

Mathematical methods for Image Processing

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invitation by
Jidesh P., NITK Surathkal

funding
Global Initiative on Academic Network

Oct. 23–27

Plan

- 1 Image restoration–Applications

Image Restoration: Linear inverse problems

Let

$$u = Hv + b$$

where

$$H : \mathbb{R}^{N^2} \longrightarrow \mathbb{R}^P$$

We know u and H . We look for an estimate of v .

We minimize the Rudin-Osher-Fatemi (ROF) model

$$\min_{w \in \mathbb{R}^{N^2}} E(w),$$

where

$$E(w) = TV_\varepsilon(w) + \lambda \|Hw - u\|_2^2.$$

To do so, we implement a gradient descent algorithm and need to calculate

$$\nabla E(w).$$

Image Restoration: Linear inverse problems

Let $w, w' \in \mathbb{R}^{N^2}$, we have

$$\begin{aligned}\|H(w + w') - u\|_2^2 &= \langle (Hw - u) + Hw', (Hw - u) + Hw' \rangle \\ &= \langle Hw - u, Hw - u \rangle + 2\langle Hw', Hw - u \rangle \\ &\quad + \langle Hw', Hw' \rangle \\ &= \|Hw - u\|_2^2 + \langle w', 2H^*(Hw - u) \rangle + o(\|w'\|)\end{aligned}$$

where H^* is the adjoint of H .

We therefore have¹

$$\nabla E(w) = \nabla TV_\varepsilon(w) + 2\lambda H^*(Hw - u).$$

It is easy to compute as soon as we can compute H and H^* .

¹Remember

$$E(w) = TV_\varepsilon(w) + \lambda \|Hw - u\|_2^2.$$

Image Restoration, denoising : $H = H^* = Id$



Top: noisy images; Bottom: denoised images .

Image Restoration, denoising : $H = H^* = Id$



Figure: Denoising : $\sigma = 20$ and $\lambda = +\infty, 0.5, 0.05, 0.017$ and 0.005 . Clean image.

Image Restoration, deblurring : H is a convolution

We have for all $w \in \mathbb{R}^{N^2}$

$$(Hw)_{m,n} = (h * w)_{m,n} = \sum_{m',n'=0}^{N-1} h_{m-m',n-n'} w_{m',n'}$$

for known convolution kernel $h \in \mathbb{R}^{N^2}$.

There are many algorithms to compute H .

Image Restoration, deblurring : H is a convolution

For w and $w' \in \mathbb{R}^{N^2}$, we have

$$\begin{aligned}\langle Hw, w' \rangle &= \sum_{m,n=0}^{N-1} (Hw)_{m,n} w'_{m,n} \\ &= \sum_{m,n=0}^{N-1} \sum_{m',n'=0}^{N-1} h_{m-m',n-n'} w_{m',n'} w'_{m,n} \\ &= \sum_{m',n'=0}^{N-1} w_{m',n'} \sum_{m,n=0}^{N-1} h_{m-m',n-n'} w'_{m,n} \\ &= \sum_{m',n'=0}^{N-1} w_{m',n'} (\tilde{h} * w')_{m',n'}\end{aligned}$$

where $\tilde{h}_{x,y} = h_{-x,-y}$, for all $x, y \in \mathbb{Z}$.

So

$$(H^* w')_{m,n} = (\tilde{h} * w')_{m,n}, \quad \forall (m, n) \in \{0, \dots, N-1\}.$$

Image Restoration, deblurring : H is a convolution



Top: blurred image; Bottom: restored and ideal image.

Image Restoration, inpainting : H multiplies by a mask

We know an image in a region $\mathcal{C} \subset \{0, \dots, N-1\}^2$. We set for all $w \in \mathbb{R}^{N^2}$

$$(Hw)_{m,n} = M_{m,n} \cdot w_{m,n}$$

for known mask

$$M_{m,n} = \begin{cases} 1 & , \text{ if } (m, n) \in \mathcal{C} \\ 0 & , \text{ otherwise} \end{cases}$$

Computing Hw is straightforward.

