Super-resolution Guided Pore Detection for Fingerprint Recognition

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Introduction

- The need for reliable feature extraction from fingerprint samples is prevalent as these features are highly distinctive in nature.
- Fingerprint sample collection process is costly demanding high-end sensors.
- The solution can be reconstructing high-resolution fingerprint samples from the available low-resolution ones.
- Super-resolution (SR) can be utilized to enhance the quality of low-resolution fingerprints.

Motivation

- Features from minutiae and ridge patterns are quite attainable from low-resolution images while using pore features is practical only if the fingerprint is of high quality.

- A joint learning-based framework has been proposed that combines both super-resolution and pore detection networks.

- Our modified single image Super-Resolution Generative Adversarial Network (SRGAN) framework helps to reliably reconstruct high-resolution fingerprint samples from low-resolution ones helping the pore detection network to identify pores with a high accuracy.

Architecture

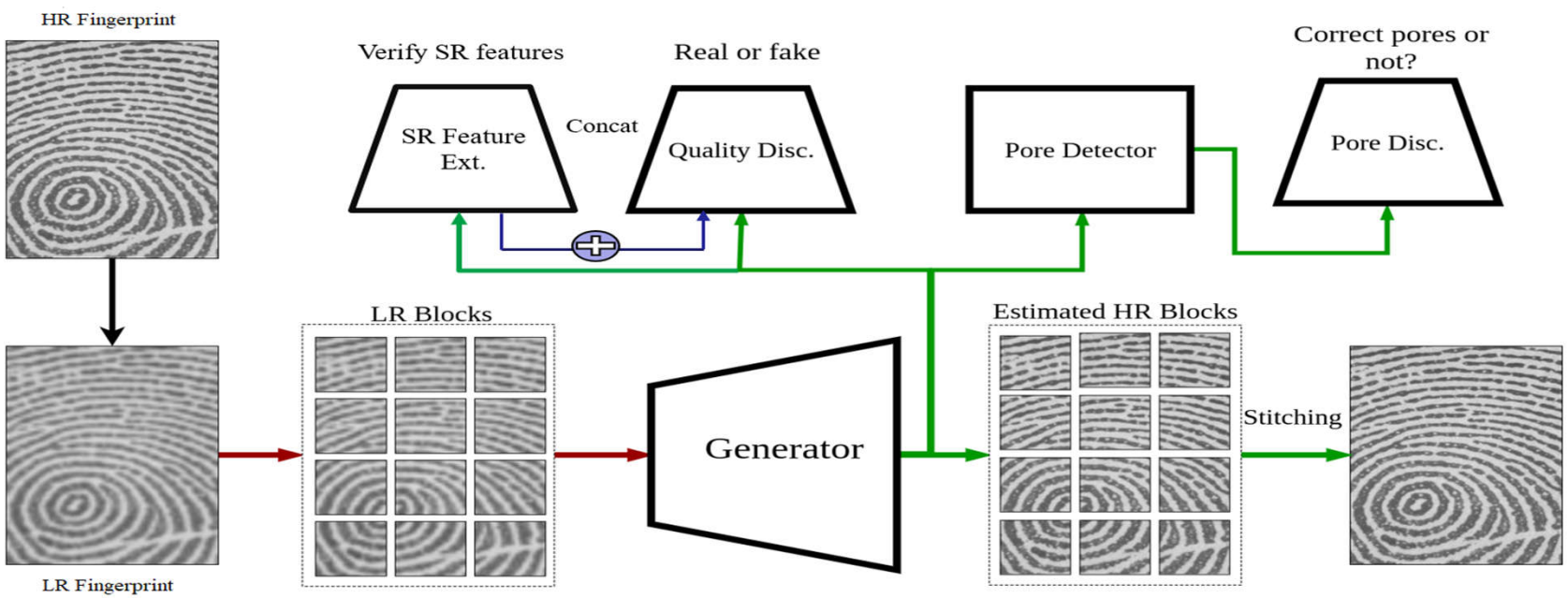

Fig 1. Complete diagram of our proposed framework including the generator, quality discriminator, pore detector, pore discriminator and SR feature extractor

