Belief Propagation Optical Flow for High-Resolution Image Morphing

Christian Lipski, Christian Linz, Marcus Magnor*
Computer Graphics Lab, TU Braunschweig

Figure 1: *Belief Propagation Optical Flow. Left to right: two* 1920×1080 *input images* A *and* B*, optical flow from* A *to* B*, flow symmetry and rendered result. We specifically tailored our optical flow for image morphing in the presence of large motion and occlusions. We incorporate recent advances in computer vision to produce visually convincing results.*

Abstract

Over the last decade, considerable progress has been made on the so-called early vision problems. We present an optical flow algorithm for image morphing that incorporates recent advances in feature matching, energy minimization, stereo vision and image segmentation. At the core of our flow estimation we use Efficient Belief Propagation for energy minimization. While state-of-the-art algorithms only work on thumbnail-sized images, our novel feature downsampling scheme in combination with a simple, yet efficient data term compression can cope with high-resolution data. The incorporation of SIFT features into data term computation further resolves matching ambiguities, making long-range flows possible. We detect occluded areas by evaluating the symmetry of the flow fields, we further apply Geodesic matting to automatically inpaint these regions.

Keywords: optical flow, belief propagation, 2D Morphing & Warping

1 Motivation

With renewed research on early-vision problems, many promising strategies have evolved that cope with these often ill-posed tasks. However, optical flow-based image warping/morphing is still a challenging problem, especially when the input images feature long-range motion and large occluded areas. With the increasing availability of high-resolution content, the requirements for correspondence estimation between images are further increased. High resolution images often exhibit many ambiguous details, where their low resolution predecessors only show uniformly colored areas. While incorrect correspondences in the low-res images are not conceivable, high resolution images suffer from blurring or ghosting artifacts in these regions. Liu et al. [2008] recently proposed an optical flow for matching images possibly showing different scene content. We pick up on their idea to incorporate dense SIFT feature descriptors, yet we use them for a different purpose. While they identify visually similar regions in low-resolution images, we use them as a descriptor for fine detail in high-resolution images.

*e-mail:{lipski,linz,magnor}@cg.cs.tu-bs.de

2 Our Approach

We cast the computation of optical flow as a discrete labeling problem and use Efficient Belief Propagation for energy minimization, as proposed by Felzenszwalb et al. [2006]. In order to match fine structural details in two images, we compute a SIFT descriptor for each pixel. To avoid ambiguous descriptors and to speed up computation, we choose one descriptor in a $n \times n$ (typically $n = 4$) grid cell as its representative. We compute an initial lower resolution flow on images that are downsampled by factor n.

The 131-dimensional descriptor of each pixel is a combination of the mean color (3-dimensional) and the representative SIFT descriptor of this cell (128-dimensional). The L1-norm of this vector describes dissimilarity between two pixels. While the original Belief Propagation implementation by Felzenszwalb et al. [2006] might not retain crisp borders due to the grid-based message passing scheme, we employ a non-grid-like regularization technique as proposed by Smith et al. [2009]. As memory consumption of Belief Propagation on this scale is still too high for long-range correspondence estimation, we use a simple minima-preserving data term compression. During Belief Propagation, a symmetry term ensures consistent results. Occluded regions are identified and inpainted: Assuming that each occluded area is surrounded by two independently moving regions, we use Geodesic Matting [Bai and Sapiro 2009] to propagate flow information. The resulting flow is upsampled to its original size and refined locally.

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