Learning Deep Models for Face Anti-spoofing via Auxiliary Supervision

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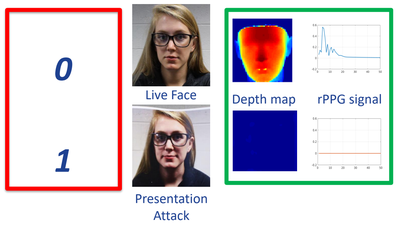
Introduction

✗ **Binary Supervision**



✓ **Auxiliary Supervision**

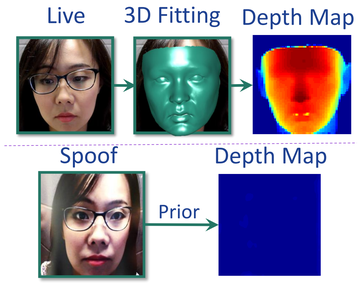
- Simply training a binary classifier leads to overfitting.
- There are auxiliary information that can help.
- We prefer a model that can explain its decision.

Auxiliary Supervisions

➢ Auxiliary spatial supervision: **Depth Map Estimation**

$$\mathbf{S}_F = \mathbf{S}_0 + \sum_{i=1}^{N_{id}} \alpha_{id}^i \mathbf{S}_{id}^i + \sum_{i=1}^{N_{exp}} \alpha_{exp}^i \mathbf{S}_{exp}^i$$

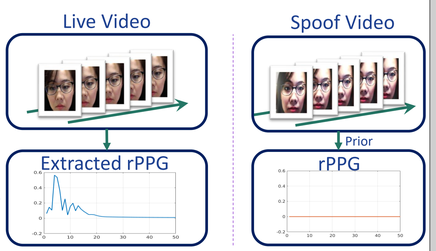
$$\mathbf{S} = s\mathbf{R}\mathbf{S}_F + \mathbf{t}$$



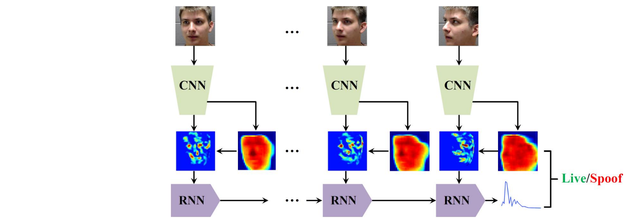
- Normalize the z values of the 3D vertices within [0, 1].
- Apply the Z-Buffer algorithm.

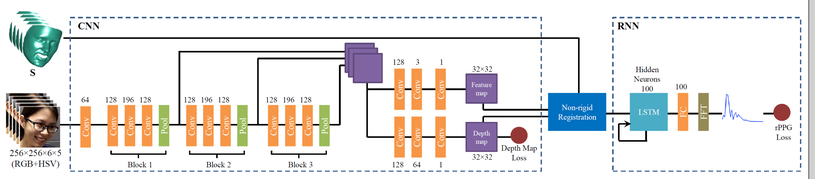
➢ Auxiliary temporal supervision: **rPPG Signal Estimation**

- rPPG signal provides temporal information about liveness of the face.
- Related to changes in the intensities of the face skin over time.
- Intensity changes are highly correlated with the blood flow.



Proposed Method

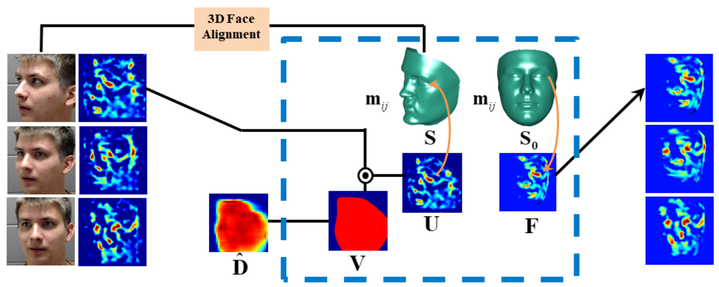




Non-rigid Registration Layer

➢ Non-rigid registration layer

- Register the CNN feature maps for LSTM training.
- Use 3D face shape to do non-rigid registration.
- Differentiable



$$\mathbf{V} = \hat{\mathbf{D}} \geq threshold.$$

$$\mathbf{F}(i,j) = \mathbf{U}(\mathbf{S}(\mathbf{m}_{ij},1), \mathbf{S}(\mathbf{m}_{ij},2))$$

➢ Classification score

- Compute the estimated depth map
- Compute the estimated rPPG signal

$$score = ||\hat{\mathbf{f}}||_2^2 + \lambda||\hat{\mathbf{D}}||_2^2$$

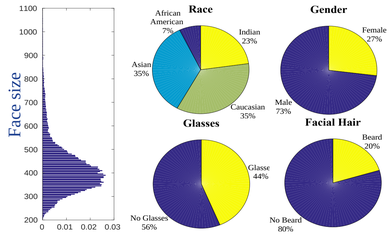
➢ Demo systems

- 3 FPS on phone
- 26 FPS on laptop

Experimental Results

➢ Spoofing in the Wild (SiW) Databases

- Contain 165 subjects
- Pose range from -90° to 90°
- Include print, replay, funny eye, and mannequin head attack
- Lighting variation
- Scene variation



Protocol	Subset	Subject #	Attack	APCER	BPCER	ACER
Various face pose and expression	Train	90	First 60 Frames	3.58%	3.58%	3.58%
	Test	75	All			
Cross spoof medium	Train	90	3 display	0.57±0.69%	0.57±0.69%	0.57±0.69%
	Test	75	1 display			
Cross PA	Train	90	print (display)	8.31±3.81%	8.31±3.80%	8.31±3.81%
	Test	75	display (print)			

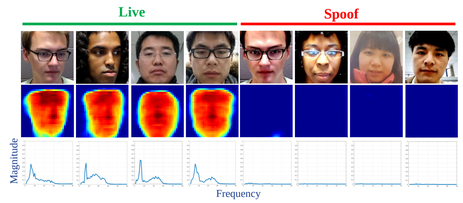
➢ Intra-test on Oulu

Protocol	Method	APCER	BPCER	ACER
Various illumination conditions	CPqD	2.9%	10.8%	6.9%
	GRADIANT	1.3%	12.5%	6.9%
	Proposed method	**1.6%**	**1.6%**	**1.6%**
Different spoof medium	MixedFASNet	9.7%	2.5%	6.1%
	Proposed method	**2.7%**	**2.7%**	**2.7%**
	GRADIANT	3.1%	1.9%	2.5%
Different camera devices	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%
	Proposed method	**2.7±1.3%**	**3.1±1.7%**	**2.9±1.5%**
All above challenges	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%
	Proposed method	**9.3±5.6%**	**10.4±6.0%**	**9.5±6.0%**

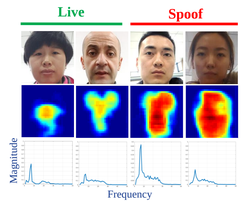
➢ Cross-test on CASIA and IDIAP

Method	Train	Test	Train	Test
	CASIA MFSD	Replay Attack	Replay Attack	CASIA MFSD
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%**	

➢ Successful cases



➢ Failure cases



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* denotes equal contribution by the authors.