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Augmentation Data Synthesis via GANs: Boosting Latent Fingerprint Reconstruction

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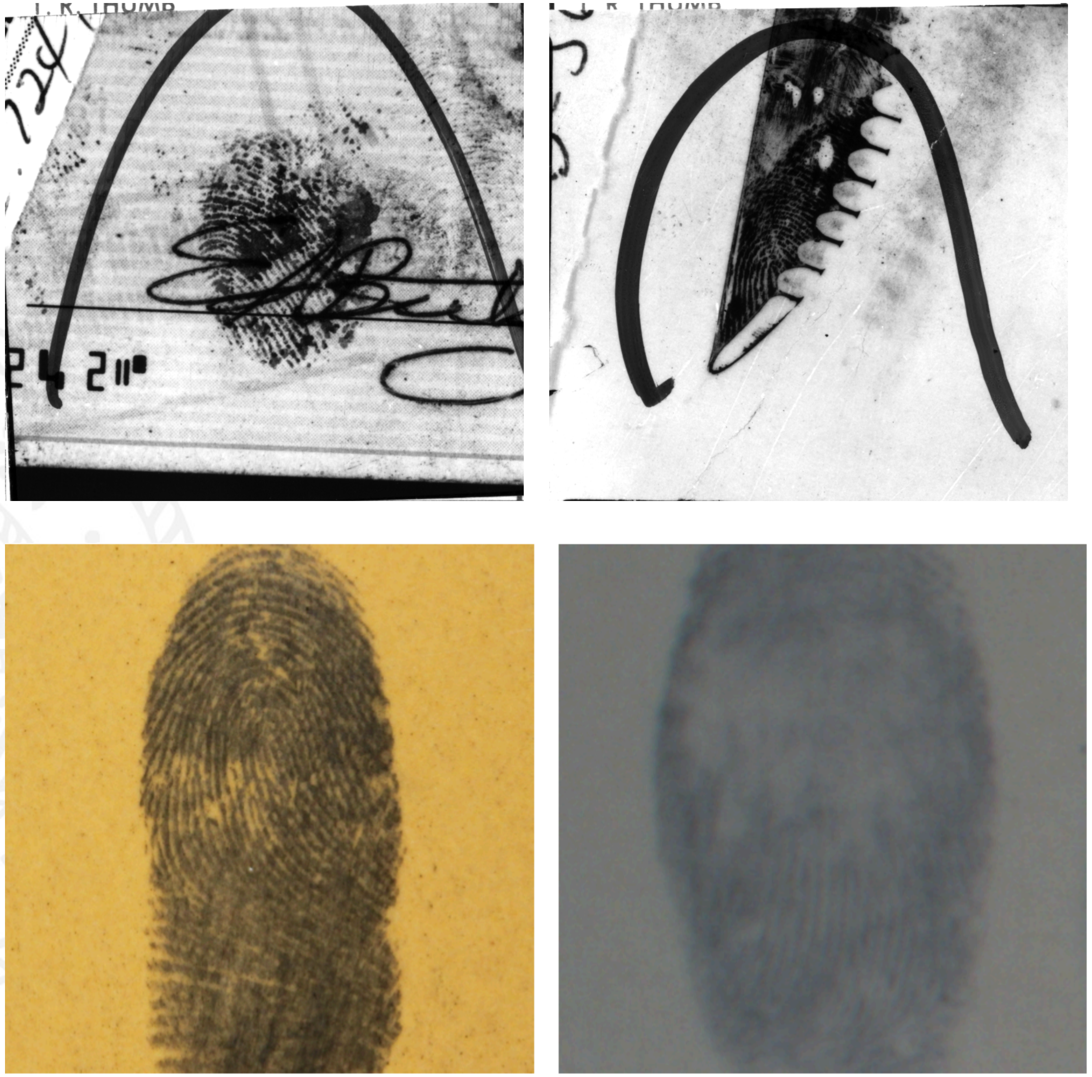
Introduction

What is Latent fingerprint
And the research difficulties

Latent Fingerprint



Latent fingerprint are degraded, fingerprint images.

- Unintentionally left on crime scene
- Collected in the uncontrolled environments.

Attributes:

- Ridge corruption
- Uneven image contrast
- Various overlapping patterns such as lines, printed letters, handwritings or even other overlapped fingerprints.

Automated Fingerprint Identification System (AFIS) can not show full pertential on latent fingerprints. **Reconstruction** is needed.

The difficulties lies in reconstruction:

- Complex and misleading latent features
- The shortage of paired training data

Basic Ideas:

- Regularization. Introduce prior knowledge
- **Data augmentation**

Main Contributions

- We propose an effective GAN-based latent fingerprint synthesis framework AugNet to translate adequate clean fingerprint to latent fingerprint, which can build the latent-clean paired augmentation set. We are the first to improve the fingerprint reconstruction performance by adopting GAN-based augmentation data.
- The proposed augmentation-reconstruction framework gets the impressive results about the latent fingerprint identification. Without any fine-tuning, the boosted reconstruction model generalizes well and gets the highest performance on three authentic dataset.

