Face De-Spoofing: Anti-spoofing via Noise Modeling

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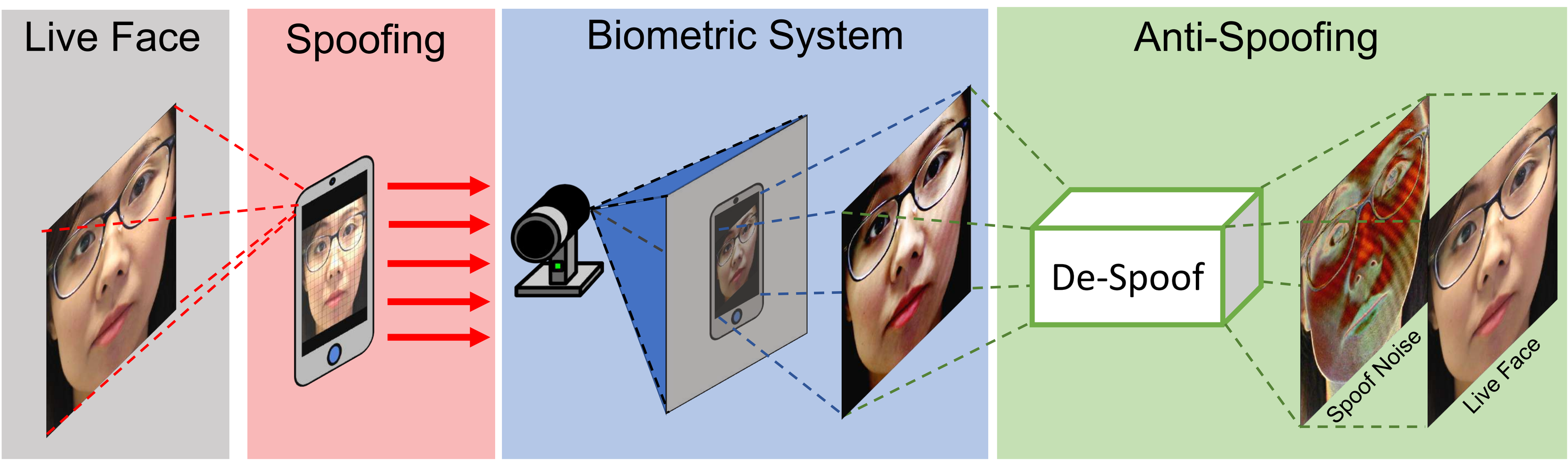
Introduction



- Decompose a spoof face into spoof noise and live face
- Analyze the properties of the spoof noise
- Focus on print and replay attack

A Case Study of Spoof Noise Pattern

➤ What are the causes of spoof noise pattern?

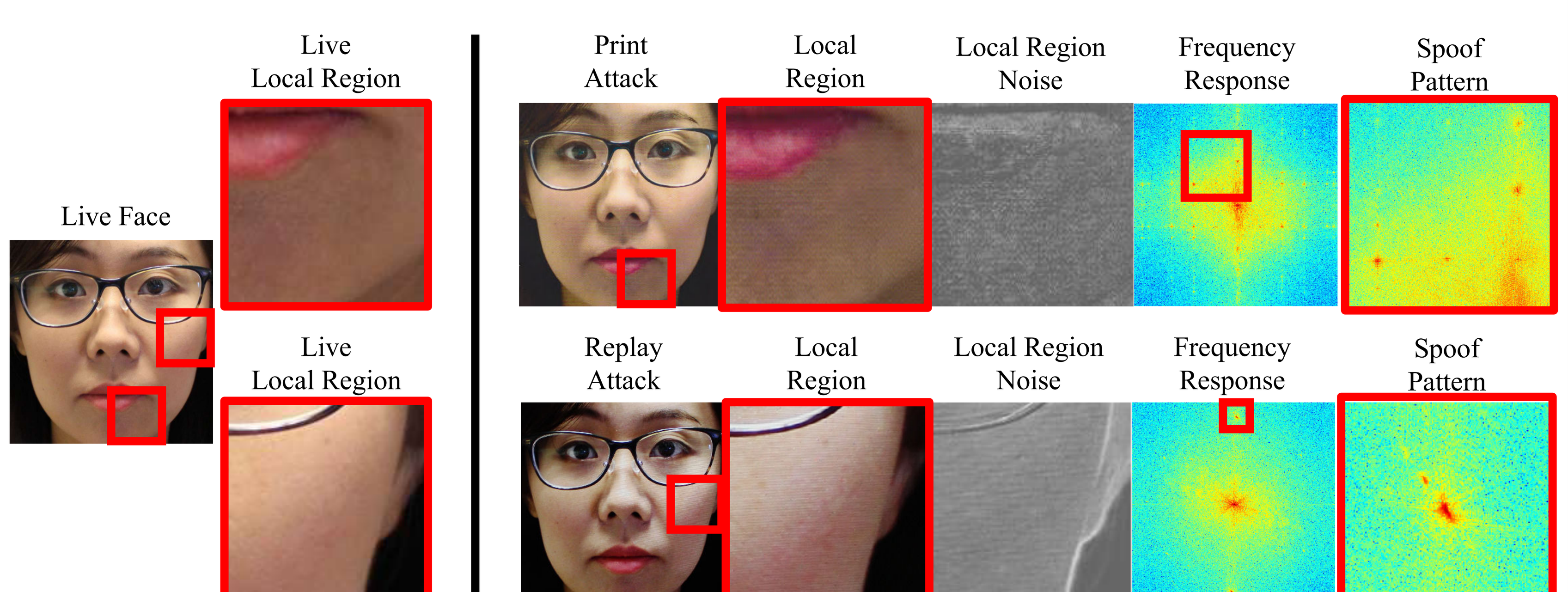
- Color Distortions
- Display artefacts
- Presenting artefacts
- Imaging artefacts

