



Motivation

- Optimizing combination weights of fixed deep features brings strict constraints that maintain image structure even using aggressive enhancing regularizations
- Application for both learning and non-learning computational imaging techniques

Principle

Two-stage optimization



Stage 1: fitting decoder to output pre-reconstruction (for non-learning methods) $min_{\theta} \| Net_{\theta}(I_d, \lambda = 1) - I_n \|^2$

Color and texture enhancing term Stage 2: weighting deep features $p_c(z) = exp(-(s(z) + c(z) + u(z)))$ $min_{\lambda}p_{c}(Net(I_{d},\lambda)) + p_{e}(Net(I_{d},\lambda))$ $p_e(z) = exp(-\nabla z)$

Generalized Imaging Augmentation via LINEAR Optimization of Neurons (LION) Daoyu Li^{1,†}, Lu Li^{1,†}, Bin Li², Liheng Bian^{1,*}

¹University of Beijing Institute of Technology, ²Beijing University of Posts and Telecommunications

Pre-reconstruction Output Deep feature domain Measurement Pre-reconstruction



Experiments

LION outperforms optimizing all weights



Measurement

Pre-reconstruction Optimizing all weights Optimizing all weights $min p_c + p_e + p_d$ $min p_c + p_e$

LION for various applications



Lensless #3

LION $min p_c + p_e$

Ground truth