Method

Problem Formulation

Architecture of the Framework

Objective Functions

Method – Problem Formulation

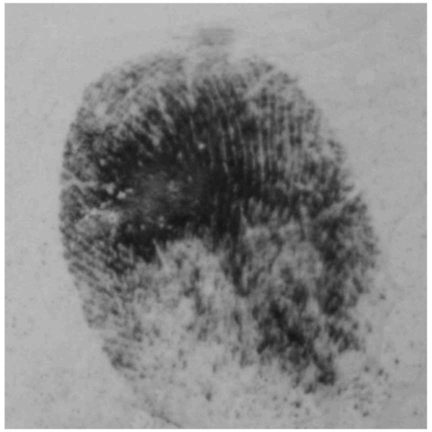
Ultimate Goal:

Learn a pixel- level binary classification model *f* -- transforms a latent fingerprint image *X* to its corresponding ideal clear binarized one *Y*.
Thus, large-scale paired latent-binarized(GT) fingerprint is needed.

Accessible data:

Large-scale of isolated clear fingerprint. $\{Y_i\}_{i=1,\ldots,m}$
Small-scale of latent fingerprint with their binarized one. $\{< X_i, Y_i^l >\}_{i=1,\ldots,n}$.
where $m \gg n$





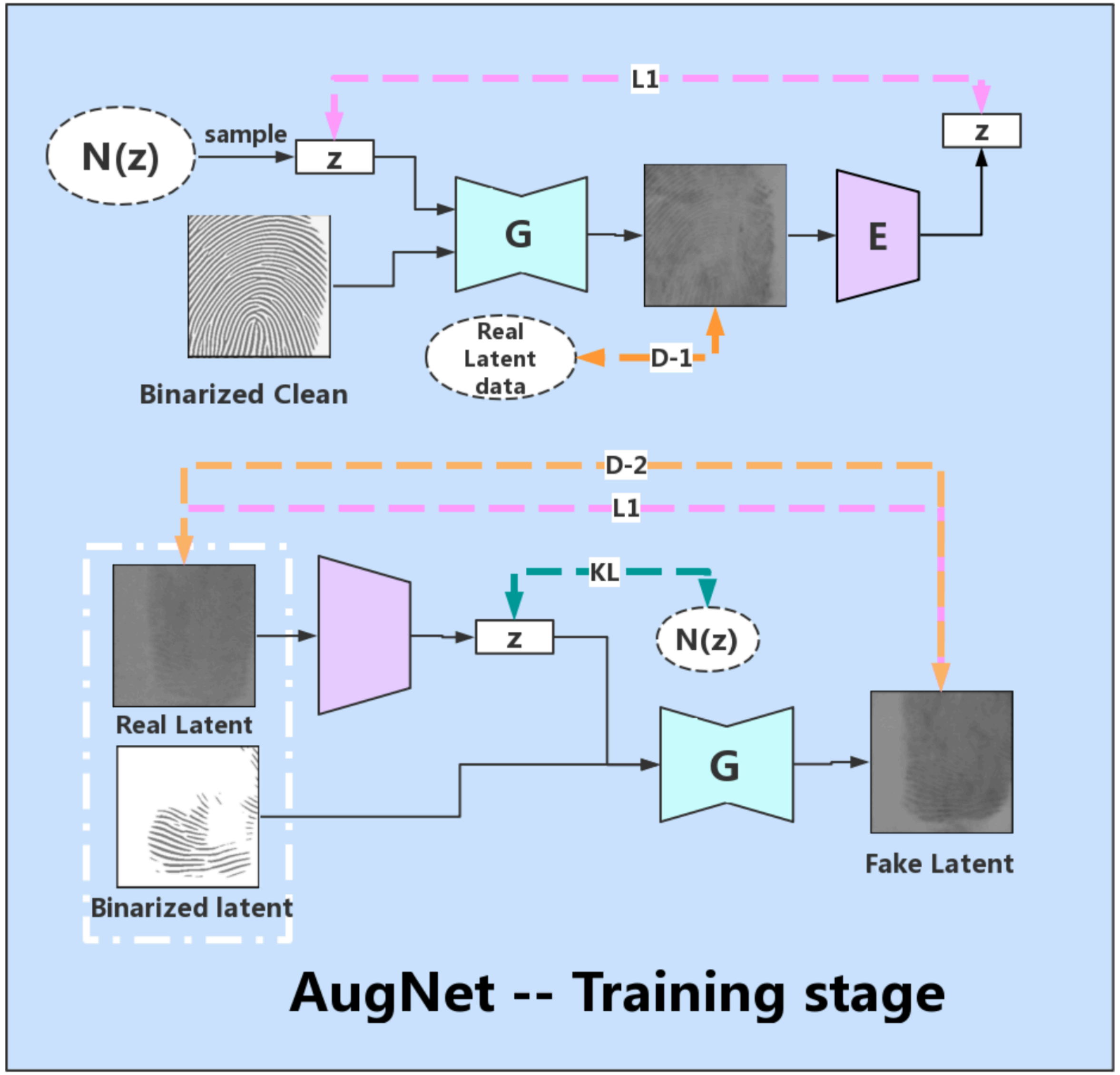

Method – Problem Formulation

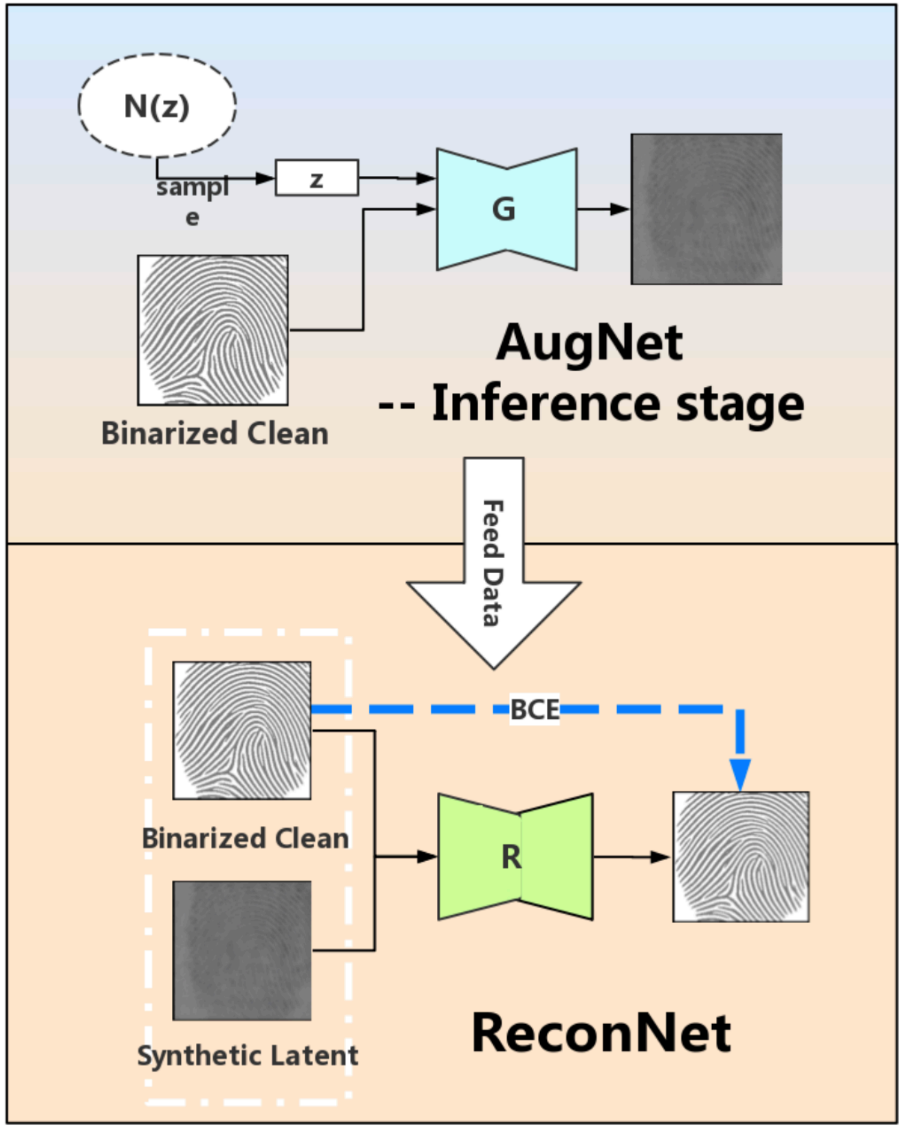
Augmentation Strategy:

