



Adaptive guided image filter for warping in variational optical flow computation

Zhigang Tu^{a,b}, Ronald Poppe^{a,b}, Remco C. Veltkamp^{a,b,*}

^a School of Computing, Informatics, Decision System Engineering, Arizona State University, USA

^b Department of Information and Computing Sciences, Utrecht University, Utrecht, The Netherlands

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ABSTRACT

The variational optical flow method is considered to be the standard method to calculate an accurate dense motion field between successive frames. It assumes that the energy function has spatiotemporal continuities and appearance motions are small. However, for real image sequences, the temporal continuity assumption is often violated due to outliers and occlusions, causing inaccurate flow vectors at these regions. After each warping operation, errors are generated at the corresponding regions of the warped interpolation image. This results in an inaccurate discrete approximation of the temporal derivative and thus ends up affecting the accuracy of the estimated flow field. In this paper, we propose an adaptive guided image filter to correct these errors in the warped interpolation image. A guidance image is reconstructed by considering both the feature of the reference image as well as the difference between the warped interpolation image and the reference image, to guide the filtering of the warped interpolation image. To adjust the smoothing degree, the regularization parameter in the guided image filter is adaptively selected based on a confidence measure. Extensive experiments on different datasets and comparison with state-of-the-art variational optical flow algorithms demonstrate the effectiveness of our method.

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1. Introduction

Estimation of the apparent motion of a scene plays a fundamental role in computer vision and image processing. Currently, one of the most successful techniques that addresses this problem is the variational optical flow method [1,2], which formulates an energy function by aggregating a data term and a smoothness term. Minimizing the energy function can get the motion of each pixel. Technically speaking, the minimization involves solving the corresponding Euler–Lagrange equations of the energy function numerically [3]. The calculated flow field is a dense field of displacement vectors, which describes how corresponding pixels in consecutive frames match. The direction and magnitude of each flow vector indicate where and how far a pixel moved. This property ensures the optical flow method is widely used in, for example, object tracking [4] and segmentation [5], super-resolution reconstruction [6], and medical diagnostics [7].

The variational optical flow method proposed by Horn and Schunck (HS) [8] is based on two assumptions: 1) the *brightness*

constancy assumption (BCA), which assumes that the brightness of a pixel does not change along its motion trajectory over time; and 2) the *smoothness assumption*, which assumes that the flow field is smooth and ensures the optical flow problem is well posed. In practice, these two assumptions are rarely satisfied. Especially under challenging conditions, such as outliers (e.g., image noise and estimated flow errors [9]), large displacements, occlusions and illumination changes, the performance of HS is notably worse [40]. Furthermore, the HS model is too slow to be implemented in real-time as the large and sparse partial differential equations (PDEs) is computationally expensive. Fortunately, in the past 30 years, considerable progress has been achieved. The progress can be divided into two classes: 1) different advanced concepts are integrated into the variational framework, to enable the methods to preserve discontinuity [5,10,11], to handle large displacements [1,2,20], to treat illumination changes [12,13], to be robust with respect to outliers [9,15], and to tackle occlusions [9,16,17]; and 2) efficient and advanced optimization schemes are presented to target real-time use [3,18].

The popular variational algorithms are focused on how to improve the data term (Eq. (1)) by incorporating new assumptions [19], or to design advanced smoothness constraints that preserve discontinuity. There are few literatures concern the basic feature of the numerical computation, where the flow field is computed from

* Corresponding author at: School of Computing, Informatics, Decision System Engineering, Arizona State University, USA.

E-mail addresses: Zhigang.Tu@asu.edu (Z. Tu), R.W.Poppe@uu.nl (R. Poppe), R.C.Veltkamp@uu.nl (R.C. Veltkamp).

the spatiotemporal derivatives of image intensities. Therefore, the input images and the intermediate warped interpolation image $\mathbf{I}_{\text{warp}}$ ($\mathbf{I}_{\text{warp}}$ refers to the warped interpolation image based on the flow field calculated in the previous step, see Eq. (2)) are constrained to be continuous and differentiable in space-time. Simultaneously, the flow vector should be small and valid at every pixel. Errors are typically produced in the intermediate flow fields due to outliers and occlusions. Subsequently, $\mathbf{I}_{\text{warp}}$ will contain errors caused by these inaccurate flow vectors. Furthermore, the spatiotemporal derivatives will be distorted. Consequently, the accuracy of the final estimated flow field will be degraded. Correcting errors of the intermediate flow fields and the $\mathbf{I}_{\text{warp}}$ during optimization is a good way to improve the performance of the variational algorithms.

Till now, the majority of variational optical flow algorithms try to reduce errors during the numerical computation, concentrating on applying different filters to smooth the intermediate flow fields to remove outliers or to correct flow errors by integrating useful information [10,21].

Xiao et al. [17] proposed a multi-cue driven adaptive bilateral filter (BF), which enables smoothing of the flow field with highly desirable motion discontinuity preservation. The algorithm can handle occlusions partially, but, BF is time consuming. Wedel et al. [12] introduced a median filter (MF) to denoise the flow field, but the MF over-smooths motion boundaries of the flow field. Sun et al. [10] proposed a modified weighted median filter (WMF) to prevent this kind of over-smoothing, but the weight is easily influenced by textured, noisy pixels and illumination changes. Recently, Rashwan et al. [22] improved the weight by using the saliency of image gradients to replace the intensity-based measure. Tu et al. [16] proposed a novel combined post-filtering (CPF) method to efficiently remove outliers and handle occlusions simultaneously.

