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Variational optical flow computation assisted by robust point matching

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ABSTRACT

Lots of optical flow methods are based on coarse-to-fine strategy. However, most of coarse-to-fine optical flow techniques face two important problems: namely (1) large displacements of small structures are usually estimated in an incorrect manner and (2) large affine motions of non-rigid objects cannot be computed accurately. In this paper, we present an optical flow computation methodology that integrates robust point matching into a variational optical flow model to deal with the above-mentioned difficulties. Experimental results are demonstrated for a variety of image sequences to validate the effectiveness.

1. Introduction

Optical flow is of great importance for motion detection in the visual system of humans and other visual species [1]. It is also very important for many computer vision fields, such as object tracking [2], motion segmentation [3] and medical image registration [4].

So far, optical flow techniques have been studied for several years. Many of the contemporary optical flow methods are based on the variational framework introduced by Horn and Schunck [5] and the coarse-to-fine refinement strategy presented by Lucas and Kanade [6]. Currently, almost all of the top-ranked approaches in the Middlebury benchmark make use of this combination of variational framework and coarse-to-fine strategy [7]. On the one hand, variational methods provide accurate techniques for small displacement computation [8–10]. On the other hand, coarse-to-fine strategies, which almost have become the de-facto standard in optical flow computation, provide the ability of dealing with large displacements [8,10,11]. However, there exist some difficulties in traditional strategies during handling large displacements of small structures. For example, incorrect estimation for small structures with large motions: at the coarse scales, small structures are no longer visible, thus the motions of small structures are usually estimated by the motions of nearby large structures, which may result in errors when the relative motion of a small structure is larger than its own scale. Furthermore, almost all of the optical flow methods do not consider affine transformation in the large motions of non-rigid objects.

In order to solve the above-mentioned problems, some recent researches try to integrate the reliable local feature matching into traditional optical flow algorithms. In contrast to single pixels only with gray value, local feature descriptors are more suitable for accurate global matching due to the uniqueness of descriptors. This type of descriptor matching techniques, which can obtain sparse correspondences for large displacements in image matching, has been widely applied in lots of fields. However, there may exist outliers in point correspondences due to the missing of regularity constraints of matching points. Considering the characteristics of both optical flow and feature point matching, to construct a more robust optical flow method that can deal with large displacements, we may combine the ability of feature descriptor matching to generate lots of correct large displacement correspondences with the ability of variational techniques to efficiently produce highly accurate, dense motion fields without outliers.

There are some literatures, called descriptor-based methods in this paper, which combine the advantages of traditional optical flow with feature descriptor matching techniques. This combination can guide the optical flow computation of small structures with large displacements in the right direction. For example, [12] presents a method in which large motions are estimated based on a correlation term and integrated into a variational model. The work in [13], which can reduce the reliance of flow estimates on their initial values propagated from the coarse level and enable recovering many motion details in each scale, integrates the feature matching into an energy minimization framework. Liu et al. [14] computes dense correspondences between two different scenes

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by computing dense field of SIFT descriptors and optimizing via belief propagation. Stoll et al. [11] proposes a three-step adaptive feature points selection strategy by which feature matches that may potentially improve the optical flow estimation are integrated into the variational optical flow. Leordeanu et al. [15] presents a sparse-to-dense matching method that starts from the higher level of sparse matching with rich appearance and geometric constraints collected over extended neighborhoods. Weinzaepfel et al. [16] proposes an optical flow method that allows to boost performance on fast motions by using descriptor matching algorithm. Another related work is [17] which combines the advantages of both variational energy minimization methods and region correspondences. The very related work is the technique presented by [1], where the method can acquire accurate optical flow by integrating rich descriptors into the variational optical flow framework.

Though some literatures have combined traditional optical flow algorithms with feature descriptor matching techniques, there still exist some problems. On the one hand, although some of the exiting methods can obtain good results for large displacement, few researches take the large affine motion into account. On the other hand, incorrect matches may lead to large errors of optical flow estimation in existing descriptor-based methods.

To overcome the above-mentioned difficulties, we present a novel method which is close to the work in [1,18], and the main difference of our work is that a robust point matching technique is adopted to assist the variational optical flow computation. The contributions of this paper are as follows: (1) We propose a robust point matching technique to generate dense point correspondences. (2) We present a method by integrating the robust point correspondences into a variational optical flow model, where we use the similar variational framework to the work [1,18], but we can obtain more accurate results both for small and large displacements compared with similar works. (3) Our method is more suitable to deal with affine motion due to the using of affine transformation hypothesis during robust point matching in contrast with similar works.

