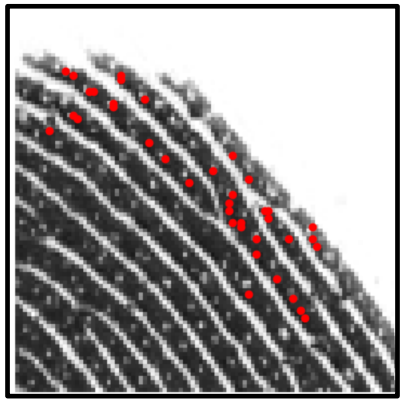
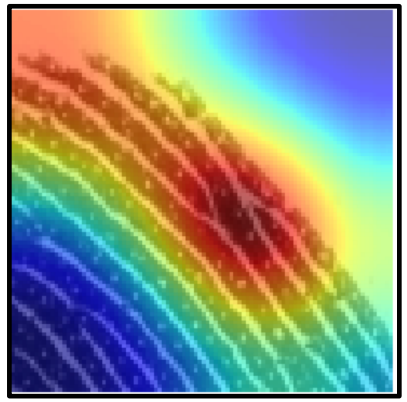
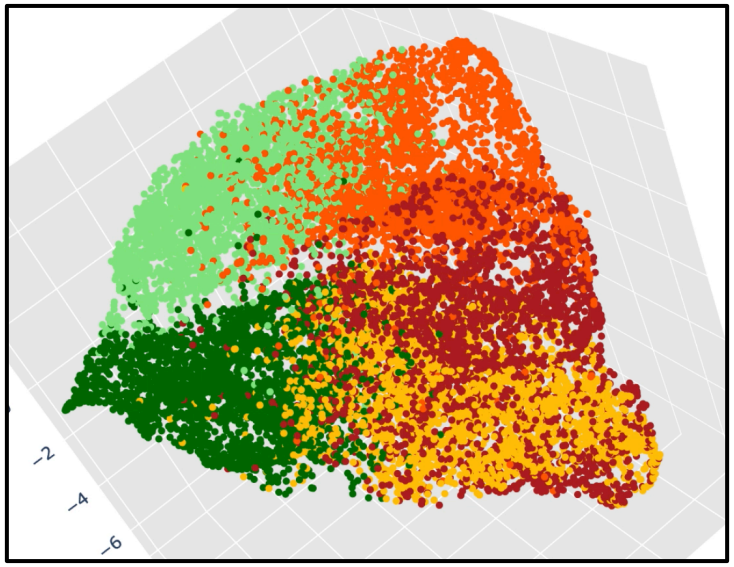
Fingerprint Spoof Detector Generalization

IEEE Transactions on Information Forensics and Security (TIFS), 2020







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Applied Scientist @ Amazon Inc.

Prof. Anil K. Jain

University Distinguished Professor

Michigan State University

IARPA R&D Contract No. 2017 - 17020200004

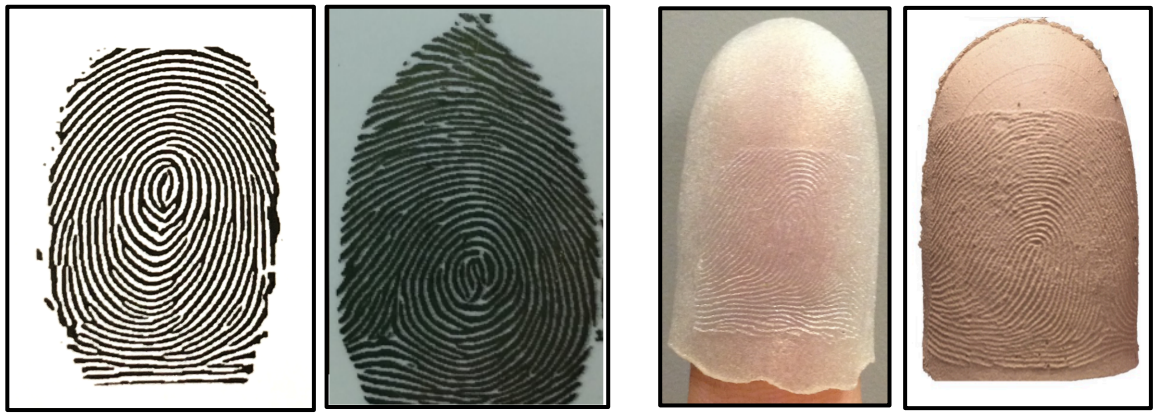
Fingerprint Presentation Attack Detection

"presentation to the biometric data capture subsystem with the goal of interfering with the operation of the biometric system"

- ISO standard IEC 30107-1:2016(E)