Build a generative model *g* to construct effective clear-latent pairs $<\tilde{X}, Y>$ by leveraging the abundant clean binarized fingerprint $\{Y_i\}_{i=1,\ldots,m}$
Keep these synthesized data indistinguishable from real latent ones.
Concerns:

- Transformation *g* should guarantees the synthesized latent fingerprint keeps its identification information and be paired with the conditional input Y.
- Degradation patterns should be derived from real latent, be disentangled with the ridge content of fingerprints, and are easy to be sampled despite its complexity.

Method – Architecture





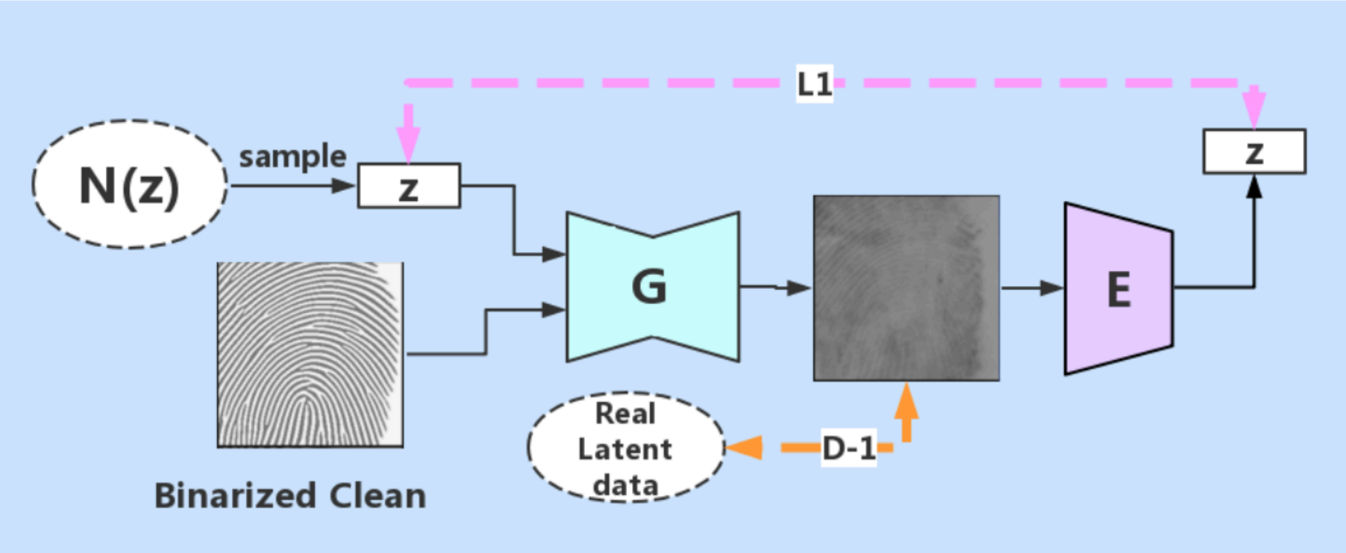
Method – Objective Functions

1. Learner E to encode the degradation patterns as *latent code*.
KL constrains it to follow a normal distribution. For sample convenience.