2. Variational model of optical flow

We here let I_1 and I_2 denote the first and the second image to be aligned, let $\mathbf{x} := (x, y)^T$ be a point in the image domain, and let $\mathbf{w} := \mathrm{w}(\mathrm{x}) := (u, v)^T$ represent the optical flow field. We adopt a robust variational optical flow framework similar to that used in [1,18], but lots of changes are made:

$$E(\mathbf{w}) = E_{color}(\mathbf{w}) + \gamma E_{grad}(\mathbf{w}) + \alpha E_{smooth}(\mathbf{w}) + E_{ncc}(\mathbf{w}_1) + \beta E_{match}(\mathbf{w}, \mathbf{w}_1) \tag{1}$$

where $E_{color}(\mathbf{w})$ is a color or gray consistency assumption:

$$E_{color}(\mathbf{w}) = \int_\Omega \psi(|I_2(\mathbf{x}+\mathbf{w}) - I_1(\mathbf{x})|^2)d\mathbf{x} \tag{2}$$

Here, we use $\psi(s^2) = \sqrt{s^2+\epsilon^2}$, $\epsilon = 0.001$, which allows to cope with occlusions and large displacements.

$E_{grad}(\mathbf{w})$ denotes gradient constraint which supplements the gray consistency constraint $E_{color}(\mathbf{w})$:

$$E_{grad}(\mathbf{w}) = \int_\Omega \psi(|\nabla I_2(\mathbf{x}+\mathbf{w}) - \nabla I_1(\mathbf{x})|^2)d\mathbf{x} \tag{3}$$

$E_{smooth}(\mathbf{w})$ is the smooth term by which ambiguous solutions can be avoided:

$$E_{smooth}(\mathbf{w}) = \int_\Omega \psi(|\nabla u(\mathbf{x})|^2 + |\nabla v(\mathbf{x})|^2)d\mathbf{x} \tag{4}$$

The combination of $E_{color}(\mathbf{w})$, $E_{grad}(\mathbf{w})$, and $E_{smooth}(\mathbf{w})$ is the general optical flow form [1], by which large displacements can be estimated. However, this general form does not consider the motions of small structures due to the using of coarse-to-fine framework. Therefore, in order to accurately measure the motions of small structures, we here extract more robust point correspondences and neglect the matching points' regularity constraint. Matching points without a regularity constraint can be performed efficiently using current descriptor matching techniques in a globally optimal manner, which can be formulated as another energy term:

$$E_{ncc}(\mathbf{w}_1) = \int_\Omega \delta(\mathbf{x})(1 - |\rho(\mathbf{x})|^2)d\mathbf{x} \tag{5}$$

In this term, $\mathbf{w}_1$ is the correspondence vectors to be obtained. $\rho(\mathbf{x}) = NCC(\mathbf{x}+\mathbf{w}_1, \mathbf{x})$ is the matching score of each correspondence, where $NCC(\cdot, \cdot)$ denotes the function of NCC (Normalized Cross Correlation).

Next, we integrate the matched points into the variational approach by adding another term:

$$E_{match}(\mathbf{w}, \mathbf{w}_1) = \int_\Omega \delta(\mathbf{x})\rho(\mathbf{x})\zeta(\mathbf{x})\psi(|\mathbf{w}(\mathbf{x}) - \mathbf{w}_1(\mathbf{x})|^2)d\mathbf{x} \tag{6}$$

where $\delta(\mathbf{x})$ is 1 if there is a correspondence available at point $\mathbf{x}$ in I_1; otherwise it is 0. Each correspondence is weighted by its matching score $\rho(\mathbf{x})$. Because a feature point located at an edge is unreliable, we here identify unreliable locations where feature matches would potentially lead to outliers. Therefore, we adopt an edge function $\zeta(\mathbf{x})$, if point $\mathbf{x}$ is located at an edge, $\zeta(\mathbf{x})$ is set to 0; otherwise it is 1. To obtain $\zeta(\mathbf{x})$, Canny edge detector [19] is adopted.

3. Minimization

Since Eq. (1) is a highly non-convex function, reasonable minimization schemes are needed to find a good solution.

Similar to that work in [1], the part of point matching, namely Eq. (5), can be decoupled from Eq. (1) and solved independently via direct matching. It is a discrete optimization problem to minimize Eq. (5) with respect to $\mathbf{w}_1$. Due to the missing of regularity constraint of point correspondences in Eq. (5), we can optimize it independently.

Therefore, two steps are used to minimize Eq. (1): Firstly, we independently solve Eq. (5) by using robust point matching method introduced in Section 3.1; secondly, we minimize the remainder of Eq. (1) by the method described in Section 3.2.

3.1. Robust point matching

Here, our aim is to extract more robust point correspondences used to assist the optical flow computation by minimizing Eq. (5) via discrete optimization. We introduce a sparse-to-dense technique to perform this task. This technique includes two steps: extracting some reliable point correspondences as seeds, and expanding from the seeds to obtain dense matching points between two images [20]. We here adopt a region expansion technique to perform point matching because region expansion techniques have been validated to be very robust in lots of applications [21,22,20].

Before elaborating the robust point matching method, we first introduce a photometric discrepancy function which will be used later.

3.1.1. Photometric discrepancy function

We assume there exists affine transformation between an image patch P_1 in I_1 and its corresponding patch P_2 in I_2. Under this assumption, we design a local energy function in which the