U-Finger

Multi-Scale Dilated Convolutional Network for Fingerprint Image Denoising and Inpainting

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Why Deep Neural Network ?

- Fingerprint restoration and enhancement have been traditionally studied using classical example-based and regression methods.

- These techniques assume the type of noise (Gaussian, speckle and "salt and pepper") as shown below in the images and are not effective against non-linear/discrete noises.

- There have been very few inpainting techniques such as patented technique of Harris Corp. But these have limitations on the portion of the fingerprint that is missing.

Salt & Pepper noise

Speckle Noise

- The challenge dataset has fingerprints with different sets of noise along with degraded patches of ridges which needs to be restored.

- There are no traditional techniques developed to handle multiple noises along with inpainting, it needs to be done one after other which just accumulates the error from one stage to the other.

Gaussian Noise

- There have been lots of success of deep learning-based natural image denoising/inpainting/super resolution methods. This has not been much taken into consideration for fingerprint processing.

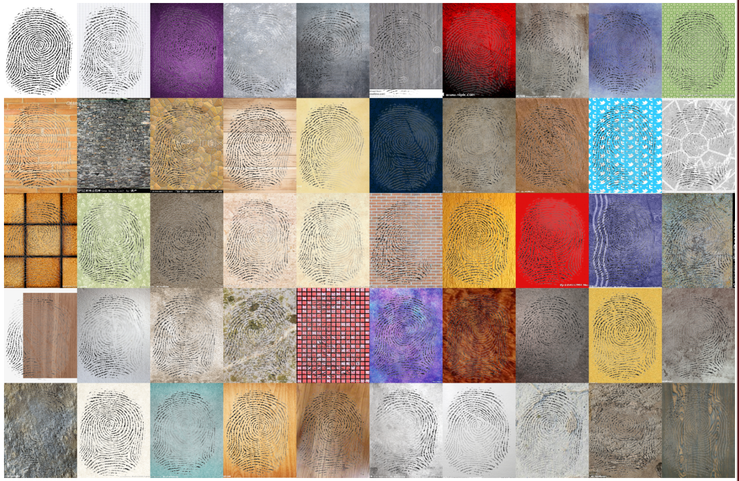
- Neural networks are capable of learning the patterns of the fingerprints and extract them from several set of background noises while maintaining the integrity of the fingerprint.

- Along with denoising, neural networks are efficient in inpainting compared to traditional techniques. Traditional techniques rely normally on the information/pattern present in just that image which is being processed (locally), but neural network uses pattern information that it has learned from several finger prints (globally).

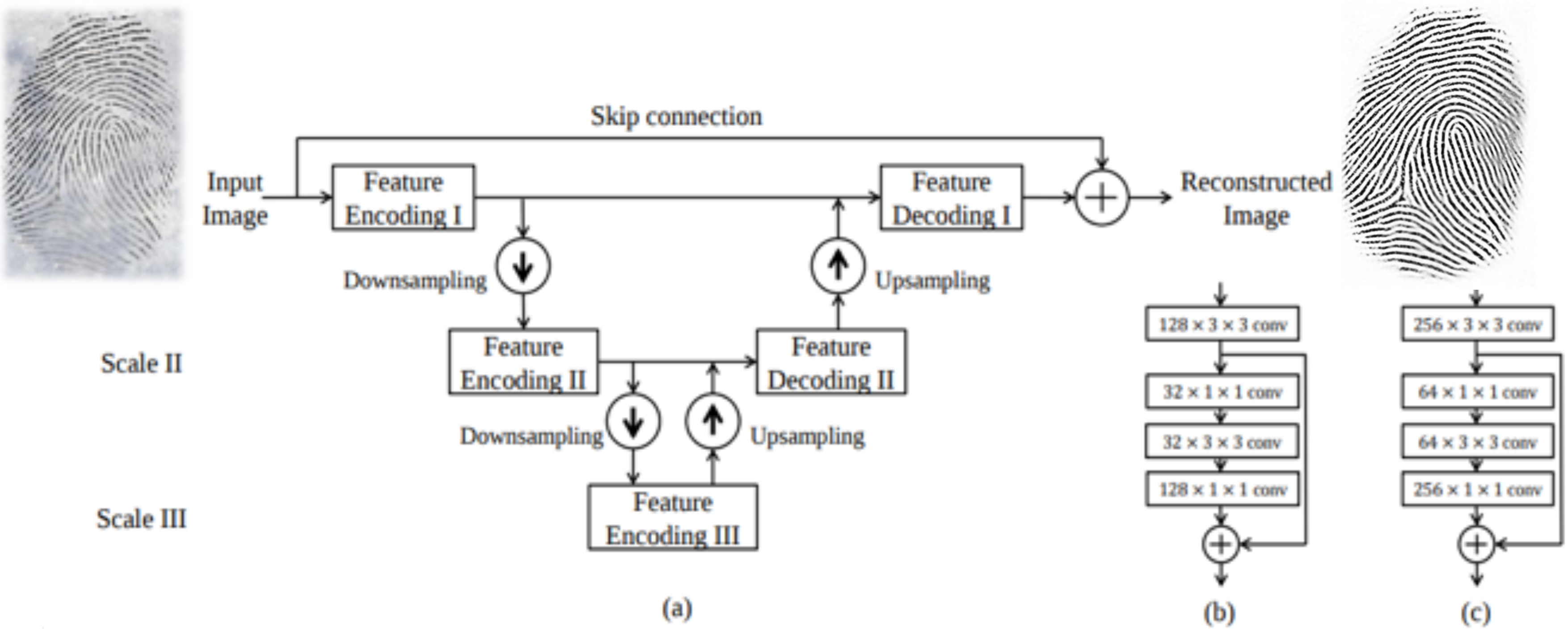
- Neural networks are capable of handling discrete noises as well as other noises mentioned above and at the same time can perform inpainting efficiently.