➤ What are the characteristics of spoof noise pattern?

- Repetitive
- Ubiquitous

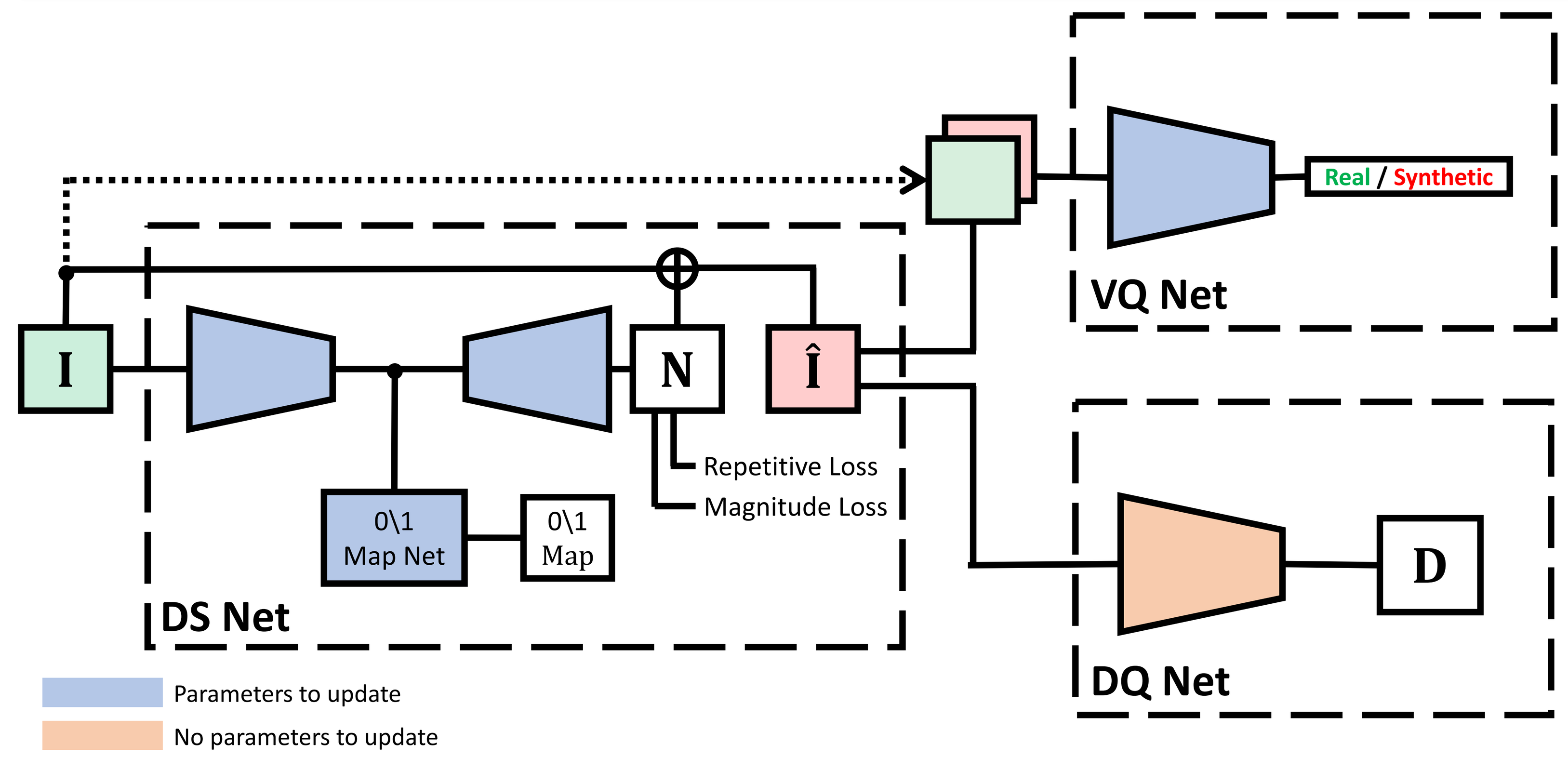
➤ How to model the spoofing process?