$$\mathcal{L}_{KL} = \mathbb{E}_{X_i \sim \{X_i\}_{i=1,\dots,n}}[KL(E(X_i)||\mathcal{N}(0,I))],$$

2. Force the synthezised fingerprint as real (From the clean binarized fingerprint)

$$\mathcal{L}_{GAN1} = \mathbb{E}_{X_i \sim \{X_i\}_{i=1,\dots,n}}[log(D_1(X_i)]$$
$$+ \mathbb{E}_{Y_i \sim \{Y_i\}_{i=1,\dots,m}, z \sim N}[log(1 - D_1(G(Y_i, z)))].$$



3. Keep the *latent code* meaningful. (Could be re-extracted)

$$\mathcal{L}_Z = ||z - E(G(Y, z))||_1.$$

Method – Objective Functions

4. L1 constraint

$$\mathcal{L}_{L1} = ||X - G(Y^l, E(X))||_1,$$

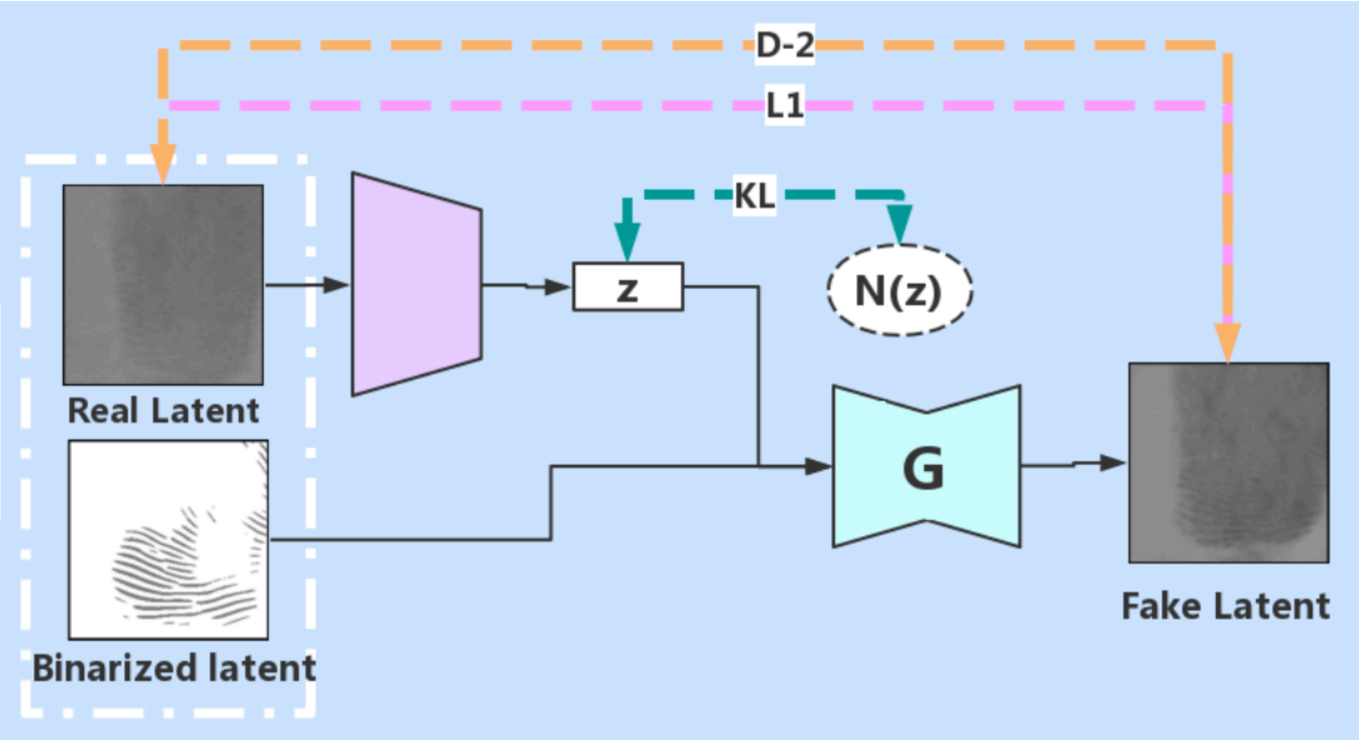
5. Make the synthezised fingerprint
as real (From the latent

$$\mathcal{L}_{GAN2} = \mathbb{E}_{X_i \sim \{X_i\}_{i=1,\ldots,n}}[log(D_2(X_i)]$$
$$+ \mathbb{E}_{Y_i^l \sim \{Y_i^l\}_{i=1,\ldots,n}}[log(1 - D_2(G(Y_i^l, E(X_i))))]$$

Overall Objective Function:

$$\mathcal{L}_{AugNet} = \lambda_{GAN1}\mathcal{L}_{GAN1} + \lambda_{GAN2}\mathcal{L}_{GAN2}$$
$$+ \lambda_{KL}\mathcal{L}_{KL} + \lambda_{L_1}\mathcal{L}_{L_1} + \lambda_z\mathcal{L}_z.$$

Sythesis the latent fingerprint from the *latent code* and the paired binarized one.

