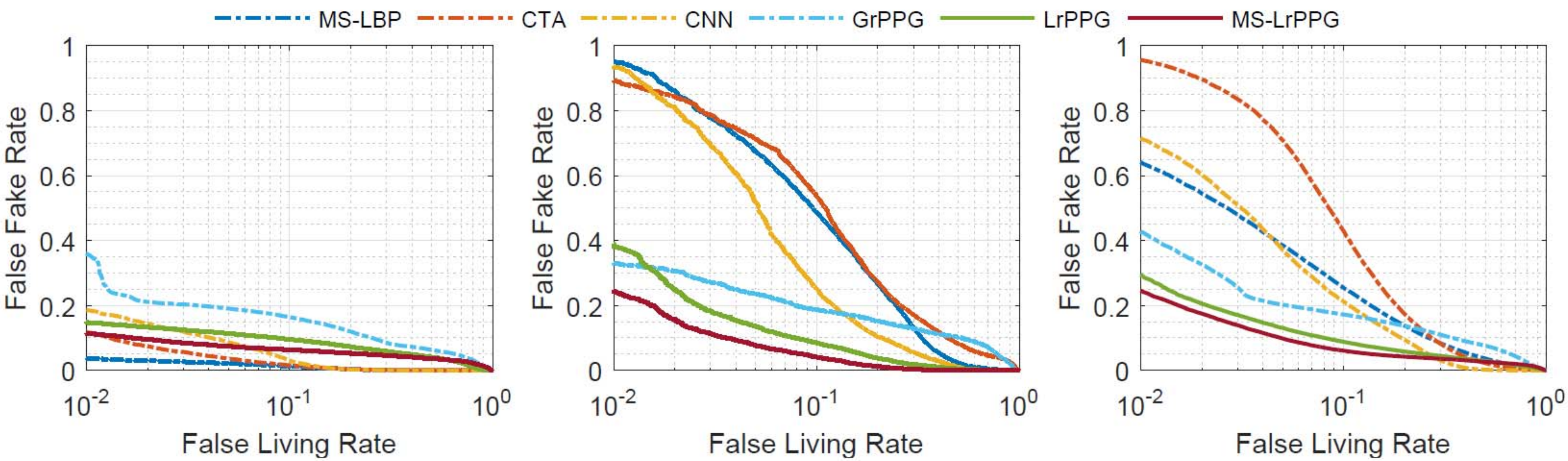
	HTER_dev	HTER_test	EER	AUC	FFR@ FLR=0.1	FFR@ FLR=0.01
MS-LBP[2]	15.7 ± 4.2	16.2 ± 22.6	16.6	91.0	25.4	64.2
CTA [1]	18.4 ± 5.8	19.5 ± 21.5	18.9	87.7	42.9	95.7
CNN [6]	13.5 ± 5.9	14.6 ± 20.6	14.5	93.5	21.2	71.5
GrPPG	15.3 ± 2.9	15.5 ± 18.5	15.2	91.1	17.2	42.8
LrPPG [5]	8.69 ± 1.5	9.16 ± 11.9	9.21	95.7	8.79	29.4
MS-LrPPG	$\mathbf{6.93 \pm 1.2}$	$\mathbf{6.92 \pm 11.1}$	**7.41**	**96.4**	**6.07**	**24.6**

HKBU MARs V2

	HTER_dev	HTER_test	EER	AUC	FFR@ FLR=0.1	FFR@ FLR=0.01
MS-LBP[2]	20.5 ± 8.9	24.0 ± 25.6	22.5	85.8	48.6	95.1
CTA [1]	22.4 ± 10.4	23.4 ± 20.5	23.0	82.3	53.7	89.2
CNN [6]	13.7 ± 10.8	14.8 ± 22.2	15.2	91.4	25.1	93.5
GrPPG	15.4 ± 6.7	16.1 ± 20.5	16.4	89.4	18.6	32.9
LrPPG [5]	8.43 ± 2.9	8.67 ± 8.8	9.07	97.0	8.51	38.9
MS-LrPPG	$\mathbf{6.07 \pm 2.6}$	$\mathbf{6.44 \pm 7.6}$	**6.38**	**98.5**	**4.08**	**24.5**

1. Z. Boulkenafet, J. Komulainen, and A. Hadid, "Face spoofing detection using colour texture analysis", *TIFS*, 2016
2. N. Erdogmus and S. Marcel, "Spoofing face recognition with 3d masks", TIFS, 2014
5. S. Liu, P C. Yuen, S. Zhang, and G. Zhao, "3D Mask Face Anti-spoofing with Remote Photoplethysmography" , ECCV, 2016.
6. J. Yang, Z. Lei, and S. Z. Li, "Learn convolutional neural network for face anti-spoofing", arXiv, 2014.

Experimental Results: Intra-database



(a) 3DMAD (b) HKBU-MARsV2 (c) Combined

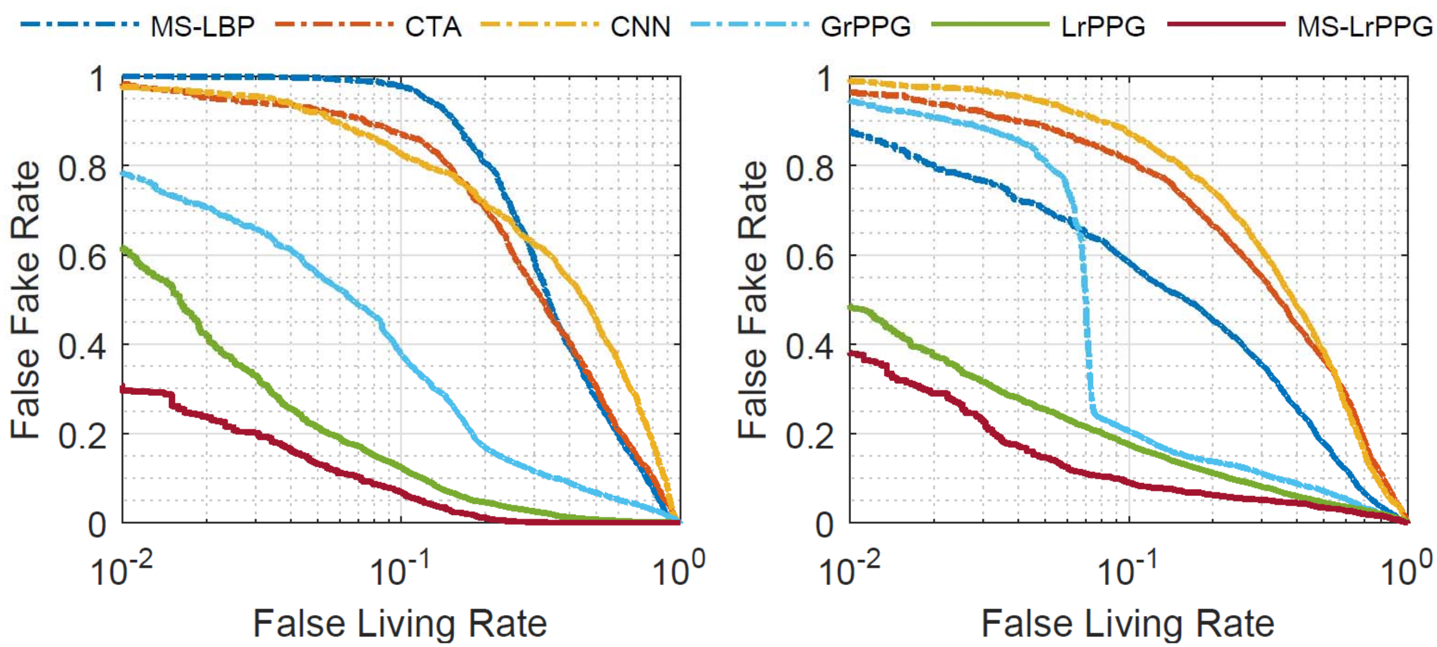
Experimental Results

- Cross-database experiments

	3DMAD→HKBU-MARsV2					HKBU-MARsV2→3DMAD				
	HTER(%)	EER(%)	AUC(%)	FFR@ FLR=0.1	FFR@ FLR=0.01	HTER(%)	EER(%)	AUC(%)	FFR@ FLR=0.1	FFR@ FLR=0.01
MS-LBP[2]	53.0 ± 3.6	39.8	60.4	97.8	100.0	32.8 ± 11.5	32.5	75.3	58.5	87.8
CTA [1]	40.1 ± 7.8	40.2	62.1	87.1	98.3	47.7 ± 5.4	42.5	60.5	81.2	96.5
CNN [6]	50.0 ± 0.0	47.8	54.6	82.6	97.9	50.0 ± 0.0	44.3	58.6	87.3	99.3
GrPPG	29.2 ± 9.7	20.4	87.7	34.8	62.8	18.4 ± 8.3	16.8	89.9	27.1	53.9
LrPPG [5]	16.8 ± 5.0	10.9	95.6	12.4	61.7	17.4 ± 4.4	14.0	92.3	17.4	48.7
MS-LrPPG	**13.2 ± 4.8**	**8.35**	**98.0**	**6.83**	**30.6**	**11.0 ± 2.0**	**9.59**	**95.0**	**9.00**	**38.2**

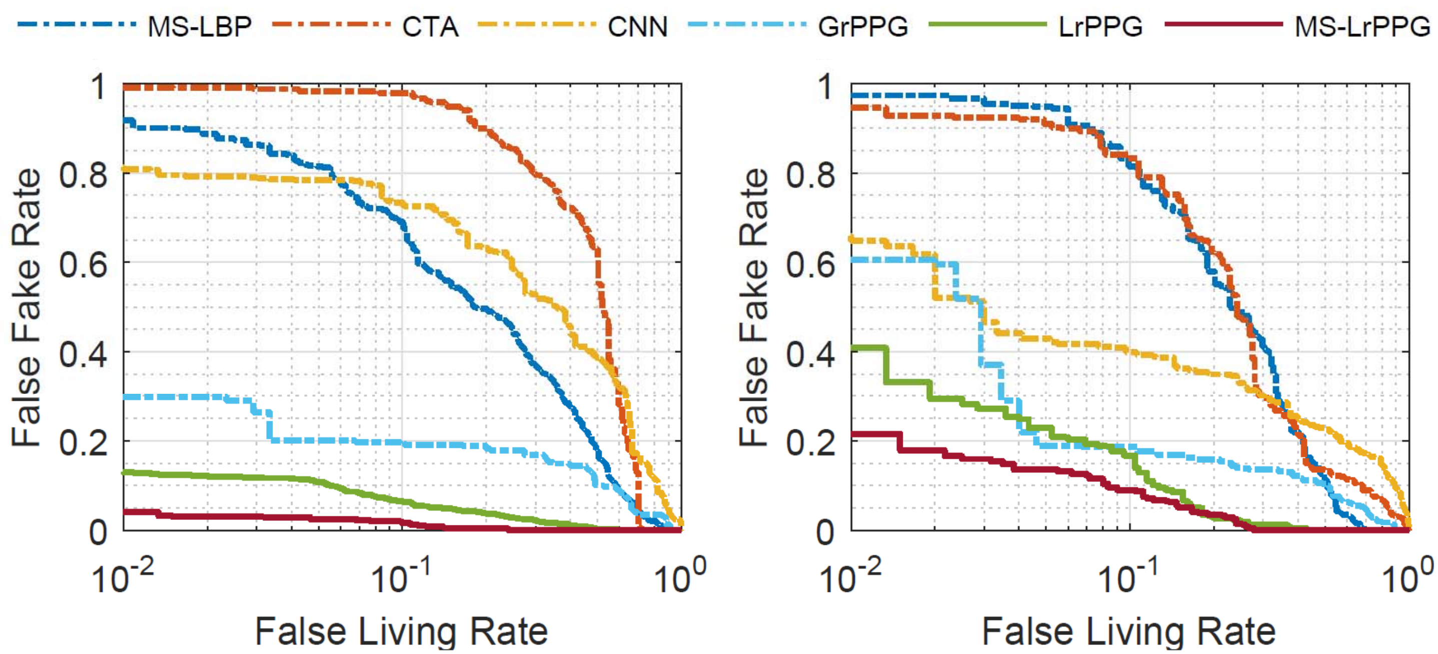
- Our proposed method is robust encountering the cross-database scenario
- The appearance based method exposes the aforementioned drawbacks in the cross-database scenario

Experimental Results: Cross-database



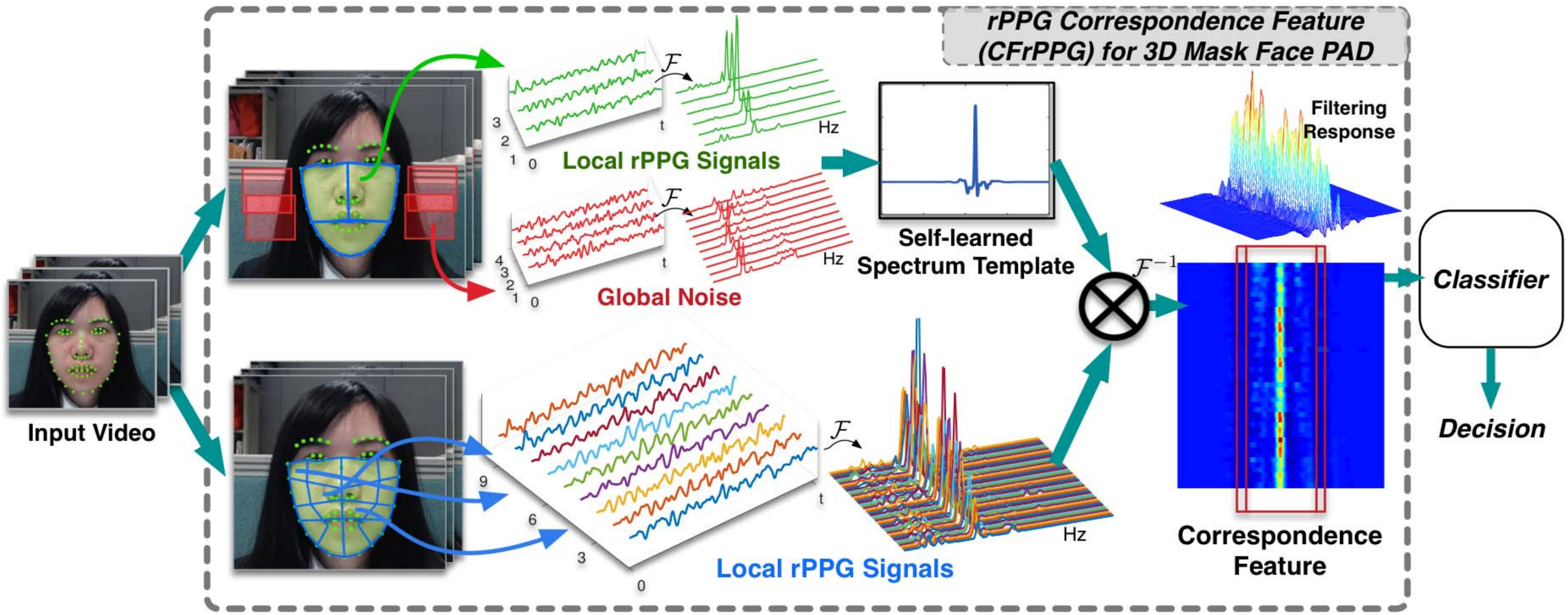
(a) 3DMAD→HKBU-MARsV2 (b) HKBU-MARsV2→3DMAD

Experimental Results: Cross-mask



(a) TMF to RF (HKBU-MARsV2) (b) RF to TMF (HKBU-MARsV2)

New Method: rPPG Correspondence Feature

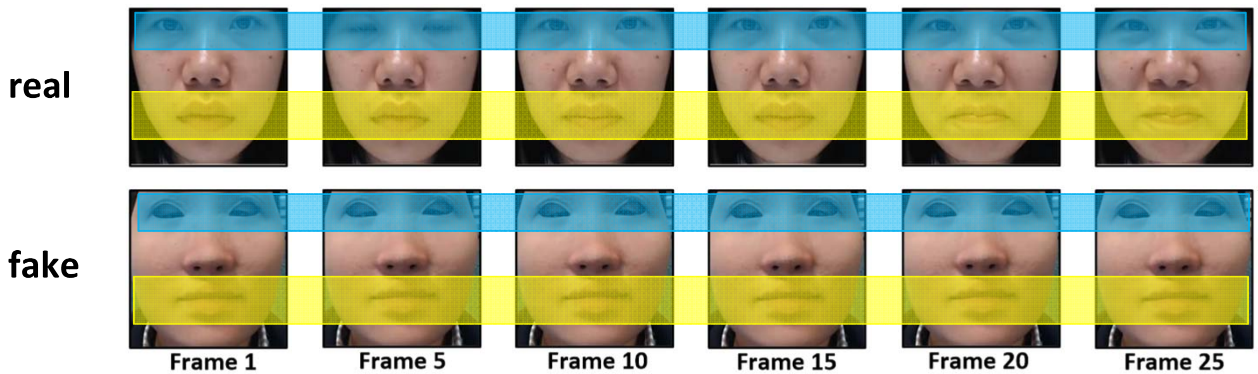


S Q Liu, X Y Lan and P C Yuen, "Remote Photoplethysmography Correspondence Feature for 3D Mask Face Presentation Attack Detection", *ECCV*, 2018

Deep Learning Approach

Joint Discriminative Learning of Deep Dynamic Textures

- **Basic Idea**



- Eye blinking
- Lip movements
- Some other facial components movements

Captured by dynamic textures

Reference:
1. R Shao*, X Y Lan* and P C Yuen, “Deep Convolutional Dynamic Texture Learning with Adaptive Channel-discriminability for 3D Mask Face Anti-spoofing”, *IAPR/IEEE International Joint Conference on Biometrics (IJCB)*, Oct 2017
2. R Shao*, X Y Lan* and P C Yuen, “Joint Discriminative Learning of Deep Dynamic Textures for 3D Mask Face Anti-spoofing”, *IEEE Transactions on Information Forensics and Security (TIFS)*, In press, 2019.

Joint Discriminative Learning of Deep Dynamic Textures

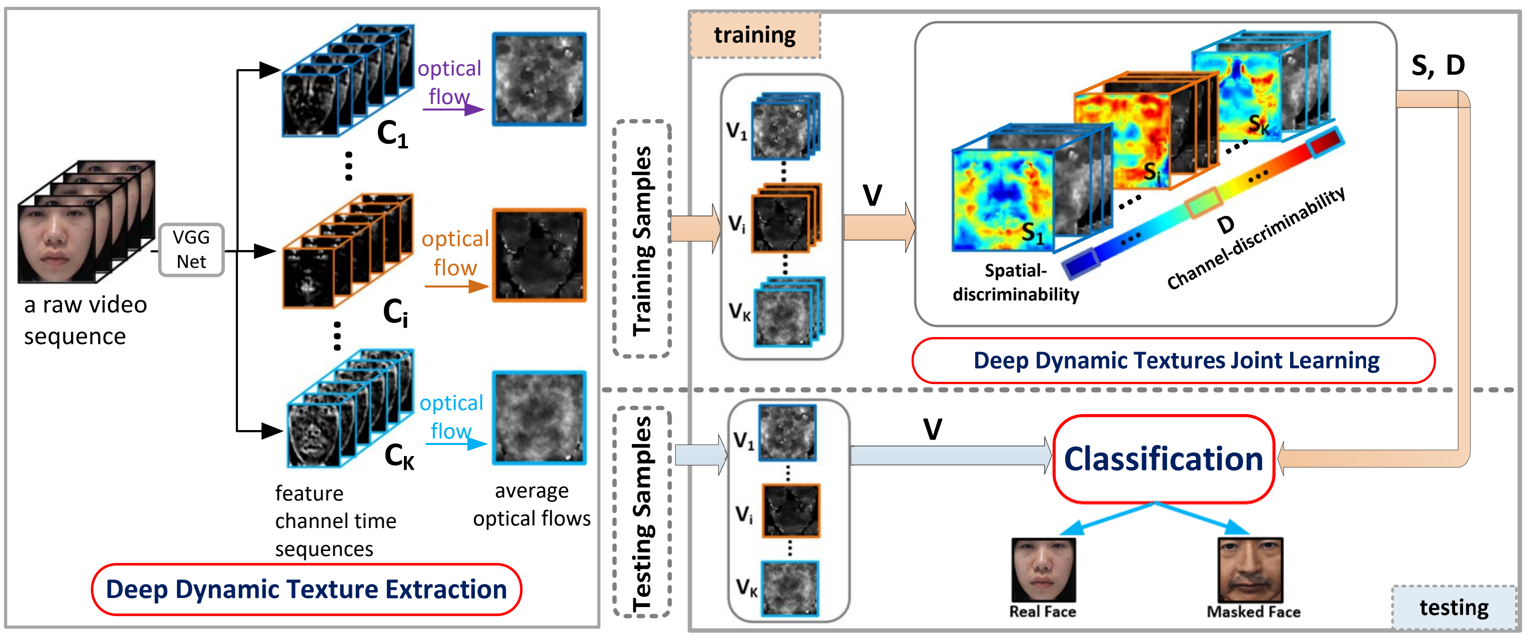
- **Challenges**
  - A large portion of these facial movements are **subtle**
  - Hand-crafted features are not fine-grained and descriptive enough to capture these **subtle** dynamic texture differences between real faces and 3D masks.