Network Components

1. Super-resolution Model
   - High-resolution fingerprint images are generated from low-resolution image
2. Deep ID Extractor
   - A Siamese verifier with contrastive loss is used
3. Pore Detection Model
   - A binarized pore map is created highlighting the position of the pores

Losses

- MSE Loss

$$l_{MSE} = \frac{1}{N}\sum_{n=1}^{N}\frac{1}{WH}\sum_{w=1}^{W}\sum_{h=1}^{H}\left\|(I_n^{HR})_{w,h} - G(I_n^{LR})_{w,h}\right\|^2$$

- Adversarial Loss

$$\ell_{adv} = \min_G \max_D [E_{I^{HR}\sim P_{train}(I^{HR})}[logD(I^{LR}, I^{HR})] + E_{I^{LR}\sim P_G(I^{LR})}[log(1 - D(I^{LR}, G(I^{LR})))],$$

- Perceptual Loss

$$\ell_{per}^{SR} = \frac{1}{N}\sum_{n=1}^{N}\frac{1}{C_jW_jH_j}\sum_{c=1}^{C_j}\sum_{w=1}^{W_j}\sum_{h=1}^{H_j}||\phi_j^c(I_n^{HR})_{w,h} - \phi_j^c(G(I_n^{LR})_{w,h}||^2,$$

- Ridge Loss

$$\ell_{ridge}^{J} = \sum_{j=1}^{J}||G_j^{\phi}(\tilde{y}) - G_j^{\phi}(y)||_F^2.$$

Experimental Results

A large overlap among the scores of the generated and real HR fingerprints is visible which indicates the qualitative similarity of the generated fingerprint samples of our model to the real HR fingerprint samples.

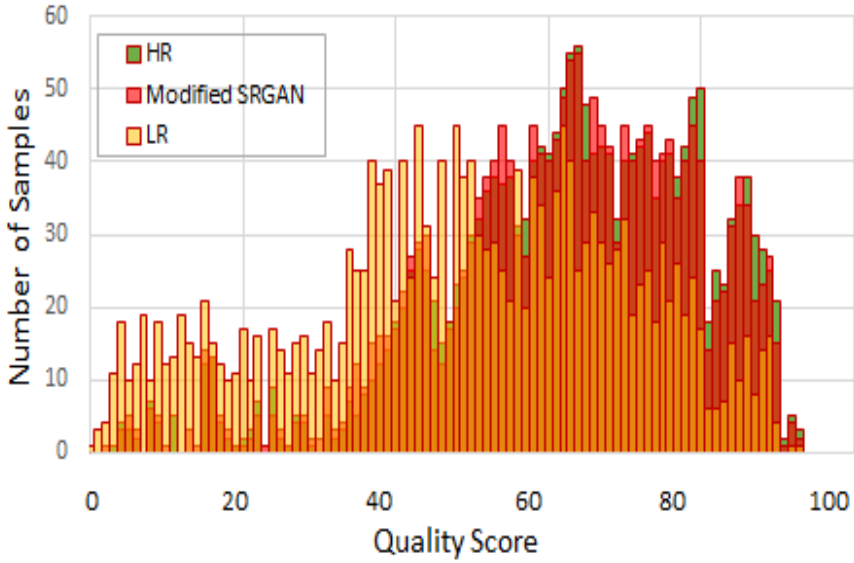

Fig2. Image quality comparison of LR, real HR and generated samples from our modified SRGAN for an upscale factor 2×.

Experimental Results(cont.)

Decrease in EER is almost twice for the super-resolved high-resolution samples (1000-ppi) from their corresponding ground-truth (500-ppi) samples which ensures reliable reconstruction of super-resolved fingerprints.