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



* denotes equal contribution by the authors.

Proposed Method



➤ De-Spoof Net (DS Net)

- To estimate spoof noise pattern N and reconstruct the live image Î
- Use 3D face shape to do non-rigid registration.

➤ Discriminative Quality Net (DQ Net)

- To guarantee reconstructed Î is photorealistic

➤ Visual Quality Net (VQ Net)

- To guarantee reconstructed Î is recognized as live by a pretrained model

Loss Functions

➤ De-Spoof Net (DS Net)

- Repetitive Loss

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

- Zero\One Map Loss

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

- Magnitude Loss

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

➤ Discriminative Quality Net (DQ Net)

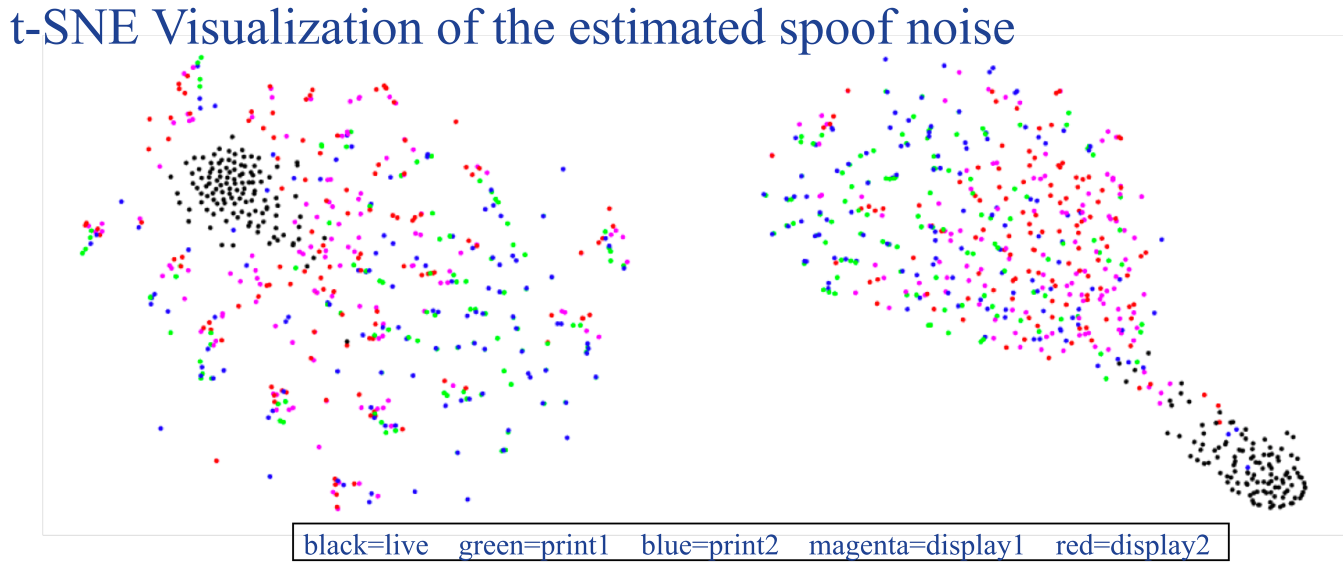
$$J_{DQ} = \left\|\mathrm{CNN}_{DQ}(\hat{\mathbf{I}}) - \mathbf{D}\right\|_1$$

➤ Visual Quality Net (VQ Net)

