Self-supervised Deep Learning for Low-dose CT Image Denoising

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INTRODUCTION

- Lowering the exposure would inevitably induce higher quantum noise
- Supervised deep learning-based denoisers can enhance the low-dose CT (LDCT) image substantially
- Its success requires massive of pixel-level paired LDCT and normal dose CT (NDCT)
- Hardly to collect in real clinical practice

AIM

- Propose a probabilistic deep self-learning framework by only using the LDCT (PSL), alleviating the paired data scarcity problem

METHODS

- Image prior: Gaussian distribution

$$X \sim N(\mu_X, \sigma_X^2)$$

- Noise: Gaussian distribution

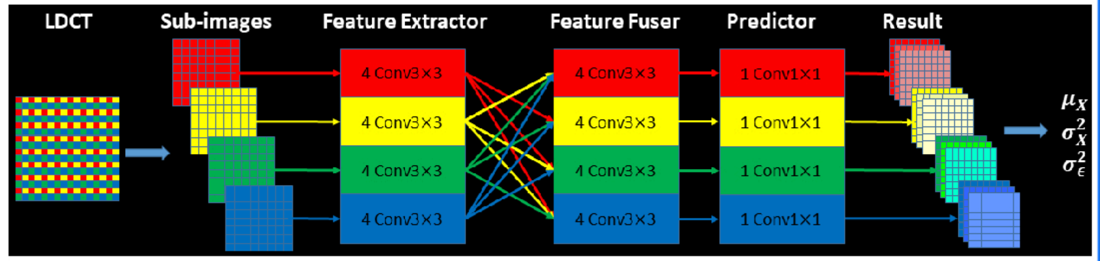
$$\epsilon \sim N(0, \sigma_\epsilon^2)$$

- Main assumption: a set of pixels Y^E are predictable using the information of the rest pixels Y^C in the image

$$max \prod_{t=0}^{T-1} P(Y_t^E | Y_t^C)$$

- Shift-invariant property: there exist strong correlations among the down sampled 4 sub-images since their starting positions are close enough with each other.

ARCHITECTURE



- Training phase:

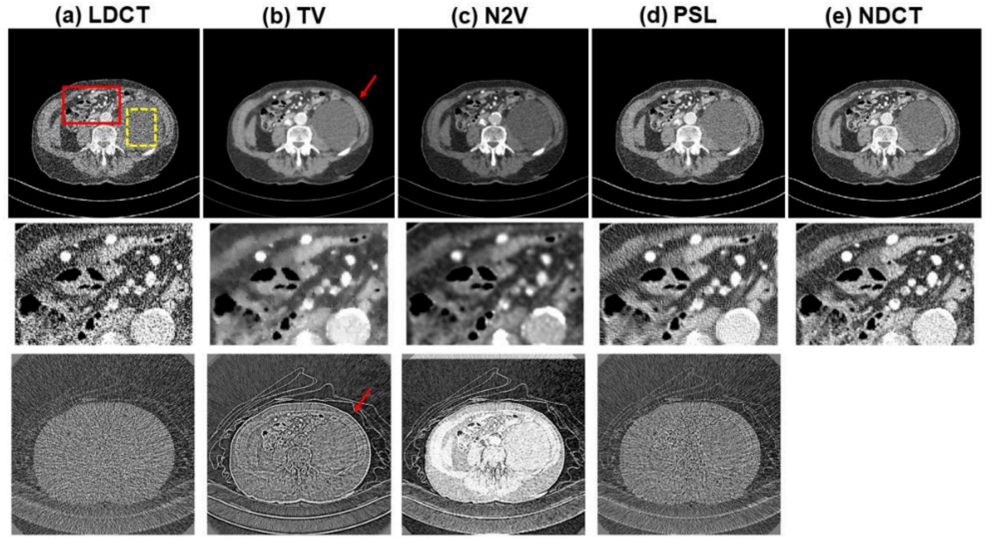
$$\arg_W \min \sum_{t=0}^{T} \sum_{E\in\{UL,UR,LL,LR\}} \frac{\left(Y_t^E - \mu_{X_t}^E\right)^2}{\left(\sigma_{X_t}^2\right)^E + \left(\sigma_{\epsilon_t}^2\right)^E} + \log\left(\left(\sigma_{X_t}^2\right)^E + \left(\sigma_{\epsilon_t}^2\right)^E\right) + \frac{\left|\mu_{X_t}^E - \frac{1}{3}\sum_C \mu_{X_t}^C\right|}{\lambda} - 0.1\left(\sigma_{\epsilon_t}^2\right)^E$$