Silicone | Gelatin | Latex Body Paint | Play Doh

Gummy Fingers

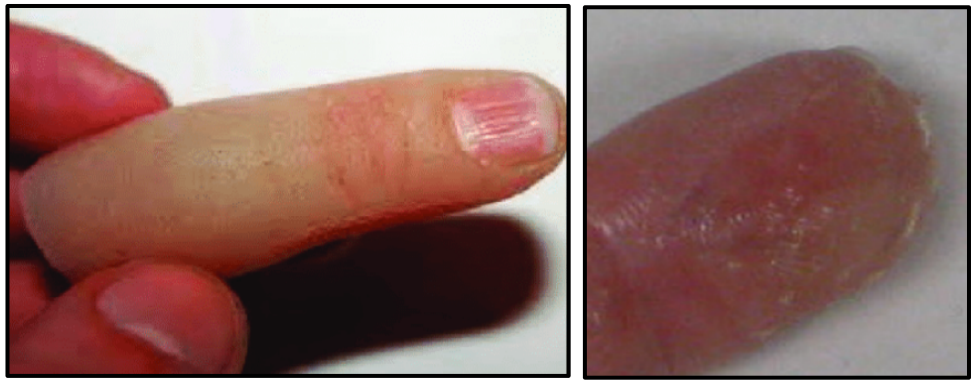


2-D Printed Spoofs | 3-D Printed Spoofs

Printed Fingerprint Targets

Transplanted skin from sole | Acid Burns | Stitched Fingers

Altered Fingers



Cadaver Fingers

Fingerprint Spoof Attacks


2D printed paper


3D targets


Conductive ink on paper

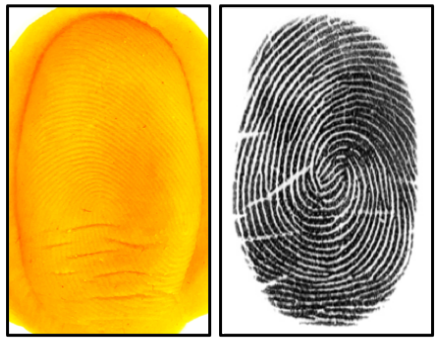

Dragon Skin


Gelatin


Gold fingers


Latex body paint


Monster liquid latex


Play doh


Silicone


Transparency


Wood glue

Requirements

- Accurate and Robust

Office of the Director of National Intelligence
IARPA
BE THE FUTURE

True Detection Rate > 97% @
False Detection Rate = 0.2%




Bonafide noisy fingerprint images

Requirements

- Accurate and Robust
- Low-cost and Interoperable

SilkID SLK20R

Lumidigm V302

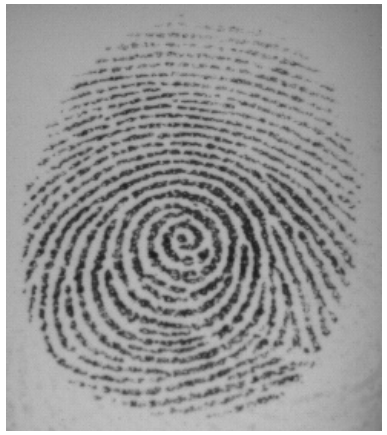
Single-finger Readers

CrossMatch Guardian 200

Slap Reader

WoodGlue EcoFlex Gelatin Latex Silgum

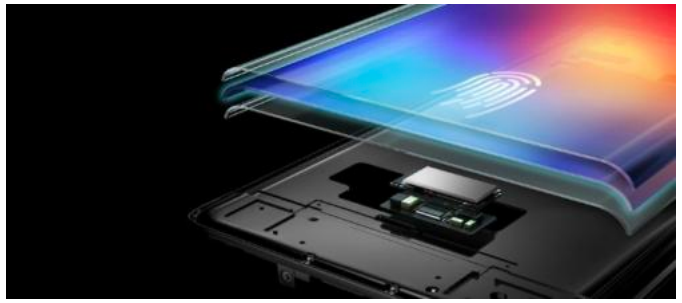
Spoof Attacks



Live Fingerprint

Requirements

- Accurate and Robust
- Low-cost and Interoperable
- **Efficient**



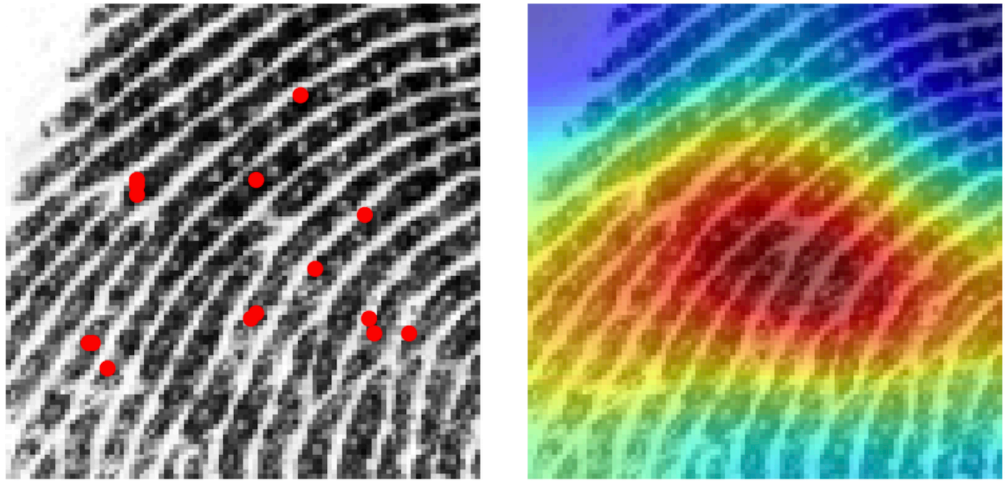
Vivo's in-display screen fingerprint reader

ZKTeco Access Control Unit

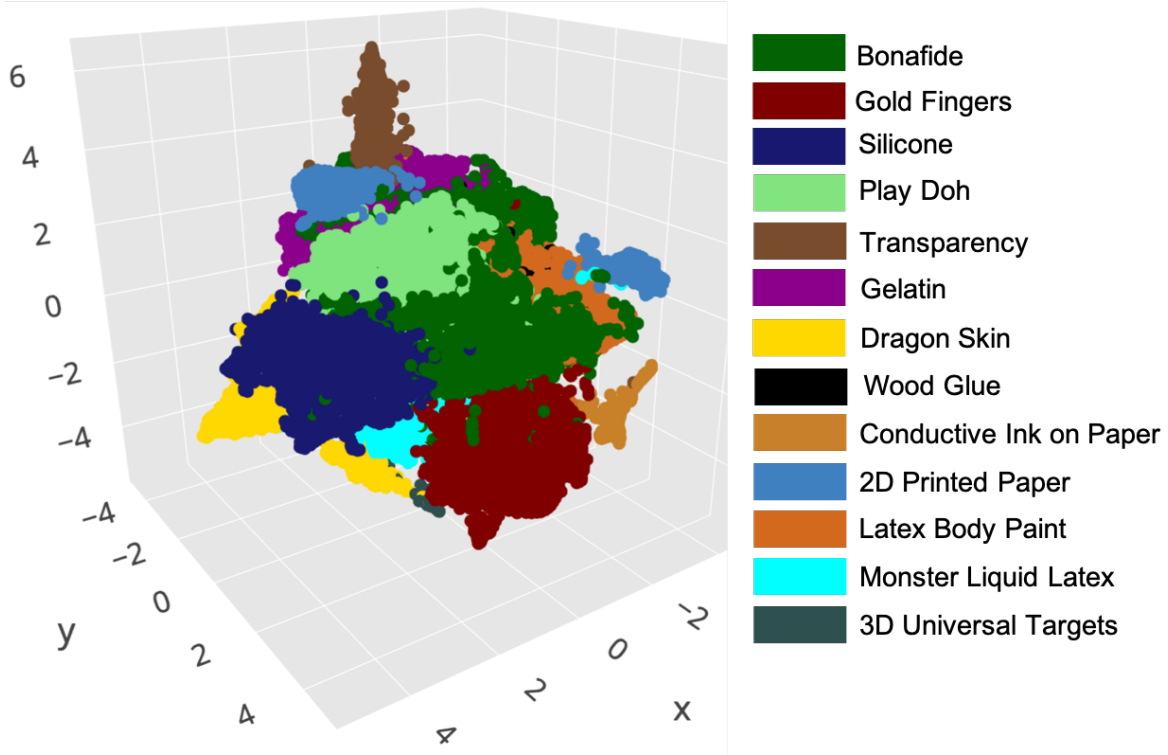
Commodity Smartphone Redmi Note 4 ($150)

Requirements

- Accurate and Robust
- Low-cost and Interoperable
- Efficient
- Interpretable and Generalizable

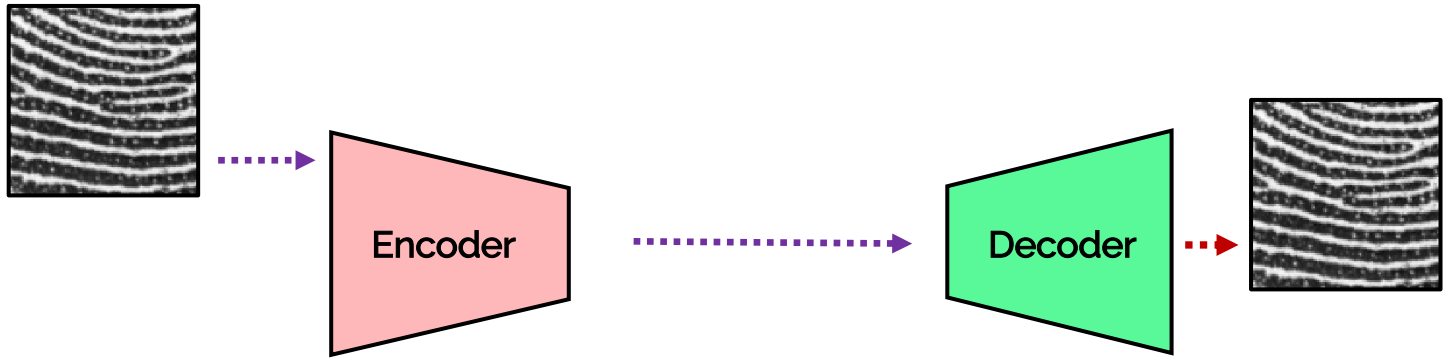


CNN Fixations



3D t-SNE representation

Proposed Approach: Universal Material Generator



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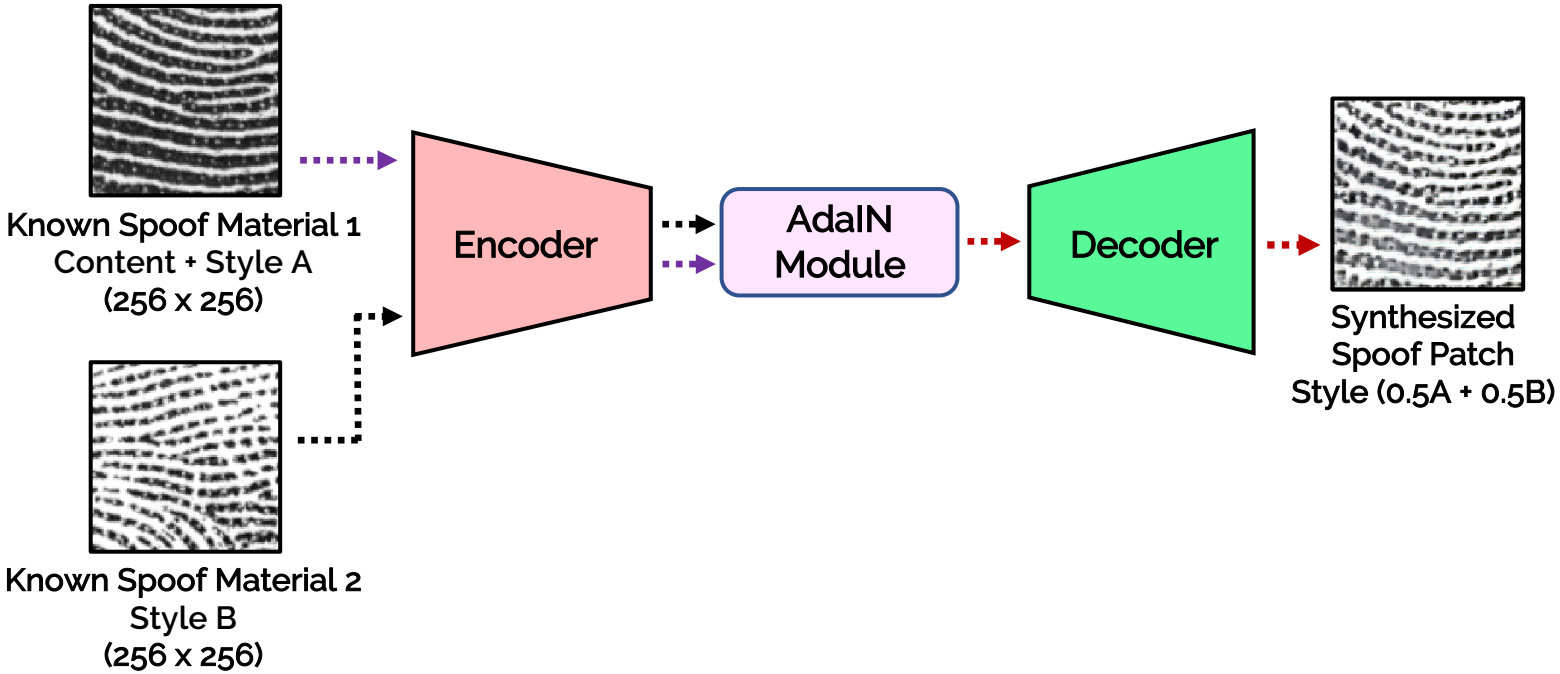

$$AdaIN(x, y) = \sigma(y)\left(\frac{x - \mu(x)}{\sigma(x)}\right) + \mu(y)$$

[1] Huang, Xun, and Serge Belongie. "Arbitrary style transfer in real-time with adaptive instance normalization." In *Proceedings of the IEEE International Conference on Computer Vision*, pp. 1501-1510. 2017.

