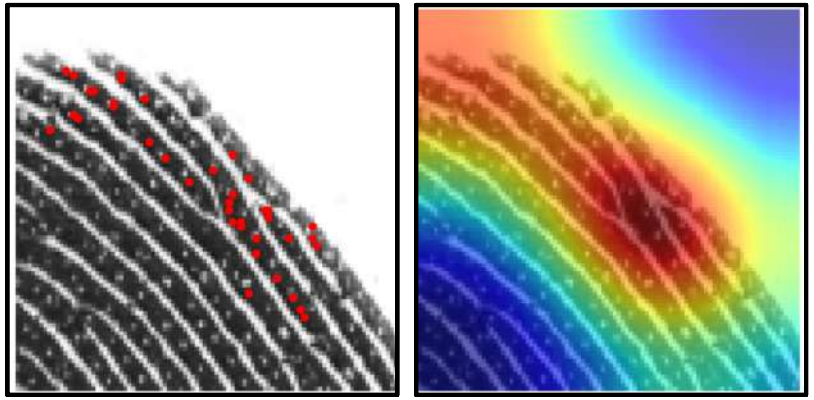
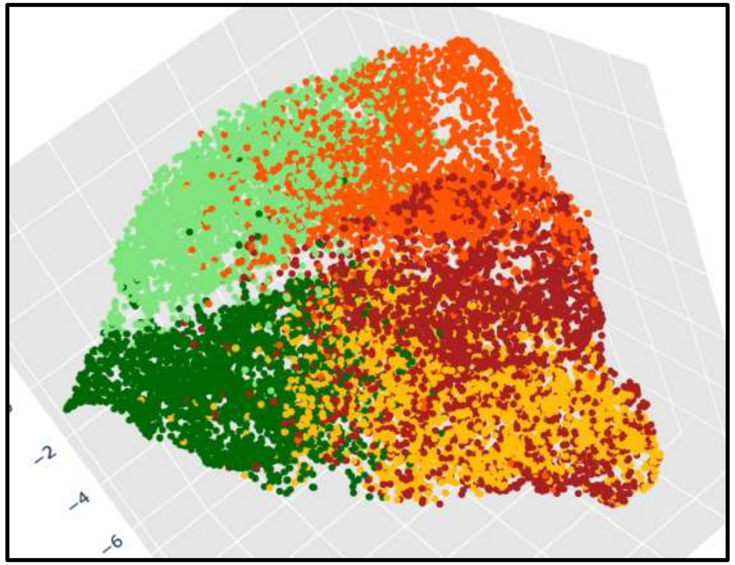
An Accurate, Efficient, and Robust Fingerprint Presentation Attack Detector





Tarang Chugh

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PhD Committee: Prof. X. Liu, Prof. V. Mandrekar, Prof. A. Ross

April 7, 2020

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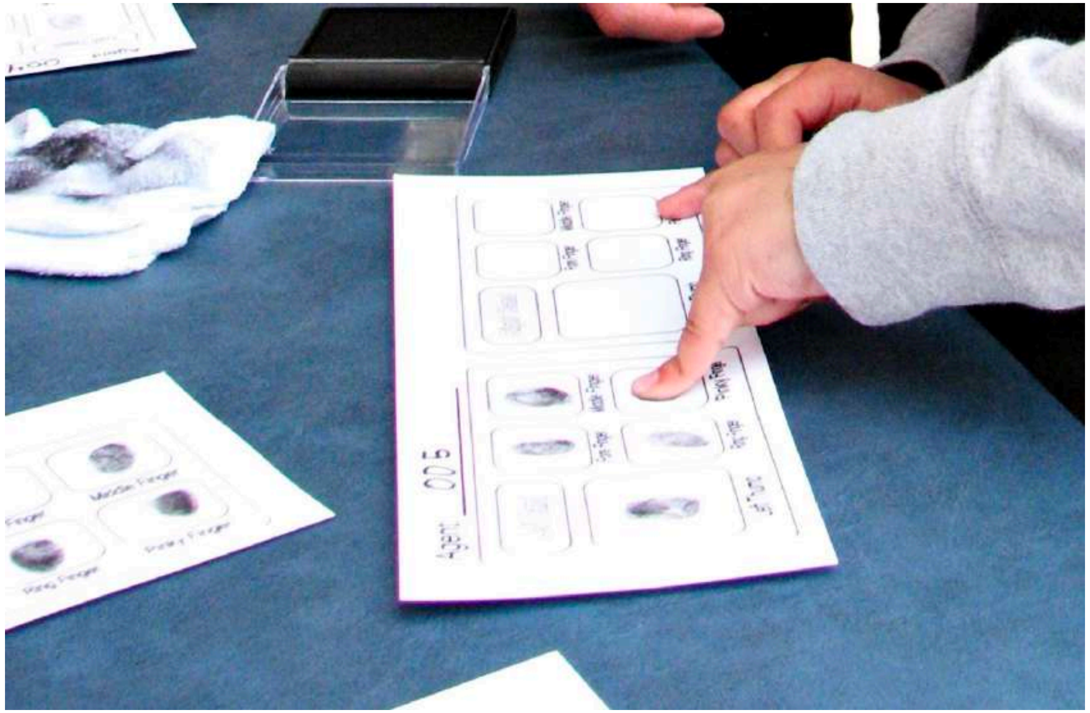
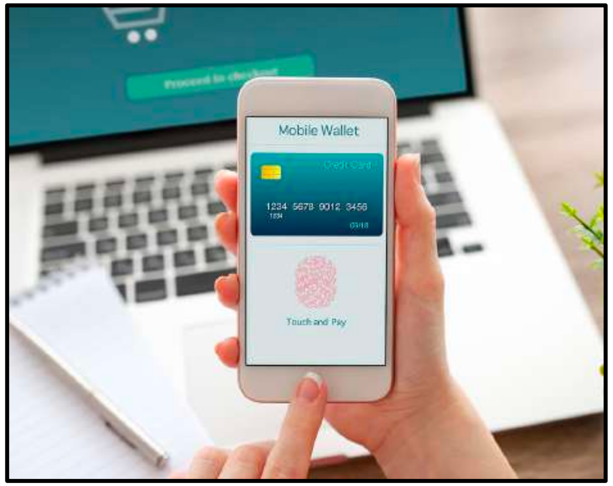
IARPA R&D Contract No. 2017 - 17020200004

My first encounter with Fingerprints



Fingerprint Recognition

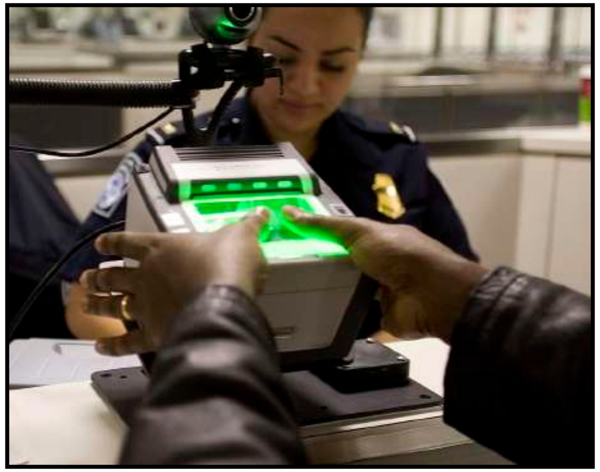


Mobile Payment


Biometric Boarding System

ATM User Authentication

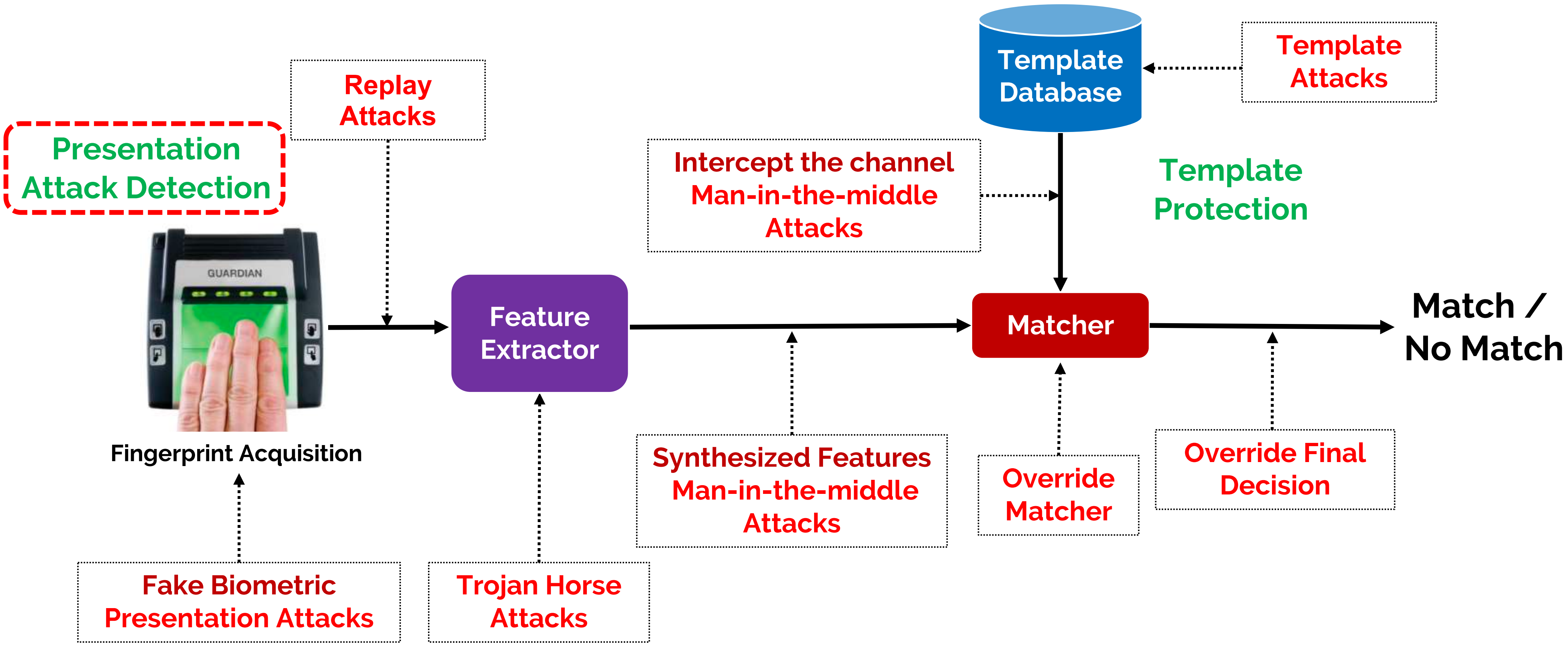

Public Distribution System


International Border Crossing


Access Control

1. https://www.computerworld.com/article/3063544/android-apps-fingerprint-support.html, 2. https://www.hindustantimes.com/india-news/aadhaar-verification-at-airports-raises-need-for-stricter-data-privacy-regulations/story-pNJYBM7mJkhRrFJElYX2RJ.html, 3. https://www.arabnews.com/node/1373991/business-economy, 4. http://karnatakatoday.in/new-kyc-of-ration-card/, 5.https://en.wikipedia.org/wiki/Office_of_Biometric_Identity_Management, 6. https://campuslifesecurity.com/articles/2018/10/16/texas-high-school-deploys-fingerprint-access-control.aspx?admgarea=Topics

