Large Displacement Optical Flow for Volumetric Image Sequences

Benjamin Ummenhofer

[o] Vision COMPUTER VISION University of Freiburg

bioss CENTRE FOR BIOLOGICAL SIGNALLING STUDIES

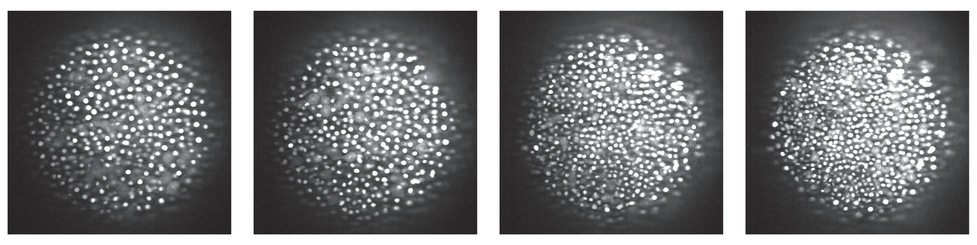
UNI FREIBURG

1 Motivation

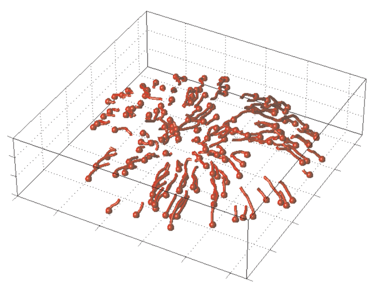
3D Optical flow can be used to analyze biological and medical datasets. For instance, we can use the flow field to determine cell trajectories or the growth of tissue.

Example: Object trajectories

- Image sequence (Zebrafish nuclei)



- Trajectories extracted from optical flow



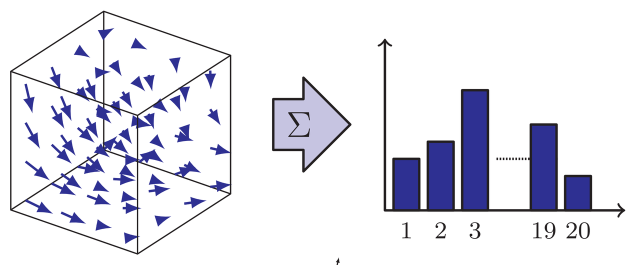
- Algorithm requirements: Capturing of large motions, high accuracy, short runtimes

2 Descriptor Matching

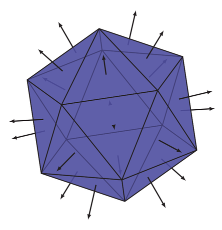
As in Brox et al. [1] we use a coarse flow field that is based on descriptor matching to capture large motions. For the computation we use 3D Histograms of Oriented Gradients (HOG) descriptors.

3D HOG Descriptor

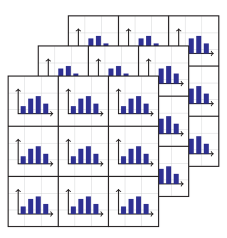
- Gradients are summed up into histograms with 20 bins



- Each bin corresponds to a spatial direction defined by an icosahedron



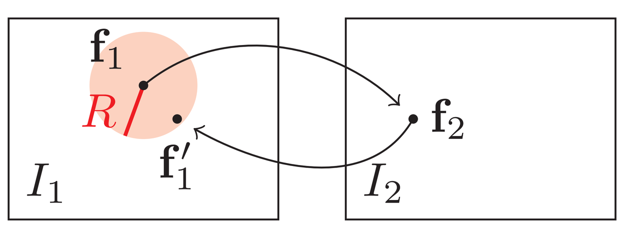
- The final descriptor consists of 27 neighbouring histograms



- Descriptors are computed densely over the image

Correspondence search

- Performed for a subset to reduce computation time
- Reverse matching to check consistency

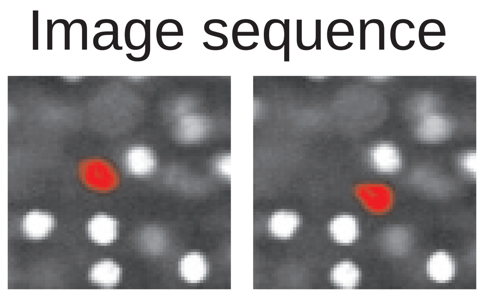


- Correspondences are weighted to account for uncertainties

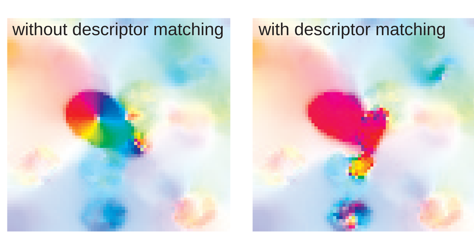
$$\rho = \underbrace{\frac{d_2 - d_1}{d_2}}_{\text{match uncertainty}} \cdot \underbrace{\left(1 - \frac{r}{R}\right)}_{\text{reverse match uncertainty}}$$

Large displacement results

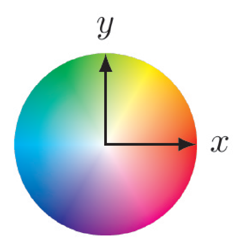
Image sequence



flow field



flow color coding

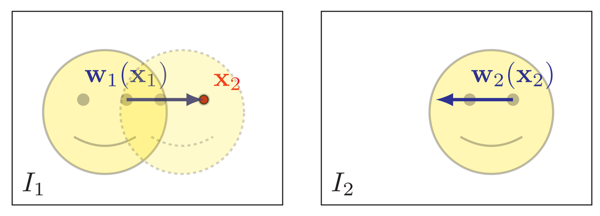


3 Symmetry Constraint

In general computing the backward flow of a sequence does not give the symmetrical solution that corresponds to the forward flow. The symmetry constraint from Alvarez et al. [2] pushes the computation towards a symmetrical solution.

