Joint Noise Level Estimation from Personal Photo Collections

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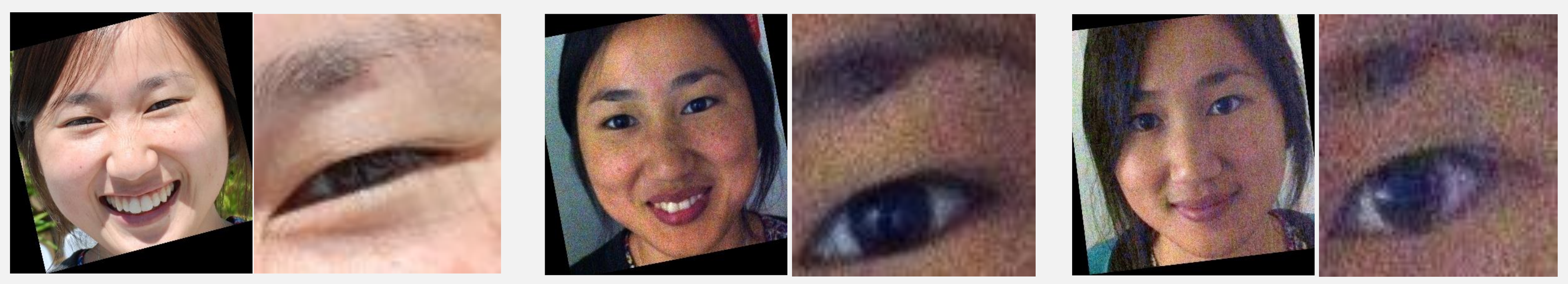
Goal

- Given a set of face images from the same person, taken under different lighting and cameras, estimate the noise levels in each image



- $\boldsymbol{I}_n = \boldsymbol{I}_{orig} + \boldsymbol{n}$, i.i.d, zero mean. σ = noise level $\triangleq std[\boldsymbol{n}]$
- This is difficult because we cannot decouple $\boldsymbol{n}$ from $\boldsymbol{I}_n$

Contributions

- **Key observation**: given two noisy images, the noise levels are correlated if they share the same underlying image content, since $\sigma_1^2 - \sigma_2^2 = var[\boldsymbol{I}_{n,1}] - var[\boldsymbol{I}_{n,2}]$
- We formulate the estimation as maximizing the joint probability distribution between all images' noise levels
- The joint distribution is conditioned on the pair-wise *relative* noise levels $\{\rho_{ij} | \rho_{ij} \triangleq \sigma_i^2 - \sigma_j^2\}$. We use a two-stage optimization that first estimates $\{\rho_{ij}\}$, then $\{\sigma_i\}$

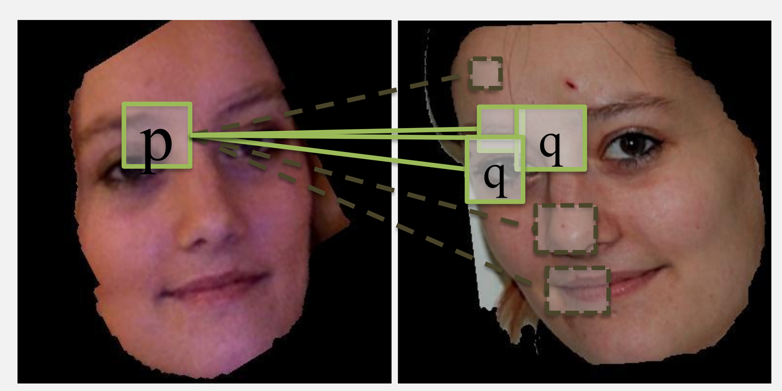
Overview

Starting from a face image collection:

- Preprocess: geometrically and photometrically align the images with affine transform and color match
- Two-stage optimization:
  - Estimating $\{\rho_{ij}\}$: We take a patch-based method. We first find the patch correspondence between $\boldsymbol{I_i}$ and $\boldsymbol{I_j}$, then find the best estimated relative noise $\{\rho_{ij}^*\}$ from the patch pairs.
  - With $\{\rho_{ij}^*\}$, estimate $\{\sigma_i\}$ by constraining $\sigma_i^2 - \sigma_j^2 = \rho_{ij}^*$