Dataset and Technical Challenges

- Synthesized dataset of realistic fingerprints.
- Developed algorithms will be evaluated based on reconstruction performance (MSE, PSNR and SSIM).
- **Complicated mixed degradation types:** blur, brightness, contrast, elastic transformation, occlusion, scratch, resolution, rotation, and so on.
- **Different from natural images**, fingerprint images are composed of usually thin textures and edges, and it is critical to preserve and keep them sharp during the restoration process for their reliable recognition/verification from those patterns.



U-Finger



(a) Overview of our adopted network. (b) Architecture of the feature encoding module. (c) Architecture of the feature decoding module.

Experimental Results

- The model is trained for 1,500,000 iterations using the stochastic gradient descent (SGD) solver with the batch size of 8.
- Gray scaled inputs images.

MSE, PSNR and SSIM Results on Validation Set.

	MSE	PSNR	SSIM
Base-model	0.029734	15.8747	0.77016
Base-model without padding	0.025813	16.4782	0.78892
U-Finger	**0.023579**	**16.8623**	**0.80400**

Ranking

User	RANK	MSE	PSNR	SSIM
CVxTz	1.0000 (1)	0.0189 (1)	17.6968 (1)	0.8427 (1)
rgsl888	**2.3333 (2)**	**0.0231 (2)**	**16.9688 (2)**	**0.8093 (3)**
hcilab	3.3333 (3)	0.0238 (3)	16.6465 (3)	0.8033 (4)
sukeshadigav	3.3333 (3)	0.0268 (4)	16.5534 (4)	0.8261 (2)

Results @ official website

Denoising and inpainting results of models

(a) (b) (c) (d) (e)

(a) Original (b) Base-model (c) Base-model with no padding (d) U-Finger (e) Ground truth.

Influence of padding

- Padding is normally used to satisfy the need to have particular sized output while performing convolution.

- But, in the base model, as we are performing skip connection with input, the portion of the padding will just take in all the error values from inputs section, which effects all the metrics of evaluation seriously.

- This can be observed in the following set of images, the highlighted portion is not edge of the picture, its noise propagated from the input through skip connection while having padding, but the U-finger does not have this issue.