Joint Discriminative Learning of Deep Dynamic Textures

- **Deep Dynamic Features**
  - CNN learns features from large-scale visual data with the feature hierarchy structure.
  - Powerful abstract concept recognition ability of features in the higher layer of CNN is derived from the rich descriptive low-level features in the lower layer.
  - Deep textures of the lower convolutional layer have strong description ability.
  - The dynamic feature estimated from these descriptive deep textures is more able to differentiate subtle facial motion differences than hand-crafted dynamic textures.

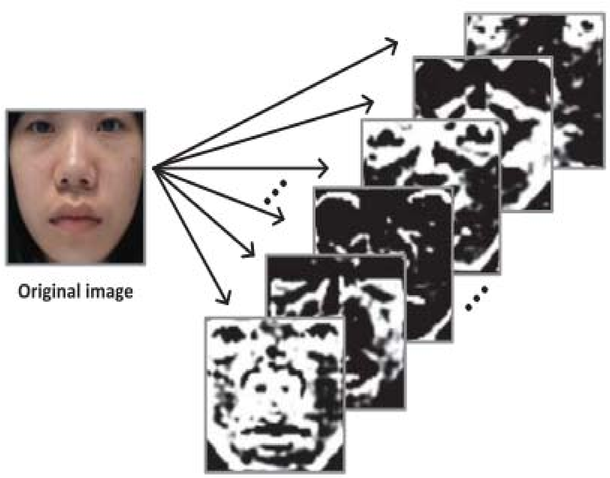
Joint Discriminative Learning of Deep Dynamic Textures

- ## Framework



Joint Discriminative Learning of Deep Dynamic Textures

- **Deep Dynamic Texture Extraction**



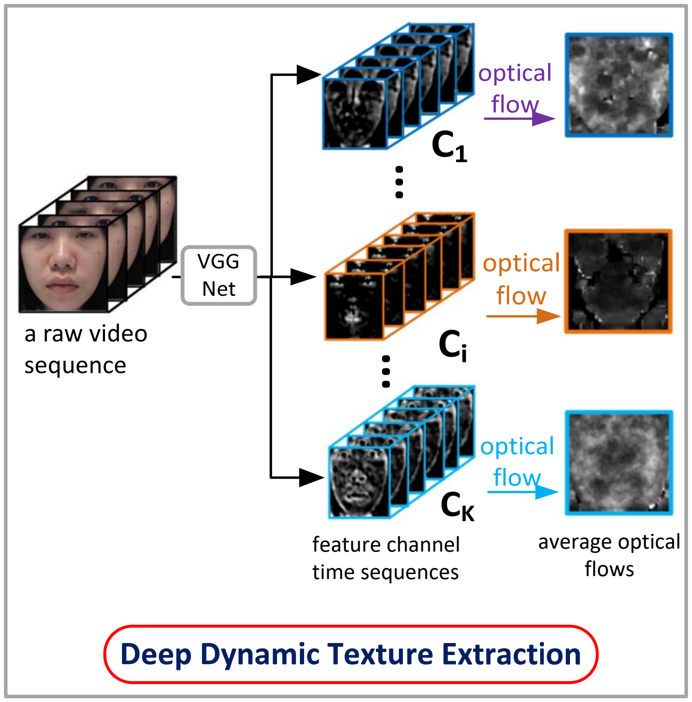
(The responses in feature channels of a lower convolutional layer of a sample)

- An image is decomposed into various texture responses in feature channels of a convolutional layer

- Every facial local region can be described by various fine-grained deep textures
  -> Motion information of every facial local region can be described by the proposed visual cues of multiple deep dynamic textures
  -> Differentiate the various subtle motion differences between the real face and 3D mask

Joint Discriminative Learning of Deep Dynamic Textures

- **Deep Dynamic Texture Extraction**

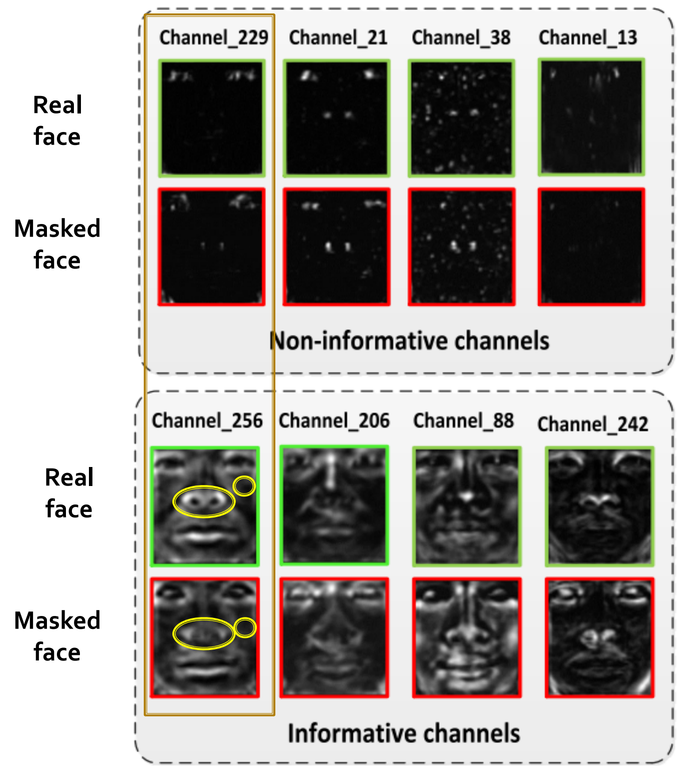


- Given an aligned face video sequence, we input each frame into a pre-trained CNN.

- Then the subtle facial motions on each feature channel (of all frames) are estimated using a motion estimation method
  -> Preliminary feature set of multiple deep dynamic textures

Joint Discriminative Learning of Deep Dynamic Textures

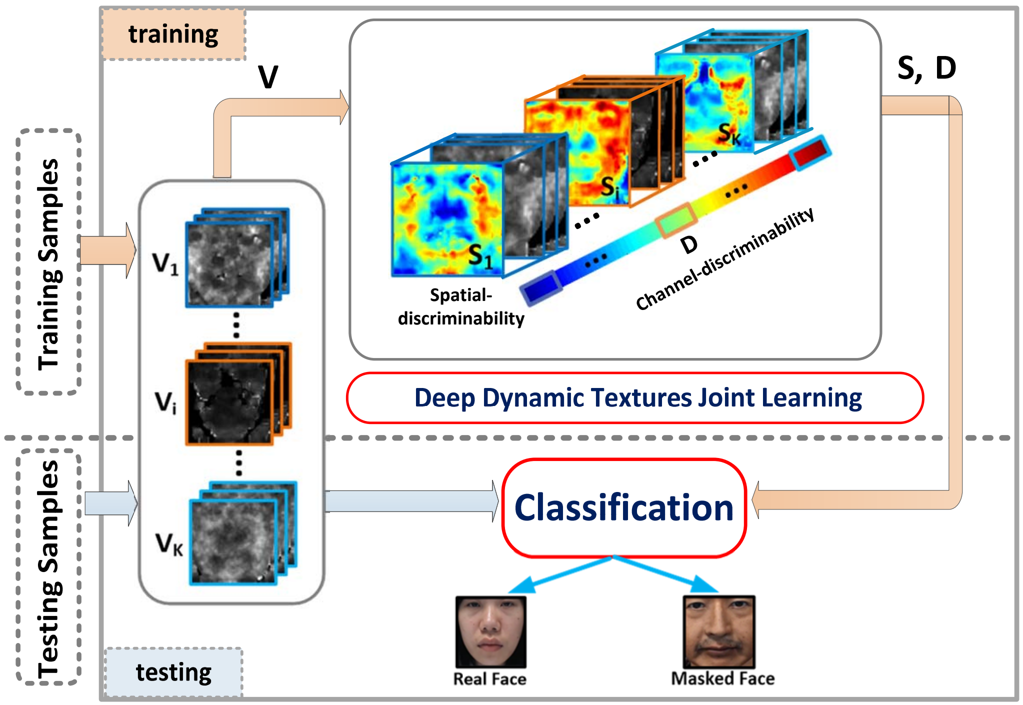
▪ Deep Dynamic Texture Joint Learning



- Not all the deep dynamic textures are useful for our task
  - Different channels give strong and weak responses of deep texture in different spatial regions
  - Divide into non-informative and informative channels
  - Deep dynamic textures in informative channels have stronger discriminability

Joint Discriminative Learning of Deep Dynamic Textures

- Deep Dynamic Texture Joint Learning

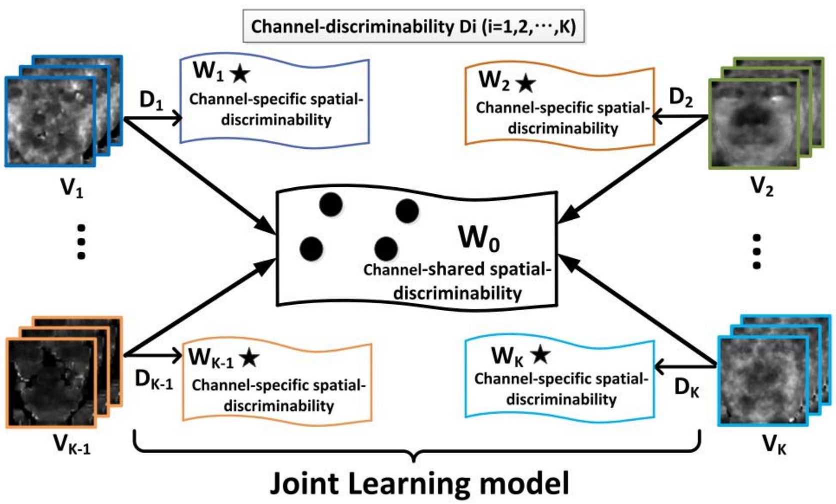


- Channel-discriminability D_i
- Spatial-discriminability S_i

Discriminative learning model:
To capture both channel- and spatial-discriminability for feature learning which enables **more discriminative** features to play **more important role** in face/mask decision

Joint Discriminative Learning of Deep Dynamic Textures

- **Deep Dynamic Texture Joint Learning**



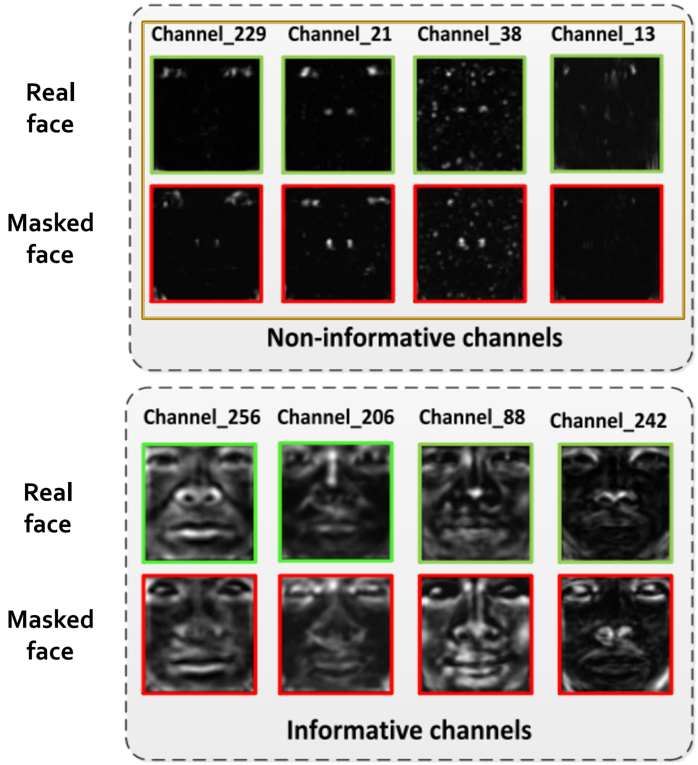
Discriminative learning model:

$$\min_{\{D_i\},\{S_i\}} \sum_{i=1}^{K} \left(D_i \| f_{S_i}(V_i) - Y \|_F^2\right) + \theta \Omega(D)$$

- $f_{S_i}(\bullet)$: classifier parameterized by the spatial discriminability of the i-th deep dynamic texture S_i
- $\{V_i\}_{i=1}^{K}$: K deep dynamic textures
- Y : Ground truth label set
- $\Omega(D)$: regularization term

Joint Discriminative Learning of Deep Dynamic Textures

- **Deep Dynamic Texture Joint Learning**



Non-informative channels are not able to produce strong responses of deep textures for both 3D masks and real faces in all spatial regions.

-> Discriminability of these channels is weak, and it is meaningless to optimize the prediction losses of these features in channels with weak discriminability.

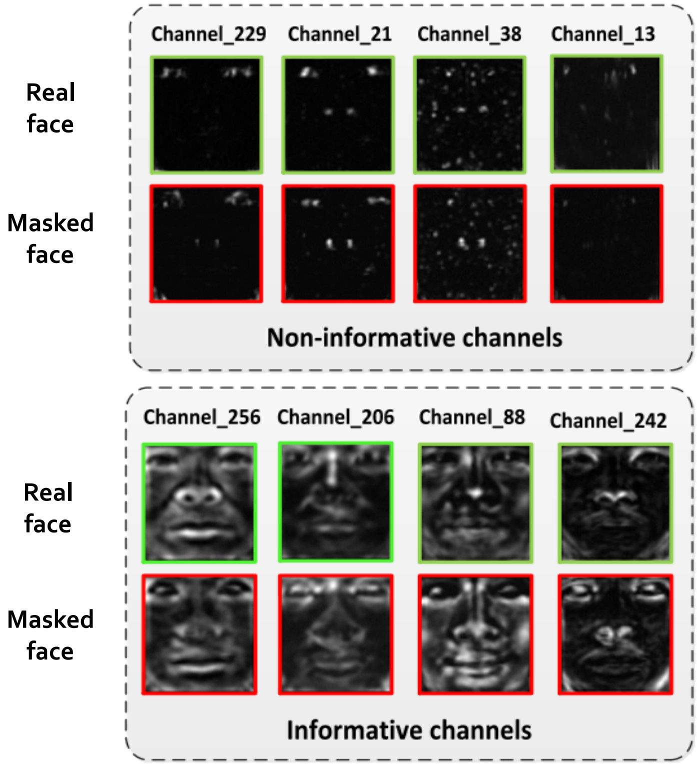
- In the informative channels:
  - Multiple deep textures share some **similar** spatial structures

    -> Channel-shared spatial-discriminability W_0
  - Some with different structures

    -> Channel-specific spatial-discriminability $\{W_i\}_{i=1}^{K}$

Joint Discriminative Learning of Deep Dynamic Textures

- ## Deep Dynamic Texture Joint Learning



Conclusion:
Deep dynamic textures in channels with **stronger channel-discriminability** (e.g. informative channels) will be more likely to share **similar spatial-discriminability** than the ones with **weaker channel-discriminability** (e.g. non-informative channels)

$$f_{S_i}(V_i) = S_i^T V_i, (i = 1,2,\ldots,K)$$
$$s.t. S_i = W_0 + \frac{1}{D_i} W_i$$

Joint Discriminative Learning of Deep Dynamic Textures

- **Deep Dynamic Texture Joint Learning**

The Joint Learning Model:

$$\min_{\{D_i\},\{W_i\},W_0} \sum_{i=1}^{K} \left(D_i \| S_i^T V_i - Y \|_F^2 + \beta \| \frac{1}{D_i} W_i \|_2^2 \right) + \lambda \| W_0 \|_2^2 + \theta \| D \|_2^2$$

$$s.t.\, S_i = W_0 + \frac{1}{D_i} W_i$$

Joint Discriminative Learning of Deep Dynamic Textures

▪ Dataset

- 3DMAD [TIFS'14 Erdogmus et.al]
  - o 255 videos recorded from 17 subjects
  - o Masks made from ThatsMyFace.com

- Supplementary (SUP) Dataset:
  - o 120 videos recorded from 8 subjects
  - o 2 Mask type: 8 subjects: ThatsMyFace (6), REAL-F (2)

Joint Discriminative Learning of Deep Dynamic Textures

Protocols

- Intra-database Experiment (LOOCV) [TIFS'14 Erdogmus et.al]
  - 3DMAD Dataset
  - Supplementary (SUP) Dataset

- Cross-database Experiment:
  - Train on 3DMAD, Test on SUP dataset
  - Train on SUP, Test on 3DMAD dataset

- Evaluation metrics:
  - False Fake Rate (FFR)
  - False Liveness Rate (FLR)
  - Area Under Curve (AUC)
  - Equal Error Rates (EER)

Experiments

Comparison features

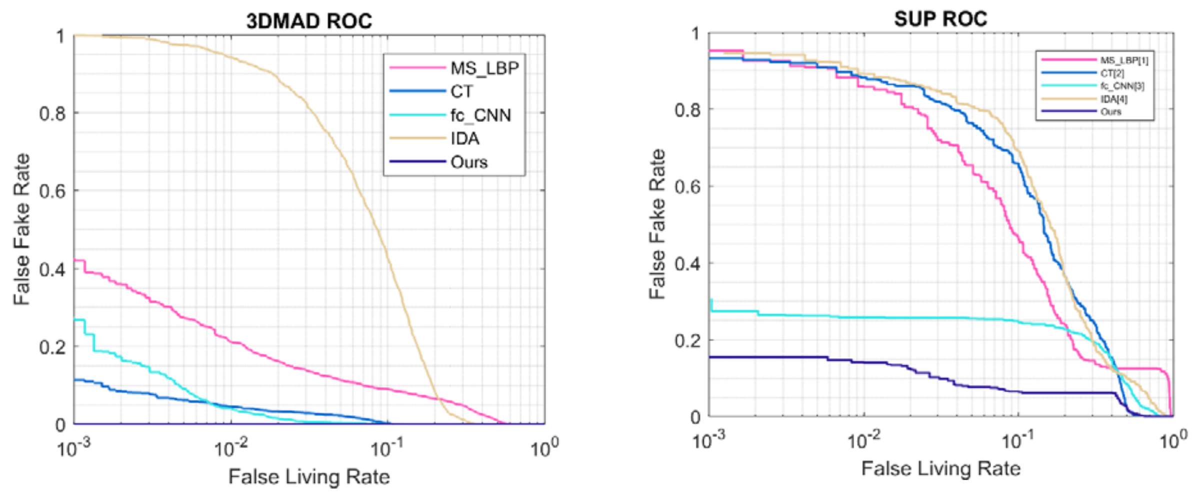
- Appearance-based features:
  - o Multi-scale LBP (MS LBP for short) [1]
  - o Color Texture (CT for short) [2]
  - o Deep features from last fully connected layer of CNN (fc CNN for short) [3]
  - o Image distortion analysis features (IDA for short) [4]
- Motion-based features:
  - o LBPTOP features [5]
  - o Multifeature videolet aggregation (Videolet for short)[6]
  - o Optical flow field (OFF for short) [7]
  - o Optical flows on Gabor features [8](OF Gabor for short)
  - o Optical flows on raw images (OF raw for short)
- Other cues-based features:
  - o rPPG features [9]

[1] Spoofing face recognition with 3D masks., 2014. IEEE transactions on information forensics and security, 2014
[2] Face spoofing detection using color texture analysis., 2016. IEEE Transactions on Information Forensics and Security, 2016
[3] Learn convolutional neural network for face anti-spoofing., 2014. arXiv
[4] Face spoof detection with image distortion analysis., 2015. IEEE Transactions on Information Forensics and Security
[5] Face liveness detection using dynamic texture., 2014. EURASIP Journal on Image and Video Processing, 2014
[6] Face anti-spoofing with multifeature videolet aggregation., 2016. Pattern Recognition, 2016 23rd International Conference on.
[7] A liveness detection method for face recognition based on optical flow field., 2009. International Conference on Image Analysis and Signal Processing.
[8] Nonlinear operator for oriented texture., 1999. IEEE Transactions on image processing.
[9] 3D mask face anti-spoofing with remote photoplethysmography., 2016. European Conference on Computer Vision. Springer International Publishing