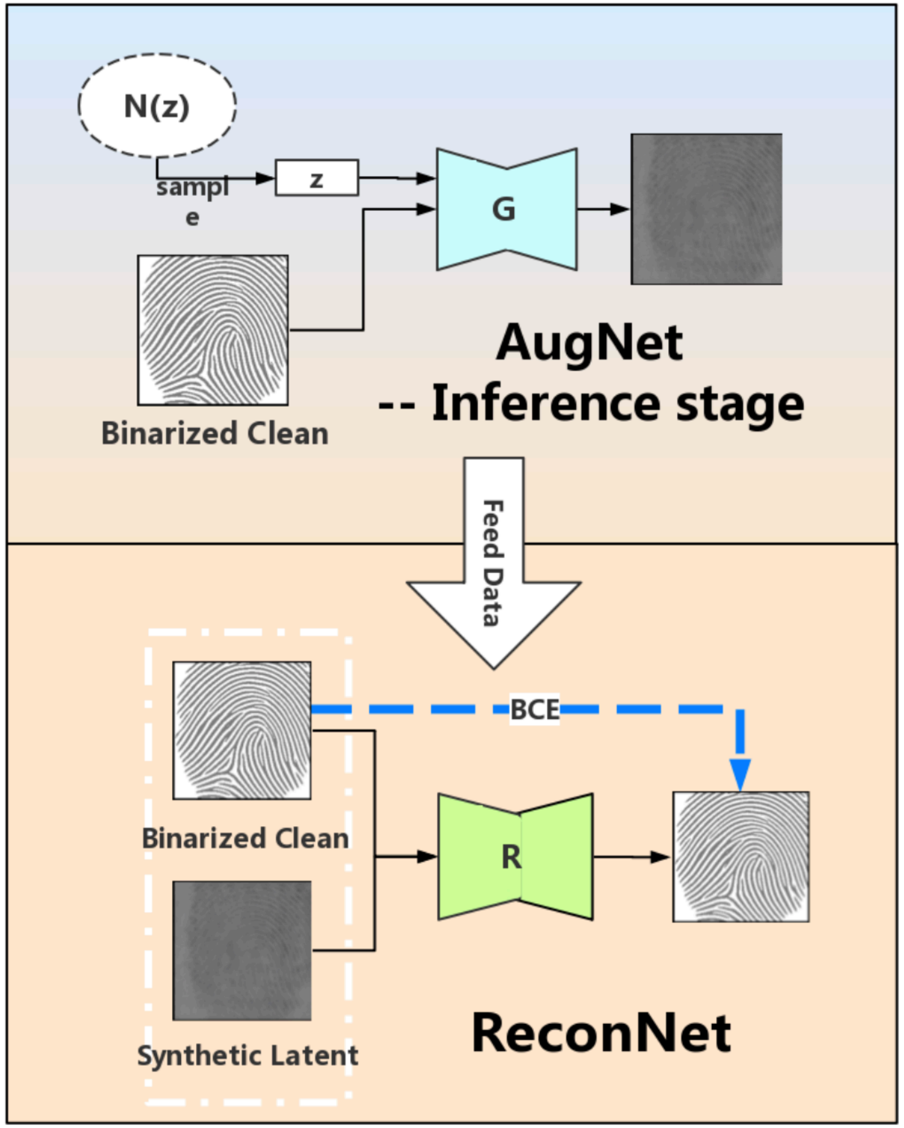


Method – Augmentation and Reconstruction

- Run the AugNet in inference mode: Generate augementation data

- Feed augmentation to Reconstruction training. As a binary classification task:

$$\mathcal{L}_{ReconNet} = -Y \log(R(\tilde{X})) - (1 - Y)\log(1 - R(\tilde{X})).$$



Method – Implementation

	AugNet-E				
Arch type	Downsampling				
Kernel Size	3	3	3	3	3
Channels	64	128	256	512	
Stride	2	2	2	2	2
Activition	ReLU				
Norm Type	Instance Norm				
Other Operations	Global Average Pooling FC to regress to an predefined Gaussian distribution				

	AugNet-D					
Arch type	Downsampling					
Kernel Size	4	4	4	4	4	4
Channels	64	128	256	512	512	1
Stride	2	2	2	2	1	1
Activition	Leaky ReLU					
Norm Type	Instance Norm					

	AugNet-G and ReconNet-R											
Arch type	U-Net											
Kernel Size	4	4	4	4	4	4	4	4	4	4	4	4
Channels	64	128	256	512	512	512	512	512	256	128	64	1
Stride	2	2	2	2	1	1	1	1/2	1/2	1/2	1/2	1
Activation	LeakyReLU(last: Tanh)											
Norm Type	Instance Norm											

Experiment

Performance Comparison

Ablation: Visual Evaluation – Synthesis, Reconstruct

Ablation: Quantitative Evaluation

Experiment – Evaluation dataset and Evaluation Metric

☐ Dataset

- NIST SD27 the most challenging dataset collected from crime scenes. Consists of 258 latent fingerprints and mated (not aligned) clean fingerprints as templates. ROI areas are adopted.
- MOLF DB4 contains 4.4k latent fingerprints and the mated (not aligned but with the same identity) clean fingerprints.
- IIIT-D contains 1k latent fingerprints but no mated clean fingerprints could be employed as templates. Latent to latent matching. Crop the central 512 regions for reconstruction, follow *gae* to split the dataset to two parts as templates and queries, make 15 times cross-matching, and report the median.

