Laplacian Derivative Based Regularization for Optical Flow Estimation in Driving Scenario

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Abstract. Existing state of the art optical flow approaches, which are evaluated on standard datasets such as Middlebury, not necessarily have a similar performance when evaluated on driving scenarios. This drop on performance is due to several challenges arising on real scenarios during driving. Towards this direction, in this paper, we propose a modification to the regularization term in a variational optical flow formulation, that notably improves the results, specially in driving scenarios. The proposed modification consists on using the Laplacian derivatives of flow components in the regularization term instead of gradients of flow components. We show the improvements in results on a standard real image sequences dataset (KITTI).

Keywords: Optical Flow, Regularization, Driver Assistance Systems, Performance Evaluation.

1 Introduction

Computer vision has got applications in innumerable ways to our lives. Recently the idea of using computer vision for driving assistance has opened new research opportunities. The need of the safety has steered driver assistance applications getting interest from both academia and major corporations as well. Having vision sensors such as cameras mounted on automotives, acquiring information from such sensors and using it to alert the driver and/or control the vehicle is the basic structure of advanced driver assistance systems (ADAS). Optical flow techniques for the motion estimation are the very necessary and important ingredients in making several ADAS applications such as egomotion estimation, moving object detection, collision avoidance, automated control a reality. Optical flow field is the motion vector field indicating the displacement of pixels between consecutive images in a sequence.

Optical flow techniques, which give dense flow fields, are formulated as variational energy minimization problems. These methods are referred to as global methods. On the other hand, the methods that produce sparse flow fields for some detected feature points on an image are referred to as local methods. The first local method has been proposed by Lucas and Kanade [1] in 1981. The variational formulation is also proposed in 1981 by Horn and Schunck [2]. There have been huge number of contributions in these three decades to improve the

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accuracy of estimated flow field. We can coarsely group such developments into: formulation of robust and higher order data terms, improving edge preserving regularizations, adding more features/information to the energy model and to the minimization techniques of the energy functions. The thesis [3] gives a detailed survey on the improvements in data term and regularization terms proposed through the last years looking for accurate results. Also an attempt to evaluate performance of several optical flow techniques is made in [4]. In recent years, the research on optical flow is getting a lot of interests [5]. Most of the research concentrates on variational methods [2], [6], [7], which produce dense flow fields. Some of the works deal with preserving flow edges (e.g., [8], [9], [10]) and formulating sophisticated data terms [11]. A recent work [12] discusses the concepts such as pre-processing, coarse-to-fine warping, graduated non-convexity, interpolation, derivatives, robustness of penalty functions, median filtering and proposes a method considering the best of the variants of discussed concepts.

All the contributions mentioned above are targeted, performed and evaluated on few standard datasets. One of the most well known optical flow benchmark dataset is Middlebury [13], which contains limited scenarios and image pairs have small displacements. This dataset do not involve much realistic characteristics. A big challenge when real dataset with realistic scenarios need to be obtained lies on the difficulty in obtaining ground-truth optical flow. Recently, Geiger et. al [14] have proposed a new real dataset of driving scenarios containing large displacements, specularity, shadows and different illuminations. They have also provided sparse ground-truth flow field. This dataset is referred to as KITTI [15]. One can think that the state of the art methods that give the best results on Middlebury dataset can also perform similarly on KITTI dataset. However, by analyzing the KITTI flow evalation we can appriciate that such a statement is wrong due to the difficulties of this particular dataset. There are few attempts those tried to adapt the existing methods to the driving scenario using epipolar geometry and rigid body motion information. The approach in [16] estimates both optical flow and fundamental matrix together. The accuracy of this method reduces when there is a dynamic scene as one can expect that the driving scenario is always dynamic.

