Mathematical methods for Image Processing

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Plan

1 Hands-on session with examples: Image zooming using the TV regularization



Check that ${\mathcal C}$ is a closed affine space. Characterize the vector space ${\mathcal C}'$ defining its direction.



Check that C is a closed affine space. Characterize the vector space C' defining its direction.

We have $C = u + \ker(Q)$. It is a affine space and $C' = \ker(Q)$.

- If $w \in C$, then Q(w u) = Q(w) Q(u) = v v = 0. Therefore, $w \in u + \ker(Q)$.
- If $w \in u + \ker(Q)$, let $w' \in \ker(Q)$ such that w = u + w'. We have

$$Q(w) = Q(u) + Q(w') = v.$$

Therefore, $w \in C$.



Check that the operator that maps any $w \in \mathbb{R}^{(KN)^2}$ to $P_{\mathcal{C}}(w) \in \mathbb{R}^{(KN)^2}$, as defined by

$$P_{\mathcal{C}}(w)_{i,j} = w_{i,j} - Q(w)_{\left[\frac{i}{K}\right],\left[\frac{j}{K}\right]} + v_{\left[\frac{i}{K}\right],\left[\frac{j}{K}\right]},$$

where [t] is integer floor function applied to t, corresponds to the orthogonal projection onto C.



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$$P_{\mathcal{C}}(w)_{i,j} = w_{i,j} - Q(w)_{\left[\frac{j}{K}\right], \left[\frac{j}{K}\right]} + v_{\left[\frac{j}{K}\right], \left[\frac{j}{K}\right]},$$

where [t] is integer floor function applied to t, corresponds to the orthogonal projection onto C.

We want to prove that

$$P_{\mathcal{C}}(w) = \operatorname{Argmin}_{w' \in \mathcal{C}} \|w' - w\|^2$$

i.e. we want to prove that

•
$$P_{\mathcal{C}}(w) \in \mathcal{C}$$

•
$$\forall w' \in \mathcal{C}, \|w - w'\|^2 \ge \|w - P_{\mathcal{C}}(w)\|^2$$



We have, for all i, j = 0...N - 1 (Notice $\left[\frac{Ki+k}{K}\right] = i$ and $\left[\frac{Kj+l}{K}\right] = j$)

$$Q(P_{\mathcal{C}}(w))_{i,j} = \frac{1}{K^2} \sum_{k,l=0}^{K-1} P_{\mathcal{C}}(w)_{Ki+k,Kj+l}$$

= $\frac{1}{K^2} \sum_{k,l=0}^{K-1} w_{Ki+k,Kj+l} + \frac{1}{K^2} \sum_{k,l=0}^{K-1} Q(w)_{i,j} + \frac{1}{K^2} \sum_{k,l=0}^{K-1} v_{i,j}$
= $Q(w)_{i,j} - Q(w)_{i,j} + v_{i,j} = v_{i,j}$

Therefore,

$$P_{\mathcal{C}}(w) \in \mathcal{C}$$



Let $w' \in \mathcal{C}$, we have

$$\langle w - P_{\mathcal{C}}(w), w' - P_{\mathcal{C}}(w) \rangle$$

$$= \sum_{i,j=0}^{N-1} \sum_{k,l=0}^{K-1} (w_{Ki+k,Kj+l} - P_{\mathcal{C}}(w)_{Ki+k,Kj+l}) (w'_{Ki+k,Kj+l} - P_{\mathcal{C}}(w)_{Ki+k,Kj+l})$$

$$= \sum_{i,j=0}^{N-1} \sum_{k,l=0}^{K-1} (Q(w)_{i,j} - v_{i,j}) (w'_{Ki+k,Kj+l} - w_{Ki+k,Kj+l} + Q(w)_{i,j} - v_{i,j})$$

$$= \sum_{i,j=0}^{N-1} (Q(w)_{i,j} - v_{i,j}) \left(\sum_{k,l=0}^{K-1} (w'_{Ki+k,Kj+l} - w_{Ki+k,Kj+l} + Q(w)_{i,j} - v_{i,j}) \right)$$



and

$$\sum_{k,l=0}^{K-1} (w'_{Ki+k,Kj+l} - w_{Ki+k,Kj+l} + Q(w)_{i,j} - v_{i,j})$$

= $K^2 Q(w')_{i,j} - K^2 Q(w)_{i,j} + K^2 Q(w)_{i,j} - K^2 v_{i,j} = 0$

Therefore, finally for any $w' \in \mathcal{C}$

$$\langle w - P_{\mathcal{C}}(w), w' - P_{\mathcal{C}}(w) \rangle = 0$$

and

$$||w - w'||^{2} = ||w - P_{\mathcal{C}}(w)||^{2} + ||w' - P_{\mathcal{C}}(w)||^{2} + 2\langle w - P_{\mathcal{C}}(w), w' - P_{\mathcal{C}}(w) \rangle$$

= $||w - P_{\mathcal{C}}(w)||^{2} + ||w' - P_{\mathcal{C}}(w)||^{2}$
$$\geq ||w - P_{\mathcal{C}}(w)||^{2}$$



Check that all the elements of C have the same mean. Conclude that (P) has a minimizer. Propose an example in which (P) has several solutions.



For any $w \in C$,

$$\sum_{i,j=0}^{N-1} \sum_{k,l=0}^{K-1} w_{Ki+k,Kj+l} = \sum_{i,j=0}^{N-1} K^2 Q(w)_{i,j}$$
$$= K^2 \sum_{i,j=0}^{N-1} v_{i,j}$$

Therefore, they all have the same mean. Rewriting

$$(P): \begin{cases} \text{minimize } E(u+w) \\ \text{under thet constraint } w \in \ker(Q), \end{cases}$$

E is convex, finite and coercive on ker $(Q) \subset \{w | \text{mean of } w \text{ is } 0\}$. (*P*) has a solution. Non-uniqueness: Take a 1D example, in which *u* is an increasing function.

Check that

$$\nabla E(w) = 2\left(D_x^*(X) + D_y^*(Y)\right),$$

where D_x^* et D_y^* are as in the Hands-on session 1, and

$$X_{i,j} = \varphi_{\beta}'(|\nabla w_{i,j}|^2) D_x w_{i,j},$$
$$Y_{i,j} = \varphi_{\beta}'(|\nabla w_{i,j}|^2) D_y w_{i,j},$$
$$\in \{0, \dots, KN - 1\}^2, \text{ and where } \varphi_{\beta}'(t) \text{ is the derivative}$$

for $(i,j) \in \{0, \ldots, KN-1\}^2$, and where $\varphi'_{\beta}(t)$ is the derivative of φ_{β} at the point t.

See lecture on total variation.



Detail a projected gradient algorithm solving (P).



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Algorithm 2 Proximal gradient algorithm

Entry: β , v**Output:** Approximation of a solution of (*P*): w^*

Initialize w Set $L = \frac{8}{\sqrt{\beta}}$ While Not converged **Do** Compute $d = \nabla E(w)$ Update : $w \leftarrow P_C(w - \frac{1}{L}d)$ End while

(see lecture on TV)

(see question 4) (see question 2)