☐ Metric

Accumulative Matching Accuracy. Conducted by VeriFinger V11.0

Experiment – Performance Comparison

Best performance on three benchmarks datasets, compared with other reconstruction methods.

Methods	Matching Accuracy (%)					
	IIITD[56]			MOLF DB4[57]		
	Rank-1	Rank-10	Rank-25	Rank-1	Rank-10	Rank-25
GAE[16]	71.04	82.56	88.28	-	-	18.13
PIDI[19]	79.23	88.02	94.67	-	-	41.27
AugNet+Recon (Proposed)	**86.86**	**92.91**	**95.12**	**36.82**	**43.29**	**45.88**

Results of GAE and PIDI are evaluated by Verifinger 7.0.

Methods	Matching Accuracy (%)		
	NIST SD27[53]		
	Rank-1	Rank-10	Rank-25
GAE[16]	51.16	62.40	68.99
AugNet+Recon (Proposed)	**69.38**	**75.58**	**82.17**

Ablation Study

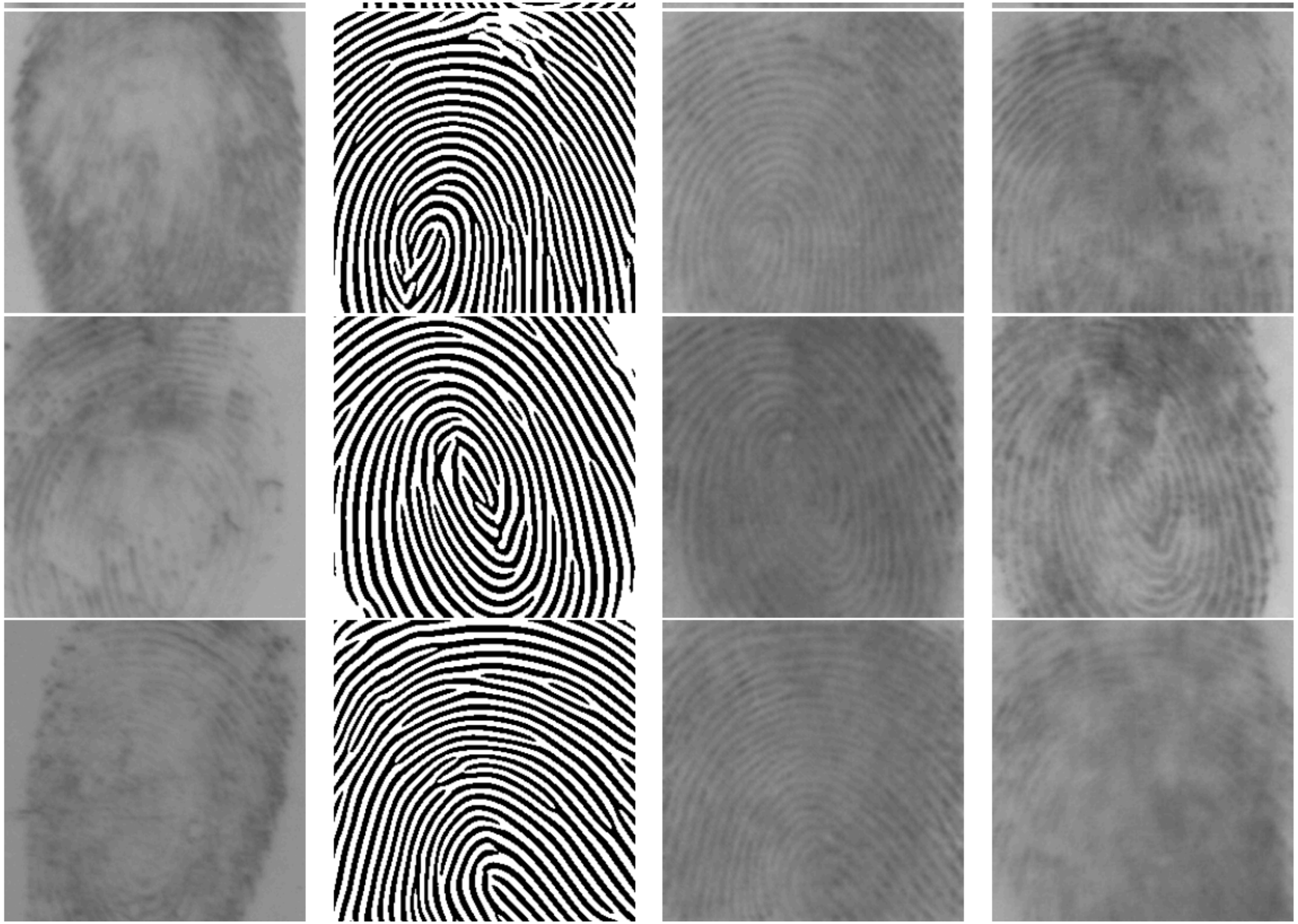
Synthesis Task:

- Synthesized by simple cGAN
- Synthesized by our AUgNet

w/wo Augmentation on Reconstruction:

