Nonlocal Regularizing Constraints in Variational Optical Flow

12th Int. Conf. Computer Vision Theory and Applications (VISAPP)
Porto, Portugal

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March 1st, 2017

Introduction

- Optical Flow → compute a correspondence field between an image pair to capture the apparent dynamical behaviour of the objects in the scene.

I_0

$\xrightarrow{(u_1(\mathbf{x}), u_2(\mathbf{x}))}$

I_1

- Classification of methods
  - **Local** → point matching ⇒ sparse flow.
    - ⋆ Lucas-Kanade[1] model: $K_\rho * (I_x u_1 + I_y u_2 + I_t)^2$
  - **Global**/**variational** → regularized energy minimization ⇒ dense flow.
    - ⋆ Horn-Schunck[2] model: $\int_\Omega (I_x u_1 + I_y u_2 + I_t)^2 d\mathbf{x} + \lambda \int_\Omega \left(|\nabla u_1|^2 + |\nabla u_2|^2\right) d\mathbf{x}$

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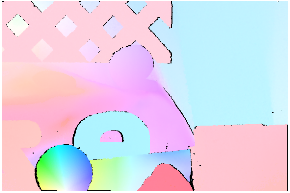
[1] B. Lucas and T. Kanade, An iterative image registration technique with an application to stereo vision, Proc. Int. Joint Conf. Artificial Intell., pp. 674-679, 1981.

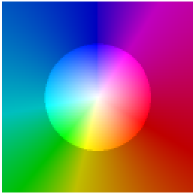
[2] B. Horn and B. Schunck, Determining optical flow, Proc. Tech. Symp. East, Int. Society for Optics and Photonics, pp. 319-331, 1981.

Introduction

- Optical Flow $\rightarrow$ compute a correspondence field between an image pair to capture the apparent dynamical behaviour of the objects in the scene.



Flow



Color coding

- Classification of methods
  - **Local** $\rightarrow$ point matching $\Rightarrow$ sparse flow.

    $\star$ Lucas-Kanade[1] model: $K_\rho * (I_x u_1 + I_y u_2 + I_t)^2$
  - **Global**/**variational** $\rightarrow$ regularized energy minimization $\Rightarrow$ dense flow.

    $\star$ Horn-Schunck[2] model: $\int_\Omega (I_x u_1 + I_y u_2 + I_t)^2 d\mathbf{x} + \lambda \int_\Omega \left(|\nabla u_1|^2 + |\nabla u_2|^2\right) d\mathbf{x}$

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State of the Art

Notations

- Ω rectangular domain in $\mathbb{R}^2$.
- $I : \Omega \times [0, T] \rightarrow \mathbb{R}$ image sequence.
- $I(\mathbf{x}, t)$ intensity at pixel $\mathbf{x} = (x, y) \in \Omega$ and time $0 \leq t \leq T$.
- $\mathbf{u} : \Omega \times [0, T] \rightarrow \mathbb{R}^2$ flow field, $\mathbf{u}(\mathbf{x}, t) = (u_1(\mathbf{x}, t), u_2(\mathbf{x}, t))$.
- Drop dependency of variables over t, so $I_0(\mathbf{x}) = I(\mathbf{x}, t)$ and $I_1(\mathbf{x}) = I(\mathbf{x}, t+1)$.

Variational framework

$$\min_{\mathbf{u}} E(\mathbf{u}) = E_d(\mathbf{u}) + \lambda E_r(\mathbf{u})$$

s.t. $\mathbf{u}$ with low energy $\Leftrightarrow$ $\mathbf{u}$ satisfying desired properties.

Brightness Constancy Assumption (BCA)

$$I(\mathbf{x} + \mathbf{u}(\mathbf{x}, t), t + 1) - I(\mathbf{x}, t) = 0, \quad \forall \mathbf{x} \in \Omega$$

- Challenges → nonlinearity in $I(\mathbf{x} + \mathbf{u}(\mathbf{x}, t), t + 1)$.
- **Optical flow constraint (OFC)**:

$$\nabla I(\mathbf{x}, t) \cdot \mathbf{u}(\mathbf{x}, t) + I_t(\mathbf{x}, t) = 0, \quad \forall \mathbf{x} \in \Omega$$

Only valid for small displacements or very smooth images!