Experiments

▪ Intra-dataset Test

Appearance-based features comparison:

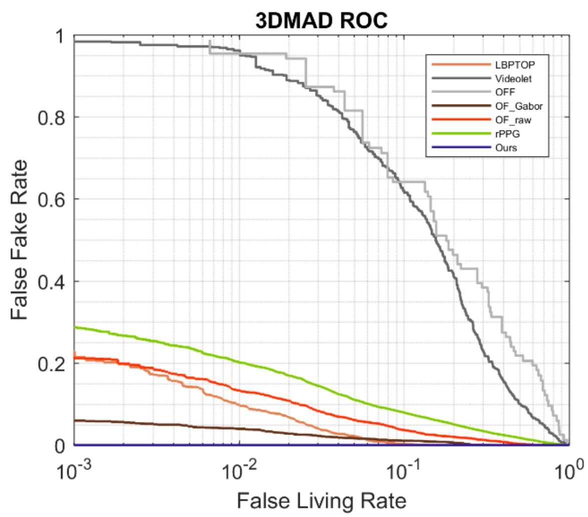


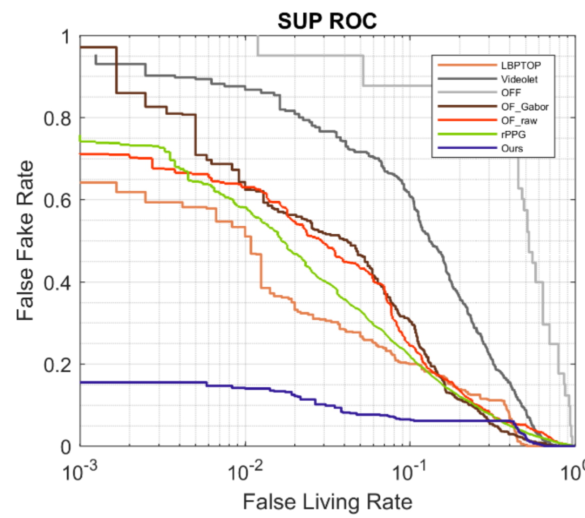
- Hand-crafted features and deep features of last fully-connected layer of CNN can achieve good results in 3DMAD dataset which are comparable with our method, but the performance of these methods drop a lot in supplementary dataset
  -> Appearance-based features are not discriminative enough to capture subtle texture differences when facing masks with good appearance quality

Experiments

▪ Intra-dataset Test

Motion-based features and other cues-based features comparison:





- Similarly, the intrinsic limitation of the hand-crafted feature leads to the same degraded performance of motion-based features and other cues-based features

-> Motion-based features and other cues-based features are not descriptive enough for **subtle** motion differentiation

Experiments

- ## Intra-dataset Test

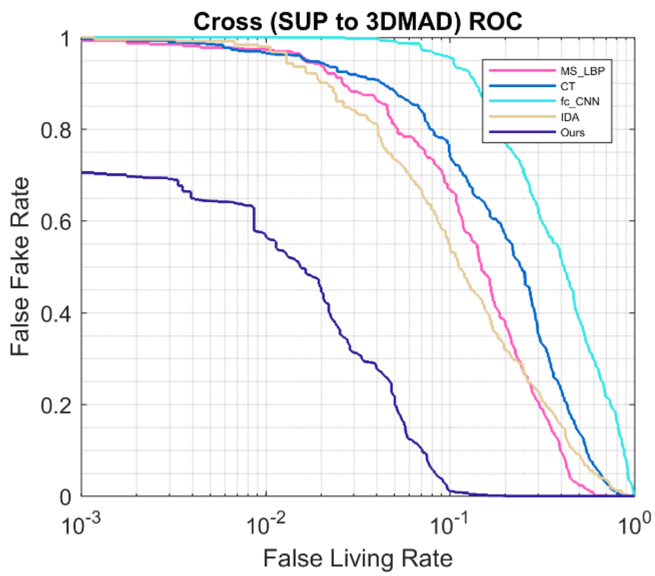
TABLE II: Experimental results of False Fake Rate at chosen False Living Rate on 3DMAD and SUP under intra-dataset test protocol.

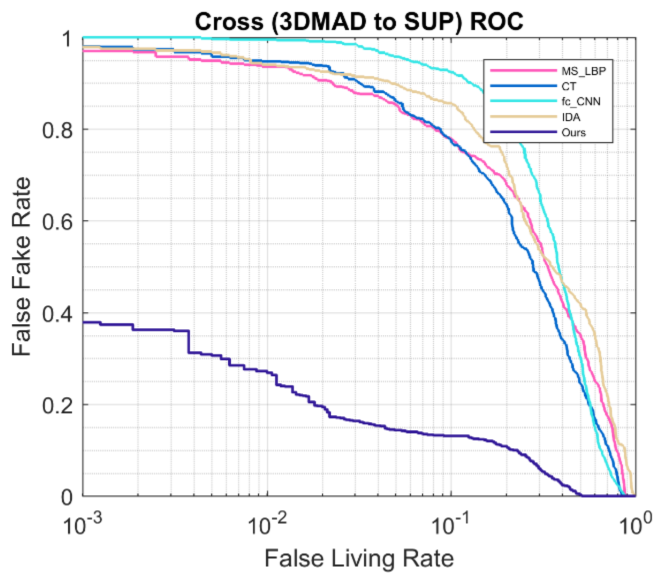
Method	3DMAD dataset			SUP dataset		
	FFR @FLR=0.001	FFR @FLR=0.01	FFR @FLR=0.1	FFR @FLR=0.001	FFR @FLR=0.01	FFR @FLR=0.1
MS_LBP[14]	42.11	21.08	9.01	94.60	85.66	46.00
CT[6]	11.37	4.45	0.24	93.05	87.93	65.44
fc_CNN[38]	26.77	3.98	0.03	27.53	25.79	24.51
IDA[36]	99.83	94.09	42.45	94.61	89.16	69.15
LBPTOP[12]	21.52	9.64	0.30	63.52	51.00	19.95
Videolet[30]	98.30	95.09	61.72	93.64	86.75	60.73
OFF[3]	97.89	95.18	64.13	99.34	95.47	87.69
OF_Gabor	5.98	3.96	1.07	94.77	62.41	30.35
OF_raw	21.19	13.31	3.69	71.05	63.00	24.40
rPPG[24]	28.76	20.15	7.97	75.73	58.13	22.08
DTAC[29]	28.34	7.86	0.20	63.06	39.96	14.16
Ours	**0**	**0**	**0**	**15.50**	**14.00**	**6.50**

Experiments

▪ Cross-dataset Test

Appearance-based features comparison:



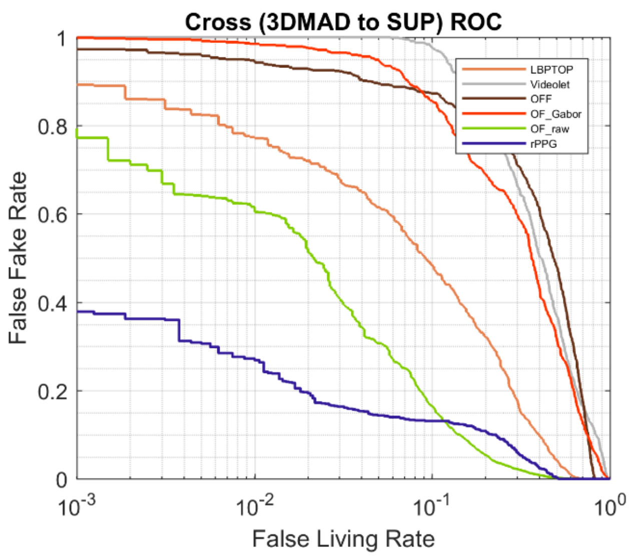


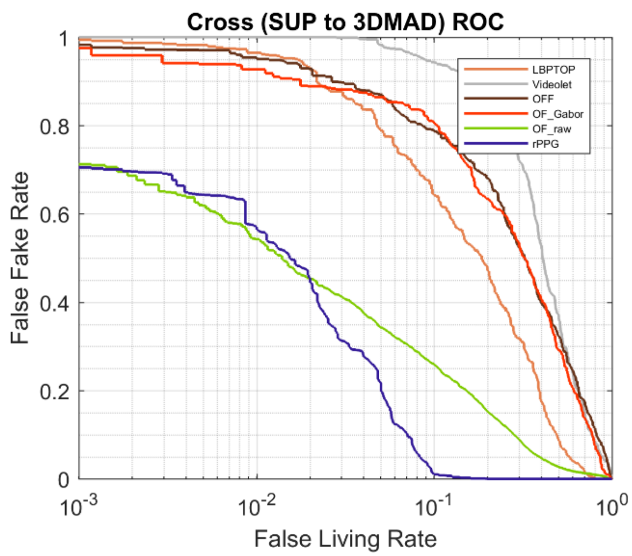
- The proposed method generalizes well between different masks
- The existing appearance-based methods have limited generalization ability

Experiments

▪ Cross-dataset Test

Motion-based features and other cues-based features comparison:





- The proposed method is more able to find invariant features cross the datasets than motion-based features and other cues-based features

Experiments

Cross-dataset Test

TABLE III: Experimental results of False Fake Rate at chosen False Living Rate on 3DMAD and SUP under cross-dataset test protocol.

Method	3DMAD to SUP dataset			SUP to 3DMAD dataset		
	FFR @FLR=0.001	FFR @FLR=0.01	FFR @FLR=0.1	FFR @FLR=0.001	FFR @FLR=0.01	FFR @FLR=0.1
MS_LBP[14]	96.95	93.62	77.87	99.29	97.29	66.82
CT[6]	97.96	94.75	77.25	99.64	96.47	73.76
fc_CNN[38]	100	99.50	92.37	100	100	95.64
IDA[36]	97.61	94.00	85.62	99.82	97.94	54.64
LBPTOP[12]	89.44	77.12	48.12	99.31	96.47	64.23
Videolet[30]	100	100	97.62	100	100	94.35
OF_Gabor	97.24	94.25	87.25	98.06	95.05	78.70
OF_raw	99.79	98.50	85.50	96.94	92.70	80.47
rPPG[24]	79.32	61.62	16.47	72.94	**54.31**	25.97
DTAC[29]	70.77	55.37	18.37	83.63	74.76	36.64
Ours	**37.35**	**26.87**	**13.12**	**70.46**	56.43	**1.05**

Experiments

- ## Intra-dataset and cross-dataset Test

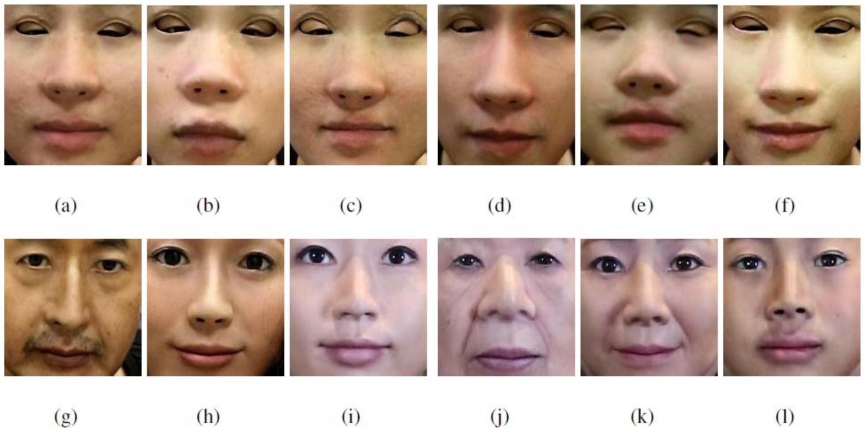
TABLE I: Experimental results of AUC curve and EER data on 3DMAD and SUP under intra-dataset and cross-dataset test protocol.

Method	3DMAD dataset		Supplementary dataset		3DMAD to SUP dataset		SUP to 3DMAD dataset	
	EER(%)	AUC(%)	EER(%)	AUC(%)	EER(%)	AUC(%)	EER(%)	AUC(%)
MS_LBP[14]	9.14	96.71	21.17	80.29	41.00	62.35	26.12	81.67
CT[6]	2.92	99.74	27.00	81.40	37.16	67.59	32.65	73.59
fc_CNN[38]	1.77	99.82	21.98	89.17	42.63	60.89	45.25	54.69
IDA[36]	16.57	90.25	25.67	79.27	44.38	57.82	25.82	80.05
LBPTOP[12]	3.46	99.60	16.50	92.71	24.97	84.99	31.06	77.67
Videolet[30]	27.19	78.69	26.81	81.31	44.88	55.83	43.58	55.60
OFF[1][3]	33.43	70.72	52.31	46.54	–	–	–	–
OF_Gabor	2.55	99.67	15.98	91.69	49.00	55.30	39.88	62.27
OF_raw	5.68	98.61	16.26	90.65	41.00	61.65	40.51	64.18
rPPG[24]	8.59	96.81	15.38	92.03	12.25	94.89	17.67	91.83
DTAC[29]	2.66	99.69	12.54	95.94	13.03	94.98	18.00	90.21
Ours	**0**	**100**	**7.33**	**96.68**	**12.75**	**95.64**	**7.60**	**97.44**

[1] The method of OFF [3] does not need training process and thus the cross-dataset test is not necessary for this method.

New dataset: HKBU-MARs

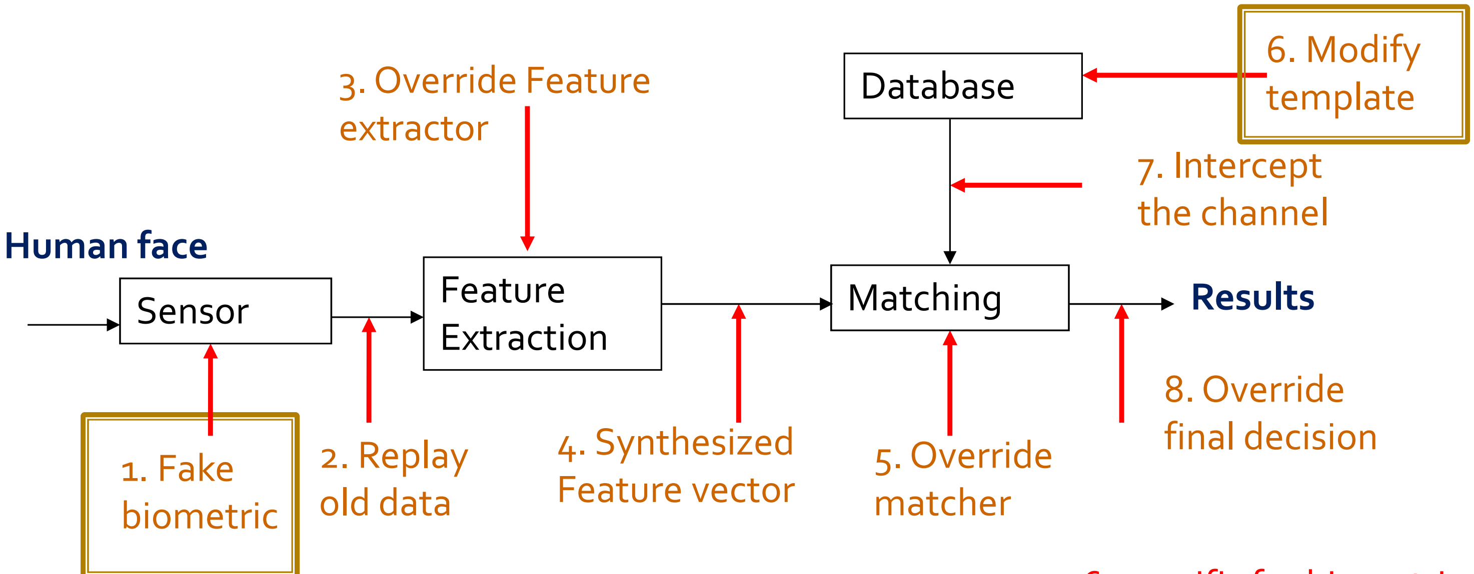
- new dataset: HKBU-MARs
- http://rds.comp.hkbu.edu.hk/mars



Part II:
Face Template Protection

Biometric Systems are INSECURE!

- Vulnerabilities: Ratha *et al.* [IBM Sys J 2001] pointed out eight possible attacks on biometric systems



