Relaxation Methods in Variational Image Processing

Jan Lellmann, Emanuel Laude, Thomas Moellenhoff, Daniel Cremers, Michael Moeller, Evgeny Strekalovskiy

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lellmann@mic.uni-luebeck.de





Cambridge Image Analysis University of Cambridge

www.damtp.cam.ac.uk/research/cia

Mathematical Image Computing University of Lübeck

www.mic.uni-luebeck.de







b = T(u)



b = T(u)+n



b = T'(u)+n'



Given measurements b, find image data u so that b = T(u) + n

T structural operator, n random noise Often the direct reconstruction is not unique, not stable, or not deterministic – we need prior knowledge

Variational methods

We reconstruct the unknown data u from the measurements b by minimizing the energy

$$\min_{u} \{ D(T(u); b) + R(u) \}$$

Intuitive (what do we want) and modular (reusable) In practice: often

$$\min_{u:\Omega\to X}\int_{\Omega}\rho(x,u(x))dx+\lambda\int_{\Omega}\sigma(\nabla u)dx$$

Convexity

Convexity assures that every local minimizer of the energy is also a global minimizer



Non-convexity I – data terms





image sequence

optical flow/registration

 $\min_{u:\Omega\to\mathbb{R}^2}\int_{\Omega}D(I^1_{\sigma}(x),I^2_{\sigma}(x+u))dx + \lambda\int_{\Omega}d\|Du\|$

Lellmann, Strekalovskiy, Kötter, Cremers '13

Non-convexity II – labeling



$$\min_{u:\Omega \to X} f(u) := D(u;I) + R(u)$$
$$X := \left\{ \blacksquare \blacksquare \blacksquare \cdots \right\}$$

With: V. Corona, C. Schönlieb, J. Acosta-Cabronero, P.~Nestor/DZNE Magdeburg



 $\min_{u:\Omega\to\mathcal{M}} \int_{\Omega} D_{\mathcal{M}}(u(x), I(x)) dx + \lambda \operatorname{TV}(u)$



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Drawback

This is generally as hard as minimizing the original energy!

$$\min_{u:\Omega\to X} \int_{\Omega} \rho(x, u(x)) dx + \lambda \int_{\Omega} \sigma(\nabla u) dx$$
























Separate exact relaxation



Lifting



Hard decisions are replaced by soft "probabilities"

Lifting

We extend the problem

 $\min_{u':\Omega\to X} f'(u')$



to the probability measures: $\min_{u:\Omega \to \mathcal{P}(X)} f(u)$

The new energy *f* should agree with *f'* on Dirac measures, and not create artificial minimizers.

Potts '52; Boykov et al. '98, '01; Kleinberg, Tardos '01 Zach et al. '08; Lellmann, Becker, Schnörr '09; Chambolle, Cremers, Pock '11 Young measures: Young '37; Currents: Schwartz '51; de Rahm '55; Federer '69 Paired calibrations: Brakke '91; Alberti, Bouchitté, Dal Maso '01

• Lifting + relaxation using the biconjugate:

$$\int_{\Omega} \rho(u(x)) dx \rightsquigarrow \int_{\Omega} \boldsymbol{\rho}^{**}(u(x)) dx$$

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• Linear relaxation (*1-sparse* solutions):

$$\boldsymbol{\rho}(z) = \begin{cases} \rho(t^i), & z = e^i, \ i \in \{1, \dots, L\}, \\ +\infty, & \text{otherwise.} \end{cases}$$

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u

$$\boldsymbol{\rho}(z) = \begin{cases} \rho(t^i), & z = e^i, \ i \in \{1, \dots, L\}, \\ +\infty, & \text{otherwise.} \end{cases}$$
$$\min_{\boldsymbol{\epsilon} \in \mathrm{BV}(\Omega, \mathcal{P}(X))} f(u) := \int_{\Omega} \langle u(x), s(x) \rangle dx + \int_{\Omega} d\Psi(Du)$$



























RGB-Depth Segmentation (Diebold et al., SSVM '15)









Kolev et al., Int. J. Comp. Vis. '09

Label bias



The solution tends strongly towards the chosen labels!



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• New: Precise relaxation (2-sparse solutions!)

$$\boldsymbol{\rho}(z) = \begin{cases} \rho((1-\alpha)t^i + \alpha t^{i+1}), & z = (1-\alpha)e^i + \alpha e^{i+1}, \\ +\infty, & \text{otherwise.} \end{cases}$$

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New: lifting + precise relaxation

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linear lifting

L=2





linear lifting

L = 4





linear lifting

L = 8





linear lifting

L = 16





linear lifting

L = 32





linear lifting

L = 32



L=2







linear lifting

L = 32



L = 4







linear lifting

L = 32



L = 8







linear lifting L = 270

precise lifting

L = 8

















input



input

exact solution



input

exact solution

lifted linear 64 labels



input

exact solution

lifted linear 64 labels lifted precise 8 labels

Mean and variance estimation



Mean and variance estimation



Mean and variance estimation



Optical flow and image registration



Optical flow and image registration





Take-home

Goal: global minimizer of nonconvex energies

Lift into larger space

Relax piecewise convex

Much smaller problems, often 2-4 labels enough



lellmann@mic.uni-luebeck.de Möllenhoff, Laude, Möller, Lellmann, Cremers, CVPR'16