Fingerprint Synthesis: Search with 100 Million Prints

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Need for a Large-scale Synthetic Fingerprint Dataset

- Automated Fingerprint Identification Systems (AFIS)
 - India's Aadhaar Project (1.26 billion ten-prints)
 - FBI's Next Generation Identification System (145.3 million ten-prints)





Person enrolling in Aadhaar

FBI's NGI system

Need for a Large-scale Synthetic Fingerprint Dataset

- Fingerprint search algorithms evaluated on small-scale datasets
- Evaluating against a gallery of 100 million fingerprints:
 - Collection of large-scale fingerprints
 - Obtain fingerprints from forensic/government agencies
 - Synthesize fingerprint images

Related Work in Fingerprint Synthesis Cappelli et al. Zhao et al. Johnson et al. Proposed: Rolled **BTAS 2012 CVPR 2013** IET 2018 Bontrager et al. Proposed: Plain Cao and Jain Attia et al.

SMC 2019

ICB 2018

BTAS 2018

Contributions of our Proposed Approach

- Fingerprint synthesis algorithm based on GANs
- Identity Loss to generate fingerprints of more unique identities
- Synthesis of 100 million fingerprint images
- Large-scale search evaluation against 100 million synthetic prints

Proposed Approach



Convolutional Autoencoder (CAE)



- Training CAE in an unsupervised fashion
- Reconstruction loss: $\mathcal{L}_{CAE} = ||x - x'||_2^2$
- Weights of G_{dec} used to initialize Generator
 G of I-WGAN

Improved-WGAN

Identity Loss

- Use DeepPrint (Engelsma *et al. PAMI 2019*) as F(x) to extract fixedlength representations
- For each latent pair (z_i, z_j) :

$$\mathcal{L}_{identity} = \frac{1}{\sum ||F(G(z_i)) - F(G(z_j))||}, (z_i \neq z_j)$$

Step 2: Training I-WGAN Adversarial Loss \mathcal{L}_{adv} **Real Fingerprints** Real D or Synthetic Fingerprints Fake? G Multivariate Input z ∈ R⁵¹² Normal Fixed-length Distribution Representations Identity Loss F(**x**) $\mathcal{L}_{identity}$

Training and Synthesis

- CAE and I-WGAN trained using 280,000 rolled fingerprint images
- Fine-tuned for synthesizing plain fingerprints using 84K plain prints
- Synthesis of 100 million rolled fingerprints using HPCC
 - 100 jobs in parallel, each job generating 1 million prints
 - Total time taken: 51 CPU hours; 1.8ms/image

Generated Fingerprints while Training



Step: 00049

Experimental Results

Fingerprint Realism

Metrics:

- Minutiae count template and block,
- Minutiae direction template and block
- Minutiae convex hull area
- Minutiae spatial distribution (2D minutiae histogram from Gottschlich et al. IET 2014)
- Block minutiae quality
- NFIQ 2.0 quality scores
- Statistical Test: Kolmogorv-Smirnov test (Massey JASA 1951) used to compute difference between the distributions of each metric

Fingerprint Realism

Datasets:

| | Plain Fingerprint datasets | Rolled Fingerprint datasets | |
|-----------|--|---|--|
| Real | CASIA-Fingerprint v5 (2000 fingerprints) | NIST SD4 (2000 enrollment fingerprints) | |
| | NIST SD302L (1951 fingerprints) | NIST SD14 (last 2000 enrollment fingerprints) | |
| | NIST SD302M (1979 fingerprints) | NIST SD302U (2000 fingerprints) | |
| Synthetic | SFinGe (2000 fingerprints) | Cao and Jain ICB 2018 (2000 fingerprints) | |
| | Proposed Approach (2000 fingerprints) | Proposed Approach (2000 fingerprints) | |

Fingerprint Realism



Comparison of synthetic plain (a) and rolled (b) fingerprints to real fingerprints using 8 metrics: minutiae count – block [A] and template [B], direction – block [C] and template [D], convex hull area [E], spatial distributions [F], block minutiae quality [G], and NFIQ 2.0 quality [H].

Imposter Scores Distribution



Imposter scores distribution computed using real rolled prints (NIST SD4) and synthetic rolled prints from Cao and Jain, and proposed approach

- 500K imposter scores computed using VeriFinger
- (Mean, STD):
 - (3.47, 2.13) Proposed
 - (3.48, 2.18) Cao and Jain
- Identity loss helped generate more diverse fingerprints

DeepPrint Search against 1 Million Fingerprints



Confidence interval for rank-N search accuracy on NIST SD4 using DeepPrint

- Gallery of 1 million synthetic fingerprints
- Confidence intervals for rank-N search accuracies
- Mean rank-1 search acc: 95.53% with conf. interval of [95.1, 95.8]

COTS Search against 1 Million Fingerprints

- Fingerprint search using NIST SD4 on synthetic rolled fingerprints
- Rank-1 search accuracies using Innovatrics SDK:

| | Proposed Approach | Cao and Jain | |
|--------------|-------------------|--------------|--|
| 250K Gallery | 91.45% | 90.85% | |
| 1M Gallery | 90.35% | 90.40% | |

 Uniqueness of our synthetic rolled prints becomes more evident at large gallery sizes

Search against 100 Million Fingerprints



Rank-N fingerprint search accuracies on NIST SD4 for galleries of 100 million synthetic fingerprints using DeepPrint as the matcher

Challenges:

- Synthesis
- Search experiment

Rank-1 search accuracy on gallery:

- Proposed approach: 89.7%
- Cao and Jain: 93.55%

Conclusions

- Propose a fingerprint synthesis algorithm based on I-WGAN and an identity loss to generate diverse and realistic fingerprints
- Show fingerprint search performance at a scale of 100 million

Ongoing work:

- Scale search to a gallery of 1 billion fingerprints
- Further improve realism and diversity of prints

Thank you!