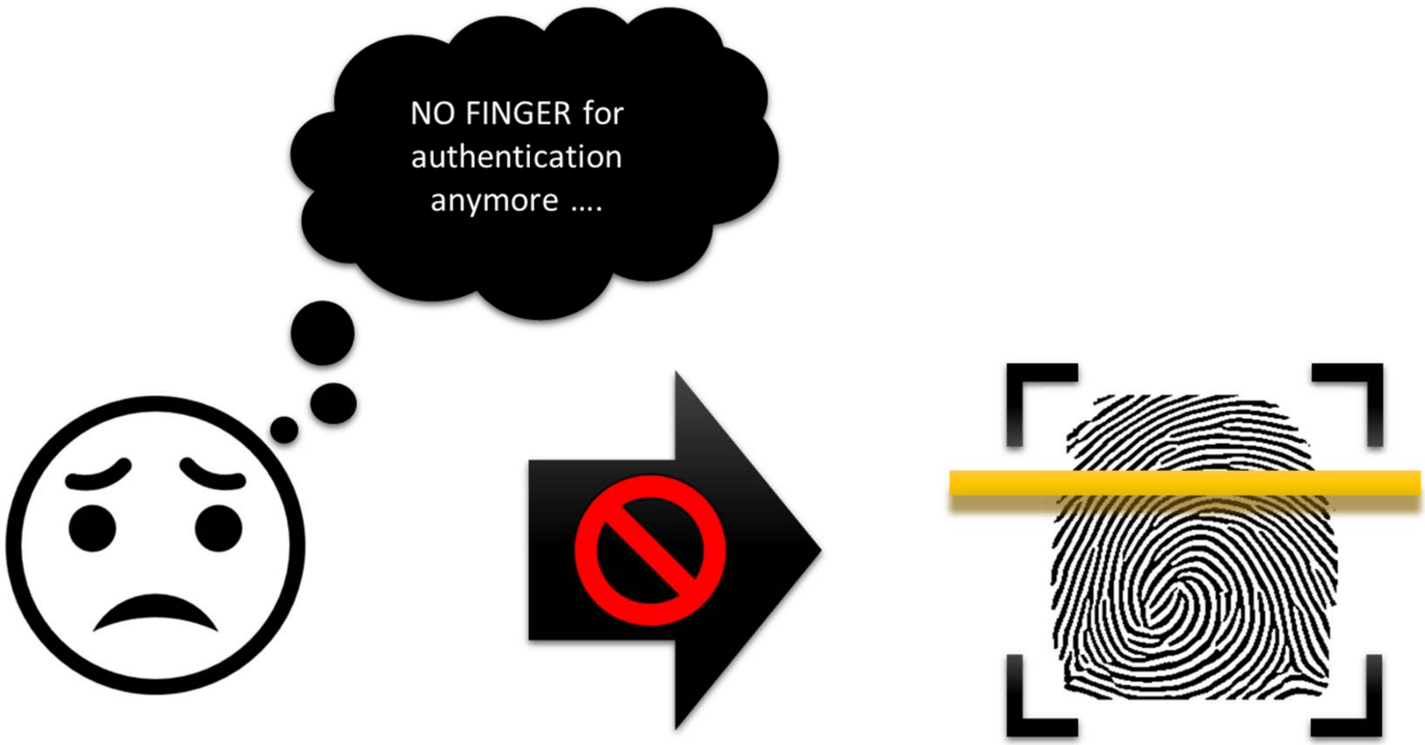
1, 6: specific for biometric systems

The Consequences of Template Attack

The stolen biometric template = Identity Theft

Courtesy of Andrew Teoh

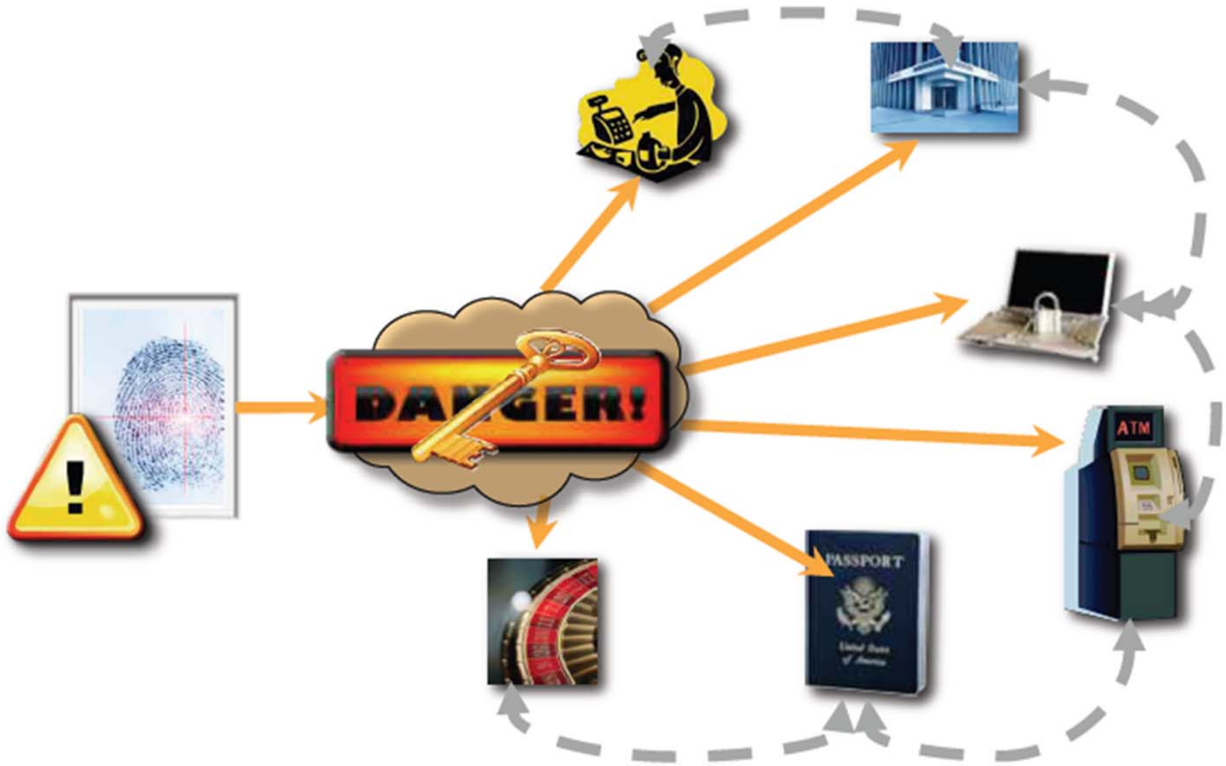
The Consequences of Template Attack



Limited Biometrics and Irrevocable

Courtesy of Andrew Teoh

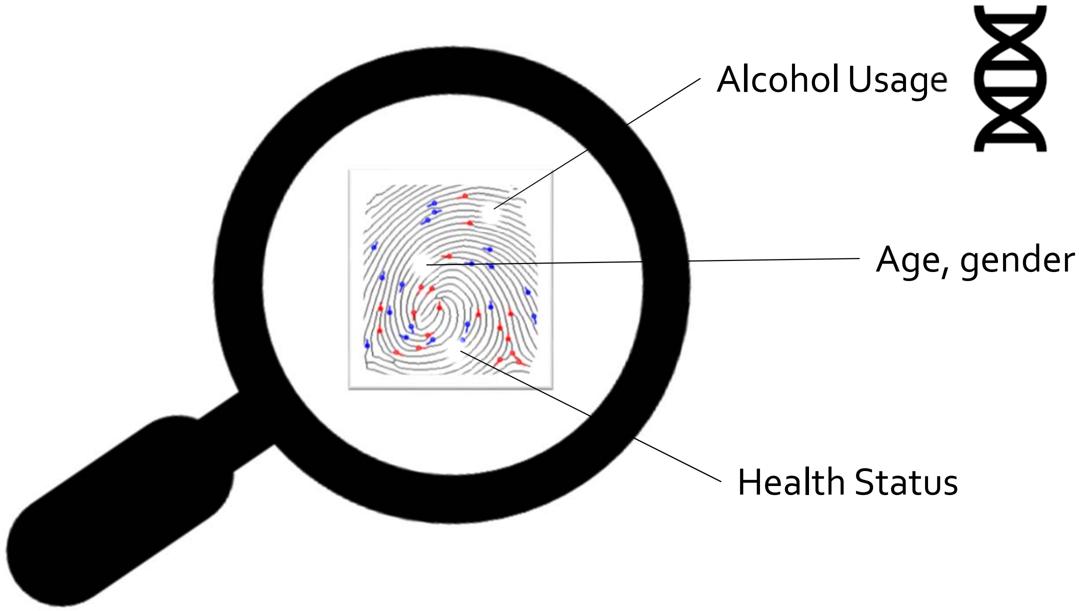
The Consequences of Template Attack



Cross-matching

Courtesy of Andrew Teoh

The Consequences of Template Attack



Privacy Leakage

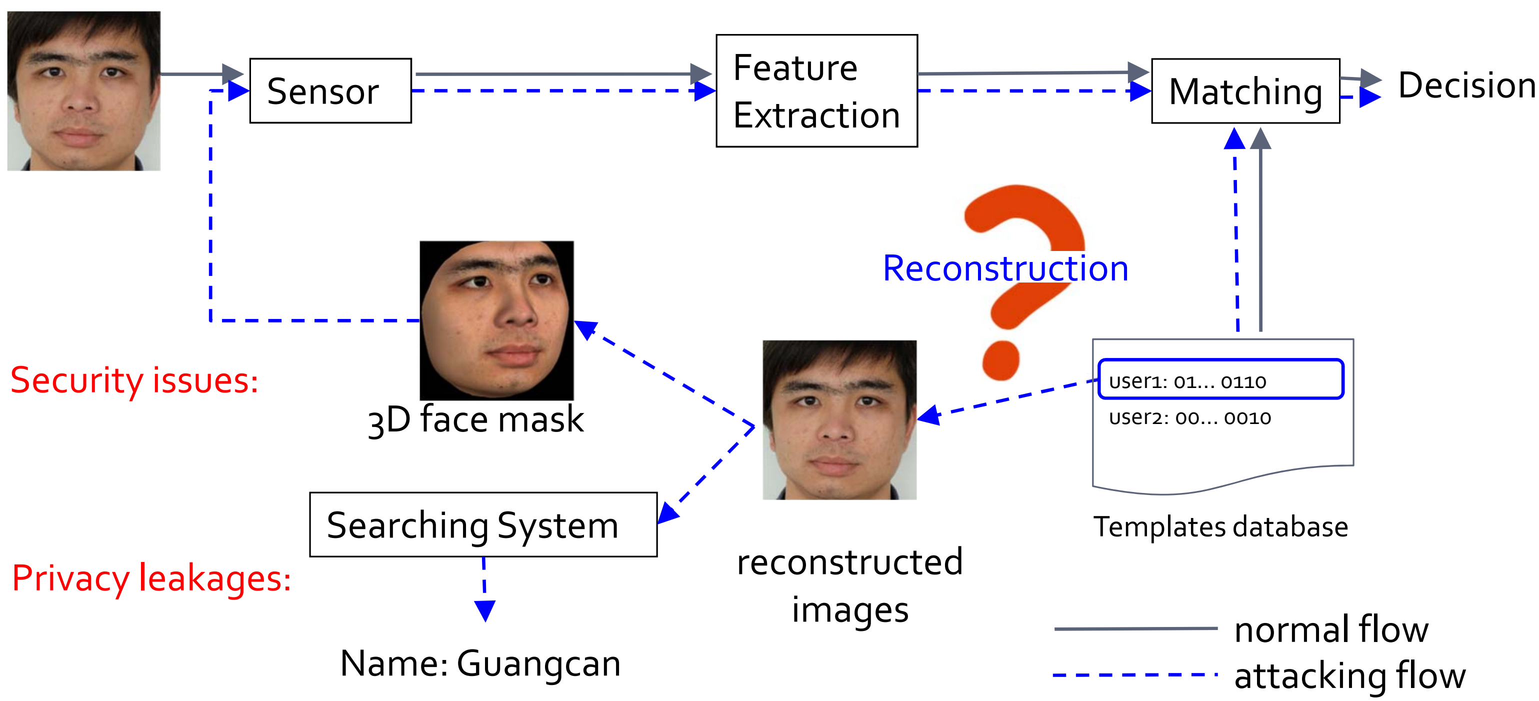
Courtesy of Andrew Teoh

Outline: Face Template Protection

1. Can we reconstruct a fake face from templates?
2. Review on existing techniques in protecting face templates
3. Our work
   a. Hybrid approach
   b. Binary Discriminative Analysis for binary template generation
   c. Binary template fusion for multi-biometric cryptosystems
   d. Entropy Measurement for Biometric Verification Systems

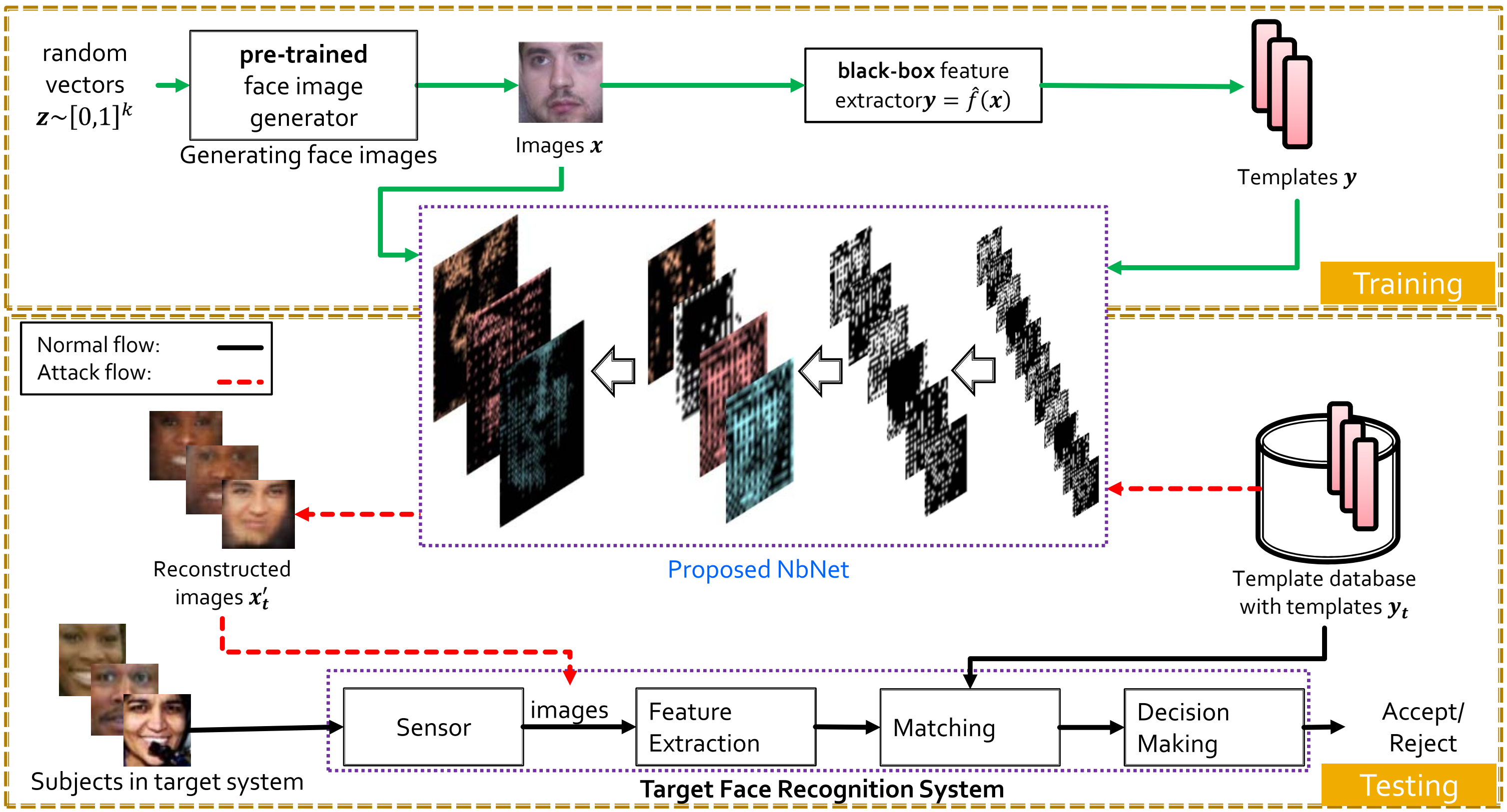
Can we reconstruct a fake face from templates?

Image Reconstruction Attack

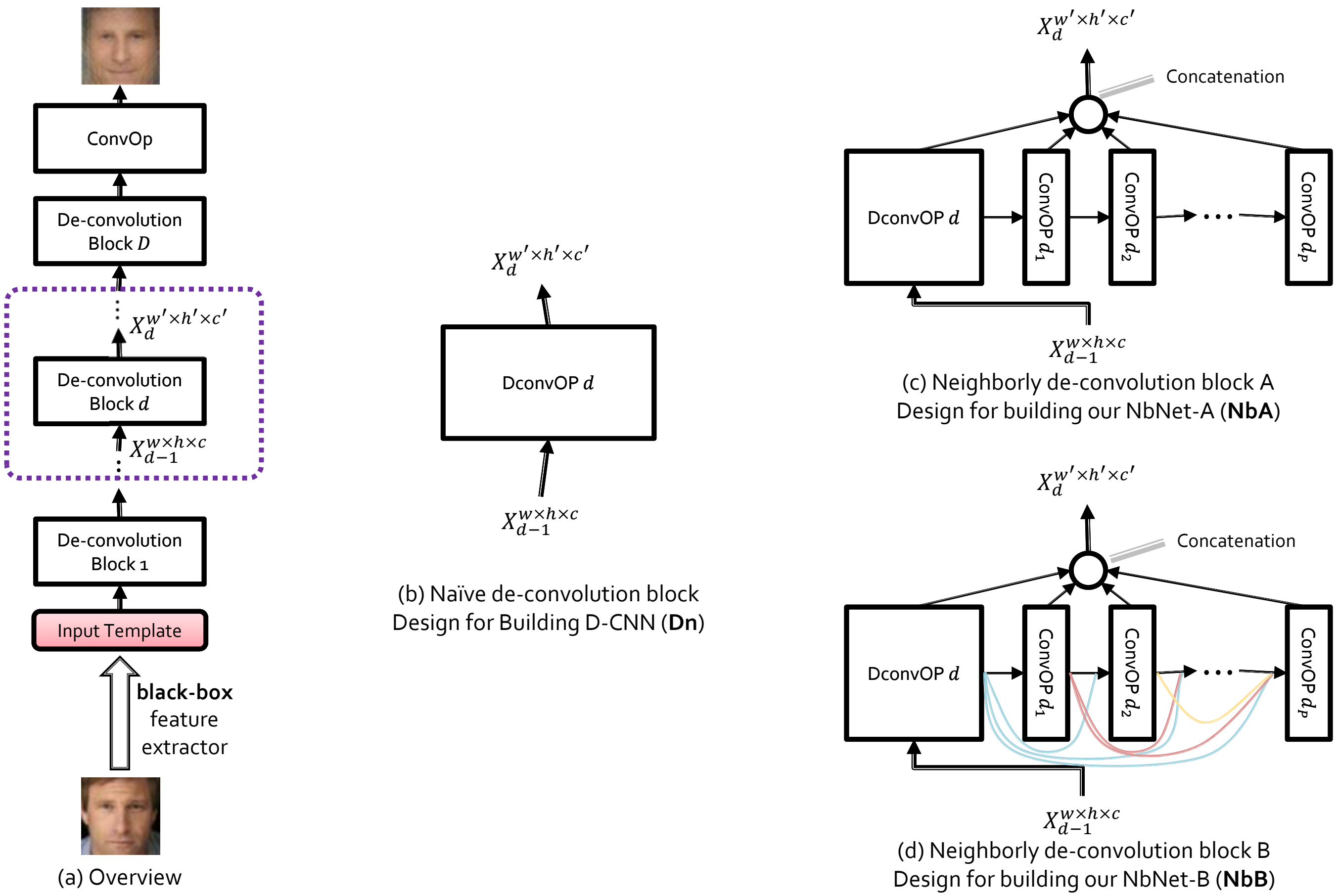


G. Mai, Kai Cao, P. C. Yuen and Anil K. Jain, On the Reconstruction of Deep Face Templates, *IEEE Transactions on Pattern Analysis and Machine Intelligence (TPAMI)*, In press, 2019

Proposed Reconstruction- Overview



Proposed NbNet for Reconstruction



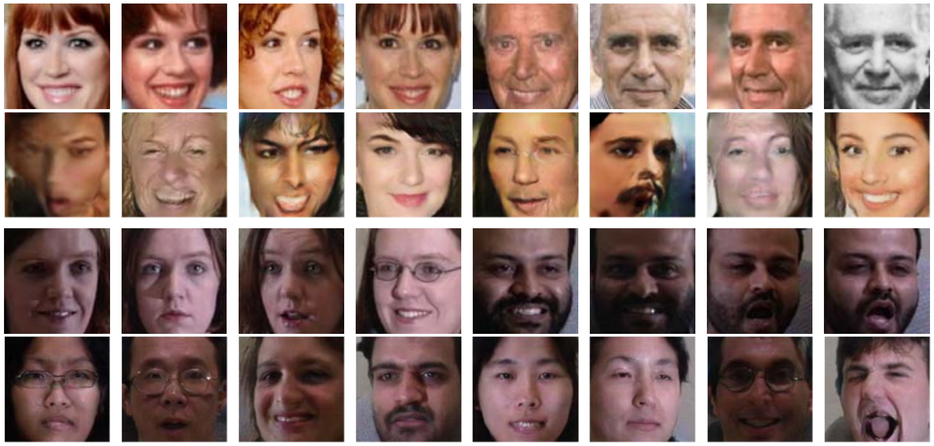
Network Details

Layer name	Output size ($c \times w \times h$)	D-CNN	NbNet-A, NbNet-B
input layer	$128 \times 1 \times 1$		
De-convolution Block (1)	$512 \times 5 \times 5$	$[5 \times 5, 512]$ DconvOP, stride 2	$[5 \times 5, 256]$ DconvOP, stride 2 $\{[3 \times 3, 8]$ ConvOP, stride $1\} \times 32$
De-convolution Block (2)	$256 \times 10 \times 10$	$[3 \times 3, 256]$ DconvOP, stride 2	$[3 \times 3, 128]$ DconvOP, stride 2 $\{[3 \times 3, 8]$ ConvOP, stride $1\} \times 16$
De-convolution Block (3)	$128 \times 20 \times 20$	$[3 \times 3, 128]$ DconvOP, stride 2	$[3 \times 3, 64]$ DconvOP, stride 2 $\{[3 \times 3, 8]$ ConvOP, stride $1\} \times 8$
De-convolution Block (4)	$64 \times 40 \times 40$	$[3 \times 3, 64]$ DconvOP, stride 2	$[3 \times 3, 32]$ DconvOP, stride 2 $\{[3 \times 3, 8]$ ConvOP, stride $1\} \times 4$
De-convolution Block (5)	$32 \times 80 \times 80$	$[3 \times 3, 32]$ DconvOP, stride 2	$[3 \times 3, 16]$ DconvOP, stride 2 $\{[3 \times 3, 8]$ ConvOP, stride $1\} \times 2$
De-convolution Block (6)	$16 \times 160 \times 160$	$[3 \times 3, 16]$ DconvOP, stride 2	$[3 \times 3, 8]$ DconvOP, stride 2 $\{[3 \times 3, 8]$ ConvOP, stride $1\} \times 1$
ConvOP	$3 \times 160 \times 160$	$[3 \times 3, 3]$ ConvOP, stride 1	
Loss layer	$3 \times 160 \times 160$	Pixel difference or perceptual loss [36]	

$[k_1 \times k_2, c]$ DconvOP (ConvOP), stride s denotes cascade of a de-convolution (convolutionan) layer with c channels, kernel size $(k_1 \times k_2)$, and stride s, batch normalization and ReLU (tanh for the bottom ConvOP) activation layer

Experiments - Training

- **Feature extractor** [1], an implementation of FaceNet [2]
- **Network arichitecture**: D-CNN (Dn), NbNet-A (NbA), NbNet-B (NbB)
- **Training approach**: Generated images & Raw images (r)
- **Loss function**: Pixel difference (M) & Perceptual Loss [3] (P)
- **Training datasets:**



VGG Raw Images:	1.94 M
VGG Gen Images:	19.2 M
Multi-PIE Raw Images:	150,760
Multi-PIE Gen Images:	19.2 M

1. https://github.com/davidsandberg/facenet (model: 20170512-110547)
2. Schroff, Florian et al. "Facenet: A unified embedding for face recognition and clustering." *CVPR2015*
3. *Johnson et. al., "Perceptual losses for real-time style transfer and super-resolution", ECCV2016*