Brox et al. [3] proposed a two nested fixed point iterations based numerical scheme to combine with the coarse-to-fine strategy to efficiently solve the variational methods. As pointed out in [1,2], this method fails to recover many motion details. Because some fine structures are smoothed out at coarse levels and then “forgotten”, therefore, they cannot be correctly estimated at final scale. Xu et al. [2] proposed an extended coarse-to-fine (EC2F) refinement framework to reduce the reliance of flow estimates on their initial values propagated from the coarse level. By integrating available matching information into the continuous flow at each scale, the lost motion of fine structures can be recovered.

These methods only consider filtering the intermediate flow fields or refining the initial flow vectors, they neglect to correct the basic elements of the PDEs – the spatiotemporal derivatives.

The correctness of the temporal derivative $\mathbf{I}_t$ completely depends on $\mathbf{I}_{\text{warp}}$, which means that $\mathbf{I}_{\text{warp}}$ heavily influences the accuracy of the estimated flow field. Currently, nearly all variational methods (e.g. [10,12,22]) simply use the temporal derivative in the numerical iteration. In contrast, we propose an adaptive guided image filter (AGIF) to filter $\mathbf{I}_{\text{warp}}$ before computing the temporal derivative. The AGIF technique is especially useful to correct errors of $\mathbf{I}_{\text{warp}}$ which are caused by outliers and occlusions.

The guided image filter (GIF), which was proposed recently by He et al. [23], smooths the input image by considering the content of a guidance image that can be another image or the input image itself. The GIF is similar to the joint bilateral filter (JBF) [24], which is able to reduce noise while preserve edges. However, the JBF is nonlinear and computationally complex. The computational time of the JBF increases exponentially as the size of the filtering window increases. In contrast, the GIF is implemented as a sequence of box filters, making it linear and efficient. More significantly, its runtime is independent of the filtering window size. Due to these

advantages, the GIF is popular in denoising [23,25], sharpness enhancement [26], optical flow computation [28] and stereo matching [27,28]. For example, Xiao et al. [39] applied the GIF to filter the three dimensional cost-volume to preserve edge information and improve operational efficiency. To treat with the problem of flickering-artifacts that is caused by the incoherent disparity maps, Liu et al. [41] proposed a novel temporal consistency enhancement algorithm based on Guided Filter and Temporal Gradient to smooth disparity sequences to improve the consistency of the sequence.

In this work, we present an AGIF technique to smooth $\mathbf{I}_{\text{warp}}$ to improve the performance of the variational optical flow method. To analyze the characteristic of the GIF as well as the relationship between the reference image and $\mathbf{I}_{\text{warp}}$, we reconstruct a guidance image which is a combination of both. The combination is based on a confidence measure which originates from the temporal derivative, as the temporal derivative can be interpreted as an indication of mismatch. Due to this contribution, the filtered $\mathbf{I}_{\text{warp}}$ can gain useful information from the reference image. Except the general edges, we can correct some intensities which are distorted due to outliers and occlusions of the before filtered $\mathbf{I}_{\text{warp}}$. Another contribution is that, we propose a method to select the optimal regularization parameter ε (Eq. (18)) adaptively based on two principles – the error degree of $\mathbf{I}_{\text{warp}}$ and the size of the input testing images. This method effectively improves the smoothing ability of the GIF.

The paper is organized as follows. Section 2 describes a fundamental CPF method and the numerical optimization process. In Section 3, we propose an AGIF technique to correct errors of the warped interpolation image. Experiments are presented in Section 4. Finally, discussion and conclusions are given in Section 5.

2. Variational optical flow model and minimization

2.1. The combined Post-filtering (CPF) method

Let $\mathbf{I}_1, \mathbf{I}_2: (\Omega \subset \mathbb{R}^2)$ be the two consecutive frames at time t and $t+1$. $\mathbf{x}=(x, y, t)^T$ denotes the locations of pixels in the spatial image domain Ω , and $\mathbf{w}=(\mathbf{u}, \mathbf{v})^T$ is the flow field describes the displacement in x -and y -direction between $\mathbf{I}_1$ and $\mathbf{I}_2$. The common assumption of flow estimation is the *brightness constancy assumption* (BCA). Based on the BCA, a data term is formed:

$$E_D(\mathbf{w}) = \int_{\Omega} |\mathbf{I}_2(\mathbf{x} + \mathbf{w}) - \mathbf{I}_1(\mathbf{x})|^2 d\mathbf{x} \quad (1)$$

where

$$\mathbf{I}_{\text{warp}} = \mathbf{I}_2(\mathbf{x} + \mathbf{w}) \quad (2)$$

is a warped interpolation image with certain interpolation method such as, cubic interpolation, bilinear interpolation [15], or bicubic interpolation [12].

The two unknowns $(\mathbf{u}, \mathbf{v})$ be determined from one single Eq. (1). To solve this aperture problem, a global smoothness assumption has been introduced, where a smoothness term can be expressed as [8]:

$$E_S(\mathbf{w}) = \int_{\Omega} |\nabla \mathbf{u}|^2 + |\nabla \mathbf{v}|^2 d\mathbf{x} \quad (3)$$

By integrating the smoothness term Eq. (3) into Eq. (1), and by using a parameter λ to steer the relative importance of the two terms, the optical flow estimation can be formulated as an energy minimization problem in which the energy function is:

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