Pair-wise Relative Noise $\{\rho_{ij}\}$ Estimation

- The two faces are not perfectly aligned
- We break down the image into patches, and estimate the patch-wise relative noise levels ζ_{pq} by $\zeta_{pq} \triangleq var[\boldsymbol{p}_{1p}] - var[\boldsymbol{p}_{2q}]$



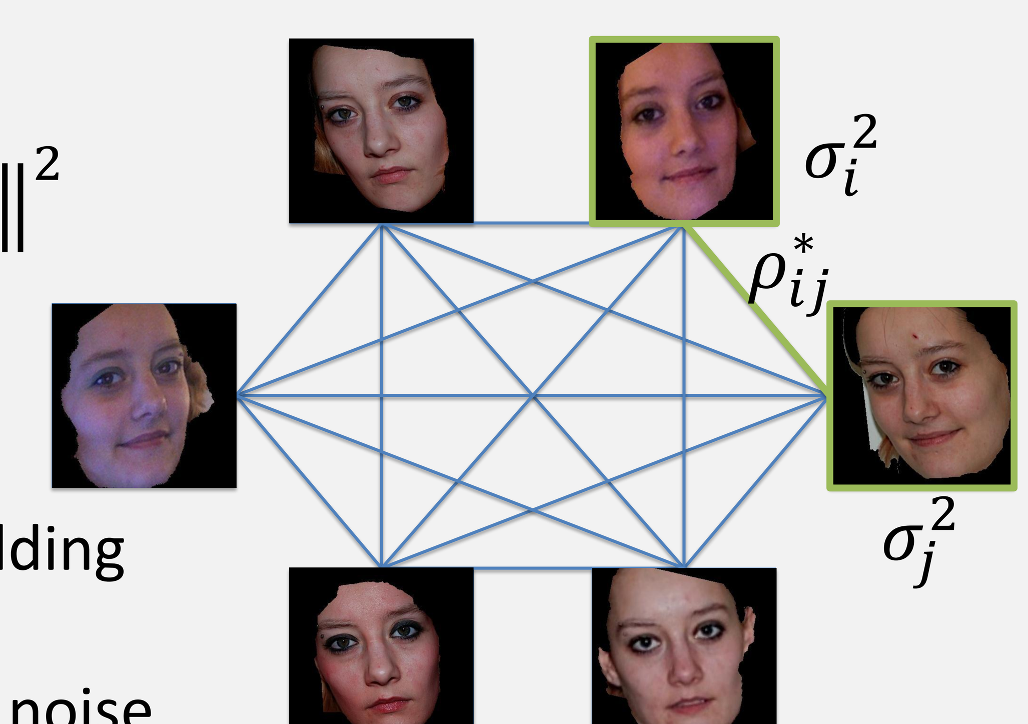
I_1 I_2

- Compute pair-wise relative noise by aggregating ζ_{pq}: $\rho_{12}^* = \frac{\sum_{p,q} c_{pq}\zeta_{pq}}{\sum_{p,q} c_{pq}}$
- $c_{pq} = \exp(-\kappa_{pq}\|\boldsymbol{p}_{1p} - \boldsymbol{p}_{2q}\|^2)$, confidence that (p,q) is a true correspondence
- For computational efficiency, we selected the best 5 q s for each p

Absolute Noise Level Estimation with Global Optimization

- We estimate $\{\sigma_i\}$ conditioning on $\{\rho_{ij}^*\}$
- $\{\sigma_i^2\}$ =argmin $\sum_{i \neq j} w_{ij} \|\sigma_i^2 - \sigma_j^2 - \rho_{ij}^*\|^2$