Experiments

- Verification (protocol: BLUFR[1], comparison: RBF [2])
  - Type-I attack: match the reconstructed image against the same one from which representation was extracted
  - Type-II attack: match the reconstructed image against a different one of the same subject
- Identification (Rank-one identification rate)
  - Type-I attack: identify the images reconstructed from the gallery set
  - Type-II attack: identify the images reconstructed from the probe set
- Testing datasets

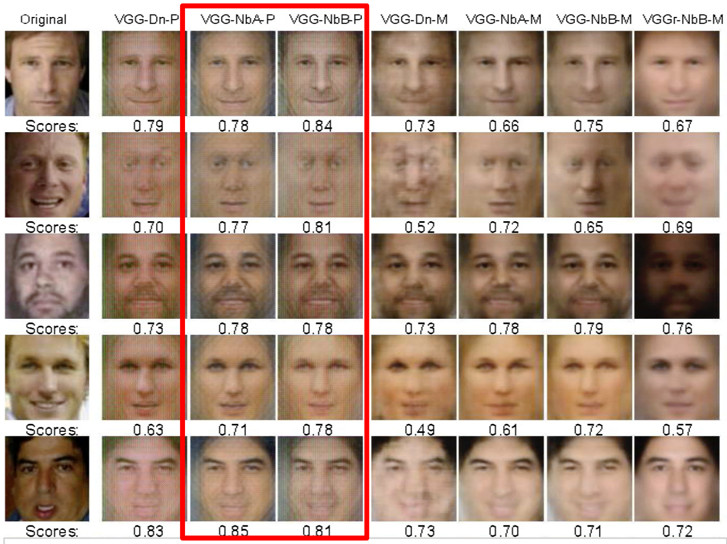
(a) LFW (Verification)

(b) FRGC V2.0 (Verification)

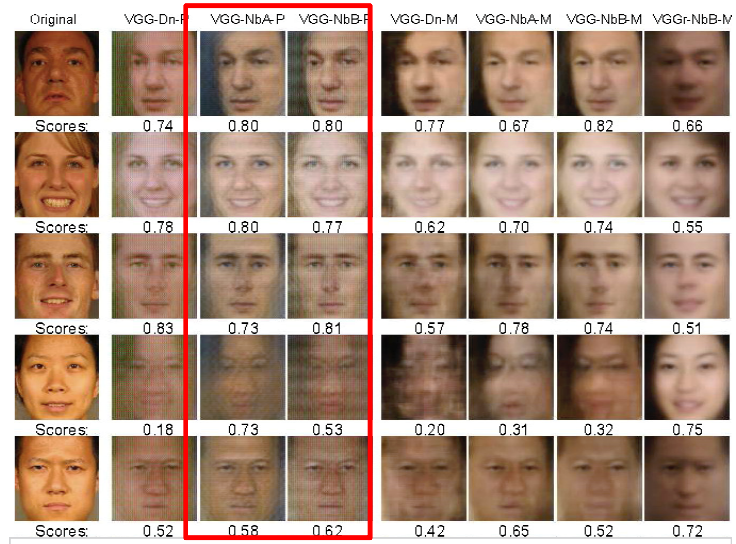
(c) Color FERET (Identification)

1. Shengcai Liao, Zhen Lei, Dong Yi, Stan Z. Li, "A Benchmark Study of Large-scale Unconstrained Face Recognition." , IJCB2014
2. Mignon, Alexis, and Frédéric Jurie. "Reconstructing Faces from their Signatures using RBF Regression." *BMVC2013*

Reconstruction of First 5 Subjects*



LFW Thresholds:
@(FAR=0.1%) = 0.51 @ (FAR=1%) = 0.38

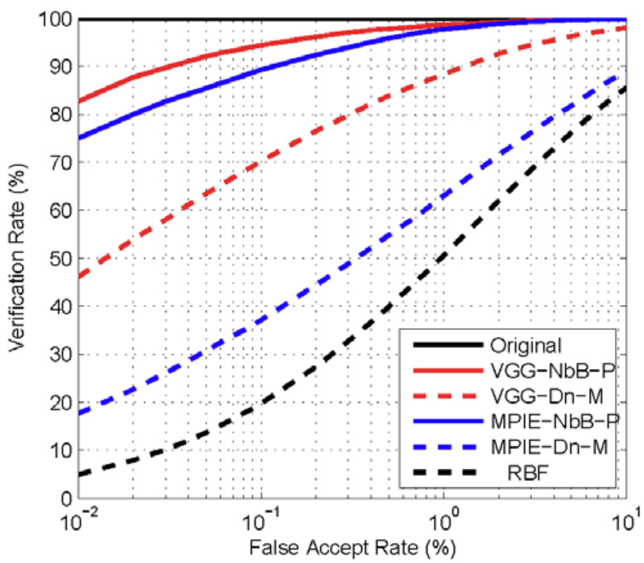


FRGC v2.0 Thresholds:
@(FAR=0.1%) = 0.80 @ (FAR=1%) = 0.64

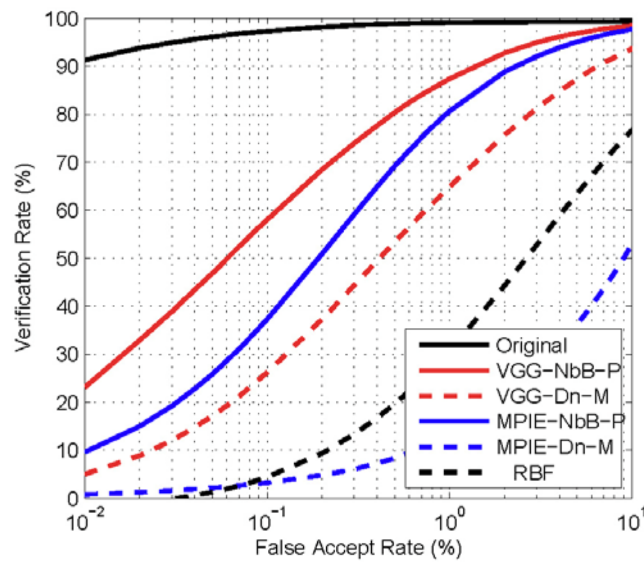
- * As specified in the image list of the BLUFR protocol [1]
- 'VGG-', 'MPIE-' denotes the face image generator is pretrained by the VGG-Face (2.6M) and MultiPIE (fontal images, 150K)
- 'VGGr-' denotes the NbNet directly trained by the raw images in VGG-Face, no face image generator is used.
- '-Dn-', '-NbA-', '-NbB-' denote the network architecture, i.e., D-CNN, NbNet-A and NbNet-B
- '-P' trained with perceptual loss
- '-M' trained with pixel-wise mean absolute error

1. Shengcai Liao, Zhen Lei, Dong Yi, Stan Z. Li, "A Benchmark Study of Large-scale Unconstrained Face Recognition." , IJCB2014

Experiments – Verification on LFW



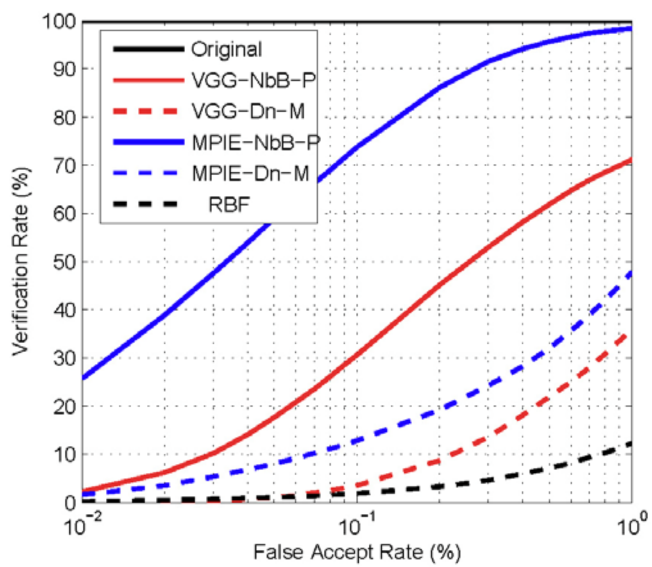
(a) Type-I attack on LFW



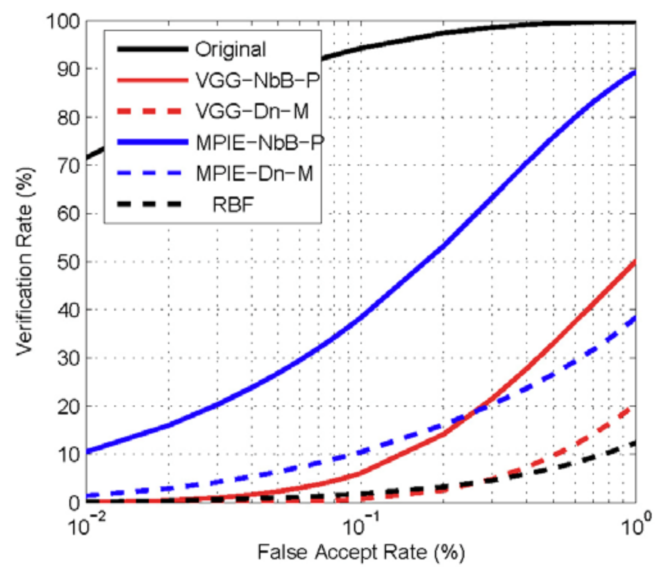
(b) Type-II attack on LFW

- Type-I attack: match the reconstructed image against the same one from which representation was extracted
- Type-II attack: match the reconstructed image against a different one of the same subject

Experiments – Verification on FRGC



(a) Type-I attack on FRGC



(b) Type-II attack on FRGC

- Type-I attack: match the reconstructed image against the same one from which representation was extracted
- Type-II attack: match the reconstructed image against a different one of the same subject

Identification with Reconstructed Images on Color FERET

Probe (partition specified by protocol)	Type-I	Type-II		
	fa	fb	dup1	dup2
Original	100.00	98.89	97.96	99.12
VGG-Dn-P	89.03	86.59	76.77	78.51
VGG-NbA-P	94.87	90.93	80.30	81.58
VGG-NbB-P	95.57	**92.84**	_84.78_	84.65
VGG-Dn-M	80.68	74.40	62.91	65.35
VGG-NbA-M	86.62	80.44	64.95	66.67
VGG-NbB-M	92.15	87.00	75	75.44
VGGr-NbB-M	81.09	74.29	61.28	62.28
MPIE-Dn-P	_96.07_	91.73	84.38	_85.53_
MPIE-NbA-P	93.86	90.22	79.89	79.82
MPIE-NbB-P	**96.58**	**92.84**	**86.01**	**87.72**
MPIE-Dn-M	73.54	64.11	53.26	49.12
MPIE-NbA-M	72.23	64.01	51.09	44.74
MPIE-NbB-M	85.61	78.22	71.06	68.42
MPIEr-NbB-M	63.88	54.54	44.57	35.96
Mixedr-NbB-M	82.19	76.11	62.09	58.77

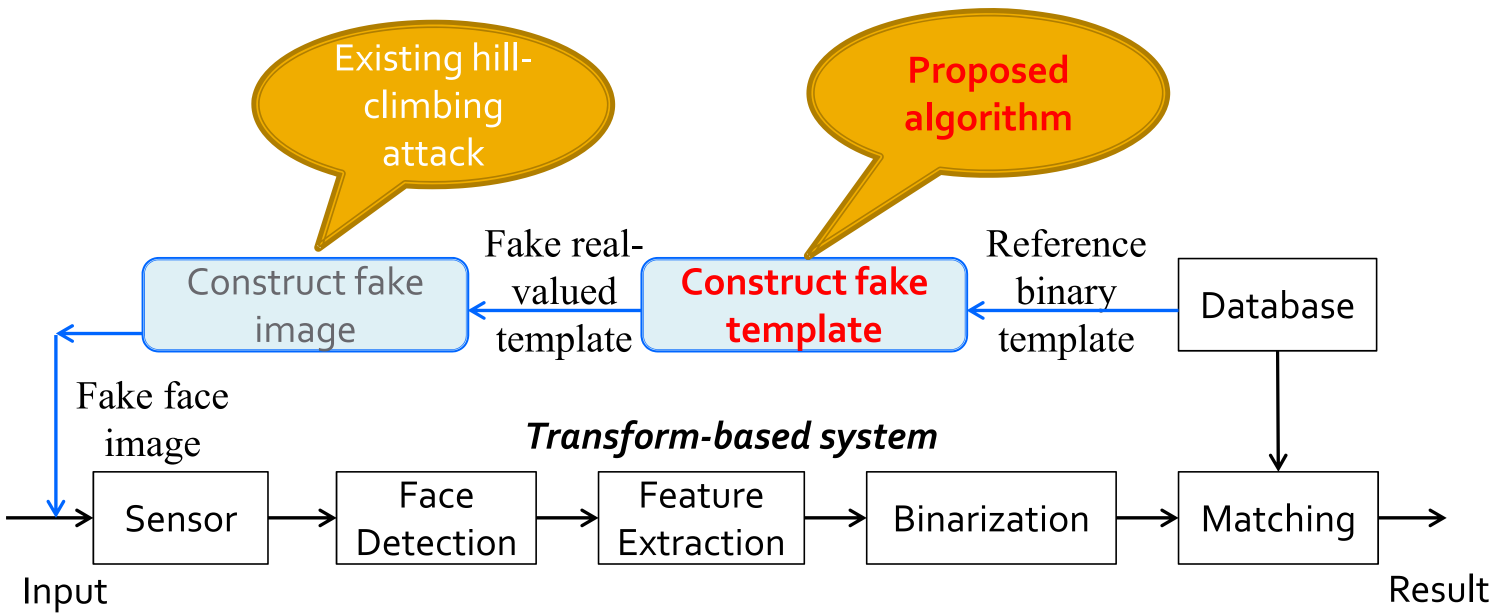
Best:
boldface
Second best:
underline

Type-I attack:
identify the images reconstructed from the gallery set (partition *fa*)

Type-II attack:
identify the images reconstructed from the images which not used in the gallery set (partition *fb*, *dup1*, *dup2*)

Binary Template is NOT Secure too!

- Attack a transform-based system (partially protected, will be introduced later) with two steps



Y C Feng, M H Lim and P C Yuen, Masquerade attack on transform-based binary-template protection based on perceptron learning, *Pattern Recognition*, 2014.

From Binary Templates to Faces

- Consider two scenarios
  - The binarization scheme is understood by the attacker
  - The binarization scheme is unknown to the attacker

- Assumptions

The reference binary templates stored in database are exposed	Attacker knows the feature extraction algorithm	Matching scores can be accessed

Masquerade attack assumptions

Hill-climbing attack assumptions

Scenario One

- Understand the binarization scheme
  - Most schemes follow “projection + thresholding” approach

$$b_{ip} = \begin{cases} 1 & : \ \mathbf{w}_p^{\mathrm{T}} \mathbf{x}_i + t_p > 0 \\ 0 & : \ \mathbf{w}_p^{\mathrm{T}} \mathbf{x}_i + t_p \le 0 \end{cases} \quad (p = 1,2 \ldots n)$$

Bits in the reference binary template

Basis

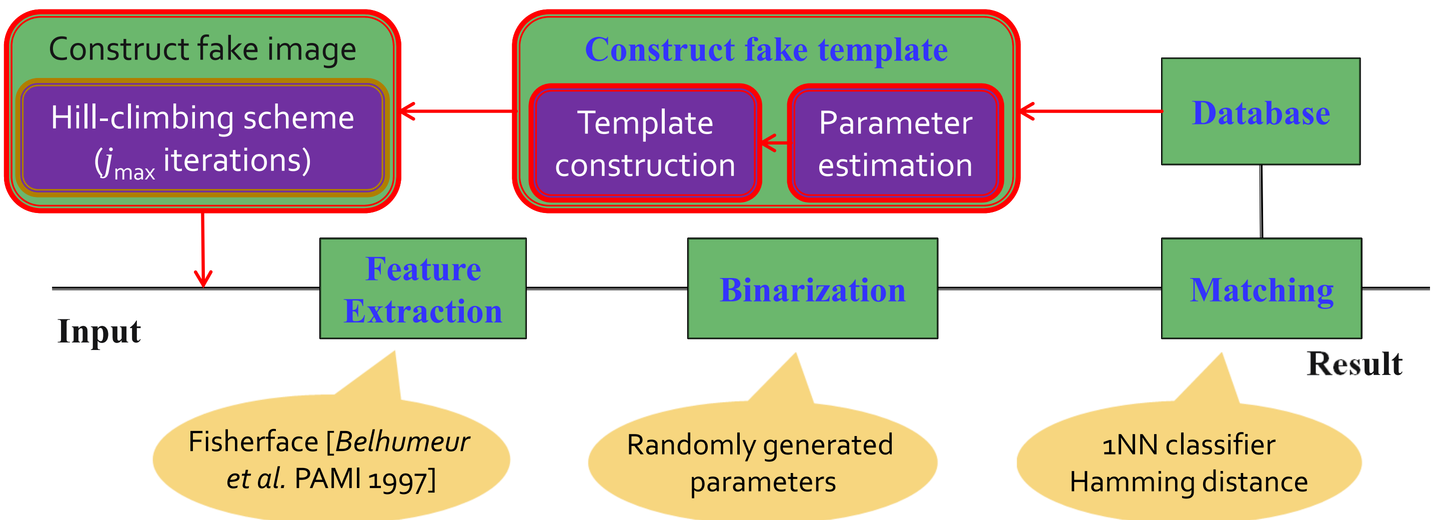
real-valued template

Thresholds

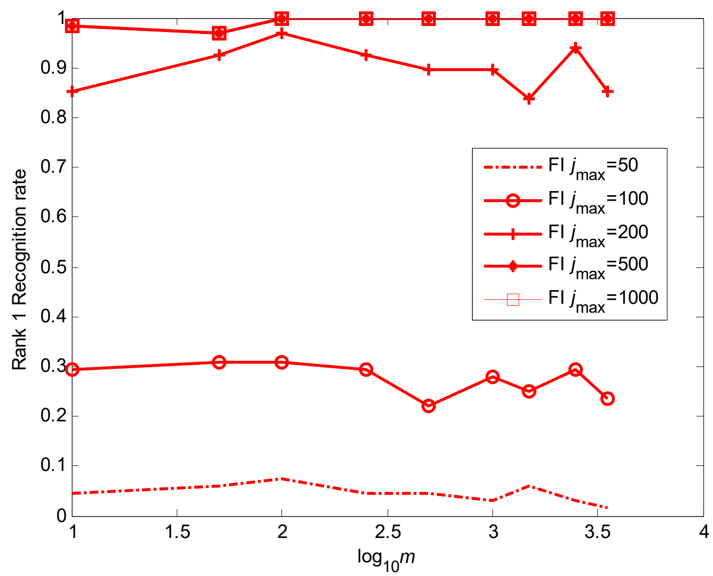
  - Two steps to construct fake template
    - Binarization parameters estimation
    - Construct fake template with estimated parameters

Scenario One

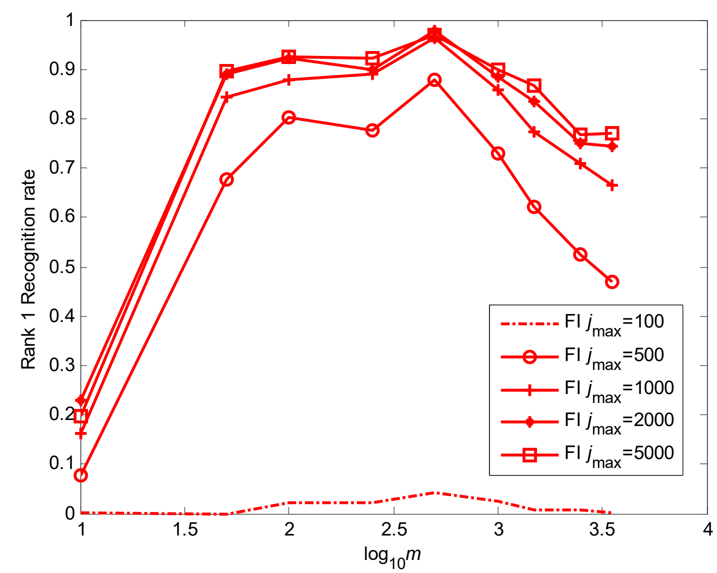
- Experimental results
  - Experiment settings
    - CMU PIE & FRGC databases employed
    - Choose different *m* (No. of local faces) in testing