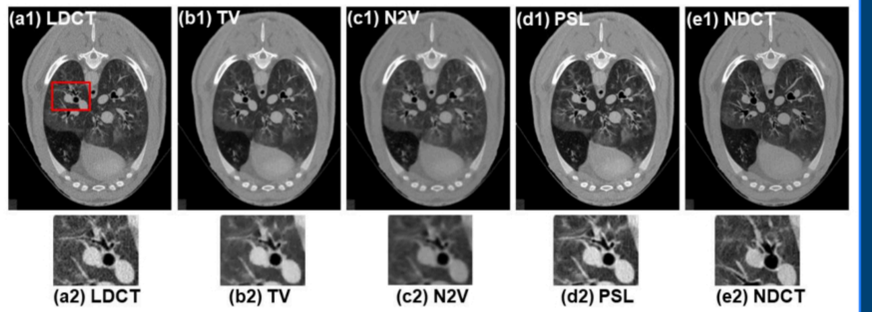
$$\left\{\mu_X^E, \left(\sigma_X^2\right)^E, \left(\sigma_\epsilon^2\right)^E\right\} = \Phi_W(Y^C)$$

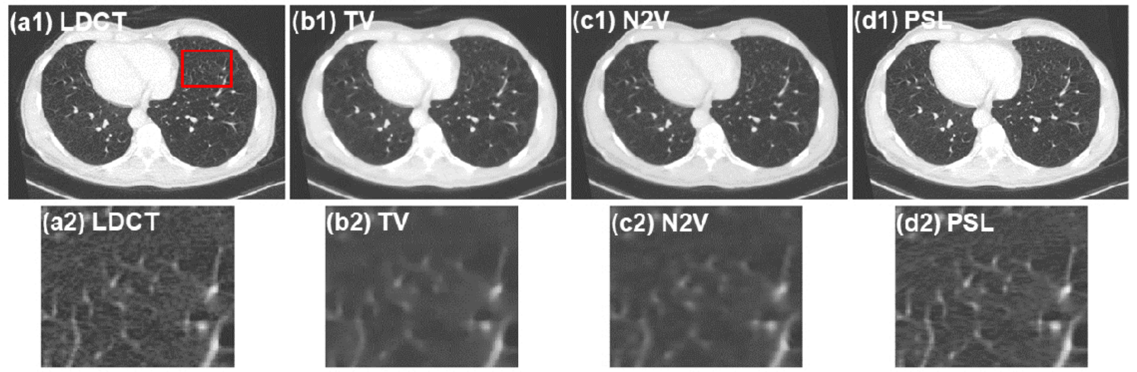
- Testing phase:

$$\overline{Y^E} = \frac{Y^E\left(\sigma_\epsilon^{-2}\right)^E + \mu_X^E\left(\sigma_X^{-2}\right)^E}{\left(\sigma_\epsilon^{-2}\right)^E + \left(\sigma_X^{-2}\right)^E}$$

RESULTS







- Compared to LDCT images, PSL increases PSNR/SSIM values from 27.61/0.5939 to 30.50/0.6797.
- outperformed the TV and N2V based denoisers
- similar image impression as the clinically used NDCT

DATASETS

- AAPM 2016 Low dose Challenge
- Split origin 10 train cases into 8/2 for training/testing

CONCLUSIONS

- A PSL framework was proposed to solve the paired data scarcity problem regarding the deep learning based LDCT denoising task
- The inherent shift-invariant property was exploited to characterizes the pixel correlations

REFERENCES

- *Krull, A., et.al, in Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition.*
- *Laine, S., et al. in Advances in Neural Information Processing Systems.*

- Preprint version of this work: https://arxiv.org/abs/2006.00327