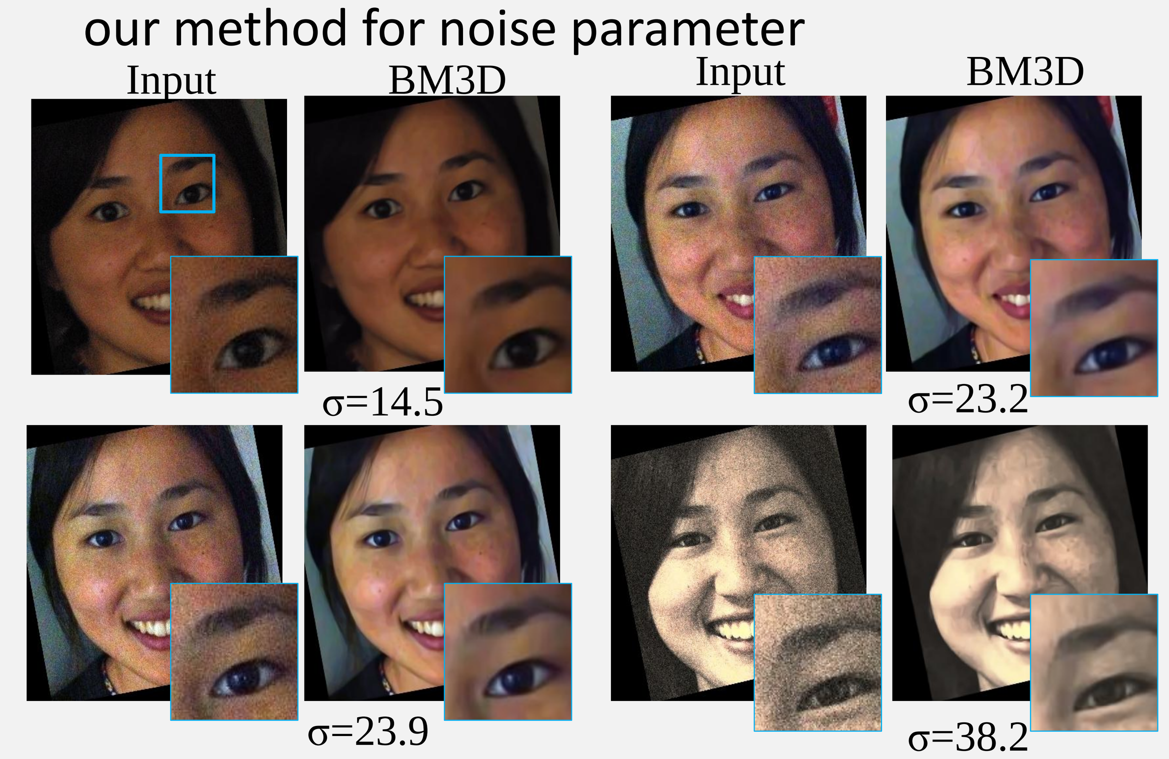
  w_{ij}: similarity between two faces



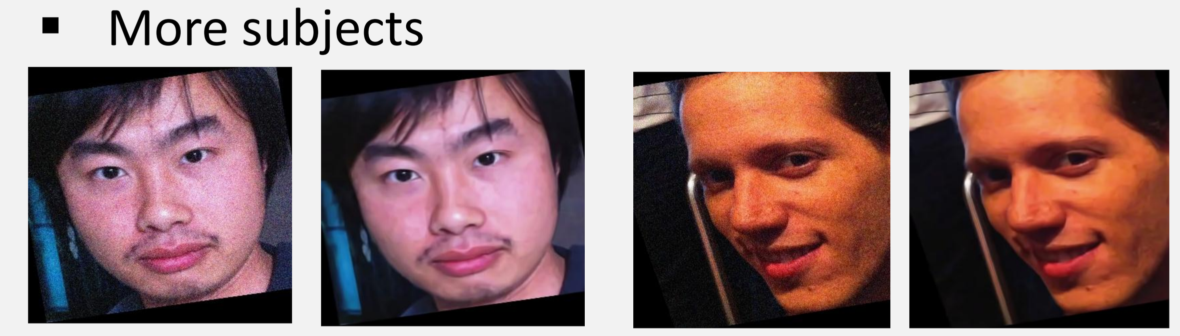
- Solving a linear system
- The system is under-determined, up to adding a constant number.
  - option 1: assign some images to be zero noise
  - option 2: assuming the collection contains clean images, assign the least noisy one to be zero. We use this one for evaluations

Results

- We show one example below with estimated noise levels and denoised result using BM3D + our method for noise parameter

