BTAS 2019

Session II: Deep Learning Approaches for Face Anti-spoofing

Host: Yaojie Liu

MICHIGAN STATE UNIVERSITY

Computer Vision Lab

Outline

- Vanilla CNNs
- Patch-based CNN methods
- CNN methods with auxiliary supervisions
- GAN-based noise modeling
- Data augmentation

Outline

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- **Vanilla CNN**
- Patch-based CNN methods
- CNN methods with auxiliary supervisions
- GAN-based noise modeling
- Data Augmentation

Vanilla CNNs

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CNN is trained to do a binary classification: live vs spoof

Live Face

Presentation Attack

0

1

Binary Supervision

Vanilla CNNs

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Learn Convolutional Neural Network for Face Anti-Spoofing, ArXiv, 2014

Learning temporal features using LSTM-CNN architecture for face anti-spoofing, ACPR, 2015

Integration of image quality and motion cues for face anti-spoofing: A neural network approach, JVCI, 2016

An Original Face Anti-spoofing Approach using Partial Convolutional Neural Network, IPTA, 2016

Cross-database face antispoofing with robust feature representation. CCBR, 2016

Vanilla CNNs

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Learn Convolutional Neural Network for Face Anti-spoofing

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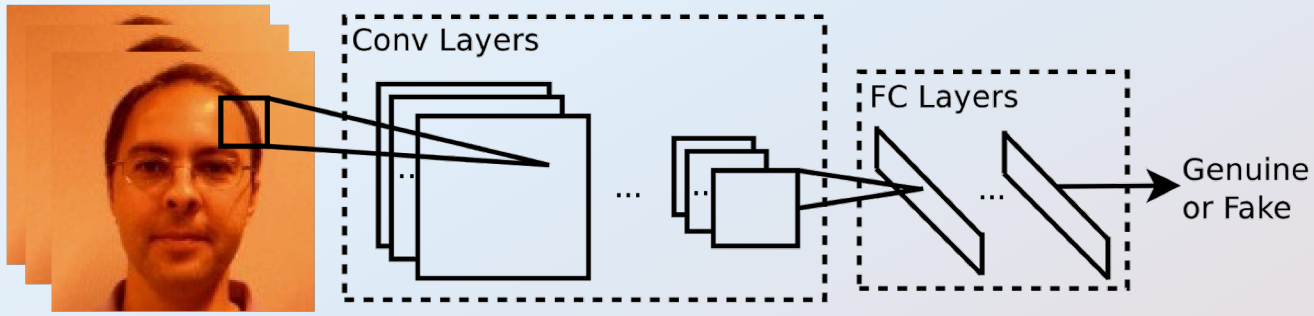
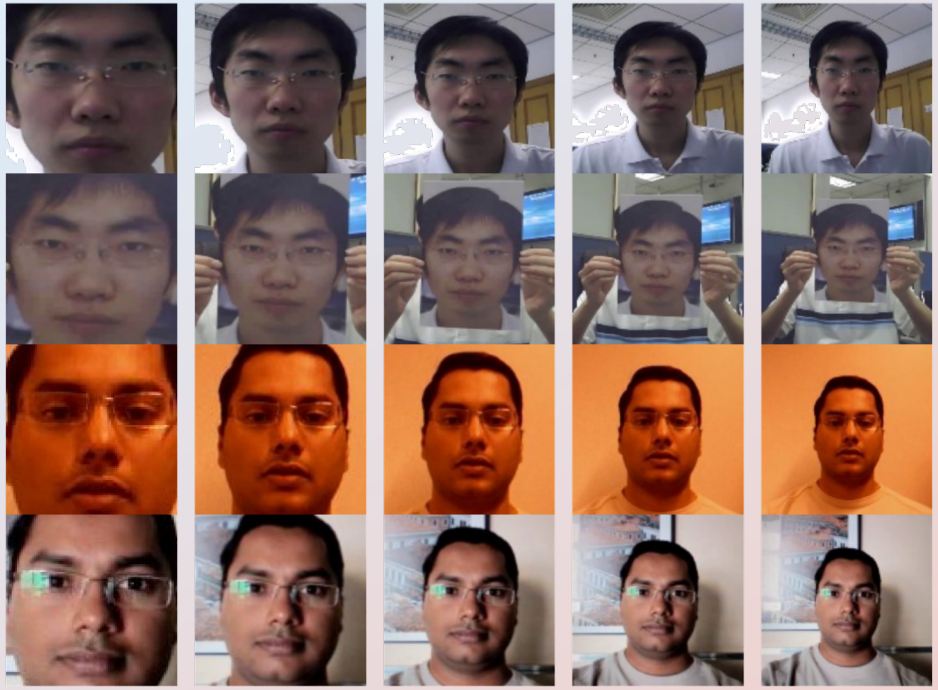
- CNN feature + SVM classifier
- Examine the influence of face scale





Yang et. al., Learn Convolutional Neural Network for Face Anti-Spoofing. arXiv 2014.

Conclusion of Face Scales

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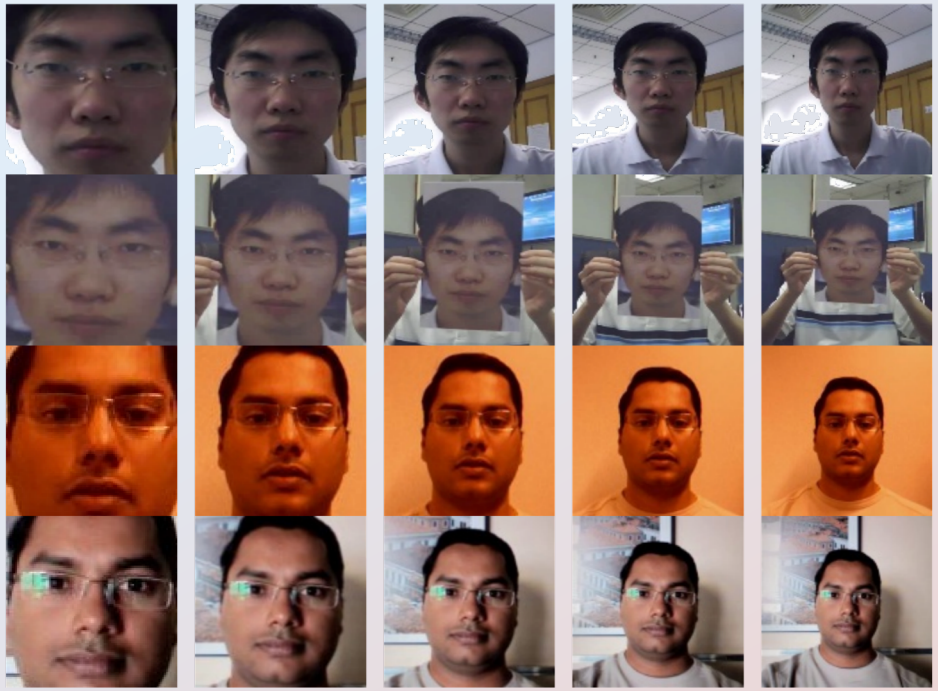
- Too small: very limited information

  →worse performance

- Too big: too much information → worse performance

- Varies from case to case
  - CASIA is best at medium res.
  - Replay is best at the largest res.



Yang et. al., Learn Convolutional Neural Network for Face Anti-Spoofing. arXiv 2014.

Learning Temporal Features using LSTM-CNN Architecture for Face Anti-spoofing

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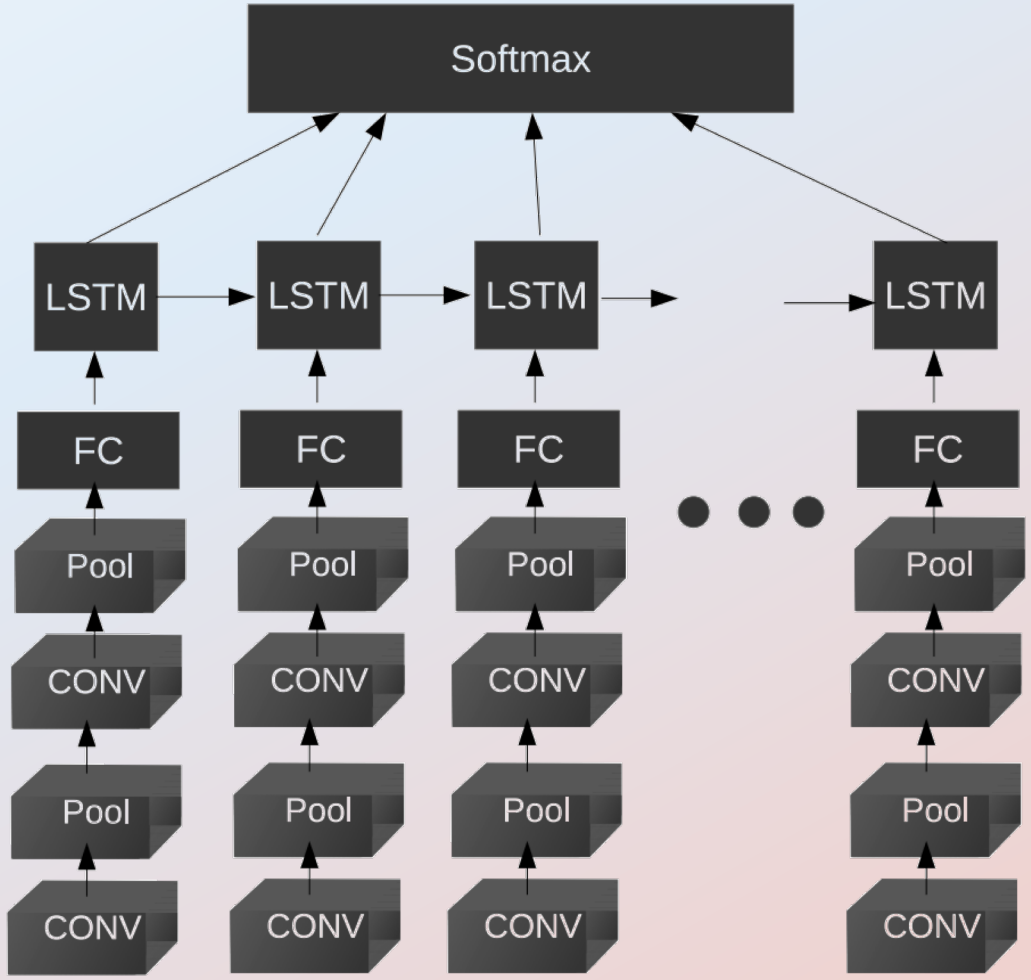
- CNN + LSTM
- Consider temporal information



Xu et. al., Learning temporal features using LSTM-CNN architecture for face anti-spoofing. ACPR 2015.

Integration of Image Quality and Motion Cues for Face Anti-spoofing: A Neural Network Approach

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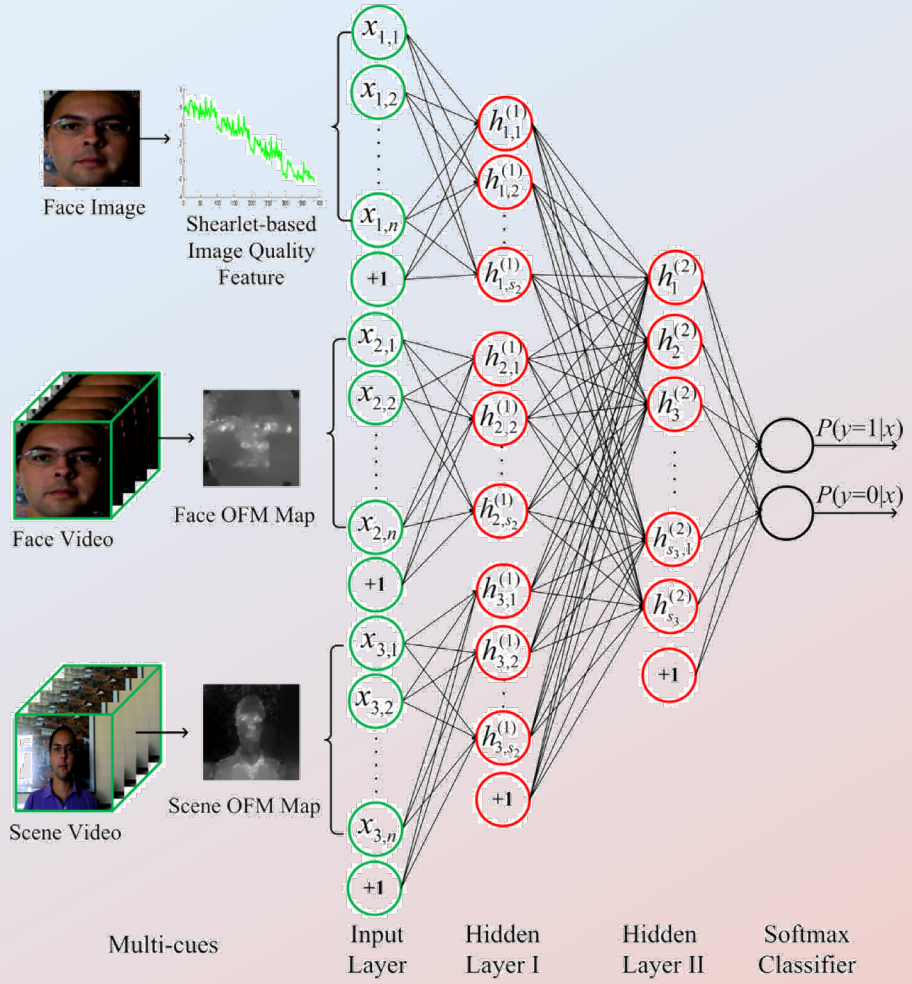
- Use handcrafted features as input
  - Shearlet-based image quality
  - Face optical flow
  - Scene optical flow



Feng et. al., Integration of image quality and motion cues for face anti-spoofing: A neural network approach. JVCI 2016.

Experiment Results

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CASIA Dataset	EER	HTER
Color LBP[1]	6.2	-
CNN + SVM[2]	-	6.25
CNN + LSTM[3]	-	5.93
Multi-cue CNN[4]	5.83	-

Replay Dataset	EER	HTER
Color LBP[1]	0.4	2.9
CNN + SVM[2]	-	2.68
CNN + LSTM[3]	-	-
Multi-cue CNN[4]	-	0

[1] Boulkenafet et. al., Face antispoofing based on color texture analysis. ICIP 2015
[2] Yang et. al., Learn Convolutional Neural Network for Face Anti-Spoofing. arXiv 2014.
[3] Xu et. al., Learning temporal features using LSTM-CNN architecture for face anti-spoofing. ACPR 2015.
[4] Feng et. al., Integration of image quality and motion cues for face anti-spoofing: A neural network approach. JVCI 2016.