Driving scenarios vary very largely by environment, weather conditions and day-light conditions. The driving environment itself involves the situations such as urban, highway, countryside with different geometry of scenes and textures. Apart from these the vehicle speed [17] and turning in road also matters causing very large displacement. So developing an optical flow technique that withstands all such difficult scenarios is a challenging research topic. Actually there is a lack of specialized methods for driving scenarios where occurs a variety of difficulties. In the current work, we propose an improvement over an existing state of the art method [12]. In this work, we specifically deal with the importance of regularization. We propose a modication to the derivative operator in the regularization that deals with large variations in speed and rotations that exist in KITTI dataset. The performance analysis done on the KITTI dataset shows that the proposed modification improves the results.

The paper is organized as follows. Section 2 gives an overview of the basic optical flow formulation and the proposed modification. Experimental results are provided in section 3 followed by the conclusions in section 4.

2 Optical Flow Overview and Proposed Modification

In this section, we first give an overview of basic variational formulation of optical flow estimation. In general, variational energy models involve a data term and a regularization term. The data term formulates the assumption of some matching characteristics typically the intensity of the pixel and it is also called brightness constancy assumption (BCA). The classical variational method of Horn and Schunck [2] assumes the constancy of brightness, which is also called optical flow constraint (OFC). The OFC can be formulated as: $I_1(\boldsymbol{x}+\boldsymbol{u}) - I_0(\boldsymbol{x}) = 0$, where I_0 and I_1 are two images, $\boldsymbol{x} = (x_1, x_2)$ is the pixel location within the image space $\Omega \subseteq \mathbf{R}^2$; $\boldsymbol{u} = (u_1(\boldsymbol{x}), u_2(\boldsymbol{x}))$ is the two-dimensional flow vector. Linearizing the above equation using first-order Taylor expansion we get OFC as: $(I_{x_1}u_1 + I_{x_2}u_2 + I_t)^2 = 0$, where subscripts denote the partial derivatives. Using only OFCs do not provide enough information to infer meaningful flow fields, making the problem ill-posed. Particularly, optical flow computation suffers from two issues: first, no information is available in non-textured regions. Second, one can only compute the normal flow, i.e., the motion perpendicular to the edges. This problem is generally known as the aperture problem. In order to solve this problem it is clear that some kind of regularization is needed. The Horn and Schunk [2] method overcomes this by assuming the resulting flow field globally smooth all over the image, that can be realized as penalizing large flow gradients ∇u_1 and ∇u_2. Combining OFC and homogeneous regularization in a single variational framework and squaring both constraints yields the following energy function:

$$E(\boldsymbol{u}) = \int_{\Omega} \{ \underbrace{(I_{x_1}u_1 + I_{x_2}u_2 + I_t)^2}_{Data\ Term} + \alpha \underbrace{(|\nabla u_1|^2 + |\nabla u_2|^2)}_{Regularization} \} \, d\boldsymbol{x}, \tag{1}$$

where α is the regularization weight. This energy function is minimized for flow vectors using corresponding Euler-Lagrange equations. Another alternative way to solve this is by using dual formulation [18].

Based on the above basic formulation, the authors in [12] proposed a formulation using median filtering in addition to the other improvements proposed in previous literature and explored by them. It is known that median filtering at every iteration of flow computation improves the results. The work in [12] incorporates this filtering heuristics into the objective function. This improved non-local median filtering based method is called C+NL. In most of the methods in literature authors try to penalize the gradient of the estimated flow vectors using different and combinations of robust penalizing functions. In a driving sequence, there occurs large variations in magnitude and orientations due to change in speed of the vehicle, turn of the vehicle, specularity, and scene dynamics. In general, driving scenarios are very dynamic with large variations. Hence, in the current work we propose to penalize the Laplacian of flow components instead of their gradients. With the basic formulation notation, the equation (1) becomes:

$$E(\boldsymbol{u}) = \int_{\Omega} \{ \underbrace{(I_{x_1} u_1 + I_{x_2} u_2 + I_t)^2}_{Data\ Term} + \alpha \underbrace{(|\triangle u_1|^2 + |\triangle u_2|^2)}_{Regularization} \} \, d\boldsymbol{x}. \quad (2)$$

In summary, we propose to modify the derivative of flow components in the regularization to second derivative as shown in equation (2) in the approach presented in [12]. We will refer to this method as C+NL-M. With second derivative regularization, it allows more variations in flow components. Hence, as shown in the next section the proposed modification results in more accurate optical flow estimations.