Fingerprint Recognition System: Vulnerabilities



https://www.youtube.com/watch?v=P8zm1i9gJuE

Big thanks to **Debayan Deb** for helping in recording and editing this video. ☺

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

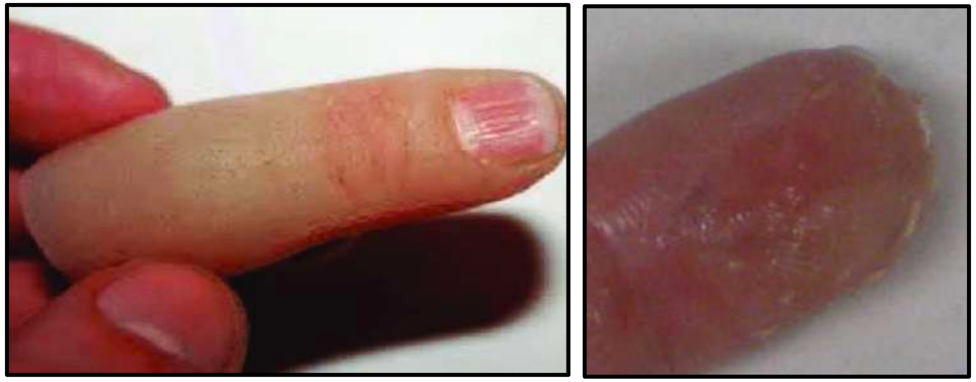
Printed Fingerprint Targets

Transplanted skin from sole

Acid Burns

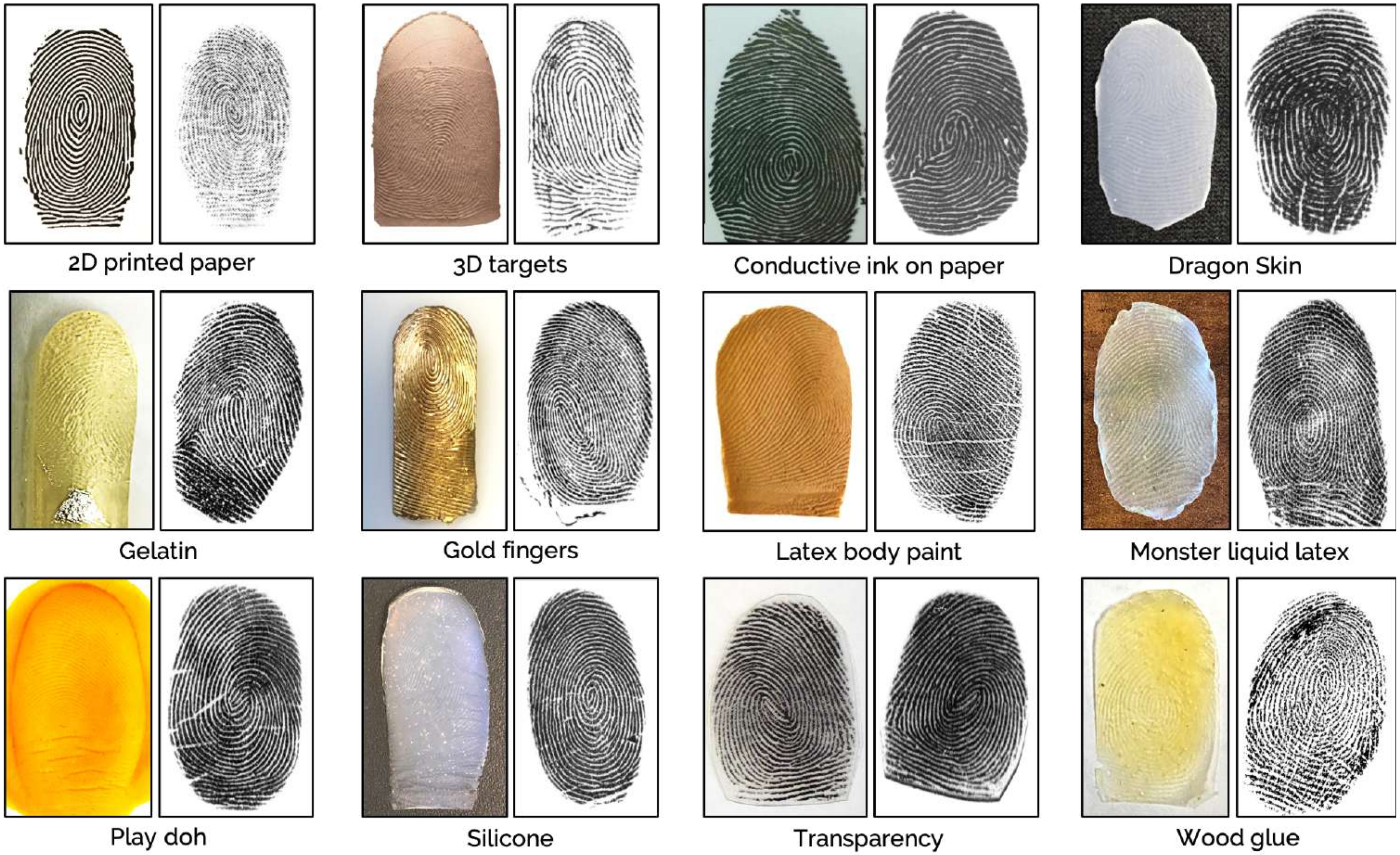
Stitched Fingers

Altered Fingers



Cadaver Fingers

Fabrication Materials



Bona fides

Requirements

- Accurate and Robust

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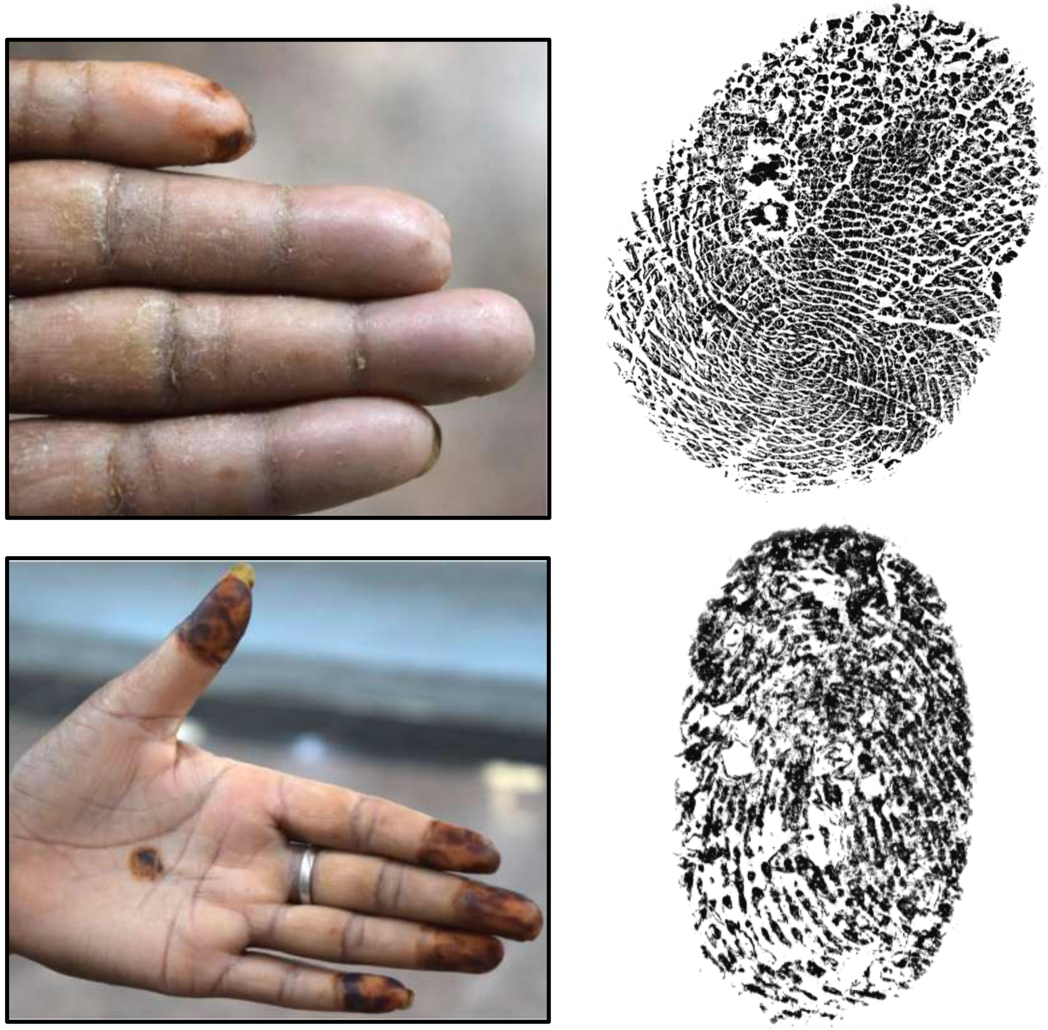
True Detection Rate > 97% @
False Detection Rate = 0.2%



Bonafide noisy fingerprint images

Requirements

- Accurate and Robust
- Low-cost and Interoperable

SilkID SLK20R

Lumidigm V302

CrossMatch Guardian 200

Single-finger Readers **Slap Reader**

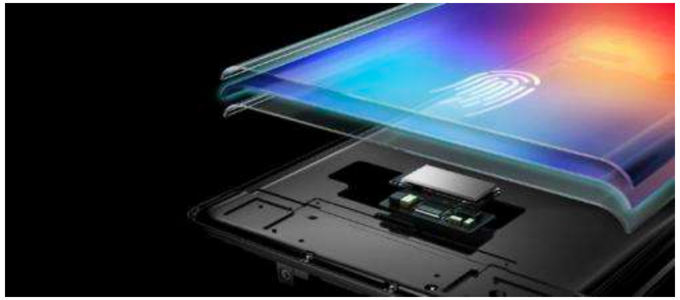
WoodGlue EcoFlex Gelatin Latex Silgum

Spoof Attacks

Live Fingerprint

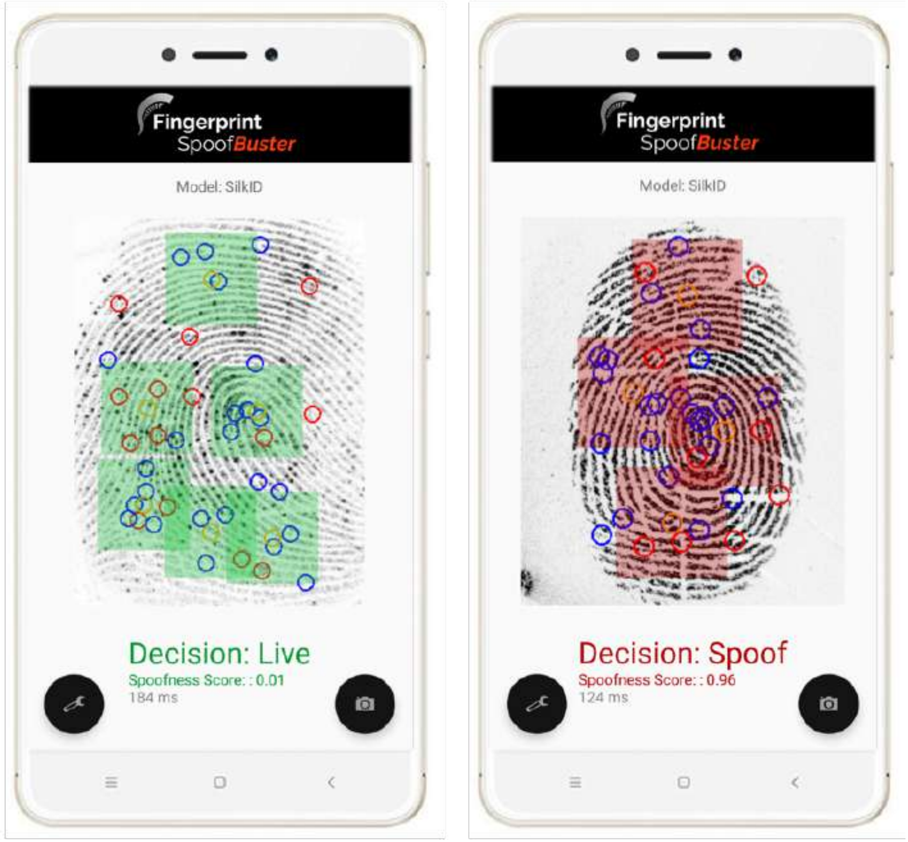
Requirements

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



Vivo's in-display screen fingerprint reader

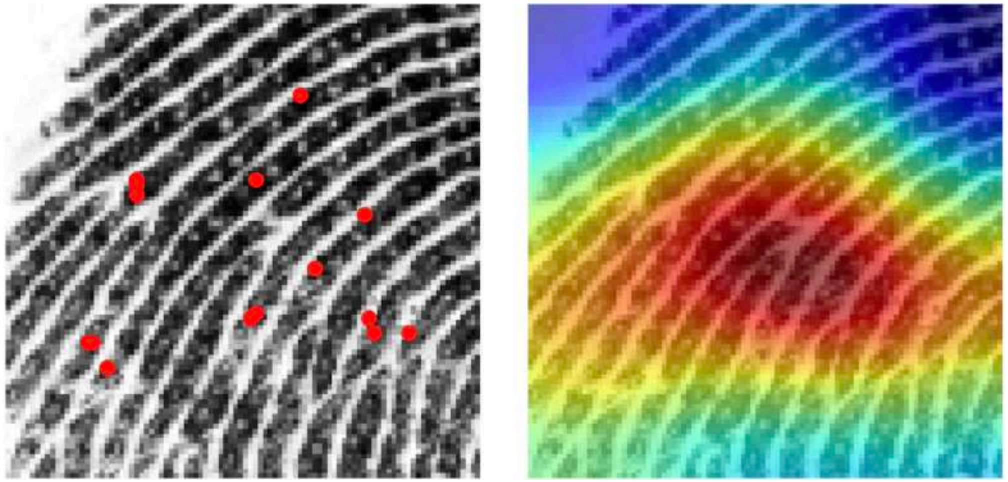
ZKTeco Access Control Unit



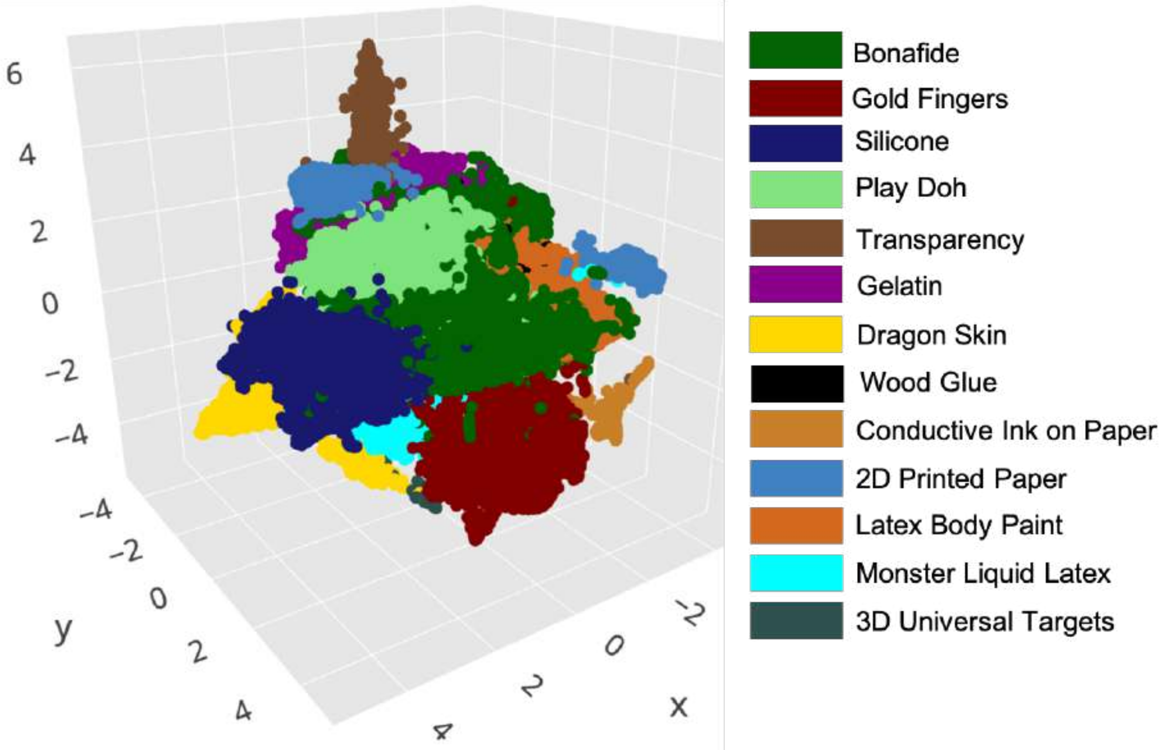
Commodity Smartphone Redmi Note 4 ($150)

Requirements

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



CNN Fixations



3D t-SNE representation

Contributions

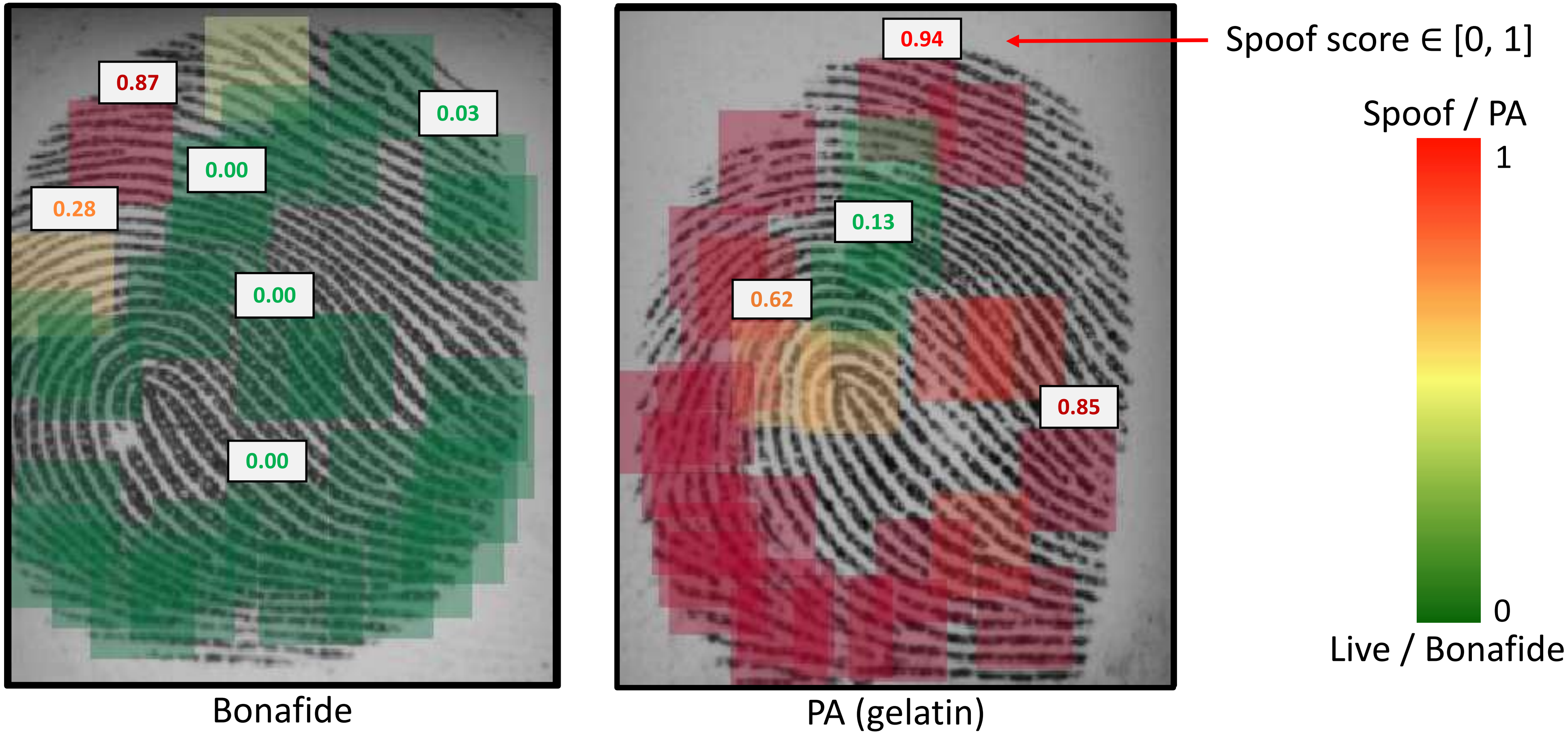
1. An accurate, efficient, interpretable, and generalizable fingerprint presentation attack detector (PAD), achieving state-of-the-art performance on publicly available datasets and large-scale government evaluations (IARPA ODIN program).
2. Investigated material characteristics to understand and interpret the generalization performance.
3. Two unique approaches to improve the generalization performance: (i) a style transfer-based wrapper, called Universal Material Generator, and (ii) a dynamic method utilizing temporal information.
4. An optimized PAD solution, called Fingerprint Spoof Buster *lite,* implemented as an Android application capable to perform spoof detection in under 100ms.