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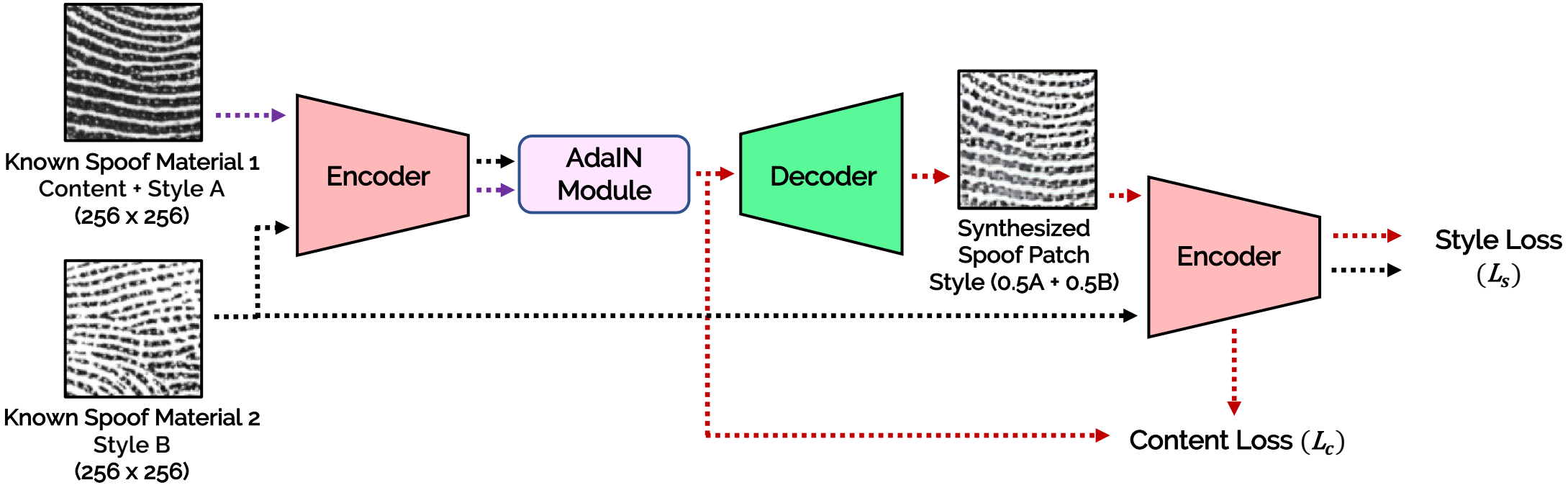

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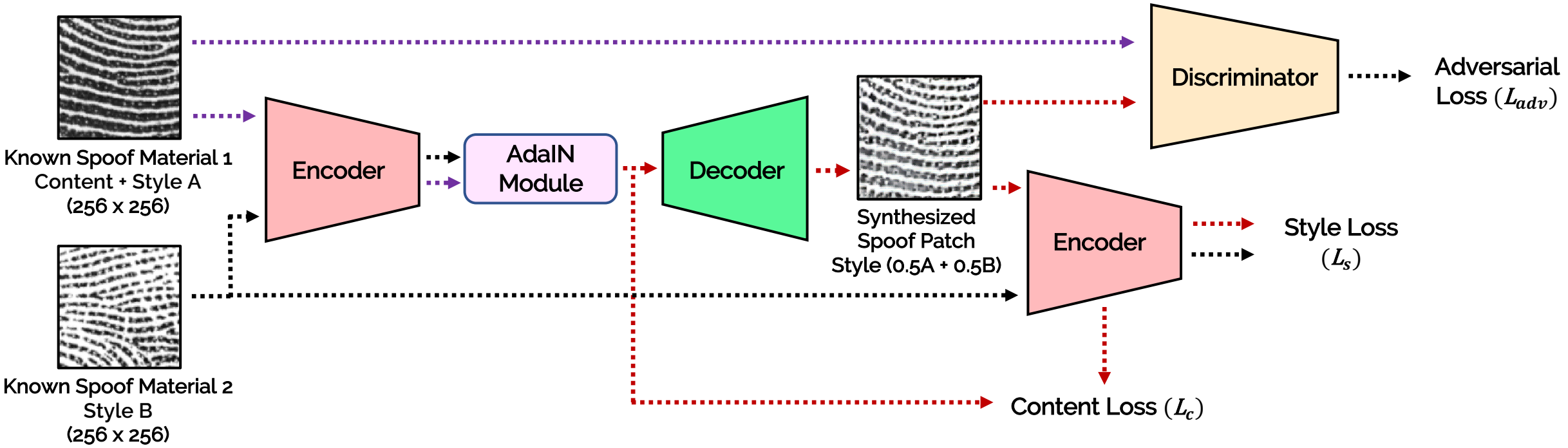

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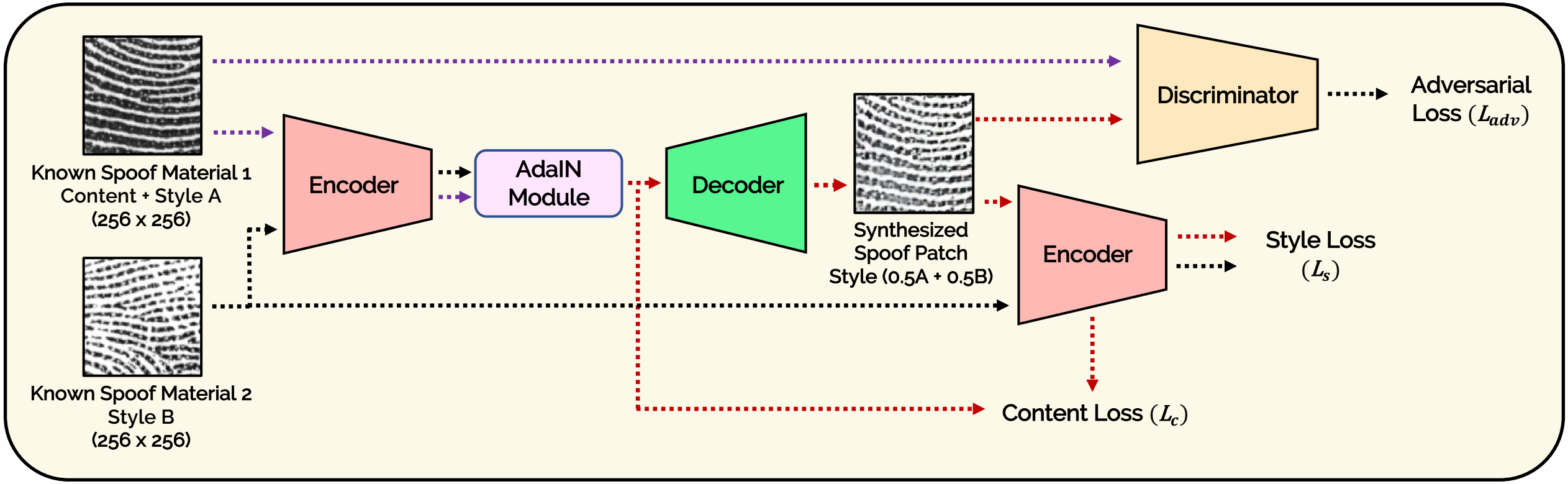

- Style transfer-based wrapper
- Transfer style (texture) characteristics between known PAs

