Automatic Latent Fingerprint Segmentation

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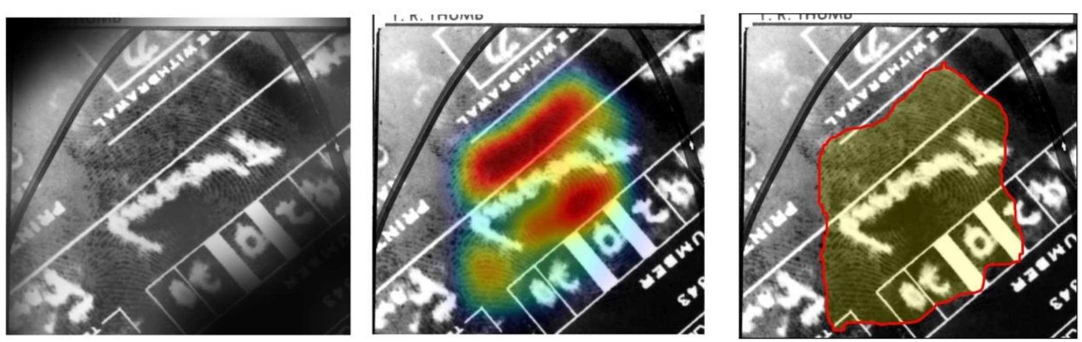
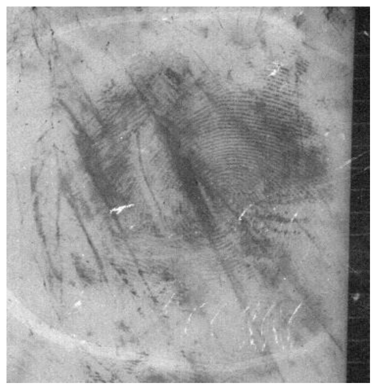
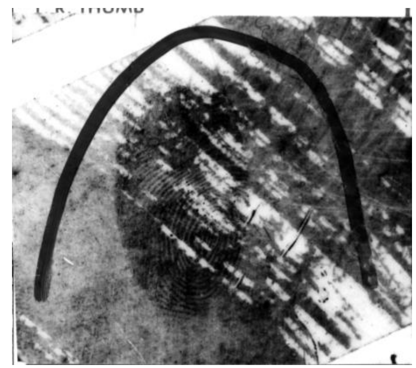
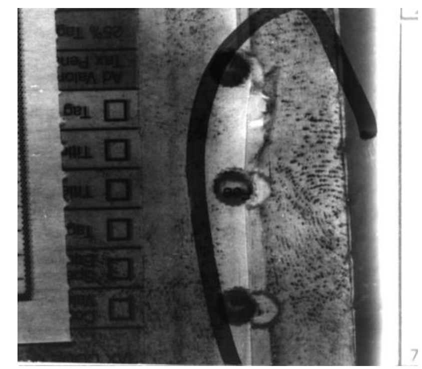


Introduction

Latent fingerprints: friction ridge impressions formed as a result of fingers touching a surface, particularly at a crime scene







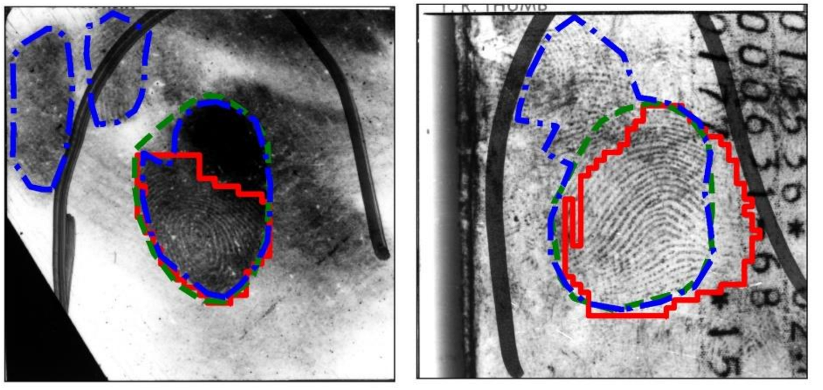
Why Latent Fingerprint Segmentation?