Existing Approaches

- Hardware-based
  - Blood Flow
  - Body Odor
  - Skin Distortion
  - Multi-spectral, multi-view, and OCT scanners
- Software-based
  - Anatomical Features (pore location and their distribution)
  - Physiological Features (perspiration)
  - Texture-based Features
    - Hand-crafted: Weber Local descriptor, Local-contrast phase descriptor
    - Machine-learned: CNN-based features

Proposed Approach

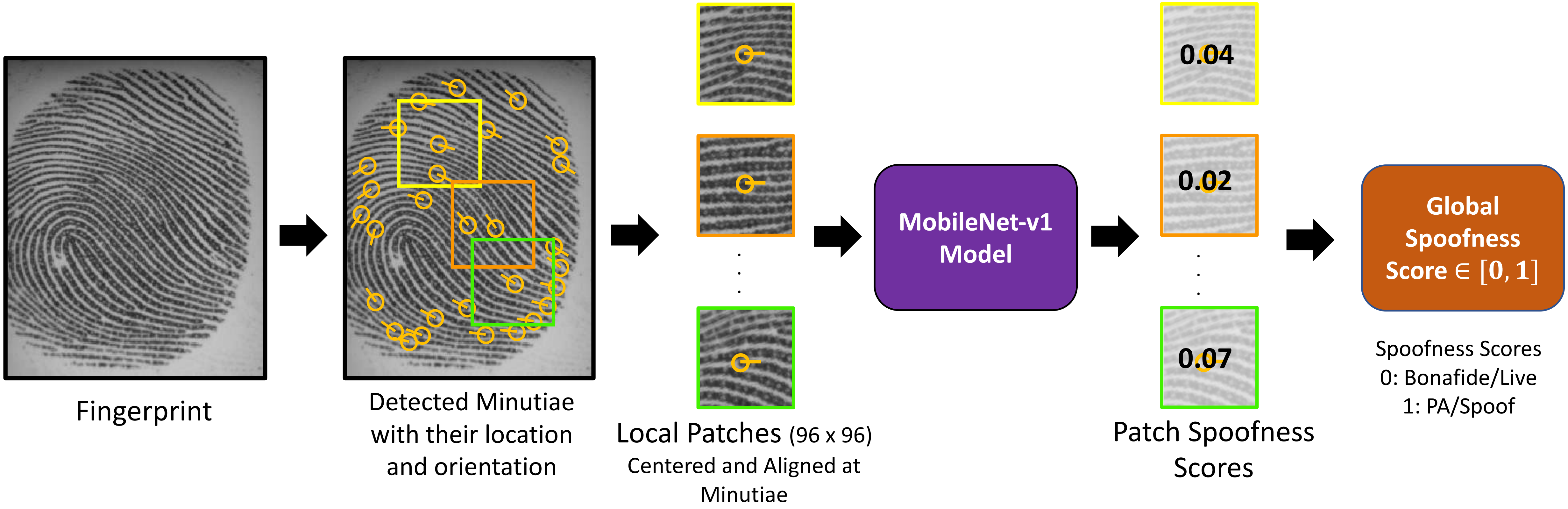
Extract minutiae and learn patch “texture” around minutiae



T. Chugh, K. Cao, and Anil K. Jain, "Fingerprint Spoof Buster: Use of Minutiae-centered Patches", in the *IEEE Transactions on Information Forensics and Security*, 2018

T. Chugh, K. Cao, A. K. Jain, "Fingerprint Spoof Detection Using Minutiae-based Local Patches", in IJCB, Denver, Colorado, 2017

Fingerprint Spoof*Buster*



Minutiae-based Patches

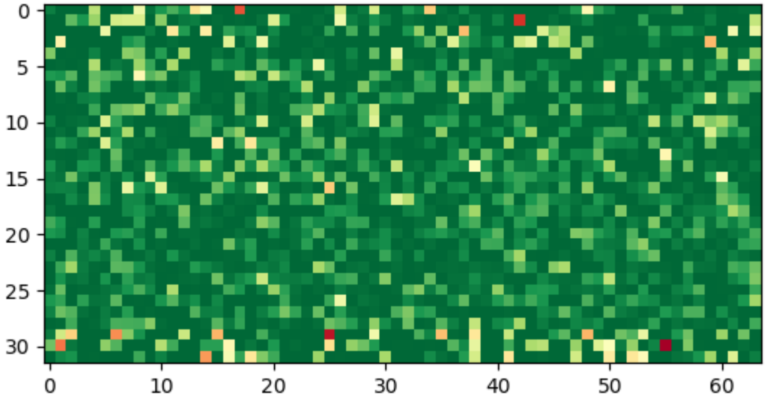
- Minutiae and associated texture difficult to reproduce in spoof fabrication
- Patches aligned by minutiae orientation
- Robust to image size
- Large amount of training data
- Spurious minutiae due to artefacts
- Localize partial spoof areas

Method	TDR (%) @ FDR=0.2%
Whole Image	70.4
Random Patches [96 x 96]	87.5
Minutiae-based Patches	
[64 x 64]	90.2
[96 x 96]	**94.0**
[128 x 128]	93.5
Fusion [96 x 96] + Whole Image	**99.6**

Performance on IARPA Odin GCT-I Crossmatch Data

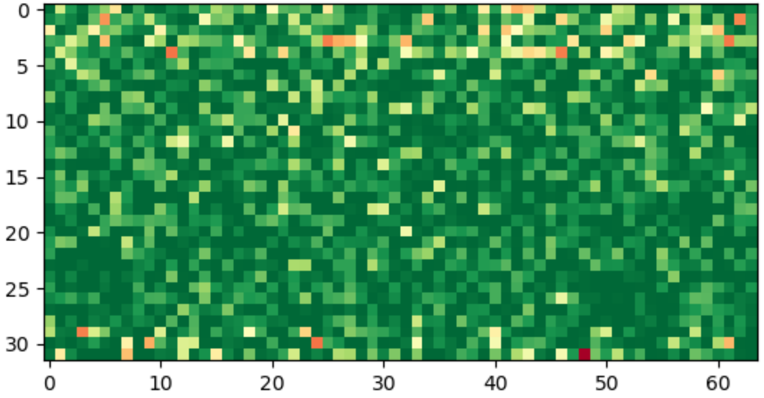
CNN Representation

Live Fingerprint Patch



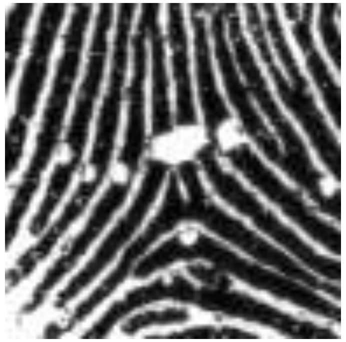
Spoofness Score: 0.00

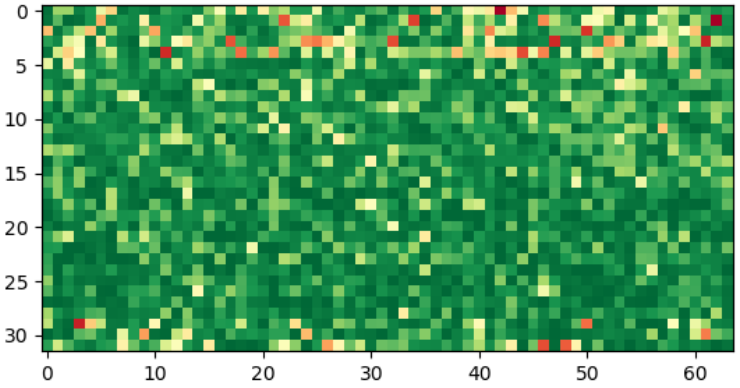
Modified Spoof Patch



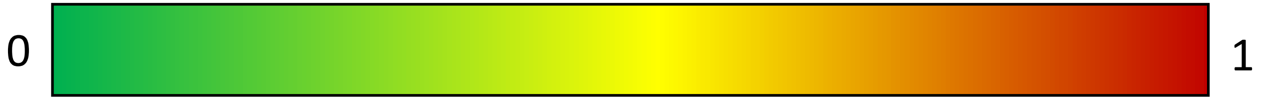
Spoofness Score: 0.94

Spoof Fingerprint Patch





Spoofness Score: 0.99



Liveness Detection (LivDet) Databases

Database	Fingerprint Sensors	#Training Images / #Testing Images	Spoof Materials
LivDet 2011	• Biometrika • Digital Persona • ItalData • Sagem	8,000 / 8,000	Ecoflex, Gelatine, Latex, PlayDoh, Silgum, Silicone, Wood Glue
LivDet 2013	• Biometrika • ItalData	4,000 / 4,000	Ecoflex, Gelatine, Latex, Modasil, Wood Glue
LivDet 2015	• Biometrika • Digital Persona • CrossMatch • GreenBit	8,983 / 10,448	Body Double, Ecoflex, Gelatine, Latex, Liquid Ecoflex, OOMOO, PlayDoh, RTV, Wood Glue
LivDet 2017	• GreenBit • Orcanthus • Digital Persona	6,598 / 11,178	Wood Glue, Ecoflex, Body Double, Gelatine, Latex, Liquid Ecoflex

Liveness Detection (LivDet) Databases

LivDet 2011

LivDet 2013

Gelatin | Ecoflex | Play Doh | Latex

LivDet 2015

Wood Glue | Body Double | Ecoflex

LivDet 2017

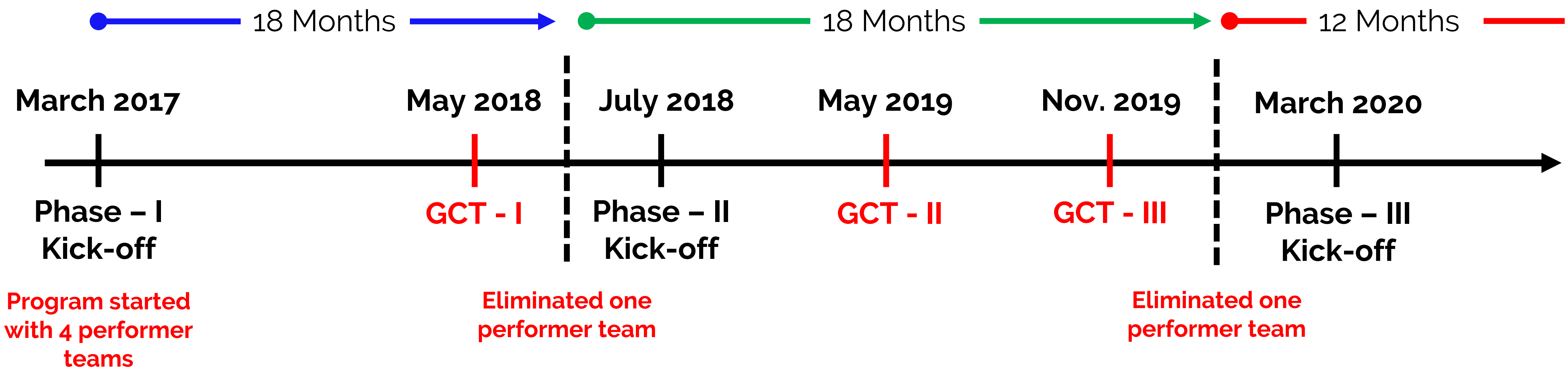
Liveness Detection (LivDet) Databases

Average Classification Accuracy (%) of best performing algorithms

Study	Approach	LivDet 2011	LivDet 2013	LivDet 2015	LivDet 2017
Hand-Crafted Features-based Approaches					
Ghiani et al., 2012	Local Phase Quantization (LPQ)	88.90	97.00	N/A	N/A
Ghiani et al., 2013	Binarized Statistical Image Features (BSIF)	92.80	97.90	N/A	N/A
Gragniello et al., 2015	Local Contrast-Phase Descriptor (LCPD)	94.30	98.70	N/A	N/A
Deep-Learning Based Approaches					
Nogueira et al., 2016 **(winner of LivDet 2015)**	Transfer Learning + CNN-VGG + Whole Images	95.50	98.90	95.50	N/A
Pala et al., 2017	Custom CNN with triplet loss + random patches	96.67	99.42	N/A	N/A
Zhang et al., 2019 **(winner of LivDet 2017)**	Slim-Residual CNN + Center of Gravity patches	N/A	98.26	96.82	95.25
Chugh et al., 2018 **Proposed Approach**	CNN-MobileNet v1 + Minutiae-based centered and aligned patches	98.33	99.75	99.03	95.44

T. Chugh, K. Cao, A. K. Jain, "Fingerprint Spoof Buster: Use of Minutiae-centered Patches", in Transactions on Information Forensics and Security (TIFS), 13(9):2190 - 2202, 2018

IARPA ODIN Program



Phase-I Goals
- Exploration phase, initial R&D
- Development data collection
- Performance Target:
  TDR > 85.0% @ FDR = 0.2%
- Performance Achieved
  TDR = 99.6% @ FDR = 0.2%

Phase-II Goals
- Robust against unknown spoofs
- Cross-material generalization
- Performance Target:
  TDR > 95.0% @ FDR = 0.2% (GCT - II)
  TDR > 97.0% @ FDR = 0.2% (GCT - III)
- Performance Achieved
  TDR = 99.87% @ FDR = 0.2% (GCT-II)
  TDR = 99.81% @ FDR = 0.2% (GCT - III)

Phase-III Goals
- Robust against unknown sensors
- Consolidation of various approaches

GCT: Government Controlled Test

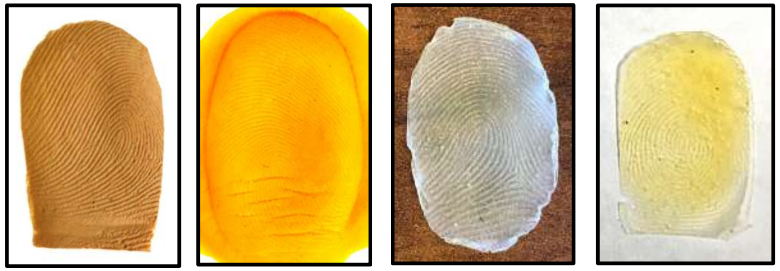
Development Databases

Database	Fingerprint Sensors	#Training Images / #Testing Images	Spoof Materials	Average TDR @ FDR=0.2%
MSU FPAD Database	• CrossMatch • Lumidigm	9,750 / 9,750	(i) Ecoflex, (ii) PlayDoh, (iii) 2D Printed on Matte Paper, (iv) 2D Printed on Transparency	**97.4%**
Precise Biometrics Spoof-Kit Database	• CrossMatch • Lumidigm	950 / 950	(i) Gelatin, (ii) Latex body paint, (iii) – (vi) Ecoflex + Coatings (silver colloidal ink, BarePaint, Nanotips), (vii) Crayola Model Magic, (viii) Wood glue, (ix) Monster Liquid Latex, and (x) 2D printed fingerprint on office paper	**96.8%**
Precise Biometrics Database	• CrossMatch	9,580 /9,580	(i) EcoFlex, (ii) Gelatin, (iii) Latex Body Paint, (iv) Model Magic, (v) PlayDoh, (vi) Silly Putty, (vii) Wood Glue	**94.6%**

Bonafide Data in MSU FPAD is collected from around 100 subjects with 9 impressions/finger.