Base model with padding

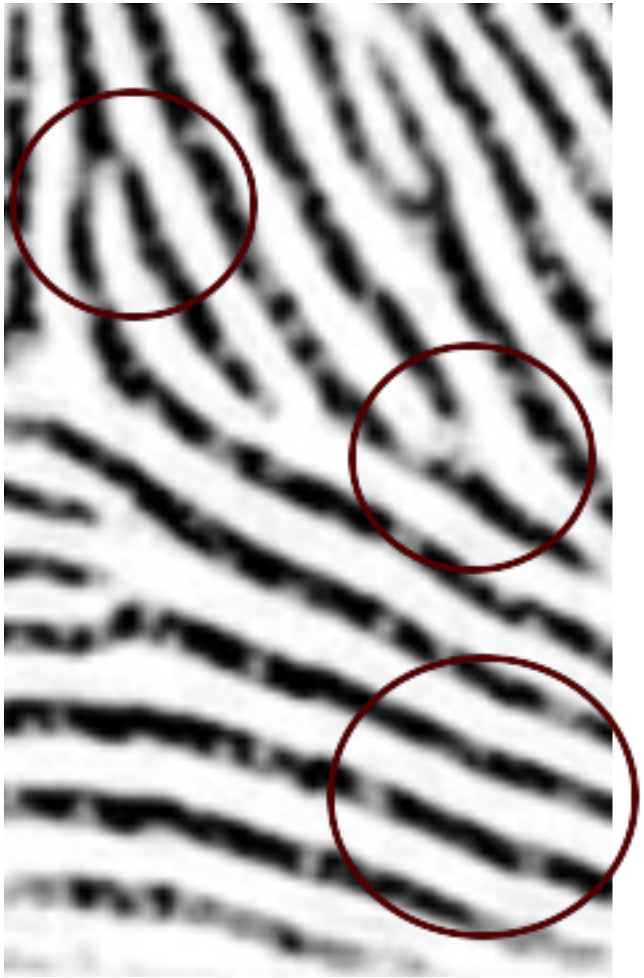
U-finger

Impact of dilation on denoising

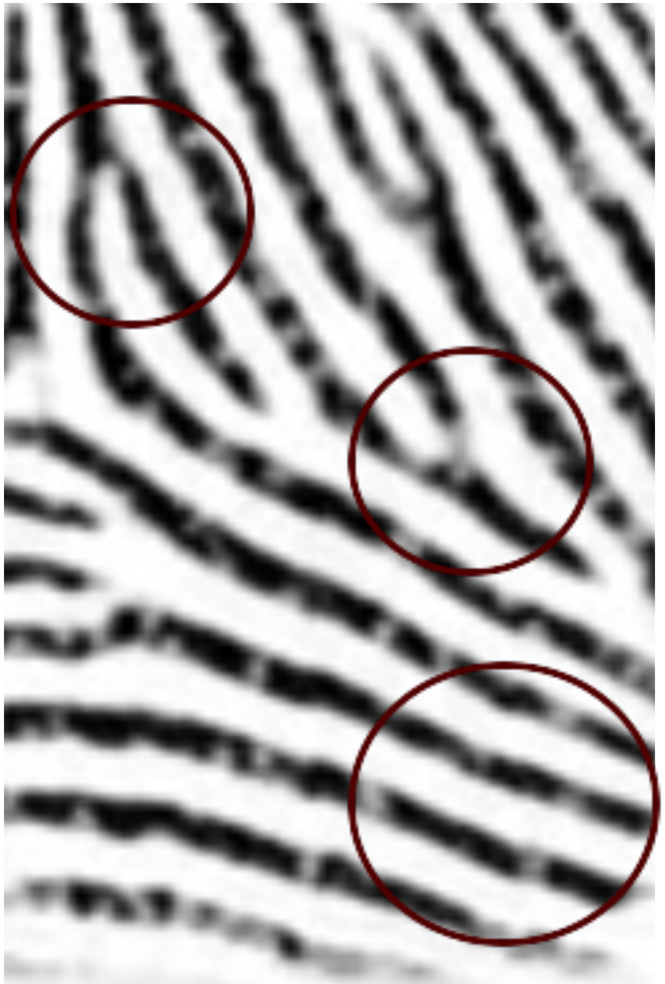
- Convolution network are best suited for generic images where information spread across whole image and doesn't loose any important pattern information while max-pooling.

- But, fingerprints hold their information just in their edges and rest are just noise. So, it requires more local, pixel-level accuracy, such as precise detection of edges.

- Dilated convolution was introduced to achieve this property. Essentially, the receptive field increases with dilation factor which helps to preserve accuracy.



Convolution network



Dilated Convolution network

Dilated convolution layers with larger receptive field helps to preserve more information compared to convolution layers which looses the information while max-pooling, ending-up with smoothened edges.

Denoising and Inpainting results at different level of loss

(a) (b) (c)

Moderate loss in fingerprint, (a) Original, (b) U-Finger (c) Ground truth.