- ReconNet without aug (Recon)
- ReconNet in adversarial manners without aug (Recon-adv)
- Augment by cGAN (Recon+cGAN)
- Augment by AugNet (Recon+AugNet)

Ablation -- Visual Evaluation on Synthesis Task

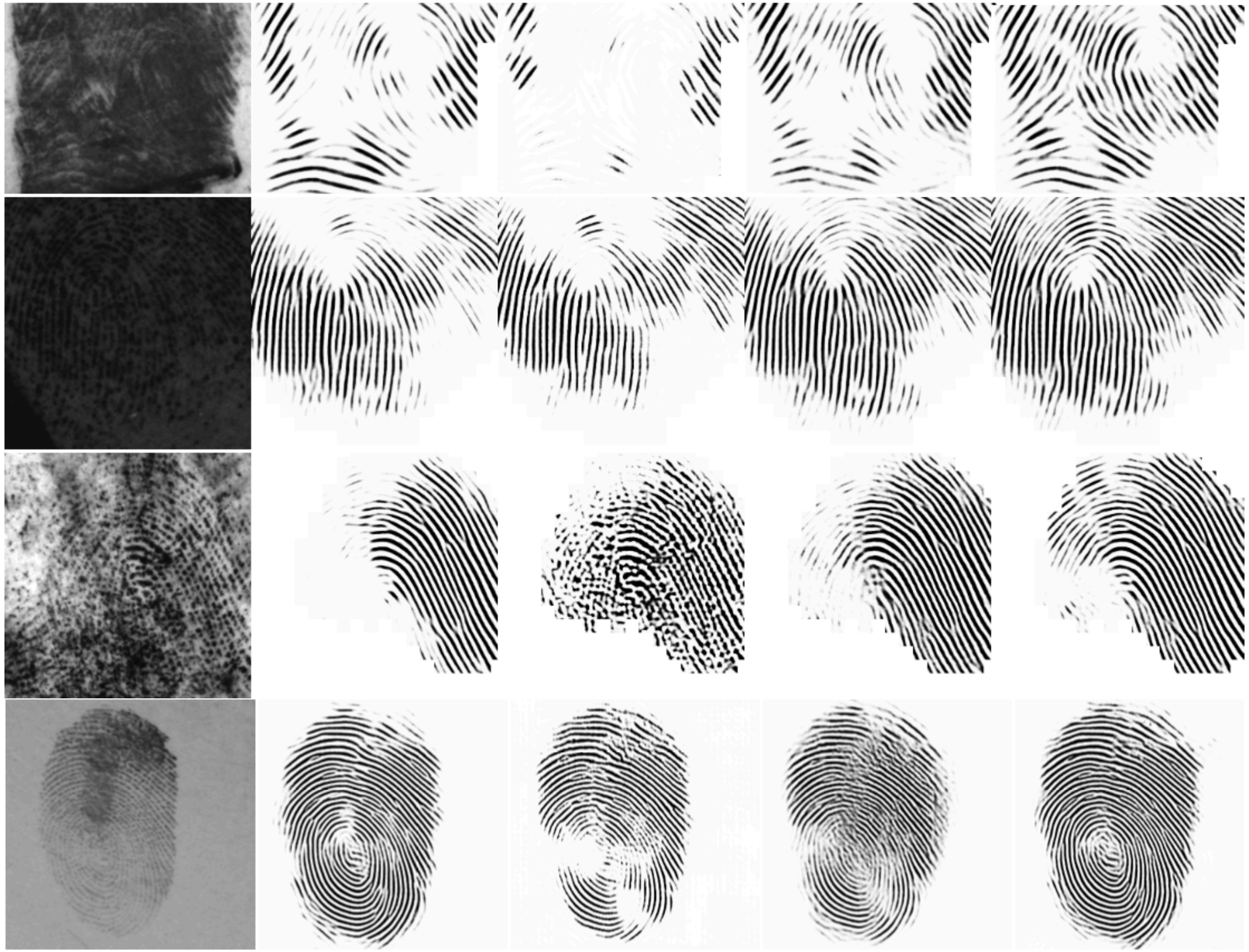


Left to right:

- Real Latent (unpaired with other)
- Binarized
- Synthesized by simple cGAN
- Synthesized by our AUgNet

- By AugNet: diverse and challenging, with more obscure ridges, breakage, uneven illumination, and some parts covered by noisy spots. More genuine.
- By cGAN: over-all uniform gray-scale, seems that ridges could be simply extracted by intensity gradient.

Ablation-- Visual Evaluation on Reconstruction Task



Left to right:

- Real Latent
- ReconNet without aug (Recon)
- ReconNet in adversarial manners without aug (Recon-adv)
- Augment by cGAN (Recon+cGAN)
- Augment by AugNet (Recon+AugNet)