Summary

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- Fusing inputs (scale, handcrafted features, etc.) can help
- Improve the overall performance compared to non-CNN methods
- Binary classifier might lead to overfitting

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- **Patch-based CNN methods**
- CNN methods with auxiliary supervisions
- GAN-based noise modeling
- Data Augmentation

Patch-based CNNs

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Face Anti-Spoofing Using Patch and Depth-Based CNNs, IJCB, 2017

On the Learning of Deep Local Features for Robust Face Spoofing Detection, SIBGRAPI, 2018

Face Anti-Spoofing: Model Matters, So Does Data, CVPR, 2019

Patch-based CNNs

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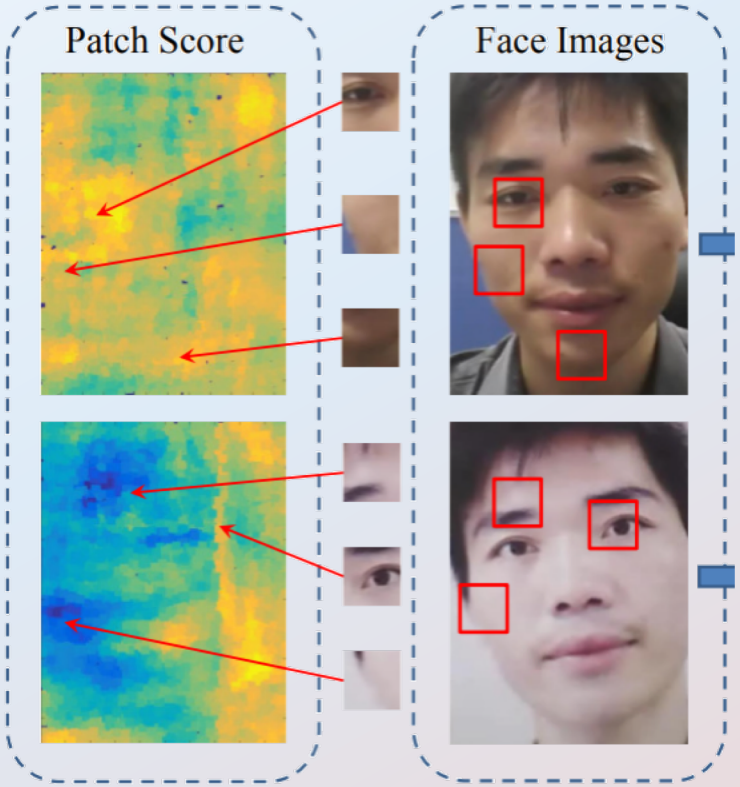
Motivation

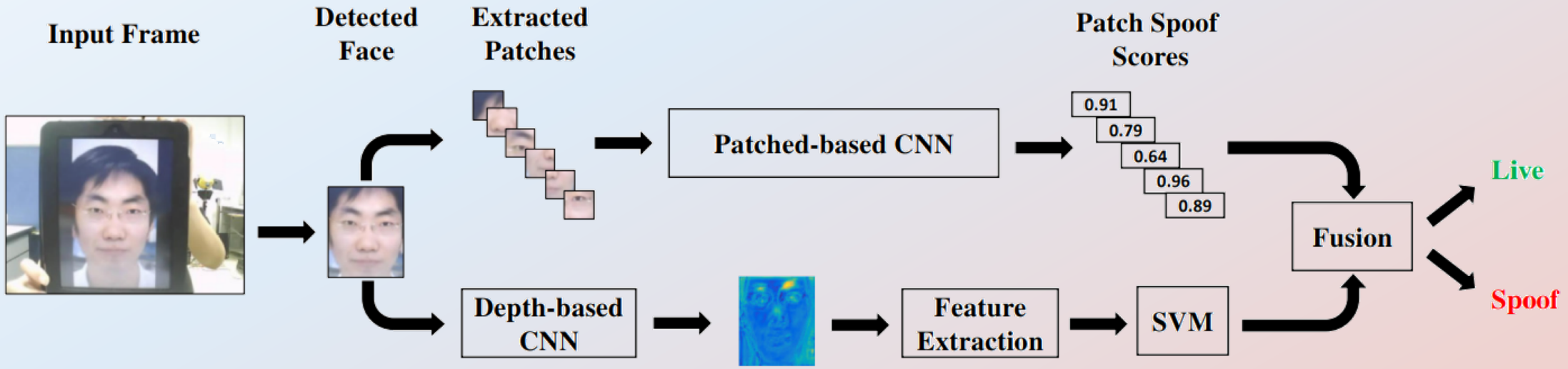
- Prevent overfitting
  - Increase the number of training samples



Yousef Atoum, Yaojie Liu, Amin Jourabloo, and Xiaoming Liu, Face anti-spoofing using patch and depth-based CNNs. IJCB 2017.

Patch CNN

- Input face: RGB+HSV, patch size 96*96
- Patch CNN: classify each patch as a live or spoof patch
- Fuse the score by average



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Color LBP[1]	6.2	-
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Multi-cue CNN[4]	5.83	-
Patch CNN + Depth CNN[5]	2.67	2.27

Replay Dataset	EER	HTER
Color LBP[1]	0.4	2.9
CNN + SVM[2]	-	2.68
CNN + LSTM[3]	-	-
Multi-cue CNN[4]	-	0
Patch CNN + Depth CNN[5]*	0.79	0.72

* Only use tight cropped face

[1] Boulkenafet et. al., Face antispoofing based on color texture analysis. ICIP 2015
[2] Yang et. al., Learn Convolutional Neural Network for Face Anti-Spoofing. arXiv 2014.
[3] Xu et. al., Learning temporal features using LSTM-CNN architecture for face anti-spoofing. ACPR 2015.
[4] Feng et. al., Integration of image quality and motion cues for face anti-spoofing: A neural network approach. JVCI 2016.
[5] Yousef Atoum, Yaojie Liu, Amin Jourabloo, and Xiaoming Liu, Face anti-spoofing using patch and depth-based CNNs. IJCB 2017.

Patch-based CNNs

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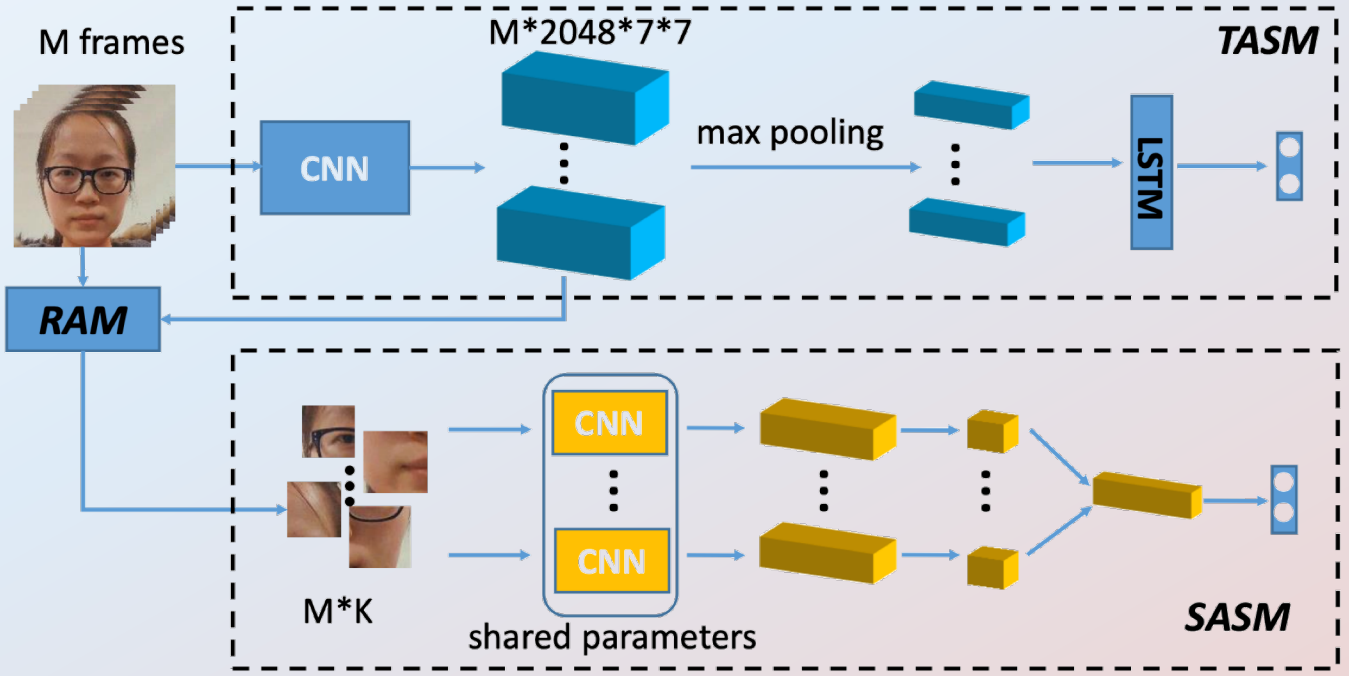
STASN

- Temporal Anti-Spoofing Module (TASM): conv-LSTM
- Region Attention Module (RAM): locating the discriminative and significant sub-regions
- Spatial Anti-Spoofing Module (SASM): patch CNN



Yang et. al., Face Anti-Spoofing: Model Matters, So Does Data, CVPR 2019

Region Attention Module (RAM)

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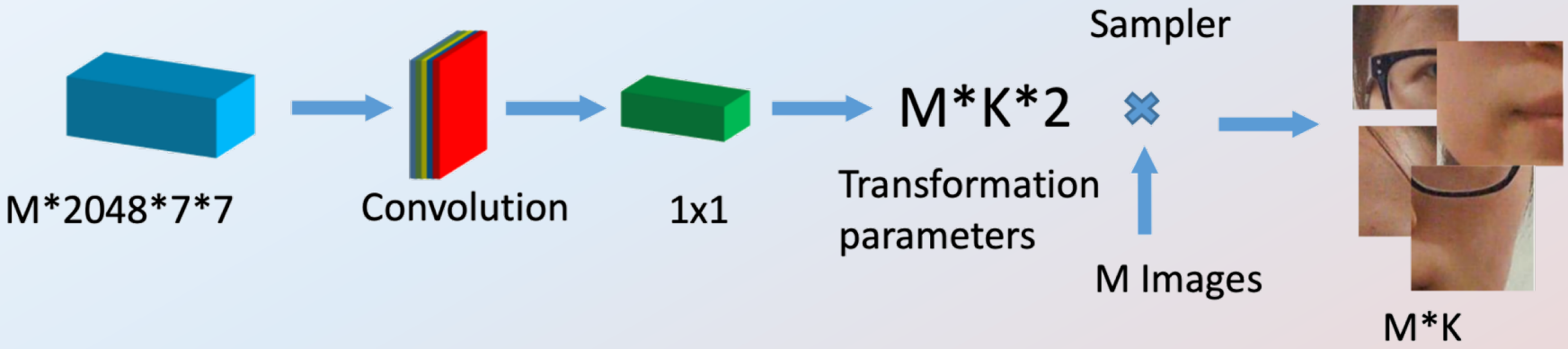
Locates the discriminative and significant sub-regions

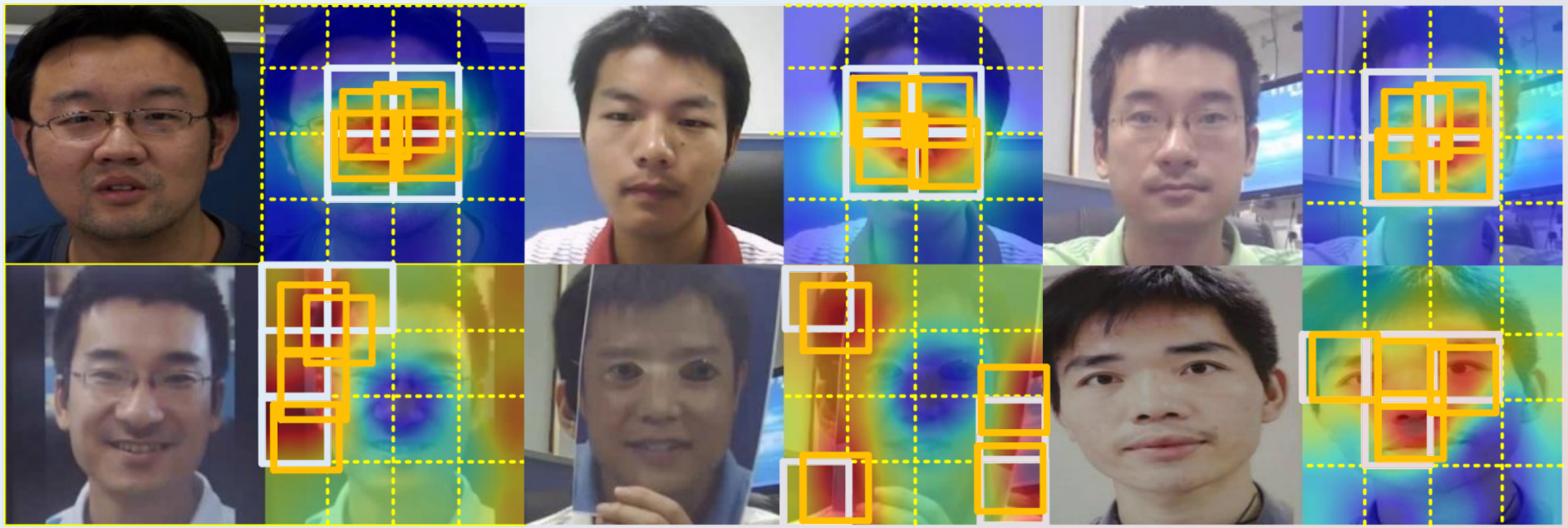
- RAM output 2*K parameters: offsets and translation of K patches



Yang et. al., Face Anti-Spoofing: Model Matters, So Does Data, CVPR 2019

Examples of Attention

- Live attentions are on face
- Spoof attentions are diverse



Yang et. al., Face Anti-Spoofing: Model Matters, So Does Data, CVPR 2019

Drawbacks

- Trade-off between efficiency and performance (more patches or less?)
- Not end-to-end training
- Patch scale

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- **CNN methods with auxiliary supervisions**
- GAN-based noise modeling
- Data Augmentation