For large displacements:

- Embed minimization in a coarse-to-fine warping[3].
- Postpone any linearization to numerical scheme[4].

- Shortcomings → sensitive to additive illumination changes in the scene.

[3] M. Black and P. Anandan, The robust estimation of multiple motions: Parametric and piecewise smooth flow fields, Comput. Vis. Image Underst., vol. 63(1), pp. 75-104, 1996.

[4] T. Brox, A. Bruhn, N. Papenberg and J. Weickert, High accuracy optical flow estimation based on a theory for warping, Proc. ECCV, LNCS vol. 3024, pp. 25-36, 2004.

Gradient Constancy Assumption (GCA)[5]

$$\nabla I\left(\mathbf{x}+\mathbf{u}(\mathbf{x},t),t+1\right)-\nabla I\left(\mathbf{x},t\right)=0,\quad \forall\mathbf{x}\in\Omega$$

- Benefits $\rightarrow$ robust to additive illumination changes.
- Shortcomings w.r.t. BCA:
  - More sensitive to noise.
  - Performing poorly in smooth regions.

$\Downarrow$

combine BCA & GCA as data-fidelity term

- Higher-order constancy conditions much more sensitive to noise than GCA.

[5] T. Brox, A. Bruhn, N. Papenberg and J. Weickert, High accuracy optical flow estimation based on a theory for warping, Proc. ECCV, LNCS vol. 3024, pp. 25-36, 2004.

Window Regularized Constraints $\rightarrow$ flow constant over each neighbourhood

- Integrate local information by **regularizing BCA isotropically**[6]:

$$\int_{\Omega} K_{\rho}(\mathbf{x}-\mathbf{y})\,\psi\left(\left|I_1\left(\mathbf{y}+\mathbf{u}(\mathbf{x})\right)-I_0(\mathbf{y})\right|\right)d\mathbf{y}, \quad \forall \mathbf{x}\in\Omega$$

  - Benefits $\rightarrow$ robust to very high noise.
  - Shortcomings $\rightarrow$ blur motion discontinuities!

- **Truncated Normalized cross correlation**[7]:

$$\min\left\{1, 1-\int_{\mathcal{N}(\mathbf{x})}\frac{(I_0(\mathbf{y})-\mu_0(\mathbf{x}))}{\sigma_0(\mathbf{x})}\cdot\frac{(I_1(\mathbf{y}+\mathbf{u}(\mathbf{x}))-\mu_1(\mathbf{x}+\mathbf{u}(\mathbf{x})))}{\sigma_1(\mathbf{x}+\mathbf{u}(\mathbf{x}))}d\mathbf{y},\right\}, \forall \mathbf{x}\in\Omega$$

  - Disregard negative correllations to gain robustness against occlusions.
  - Benefits $\rightarrow$ Robust to multiplicative and linear illumination changes.
  - Shortcomings $\rightarrow$ Highly nonlinear!

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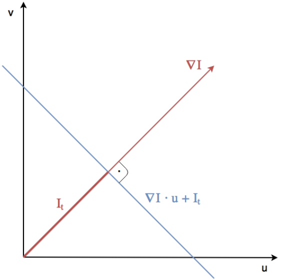
[6] A. Bruhn, J. Weickert and C. Schnörr, Lucas/Kanade meets Horn/Schunck: Combining local and global optic flow methods, Int. J. Comput. Vis., vol. 61(3), pp. 211-231, 2005.

[7] M. Werlberger, T. Pock and H. Bischof, Motion estimation with non-local total variation regularization, CVPR, pp. 464-471, 2010.