- Crucial step in the latent matching algorithm
- Different croppings of a latent lead to different recognition accuracies

Introduction

Why latents are challenging?

- Captured in an uncontrolled setting,
- Typically noisy and distorted
- Poor ridge clarity.

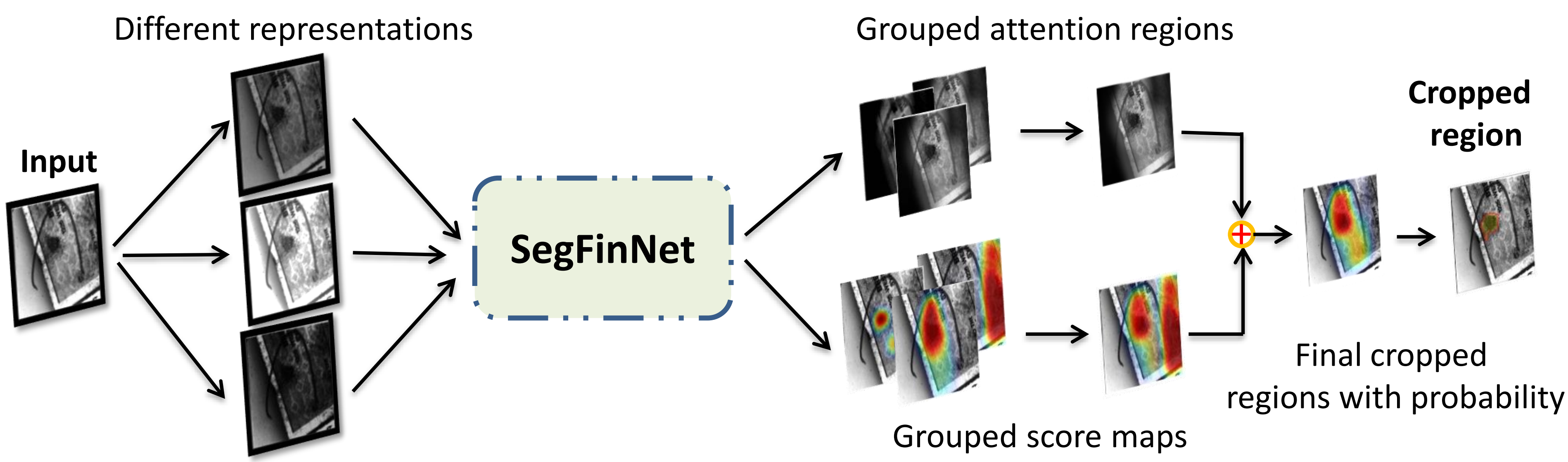


Different groundtruths (R,G,B)
for two latents in NIST SD27

Problems with manual cropping?

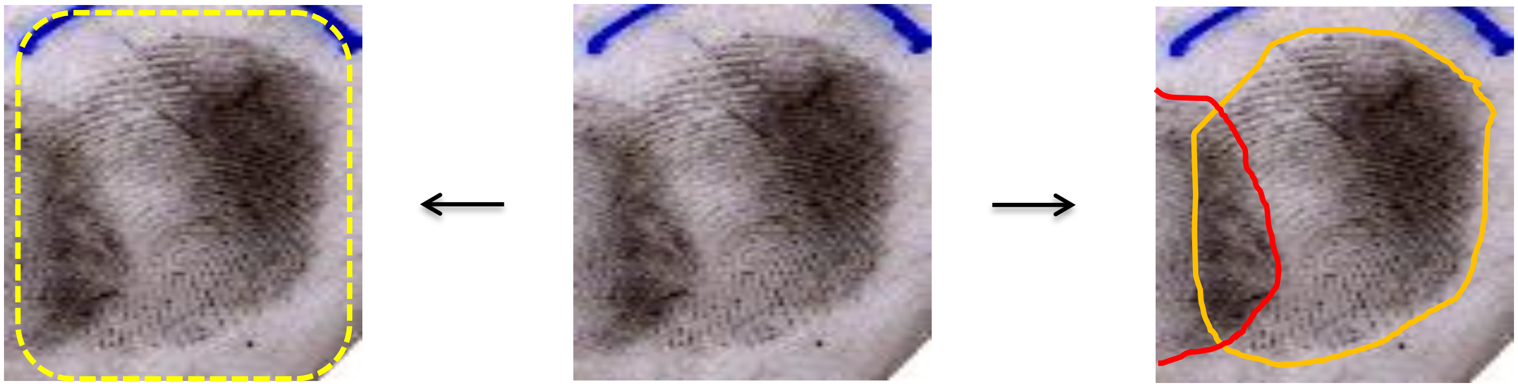
- Takes time!
- Different examiners may provide different croppings

