Toward robust estimation of specular flow

Yair Adato[1]
http://www.cs.bgu.ac.il/~adato
Todd Zickler[2]
http://www.eecs.harvard.edu/~zickler
Ohad Ben-Shahar[1]
http://www.cs.bgu.ac.il/~ben-shahar

[1] Department of Computer Science,
Ben Gurion University,
Israel
[2] School of Engineering and Applied Science,
Harvard University,
MA, USA

Inference from visual scenes that contain highly specular objects is a particularly challenging computational problem. Most recent contributions to such problems have exploited the *specular flow* –the vector field that is induced on the image plane as a result of a relative motion between the camera, object, or environment– to facilitate diverse tasks such as shape inference, 3D pose estimation and detection of rigid objects (see references in the paper).Unfortunately, however, reliably estimation of specular flow from image sequences is an open question that was never addressed formally before, except for using (unsuccessfully) standard *optical flow* technique [1].

In this paper we first argue that existing optical flow algorithms are incapable of reliable specular flow estimation due to their typical regularization criteria that conflict the unique and singular structure of specular flows. More precisely, we observe that all flavors of the smoothness term disagree with the fact that the specular flow magnitude can become very large or even unbounded in certain regions. Furthermore, they do not address well the orientation singularities, which are related to surface *curvature* instead of the image gradient (see Fig. 1).

To validate our predication qualitatively and not only quantitatively, one should use ground truth data with which different algorithms can be compared. Unfortunately, the standard Middlebury optical flow dataset [2] is missing several important cases like specular and transparent scenes and it cannot be used in this task. To overcome this gap, we present technical steps for establishing a full scale benchmark database contains a real image sequences with their corresponding specular flow ground truth. While a full fledge benchmark site is currently under construction, these preliminary data sets are already available publicly [3] and we hope they would promote much research on specular flow estimation.

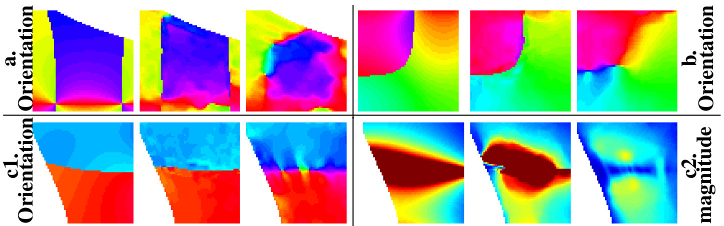

Figure 1: A close up of three regions of interest of an estimated specular flow. All panels show ground truth on the left, result of our proposed algorithm in the center. The results by existing state-of-the-art algorithmson the right exhibit typical qualitative failures: large regions where the orientation error is significant (a), smooth transition instead a fixed orientation jump at the singularity (b), and inference of smaller magnitude instead of large one around parabolic singularities (c).

Specular flow estimation

To extend existing methods to handle specular flow we suggest to generalize the optical flow variational framework such that the advantages of existing regularizations is kept in most regions, while more appropriate regularization is employed where the flow violates the smoothness assumption. Assuming one can tell (exactly or approximately) the division of the image plane into regions of different properties, an optical flow model that switches (spatially) between the appropriate terms will have the following general form:

$$E(u,v) = \int_\Omega \sum_i \eta_i(x,y) E_i(dI,u,v)dxdy \quad s.t \quad \eta_i(x,y) \geq 0 \wedge \sum_i \eta_i(x,y) = 1 \tag{1}$$

where u,v is the sought-after flow, dI stands for the image derivatives, E_i is a (data or regularization) term appropriate for regions of type i, and $\eta_i(x,y)$ is a spatial *confidence function* that describes the degree of compatibility of each point to this type of region. The normalization constraint $\sum_i \eta_i(x,y) = 1$ reflects a prior that region types are mutually exclusive (in the probabilistic sense), but if necessary it can be removed. Note that unlike in previous approaches, this new framework allows to reduce completely the influence of the data term in certain regions.