Aperture problem



- OFC $\perp \nabla I \;\Rightarrow\; \mathbf{u}(\mathbf{x}) = -I_t(\mathbf{x}) \dfrac{\nabla I(\mathbf{x})}{|\nabla I(\mathbf{x})|^2}$ if $\nabla I(\mathbf{x}) \neq \mathbf{0}$.
- Data constraints not sufficient to uniquely estimate $\mathbf{u} \Rightarrow$ ill-posed inverse problem!
- Regularization $\rightarrow$ smoothness in regions of coherent motion while preserving flow discontinuities at boundaries of moving objects.

- **Total variation regularization**:

$$\int_\Omega (|\nabla u_1| + |\nabla u_2|)\, d\mathbf{x}$$

  - Shortcomings → staircasing effect, rounded and dislocated contours!

- **Nonlocal regularization**:

$$\int_\Omega \int_{\mathcal{N}(\mathbf{x})} \omega(\mathbf{x}, \mathbf{y}) \cdot \phi(\mathbf{u}(\mathbf{y}) - \mathbf{u}(\mathbf{x}))\, d\mathbf{y}\, d\mathbf{x}$$

  - Use coherence of neighbouring pixels to enforce similar motion patterns.
  - Support weights based on spatial closeness and intensity similarity:

$$\omega(\mathbf{x}, \mathbf{y}) = \exp\left(-\frac{\|\mathbf{x} - \mathbf{y}\|^2}{h_s^2} - \frac{\|I_0(\mathbf{x}) - I_0(\mathbf{y})\|^2}{h_c^2} \right)$$

  - Shortcomings → copy image details into flow!

Nonlocal Regularizing Optical Flow Constraints

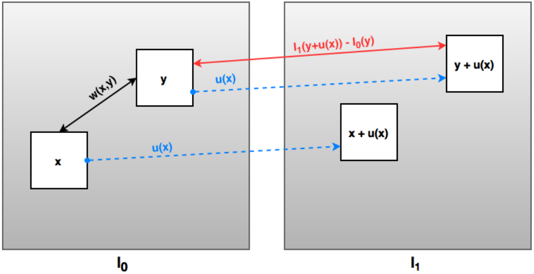
- We propose two new nonlocal data-fidelity terms.
- Nonlocal similarity measures restricted to regularization term so far.
- We use nonlocal similarity configurations in optical flow constraints:
  - Image geometry used to regularize the flow and locate flow discontinuities.
  - Motion patterns enforced through coherence of similar pixels.
  - Similarity measure $\rightarrow$ patch comparison.
- Main goal $\rightarrow$ compare performance of proposed data terms w.r.t. to BCA.

Nonlocal Regularizing Optical Flow Constraints

Nonlocal Brightness Constancy Assumption (NLBCA)

$$E_\gamma(\mathbf{u}) = \int_\Omega \int_\Omega \omega(\mathbf{x}, \mathbf{y}, I_0(\mathbf{x}), I_0(\mathbf{y})) \cdot \psi(|I_1(\mathbf{y} + \mathbf{u}(\mathbf{x})) - I_0(\mathbf{y})|)\, d\mathbf{y}\, d\mathbf{x}$$

$$\omega(\mathbf{x}, \mathbf{y}, I_0(\mathbf{x}), I_0(\mathbf{y})) = \frac{1}{\Gamma(\mathbf{x})} \cdot \exp\left(-\frac{\|\mathbf{x} - \mathbf{y}\|^2}{h_s^2}\right) \cdot \exp\left(-\frac{d_\rho\left(I_0(\mathbf{x}), I_0(\mathbf{y})\right)}{h_c^2}\right)$$



- Regularizes BCA $\rightarrow$ coherent motion of similarly appearing neighborhoods.
- Assumption $\rightarrow$ close pixels with similar patch configuration have similar flow.
- Bilateral weight distribution[8].

[8] K. Yoon and I. Kweon, Adaptive support-weight approach for correspondece search, IEEE Trans. Pattern Anal. Mach. Intell., vol. 28(4), pp. 650-656, 2006.