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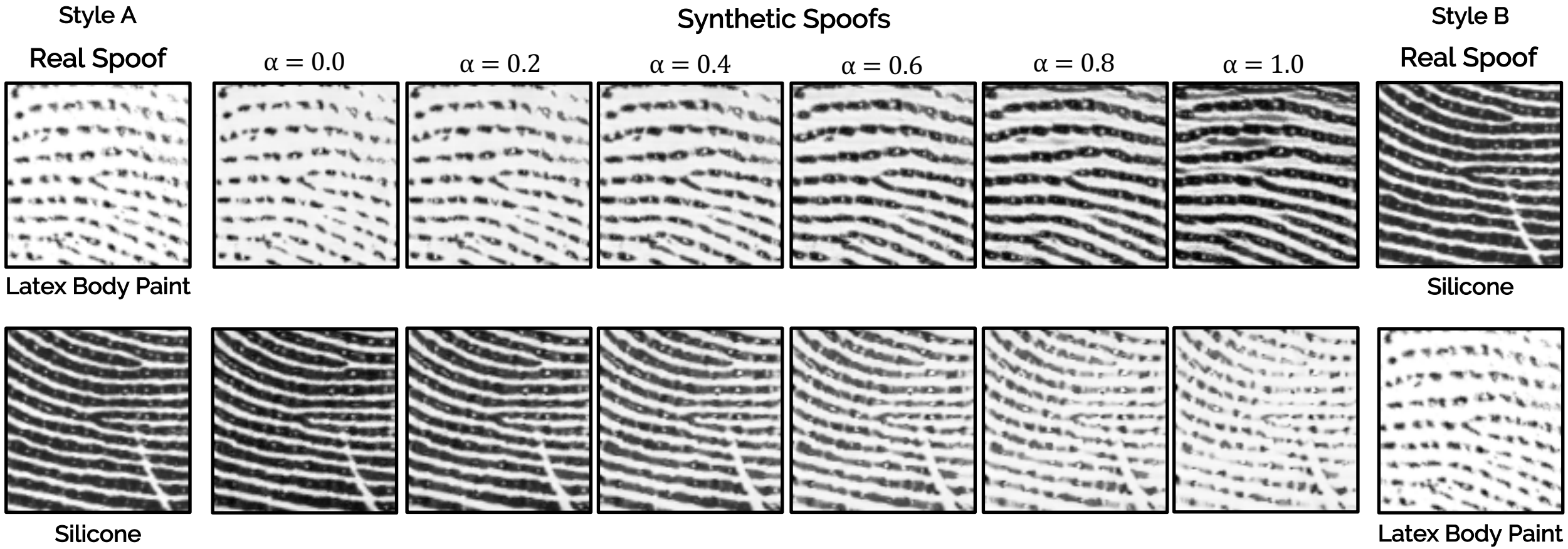
Control Extent of Style Transfer



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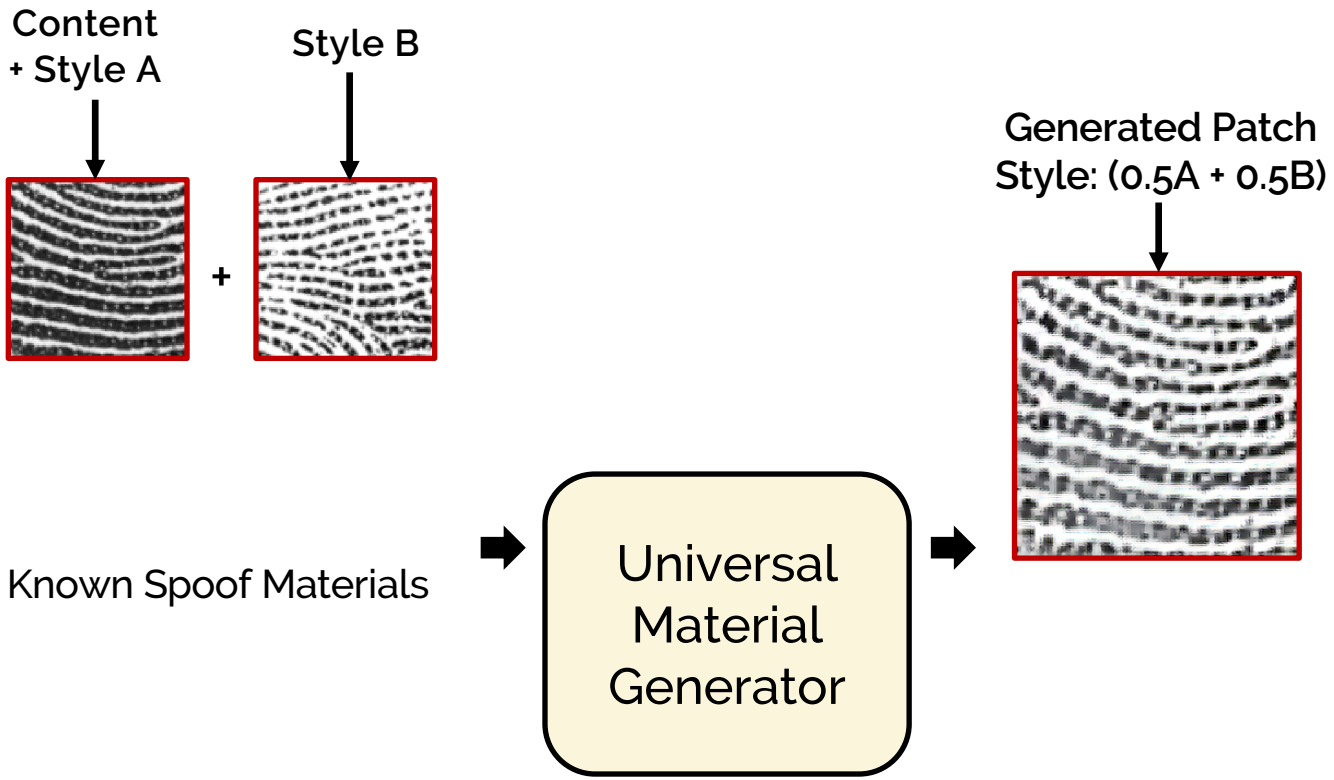

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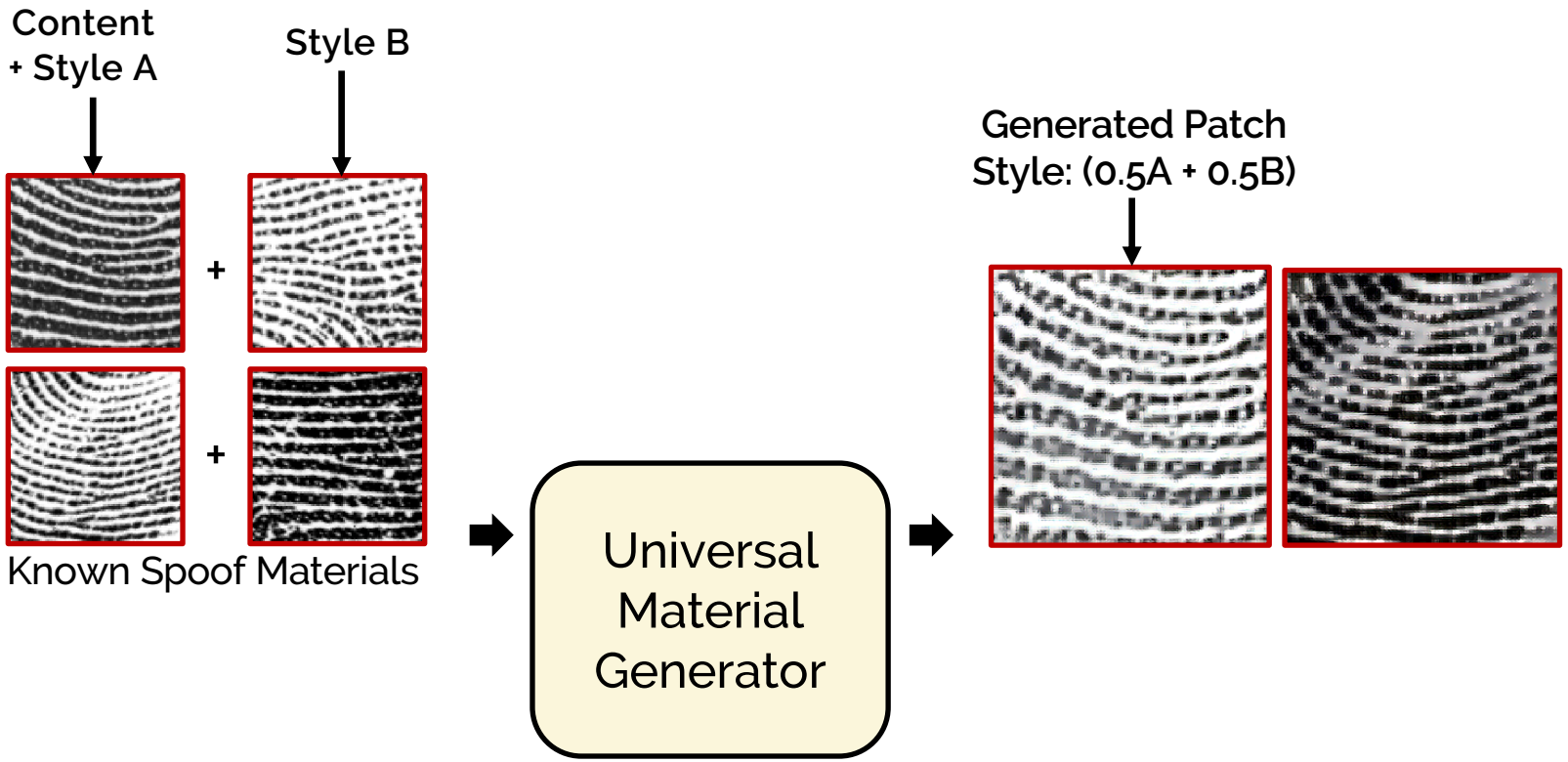