CNN Methods with Auxiliary Supervisions

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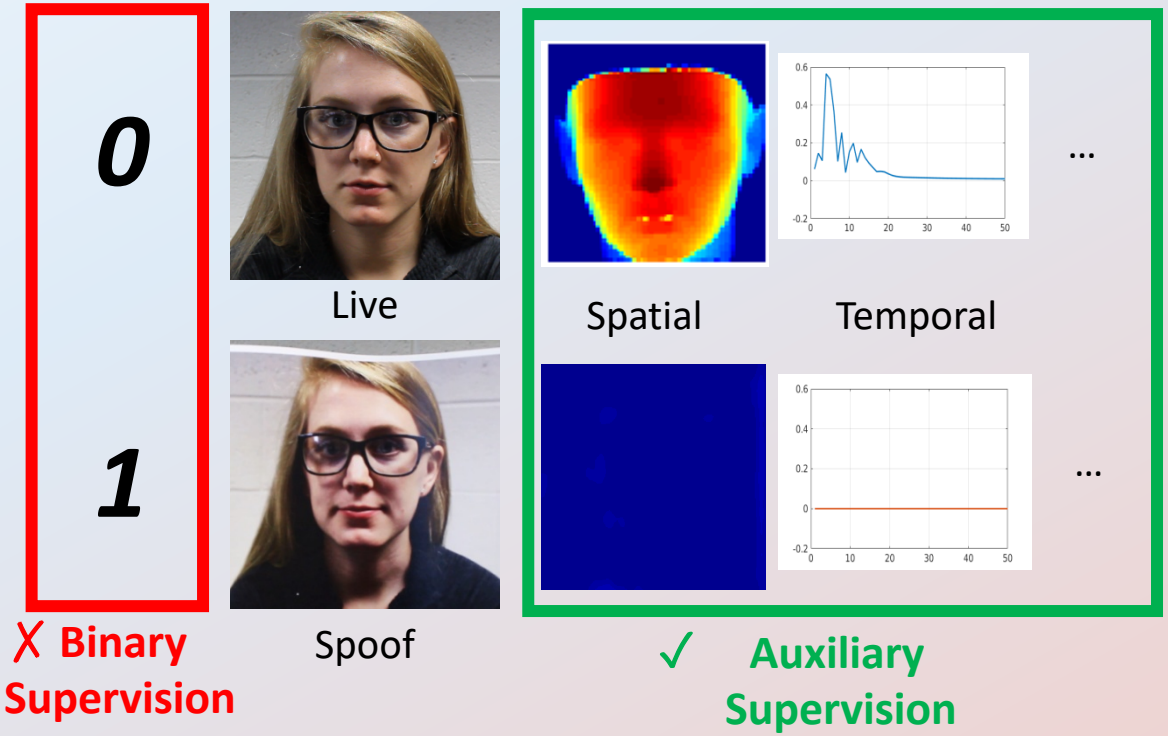
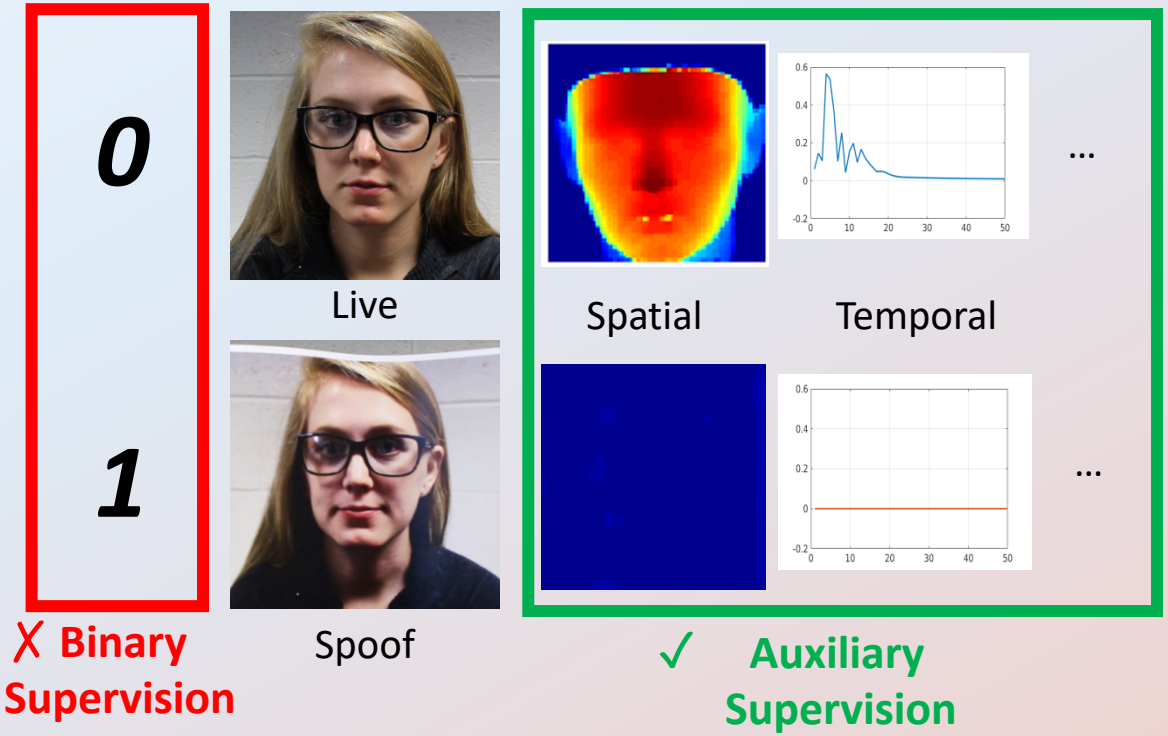
Auxiliary information: signals/biometric features with distinctive difference between live and spoof

- Depth map
- Heart beat signal (rPPG)
- Optical flow
- …



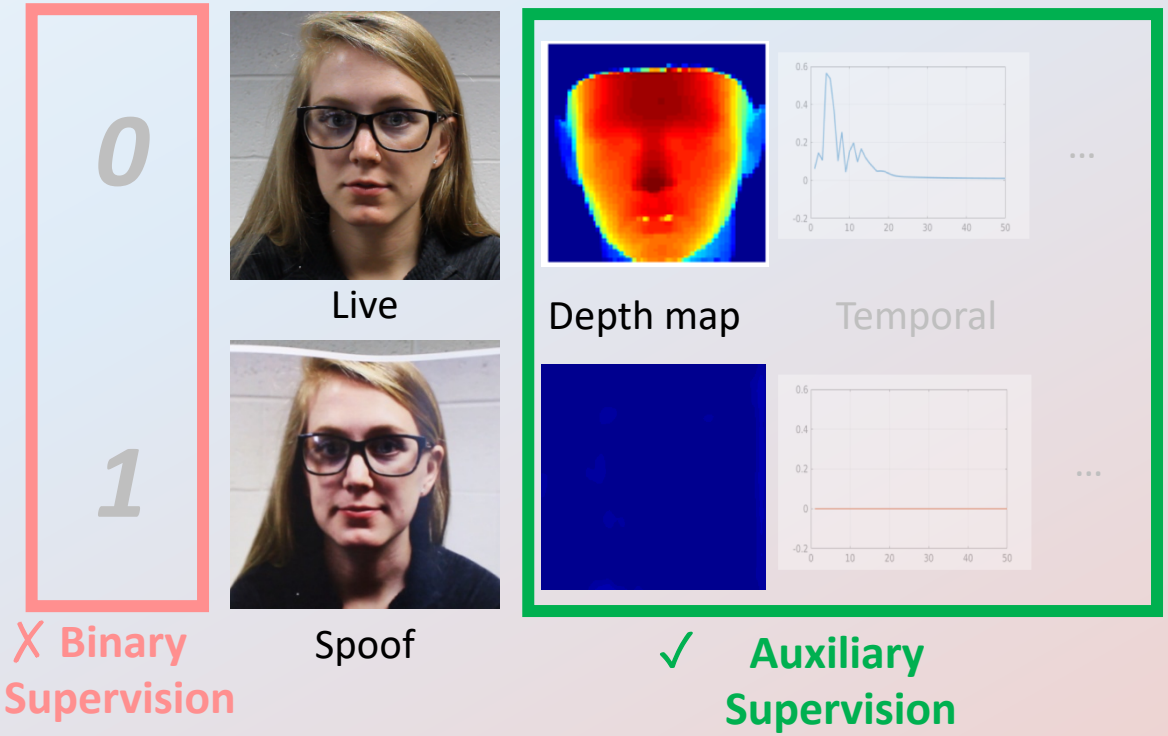
Why Auxiliary Supervision?

- Provide specific attention for CNN
- Make CNN explainable



Depth Map

- Provide specific attention for CNN
- Make CNN explainable



Methods using Depth Map

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Face anti-spoofing using patch and depth-based CNNs. IJCB 2017.

Learning deep models for face anti-spoofing: binary or auxiliary supervision. *CVPR 2018.*

Face de-spoofing: anti-spoofing via noise modeling. *ECCV* 2018.

Exploiting temporal and depth information for multi-frame face anti-spoofing, arXiv 2019

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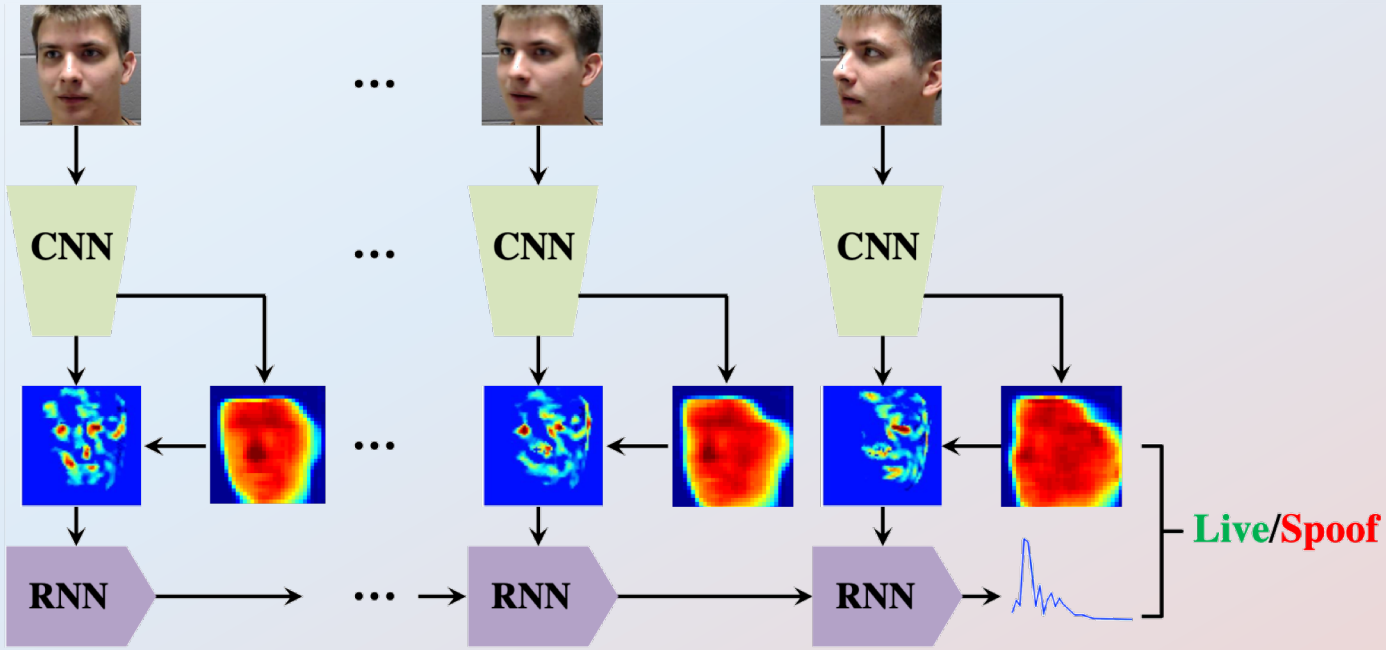
Overall Architecture

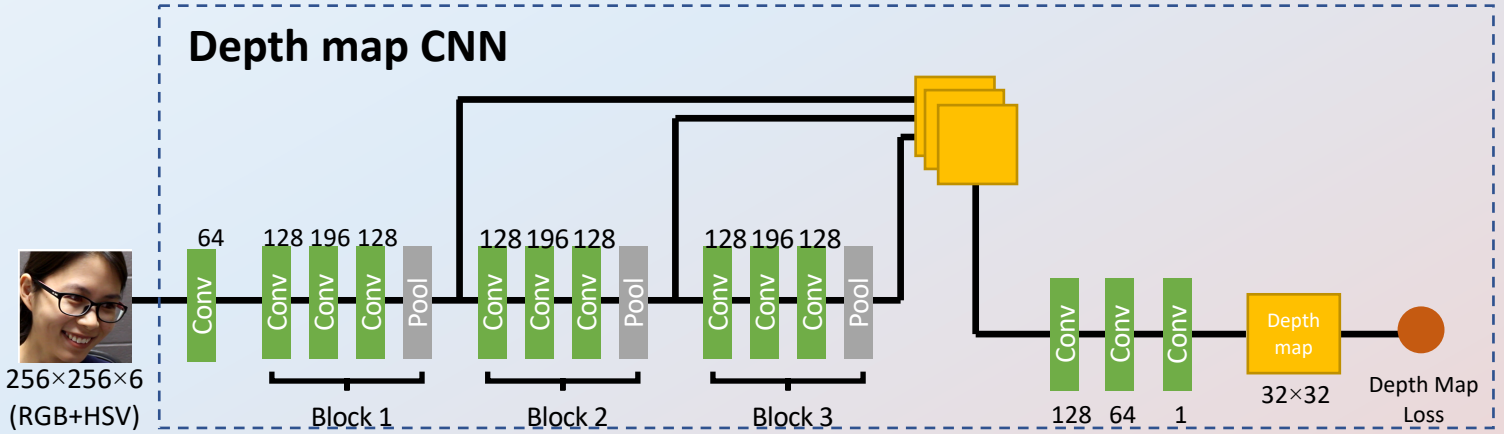
- Spatial supervision: depth map
- Temporal supervision: rPPG signal



Yaojie Liu, Amin Jourabloo, and Xiaoming Liu. Learning deep models for face anti-spoofing: Binary or auxiliary supervision. *CVPR 2018.*

Depth Map CNN

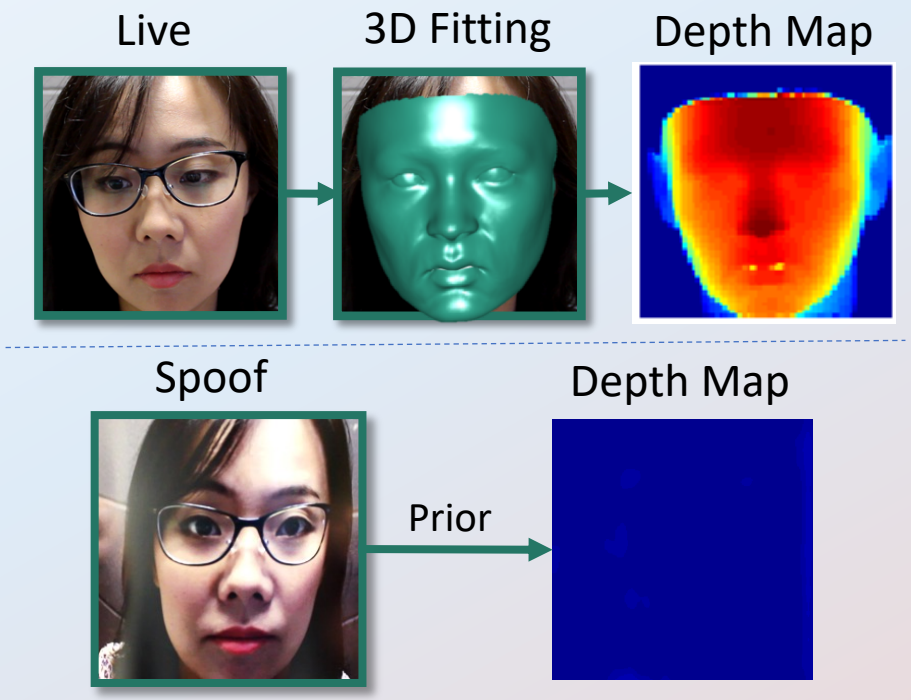
- RGB+HSV as input
- Fully convolutional network
- Short-cut connection to fuse multi-scale features
- Depth map regression loss: $\mathcal{L}_{depth} = \left\| D_{pred} - D_0 \right\|_F^1$



Yaojie Liu, Amin Jourabloo, and Xiaoming Liu. Learning deep models for face anti-spoofing: Binary or auxiliary supervision. *CVPR 2018.*

How to Obtain Depth Map Label?