Development Databases

Fingerprint spoof specimens



Liquid Latex Body Paint | PlayDoh (Orange) | Monster Liquid Latex | Wood Glue

Gelatin | Crayola Model Magic | 2D Printed on Transparency | 2D Printed on Matte Paper

Ecoflex (Silicone) | Ecoflex with Nanotips Coating | Ecoflex with BarePaint Coating | Ecoflex with Silver Colloidal Ink Coating

MSU Fingerprint Presentation Attack Dataset (FPAD) spoof images

(a) Imaged using CrossMatch Guardian 200 fingerprint reader

Live Fingerprint | PlayDoh (Orange) | Silicone (Ecoflex) | 2D Printed (Transparency Film) | 2D Printed (Matte Paper)

(b) Imaged using Lumidigm Venus 302 fingerprint reader

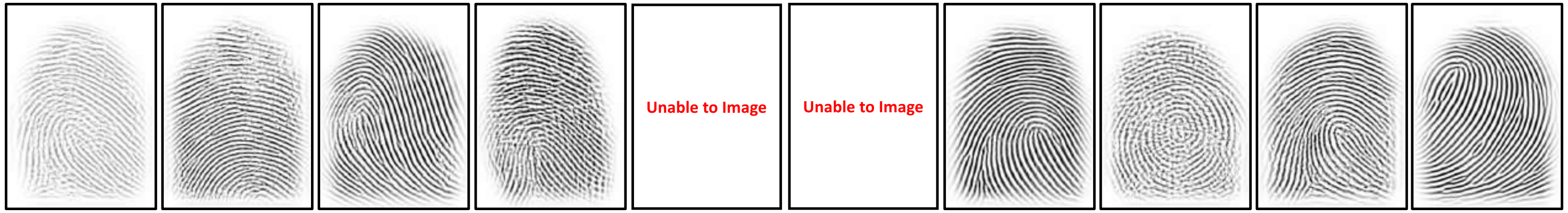
Live Fingerprint | PlayDoh (Orange) | Silicone (Ecoflex) | 2D Printed (Transparency Film) | 2D Printed (Matte Paper)

Precise Biometrics Spoof Kit (PBSK) spoof images

(a) Imaged using CrossMatch Guardian 200 fingerprint reader

Silicone (EcoFlex) | Gelatin | Latex Body Paint | Silicone (EcoFlex) with Silver Colloidal | Silicone (EcoFlex) with NanoTips | Silicone (EcoFlex) with BarePaint | Crayola Model Magic | Wood Glue | Monster Liquid Latex | 2D Printed (Office Paper)

(b) Imaged using Lumidigm Venus 302 fingerprint reader



Silicone (EcoFlex) | Gelatin | Latex Body Paint | Silicone (EcoFlex) with Silver Colloidal | Silicone (EcoFlex) with NanoTips | Silicone (EcoFlex) with BarePaint | Crayola Model Magic | Wood Glue | Monster Liquid Latex | 2D Printed (Office Paper)

Government Controlled Tests (GCT-I)

Transparency

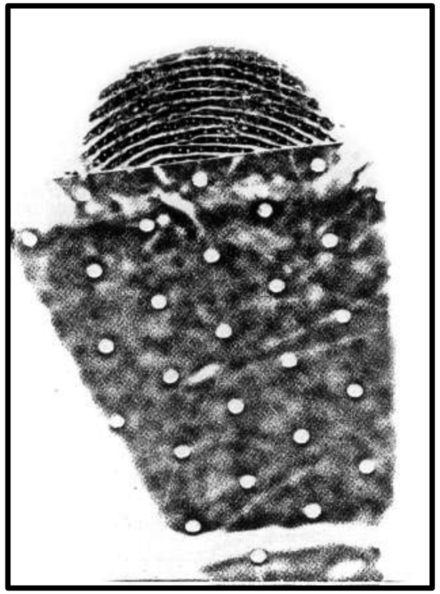
DragonSkin

Yellow Special

Veroblack Plus

Phase	Name	PA Types	#PA	#Bonafide	#Subjects	TDR @ FDR = 0.2%
Phase 1	GCT - I	4	232	6,781	400	99.60
Phase 2	GCT - II	8+	746	7,852	410	99.87
	GCT - III	12+	1,049	13,241	685	99.81

Government Controlled Tests (GCT-II)



Band-aid

Elmer's Glue

Ecoflex

Yellow Special

Veroblack Plus

Pigmented Silicone

Phase	Name	PA Types	#PA	#Bonafide	#Subjects	TDR @ FDR = 0.2%
Phase 1	GCT - I	4	232	6,781	400	99.60
Phase 2	**GCT - II**	**8+**	**746**	**7,852**	**410**	**99.87**
	GCT - III	12+	1,049	13,241	685	99.81

Government Controlled Tests (GCT-III)

Gelatin

Third Degree

Ecoflex (tan)

Nusil R-2631

Condutive Silicone

Unknown PA

Phase	Name	PA Types	#PA	#Bonafide	#Subjects	TDR @ FDR = 0.2%
Phase 1	GCT - I	4	232	6,781	400	99.60
Phase 2	GCT - II	8+	746	7,852	410	99.87
	GCT - III	**12+**	**1,049**	**13,241**	**685**	**99.81**

Bonafide Misclassifications (GCT-III)

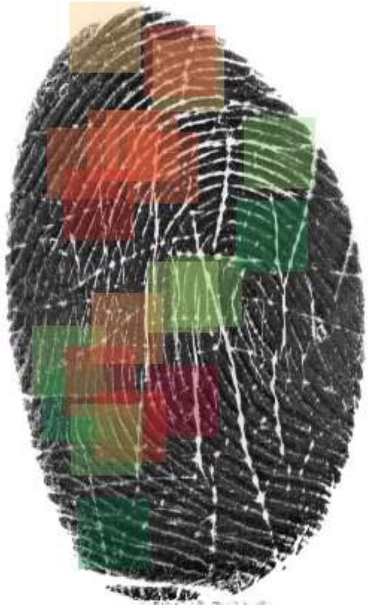
- **Bonafide** misclassified as **PA**

SS: 0.94

No minutiae detected

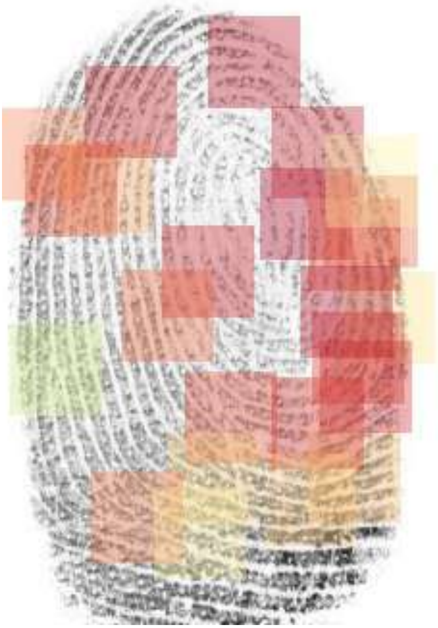
SS: 0.76

No minutiae detected



SS: 0.67

Sweaty Finger



SS: 0.65

Dry Finger

SS: 0.56

Injured Finger

SS: 0.56

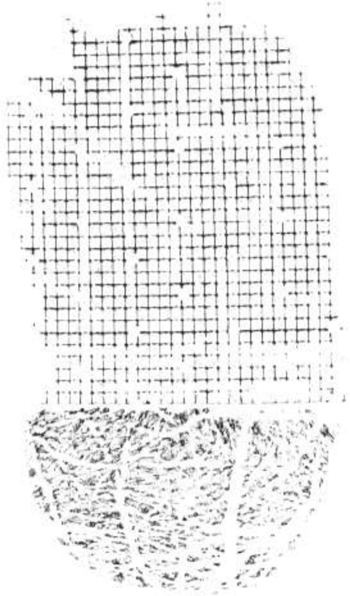
Noisy Print/ Artefacts

PA Misclassifications (GCT-III)

- **PA** misclassified as **bonafide**

SS: 0.01

Knox Clear Gelatin

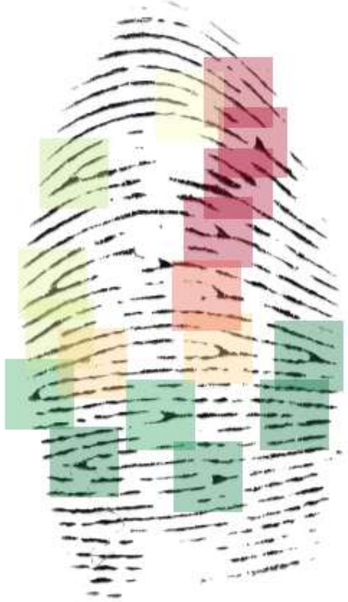


SS: 0.14

Unknown PA (Recipe 1)

SS: 0.25

Knox Clear Gelatin



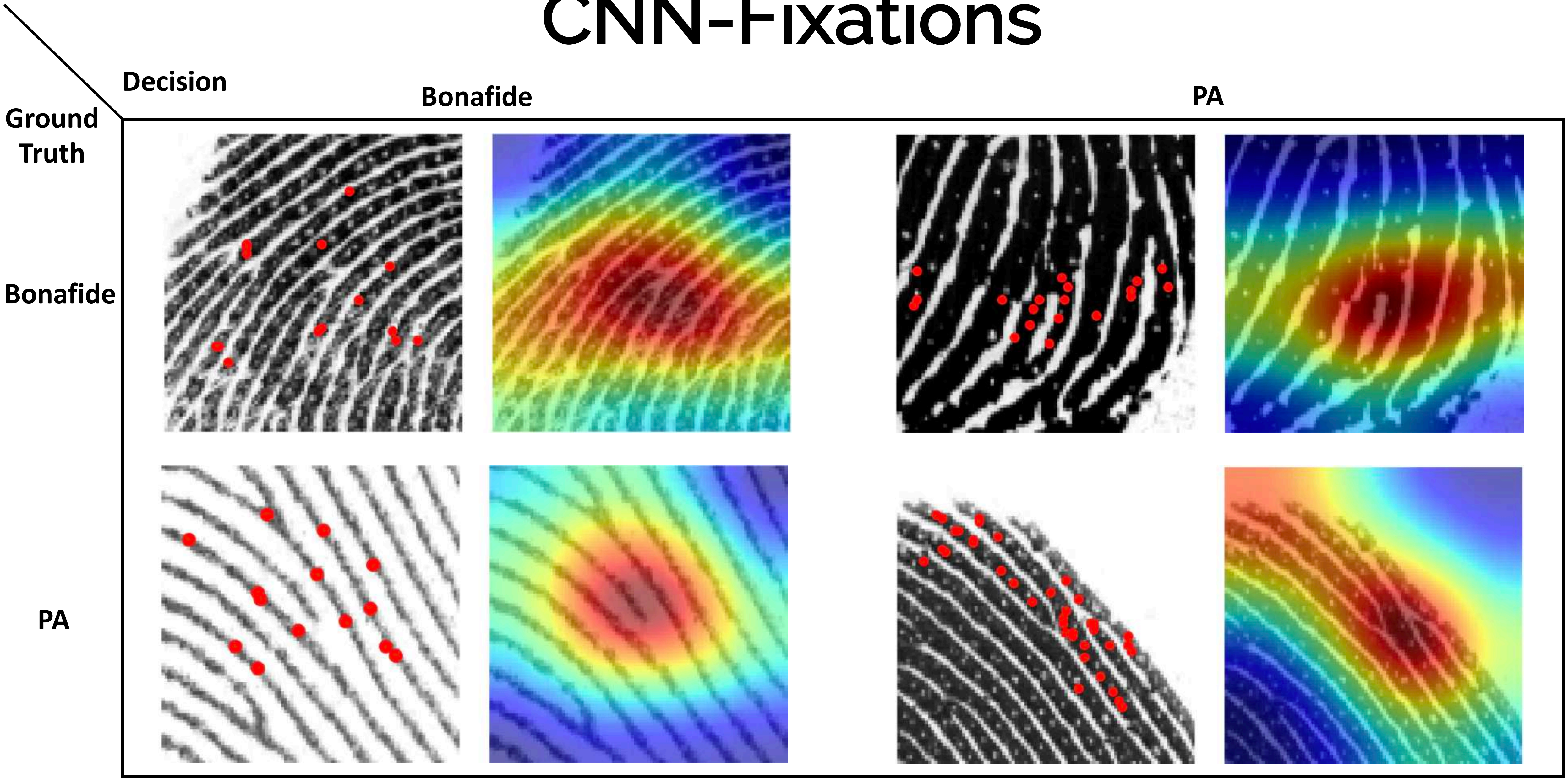
SS: 0.39

Nusil R-2631

SS: 0.42

Third Degree (Beige Suade Powder)

CNN-Fixations

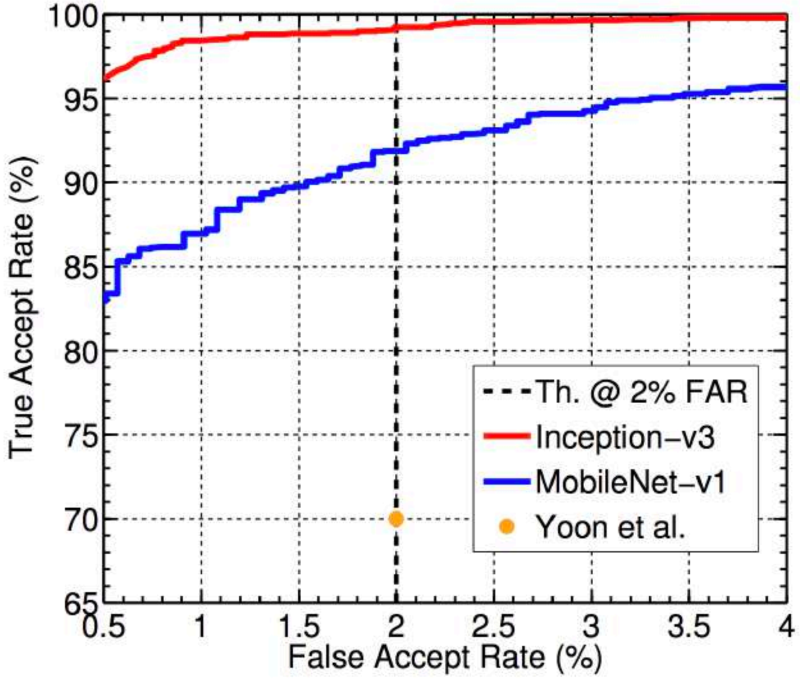


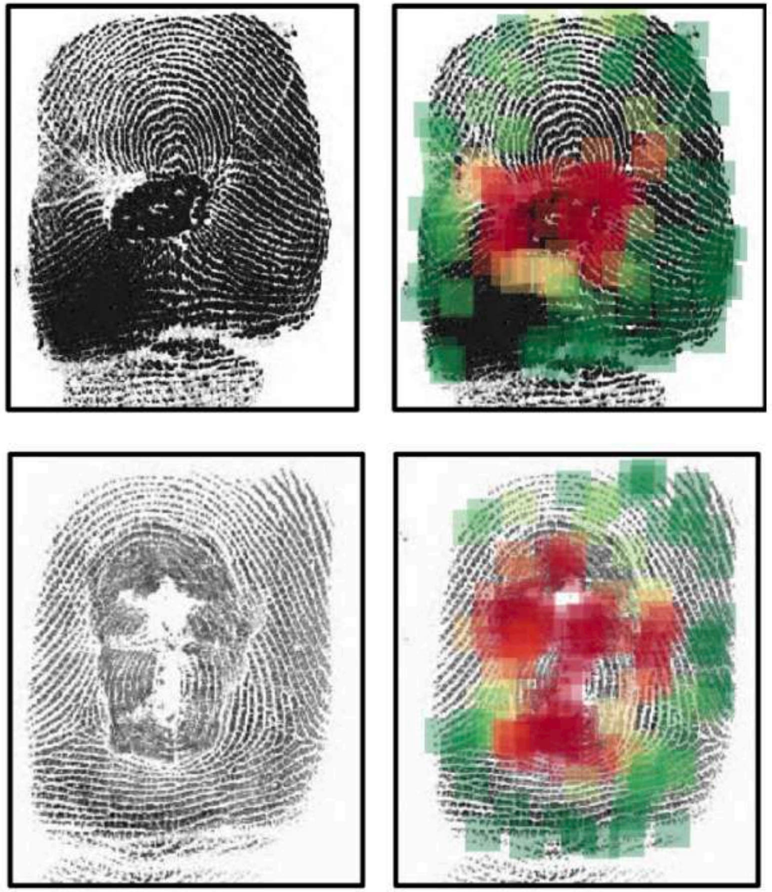
Spoof Buster focuses on pores and ridges around minutiae