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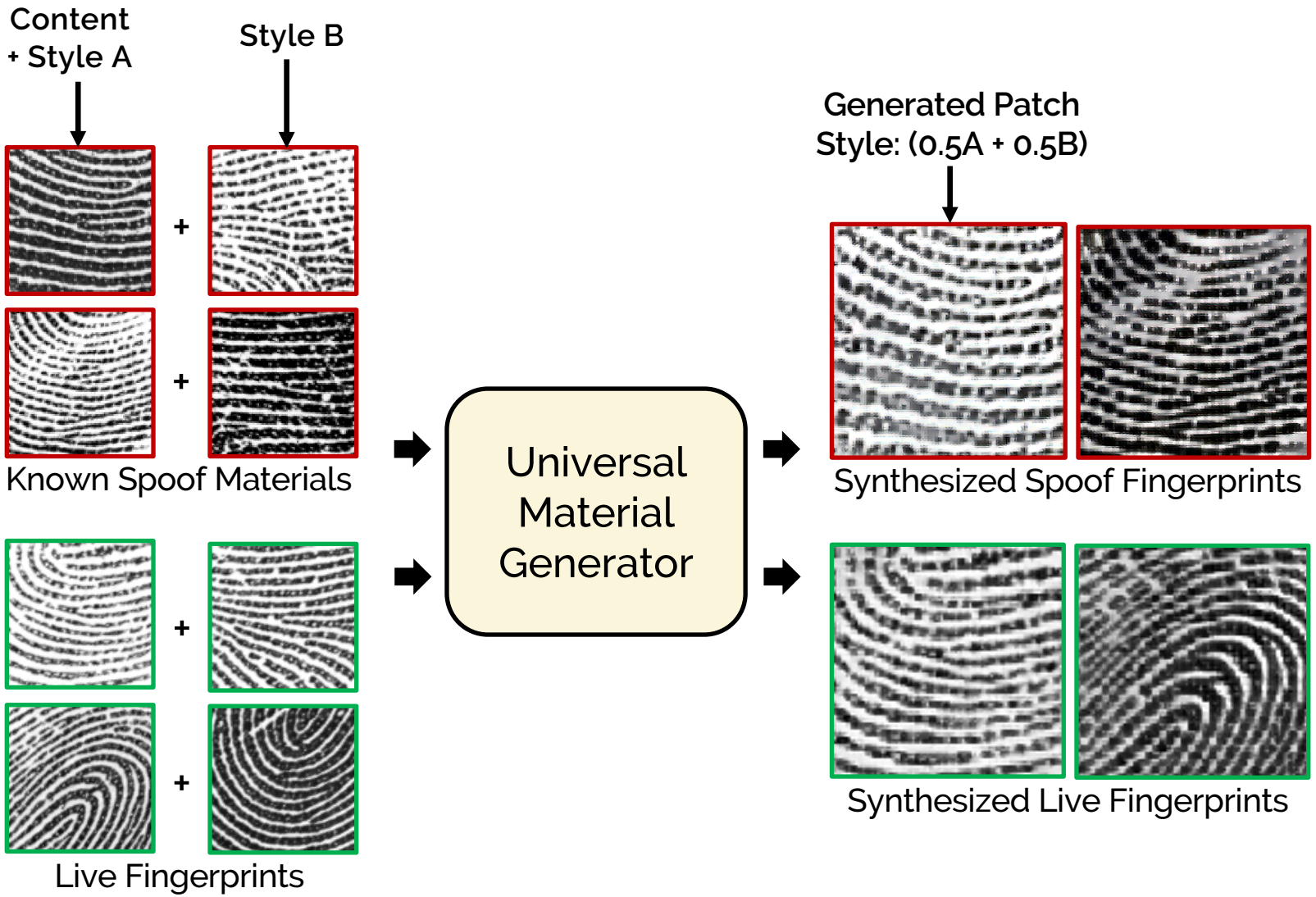

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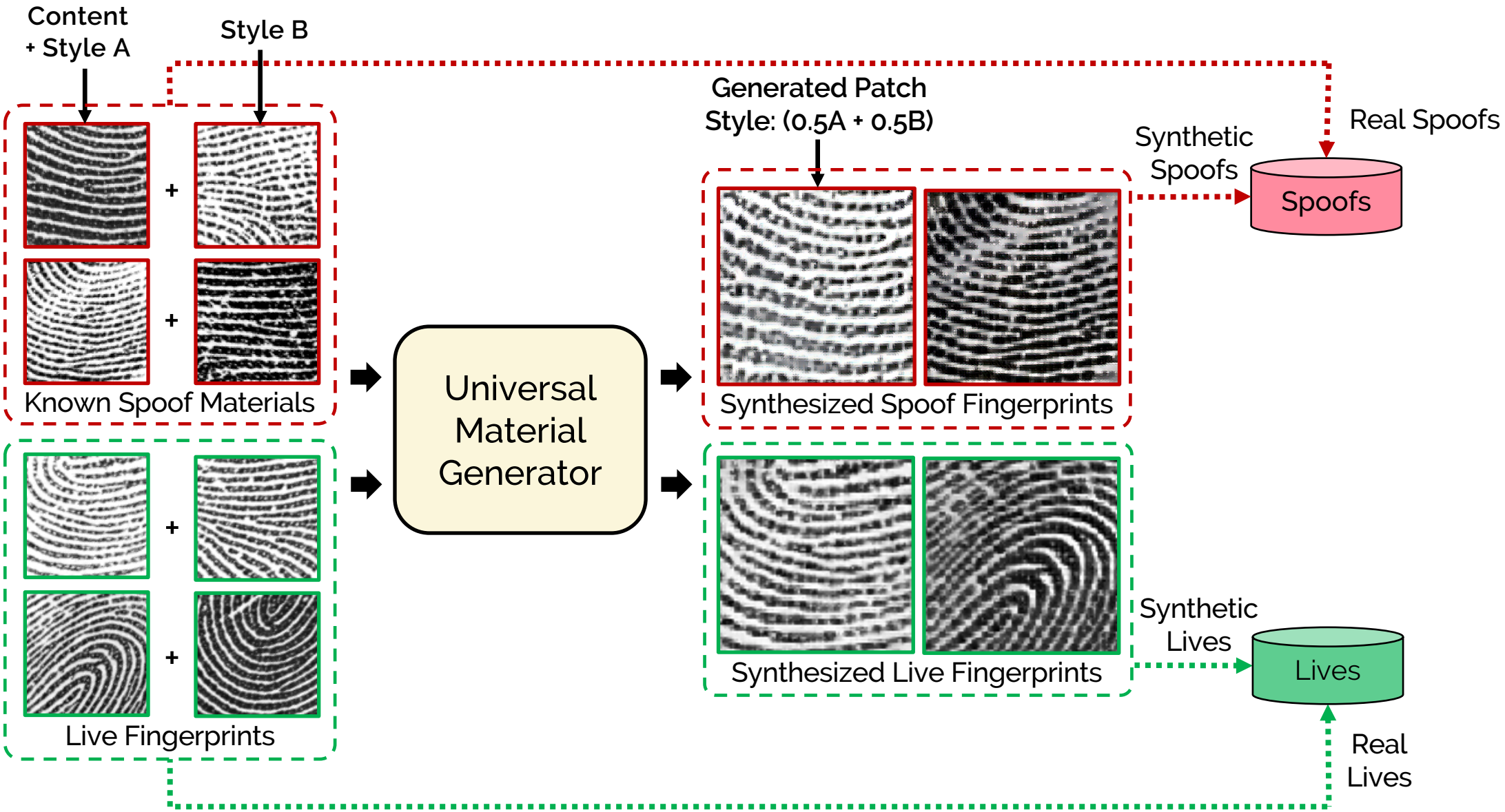