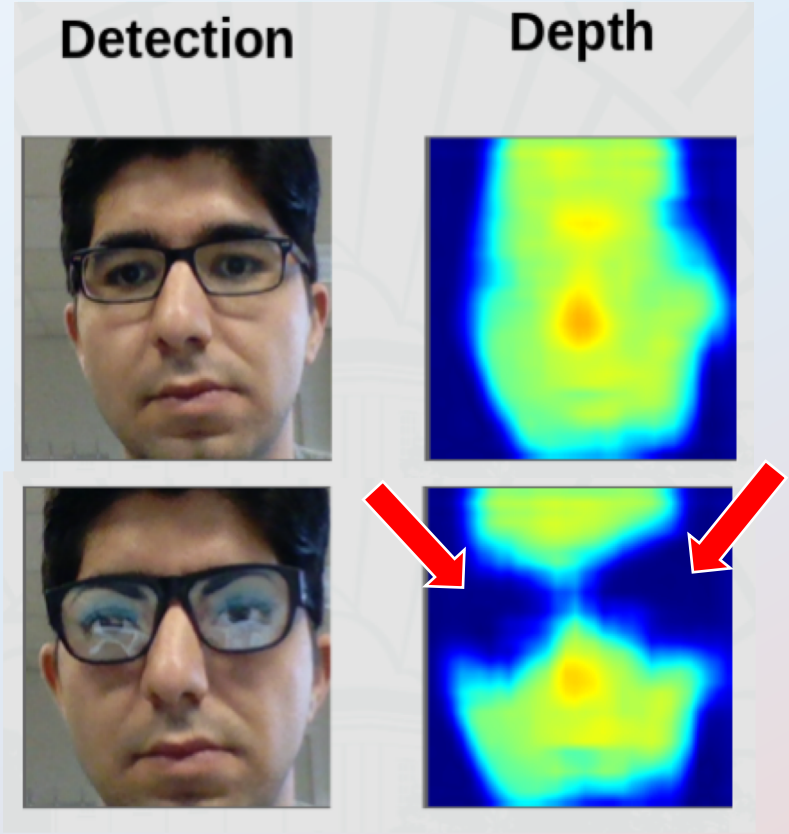
- Depth for live faces: 3D face fitting* + z-buffering rendering
- Depth for spoof faces: zero maps



Yaojie Liu, Amin Jourabloo, and Xiaoming Liu. Learning deep models for face anti-spoofing: Binary or auxiliary supervision. *CVPR 2018.*
*Yaojie Liu, Amin Jourabloo, William Ren, and Xiaoming Liu. Dense Face Alignment. *ICCVW 2017.*

Explainablity

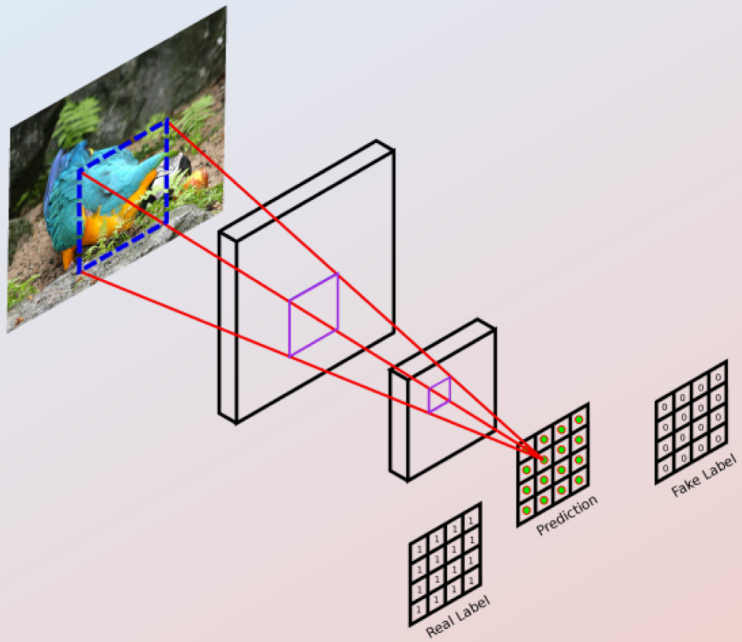
- Indicate the regions of spoof material



Yaojie Liu, Amin Jourabloo, and Xiaoming Liu. Learning deep models for face anti-spoofing: Binary or auxiliary supervision. *CVPR 2018.*

Why Depth Maps Work?

- Local response (same rationale with Patch GAN)
- More elegant than patch-based CNNs (even multiscales!)
- Depth map vs. zero/one map
  - Focus on the face region
  - Noisy background may lead to a worse convergence



Yaojie Liu, Amin Jourabloo, and Xiaoming Liu. Learning deep models for face anti-spoofing: Binary or auxiliary supervision. *CVPR 2018.*

rPPG Temporal Signal

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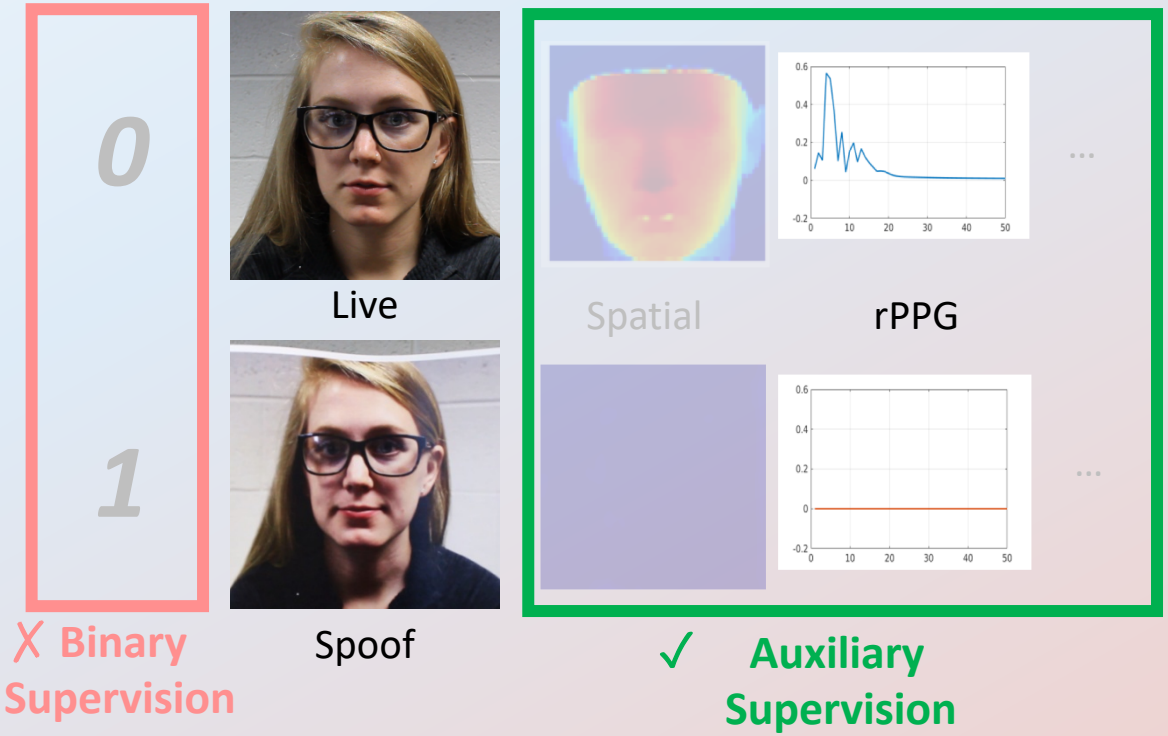
- Provide specific attention for CNN
- Make CNN explainable



What is rPPG?

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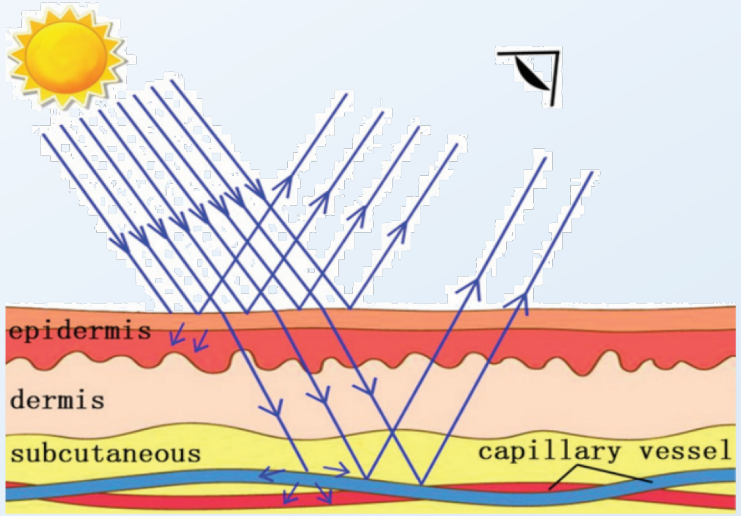
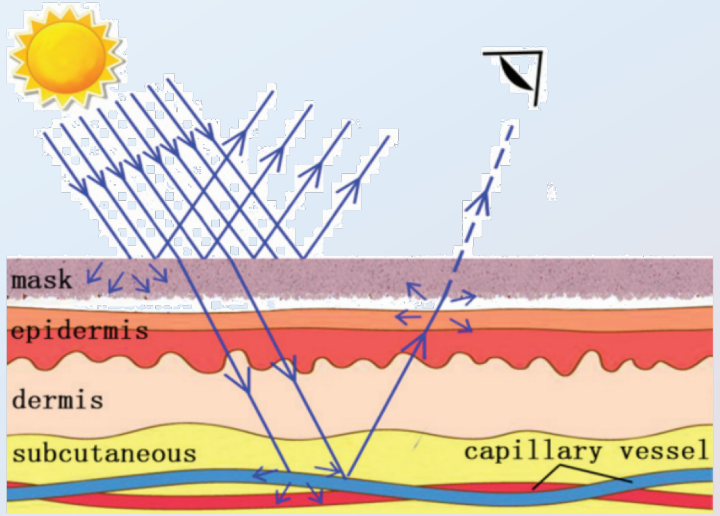
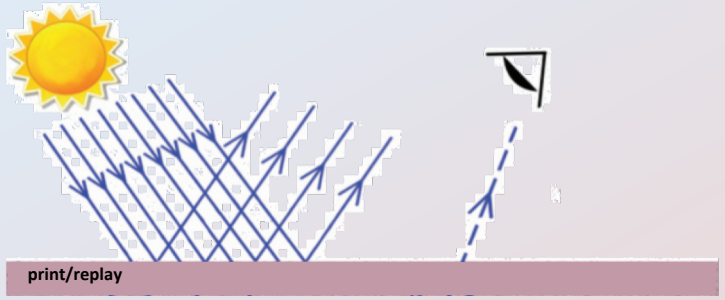
- Remote photoplethysmography: heart beat measurement from human skin using a non-contact camera



Live Face



3D Mask Spoof Face



Print/Replay Spoof Face

Methods using rPPG

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3D Mask Face Anti-spoofing with Remote Photoplethysmography, ECCV 2016

Remote Photoplethysmography Correspondence Feature for 3D Mask Face Presentation Attack Detection, ECCV 2018

Learning deep models for face anti-spoofing: binary or auxiliary supervision. *CVPR 2018.*

Methods using rPPG

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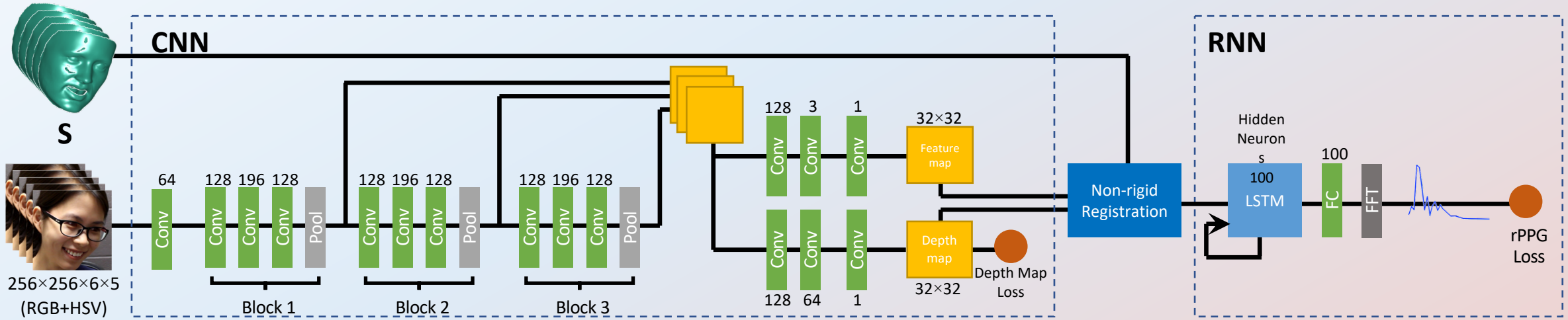
Overall Architecture

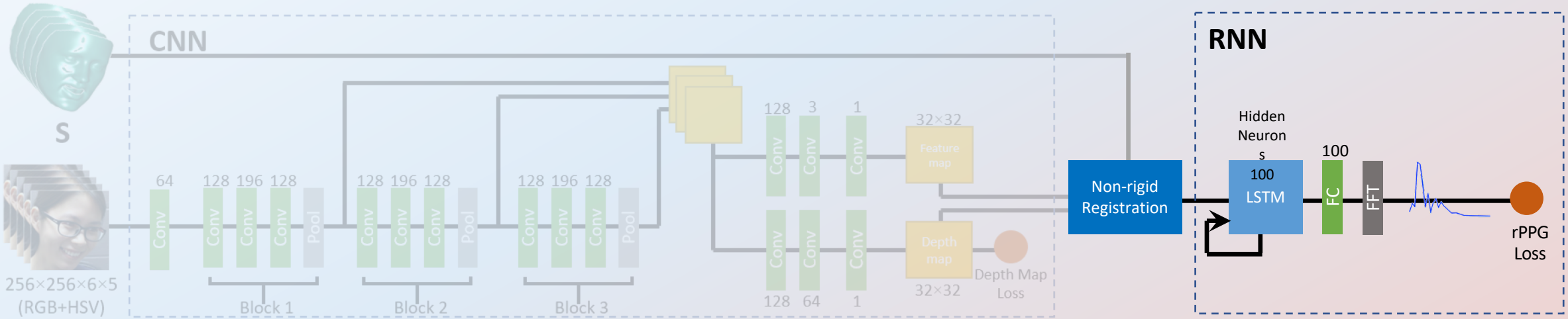
- Spatial supervision: depth map
- Temporal supervision: rPPG signal



Yaojie Liu, Amin Jourabloo, and Xiaoming Liu. Learning deep models for face anti-spoofing: Binary or auxiliary supervision. *CVPR 2018.*