Altered Fingerprint: Detection and Localization

- Altered fingerprints consist bona fide friction ridge regions as well as noisy altered regions
- Whole image-based approach utilized for detection, cascaded with minutiae-based approach for localization

- Operational dataset
  - 3,852 Bonafide fingerprints
  - 3,852 altered fingerprints



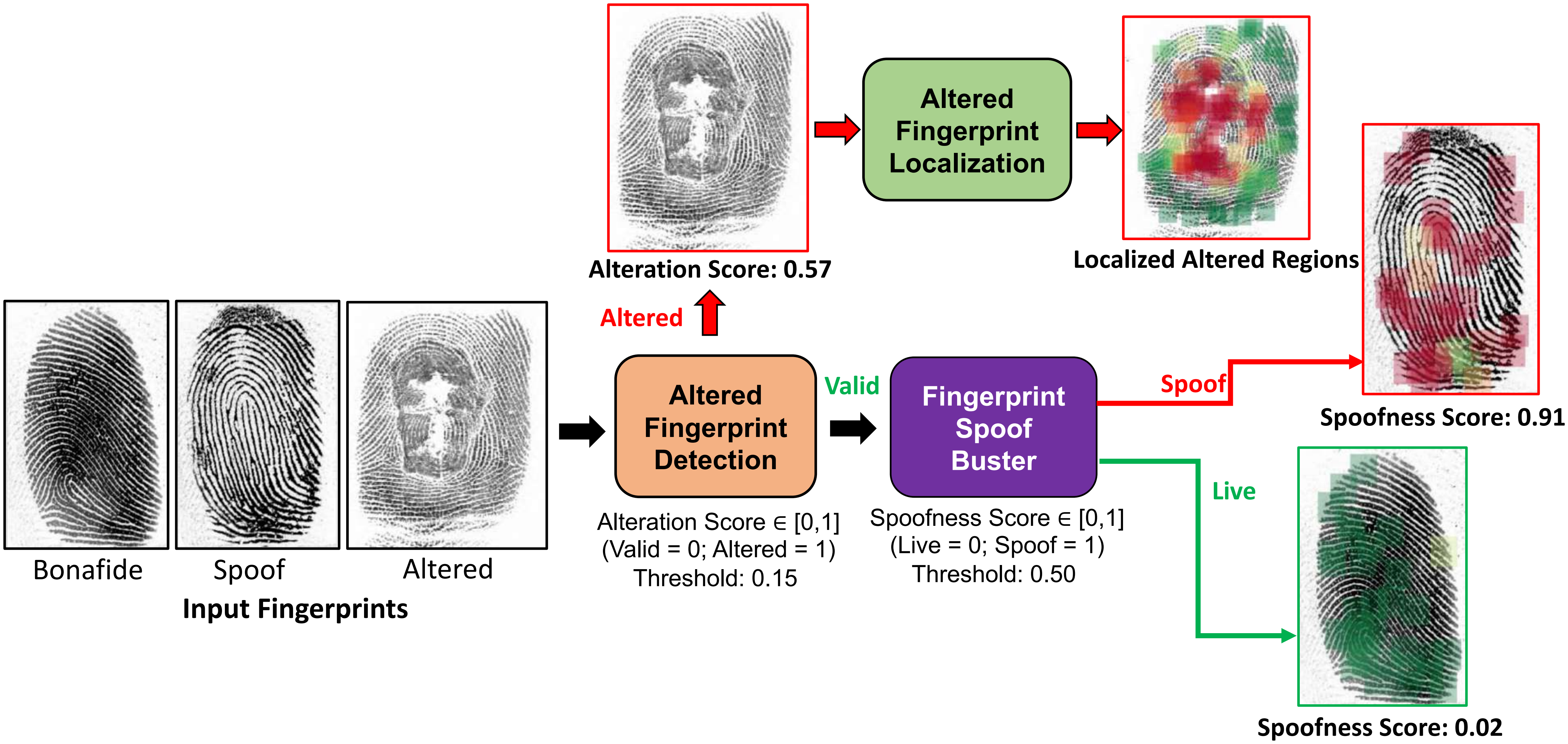


Fingerprint Alteration Localization

TDR = 99.2% +/- 0.54% @ FDR = 2% over five folds

E. Tabassi, **T. Chugh**, D. Deb, A. K. Jain, "Altered Fingerprints: Detection and Localization", in BTAS, Oct. 2018.
S. Yoon, J. Feng and A. K. Jain, "Altered Fingerprints: Analysis and Detection", *IEEE TPAMI*, Vol. 34, No. 3, pp. 451-464, March 2012.

End-to-End PA Detection



Proposed Approach: Strengths and Limitations

Strengths

- Minutiae-based local patches
  - Focus on friction ridge details; ignores white background
  - Alignment using minutiae orientation; homogeneity in training/testing data
  - Fixed amount of information in one patch; 12-13 px. ridge spacing
  - No distortion on resizing the square patches
- Training Data
  - Large amount of local patch-based data to train network from scratch (40x - 50x)
  - Diverse demographics, pressure variations, PA types
- CNN Architecture
  - Factorized larger convolutions
  - Label smoothing to prevent over-fitting
  - Fixates on ridge-valley noise, pores and their distribution, ridge width

Limitations

- Drop in performance against unknown PA materials (from TDR of 99% to 75% @ FDR = 0.2%)
- High Memory and Computation Requirements

Generalizability

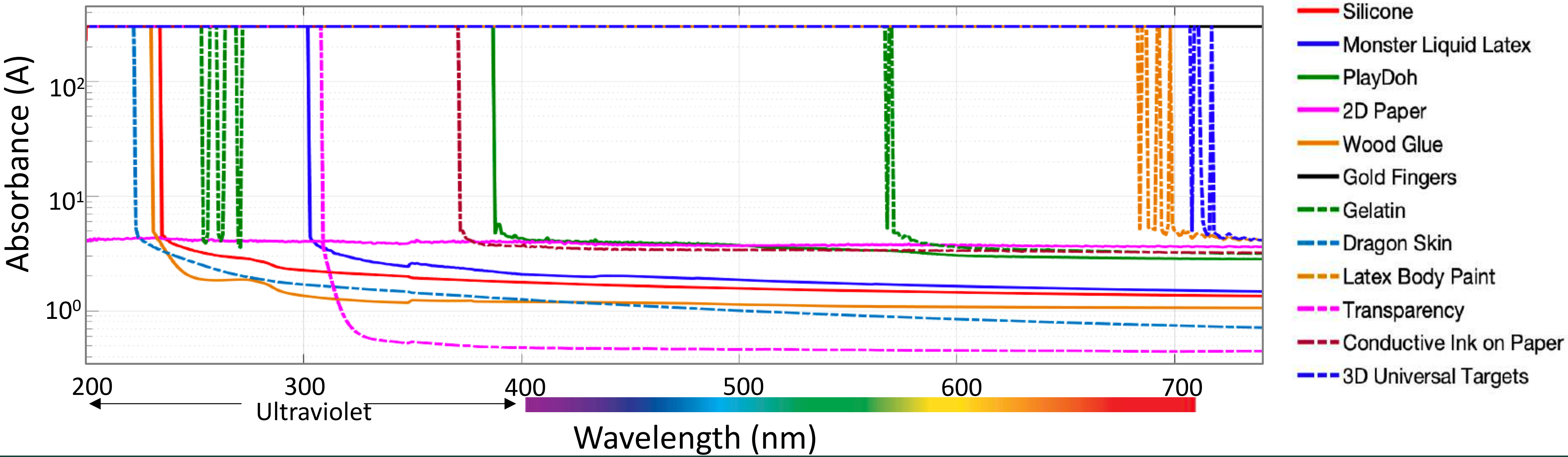
- Performance against unknown and unseen PA materials
- Leave-one-out protocol to evaluate generalization performance
- One material is left out from training, and then tested on it
- Some materials (e.g. Dragon Skin) are easier to detect compared to others (e.g. gelatin); but the reasons are unknown

PA Material Class	# Images	Generalization Performance TDR(%) @ FDR = 0.2%
Silicone	1,160	67.62
Monster Liquid Latex	882	94.77
Play Doh	715	58.42
2D Printed Paper	481	55.44
Wood Glue	397	86.38
Gold Fingers	295	88.22
Gelatin	294	54.95
Dragon Skin	285	97.48
Transparency	137	76.35
Conductive Ink	50	90.00
3D Univ. Targets	40	95.00
Total PAs	4,932	75.24

Generalization Performance Explained

- Investigated material characteristics (two optical and two physical)
- Optical Properties
  - UV-Vis Spectroscopy

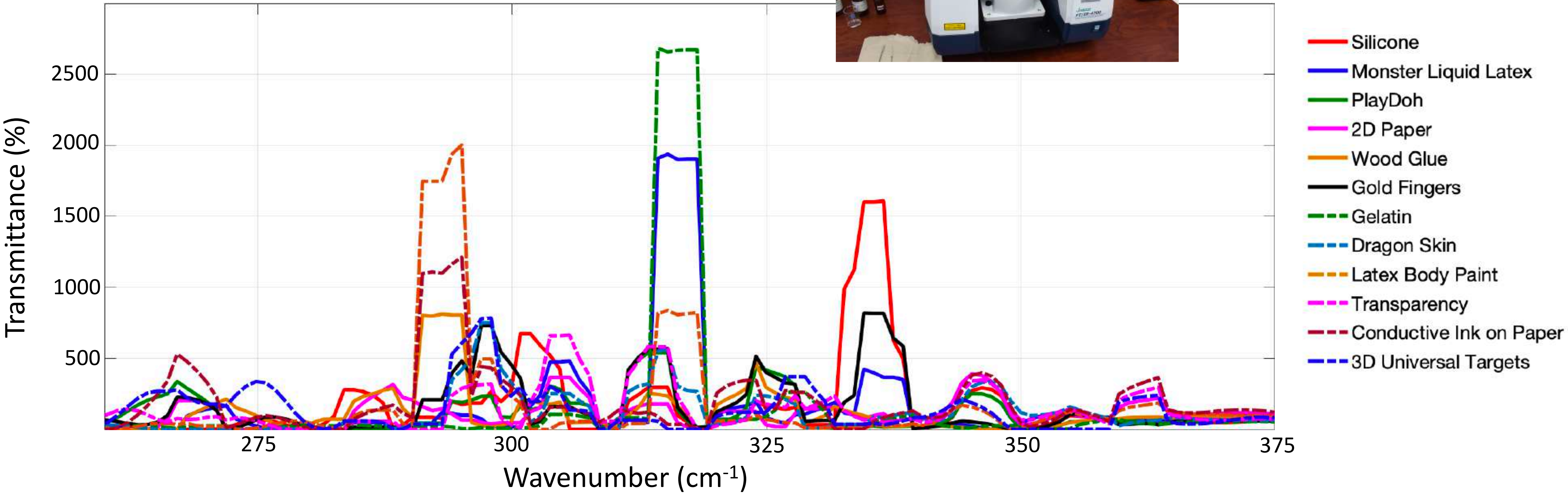
Perkin Elmer Lambda 900
UV/Vis/NIR Spectrometer



Generalization Performance Explained

- Investigated material characteristics (two optical and two physical)
- Optical Properties
  - UV-Vis Spectroscopy
  - FT/IR Spectroscopy

Jasco FT/IR-4600 Spectrometer



Generalization Performance Explained

- Investigated material characteristics (two optical and two physical)
- Optical Properties
  - UV-Vis Spectroscopy
  - FT/IR Spectroscopy
- Physical Properties
  - Material Elasticity
  - Moisture Content

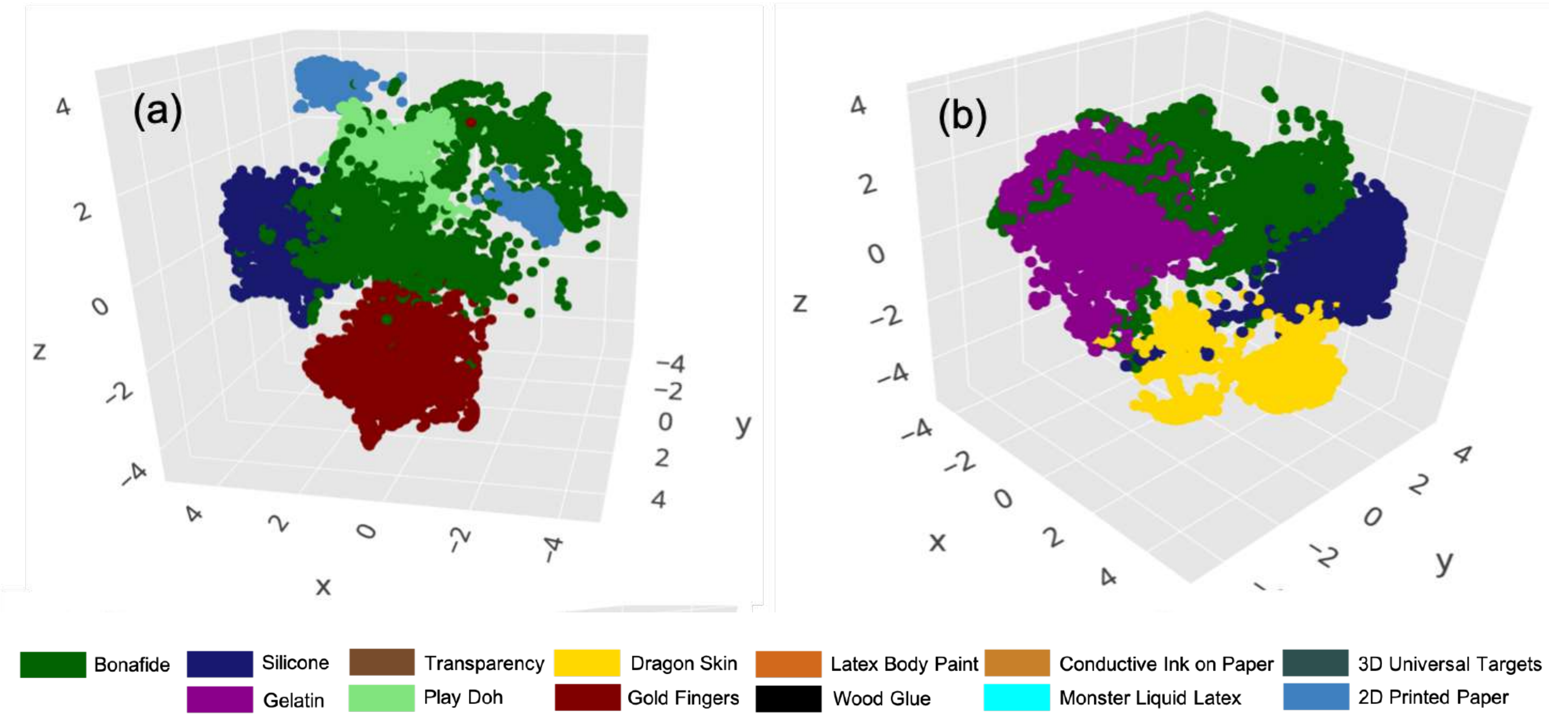
Observed Elasticity	Materials
High	Silicone, Monster Liquid Latex, Dragon Skin, Wood Glue, Gelatin
Medium	Play Doh, Latex Body Paint, 3D Universal Targets
Low	2D Paper, Gold Fingers, Transparency, Conductive Ink on Paper