Nonlocal Regularizing Optical Flow Constraints

Nonlocal Brightness Constancy Assumption (NLBCA)

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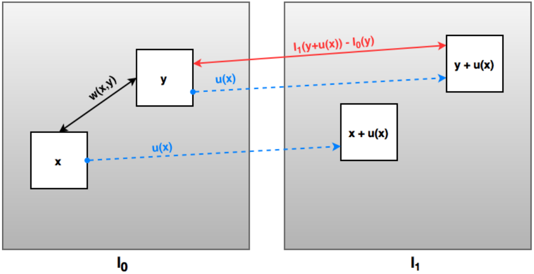

- Softer than NL regularization, which imposes image details into flow.
- Advantages w.r.t. isotropic window regularizing constraints → avoids blurring of flow close to motion discontinuities while regularizing it.

Nonlocal Regularizing Optical Flow Constraints

Nonlocal Brightness Constancy Assumption (NLBCA)

$$E_\gamma(\mathbf{u}) = \int_\Omega \int_\Omega \omega(\mathbf{x}, \mathbf{y}, I_0(\mathbf{x}), I_0(\mathbf{y})) \cdot \psi(|I_1(\mathbf{y} + \mathbf{u}(\mathbf{x})) - I_0(\mathbf{y})|)\, d\mathbf{y}\, d\mathbf{x}$$

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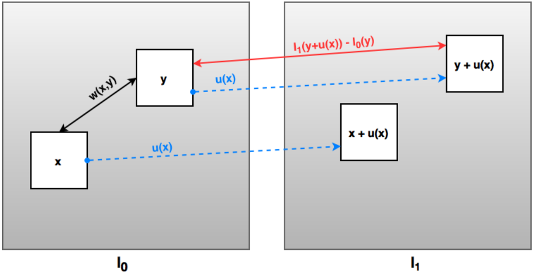


- Shortcomings → pixels with similar patch configuration having different motion!

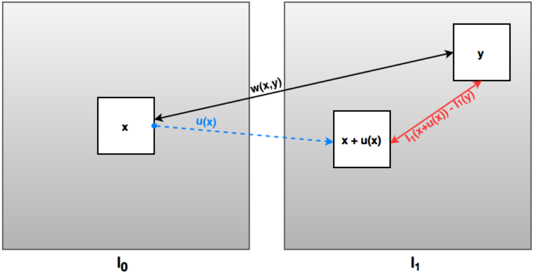
  Weights allows NLBCA matching:
  - for spatially close pixels,
  - for pixels sharing the intensity of a whole patch and not only pixel intensity.

Nonlocal Regularizing Optical Flow Constraints

Nonlocal Matching Assumption (NLMA)

$$E_\delta(\mathbf{u}) = \int_\Omega \int_\Omega \omega(I_0(\mathbf{x}), I_1(\mathbf{y})) \cdot \psi(|I_1(\mathbf{x}+\mathbf{u}(\mathbf{x})) - I_1(\mathbf{y})|)\, d\mathbf{y}\, d\mathbf{x}$$

$$\omega(I_0(\mathbf{x}), I_1(\mathbf{y})) = \frac{1}{\Gamma(\mathbf{x})} \cdot \exp\left(-\frac{d_\rho\left(I_0(\mathbf{x}), I_1(\mathbf{y})\right)}{h_c^2}\right)$$



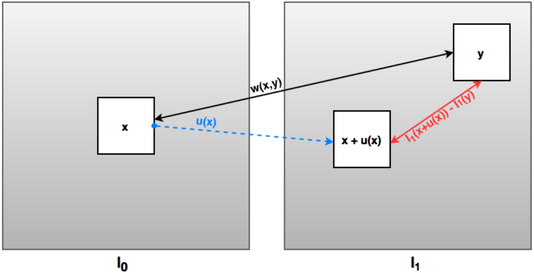
- Replaces BCA → NLMA no longer impose a constraint on motion trajectories.
- Assumption → cross-frame patch similarity preserved by flow.
- Weights not depending on spatial closeness.