(a) (b) (c)

Severe loss in fingerprint, (a) Original (b) U-Finger (c) Ground truth.

Denoising finger prints degraded with generic noise

Gaussian noise

a b c

Salt & Pepper noise

a b c

Speckle Noise

a b c

All noise (Gaussian, S&P, Speckle)

a b c

a) Noisy image, b) Denoised image and c) Ground truth

Model is capable of removing the generic noises that were considered in traditional models of denoising.

Conclusion

- The multiscale nested architecture with up-sampling and down-sampling modules proves to achieve compelling balance between preserving fine texture and suppressing artifacts.
- The usage of dilated convolutions and the removal of padding have further boosted the performance.
- The model is capable of handling discrete noises along with generic noises and comparatively better inpainting results.
- Our future work will include training with alternative loss functions (SSIM, MSSIM-L1, MSSIM-L2), as well as trying more densely connected modules.

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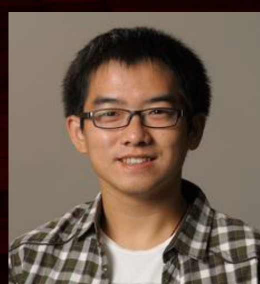

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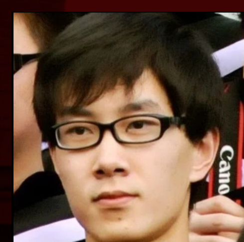

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Credits

1. Kuldeep Singh, Rajiv Kapoor, and Raunaq Nayar. Fingerprint denoising using ridge orientation based clustered dictionaries. Neurocomputing, 167:418–423, 2015.
2. Patrick Schuch, Simon Schulz, and Christoph Busch. Minutia-based enhancement of fingerprint samples. In Security Technology (ICCST), 2017 International Carnahan Conference on, pages 1–6. IEEE, 2017.
3. Mark Rahmes, Josef DeVaughn Allen, Abdelmoula Elharti, and Gnana Bhaskar Tenali. Fingerprint reconstruction method using partial differential equation and exemplar-based inpainting methods. In Biometrics Symposium, 2007, pages 1–6. IEEE, 2007.
4. Zhangyang Wang, Yingzhen Yang, Zhaowen Wang, Shiyu Chang, Jianchao Yang, and Thomas S Huang. Learning super-resolution jointly from external and internal examples. IEEE Transactions on Image Processing, 24(11):4359–4371, 2015.
5. Dass A.K., Shial R.K. (2013) An Efficient De-noising Technique for Fingerprint Image Using Wavelet Transformation. In: Meghanathan N., Nagamalai D., Chaki N. (eds) Advances in Computing and Information Technology. Advances in Intelligent Systems and Computing, vol 177. Springer, Berlin, Heidelberg.

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6. Usha.S , Kuppuswami.S, *Performance Analysis of Fingerprint Denoising Using Stationary Wavelet Transform,* I.J. Image, Graphics and Signal Processing, 2015, 11, 48-54.
7. Mark Rahmes, Josef Allen, Patrick Kelley, *Fingerprint processing system providing inpainting for voids in fingerprint data and related methods,* Harris Corporation, Melbourne, FL, 2007
8. Ding Liu, Zhaowen Wang, Yuchen Fan, Xianming Liu, Zhangyang Wang, Shiyu Chang, and Thomas Huang. Robust video super-resolution with learned temporal dynamics. In Computer Vision (ICCV), 2017 IEEE International Conference on, pages 2526–2534. IEEE, 2017.
9. Zhangyang Wang, Shiyu Chang, Yingzhen Yang, Ding Liu, and Thomas S Huang. Studying very low resolution recognition using deep networks. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, pages 4792–4800, 2016.
10. Ding Liu, Bowen Cheng, Zhangyang Wang, Haichao Zhang, and Thomas S Huang. Enhance visual recognition under adverse conditions via deep networks. arXiv preprint arXiv:1712.07732, 2017.
11. Junyuan Xie, Linli Xu, and Enhong Chen. Image denoising and inpainting with deep neural networks. In Advances in neural information processing systems, pages 341–349, 2012.

12. Ding Liu, Bihan Wen, Xianming Liu, Zhangyang Wang, and Thomas S Huang. When image denoising meets high-level vision tasks: A deep learning approach. arXiv preprint arXiv:1706.04284, 2017.

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