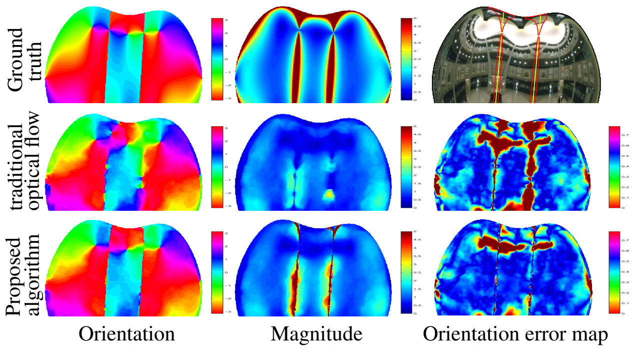

Figure 2: Comparison of the performance of state-of-the-art optical flow algorithm (middle) to our algorithm (bottom) on real specular flow sequence (top). The flows are represented by their magnitude and orientation components (see the paper for details).

In this work we will use this capacity along the –parabolic singularities– the locus of specular flow points that exhibit both magnitude singularity and orientation discontinuity of 180°. The unique flow structure along the parabolic singularities can be abstracted by the two conditions

$$\begin{gathered}(u^2+v^2-\chi^2)^2 = 0 \\ I(x,y,t) = I(x+u,y+v,t+1) = I(x-u,y-v,t+1)\end{gathered} \tag{2}$$

Hence, combined with a robust penalty function we define the "parabolic term" regularizer as follows:

$$E_p \triangleq \psi\left((I(x+u,y+v,t+1) - I(x-u,y-v,t+1))^2\right) + \psi((u^2+v^2-\chi^2)^2) \tag{3}$$

where χ is the maximum practical magnitude allowed in the estimated specular flow. One "disadvantage" of E_p is its aggressive encouragement of large-magnitude flow. Hence, by applying it to points too distant from the parabolic singularity (due to an inaccurate confidence function) we are still at risk of obtaining large scale distortions. To solve this, we also define a weaker version of the parabolic term that incorporates the orientation structure only:

$$E_n \triangleq \psi\left((I(x+u,y+v,t+1) - I(x-u,y-v,t+1))^2\right). \tag{4}$$

This "neighborhood" term is constructive for a finite-size strip around the parabolic singularity since in practical terms it can be employed for all pixels whose distance from the singularity is smaller than their optical flow magnitude. This term has an added advantage – it is significantly easier to approximate its corresponding confidence function using standard computational tools.

Using these two terms, and following our suggested computational framework (Eq. 1) we now suggest to obtain more reliable specular flow estimation by minimizing the following energy functional

$$E(u,v) = \int (\eta_0(x,y)E_d + \eta_1(x,y)E_s + \eta_2(x,y)E_n + \eta_3(x,y)E_p)\,dxdy \ , \tag{5}$$

where E_d abbreviates E_{data}, E_s abbreviates E_{smooth}, $\eta_2(x,y)$ and $\eta_3(x,y)$ are the spatial functions describing the confidence that point (x,y) is *near* or *at* a parabolic singularity, respectively.

The algorithmic framework suggested in this paper is designed to generalize optical flow algorithms in order to extend their computational domain to include non traditional behaviors such as specular singularities. In this sense, one could plug in to our framework *any* variational optical flow algorithm (i.e., by setting the proper terms in Eq. 5) to end up with a new version of that algorithm that handles specular flows better. As a proof of concept, we implemented the proposed algorithm by using relative simple data and smoothness terms and show that even with this particular choice the obtained algorithm can estimate specular flow significantly better than state-of-the-art optical flow algorithms (see Fig. 2).

[1] Y. Adato, Y. Vasilyev, O. Ben-Shahar, and T. Zickler. Toward a theory of shape from specular flow. In *Proceedings of the IEEE International Conference on Computer Vision*, 2007.

[2] S. Baker, D. Scharstein, J.P. Lewis, S. Roth, M. Black, and R. Szeliski. A database and evaluation methodology for optical flow. In *Proceedings of the IEEE International Conference on Computer Vision*, 2007.

[3] Specular flow benchmark. `http://www.cs.bgu.ac.il/~vision`.