Nonlocal Regularizing Optical Flow Constraints

Nonlocal Matching Assumption (NLMA)

$$E_\delta(\mathbf{u}) = \int_\Omega \int_\Omega \omega(I_0(\mathbf{x}), I_1(\mathbf{y})) \cdot \psi(|I_1(\mathbf{x} + \mathbf{u}(\mathbf{x})) - I_1(\mathbf{y})|)\, d\mathbf{y}\, d\mathbf{x}$$

$$\omega(I_0(\mathbf{x}), I_1(\mathbf{y})) = \frac{1}{\Gamma(\mathbf{x})} \cdot \exp\left(-\frac{d_\rho\left(I_0(\mathbf{x}), I_1(\mathbf{y})\right)}{h_c^2}\right)$$



- Cross-frame weights → combine optical flow and block matching techniques.
- Regularity of warped image → artifact suppression due to wrong flows and noise.
- Shortcomings → artifacts due to flow may not be more prominent than noise!

- Penalize deviations from both constraints with quadratic functions $\rightarrow \psi(s) = s^2$.
- Spatial coherence of flow through TV regularization.
- Linearize both constraints using first-order Taylor expansions.
- Final linearized energies for optical flow estimation:
  - **NLBCA based linearized energy**

$$E^l_\gamma(\mathbf{u}) := \int_\Omega (|\nabla u_1(\mathbf{x})| + |\nabla u_2(\mathbf{x})|)\ d\mathbf{x} + \frac{\gamma}{2} \iint_{\Omega\times\Omega} \omega(\mathbf{x}, \mathbf{y}, I_0(\mathbf{x}), I_0(\mathbf{y}))\big(I_1(\mathbf{y} + \mathbf{u}^0(\mathbf{x})) - I_0(\mathbf{y}) + \langle \nabla I_1(\mathbf{y} + \mathbf{u}^0(\mathbf{x})), \mathbf{u}(\mathbf{x}) - \mathbf{u}^0(\mathbf{x})\rangle\big)^2 d\mathbf{y} d\mathbf{x}$$

  - **NLMA based linearized energy**

$$E^l_\delta(\mathbf{u}) := \int_\Omega (|\nabla u_1(\mathbf{x})| + |\nabla u_2(\mathbf{x})|)\ d\mathbf{x} + \frac{\delta}{2} \iint_{\Omega\times\Omega} \omega(I_0(\mathbf{x}), I_1(\mathbf{y}))\big(I_1(\mathbf{x} + \mathbf{u}^0(\mathbf{x})) - I_1(\mathbf{y}) + \langle \nabla I_1(\mathbf{x} + \mathbf{u}^0(\mathbf{x})), \mathbf{u}(\mathbf{x}) - \mathbf{u}^0(\mathbf{x})\rangle\big)^2 d\mathbf{y} d\mathbf{x}$$

- **Convex relaxation** $\rightarrow$ deocupling energy terms using an auxiliary variable:

$$E^{I}_{\gamma}(\mathbf{u}) := \int_{\Omega} (|\nabla u_1(\mathbf{x})| + |\nabla u_2(\mathbf{x})|)\ d\mathbf{x} + \frac{1}{2\theta}\|\mathbf{u}-\mathbf{v}\|^2$$
$$+ \frac{\gamma}{2}\iint_{\Omega\times\Omega}\omega(\mathbf{x},\mathbf{y},I_0(\mathbf{x}),I_0(\mathbf{y}))\big(I_1(\mathbf{y}+\mathbf{u}^0(\mathbf{x})) - I_0(\mathbf{y}) + \langle\nabla I_1(\mathbf{y}+\mathbf{u}^0(\mathbf{x})), \mathbf{v}(\mathbf{x})-\mathbf{u}^0(\mathbf{x})\rangle\big)^2 d\mathbf{y}d\mathbf{x}$$
$$E^{I}_{\delta}(\mathbf{u}) := \int_{\Omega} (|\nabla u_1(\mathbf{x})| + |\nabla u_2(\mathbf{x})|)\ d\mathbf{x} + \frac{1}{2\theta}\|\mathbf{u}-\mathbf{v}\|^2$$
$$+ \frac{\delta}{2}\iint_{\Omega\times\Omega}\omega(I_0(\mathbf{x}),I_1(\mathbf{y}))\big(I_1(\mathbf{x}+\mathbf{u}^0(\mathbf{x})) - I_1(\mathbf{y}) + \langle\nabla I_1(\mathbf{x}+\mathbf{u}^0(\mathbf{x})), \mathbf{v}(\mathbf{x})-\mathbf{u}^0(\mathbf{x})\rangle\big)^2 d\mathbf{y}d\mathbf{x}$$