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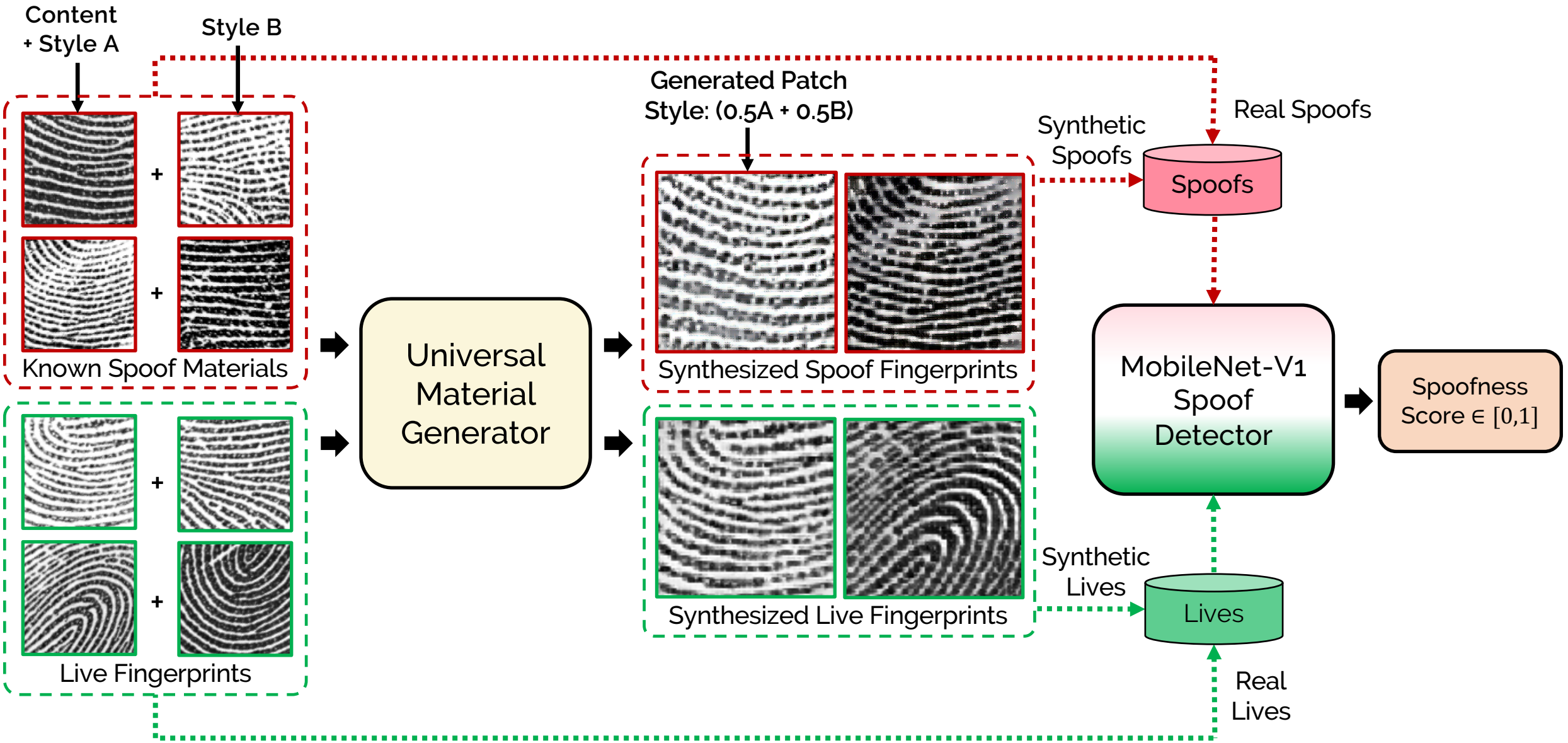
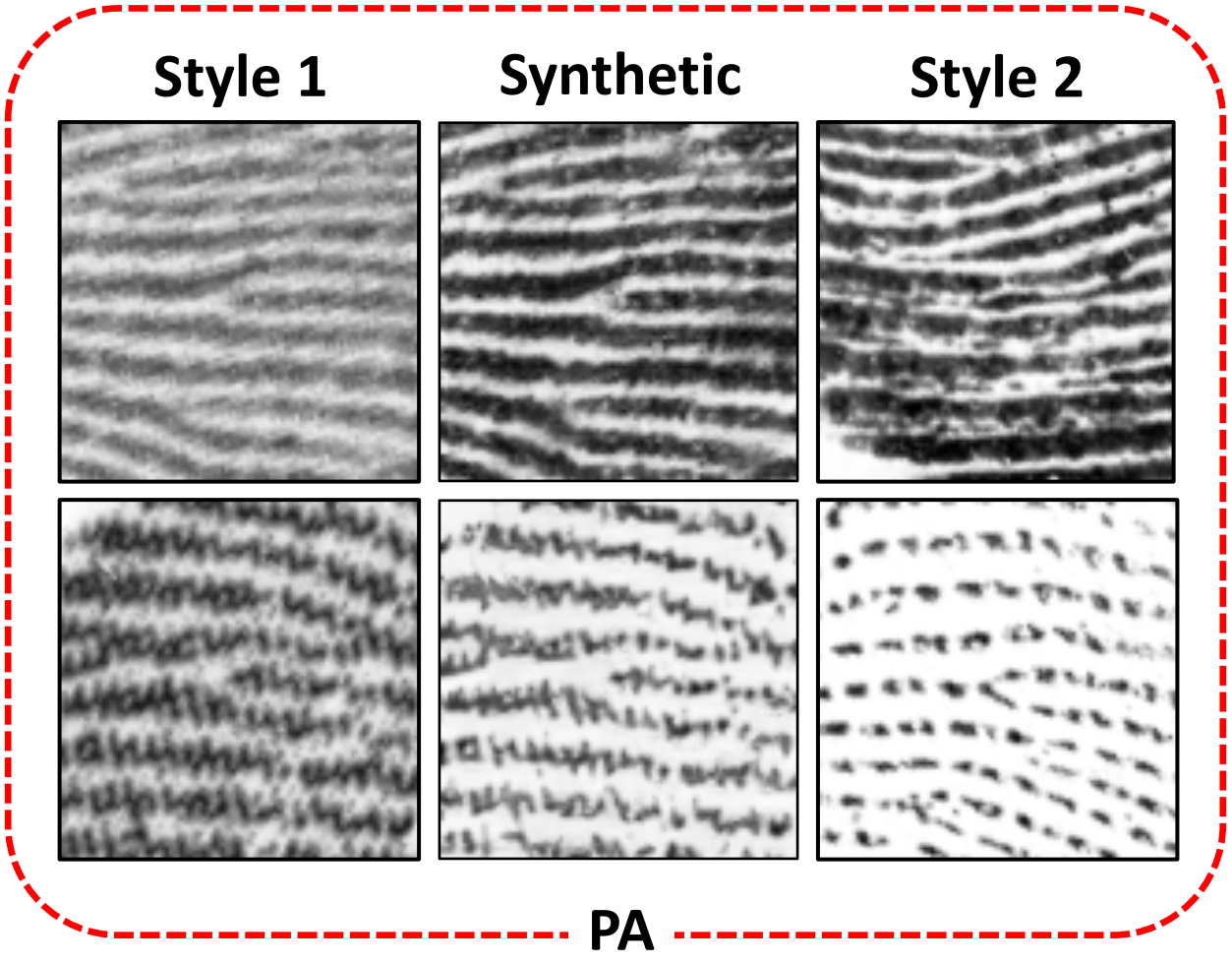
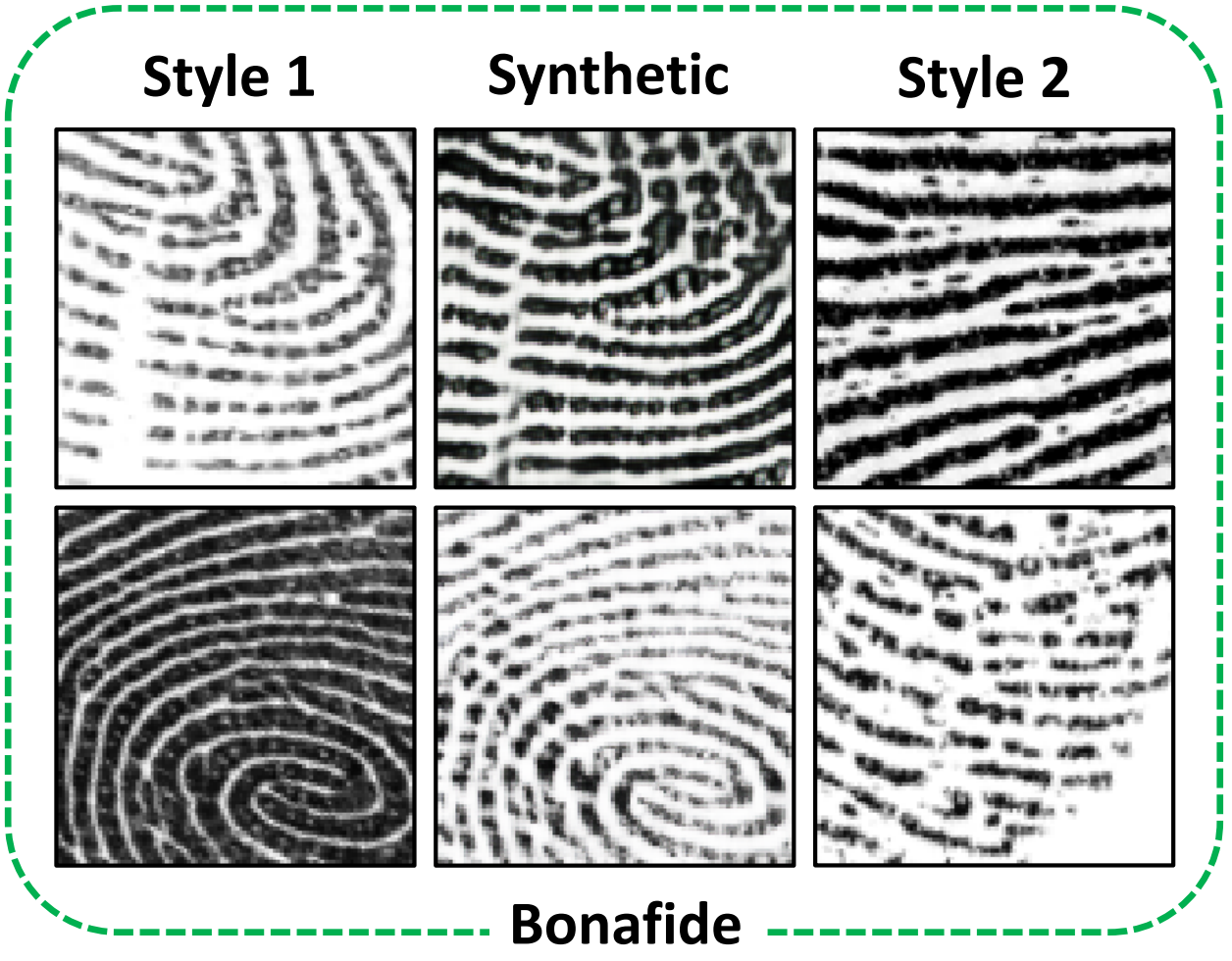