Scenario One – Results



CMU PIE

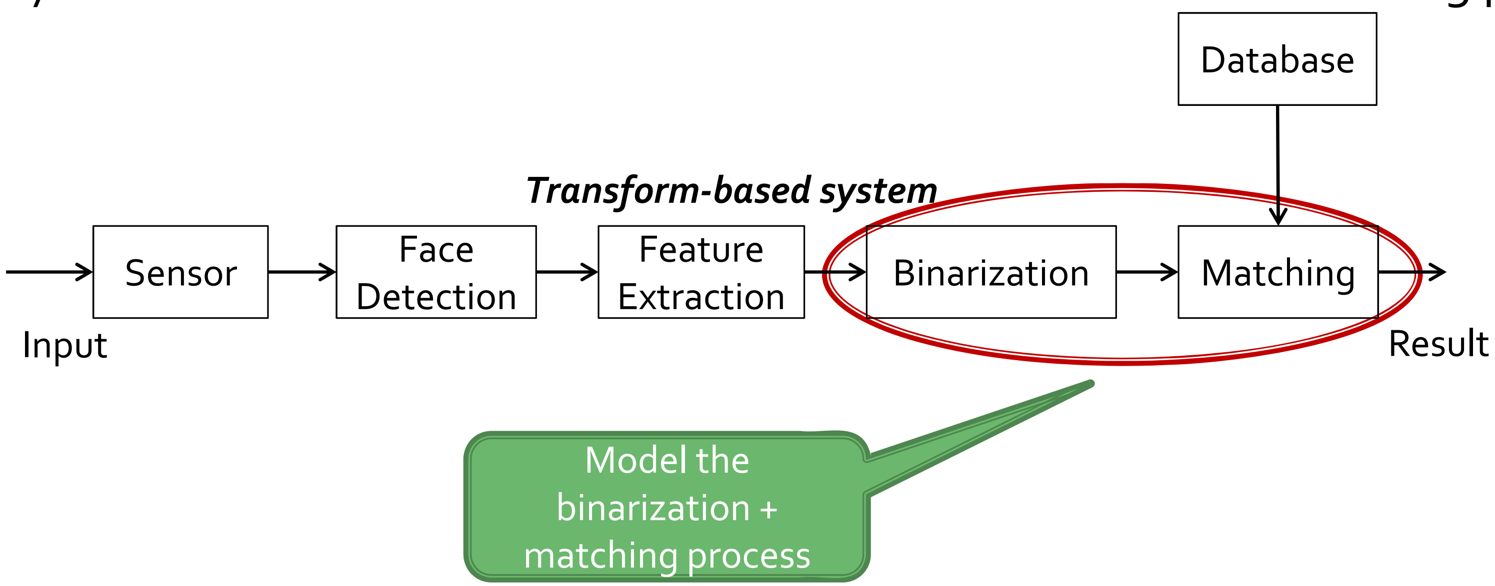


FRGC

Scenario Two

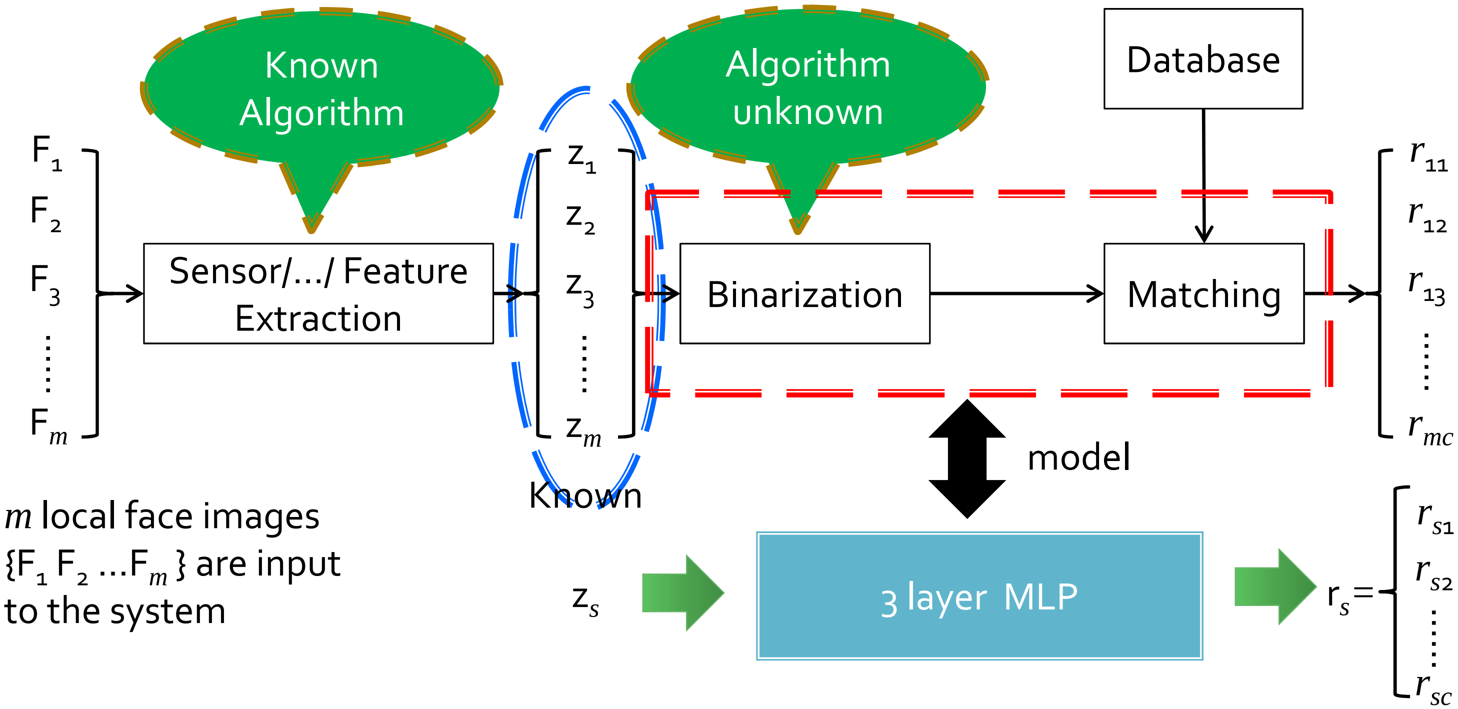
- Since the attacker does not understand the binarization algorithm, the binarization process needs to be modeled.

- Employ artificial neural networks to model the binarization and matching process



Scenario Two

- Use local faces for modeling

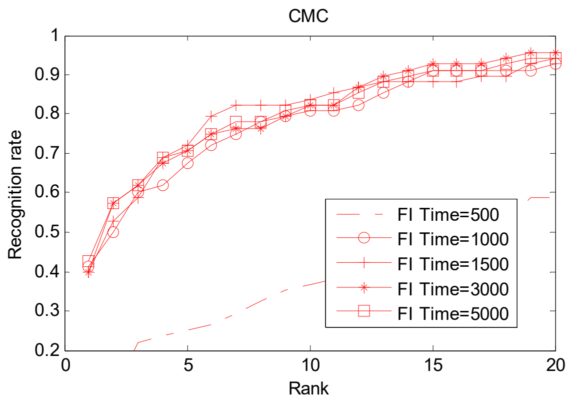


m local face images $\{F_1\ F_2\ \ldots F_m\}$ are input to the system

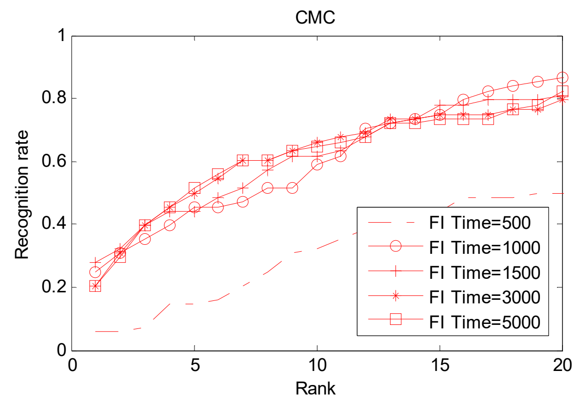
Scenario Two

- Experimental results
  - Experiment settings
    - Follow the settings in scenario one
    - Implement the proposed attack in different binarization schemes
      - Biohashing (BH)
      - Multi-stage biohashing (MBH)
      - Feature binarization (FB)
      - Discriminability-preserving transform (DP)

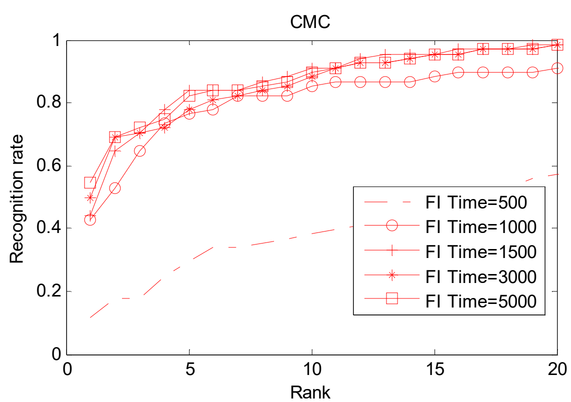
Scenario Two – CMU-PIE Results



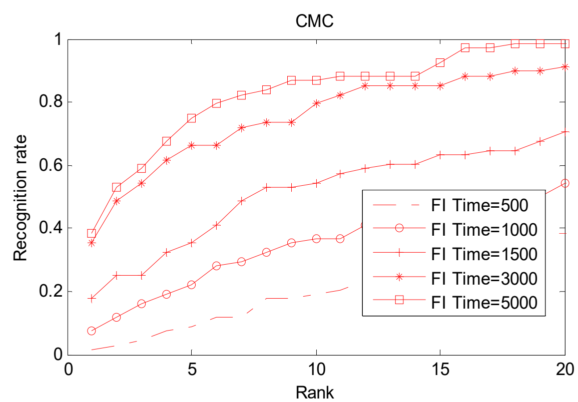
BH



MBH

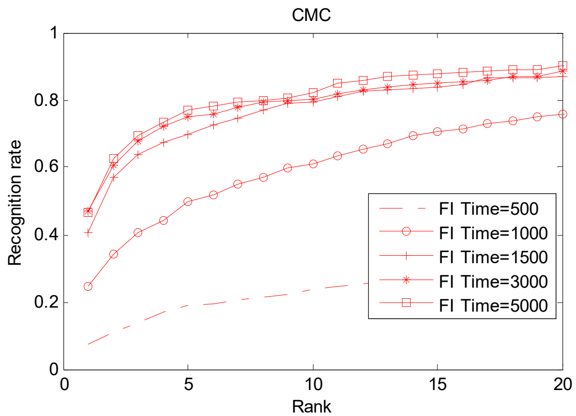


FB

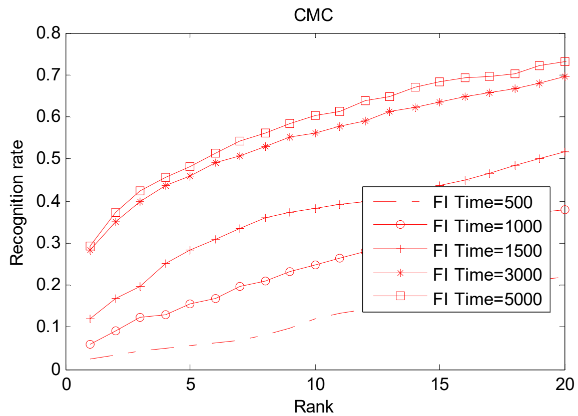


DP

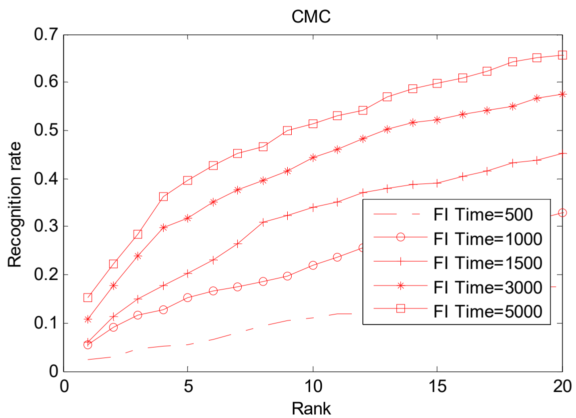
Scenario Two – FRGC Results



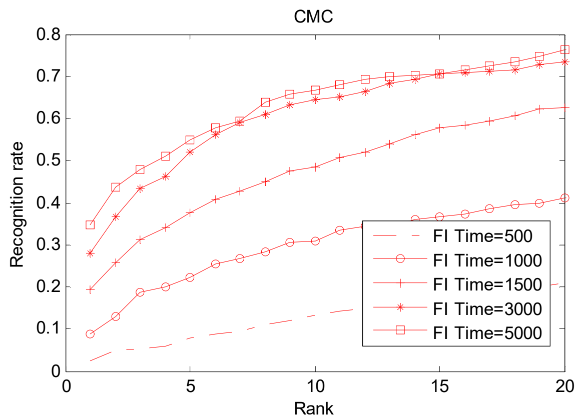
BH



MBH



FB



DP

Review on Existing Techniques

for

Face Template Protection

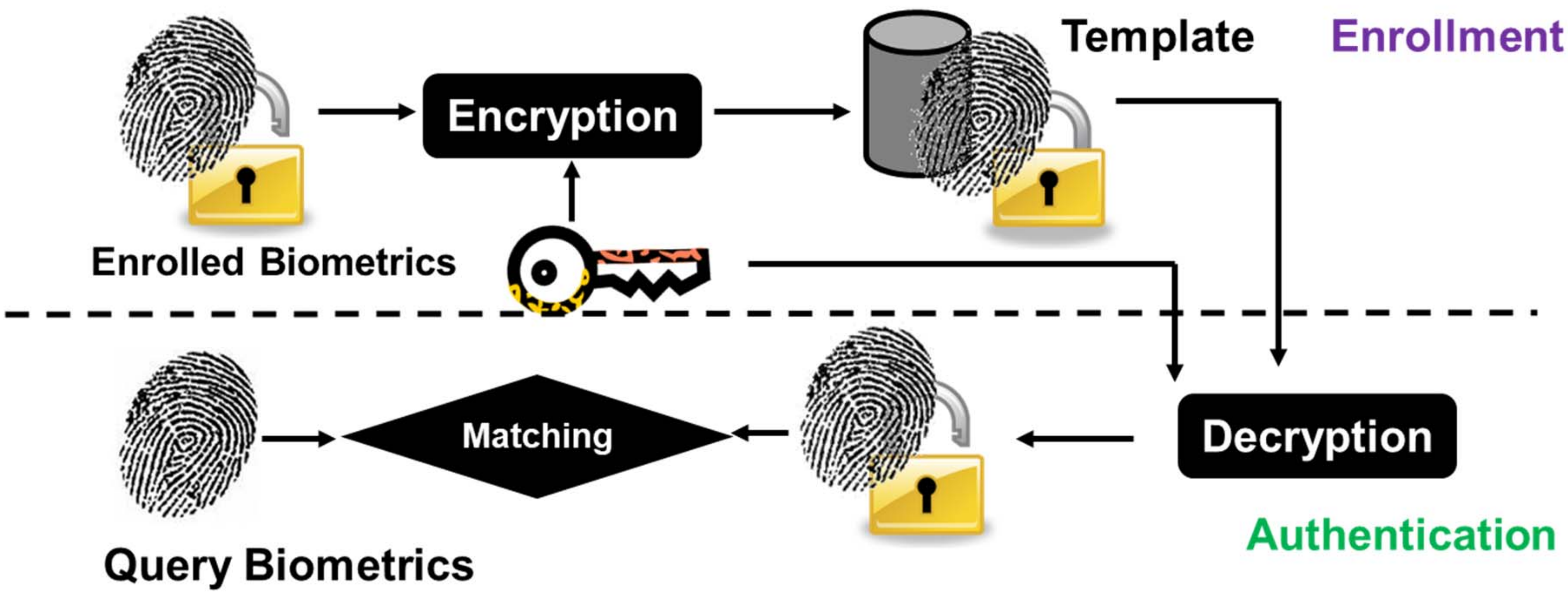
Requirements

Security	Discriminability	Cancelability
• Computationally hard to reconstruct the original template from the secure template.	• The discriminative power of the secure template should be as good as that of the original face template so that system performance will not be affected.	• The secure template can be canceled and re-issued from original template if it is stolen or lost.

Basic Idea

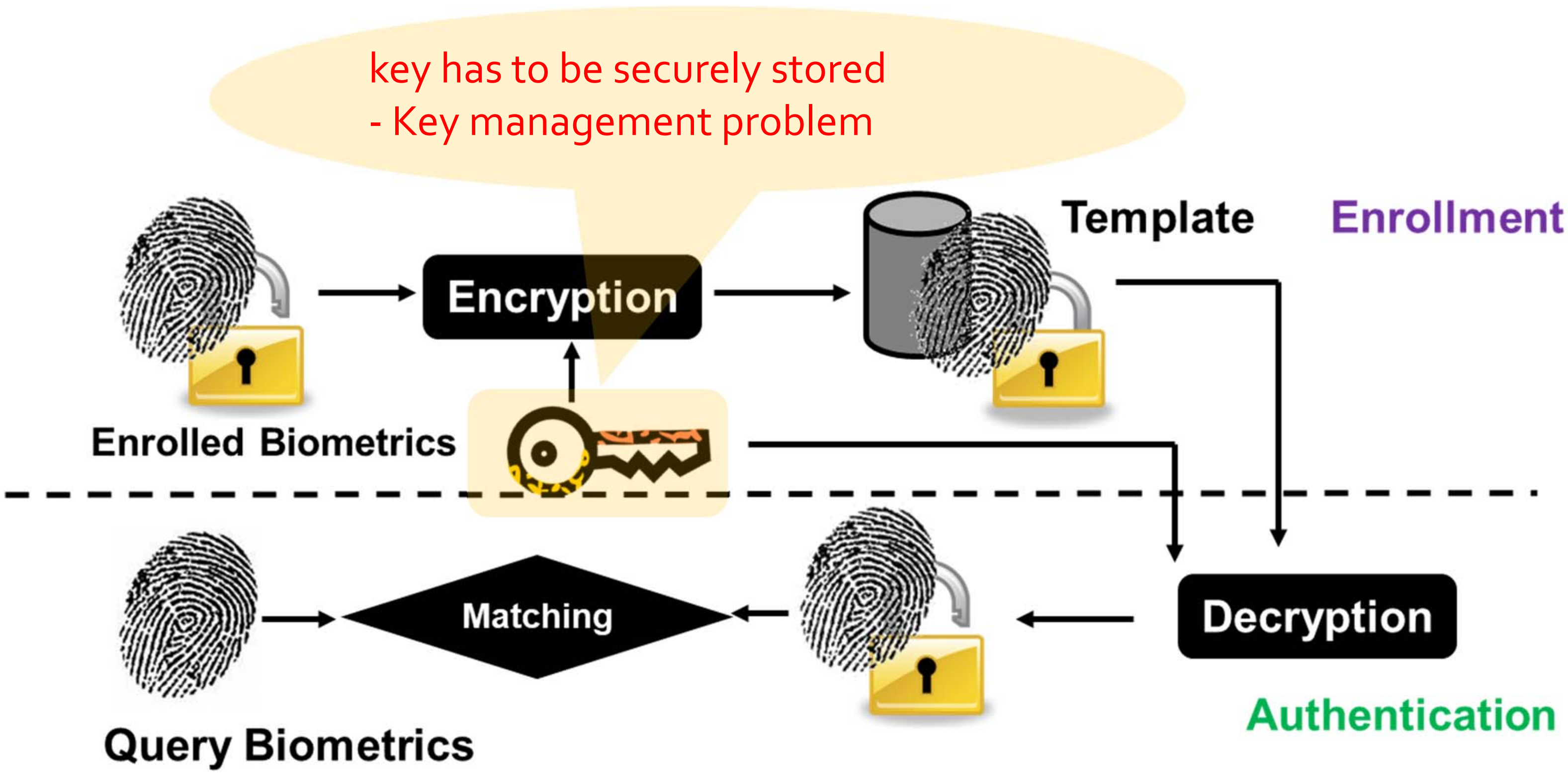
- General approach: *Never* store the original raw biometric template
- Straightforward method: Protection with traditional encryption/hashing methods (e.g. DES, MD5)
  - Small change in input cause large change in output
  - Intra-class variations => not good for matching
  - Not feasible

Present Commercial Solution



Courtesy of Andrew Teoh

Not an Ideal Solution



Courtesy of Andrew Teoh

Existing Approaches

Biometric cryptosystem

- Encrypt the original templates to a helper data
- Apply error-correcting coding methods to handle intra-class variance
- Require input in finite fields