- **Alternate minimizations**:
  i) Fixed **v**, solve TV-based problem using Chambolle's projection algorithm.
  ii) Fixed **u**, compute explicit solution in **v** using Euler-Lagrange equation.

Nonlocal interaction limited to pixels at a certain distance:

$$\omega(\mathbf{x}, \mathbf{y}, I_0(\mathbf{x}), I_0(\mathbf{y})) = \begin{cases} \frac{1}{\Gamma(\mathbf{x})} \exp\left(-\frac{\|\mathbf{x}-\mathbf{y}\|^2}{h_s^2}\right) \exp\left(-\sum_{\mathbf{z}\in\mathcal{N}_0} \frac{|I_0(\mathbf{x}+\mathbf{z}) - I_0(\mathbf{y}+\mathbf{z})|^2}{h_c^2}\right) & \text{if } \|\mathbf{x}-\mathbf{y}\|_\infty \leq \nu \\ 0 & \text{otherwise} \end{cases}$$

$$\omega(I_0(\mathbf{x}), I_1(\mathbf{y})) = \begin{cases} \frac{1}{\Gamma(\mathbf{x})} \exp\left(-\sum_{\mathbf{z}\in\mathcal{N}_0} \frac{|I_0(\mathbf{x}+\mathbf{z}) - I_1(\mathbf{y}+\mathbf{z})|^2}{h_c^2}\right) & \text{if } \|\mathbf{x}-\mathbf{y}\|_\infty \leq \nu \\ 0 & \text{otherwise} \end{cases}$$

- $\nu > 0$ prescribed parameter (research window).
- $\mathcal{N}_0$ is a rectangular window centered at origin (comparison window).
- In practice $\rightarrow$ 21×21 research window and 7×7 comparison window.

- Coarse-to-fine scheme to reduce distance between objects:
  - 5-scale image pyramid with sampling factor 2.
  - Energy minimization at each scale and propagate flow as $\mathbf{u}^{s-1}(\mathbf{x}) = 2 \cdot \mathbf{u}^{s}(\frac{\mathbf{x}}{2})$.
  - Intermediate solution used as initialization in following scale.
  - 5-warping steps to refine $\mathbf{u}^0$ and $I_1(\cdot + \mathbf{u}^0)$ at each scale.
- Flow computed on grayscale images.
- Use 7×7 median filter to increase robustness w.r.t sampling artifacts in data[9].
- Drawback $\rightarrow$ motion of small objects undergoing large displacements cannot be estimated since may disappear in the coarsest scales!

[9] A. Wedel, T. Pock, C. Zach, D. Cremers and H. Bischof, An improved algorithm for TV-L1 optical flow, Proc. Statistical and Geometrical Approached to Visual Motion Analysis, LNCS vol. 5604, pp. 23-45, 2009.

Experimental Results

- Evaluation on Middlebury benchmark[10] with known ground truth.
- Optimal trade-off parameters in terms of lowest average end-point error (AEPE):

$$\text{AEPE}(\mathbf{u}) = \frac{1}{|\Omega|} \int_\Omega \left| \mathbf{u}(\mathbf{x}) - \mathbf{u}^{\text{ref}}(\mathbf{x}) \right| d\mathbf{x}$$

- Exclude pixels in the occlusions, which are available for the Middlebury benchmark, when computing AEPE.
- Computational cost of NLBCA and NLMA equivalent to classical BCA $\rightarrow$ extra weight computation at the beginning of each scale might be easily parallelised!