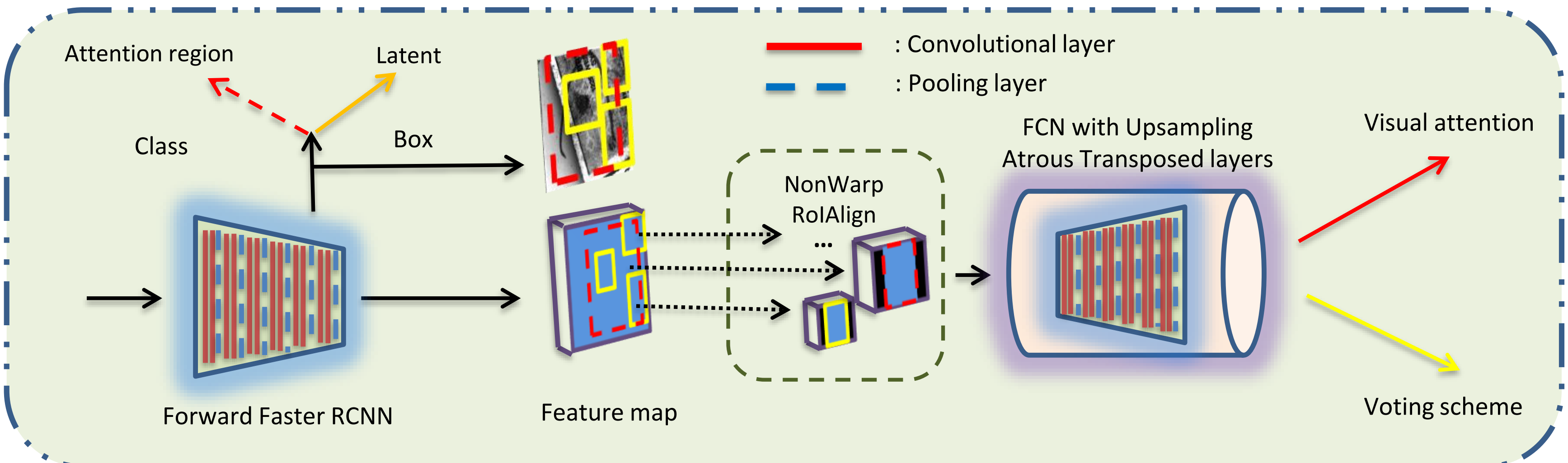
SegFinNet



Different representations
Grouped attention regions
Input
SegFinNet
Cropped region
Final cropped regions with probability
Grouped score maps

SegFinNet





Attention region
Latent
Class
Box
: Convolutional layer
: Pooling layer
FCN with Upsampling
Atrous Transposed layers
Visual attention
NonWarp
RoIAlign
...
Forward Faster RCNN
Feature map
Voting scheme

SegFinNet

SegFinNet = **Faster RCNN** + a series of **atrous transposed convolutions**

A fully automatic pixel-wise latent segmentation framework, which processes the entire input image in one shot. It also outputs multiple instances of friction ridge regions.

- ***NonWarp-RoIAlign:*** obtain precise segmentation while mapping the region of interest (cropped region) in feature map to input latent.