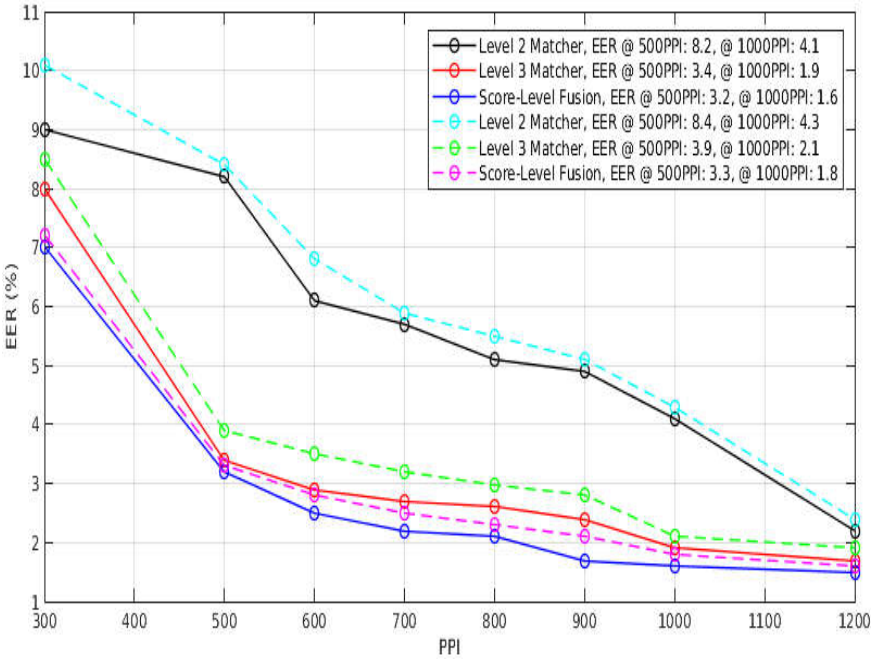

Fig3. Fingerprint recognition performance evaluated at multiple resolutions using different level features for an upscale factor 2×. Solid lines represent the EER values for the PolyU DBI dataset and dashed lines are for the EER values in the FVC2000 DB1 dataset.

Experimental Results(cont.)

Area Under the Curve (AUC) is around 99.8% using the combination of SRGAN, ridge and pore detection loss which is very close to ground truth Area Under the Curve (AUC)

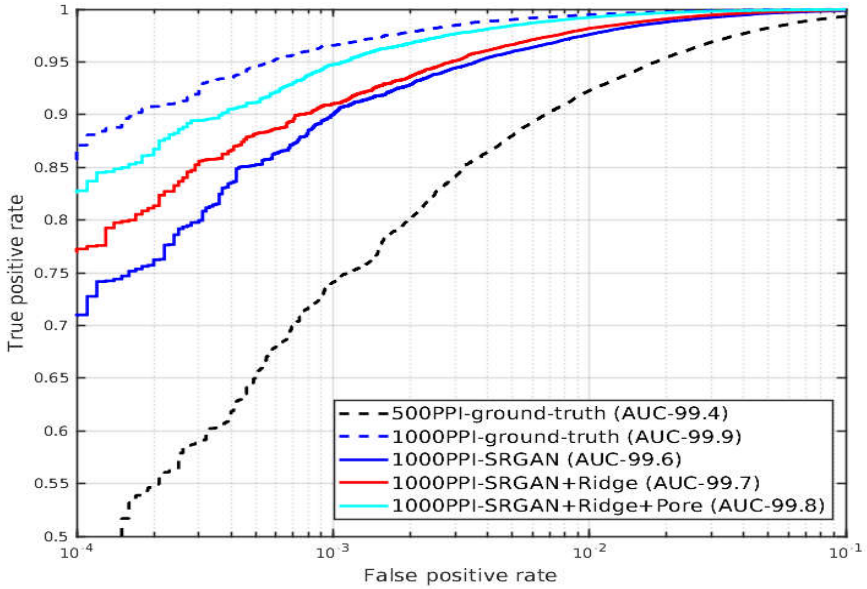

Fig4. ROC curves for real HR, generated samples from SRGAN and our modified SRGAN for an upscale factor 2

Conclusion

- ✓ A deep fingerprint SR model is developed which employs SRGAN to reliably reconstruct high resolution fingerprint samples.
- ✓ A jointly trained deep SR and pore detection framework is proposed that utilizes pore and ridge information present in fingerprint.
- ✓ Integration of features extracted from a deep verifier with a quality discriminator preserves the individual identity in the reconstructed samples.
- ✓ Reliable reconstruction of 1000-ppi fingerprint from its 500-ppi equivalent proves the validity of our approach.

Thank You