

Image Denoising survey

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paper: **Image Denoising: The Deep Learning Revolution and Beyond - A Survey Paper** by Michael Elad, Bahjat Kawar, Gregory Vaksman
SIAM J. Imaging Science, 2023

① What is image denoising?

$$y = x + v, \quad \text{all vectors in } \mathbb{R}^N \text{ (eg. } N = n_x \times n_y \text{)}$$

↑ ↑ ↖ noise
observed true image

* note we wlog use vectors not matrices

It's the simplest inverse problem ($y = A \cdot x + v$) i.e. $A = I$

- Assume $v \sim N(0, \sigma^2 I)$
 ↖ and σ^2 known. } "AWGN"
 Additive, white Gaussian Noise

... the simplest noise model.

→ real cameras (CCD pixel arrays) have a tiny amount of AWGN. Mostly "shot noise" due to quantum nature of discrete photons, following a Poisson distribution (partly addressed via Anscombe or other variance stabilizing distribution, model as Gaussian if photon count high)

• Why so simple?

- Fundamental: backbone of more realistic setups
 ($A \neq I$, and other noise) } indirect
- Tractable, understood
- Paper argues its a key ingredient in fancier setups } direct

• Goal

Build a denoiser D , return estimate

$$\hat{x} = D(y, \sigma)$$

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- What criterion?

For now, for good reason, use MSE (equivalently, PSNR)

* Careful: before, "MSE" is $\frac{1}{\# \text{pixels}} \sum_{i=1}^{\# \text{pixels}} (\hat{X}_i - x)^2$
and "mean" referred to this average
 $\parallel \hat{X} - x \parallel_2^2$
actual constant of little importance if it never changes

Now,

$$\text{MSE} = \mathbb{E} \parallel \hat{X} - x \parallel_2^2 := \int \parallel \hat{X} - x \parallel_2^2 \cdot p(x) dx$$

($\hat{X} = D(y, \sigma)$, $y = x + v$,
so \hat{X} is a function of x)

i.e. "mean" is used in a different sense.

That is, we're assigning a prior distribution to the set of images.

$$p(X = \begin{bmatrix} \text{sun} & \text{house} \\ \text{tree} & \end{bmatrix}) = 0.013, \quad p(X = \begin{bmatrix} \text{noise} & \text{noise} \\ \text{noise} & \text{noise} \end{bmatrix}) = 10^{-20}$$

This is the critical ingredient...

without a prior, there's no hope

Setting $\hat{X} = y$ is the best you can do.

So this is Bayesian?
not Frequentist?

Note to future years:
lecture was 1 day before
2024 presidential election

Yes, sort of...

but we don't (anymore) write down a formula for $p(x)$

(these days, we'll learn it from our dataset)

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Estimation 101

$y = x + v$, P_x is prior on X

$P_{x,y}$ is joint on $X \times Y$

whether Bayesian or not, Bayes' rule is true:

$$P_{X|Y=y}(x) = \frac{P_{X,Y}(x,y)}{P_Y(y)} = \frac{P_{Y|X=x}(y) P_X(x)}{P_Y(y)}$$

" X " refers to r.v.

" x " refers to possible value of r.v.

Maximum Likelihood Estimation (MLE) [not "Bayesian"] ^{very popular}

Find x to maximize $p(y|x)$ ("likelihood") or minimize negative log likelihood

Given x , $y = x + v$ i.e. $y \sim N(x, \sigma^2 I)$

$$\text{so } p(y|x) = \text{const.} \cdot \exp(-\|y-x\|^2 / 2\sigma^2)$$

so

$$\hat{x}_{MLE} = \underset{x}{\operatorname{argmin}} -\log(p(y|x)) = \underset{x}{\operatorname{argmin}} \frac{1}{2} \frac{1}{\sigma^2} \|y-x\|^2 = y$$

$\hat{x}_{MLE} = y$ not useful! (if $A \neq I$ it can be useful)

Maximum 'a posteriori' Estimation (MAP) [Bayesian]

Find x to maximize $p(x|y)$

$$p(x|y) = \frac{p(y|x) p(x)}{p(y)}$$

~~$p(y)$~~ unimportant

$$\underset{x}{\min} -\log(p(x|y)) = \underset{x}{\min} \underbrace{-\log(p(y|x))}_{\text{MLE term}} \underbrace{-\log(p(x))}_{\text{if } p(x) = \text{constant (i.e. uniform, uninformative) then this has no effect so MLE=MAP in this case}}$$

exploits a prior

assume $p(x) \sim e^{-\rho(x)}$

data fitting term

regularization term

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Ex Suppose $p(x) = \text{const} \cdot \exp(-\|x\|_2^2)$ ^{$\rho(x)$} ie. we prioritize small values of pixels
then MAP:

$$\min_x -\log(p(y|x)) - \log(p(x))$$

$$= \min_x \frac{1}{2\sigma^2} \|x - y\|^2 + \frac{1}{2} \|x\|^2 \quad \text{Tikhonov regularization / Ridge regression}$$

MMSE minimum MSE estimator [Bayesian]

Find \hat{x} to minimize MSE $\mathbb{E} \|\hat{x} - x\|^2$

$$\hat{x}_{\text{MMSE}} = \mathbb{E}[x|y] \quad \text{"closed form" misleading}$$

not helpful directly except in simplest cases

② "Classical" Techniques

... most (not all) involved choosing priors $p(x)$, or,
equivalently, choosing $-\log(p(x)) =: \rho(x)$