- ***Visual attention technique:*** focus only on friction ridge regions in the input image.

- ***Majority voting fusion mask:*** increase the stability of the cropped mask while dealing with different qualities of latents.

- ***Feedback scheme with weighted loss:*** emphasize the differences in importance of different objective functions (foreground-background, bounding box, etc.)

$$\mathcal{L}_{all} = \alpha\mathcal{L}_{Class} + \beta\mathcal{L}_{Box} + \gamma\mathcal{L}_{Mask}$$

where $\alpha = 2, \beta = 1, \gamma = 2$

Dataset

- **NIST SD27:** 258 latent images with their true mates
- **WVU:** 449 latent images with their mated rolled fingerprints and another 4,290 non-mated rolled images
- **MSP DB:** an operational forensic database, includes 2K latent images and over 100K reference rolled fingerprints.

Training: 1K images in MSP DB

Testing: NIST SD27, WVU, and 1K sequestered test images from the MSP DB

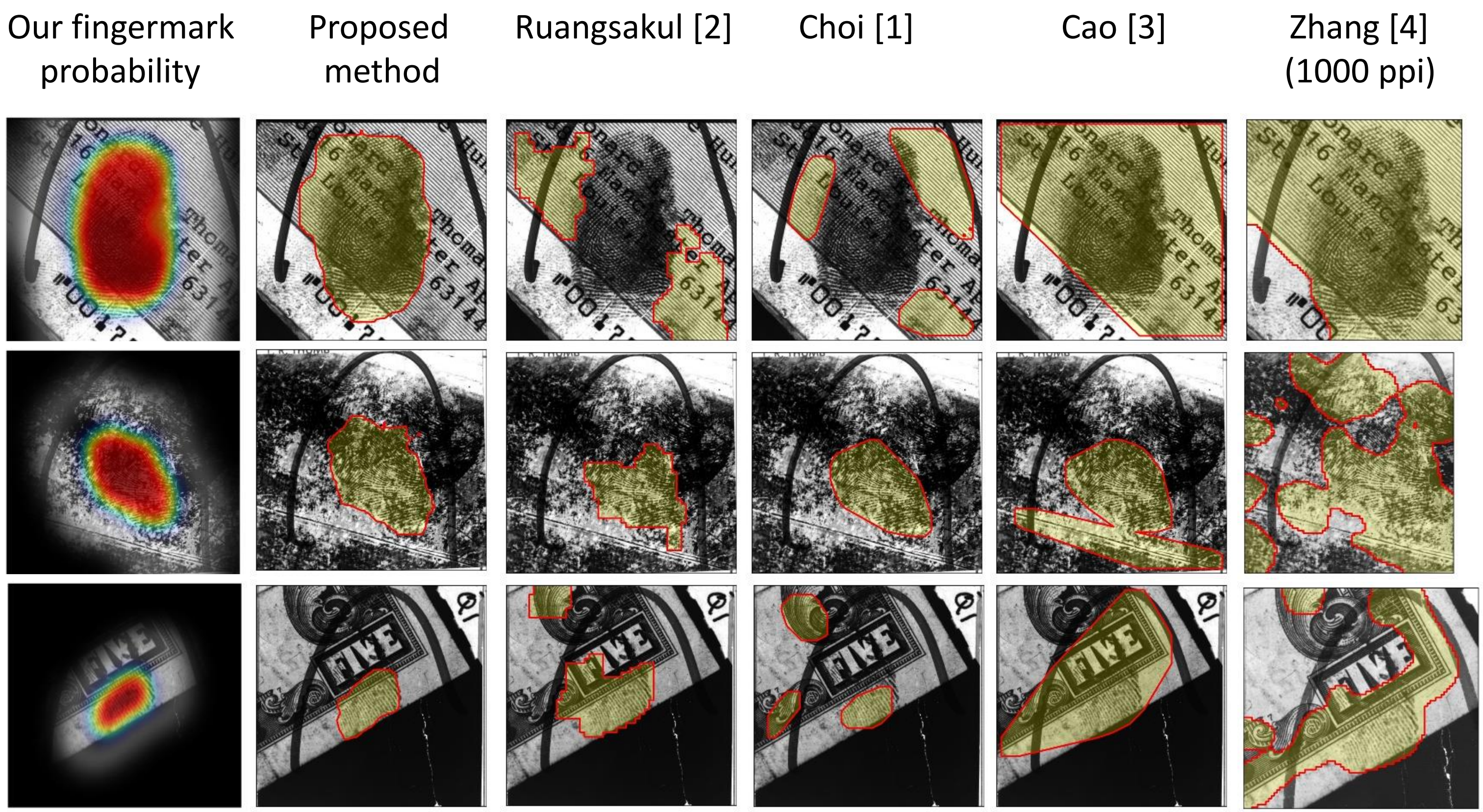
Metrics:

Let $\boldsymbol{A}$ and $\boldsymbol{B}$ be two sets of pixels in the predicted mask and groundtruth mask:

The lower, the better: **MDR** = $\frac{|\boldsymbol{B}|-|\boldsymbol{A}\cap\boldsymbol{B}|}{|\boldsymbol{B}|}$ **FDR** = $\frac{|\boldsymbol{A}|-|\boldsymbol{A}\cap\boldsymbol{B}|}{|\boldsymbol{A}|}$

The higher, the better: **IoU** = $\frac{|\boldsymbol{A}\cap\boldsymbol{B}|}{|\boldsymbol{A}\cup\boldsymbol{B}|}$

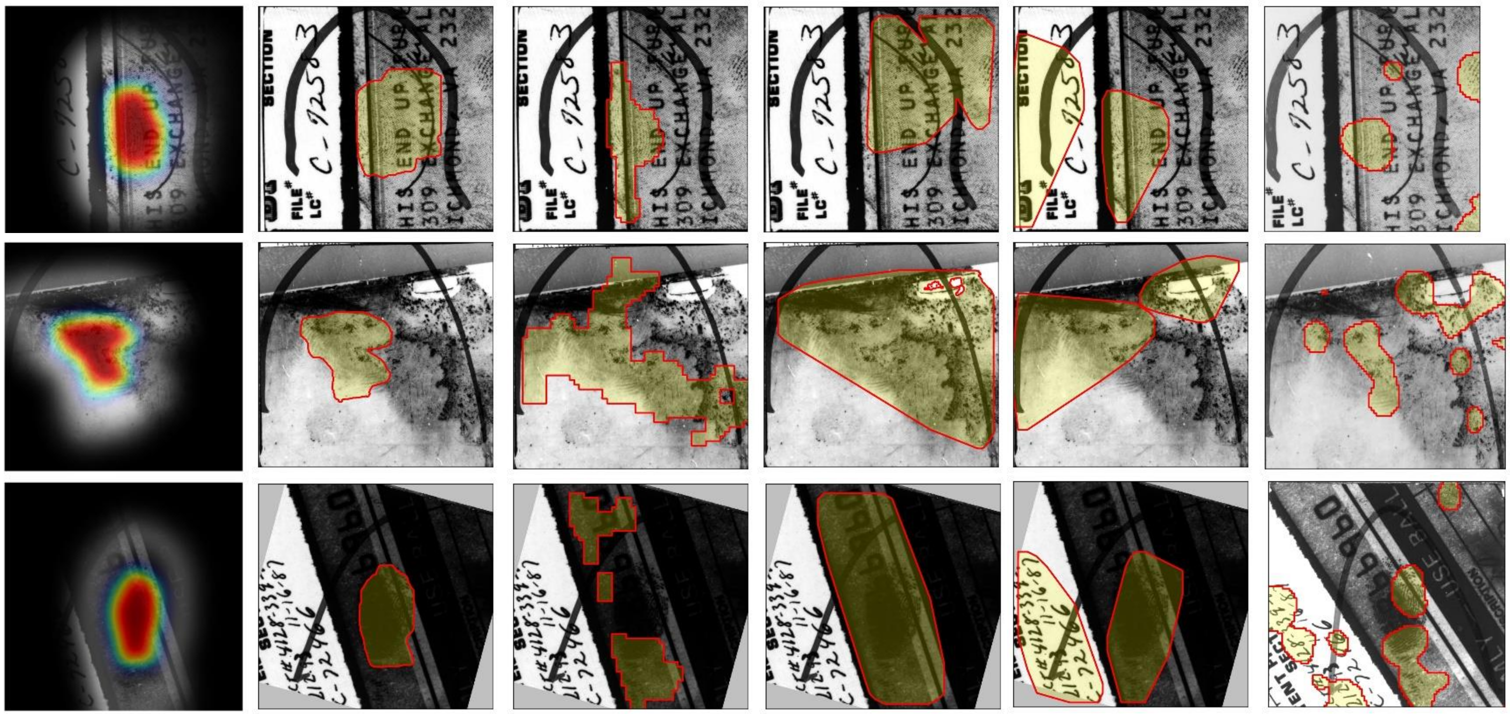
Visualization



[1] H. Choi, M. Boaventura, I. A. Boaventura, and A. K. Jain. Automatic segmentation of latent fingerprints. *IEEE BTAS*, 2012.
[2] P. Ruangsakul, V. Areekul, K. Phromsuthirak, and A. Rungchokanun. Latent fingerprints segmentation based on rearranged fourier subbands. *IEEE ICB*, 2015.