Overall RNN Architecture

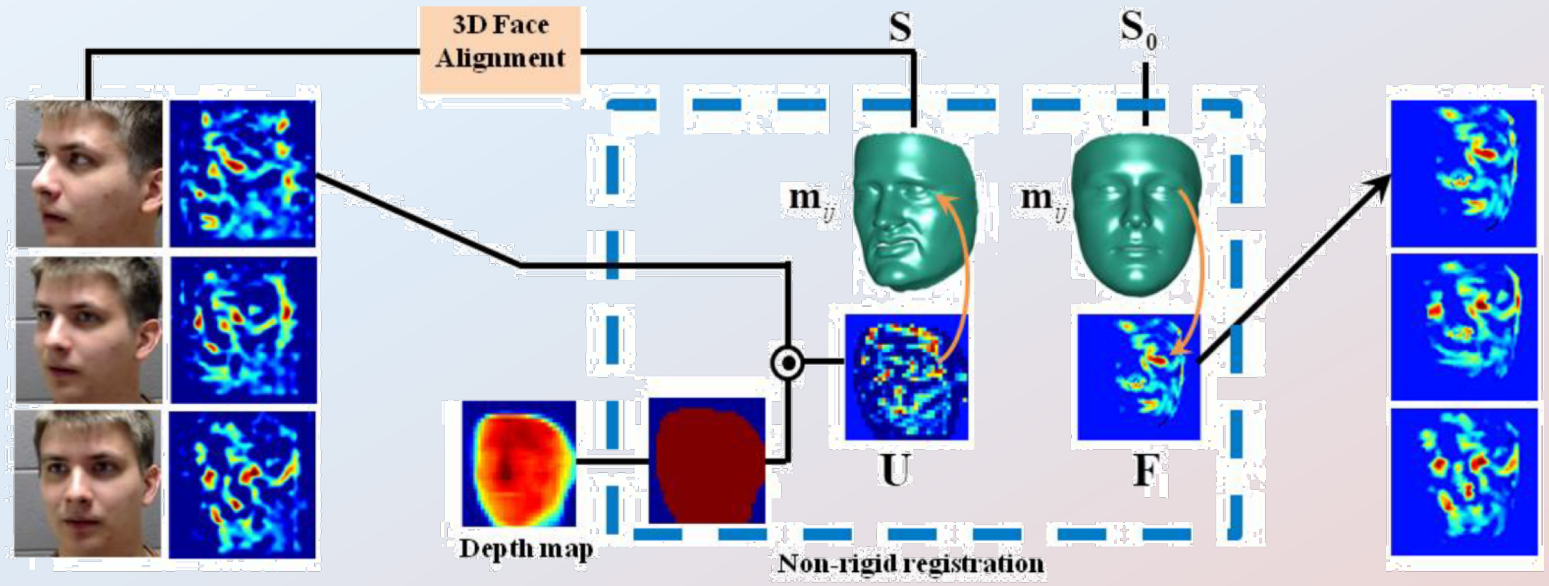
- CNN features as input
- Use non-rigid registration layer to align the features
- LSTM + FFT to predict rPPG



Yaojie Liu, Amin Jourabloo, and Xiaoming Liu. Learning deep models for face anti-spoofing: Binary or auxiliary supervision. *CVPR 2018.*

Non-rigid Registration Layer

- Use 3D shape to compute offset
- Use offset to deform the features
- Differentiable



Yaojie Liu, Amin Jourabloo, and Xiaoming Liu. Learning deep models for face anti-spoofing: Binary or auxiliary supervision. *CVPR 2018.*

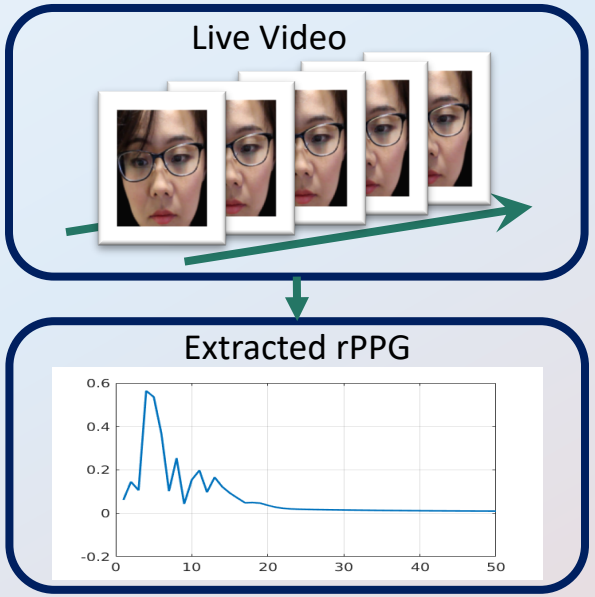
How to Obtain rPPG Label?

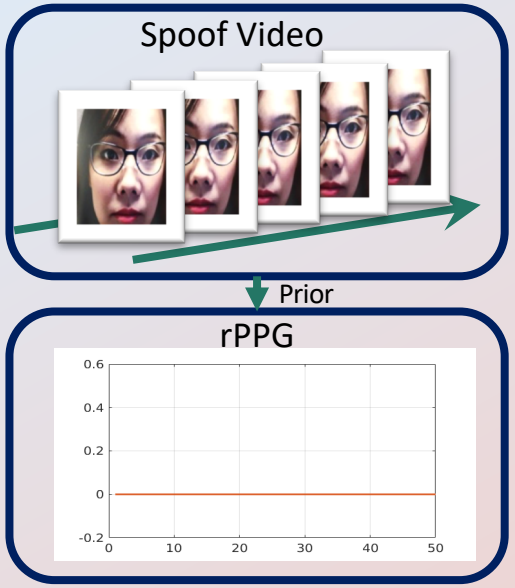
- Live faces: from off-the-shelf method*

$$S = c_1 R_n + c_2 G_n + c_3 B_n$$

$$C_{ni} = \frac{C_i}{\mu(C_i)}$$

- Spoof faces: Direct assignment as zero





Liu et. al., Learning deep models for face anti-spoofing: Binary or auxiliary supervision. *CVPR 2018.*
*Haan et. al., Robust pulse-rate from chrominance-based rPPG, IEEE Transactions on biomedical engineering

Oulu NPU Dataset

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Protocol	Method	APCER	BPCER	ACER
P1	CPqD	2.9%	10.8%	6.9%
	GRADIANT	**1.3%**	12.5%	6.9%
	Auxiliary	1.6%	**1.6%**	**1.6%**
P2	MixedFASNet	9.7%	2.5%	6.1%
	Auxiliary	**2.7%**	2.7%	2.7%
	GRADIANT	3.1%	**1.9%**	**2.5%**
P3	MixedFASNet	5.3±6.7%	7.8±5.5%	6.5±4.6%
	GRADIANT	**2.6±3.9%**	5.0±5.3%	3.8±2.4%
	Auxiliary	2.7±1.3%	**3.1±1.7%**	**2.9±1.5%**
P4	Massy_HNU	35.8±35.3	**8.3±4.1%**	22.1±17.6%
	GRADIANT	**5.0±4.5%**	15.0±7.1%	10.0±5.0%
	Auxiliary	9.3±5.6%	10.4±6.0%	**9.5±6.0%**

Yaojie Liu, Amin Jourabloo, and Xiaoming Liu. Learning deep models for face anti-spoofing: Binary or auxiliary supervision. *CVPR 2018.*

Oulu NPU Dataset

- Cross-test on CASIA and IDIAP (HTER)

Method	Train	Test	Train	Test
	CASIA MFSD	Replay Attack	Replay Attack	CASIA MFSD
Motion	50.2%		47.9%	
LBP	55.9%		57.6%	
LBP-TOP	49.7%		60.6%	
Motion-Mag	50.1%		47.0%	
Spectral cubes	34.4%		50.0%	
CNN	48.5%		45.5%	
LBP	47.0%		39.6%	
Color Texture	30.3%		37.7%	
Proposed method	**27.6%**		**28.4%**	

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Methods using Depth Map

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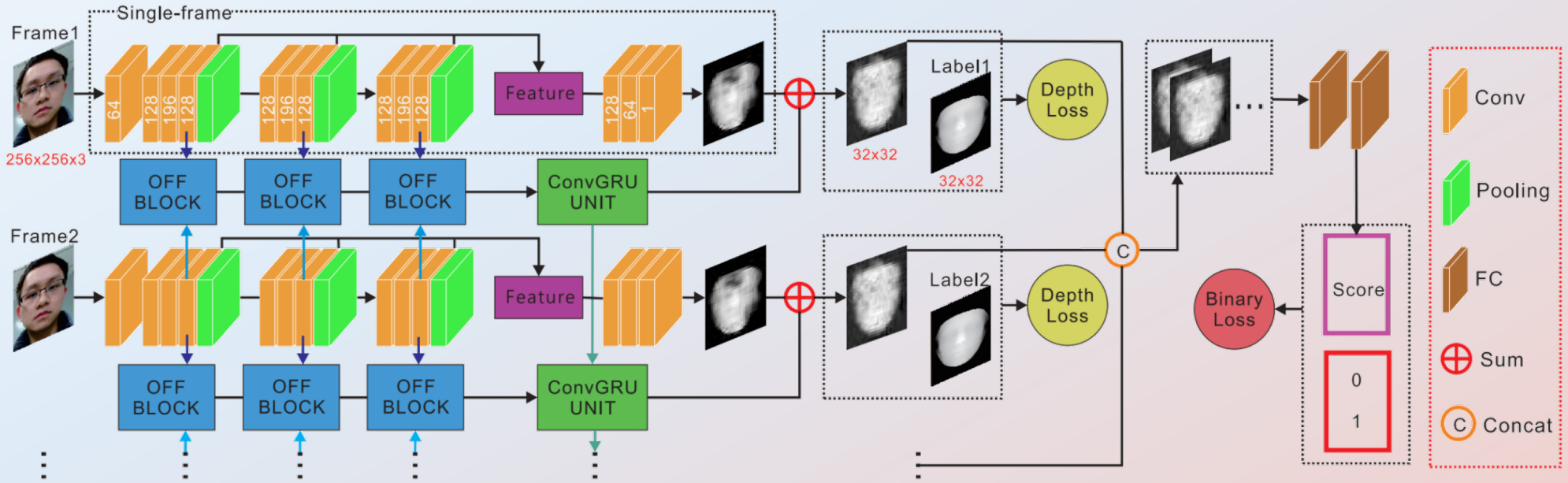
Deep tree learning for zero-shot face anti-spoofing. CVPR 2019

…

Exploiting Temporal and Depth Information for Multi-frame Face Anti-spoofing

BTAS 2019

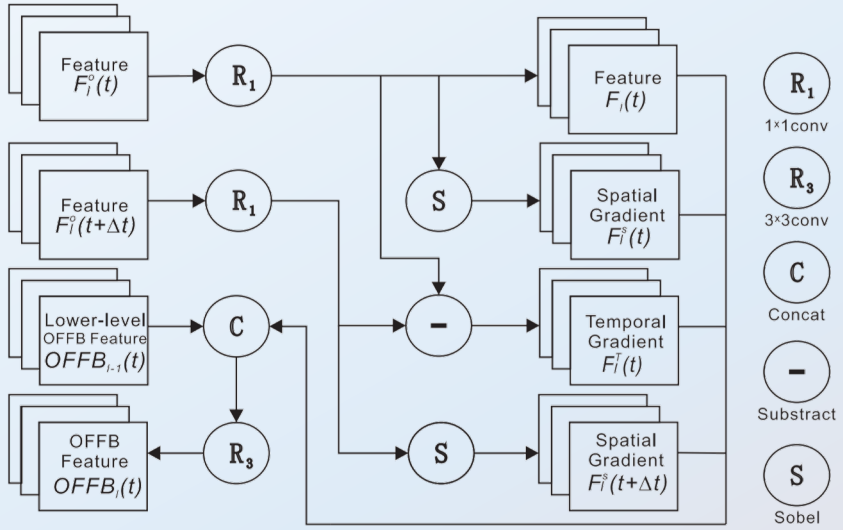
- Map single frame to depth map
- Introduce frame-to-frame motion to complete depth map
- Concat all maps to get a final score

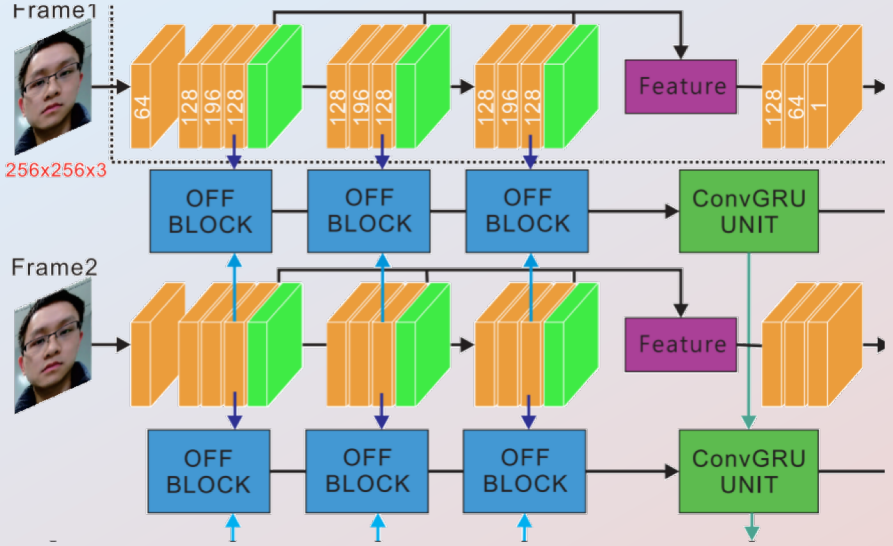


Wang et. al., Exploiting temporal and depth information for multi-frame face anti-spoofing, arXiv 2019

Temporal Blocks

- Short-term motion: OFF Block
- Long-term motion: multi-scale OFF feature to Conv Gated Recurrent Unit (GRU)





Wang et. al., Exploiting temporal and depth information for multi-frame face anti-spoofing, arXiv 2019

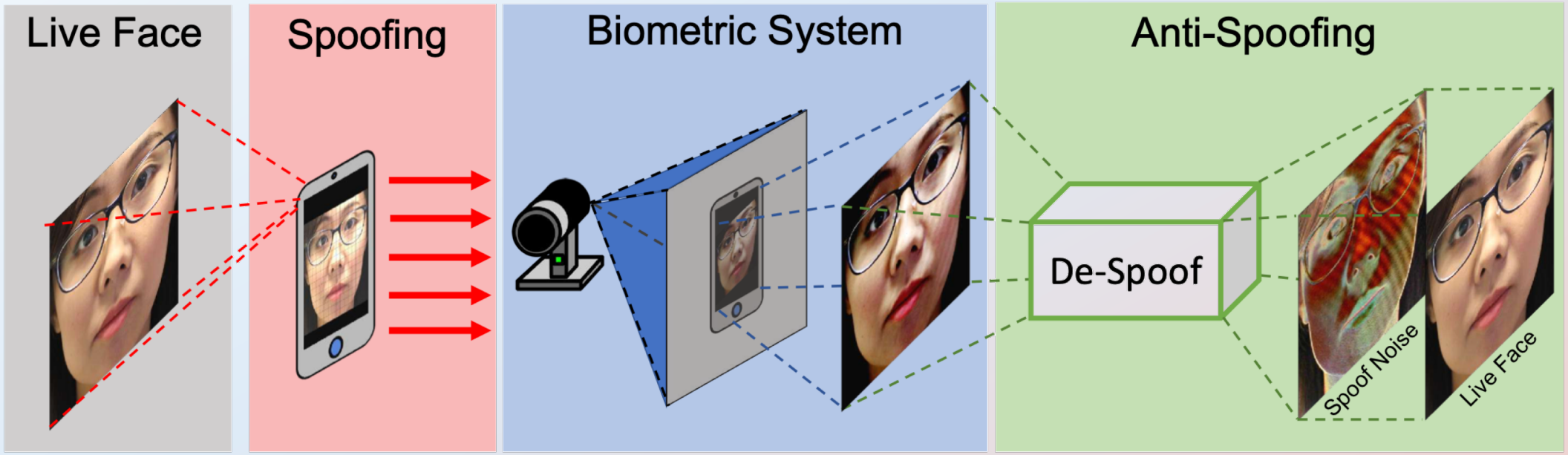
Outline

BTAS 2019

- Vanilla CNNs
- Patch-based CNN methods
- CNN methods with auxiliary supervisions
- **GAN-based noise modeling**
- Data Augmentation