Transform-based

- Transform the original templates into a new domain
- Apply one-way transforms
- Cancelable
- High trade-off between discriminability and security

Existing Approaches

- Biometric cryptosystem
  - Key-binding
    - Fuzzy commitment scheme [Juels & Watternberg, ACM CCS 1999]
    - Fuzzy vault scheme [Juels & Sudan, ISIT 2002]
  - Key-generation
- Transform-based
  - Non-invertible transform
    - Cancelable biometrics [Ratha *et al*. [IBM Sys J 2001]
  - Salting
    - Biohashing [Teoh *et al*. PAMI 2006]

Biometric Cryptosystems

Key-binding

- The cryptographic key is independent from biometric data.
- ***Advantage***: Tolerance of intra-class variations
- ***Disadvantage***: Require finite field input & Not for cancelability purpose

Key generation

- The cryptographic key is directly generated from the biometric data.
- ***Advantage***: Direct key generation
- ***Disadvantage***: Hard to generate secure and variance-tolerant key

Transform-based Approach

Non-invertible transform

- The transform is non-invertible. Even if K and $f(\mathrm{T},\mathrm{K})$ are known, T can not be retrieved.
- ***Advantage***: High security
- ***Disadvantage:*** Trade-off between security & discriminability

Salting

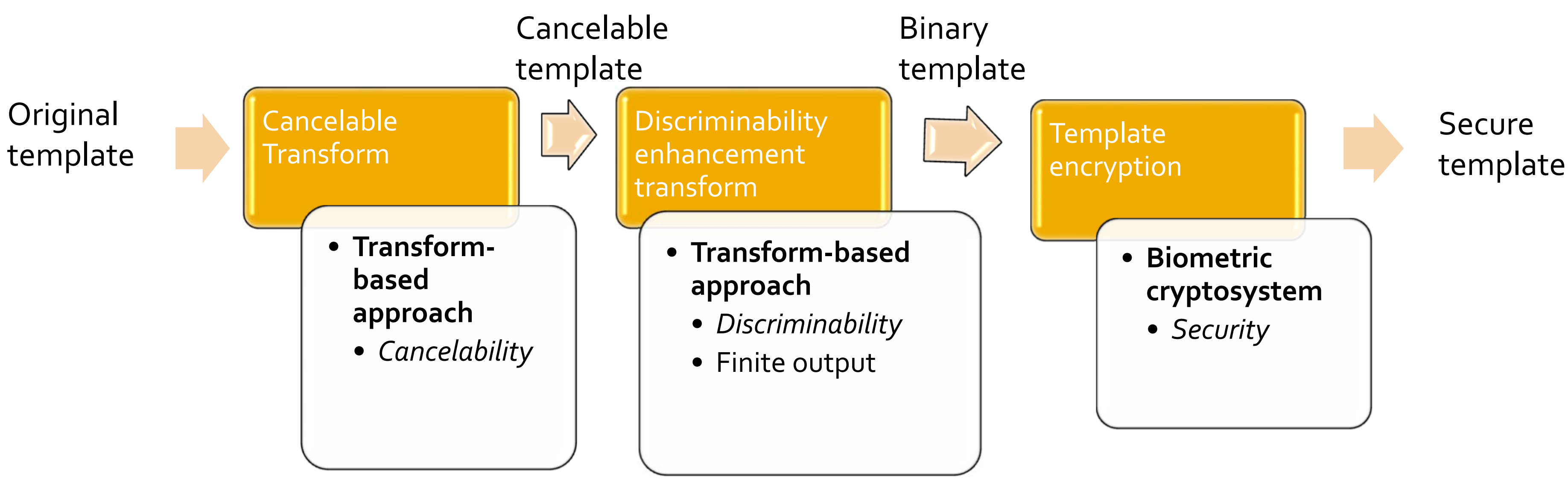
- A user-specific key is applied in transform to diverge the outputs, resulting in high performance
- ***Advantage***: Cancelable & High performance
- ***Disadvantage***: Unsecure user-specific key & invertible transform

Our Works

a. Hybrid Approach [TIFS 2010]
b. Binary Discriminative Analysis for binary template generation [TIFS 2012]
c. Binary template fusion for multi-biometric cryptosystems [IVC 2017]
d. Entropy measurement for binary template based system [IEEE TC 2016]

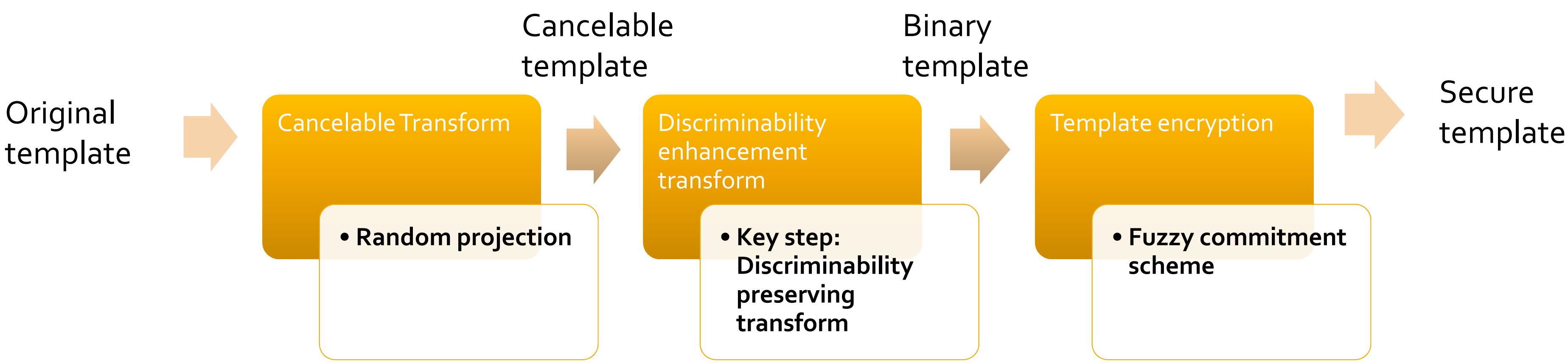
Proposed Hybrid Framework [TIFS 2010]

- One single approach cannot achieve all security, discriminability and cancelability requirements
- A three-step hybrid approach: transformation-based biometric cryptosystem



3-step Algorithm

- The three-step hybrid algorithm



- The discriminability preserving transform should
  - Convert the cancelable template into binary template
  - Preserve the discriminability via transform.

Experimental Results

- Experiment settings:
  - Database:

c : No. of individuals.
m: No. of samples for each individual.
q : No. of training samples per individual

CMU PIE

FERET

FRGC

Database	c	m	q	Variations
CMU PIE	68	105	10	Illumination, pose, expression
FERET	250	4	2	Mild expression, illumination
FRGC	350	40	5	expression, illumination, mild pose

Experimental Results

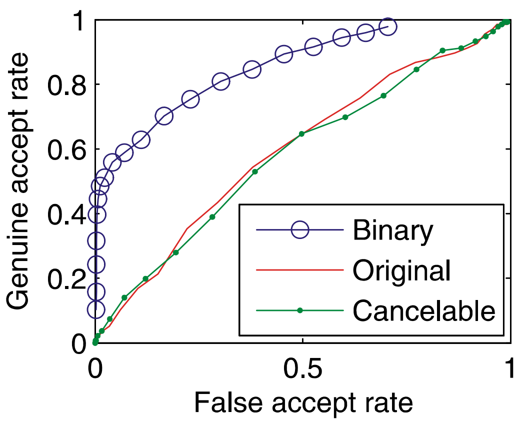
- Experiment settings
  - Fisherface [Belhumeur *et al.* PAMI 1997] applied for feature extraction
  - Experiments
    - Template discriminability
    - Recognition accuracy
    - Cancelability

Template Discriminability

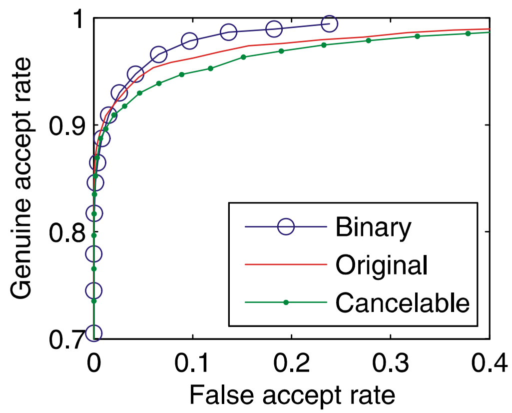
- Experimental settings
  - Choose three subsets from the CMU PIE database for experiments.
  - kr: length of the cancelable templates
  - kc: length of the binary templates

Database	c	m	q	kr	kc	Variations
CMU PIE-1	68	4	2	40	56	Pose
CMU PIE-2	250	21	4	40	84	Illumination
CMU PIE-3	350	105	10	40	210	Pose & illumination

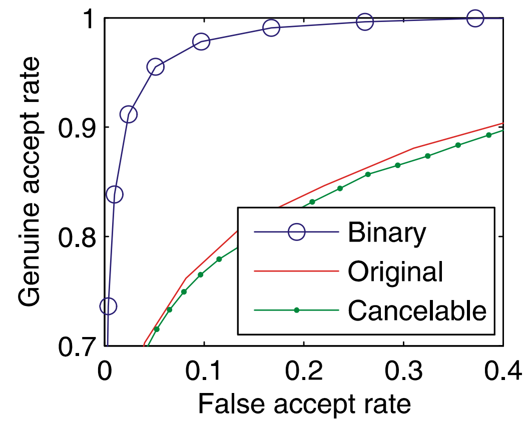
Template Discriminability



(a) Pose



(b) Illumination



(c) Pose &Illumination

- Observations
  - Overlapping rate increased: Cancelable templates lightly degrade some discriminability
  - Overlapping rate significantly decreased: binary templates enhance discriminability.
  - The recognition performance conforms it.

Recognition Accuracy

- Experimental settings
  - CMU PIE, FERET, FRGC databases used.

Database	c	m	q	kr	kc
CMU PIE	68	105	10	40	120, 150, 180, 210
FERET	250	4	2	150	120, 150, 180, 210
FRGC	350	40	5	250	150, 200, 250, 350

- Implement authentication with different kc. And comparing the performance with the
  - Original fisherface algorithm ("Original")
  - Random multispace quantization scheme ("RMQ-S") [Teoh *et al*. PAMI 2006]

Recognition Accuracy

- In the transformed-based scheme (random projection), keys can be issued in two ways.

- Experiments are done in two scenarios
  - Common key scenario ("SRC")
  - User-specified key scenario ("DRC")

Common-key Scenario

- Observation
  - The proposed hybrid algorithm outperforms the original fisherface and the RMQ algorithm

EER(%)	Fisherface	*kc*-1	*kc*-2	*kc*-3	*kc*-4	RMQ
CMU PIE	18.18	7.61	7.30	6.95	6.81	11.93
FERET	12.58	9.52	8.86	8.61	8.55	12.83
FRGC	31.75	17.93	17.40	16.70	16.68	21.87

User-specified Key Scenario

- Observation
  - The proposed hybrid algorithm outperforms the original fisherface and the RMQ algorithm

EER(%)	Fisherface	*kc*-1	*kc*-2	*kc*-3	*kc*-4	RMQ
CMU PIE	18.18	9.41	8.41	8.70	8.26	11.68
FERET	21.66	3.38	3.36	3.34	3.62	4.49
FRGC	31.75	9.03	9.18	9.08	9.13	11.03

Binary Template Generation [TIFS 2012]

- The discriminability of the binary templates receives little attention

Insufficient information carried in binary templates

Binarization process may cause distortion

Matching performed in Hamming space

Ad-hoc thresholding/ quantization

Feng [1] optimizes discriminability with user-specific parameters

Y C Feng and P C Yuen, "Binary Discriminant Analysis for Generating Binary Face Template ," *IEEE Transactions on Information Forensics and Security (TIFS), vol.* 7, no. 2, pp.613-624, 2012.

Background

- Existing schemes lack of discriminability evaluations of the binary templates
- Traditional discriminability optimization methods are not effective
  - Employ differentiation
  - Differentiation is not feasible in Hamming space
- Propose a **binary discriminant analysis (BDA)** to optimize the discriminability of the binary templates

Rationale

- Use a series of linear discriminant functions (LDF) to form a binary template $b=(b_1,b_2\ldots b_i\ldots b_k)$ from input sample x.

$$b_i(x) = \begin{cases} 0 \text{ if} & w_i^T x + t_i > 0 \\ & 1 \text{ if else} \end{cases}$$

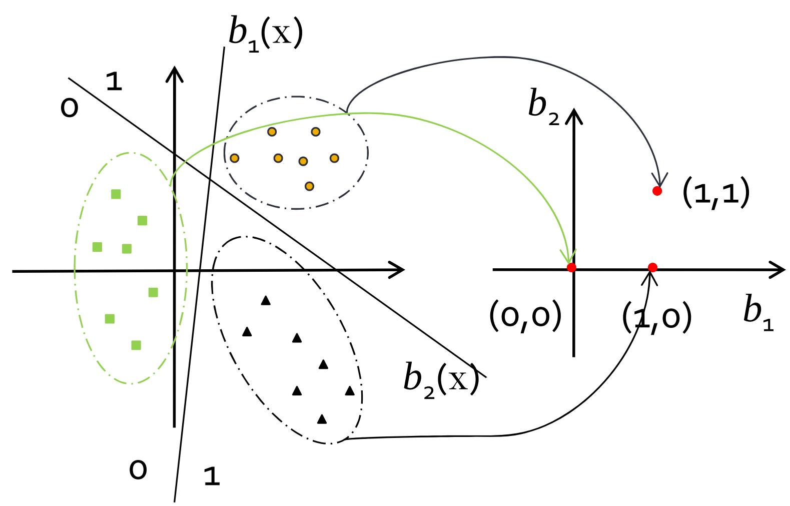
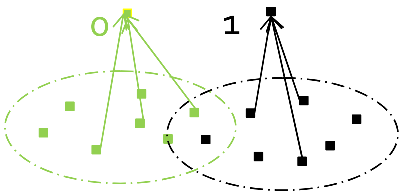


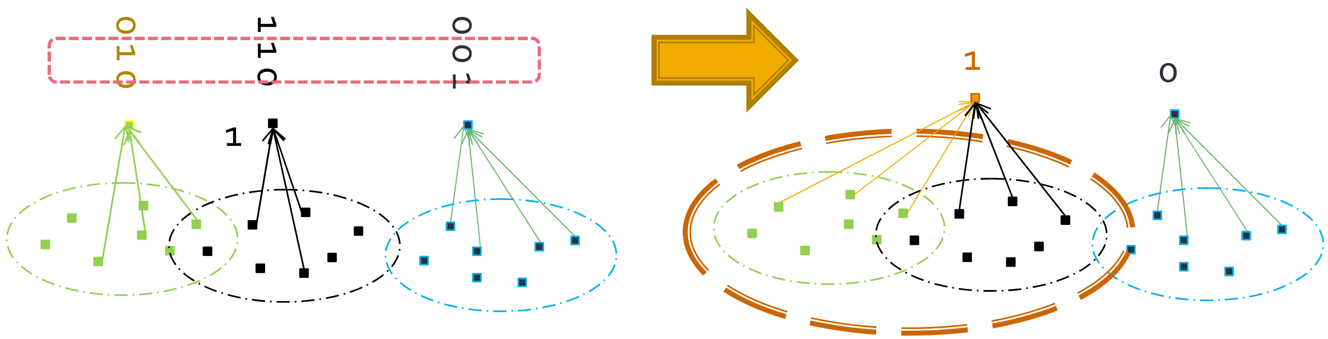
Illustration in 2-D space

Rationale

- Inspired by perceptron
  - Find a LDF to classify two classes

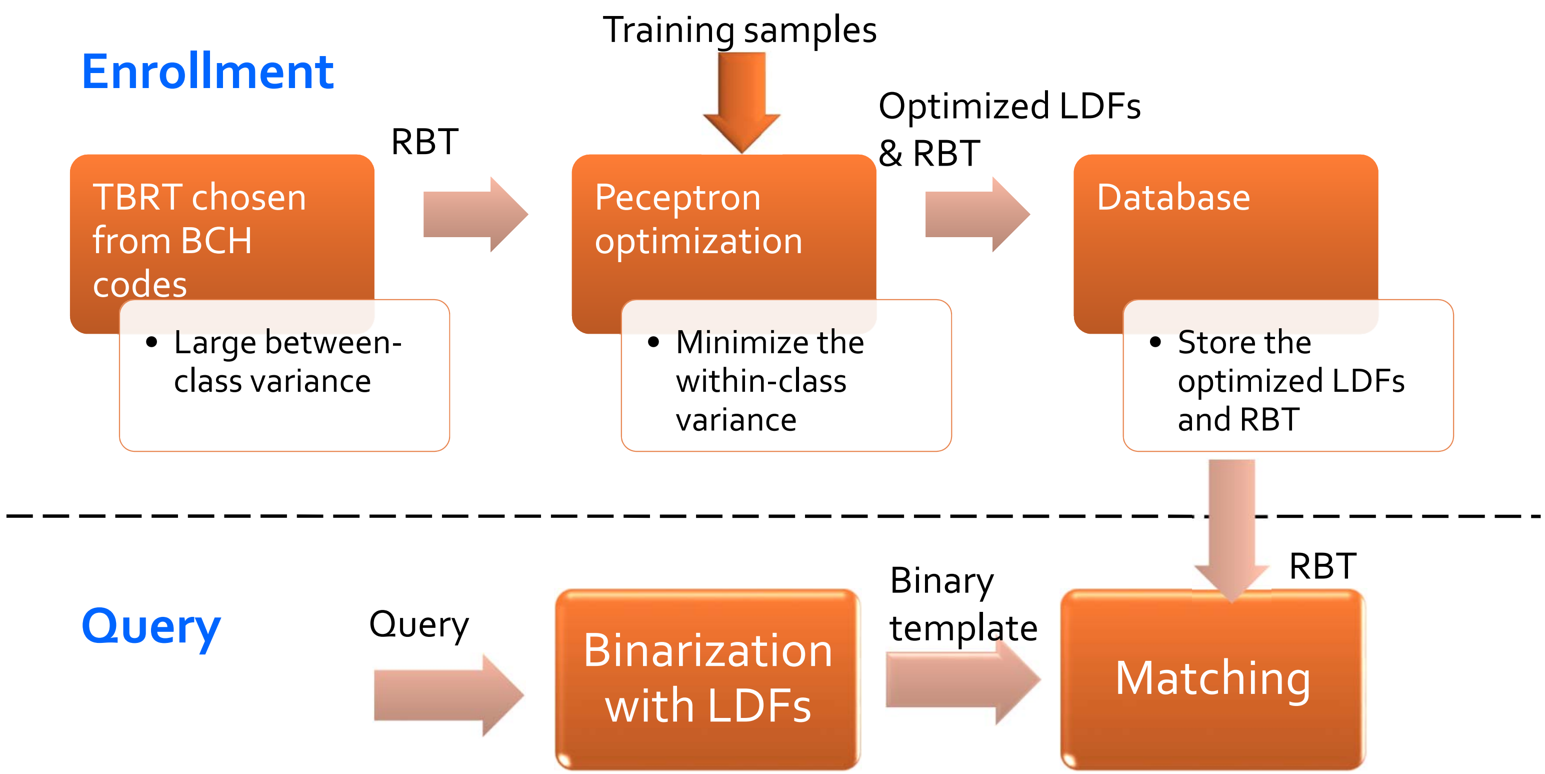


  - Construct a continuous perceptron criteria function to find optimal (w , t)
    - Can be extended to multiple classes with labels of multiple bits, just like binarization