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

Experimental Results

➤ t-SNE Visualization of the estimated spoof noise

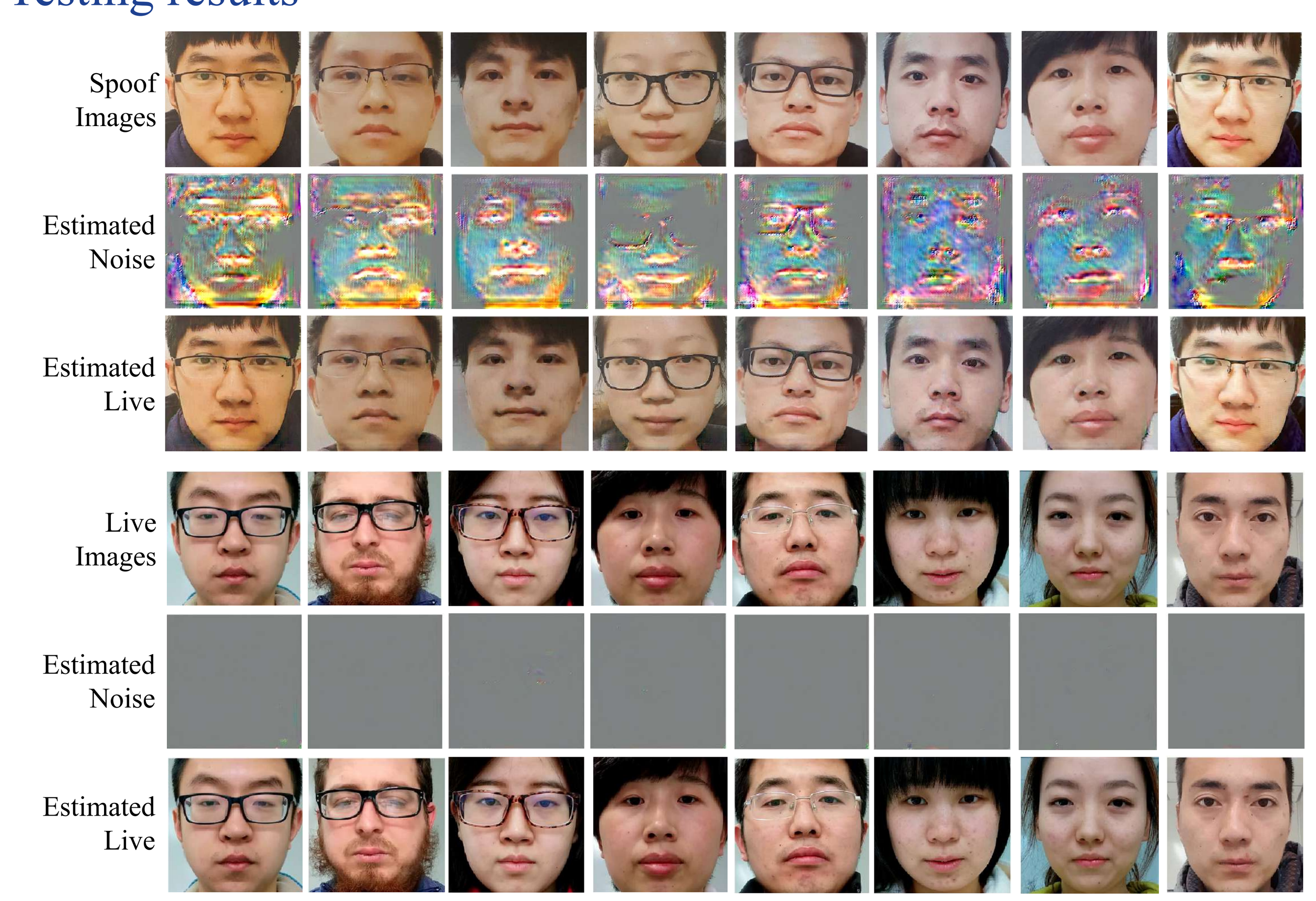


black=live green=print1 blue=print2 magenta=display1 red=display2

➤ 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%
	CVPR 18	1.6%	1.6%	1.6%
	Proposed method	**1.2%**	**1.7%**	**1.5%**
Different spoof medium	MixedFASNet	9.7%	2.5%	6.1%
	Proposed method	**4.2%**	**4.4%**	**4.3%**
	CVPR 18	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	4.0±1.8%	3.8±1.2%	3.6±1.6%
	CVPR'18	**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%
	CVPR'18	9.3±5.6%	10.4±6.0%	9.5±6.0%
	Proposed method	**5.1±6.3%**	**6.1±5.0%**	**5.6±5.7%**

➤ Testing results



➤ Acknowledgement

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