Moisture Content	Materials
High	Silicone, Play Doh, Dragon Skin
Medium	Monster Liquid latex, Wood Glue, Gold Fingers, Gelatin, 3D Universal Targets
Low	2D Paper, Latex Body Paint, Transparency, Conductive Ink on Paper

Generalization Performance Explained

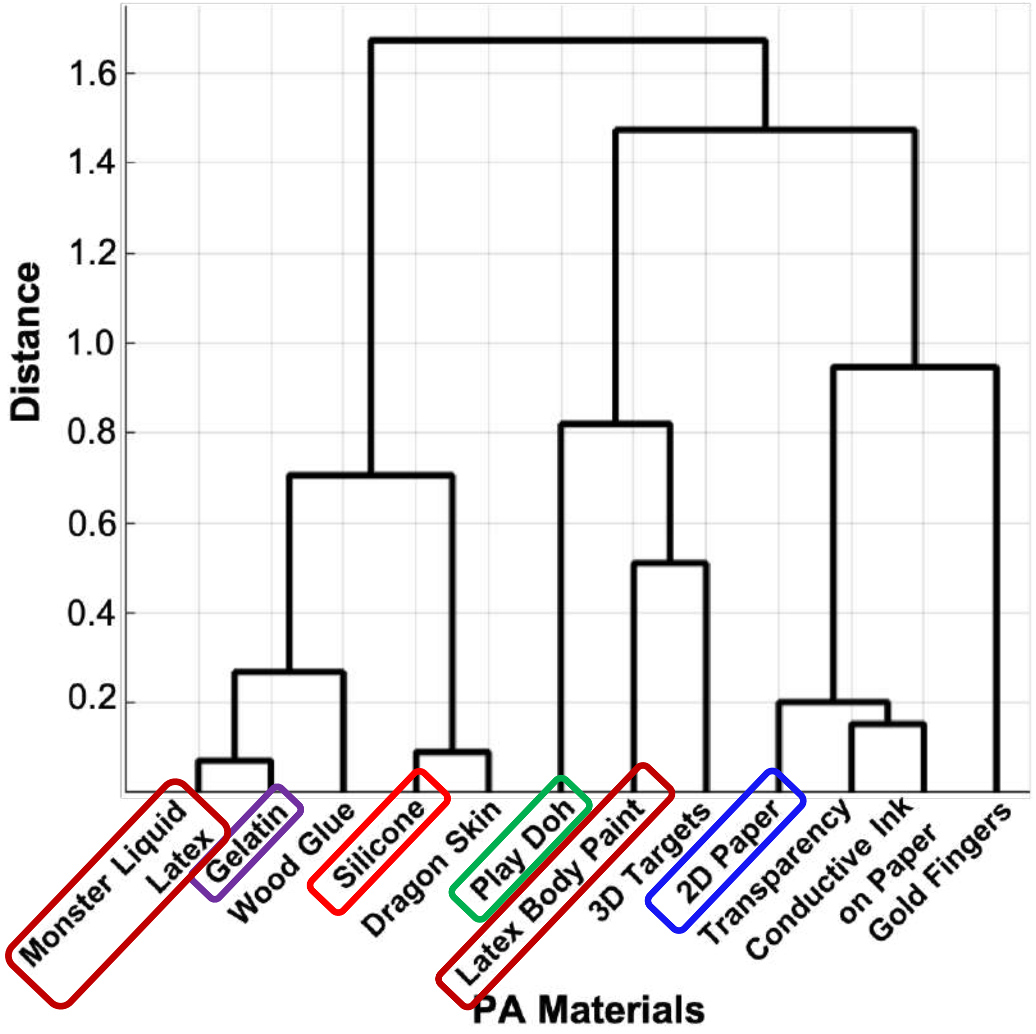
- Investigated material characteristics (two optical and two physical)
- Optical Properties
  - UV-Vis Spectroscopy
  - FT/IR Spectroscopy
- Physical Properties
  - Material Elasticity
  - Moisture Content
- Pearson Correlation

3D t-SNE Visualization



Representative Set of PA Materials

- Hierarchical clustering of PA materials based on their characteristics
- Identified a representative set of six PA materials, (i) Silicone, (ii) 2D Paper, (iii) Play Doh, (iv) Gelatin, (v) Latex Body Paint, and (vi) Monster Liquid Latex
- Almost covers the entire feature space around Bonafide
- Model trained on these six materials achieved TDR (89.8%) comparable to a model trained on 11 PA materials (90.9%)
- Random selection of six PA materials resulted in TDR ~ 68-70% @ FDR = 0.2%

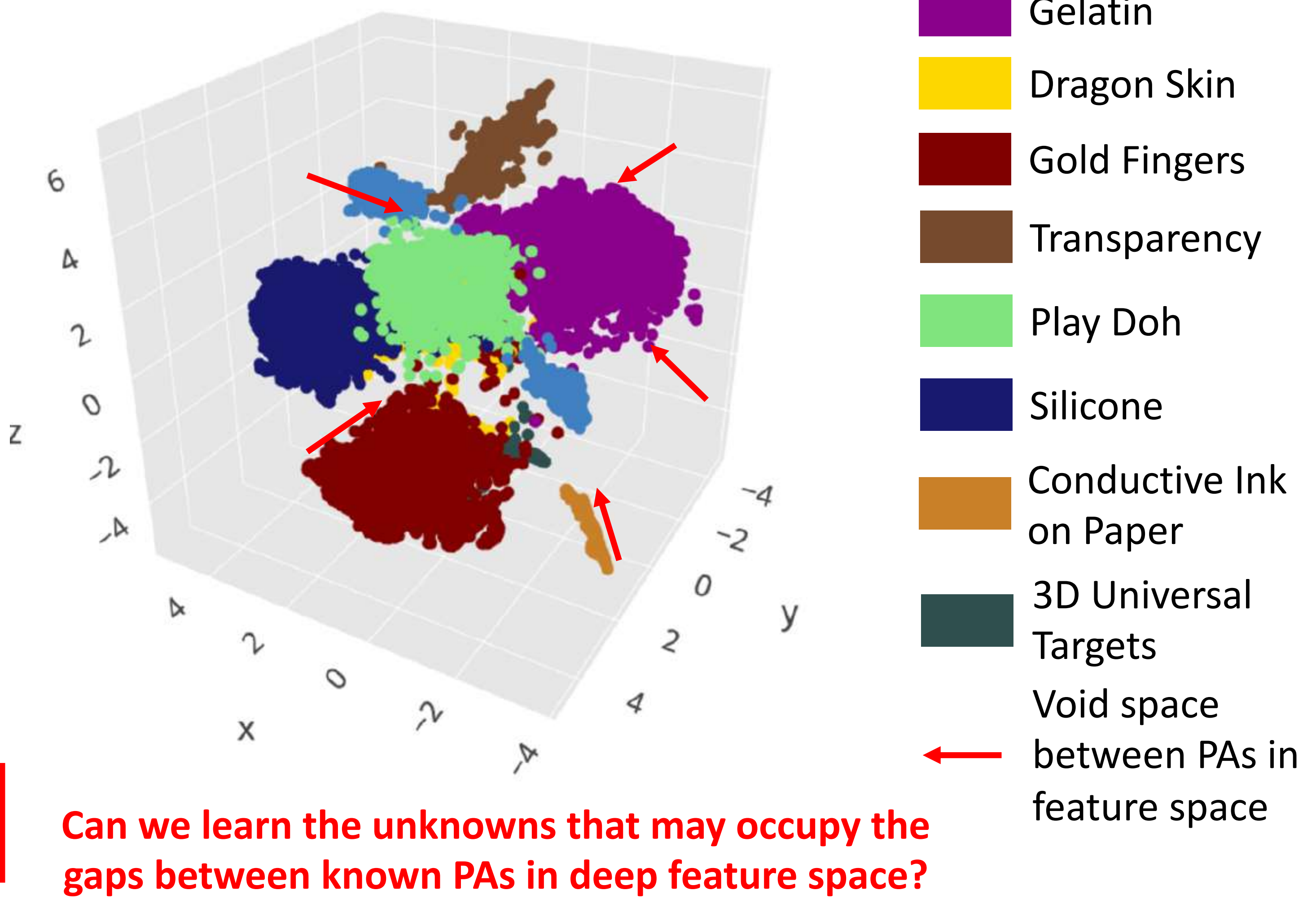


Fingerprint Spoof Generalization

Goal: Improve PAD performance against PA materials unknown during training

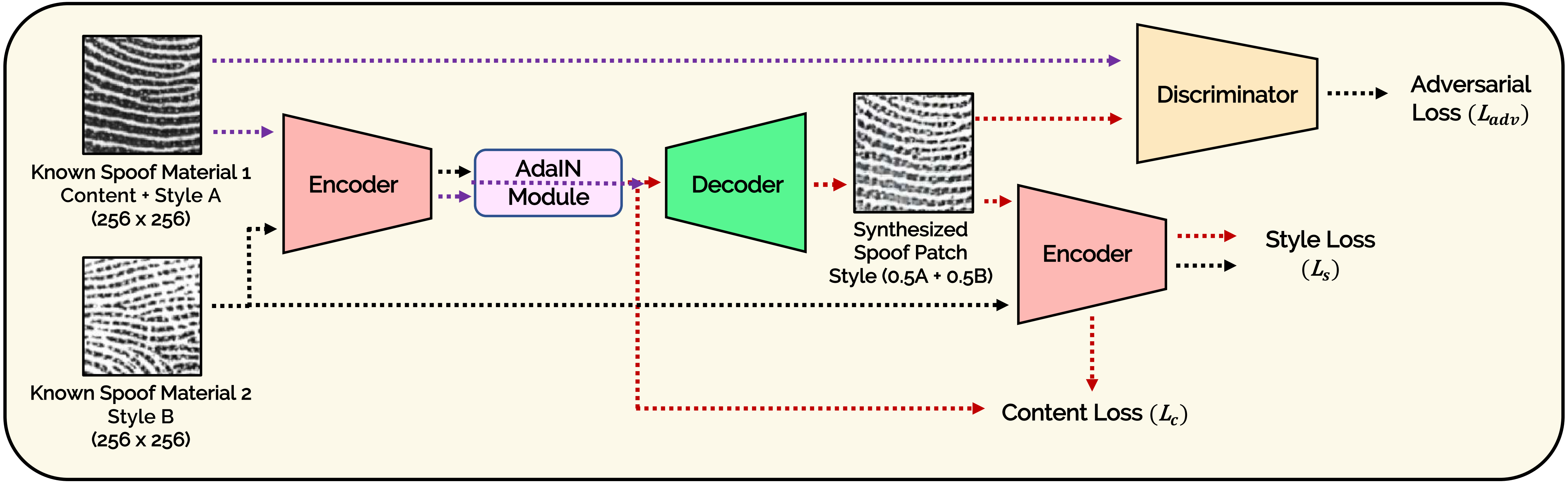
Cross-Material Performance

Fingerprint PA Material	#Images	#Local Patches	Generalization Performance (TDR (%) @ FDR = 0.2%)
Silicone	1,160	38,145	67.62
Monster Liquid Latex	882	27,458	94.77
Play Doh	715	17,602	58.42
2D Printed Paper	481	7,381	55.44
Wood Glue	397	12,681	86.38
Gold Fingers	295	9,402	88.22
Gelatin	294	10,508	54.95
Dragon Skin	285	7,700	97.48
Latex Body Paint	176	6,366	76.35
Transparency	137	3,846	95.83
Conductive Ink on Paper	50	2,205	90.00
3D Universal Targets	40	1,085	95.00
Total PAs	4,912	144,379	Weighted
Total Bonafide	5,743	228,143	Average: 75.24



T. Chugh, A. K. Jain, "Fingerprint Presentation Attack Detection: Generalization and Efficiency", Int'l Conf. on Biometrics (ICB), Crete, 2018

Proposed Approach: Universal Material Generator

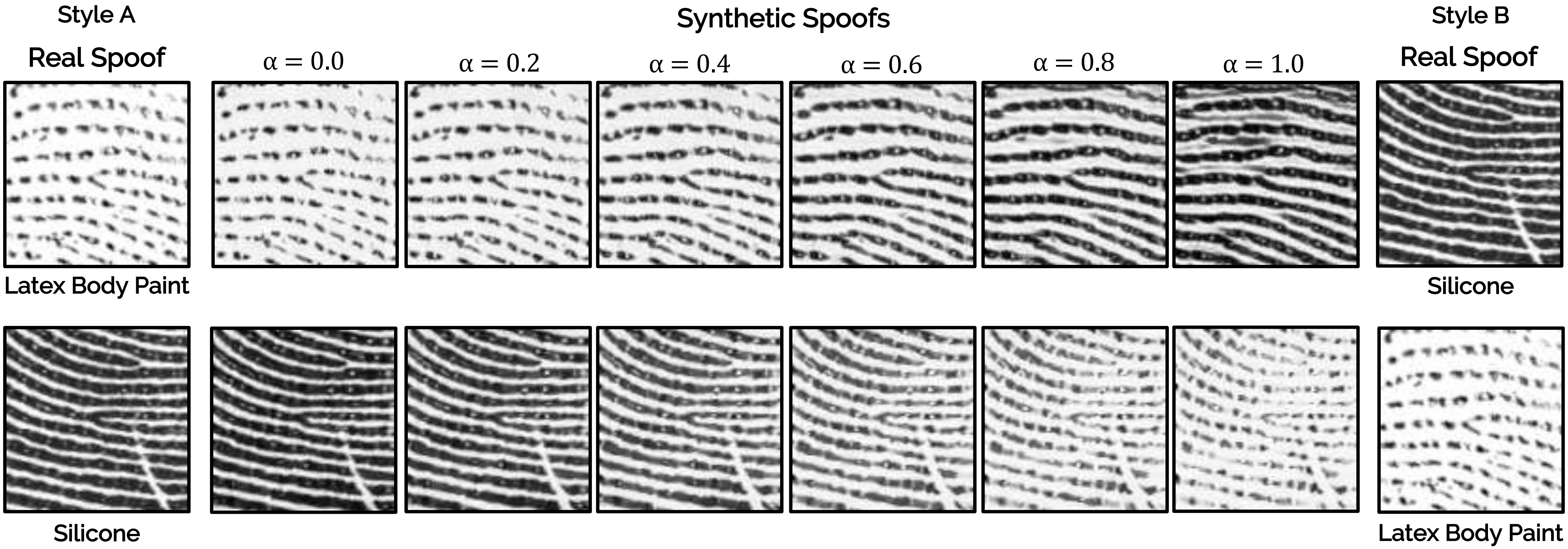


- Style transfer-based wrapper
- Transfer style (texture) characteristics between known PAs