Detailed Algorithm

- The whole procedure of the algorithm



Experimental Results

- Experiment settings

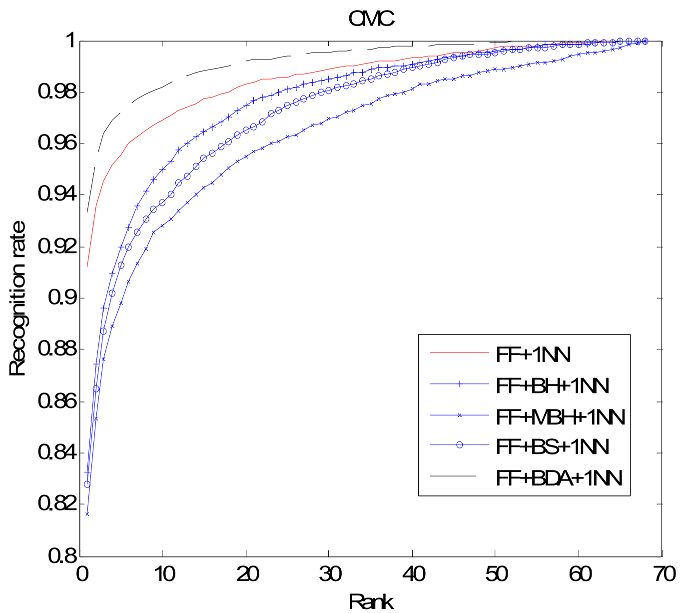
CMU PIE

FRGC

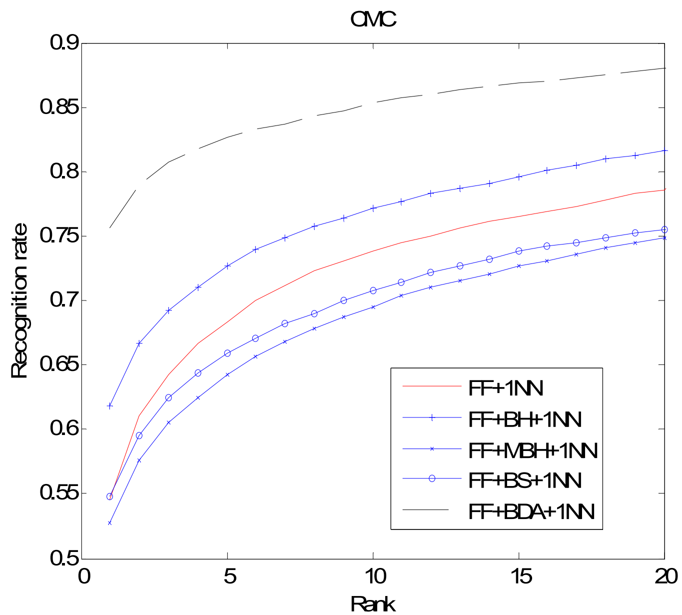
c : No. of individuals.
N_p: No. of samples for each individual.
N_t : No. of training samples per individual

Database	c	N_p	N_t	Variations
CMU PIE	68	105	10	Illumination, pose, expression
FRGC	350	40	5	expression, illumination, mild pose

Experimental Results

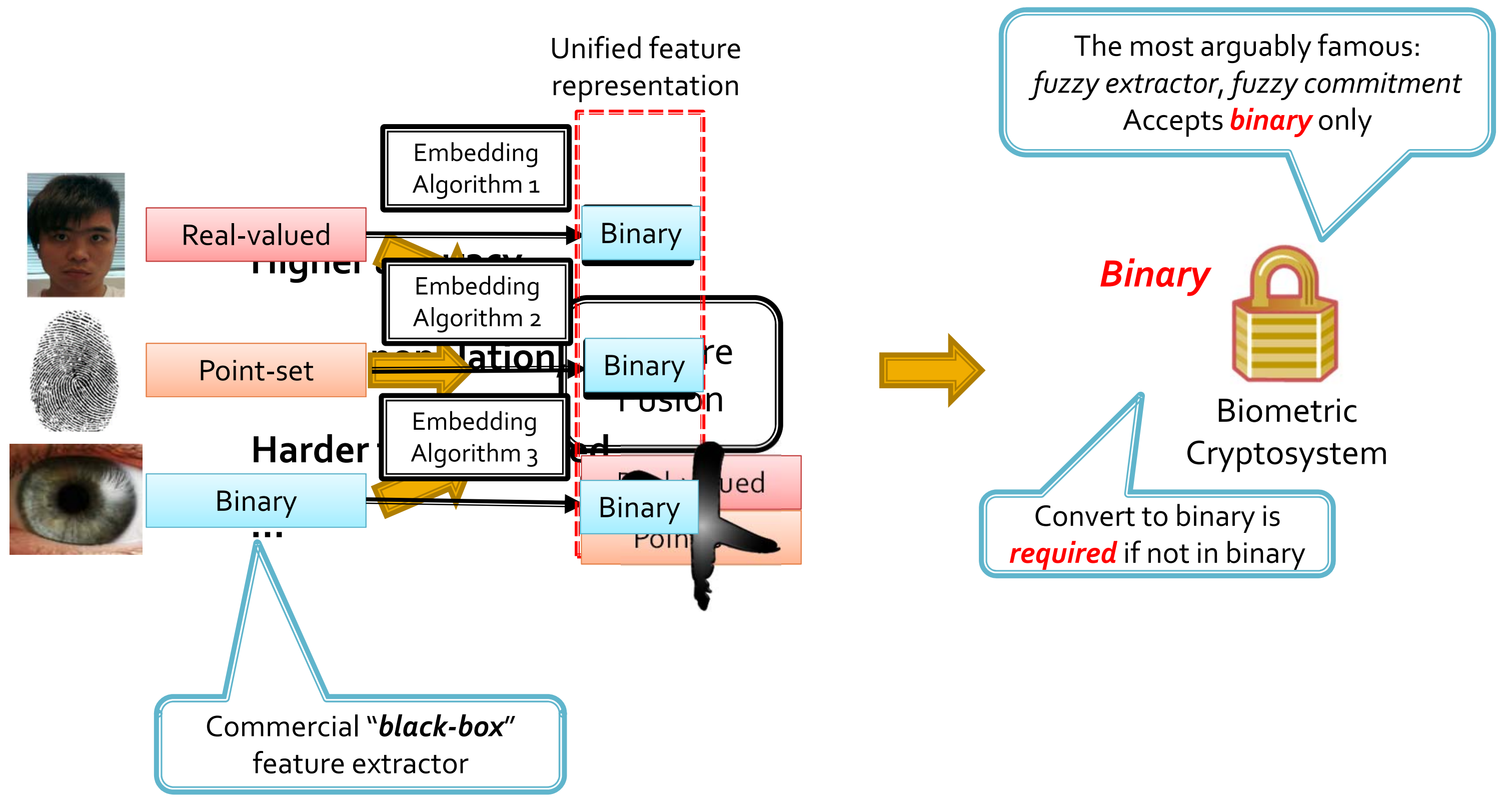


(a) CMU PIE



(b) FRGC

Binary Template Fusion for Multi-biometric Cryptosystem [IVC 2017]



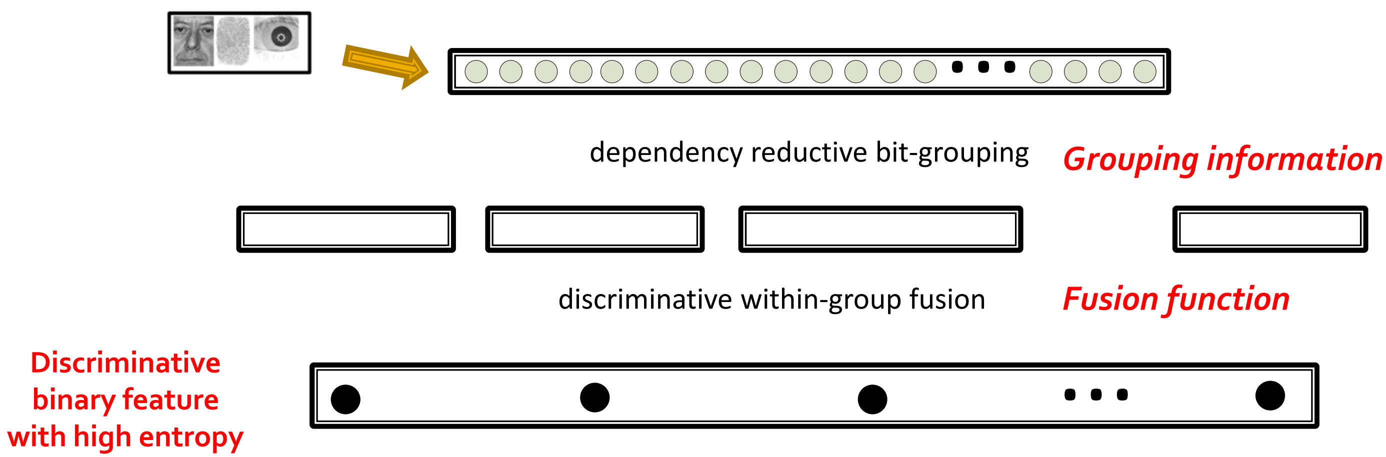
No binalization **parameters**

Criteria for Binary Template Fusion

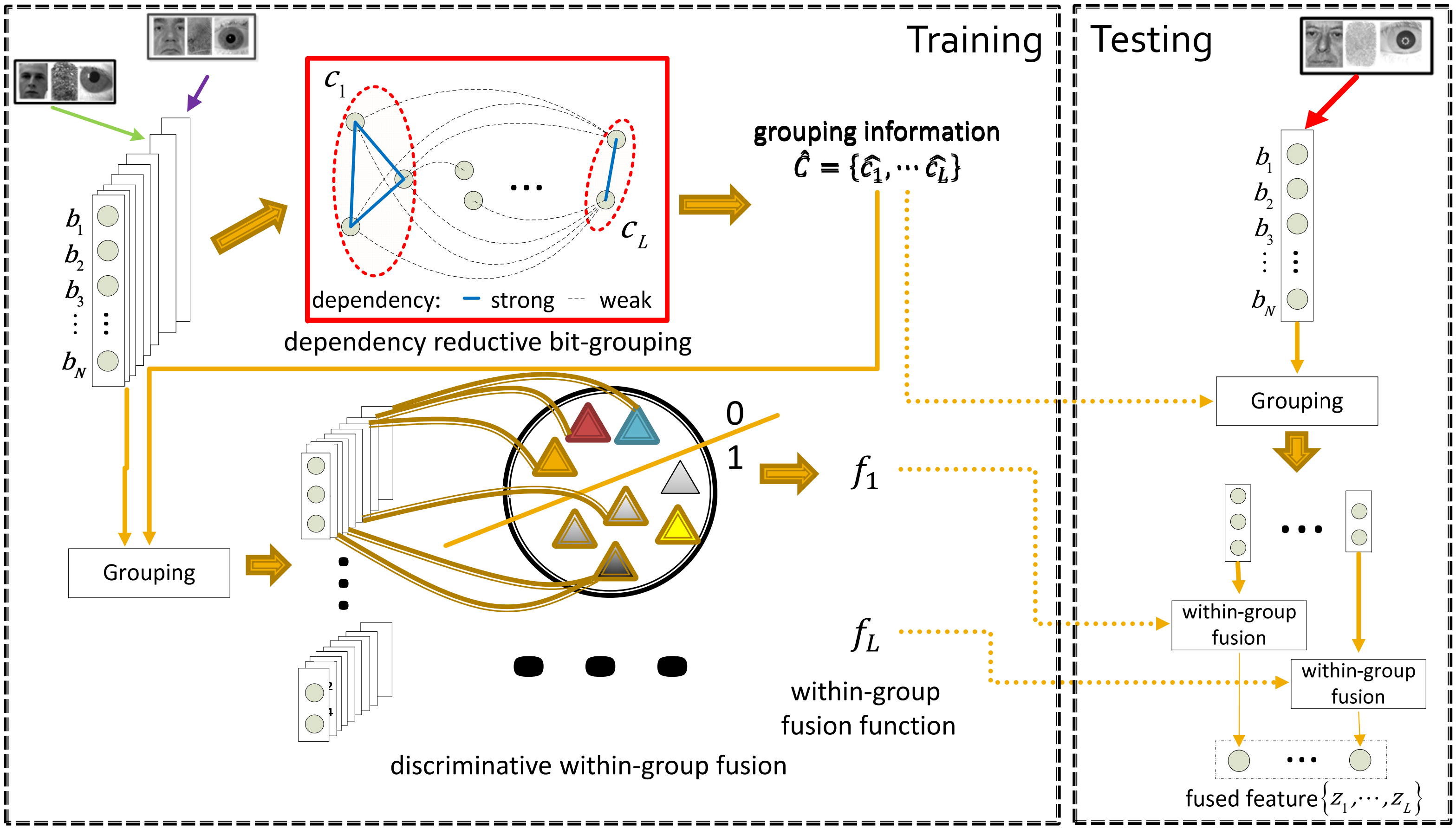
- Discriminability
  - Small intra-user variations ***of*** feature bits
  - Large inter-user variations ***of*** feature bits
- Security (high-entropy)
  - Low dependency ***among*** bits
  - High uniformity ***of*** feature bits
- Privacy
  - No information leakage from helper data

Proposed Binary Template Fusion

- Stage one: dependency-reductive bit grouping
  - Dependency among bits (**security**)
- Stage two: discriminative within-group fusion
  - Bit-uniformity (**security**), intra-user variations (**discriminability**), inter-user variations (**discriminability**)



Proposed Binary Template Fusion

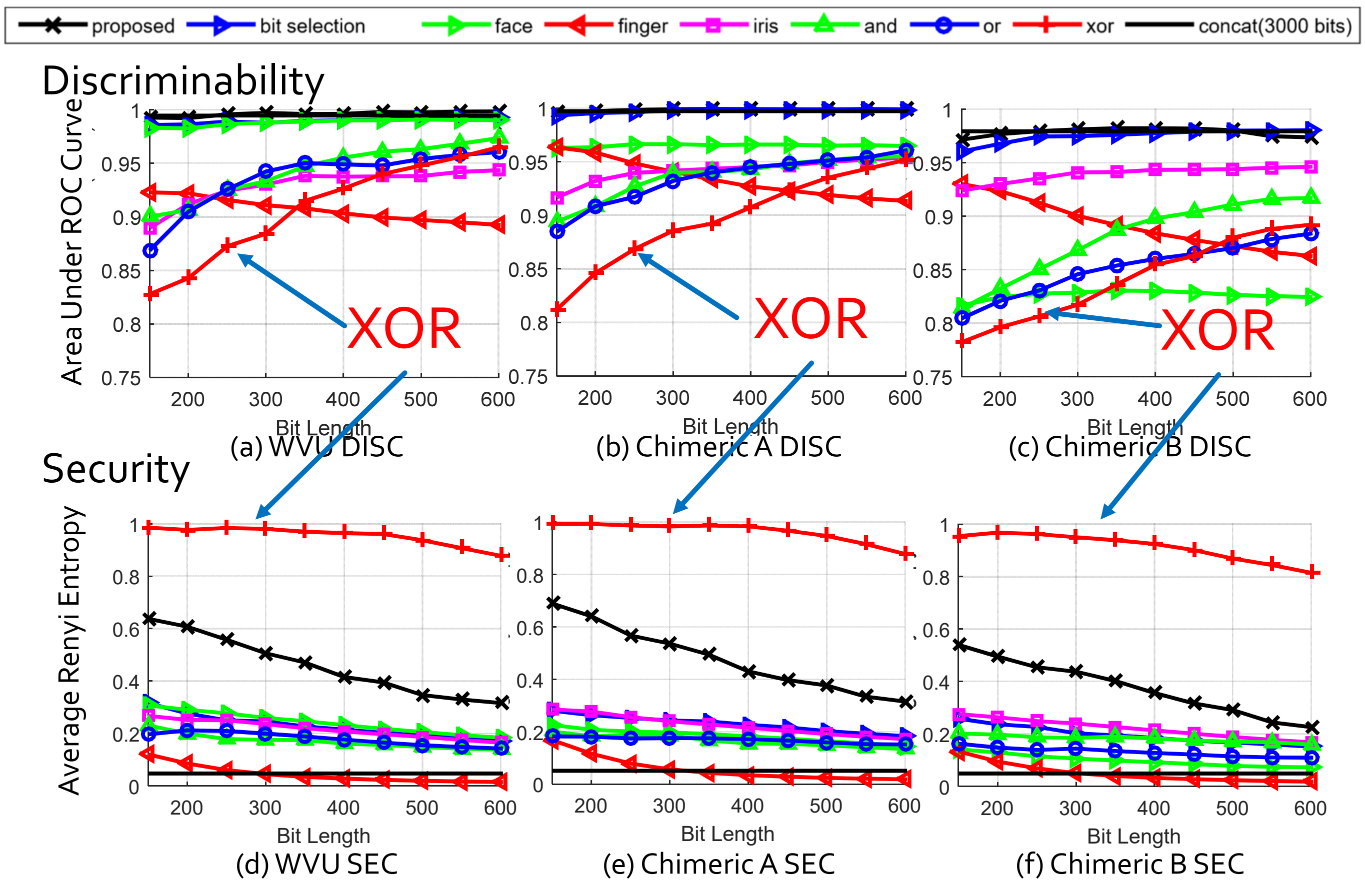


Experiments

- Evaluation
  - Discriminability (Area under ROC curve)
  - Security (average Renyi entropy, Hidano et al. BIOSIG2012)
- Experimental setting

Multimodal Database	**WVU**	**Chimeric A (FVC2000DB2 + FERET + CASIA)**	**Chimeric B (FVC2002DB2 + FRGC + ICE2006)**
Subjects	106	100	100
Training Sample	3	4	4
Testing Sample	2	4	4

Experimental Results



- Related work:

M H Lim, S Verma, G C Mai and P C Yuen, “Learning discriminability-preserving histogram representation from unordered features for multibiometric feature-fused template protection”, *Pattern Recognition*, 2016

Conclusion

- Biometrics security and privacy is an important issue for practical biometrics system
- Research work in fake biometrics detection and biometrics detection are discussed
- Security like a "cat and mouse game"
- More and continuous efforts are required

Thank you!

References (Face Template Protection)

1. G. Mai, Kai Cao, P. C. Yuen and Anil K. Jain, "On the Reconstruction of Deep Face Templates", *IEEE Transactions on Pattern Analysis and Machine Intelligence (TPAMI)*, In press, 2019
2. G. Mai, M H Lim and P C Yuen, "Binary Feature Fusion for Discriminative and Secure Multi-biometric Cryptosystems", *Image and Vision Computing*, 2016
3. M H Lim and P C Yuen, "Entropy Measurement for Biometric Verification Systems", *IEEE Transactions on Cybernetics*, 2016
4. M H Lim, S Verma, G C Mai and P C Yuen, "Learning discriminability-preserving histogram representation from unordered features for multibiometric feature-fused template protection", *Pattern Recognition*, 2016
5. Y C Feng, M H Lim and P C Yuen, "Masquerade attack on transform-based binary-template protection based on perceptron learning", *Pattern Recognition*, 2014
6. YC Feng & PC Yuen, "Binary discriminant analysis for generating binary face template", *IEEE Transactions on Information Forensics and Security*, 2012
7. YC Feng, PC Yuen, AK Jain, "A hybrid approach for generating secure and discriminating face template", *IEEE Transactions on Information Forensics and Security*, 2010

References (Face Anti-spoofing)

1. N. Erdogmus and S. Marcel, "Spoofing face recognition with 3d masks", *TIFS*, 2014
2. J. Maatta, A. Hadid, and M. Pietikainen. "Face spoofing detection from single images using micro-texture analysis", *IJCB*, 2011.
3. D. Wen, H. Han, and A. K. Jain, "Face spoof detection with image distortion analysis", *TIFS*, 2015.
4. G. Pan, L. Sun, Z. Wu, and S. Lao. "Eyeblink-based antispoofing in face recognition from a generic webcamera", *ICCV*, 2007.
5. T. de Freitas Pereira, J. Komulainen, A. Anjos, J. M. De Martino, A. Hadid, M. Pietikainen, and S. Marcel, "Face liveness detection using dynamic texture.", *EURASIP JIVP*, 2014.
6. X. Li, J. Komulainen, G. Zhao, P. C. Yuen, and M. Pietikainen, "Generalized face anti-spoofing by detecting pulse from face videos", *ICPR*, 2016.
7. S. Liu, P C. Yuen, S. Zhang, and G. Zhao, "3D Mask Face Anti-spoofing with Remote Photoplethysmography" , *ECCV*, 2016.
8. S. Liu, B. Yang, P C. Yuen, G. Zhao, "A 3D Mask Face Anti-spoofing Database with RealWorld Variations" , *CVPRW*, 2016.
9. S Liu, X Y Lan and P C Yuen, "Remote Photoplethysmography Correspondence Feature for 3D Mask Face Presentation Attack Detection", *ECCV*, 2018
10. R Shao, X Y Lan and P C Yuen, "Deep Convolutional Dynamic Texture Learning with Adaptive Channel-discriminability for 3D Mask Face Anti-spoofing", *IAPR/IEEE International Joint Conference on Biometrics (IJCB),* Oct 2017
11. R Shao, X Y Lan and P C Yuen, "Joint Discriminative Learning of Deep Dynamic Textures for 3D Mask Face Anti-spoofing", *IEEE Transactions on Information Forensics and Security (TIFS*), In press, 2019.