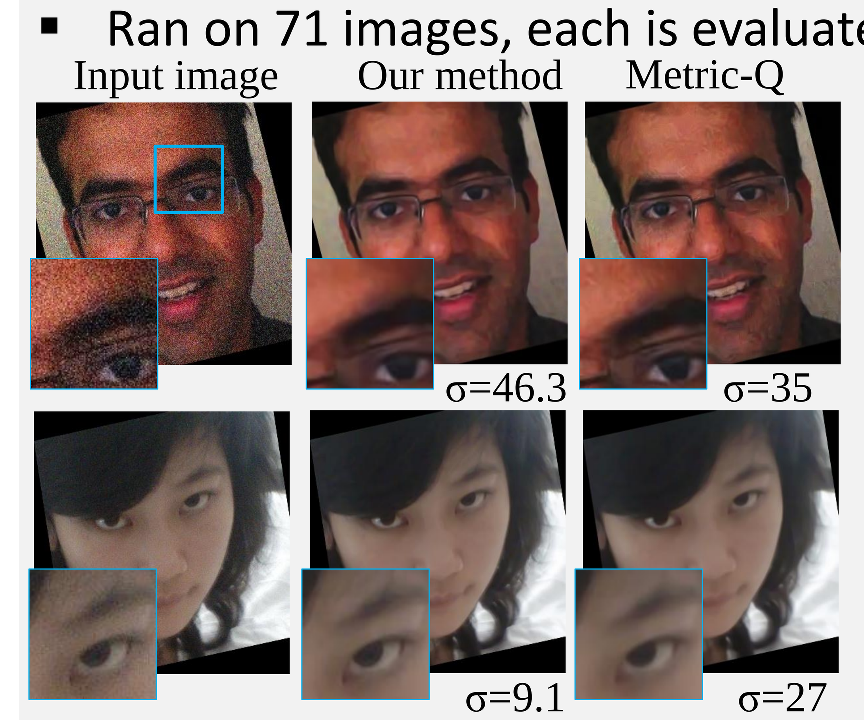


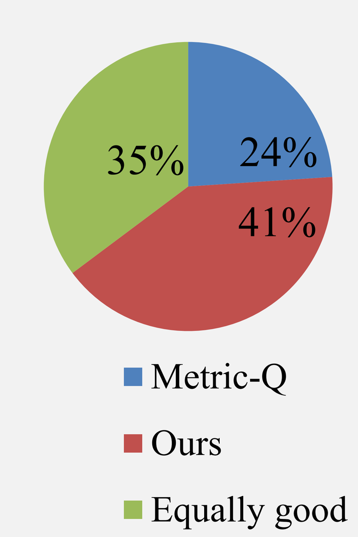
- More subjects



User Study

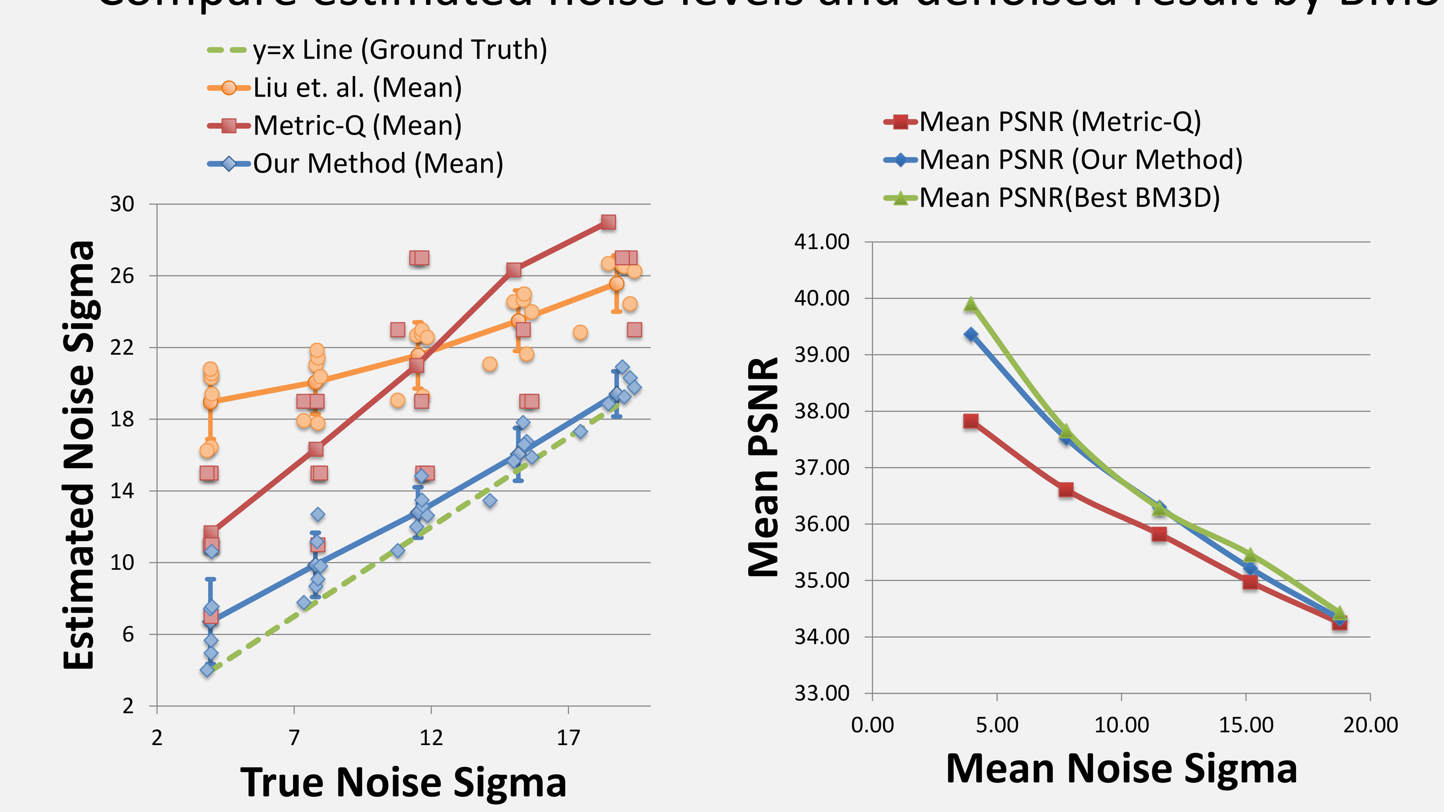
- Based on BM3D denoised result, decide which one is preferable
- Ran on 71 images, each is evaluated by 3 users