3 Experimental Results

The proposed modification has been evaluated with respect to the state of the art method C+NL, which is one of the best approach on Middlebury dataset.

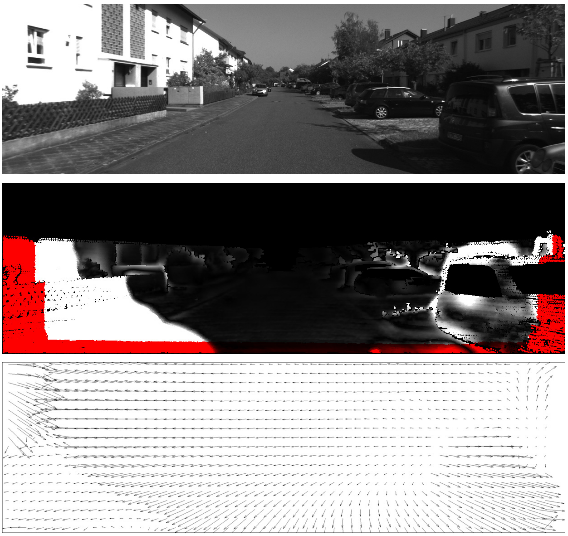

Fig. 1. Results for a pair of images; (*top*) 1^{st} image of the pair; (*middle*) error map; and (*bottom*) computed flow field.

The analysis of performance is carried out on the standard dataset KITTI [14]. This dataset contains image pairs of real driving scenarios with varied real characteristics that make optical flow computation a real challenge in such scenarios. This dataset consists of 194 training image pairs and 195 test image pairs. The results on few of the testing pairs from KITTI are shown in Figures 1, 2 and 3. In these figures, the (*top*) is the 1st image of individual pairs, (*middle*) is the error map, and the (*bottom*) is the computed flow field. The red area in the (*middle*) indicates the occluded pixels falling outside image boundary.

Table 1. Error values for the image pairs shown in Fig. 1 by C+NL

Error	Out-Noc	Out-All	Avg-Noc	Avg-All
2 pixels	32.68 %	42.11 %	11.1 px	17.5 px
3 pixels	30.74 %	40.00 %	11.1 px	17.5 px
4 pixels	29.56 %	38.48 %	11.1 px	17.5 px
5 pixels	28.56 %	37.13 %	11.1 px	17.5 px

Fig. 2. Results for a pair of images; (*top*) 1^{st} image of the pair; (*middle*) error map; and (*bottom*) computed flow field.

Table 2. Error values for the image pairs shown in Fig. 1 by C+NL-M

Error	Out-Noc	Out-All	Avg-Noc	Avg-All
2 pixels	25.27 %	32.90 %	9.1 px	16.1 px
3 pixels	22.43 %	30.04 %	9.1 px	16.1 px
4 pixels	21.14 %	28.73 %	9.1 px	16.1 px
5 pixels	20.19 %	27.75 %	9.1 px	16.1 px

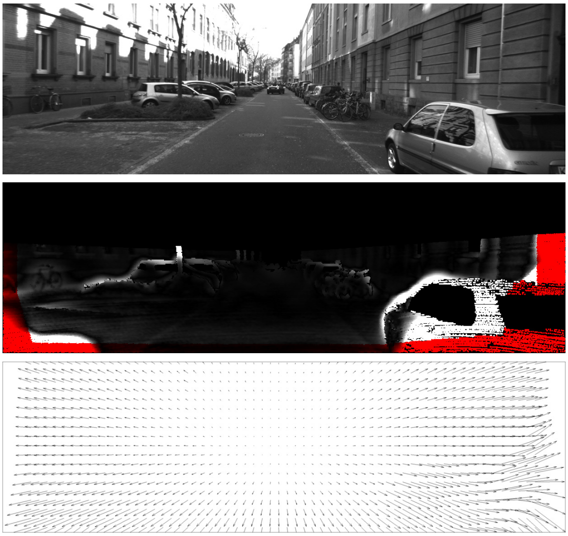

Fig. 3. Results for a pair of images; (*top*) 1^{st} image of the pair; (*middle*) error map; and (*bottom*) computed flow field.