[3] K. Cao, E. Liu, and A. K. Jain. Segmentation and enhancement of latent fingerprints: A coarse to fine ridgestructure dictionary. *IEEE TPAMI*, 2014.
[4] J. Zhang, R. Lai, and C.-C. J. Kuo. Adaptive directional total-variation model for latent fingerprint segmentation. *IEEE TIFS*, 2013.

Visualization

Our fingermark probability | Proposed method | Ruangsakul [2] | Choi [1] | Cao [3] | Zhang [4] (1000 ppi)



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Quantitative results

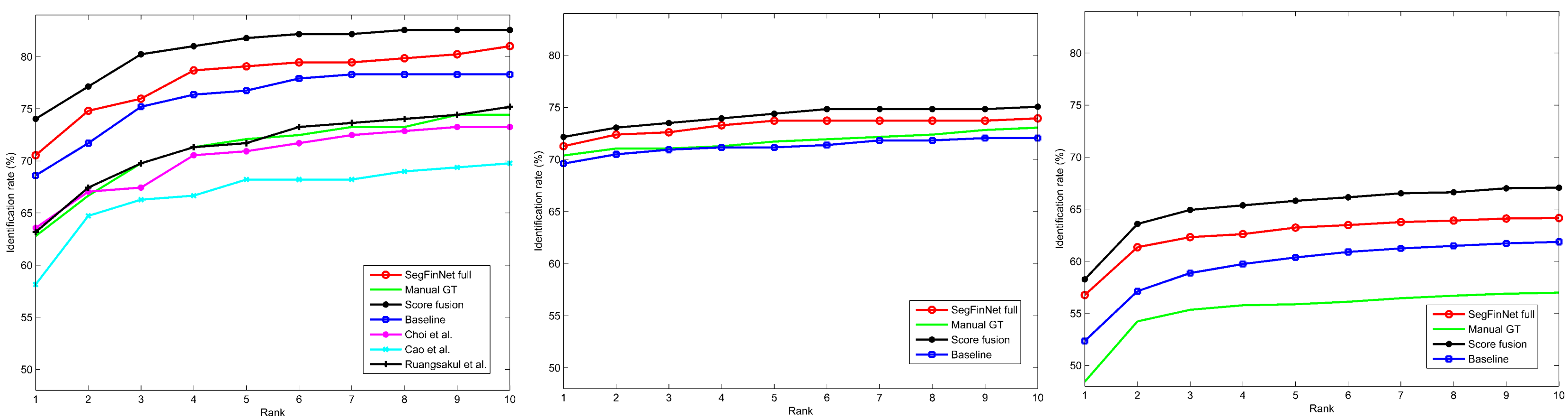
Comparison with published algorithms using pixel-wise (MDR, FDR, IoU) metrics on NIST SD27 and WVU latent databases.