Image Restoration, inpainting : H multiplies by a mask

For w and $w' \in \mathbb{R}^{N^2}$, we have

$$\begin{aligned}\langle Hw, w' \rangle &= \sum_{m,n=0}^{N-1} (Hw)_{m,n} w'_{m,n} \\ &= \sum_{m,n=0}^{N-1} (M_{m,n} w_{m,n}) w'_{m,n} \\ &= \sum_{m,n=0}^{N-1} w_{m,n} (M_{m,n} w'_{m,n}) \\ &= \langle w, Hw' \rangle\end{aligned}$$

So $H^* = H$.

Image Restoration, inpainting : H multiplies by a mask



Top: Image with missing pixels; Bottom: restored and ideal image

Image Restoration: Zooming in

We consider the composition

$$H = S \circ C$$

of a convolution $C : \mathbb{R}^{(KN)^2} \rightarrow \mathbb{R}^{(KN)^2}$ and sampling $S : \mathbb{R}^{(KN)^2} \rightarrow \mathbb{R}^{N^2}$ defined by

$$(Sw)_{m,n} = w_{Km,Kn} \quad , \text{ for all } m, n = 0..N-1.$$

We have

$$(S \circ C)^* = C^* \circ S^*.$$

We only need to calculate $S^* : \mathbb{R}^{N^2} \rightarrow \mathbb{R}^{(KN)^2}$.

Image Restoration: Zooming in

For $w \in \mathbb{R}^{(KN)^2}$ and $w' \in \mathbb{R}^{N^2}$, we have

$$\begin{aligned}\langle Sw, w' \rangle &= \sum_{m,n=0}^{N-1} (Sw)_{m,n} w'_{m,n} \\ &= \sum_{m,n=0}^{N-1} w_{Km,Kn} w'_{m,n} \\ &= \sum_{m,n=0}^{N-1} \sum_{k,l=0}^{K-1} w_{Km+k,Kn+l} (S^* w')_{Km+k,Kn+l} \\ &= \langle w, S^* w' \rangle\end{aligned}$$

with

$$(S^* w')_{Km+k,Kn+l} = \begin{cases} w'_{m,n} & , \text{ if } (k, l) = (0, 0) \\ 0 & , \text{ otherwise} \end{cases}$$

S^* zooms the image by interlacing 0. The result $S^* w'$ is a kind of "Dirac comb".

Image Restoration: Zooming in



Un-zoomed; zoomed (x4) by two methods

Image Restoration: De-compression

The lossy part of the compression of an image u consists in

- Compute Wu , where W is a unitary matrix or transform (JPEG 2000 ; wavelet, JPG : local cosine)
- Quantize every entry
- Encode the quantization interval

Therefore for any entry i of Wu we only know that

$$\tau_i^- \leq (Wu)_i < \tau_i^+$$

where τ_i^- and τ_i^+ are the known bounds of the quantization interval.

We estimate u by solving

$$\begin{cases} \min_w TV_\varepsilon(w) \\ \text{such that } \tau_i^- \leq (Ww)_i \leq \tau_i^+ \quad , \forall i. \end{cases}$$

Solved by a projected gradient descent algorithm (i.e. proximal gradient algorithm).

Image Restoration: De-compression

We denote

$$\mathcal{C} = \{w \in \mathbb{R}^{N^2} \mid \forall i, \tau_i^- \leq (Ww)_i \leq \tau_i^+\}$$

We denote $P_{\mathcal{C}}(w)$ the projection of any $w \in \mathbb{R}^{N^2}$ onto \mathcal{C} and have

$$\begin{aligned} P_{\mathcal{C}}(w) &= \operatorname{Argmin}_{w' \in \mathcal{C}} \|w - w'\|^2 \\ &= \operatorname{Argmin}_{\forall i, \tau_i^- \leq (Ww')_i \leq \tau_i^+} \sum_i ((Ww')_i - (Ww)_i)^2 \end{aligned}$$

We can prove that

$$(WP_{\mathcal{C}}(w))_i = \operatorname{Argmin}_{\tau_i^- \leq t \leq \tau_i^+} (t - (Ww)_i)^2$$

and therefore

$$(WP_{\mathcal{C}}(w))_i = \begin{cases} \tau_i^+ & , \text{ if } \tau_i^+ \leq (Ww)_i \\ (Ww)_i & , \text{ if } \tau_i^- \leq (Ww)_i \leq \tau_i^+ \\ \tau_i^- & , \text{ if } (Ww)_i \leq \tau_i^- \end{cases}$$

Image Restoration: De-compression



Top: compressed images (for different compression levels). Bottom: restored images