Motivations

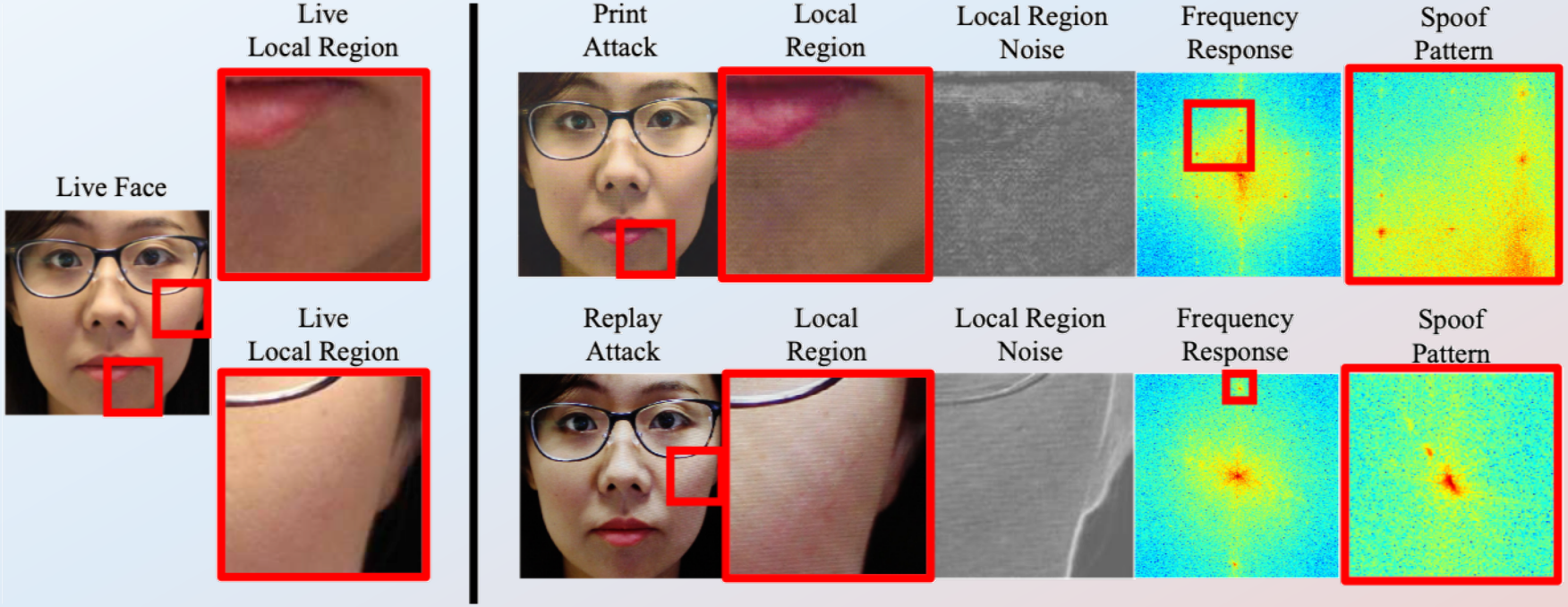
- Model the spoof patterns as noise
- De-spoofing: Decompose the spoof noise for face anti-spoofing.



Amin Jourabloo, Yaojie Liu, and Xiaoming Liu. Face De-spoofing: Anti-spoofing via noise modeling. *ECCV* 2018.

A Case Study

- Careful alignment the spoof with the live
- Subtraction live from spoof
- FFT analysis

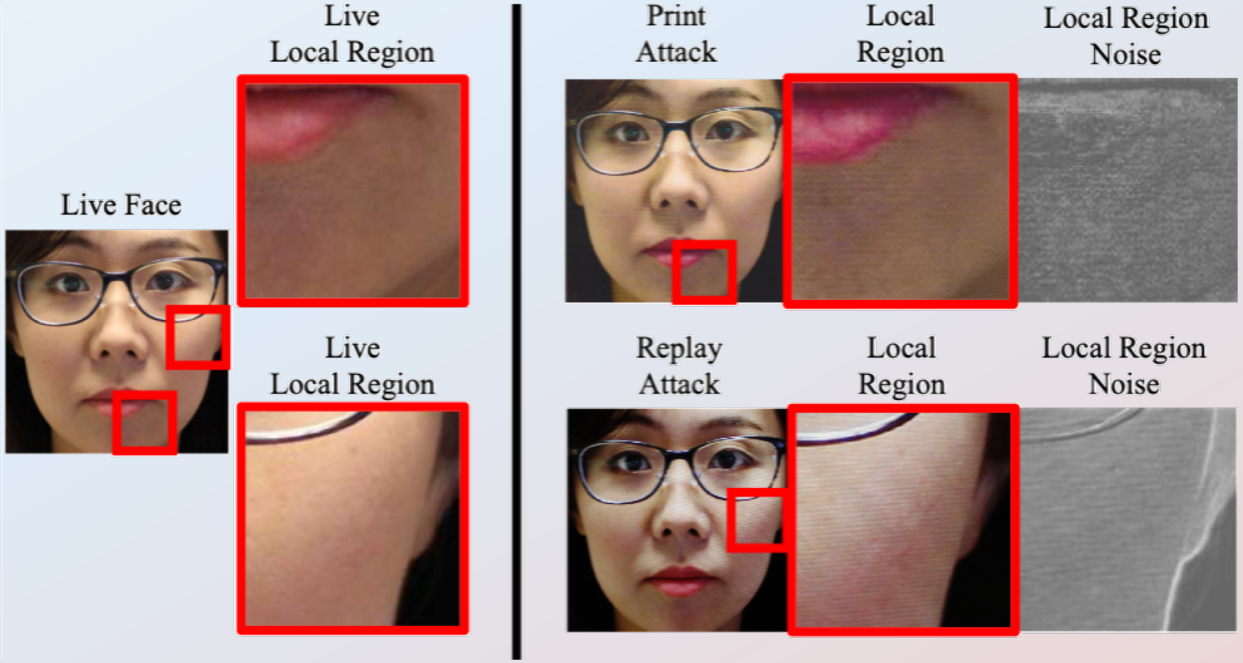


Amin Jourabloo, Yaojie Liu, and Xiaoming Liu. Face De-spoofing: Anti-spoofing via noise modeling. *ECCV* 2018.

The Cause of Spoof Noise Pattern?

BTAS 2019

- Color distortion
- Display artifacts
- Presenting artifacts
- Imaging artifacts



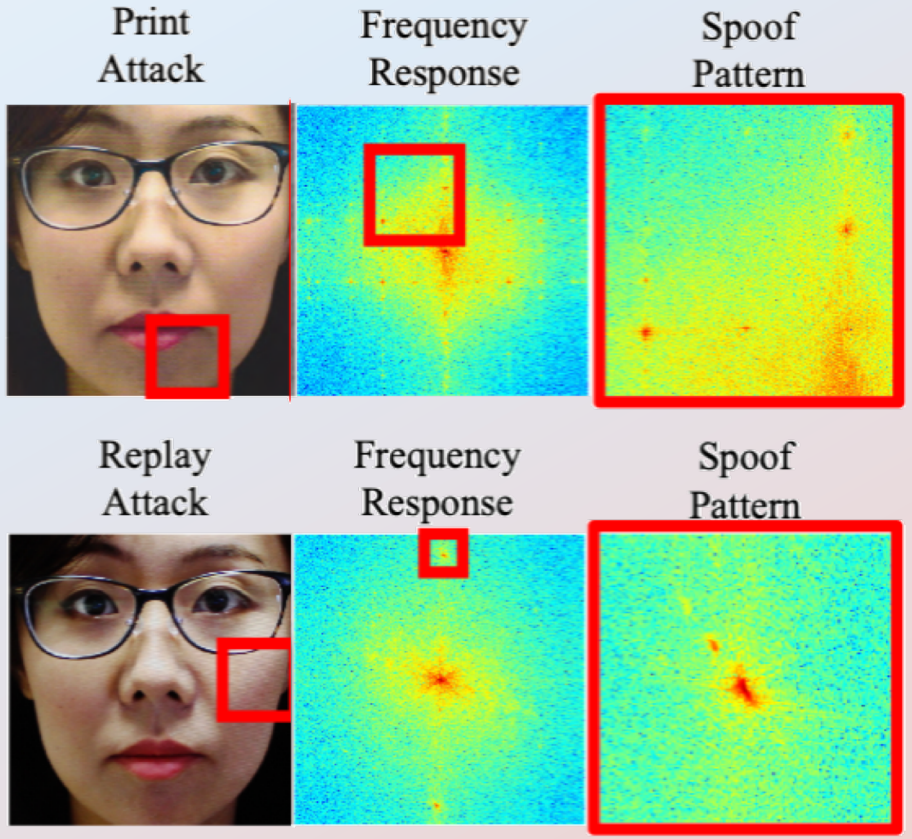
Amin Jourabloo, Yaojie Liu, and Xiaoming Liu. Face De-spoofing: Anti-spoofing via noise modeling. *ECCV* 2018.

Properties of the Spoof Noise Pattern

BTAS 2019

- Repetitive
- Ubiquitous

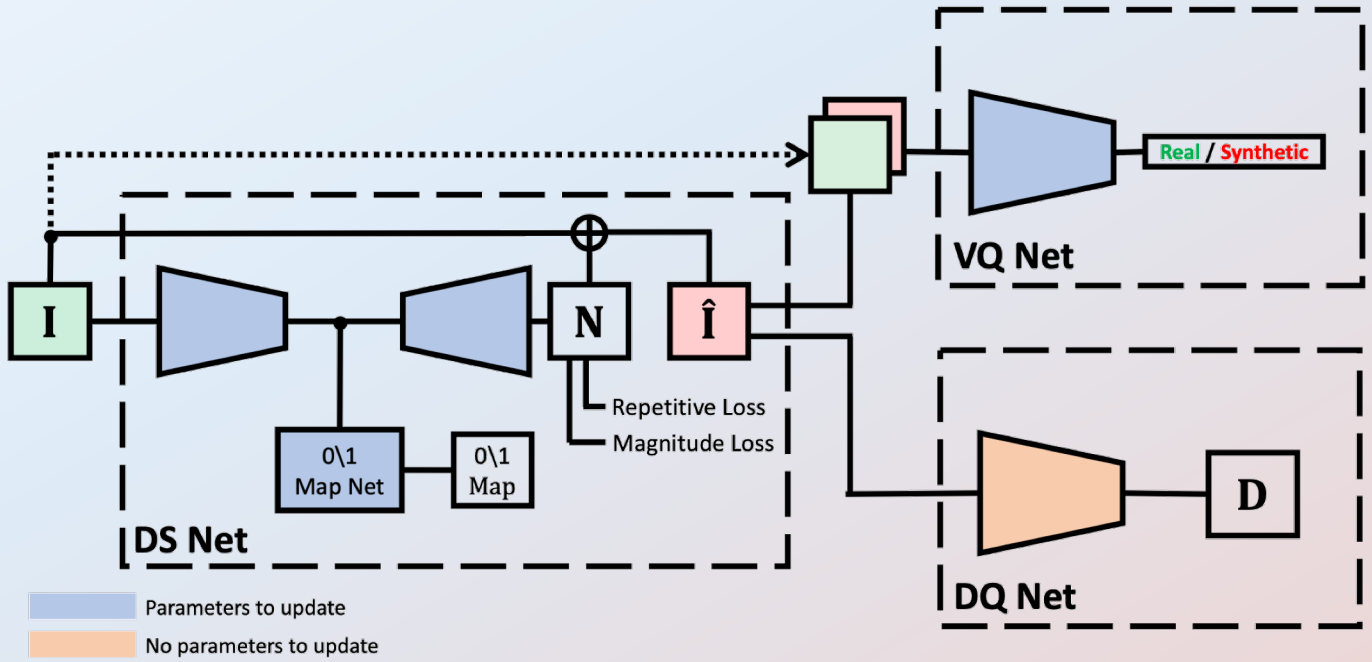
$$\mathbf{x} = \mathbf{A}\hat{\mathbf{x}} + \mathbf{n} = \hat{\mathbf{x}} + (\mathbf{A} - \mathbb{I})\hat{\mathbf{x}} + \mathbf{n} = \hat{\mathbf{x}} + N(\hat{\mathbf{x}})$$



Amin Jourabloo, Yaojie Liu, and Xiaoming Liu. Face De-spoofing: Anti-spoofing via noise modeling. *ECCV* 2018.

Overall Architecture

- **De-Spoofing Net**: estimate spoof noise pattern N and reconstruct live image I
- **Discriminative Quality Net**: guarantee reconstructed I is live
- **Visual Quality Net**: guarantee reconstructed I is photorealistic



Amin Jourabloo, Yaojie Liu, and Xiaoming Liu. Face De-spoofing: Anti-spoofing via noise modeling. *ECCV* 2018.

Training

De-Spoofing Net: Estimate spoof noise pattern N and reconstruct live image I

- Repetitive loss

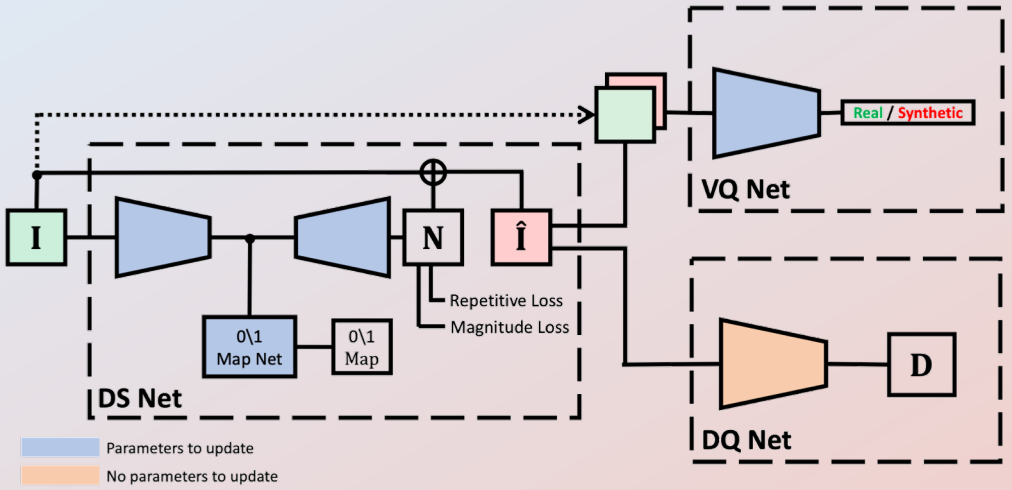
$$J_r = \begin{cases} -\max(H(\mathcal{F}(\mathbf{N}), k)), & \mathbf{I} \in Spoof \\ \|\max(H(\mathcal{F}(\mathbf{N}), k))\|_1, & \mathbf{I} \in Live \end{cases}$$

- Ubiquitous loss: zero/one map loss

$$J_z = \|\mathrm{CNN}_{01map}(\mathbf{F}; \Theta) - \mathbf{M}\|_1$$

- Magnitude loss

$$J_m = \|\mathbf{N}\|_1 \text{ , for live}$$



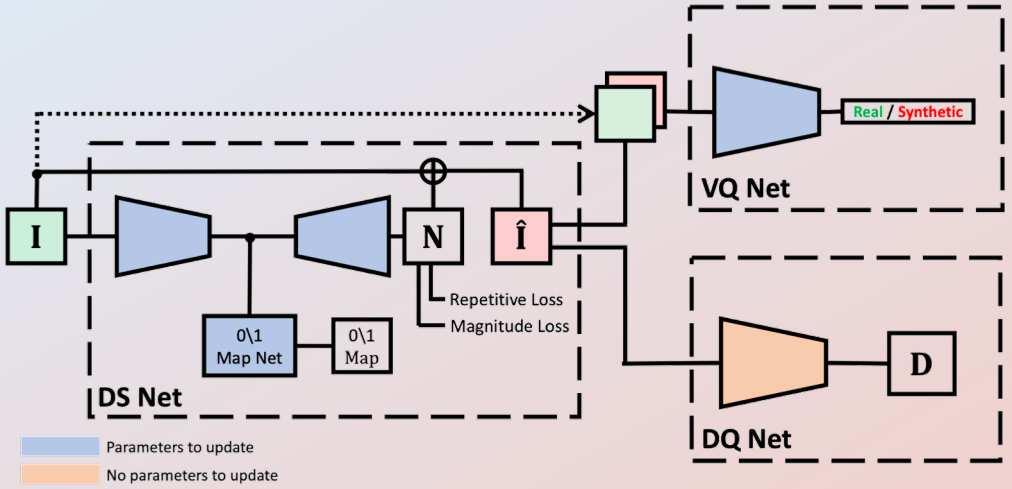
Amin Jourabloo, Yaojie Liu, and Xiaoming Liu. Face De-spoofing: Anti-spoofing via noise modeling. *ECCV* 2018.