Dataset	Algorithm	MDR	FDR	IoU
NIST SD27	Choi [1](#)	14.78%	47.99%	43.28%
	Zhang [4]	14.10%	26.13%	N/A
	Ruangsakul [2](#)	24.56%	36.48%	52.05%
	Cao [3](#)	12.37%	46.66%	48.25%
	Liu [5]	13.32%	24.21%	N/A
	Zhu [6]	10.94%	11.68%	N/A
	Ezeobiejesi [7](*)	1.25%	0.04%	N/A
	Proposed method	**2.57%**	**16.36%**	**81.76%**
WVU	Choi [1]	40.88%	5.63%	N/A
	Ezeobiejesi [7](*)	1.64%	0.60%	N/A
	Proposed method	**13.15%**	**5.30%**	**72.95%**

(#) We reproduce the results based on masks and groundtruth provided by authors.
(*) Its metrics are on reported patches.

Identification results

- **Baseline:** Gray scale latent image
- **Manual GT:** Groundtruth masks
- **SegFinNet with AM:** Using visual attention mechanism only
- **SegFinNet with VF:** Using majority voting mask technique only
- **SegFinNet full:** Full modules
- **Score fusion:** Sum of score level fusion: input latent, SegFinNet, SegFinNet+AM, and SegFinNet+VF



(a) (b) (c)

Matching results with a state-of-the-art COTS matcher on
(a) NIST SD27, (b) WVU, and (c) MSP database against 100K background images.

Identification results

Matching results with Verifinger on
NIST SD27 and WVU latent database against 27K background+.

Dataset	Methods	Rank-1	Rank-5
NIST SD27	Choi [1]	11.24%	12.79%
	Ruangsakul [2]	11.24%	11.24%
	Cao [3]	11.63%	12.01%
	Manual GT	10.85%	11.63%
	Baseline	8.14%	8.52%
	Proposed method	**12.40%**	**13.56%**
	Score fusion	13.95%	16.28%
WVU	Manual GT	25.39%	26.28%
	Baseline	26.28%	27.61%
	Proposed method	**28.95%**	**30.07%**
	Score fusion	29.39%	30.51%

(+) To make a fair comparison to existing works [1,2,3], we report matching performance for Verifinger on 27K background from NIST 14

Running Time

Performance of SegFinNet with different configurations.
AM: attention mechanism, *VF:* voting fusion scheme

Dataset	Configuration	Time(ms)	IoU
NIST SD27	SegFinNet w/o AM & VF	248	46.83%
	SegFinNet with AM	274	50.60%
	SegFinNet with VF	396	78.72%
	SegFinNet full	**457**	**81.76%**
WVU	SegFinNet w/o AM & VF	198	51.18%
	SegFinNet with AM	212	62.07%
	SegFinNet with VF	288	67.33%
	SegFinNet full	**361**	**72.95%**

Experiments are conducted on a desktop with i7-7700K CPU@3.60 GHz, GTX 1080 Ti (GPU), 32 GB RAM and Linux operating system

Running Time

Performance of SegFinNet with different configurations.
AM: attention mechanism, *VF:* voting fusion scheme

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Attention mechanism:

- \+ Solve problem "where to look"
- \- Not so robust to illumination

Voting fusion:

- \+ Robust to noise
- \- Longer time to process

Conclusion

SegFinNet

- Utilizes *fully convolutional neural network* and *detection based approach:* process the full input image instead of dividing it into patches.
- Outperforms both human ground truth cropping for latents and published segmentation algorithms.
- Boosts the hit rate of a state of the art COTS latent fingerprint matcher.

Future work

- End-to-end matching framework using learned and shared parameter.
- Baseline for overlapped latent fingerprints separation problem

Thank you for your attention

Q&A