Symmetry constraint

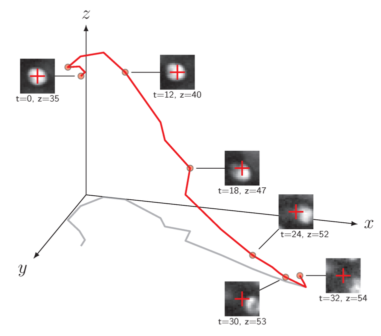
- The forward flow and the backward flow vector at corresponding positions must be inverse to each other



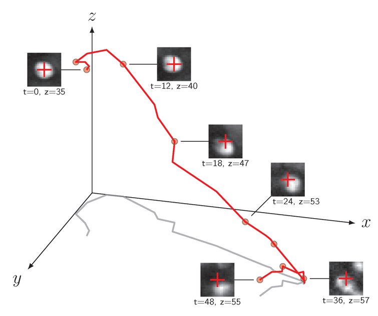
$$\mathbf{x}_1 = \mathbf{x}_2 + \mathbf{w}_2\underbrace{(\mathbf{x}_1 + \mathbf{w}_1(\mathbf{x}_1))}_{\mathbf{x}_2}$$

Cell tracking results

Without symmetry constraint



With symmetry constraint



4 Variational Model

Optical flow is described as an energy minimization problem. Minimization is carried out in a coarse to fine scheme. Forward and backward flow are alternately computed.

Energy functional

- Forward flow energy

$$E_1(\mathbf{w}_1) = E_{\text{grey}}(\mathbf{w}_1) + E_{\text{grad}}(\mathbf{w}_1) + E_{\text{smooth}}(\mathbf{w}_1) + E_{\text{match}}(\mathbf{w}_1) + E_{\text{symm}}(\mathbf{w}_1)$$

- Energy terms include
  - Image data
  - Smoothness
  - Descriptor matches
  - Symmetry

$$E_{\text{grey}}(\mathbf{w}_1) = \int_\Omega \Psi\left(|I_2(\mathbf{x}+\mathbf{w}_1) - I_1(\mathbf{x})|^2\right) d\mathbf{x}$$

$$E_{\text{grad}}(\mathbf{w}_1) = \gamma \int_\Omega \Psi\left(|\nabla I_2(\mathbf{x}+\mathbf{w}_1) - \nabla I_1(\mathbf{x})|^2\right) d\mathbf{x}$$

$$E_{\text{smooth}}(\mathbf{w}_1) = \alpha \int_\Omega \Psi\left(|\nabla u_1(\mathbf{x})|^2 + |\nabla v_1(\mathbf{x})|^2 + |\nabla w_1(\mathbf{x})|^2\right) d\mathbf{x}$$

$$E_{\text{match}}(\mathbf{w}_1) = \beta \int_\Omega \delta(\mathbf{x})\rho(\mathbf{x})\Psi\left(|\mathbf{w}_1(\mathbf{x}) - \mathbf{w}_D(\mathbf{x})|^2\right) d\mathbf{x}$$

$$E_{\text{symm}}(\mathbf{w}_1) = \zeta \int_\Omega \Psi\left(|\mathbf{w}_1(\mathbf{x}) + \mathbf{w}_2(\mathbf{x}+\mathbf{w}_1(\mathbf{x}))|^2\right) d\mathbf{x}$$

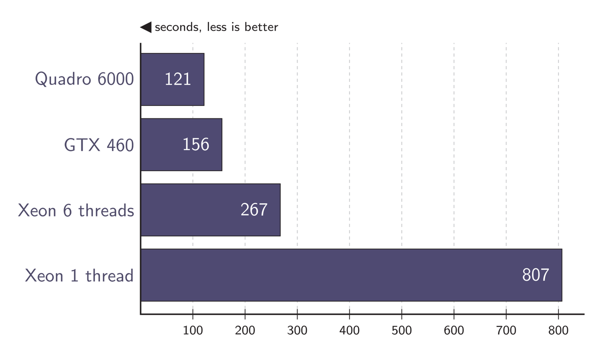
with ψ as the TV penalizer: $\Psi(s^2) = \sqrt{s^2 + \epsilon}$

5 GPU Implementation

We have implemented our algorithm on the GPU using the CUDA toolkit. We use conjugate gradient to solve the linear system in parallel.

Runtime

- Processing time for a volume with 205x205x41 voxels



- Major time consumption
  - Descriptor matching
  - Linear system solver (Conjugate gradient)

References:

[1] Brox, T., Malik, J.: Large displacement optical fow: descriptor matching in variational motion estimation. IEEE Transactions on Pattern Analysis and Machine Intelligence 33(3), 500-513 (2011)

[2] Alvarez, L., Deriche, R., Papadopoulo, T., Sanchez, J.: Symmetrical Dense Optical Flow Estimation with Occlusions Detection. International Journal of Computer Vision 75(3), 371-385 (2007)