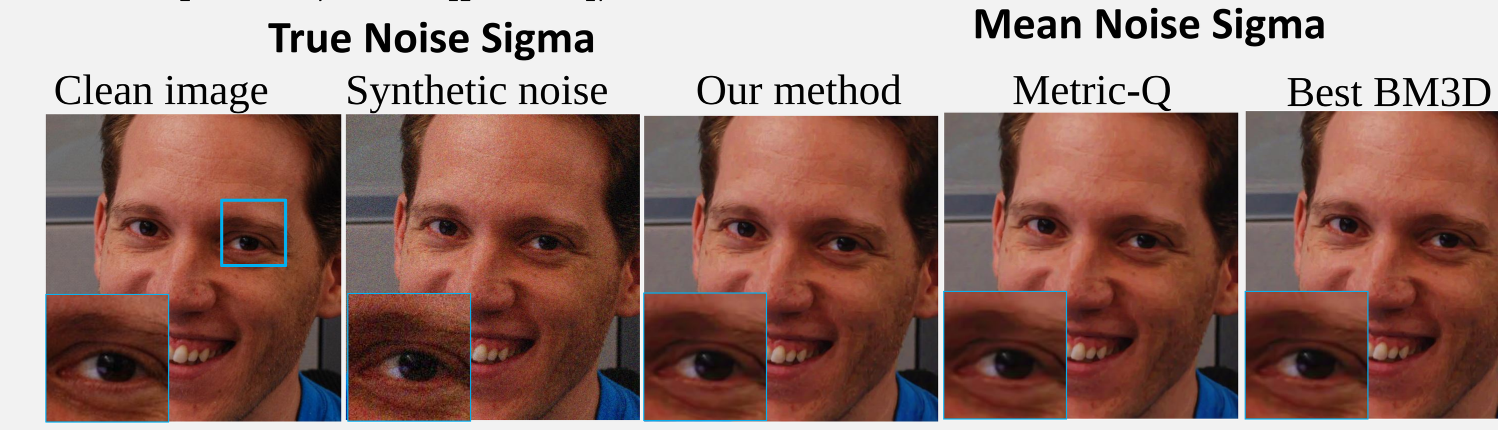




Ground Truth Experiment and Comparison

- Add synthetic Gaussian noise with different parameters
- Compare estimated noise levels and denoised result by BM3D





	Clean image	Synthetic noise	Our method	Metric-Q	Best BM3D
σ		19.25	20.31	27	23
PSNR		22.33	34.65	34.53	34.65

Selected References

C. Liu, R. Szeliski, S. Kang, C. Zitnick, and W. Freeman. Automatic estimation and removal of noise from a single image. IEEE Transactions on Pattern Analysis and Machine Intelligence, 30(2), 2008

X. Zhu and P. Milanfar. Automatic parameter selection for denoising algorithms using a no-reference measure of image content. IEEE Transactions on Image Processing, 19(12), 2010.

Acknowledgements

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