Training

Discriminative Quality Net: guarantee reconstructed I is live

- Depth map loss

$$J_{DQ} = \left\| \mathrm{CNN}_{DQ}(\hat{\mathbf{I}}) - \mathbf{D} \right\|_1$$



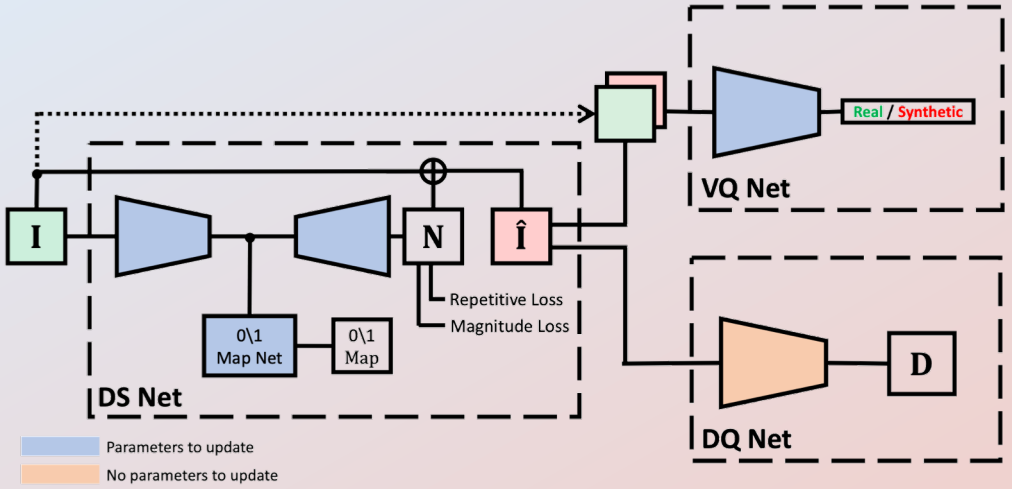
Amin Jourabloo, Yaojie Liu, and Xiaoming Liu. Face De-spoofing: Anti-spoofing via noise modeling. *ECCV* 2018.

Training

Visual Quality Net: guarantee reconstructed I is photorealistic

- GAN loss

$$J_{VQ_{train}} = -\mathbb{E}_{\mathbf{I}\in\mathcal{R}} \log(\mathrm{CNN}_{VQ}(\mathbf{I})) - \mathbb{E}_{\mathbf{I}\in\mathcal{S}} \log(1 - \mathrm{CNN}_{VQ}(\mathrm{CNN}_{DS}(\mathbf{I})))$$

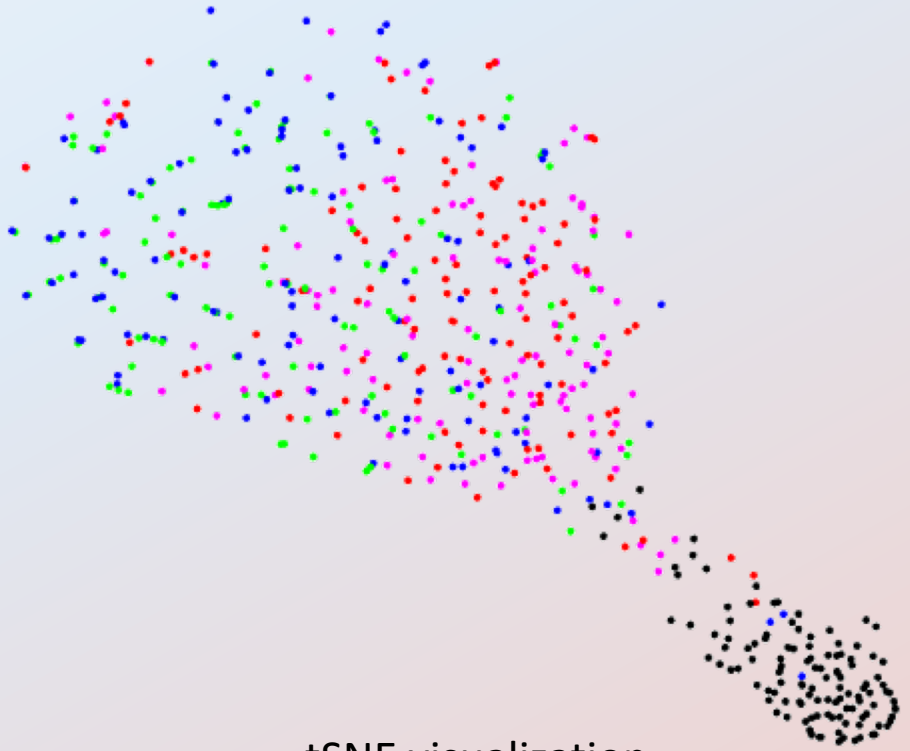


Amin Jourabloo, Yaojie Liu, and Xiaoming Liu. Face De-spoofing: Anti-spoofing via noise modeling. *ECCV* 2018.

Noise Classification

Actual \ Predicted	live	print	display
live	59	1	0
print	0	88	32
display	13	8	99

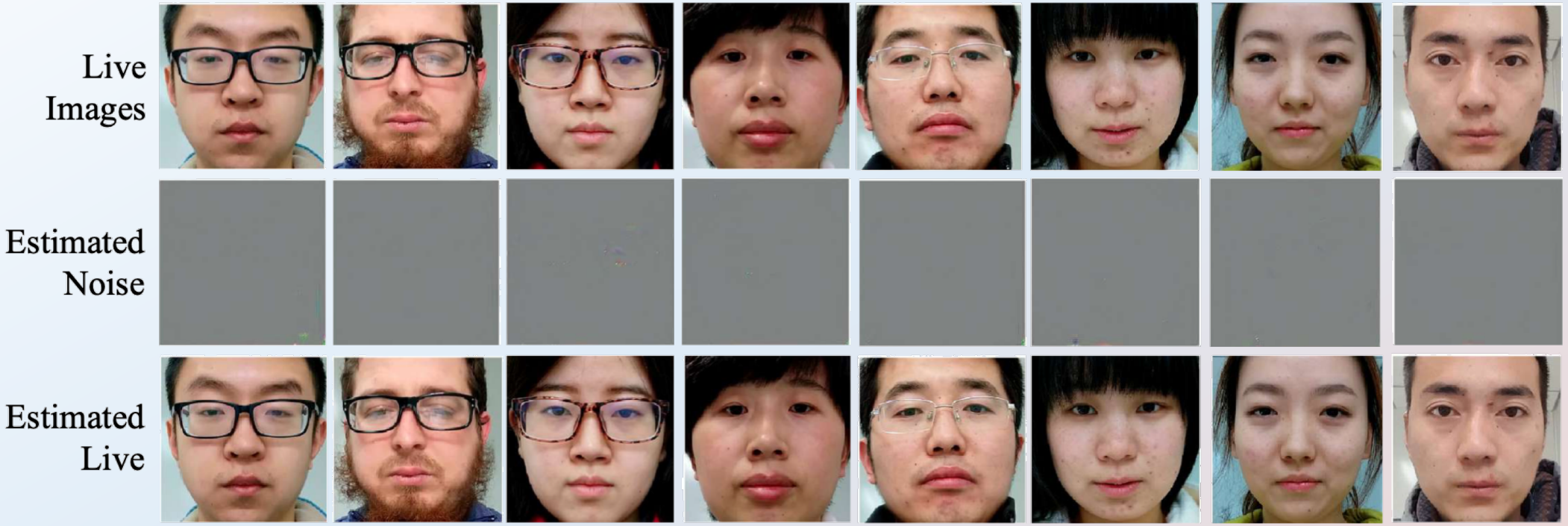
Actual \ Predicted	live	print1	print2	display1	display2
live	59	0	1	0	0
print1	0	41	2	11	6
print2	0	34	11	9	6
display1	10	6	0	13	31
display2	8	7	0	6	39



tSNE visualization

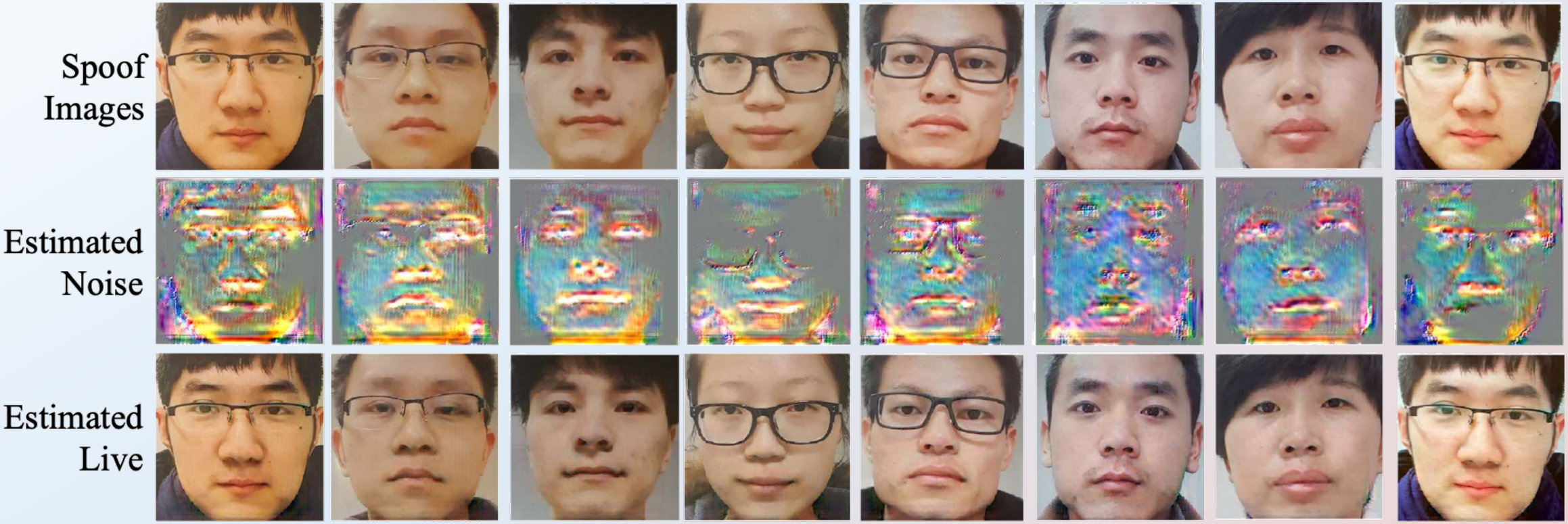
Amin Jourabloo, Yaojie Liu, and Xiaoming Liu. Face De-spoofing: Anti-spoofing via noise modeling. *ECCV* 2018.

Results of Live



Amin Jourabloo, Yaojie Liu, and Xiaoming Liu. Face De-spoofing: Anti-spoofing via noise modeling. *ECCV* 2018.

Results of Spoof



Amin Jourabloo, Yaojie Liu, and Xiaoming Liu. Face De-spoofing: Anti-spoofing via noise modeling. *ECCV* 2018.

Testing on Oulu

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Protocol	Method	APCER	BPCER	ACER
P1	CPqD	2.9%	10.8%	6.9%
	GRADIANT	1.3%	12.5%	6.9%
	Auxiliary	1.6%	**1.6%**	1.6%
	DS Net	**1.2%**	1.7%	**1.5%**
P2	MixedFASNet	9.7%	2.5%	6.1%
	Auxiliary	**2.7%**	2.7%	2.7%
	GRADIANT	3.1%	**1.9%**	**2.5%**
	DS Net	4.2%	4.4%	4.3%
P3	MixedFASNet	5.3±6.7%	7.8±5.5%	6.5±4.6%
	GRADIANT	**2.6±3.9%**	5.0±5.3%	3.8±2.4%
	Auxiliary	2.7±1.3%	**3.1±1.7%**	**2.9±1.5%**
	DS Net	4.0±1.8%	3.8±1.2%	3.6±1.6%
P4	Massy_HNU	35.8±35.3	8.3±4.1%	22.1±17.6%
	GRADIANT	**5.0±4.5%**	15.0±7.1%	10.0±5.0%
	Auxiliary	9.3±5.6%	10.4±6.0%	9.5±6.0%
	DS Net	5.1±6.3%	**6.1±5.0%**	**5.6±5.7%**

Amin Jourabloo, Yaojie Liu, and Xiaoming Liu. Face De-spoofing: Anti-spoofing via noise modeling. *ECCV* 2018.