[10] S. Barker, D. Scharstein, J. Lewis, S. Roth, M. Black and R. Szeliski, A database and evaluaton methodology for optical flow, Int. J. Comput. Vis., vol. 92(1), pp. 1-31, 2011.

Experimental Results

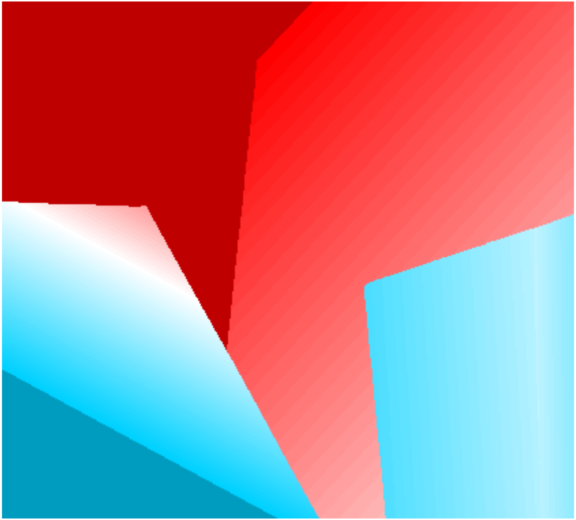
Comparison of Data Constraints on Venus Sequence

I_0

Experimental Results

Comparison of Data Constraints on Venus Sequence

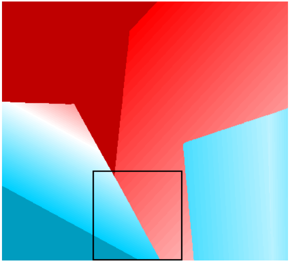
I_1



Ground-truth flow

Experimental Results

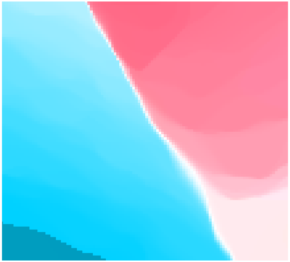
Comparison of Data Constraints on Venus Sequence



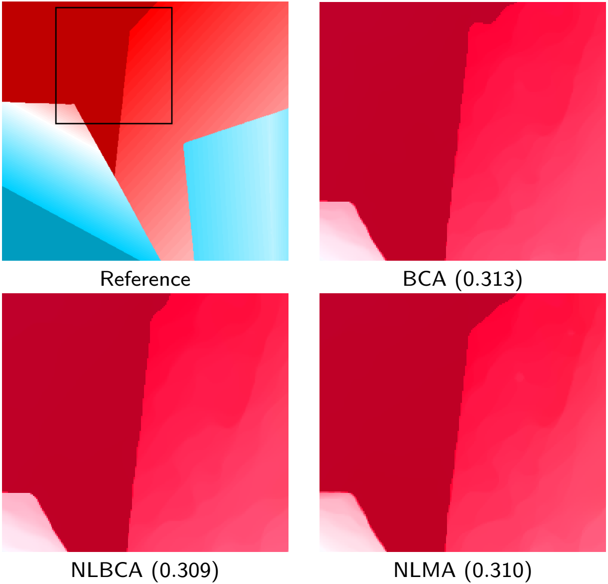
Reference

BCA (0.313)

NLBCA (0.309)



NLMA (0.310)



Reference
BCA (0.313)
NLBCA (0.309)
NLMA (0.310)