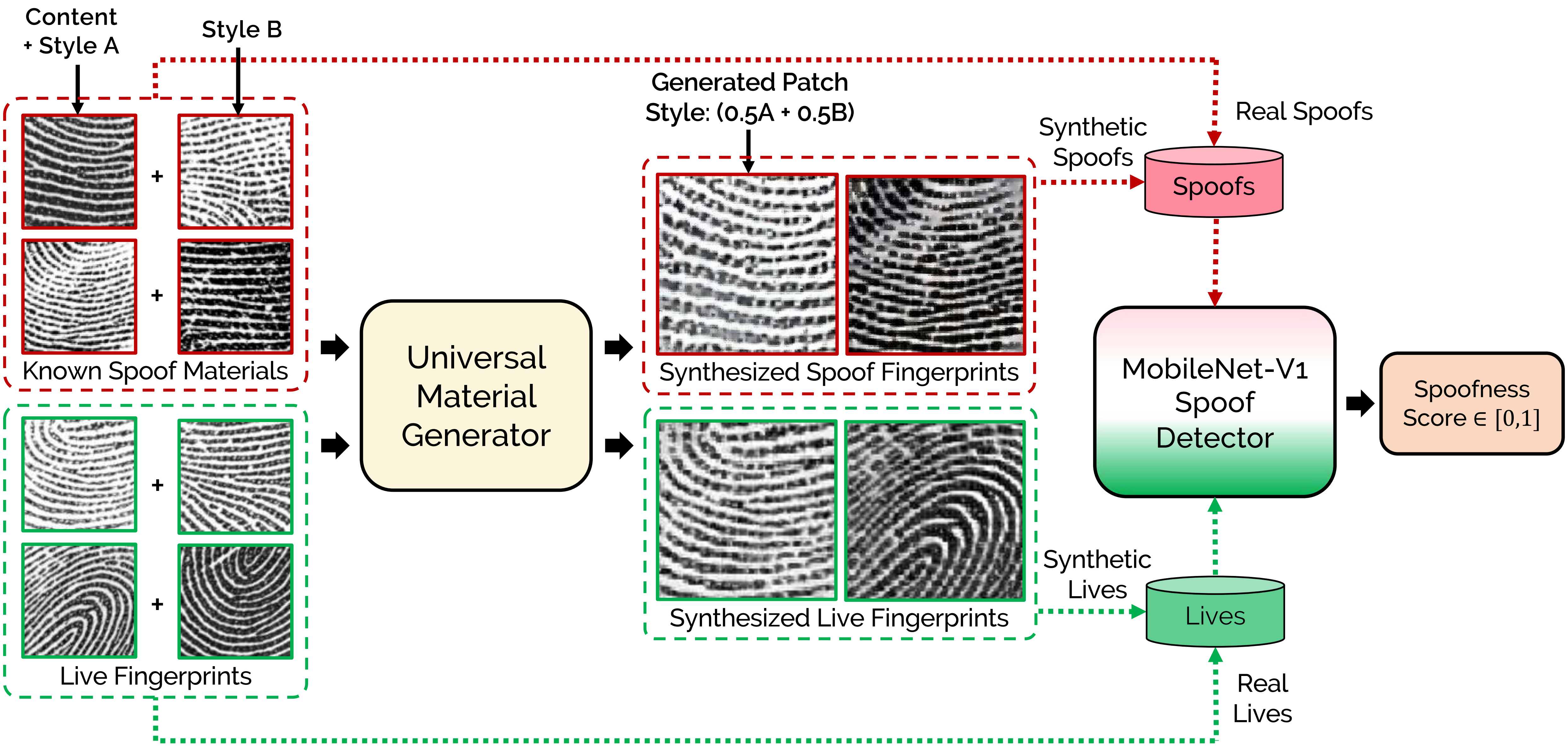
$$AdaIN(x, y) = \sigma(y)\left(\frac{x - \mu(x)}{\sigma(x)}\right) + \mu(y)$$

[1] T. Chugh and A. K. Jain, "Fingerprint Spoof Generalization", arXiv:1912.02710, 2019
[2] 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.

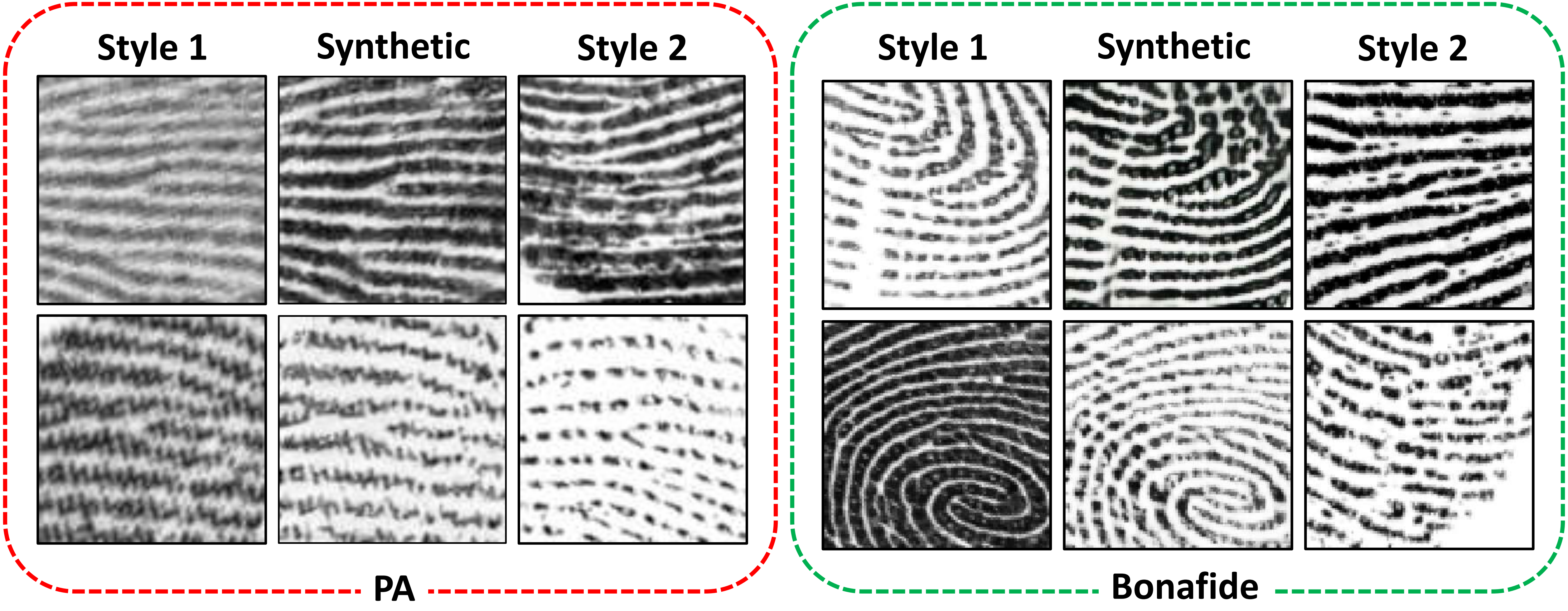
Control Extent of Style Transfer



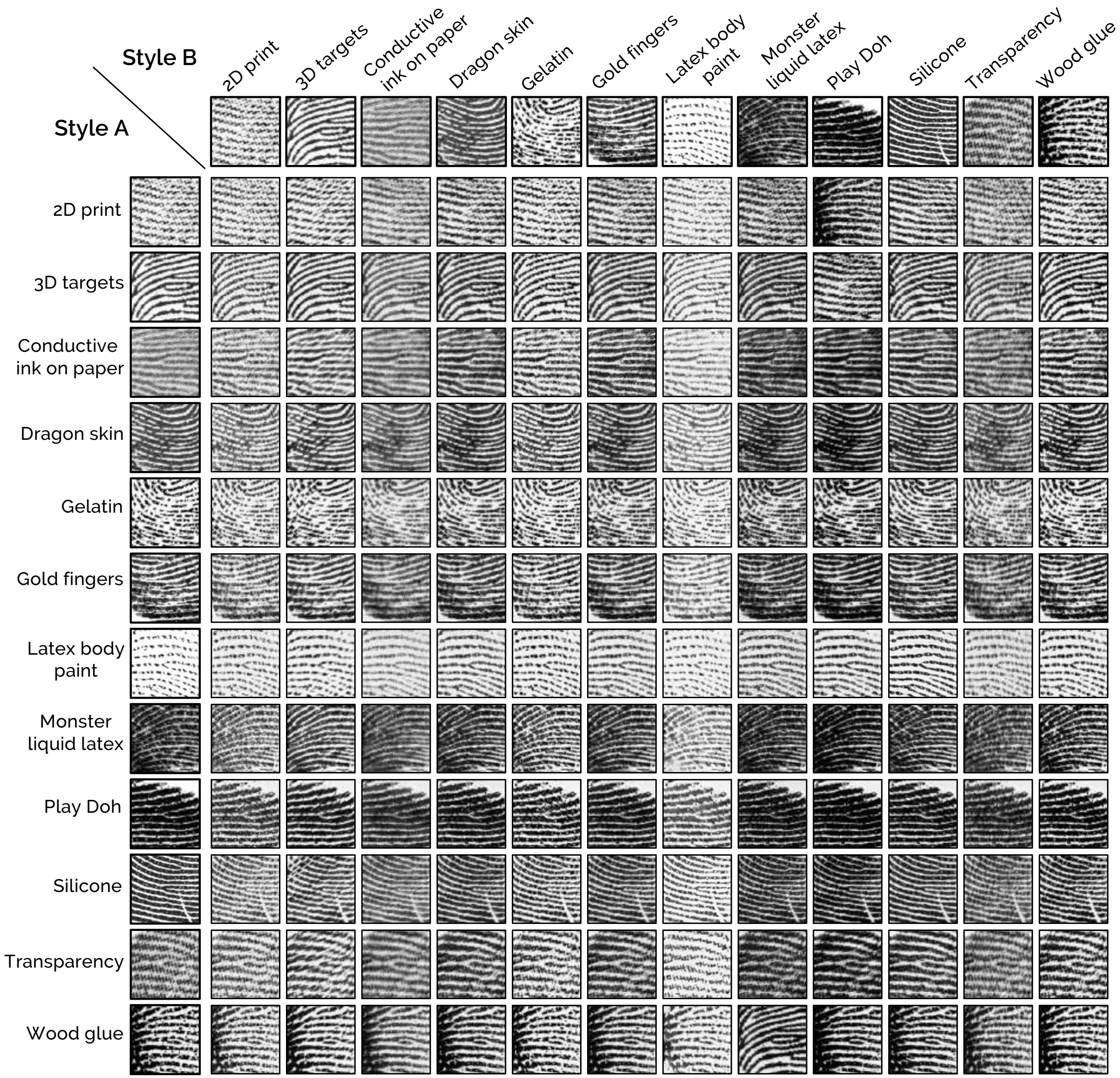
Proposed Approach: Universal Material Generator

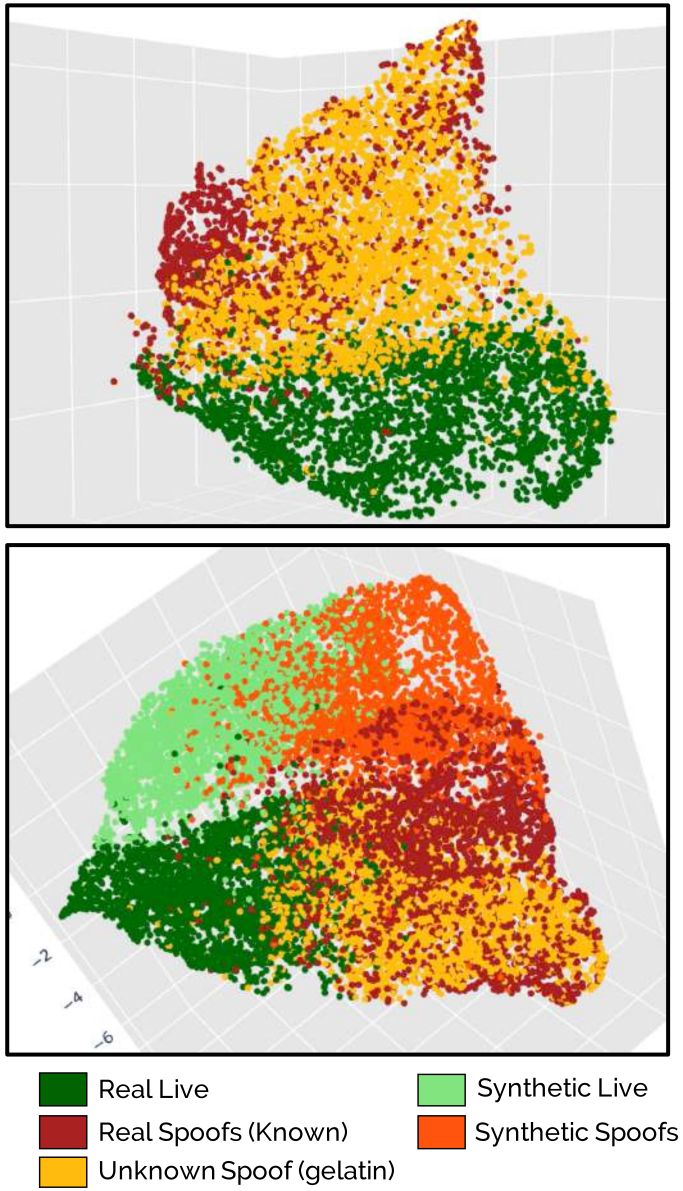


Universal Material Generator: Samples



Universal Material Generator: Samples





[3D Plot]()

Fingerprint Spoof Generalization: Results

Unknown Spoof Material	# Images	# Local Patches	Generalization Performance (TDR @ FDR = 0.2%)	
			Fingerprint Spoof Buster (FSB) [31]	Proposed Approach (FSB + UMG wrapper)
Silicone	1,160	38,145	67.62	**98.64**
Monster Liquid Latex	882	27,458	94.77	**96.24**
Play Doh	715	17,602	58.42	**72.36**
2D Printed Paper	481	7,381	55.44	**80.22**
Wood Glue	397	12,681	86.38	**98.97**
Gold Fingers	295	9,402	88.22	**88.59**
Gelatin	294	10,508	54.95	97.96
Dragon Skin	285	7,700	97.48	**100.00**
Latex Body Paint	176	6,366	76.35	**89.72**
Transparency	137	3,846	95.83	**100.00**
Conductive Ink on Paper	50	2,205	90.00	**100.00**
3D Universal Targets	40	1,085	95.00	**100.00**
Total PAs	**4,912**	**144,379**	Weighted Average (± weighted s.d.)	
Total Bonafide	**5,743**	**228,143**	**75.24 (± 15.21)**	**91.78 (± 9.43)**