Universal Material Generator: Samples





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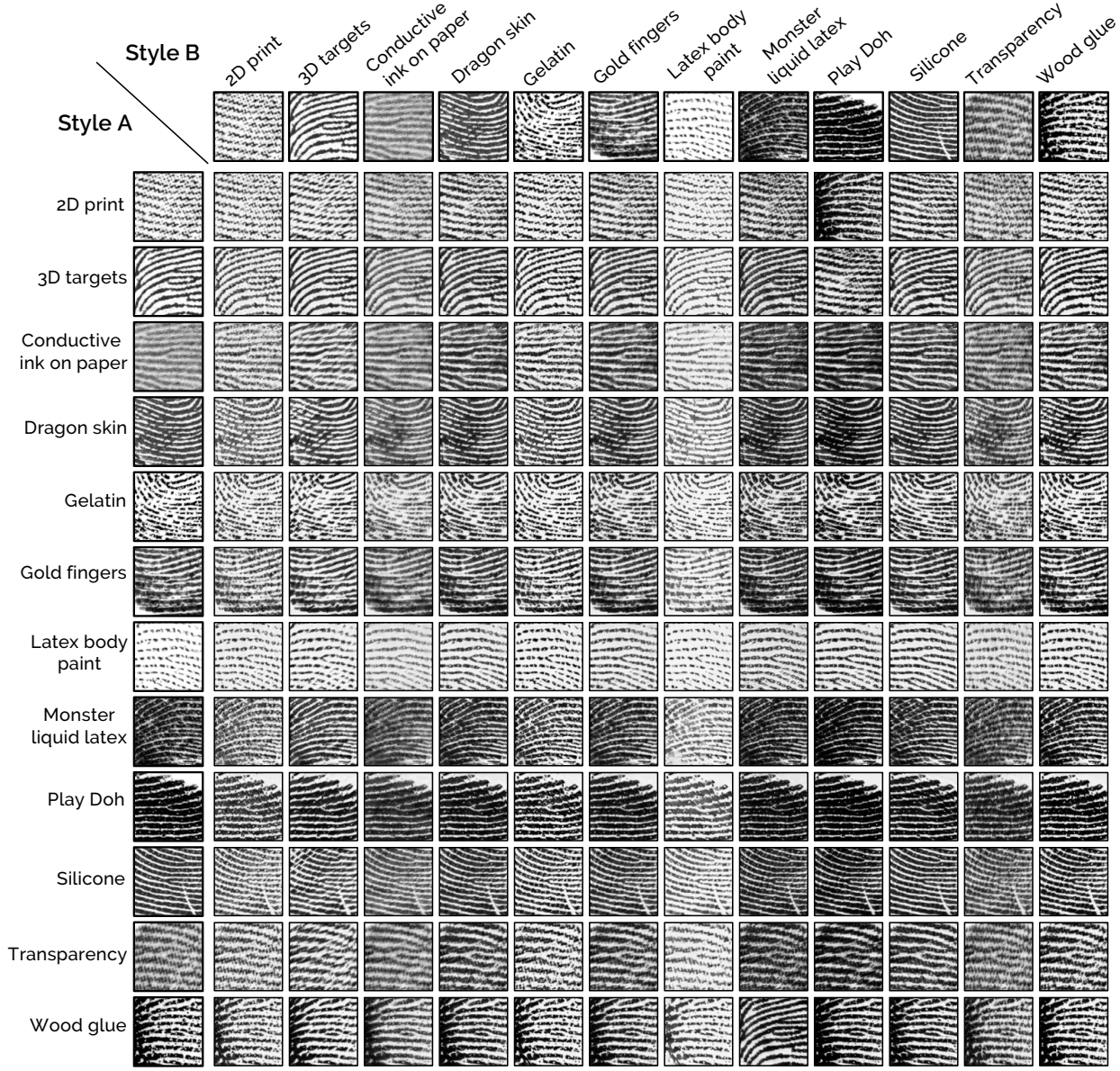
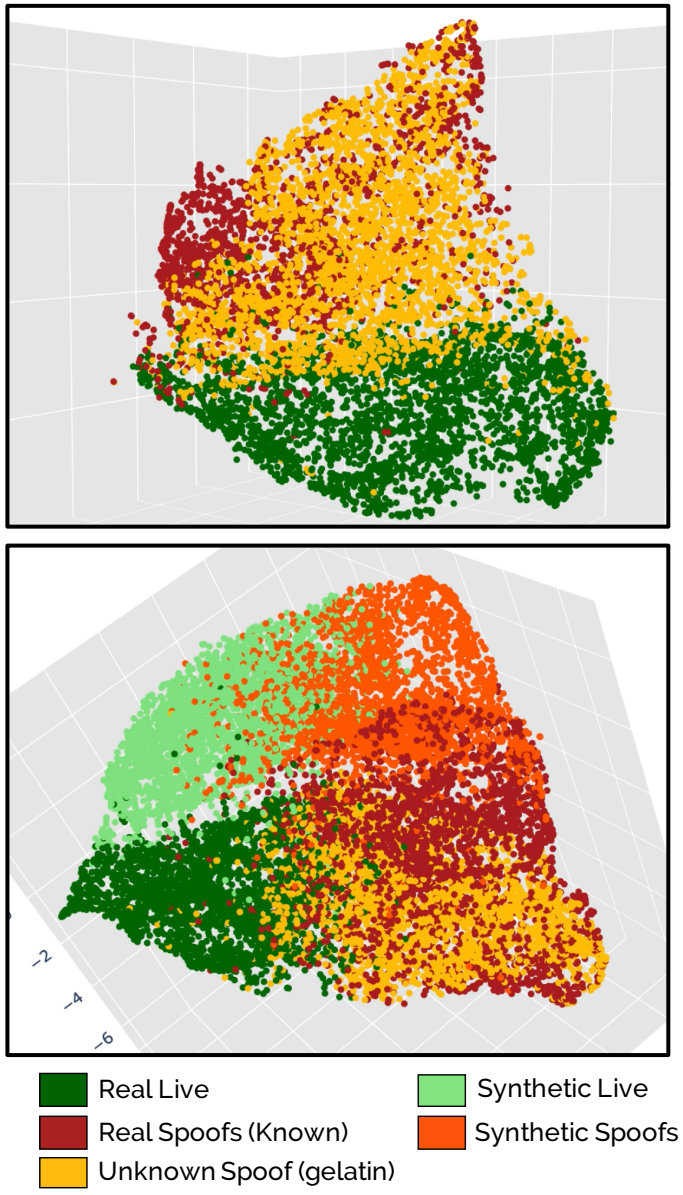