Experimental Results

Comparison of Data Constraints on Rubberwhale Sequence

I_0

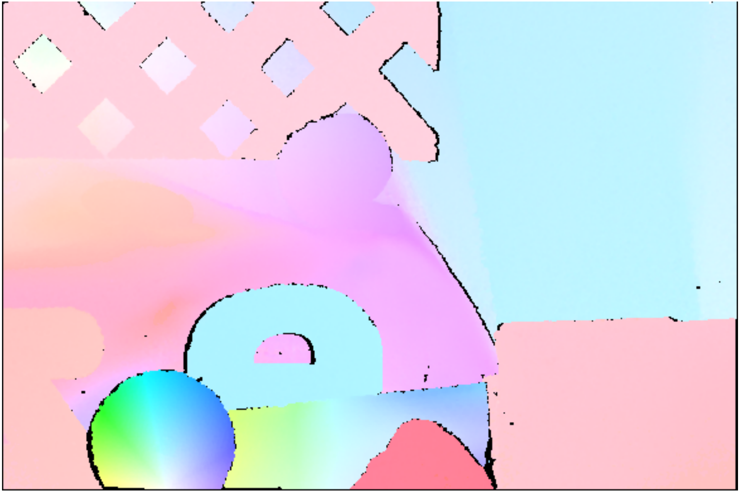
Experimental Results

Comparison of Data Constraints on Rubberwhale Sequence

I_1

Experimental Results

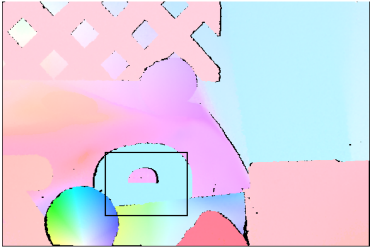
Comparison of Data Constraints on Rubberwhale Sequence



Ground-truth flow

Experimental Results

Comparison of Data Constraints on Rubberwhale Sequence



Reference

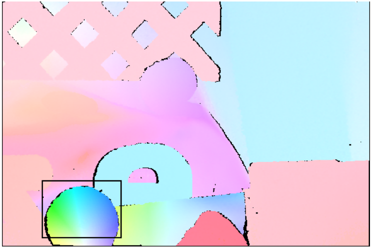
BCA (0.209)

NLBCA (0.154)

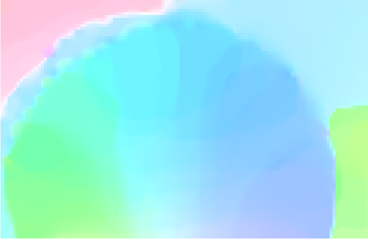
NLMA (0.199)

Experimental Results

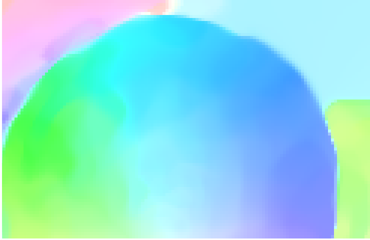
Comparison of Data Constraints on Rubberwhale Sequence



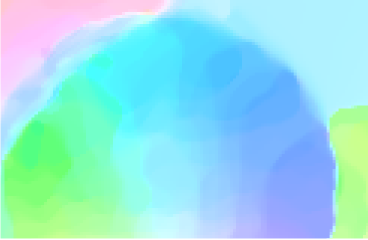
Reference



BCA (0.209)



NLBCA (0.154)



NLMA (0.199)

Experimental Results

Comparison of Data Regularizing Constraints with Nonlocal Regularization on Venus Sequence

I_0

Experimental Results

Comparison of Data Regularizing Constraints with Nonlocal Regularization on Venus Sequence

I_1

Ground-truth flow

Experimental Results

Comparison of Data Regularizing Constraints with Nonlocal Regularization on Venus Sequence

Reference

Nonlocal regularization

NLBCA

NLMA

Conclusions

- We have introduced two nonlocal regularizing constraints for variational optical flow estimation.
- Preliminar results illustrate
  - superiority of NLBCA w.r.t. classical BCA,
  - similar performances of NLMA and BCA while being completely different,
  - image self-similarity can be better taken advantage of in the data-fidelity terms rather than in the regularization prior.
- Limitations are in the optimization strategy rather than in the models themselves.
- Future work:
  - Exhaustive performance comparison.
  - Postpone the linearization to the numerical scheme and use nonlinear formulations directly.
  - Derive new nonlocal regularizing data constraints, including also GCA-based and photometric invariant color spaces.
  - Combine different data constraints.

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March 1st, 2017