Performance improved from TDR = 75.24% to 91.78% @ FDR = 0.2%

Fabricating Unknown Spoofs

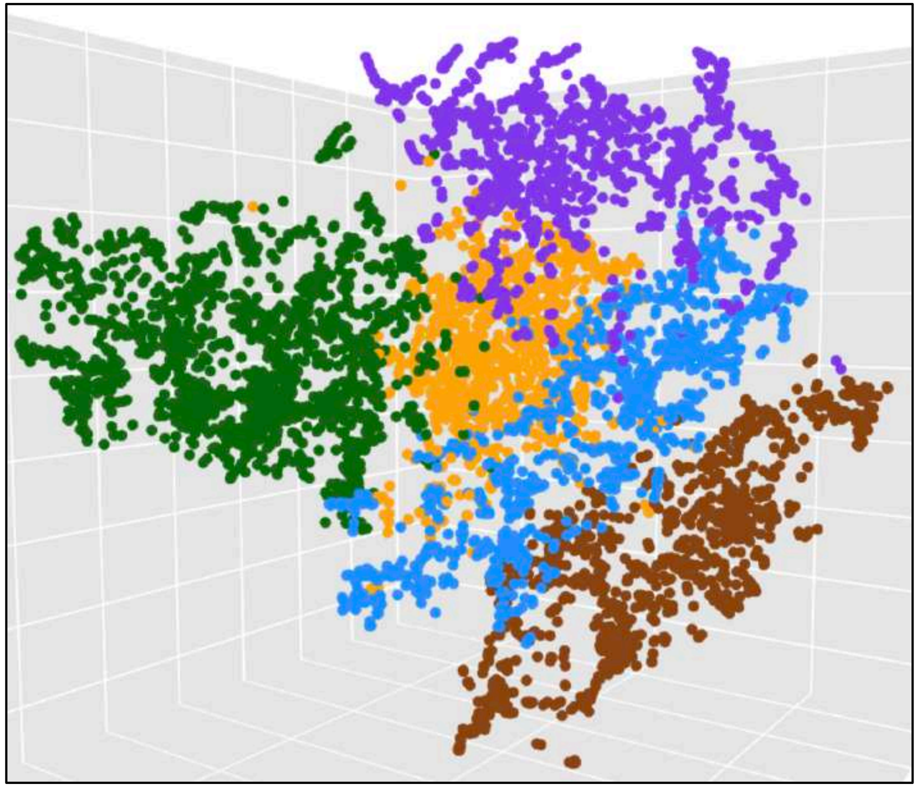
Spoof Mixture

(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)



Silicone (real spoof)
Real Live
Latex Body Paint (real spoof)
Real Spoof Mixture (silicone + latex body paint)
Synthetically Generated Spoof
(style transfer b/w silicone and latex body paint)

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

Cross-Sensor PA Detection

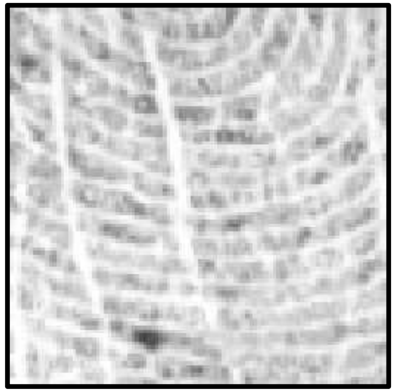
LivDet 2017

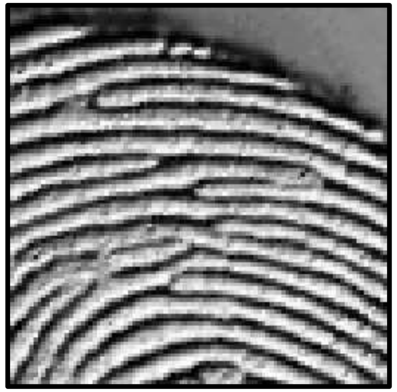

Digital Persona

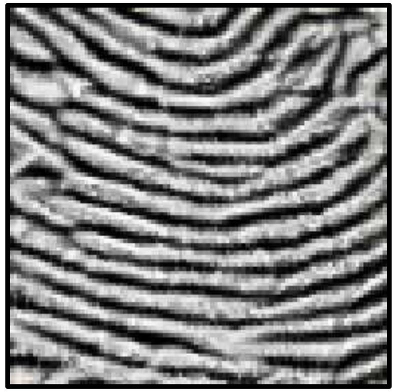

Green Bit


Orcanthus

UMG Style Transfer


(a) Real Live Patch
Digital Persona


(b) Real Live Patch
Orcanthus


(c) Synthesized Live Patch
UMG Wrapper

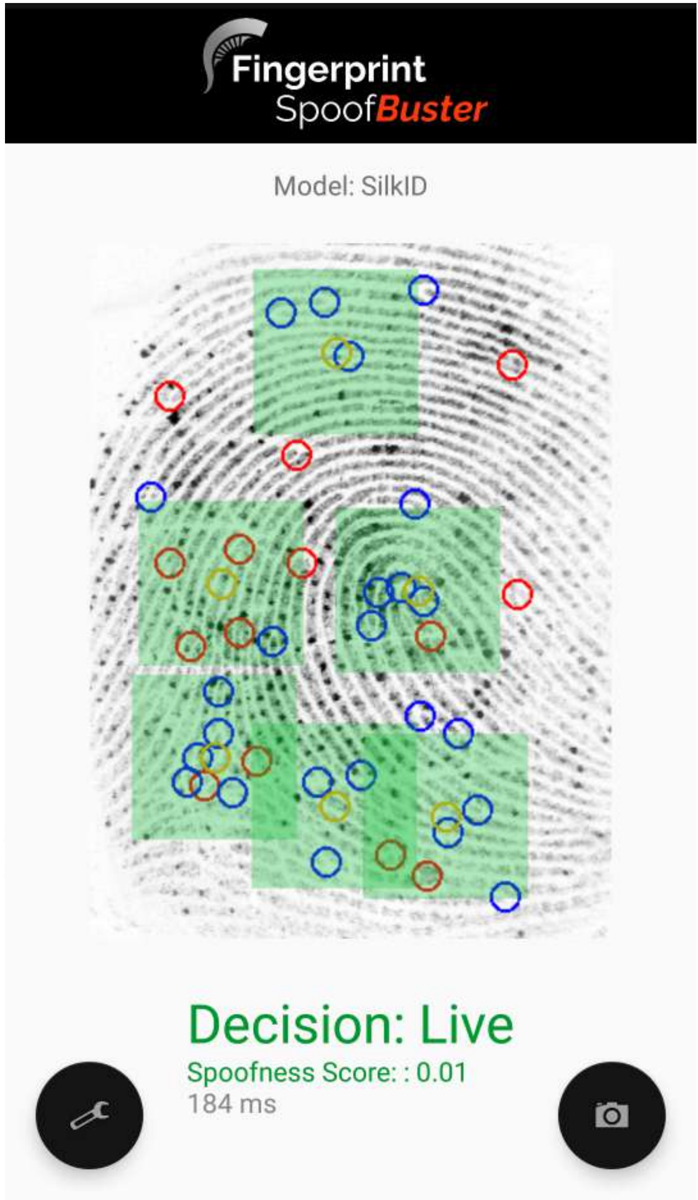
LivDet 2017		Fingerprint Spoof Buster [26]		Fingerprint Spoof Buster + UMG wrapper	
Sensor in Training	**Sensor in Testing**	**ACE (%)**	**TDR @ FDR = 1.0%**	**ACE (%)**	**TDR @ FDR = 1.0%**
Green Bit	Orcanthus	49.43	0.00	**66.05**	**21.52**
Green Bit	Digital Persona	89.37	57.48	**94.81**	**72.91**
Orcanthus	GreenBit	69.93	8.00	**81.75**	**30.91**
Orcanthus	Digital Persona	57.99	4.97	**76.36**	**28.46**
Digital Persona	GreenBit	89.54	57.06	**96.35**	**85.21**
Digital Persona	Orcanthus	49.32	0.00	**68.44**	**20.38**
Mean ± s.d.		67.60 ± 18.53	21.25 ± 28.07	**80.63 ± 12.88**	**43.23 ± 28.31**

Efficiency

- Current approach utilize all minutiae-based patches
- **Idea**: Reduce redundant computations
- **Approach**: K-means clustering followed by weighted fusion

Time required to evaluate minutiae-based patches

# Minutiae Clusters	Time Required (in ms)	TDR (%) @ FDR = 0.2% (GCT Data)
5	53 ± 10	93.9
10	$\mathbf{98 \pm 8}$	**95.3**
15	151 ± 11	95.3
20	202 ± 10	95.3
25	247 ± 24	95.3
30	301 ± 25	95.3
All Minutiae (avg. = 35)	$\mathbf{510 \pm 26}$	**95.7**

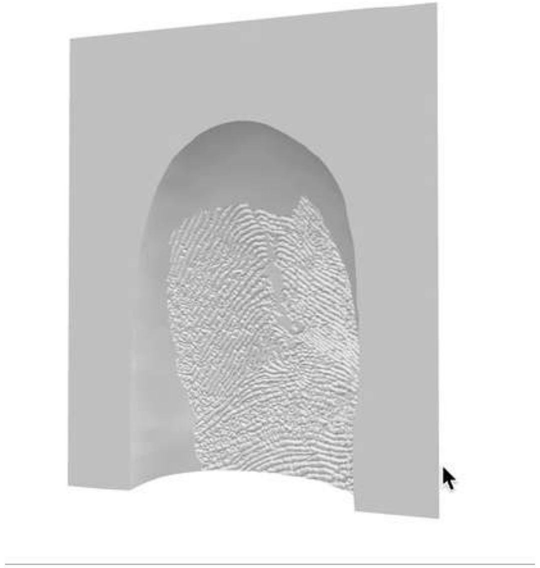


Summary

- Proposed a minutiae-based approach for fingerprint PAD
- Achieved state-of-the-art detection performance on publicly available LivDet databases, and excellent performance in IARPA ODIN program evaluations.
- Avg. detection time: < 100ms (Samsung S8); <30ms on GPU (1080Ti)
- Investigated material characteristics to understand and improve generalization performance; identified a subset of 6 crucial PA materials
- Proposed a style transfer-based wrapper to improve the generalization performance

Possible Future Directions

- Cross-sensor performance using adversarial representation learning
- Interpretability of CNN learnings
- Discovering new PA types; Further improve generalization performance
- Altered Fingerprint Generation



3D Printing Altered Fingerprint Targets

List of Publications

Journal Articles

- **T. Chugh** and A. K. Jain, *Fingerprint Spoof Generalization*, arXiv:1912.02710, (under-review in TIFS), 2019
- **T. Chugh**, K. Cao, and A. K. Jain. *Fingerprint Spoof Buster: Use of Minutiae centered Patches*. IEEE Transactions on Information Forensics and Security (TIFS), 13(9):2190 - 2202, 2018.
- **T. Chugh**, K. Cao, J. Zhou, E. Tabassi, and A. K. Jain. *Latent Fingerprint Value Prediction: Crowd-based Learning*. IEEE Transactions on Information Forensics and Security (TIFS), 2017.

Conference Proceedings and Technical Reports

- **T. Chugh** and A. K. Jain, *Fingerprint Spoof Detection: Temporal Analysis of Image Sequence*, arXiv:1912.08240, 2019.
- **T. Chugh** and Anil K Jain. *OCT Fingerprints: Resilience to Presentation Attacks*. arXiv preprint arXiv:1908.00102, 2019.
- **T. Chugh** and Anil K Jain. *Fingerprint Presentation Attack Detection: Generalization and Efficiency*, In IEEE Int'l Conf. on Biometrics (ICB), 2019.
- R. Gajawada, A. Popli, **T. Chugh**, A. Namboodiri, and . K. Jain. *Universal Material Translator: Towards Spoof Fingerprint Generalization.* In IEEE Int'l Conf. on Biometrics (ICB), 2019.
- E. Tabassi, **T. Chugh**, D. Deb, and A. K. Jain. *Altered Fingerprints: Detection and Localization*. In IEEE In'l Conf. on Biometrics Theory, Applications and Systems (BTAS), 2018.
- **T. Chugh**, K. Cao, and A. K Jain. *Fingerprint Spoof Detection Using Minutiae-based Local Patches*. In Proc. IEEE Int'l Joint Conf. on Biometrics (IJCB), 2017.
- **T. Chugh**, S. S. Arora, A. K. Jain, and N. G. Paulter. *Benchmarking fingerprint minutiae extractors*. In IEEE Int'l Conf. of the Biometrics Special Interest Group (BIOSIG), 2017.
- K. Cao, **T. Chugh**, J. Zhou, E. Tabassi, and A. K. Jain. *Automatic latent value determination* In IEEE Int'l Conf. on Biometrics (ICB), 2016.

Acknowledgement

Prof. Anil K. Jain

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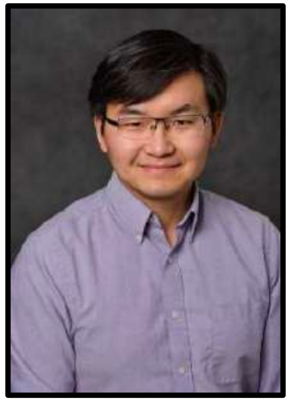
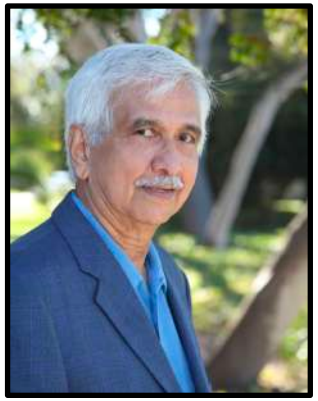


Prof. Xiaoming Liu



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Prof. Anoop M. Namboodiri

Chris Perry

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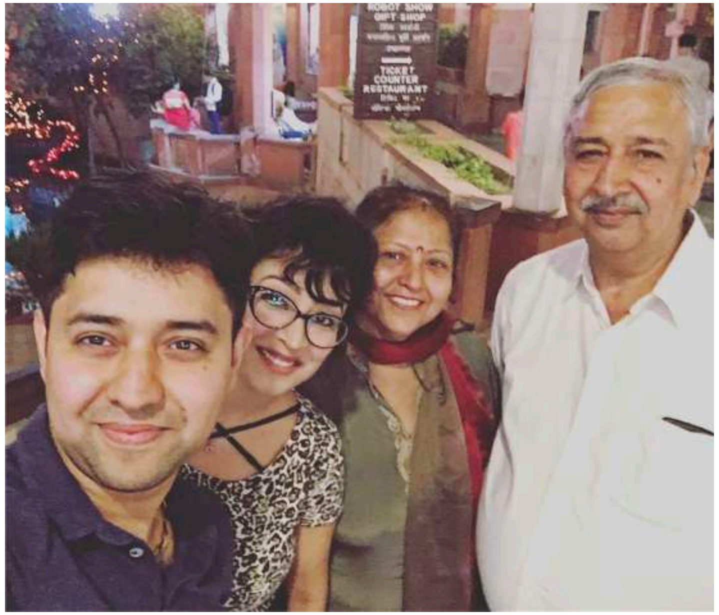
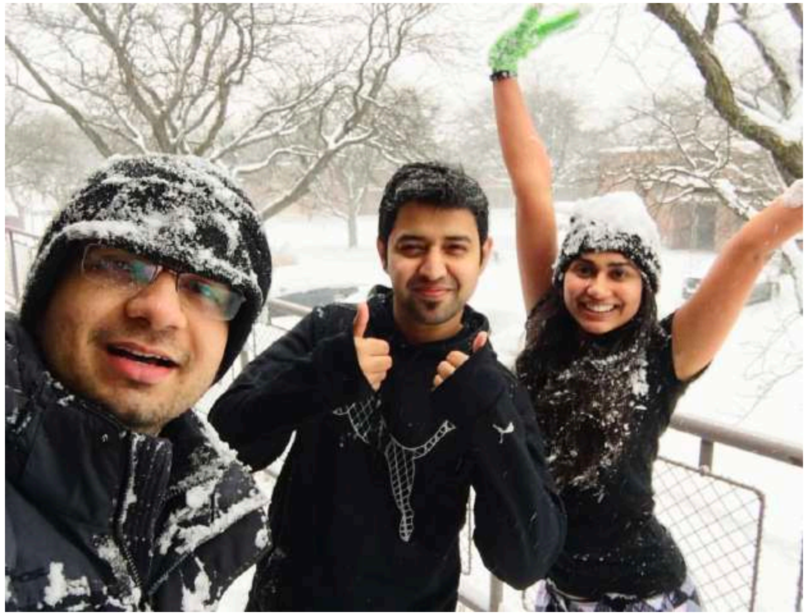
Acknowledgement





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Happy to answer any questions!