Outline

BTAS 2019

- Vanilla CNNs
- Patch-based CNN methods
- CNN methods with auxiliary supervisions
- GAN-based noise modeling
- **Data Augmentation**

Data Augmentations

BTAS 2019

Face Anti-Spoofing: Model Matters, So Does Data, CVPR, 2019

Presentation Attack Detection for Face in Mobile Phones, Selfie Biometrics, 2019

Style Transfer Applied to Face Liveness Detection with User-Centered Models, arXiv, 2019

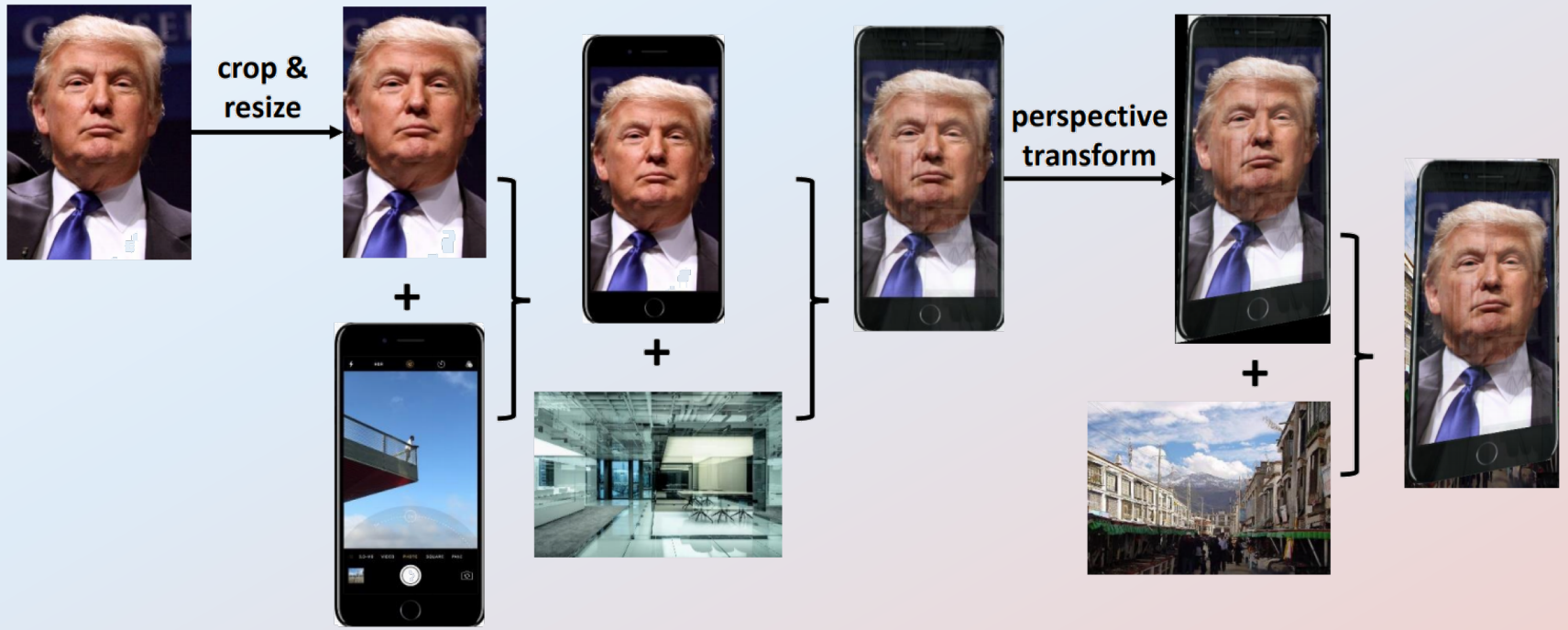
Improving Face Anti-Spoofing by 3D Virtual Synthesis, arXiv, 2019

Face Anti-Spoofing: Model Matters, So Does Data

BTAS 2019

Synthesize

- Blurriness: random strength Gaussian blurring
- Reflection: $\mathbf{X}'_r = (1-\alpha)\,\mathbf{X}' + \alpha\mathbf{X}_r$
- Distortion: Perspective projection



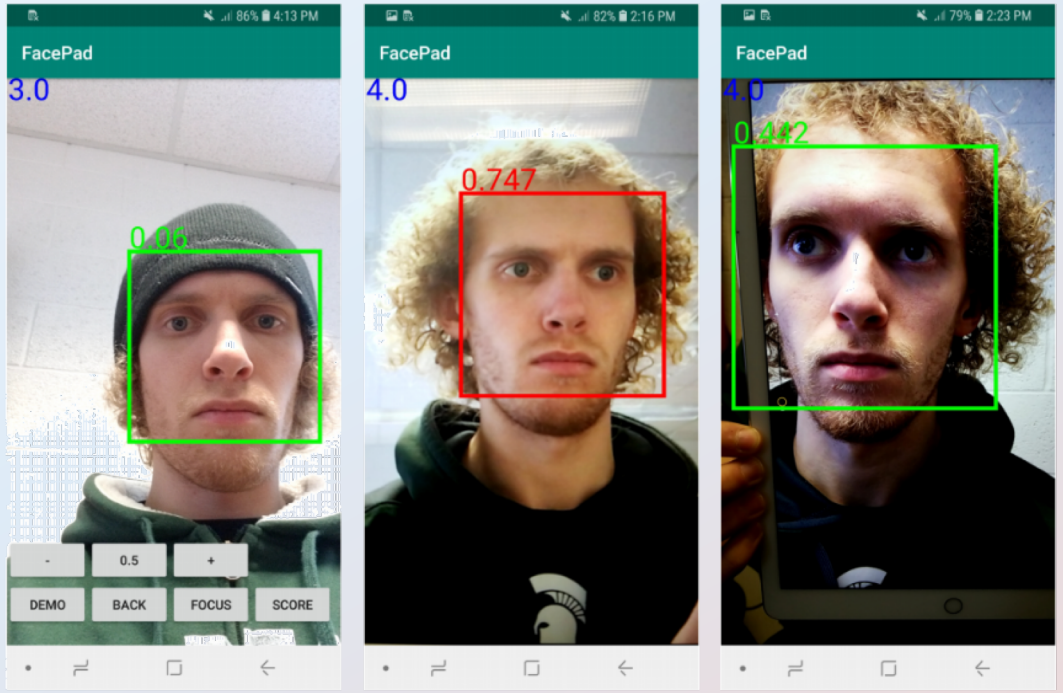
Yang et. al., Face Anti-Spoofing: Model Matters, So Does Data, CVPR 2019

Presentation Attack Detection for Face in Mobile Phones

BTAS 2019

Random perturbation:

- Contrast
- Lightness



Liu et. al., Presentation Attack Detection for Face in Mobile Phones, Selfie Biometrics, 2019

Style Transfer

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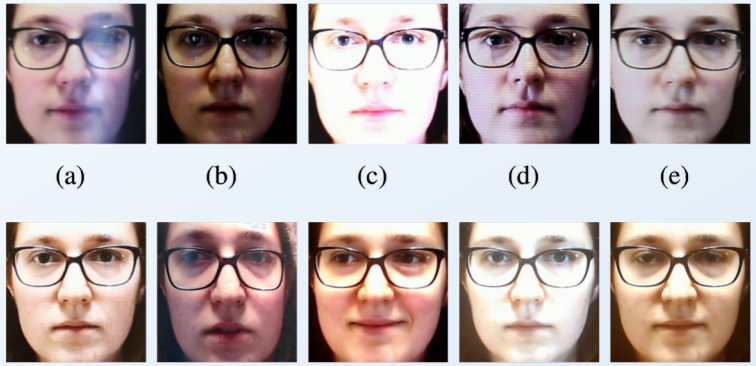
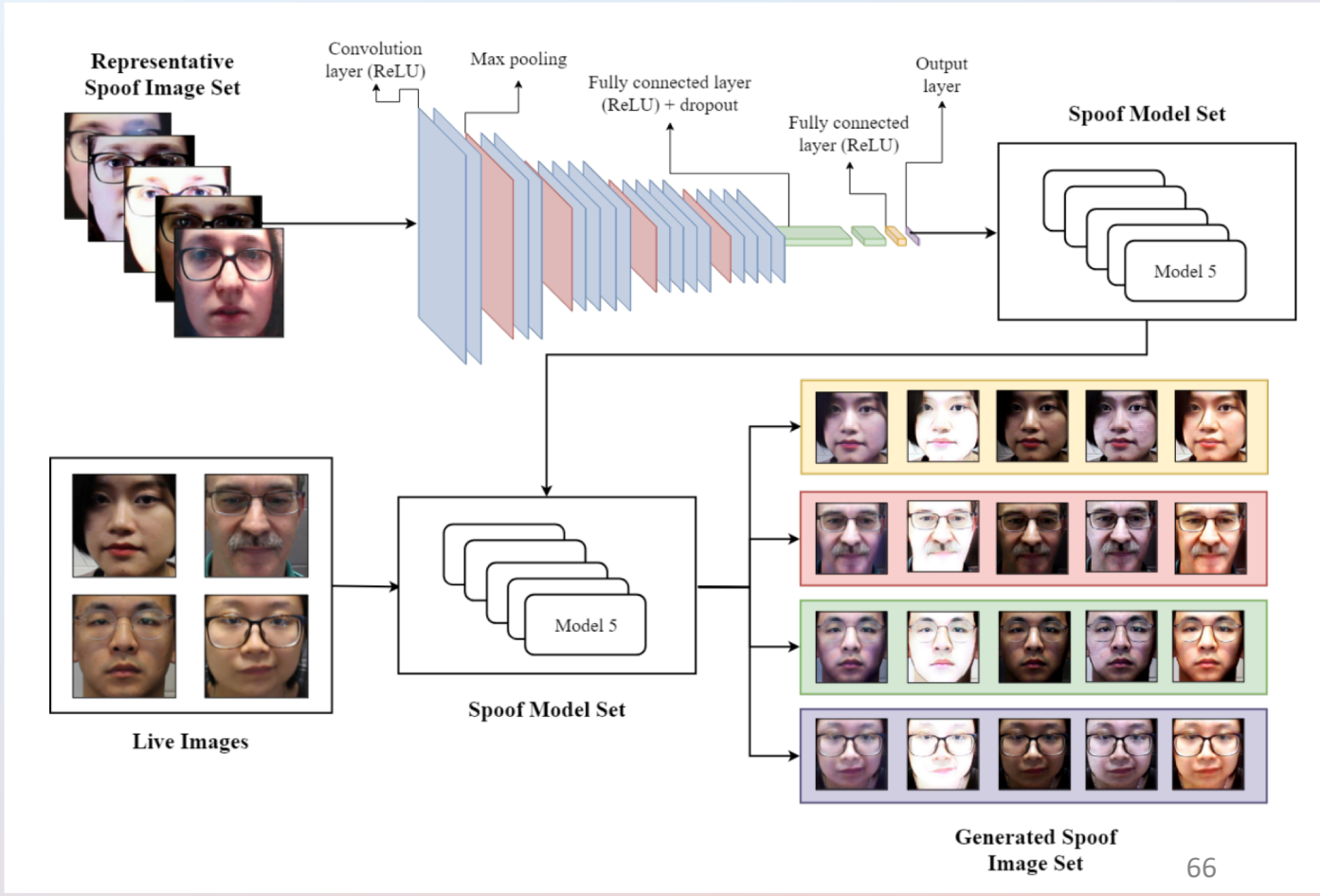
Use CNN for data augmentation

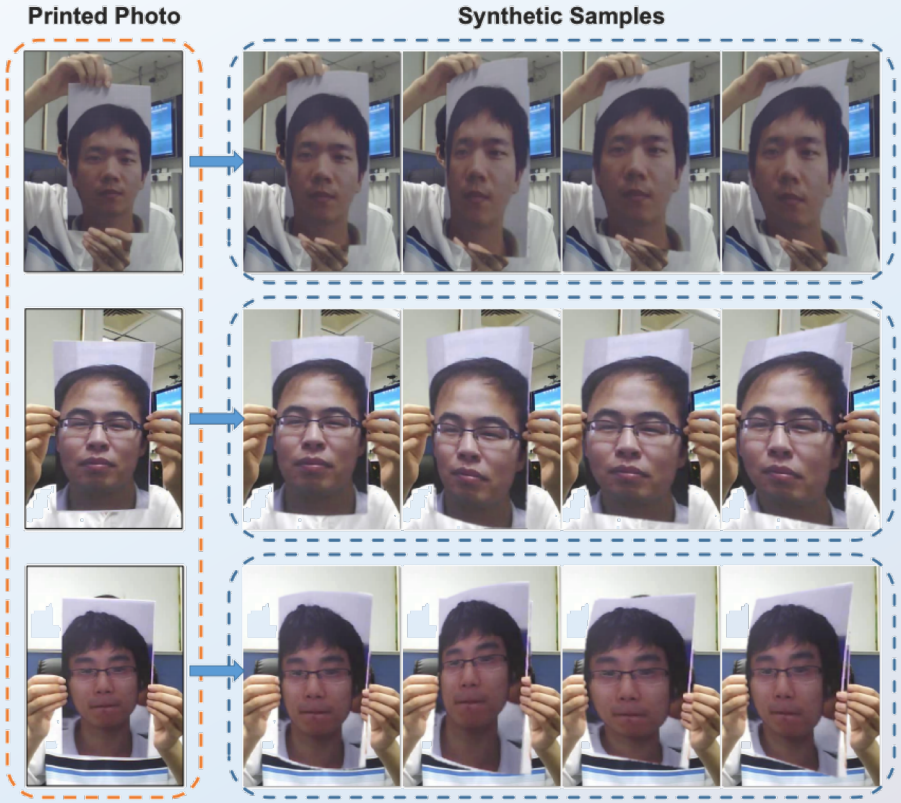


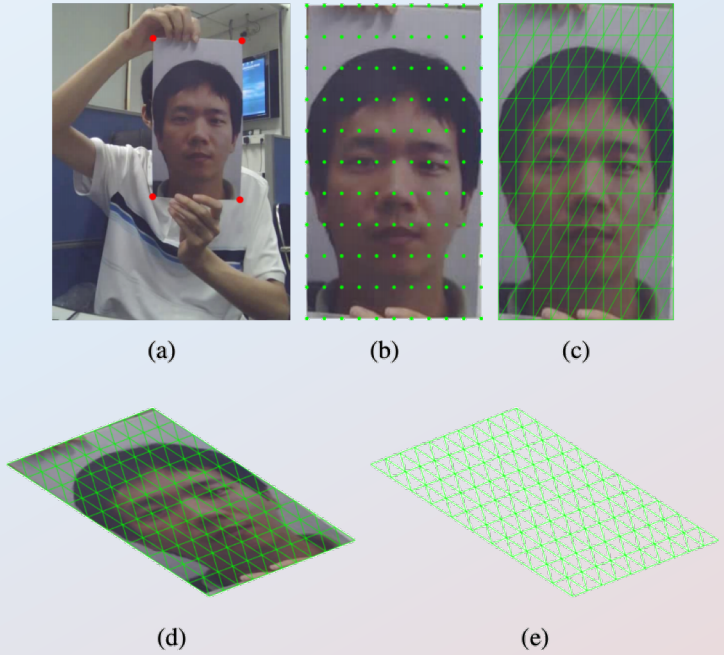


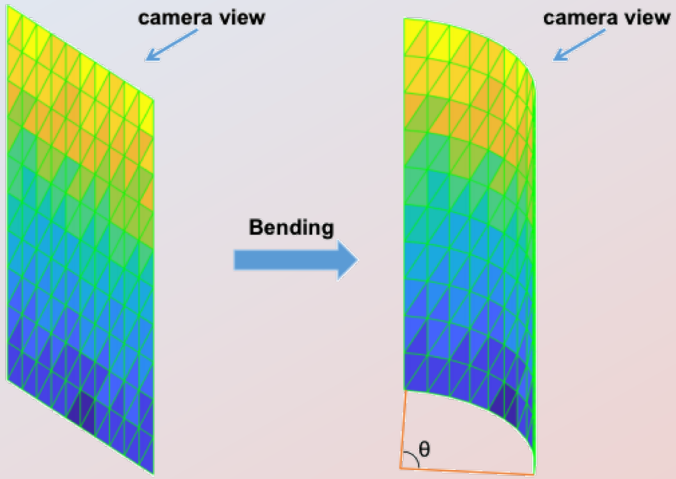
Laurensi et. al., Style Transfer Applied to Face Liveness Detection with User-Centered Models, arXiv, 2019

3D Synthesis

Use CNN to deform the face based on 3D shape







Guo et. al., Improving Face Anti-Spoofing by 3D Virtual Synthesis, arXiv, 2019

Summary

- We review deep learning based methods
- Binary CNN may lead to overfitting
- Advanced design is required
  - Multiple input features
  - Auxiliary supervision
  - Noise modeling
  - Data augmentation

BTAS 2019

End of Session II

Q & A

MICHIGAN STATE UNIVERSITY

Computer Vision Lab

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End of Session II

15 Minutes Break.

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