Optical flow estimation with regularization and ADMM

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- Introduction

Optical flow is the basic estimation of a dense motion field, corresponding to the displacement of each image sequence pixel. The notion of optical flow literally refers to the displacements of intensity patterns. This definition originates from a physiological description of the visual perception of the world through image formation on the retina. Optical flow only represents motion of intensities in the image plane, and not necessarily accounts for the actual 3D motion in the physical scene[1].

This definition of optical flow states that intensity of moving pixels remains constant during motion, and the main difficulty is to cope with the uncertainty due to the ill-posed nature of the problem, called aperture problem. However, motion of interest in computer vision is in practice the motion field. The terms optical flow and motion field are usually mixed up.

The deformation of organs or the estimation of blood flow are examples of medical applications that can require optical flow computation. In microscopy, dense motion can inform about cell deformation, motion of cellular structures, or help for individual cell tracking. Robots or vehicle navigation also exploit optical flow as input of control systems for automatic guidance, obstacle detection and avoidance. Automated video surveillance, facial expression and gesture recognition, crowd motion, pedestrian behavior, fluid flow analysis are other examples.

The MPI-Sintel Flow dataset[2,3], introduces a naturalistic dataset for optical flow evaluation derived from the open source CGI movie Sintel. The value of synthetic datasets is to train and evaluate optical flow algorithms, one would ideally use a large number of natural video sequences and the corresponding ground truth optical flow. With ground truth available, two error measures are commonly used for evaluating the performance of optical flow algorithms, namely the Angular Error (AE) and the Endpoint Error (EPE)[4].

The goal of this research project is to implement a simple optical flow solver, test a few regularizers with ADMM, run and evaluate the algorithms on the Sintel dataset.

- Related work

Relevant implementations of related work are presented as follows. These are partial transcriptions of mentioned literature.

Regularized models

The global form of the motion field can be imposed by an explicit regularization term. Motion discontinuities are then no more represented by the boundaries of the regions delimiting parametric motion fields, but they are involved in the global model, often considered as outliers w.r.t. smoothness assumptions. The variational approach has been initially proposed by Horn and Schunck [4] and is usually referred to as the global approach, since the regularization term interconnects all the pixels of the image and thus requires the optimization of the objective energy to be performed globally. In its most general form, the energy minimized by global regularization methods can be written as:

$$E_{\text{global}}(w) = \int_{\Omega} \rho_{data}(x, I_1, I_2, w) + \lambda \rho_{reg}(x, w) dx \quad (1)$$

where $\rho_{data}(x, I_1, I_2, w)$ is the data potential, $I_1 = I(\cdot, t)$ and $I_2 = I(\cdot, t+1)$ denote two successive frames, $\rho_{data}(x, I_1, I_2, w)$ is the data potential, $\rho_{reg}(x, w)$ is the regularization potential encoding an a priori assumption on the field w, and k is a parameter tuning the balance between the two terms. Broadly speaking, the regularization potential aims at smoothing the motion field in regions of coherent motion while preserving motion discontinuities at the boundaries of moving objects. Finding the trade-off can also be partially addressed in the adaptation of the balance parameter k.

A major interest of the global variational framework is its versatility, allowing one to model different forms of flow fields by combining different data and regularization terms.

Regularization Models:

i) **Spatial flow gradient constraint**

The most natural and widely used way to impose smoothness of the motion field is to penalize the magnitude of the flow gradient [5]:

$$\rho_{reg}(x, w) = h(x, I_1)\, \phi(\|\nabla w(x)\|^2) \quad (2)$$

where $\phi(\cdot)$ is the penalty function and $h(x, I_1)$ is a weighting function.

ii)**Flow-driven regularization**

In flow-driven approaches, no relation between the form of the flow field and the structure of the image is assumed. The weighting function is thus $h(x, I_1) = 1, \forall x \in \Omega.$

The seminal formulation of [4] adopts a quadratic penalization function:

$$\rho_{reg}(x, w) = \nabla u(x)^2 + \nabla v(x)^2. \quad \text{with } w(x) = (u(x), v(x))^{\top} \quad (3)$$

Among the wide panel of robust functions, the popular parameter-free Total Variation (TV) prior, has interesting and useful properties. A series of optical flow estimation methods have exploited this idea for fast and accurate minimization [6].

iii)**Non-local regularization**

The gradient of the flow can only provide a local constraint on the interaction between pixels. Assuming long range interaction scan capture more precisely the form of the motion field. Such non-local regularization has been recently investigated by describing the structure of the flow in an extended neighborhood in a discrete setting as:

$$\rho_{reg}(x, w) = \sum_{y \in \mathcal{N}(x)} k(x, y, I_1)\, \phi\left(\|w(x) - w(y)\|^2\right). \quad (4)$$

The weights $k(x,y,I_1)$ indicate which pixel y should share a similar motion with pixel x. They are derived from the bilateral filter, favoring small distances in the spatial and color spaces[7]:

Optimization:

The optimization strategy employed to minimize (1) has a decisive influence on the final result.

Proximal splitting. A successful optimization method based on alternate minimization of simple sub-problems has been proposed [8] and used for optical flow. The data and regularization terms are splitted and associated to separate variables, which are quadratically coupled by a third term:

A large number of variants and generalizations of this proximal splitting idea exist, among which the alternating direction method of multipliers (ADMM) [9] or the formalization in a primal–dual framework is described.

In a general point of view, the independence of the optimization of data and regularization parts allows one to design dedicated minimization schemes in a variety of cases. The restriction is to be able to compute the proximal operators, and the convergence is ensured only for convex energies.

-Project overview

Implement a simple optical flow solver, test a few regularizers with ADMM, run and evaluate the algorithms on the Sintel dataset.

- **Milestones and timeline**

Week1:

Download video images and tools of the MPI-Sintel Flow dataset. Preliminarily implement a simple Horn and Schunck[4] optical flow estimation algorithm in Matlab. Perform testing and validation of the algorithm using Sintel tools. Evaluate the algorithm performance with AE and EPE.

Week2:

Implement the algoritm[6] with regularizers TV-L^1 for the Optical Flow estimation problem. Collect images from the bamboo_3 and the mountain scenes data sets. Test the results of the optical flow estimation with the Sintel ground truth, use tools available.

Week3:

Implement the non-local regularization algorithm from ref. [7], and test with Sintel dataset.

Week4:

Fully implement developed algorithms. Run algorithms on full data sets, the bamboo_3 and mountain scenes in the Sintel dataset. Compare results with all methods.

Complete analysis and write report.

- **References**

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