By AugNet+Recon:

restore more noisy areas

bring fewer furious ridges

Ablation: Quantitative Evaluation on Reconstruction

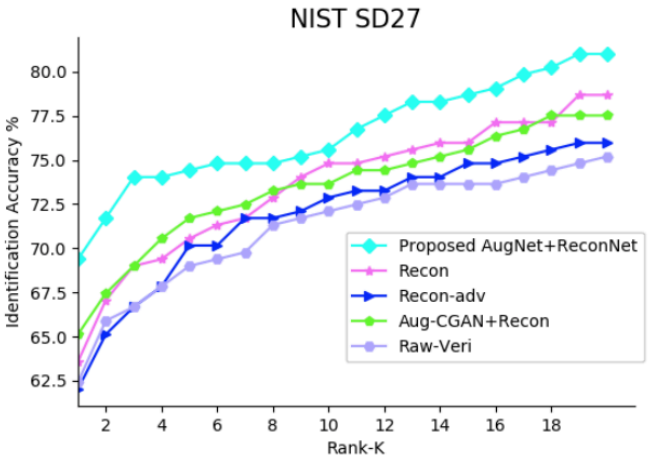
Methods	Matching Accuracy (%) of **IIITD**[56]			
	Rank-1	Rank-5	Rank-10	Rank-20
Raw	**86.86**	90.13	91.65	92.66
Recon-only	84.30	88.35	91.39	91.90
Recon-adv	86.08	90.63	92.40	93.67
Aug-cGAN+Recon	85.32	89.62	91.65	93.42
AugNet+Recon	**86.86**	**91.65**	**92.91**	**94.43**

Methods	Matching Accuracy (%) of **MOLF DB4**[57]			
	Rank-1	Rank-5	Rank-10	Rank-20
Raw	33.18	37.39	39.55	41.14
Recon-only	35.11	38.75	40.80	42.39
Recon-adv	**37.16**	**40.91**	43.18	44.77
Aug-cGAN+Recon	34.43	39.31	41.36	44.09
AugNet+Recon	36.82	40.57	**43.29**	**45.57**

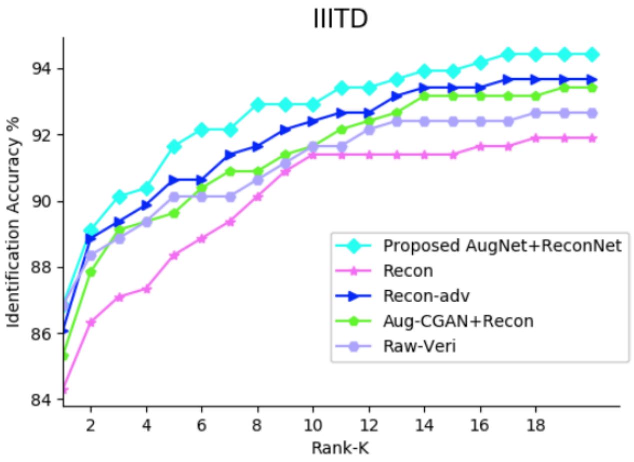
Methods	Matching Accuracy (%) of **NIST SD27**[53]			
	Rank-1	Rank-5	Rank-10	Rank-20
Raw	62.40	68.99	72.09	75.19
Recon-only	63.57	70.54	74.80	78.68
Recon-adv	62.01	70.15	72.87	75.97
Aug-cGAN+Recon	65.12	71.70	73.64	77.52
AugNet+Recon	**69.38**	**74.42**	**75.58**	**81.01**

1. Recon(without augmentation) performs poorly. Without the aid of large data or regularization.
2. Recon-adv (adversarial learned, without augmentation) has a large variance. Good on MOLF DB4 and IIITD, but unpleasant on NIST SD27. It heavily depends on the dataset distribution.
3. Synthesis of cGAN will bring some improvement. GAN-based augmentation makes sense. AugNet introduces more worth-to-learn data which improves the learning effectivenes.
4. Comparing proposed frame and Recon-adv, under small training set, generating latent fingerprints as augmentation (clean -> latent -> clean) is less ill-posed than directly reconstructing latent fingerprints (latent -> clean), that’s why we take a detour to generate augmentation.

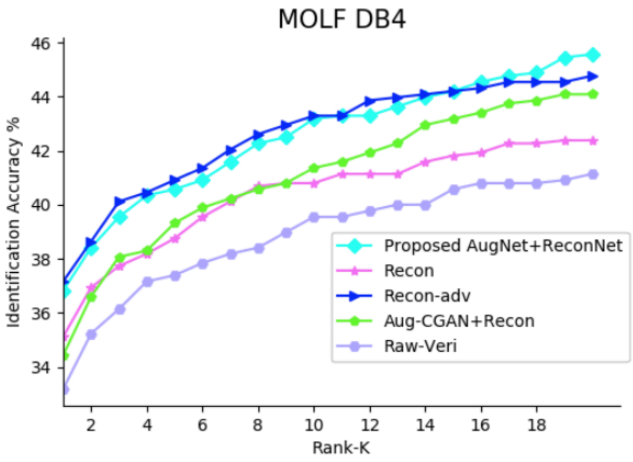
Ablation: Quantitative Evaluation on Reconstruction



(a) NIST SD27[53]



(b) IIITD[56]



(c) MOLF DB4[57]

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Conclusion and Future Work

Conclusion

We alleviate paired data shortage for latent fingerprint reconstruction by data augmentation in an adversarial generative manner. We leverage the large-scale clean fingerprint dataset to build a paired clean-latent training set by a carefully-designed augmentation model. The experiment result shows that our proposed augmentation method improves reconstruction results and further greatly improves the ultimate identification performance.

Future Work:

- Synthesis Evaluation metrics. There is no clear metric to explicitly define id-info between enhanced version and original fingerprint. Thus exploring an id-relevant metric is in argent need for quantifying both enhanced/reconstructed results and synthesized fingerprint.
- Augmentation for boosting other tasks. By slightly modifying some settings, we are to use the framework to generate augmentation data for boosting other tasks, like minutiae detection and latent fingerprint identification.

Thanks!