Fingerprint Spoof Generalization: Results

MSU FPAD-v2 Dataset: 4,912 spoofs (12 materials), 5,743 live images

True Detection Rate @ False Detection Rate = 0.2%			
Base CNN		**Base CNN + UMG wrapper**	
Slim-Res CNN [2]	Fingerprint Spoof Buster [3]	Slim-Res CNN + UMG	Fingerprint Spoof Buster + UMG
73.1 ± 15.7	75.2 ± 16.6	**90.6 ± 10.2**	**91.8 ± 10.3**

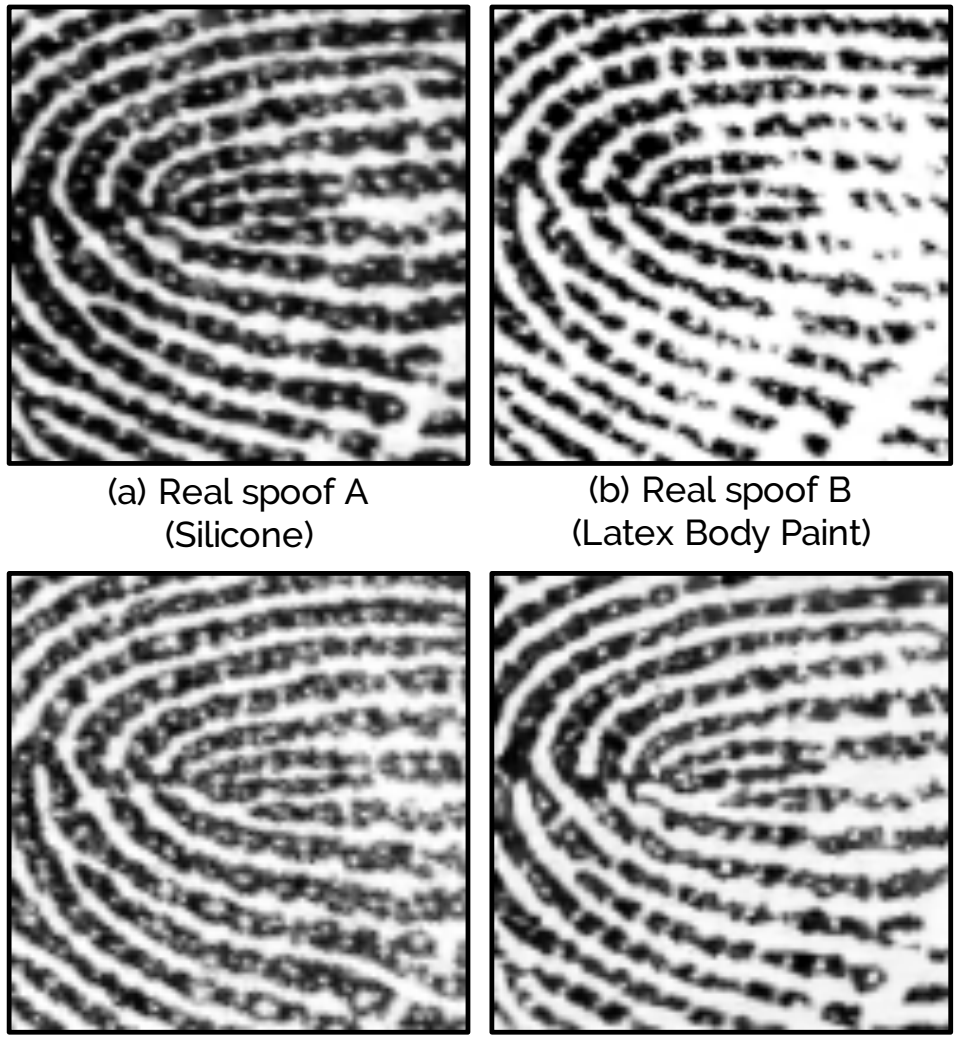
LivDet-2017 Dataset: 9,665 spoofs (6 materials), 8,091 live images

True Detection Rate @ False Detection Rate = 1.0%			
Base CNN		**Base CNN + UMG wrapper**	
Slim-Res CNN [2]	Fingerprint Spoof Buster [3]	Slim-Res CNN + UMG	Fingerprint Spoof Buster + UMG
72.6 ± 15.4	73.3 ± 15.5	**78.3 ± 11.9**	**80.7 ± 10.0**

[2] Y. Zhang, D. Shi, X. Zhan, D. Cao, K. Zhu, and Z. Li. Slim-Res CNN: A Deep Residual Convolutional Neural Network for Fingerprint Liveness Detection. IEEE Access, 7:91476–91487, 2019.
[3] T. Chugh, K. Cao, and A. K. Jain. Fingerprint Spoof Buster: Use of Minutiae-centered Patches. IEEE Transactions on Information Forensics and Security, 13(9):2190–2202, 2018.

Fabricating Unknown Spoofs

Spoof Mixture

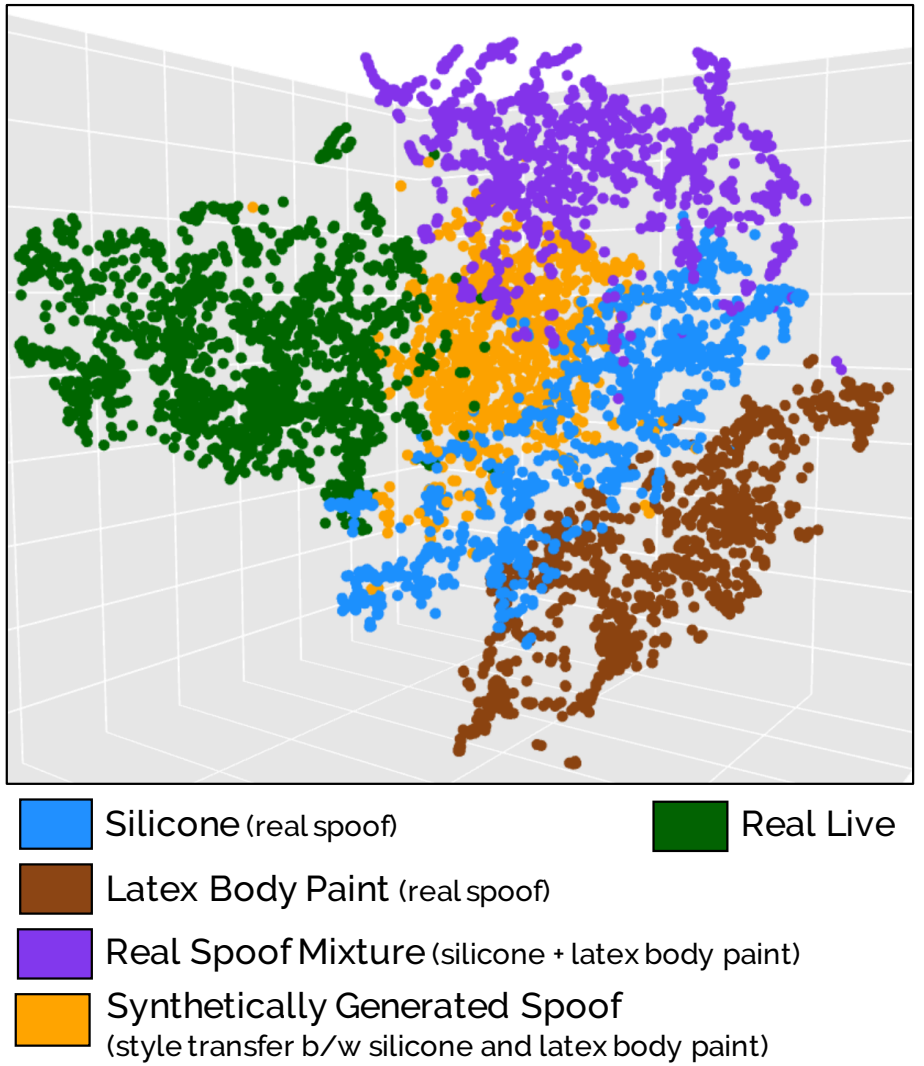


(a) Real spoof A (Silicone)

(b) Real spoof B (Latex Body Paint)

(c) Real spoof mixture (spoof A + spoof B)

(d) Synthesized Spoof (spoof A + spoof B)



Performance improved from TDR = **83.33%** to **95.83%** @ FDR = 0.2%

Summary

- Proposed a style-transfer based wrapper to improve the generalization performance
- Achieved state-of-the-art performance on publicly available LivDet-2017 and MSU FPAD-v2 datasets
- No affect on spoof detection time, < 100ms for Spoof Buster and Slim-Res CNN
- Requires ~2 hours for training UMG wrapper and 1 hour to generate 100,000 patches on Nvidia GTX 1080Ti GPU

Thank You