The evaluation performed by the KITTI server computes the average number of bad pixels for non-occluded or all pixels for available ground-truth. This evaluation is performed over the optical flow computed on testing set with our modified approach that has been uploaded to the KITTI server. Table 1 shows the errors for the image pair shown in Fig. 1 for the approach C+NL, whereas Table 2 shows the errors for the same pair for the proposed approach C+NL-M. It can be appreciated that C+NL-M gives better results and as presented below C+NL-M is ranked higher than the C+NL by the KITTI evaluation procedure. It should be noted that both C+NL and C+NL-M in this work use fast version of their implementations.

The evaluation table ranks all methods according to the number of non-occluded erroneous pixels at the specified end-point error threshold. At the time of submission (on 5th April 2013), our proposed method ranks 8^{th}, whereas C+NL ranks 16^{th} for 2 pixel threshold. The ranking table from the KITTI web service is shown in Fig. 4. For 3 pixel threshold our method ranks at 9^{th} as shown in Fig. 5. This shows that changing the regularization to Laplacian notably improves the results, specifically in the sequences of driving scenarios. At the time of acceptance of this publication, the previous entry of C+NL in [15] has been replaced by a modified version by the original authors. Note that our proposed modified method better performs compared to the original approach in [12].

Rank	Method	Setting	Out-Noc	Out-All	Avg-Noc	Avg-All	Density	Runtime	Environment	Compare
1	PCBP-Flow	ms	**6.33 %**	**11.59 %**	**0.9 px**	**2.2 px**	100.00 %	3 min	4 cores @ 2.5 Ghz (Matlab + C/C++)	
Koichiro Yamaguchi, David McAllester and Raquel Urtasun. Robust Monocular Epipolar Flow Estimation. CVPR 2013.										
2	MotionSLIC	ms	6.72 %	14.06 %	1.0 px	2.7 px	100.00 %	11 s	1 core @ 3.0 Ghz (C/C++)	
Koichiro Yamaguchi, David McAllester and Raquel Urtasun. Robust Monocular Epipolar Flow Estimation. CVPR 2013.										
3	PR-Sceneflow		6.91 %	12.39 %	1.3 px	3.3 px	100.00 %	150 sec	4 core @ 3.0 Ghz (Matlab + C/C++)	
Anonymous submission										
4	TGV2ADCSIFT		8.86 %	18.47 %	1.6 px	4.5 px	100.00 %	8s	GPU @ 1.5 Ghz (C/C++)	
Anonymous submission										
5	Data-Flow		10.86 %	19.00 %	2.3 px	5.7 px	100.00 %	3 min	2 cores @ 2.5 Ghz (Matlab + C/C++)	
Anonymous submission										
6	TGV2CENSUS		13.33 %	21.11 %	2.9 px	6.6 px	100.00 %	4 s	GPU+CPU @ 3.0 Ghz (Matlab + C/C++)	
Manuel Werlberger. Convex Approaches for High Performance Video Processing. 2012.										
Rene Ranftl, Stefan Gehrig, Thomas Pock and Horst Bischof. Pushing the Limits of Stereo Using Variational Stereo Estimation. IEEE Intelligent Vehicles Symposium 2012.										
7	fSGM		14.56 %	25.94 %	3.2 px	12.2 px	100.00 %	60 s	1 core @ 2.4 Ghz (C/C++)	
Simon Hermann and Reinhard Klette. Hierarchical Scan Line Dynamic Programming for Optical Flow using Semi-Global Matching. Intelligent Mobile Vision, ACCV-Workshop 2012.										
8	C+NL-M		21.13 %	28.37 %	7.4 px	14.5 px	100.00 %	5 min	2 cores @ 2.5 Ghz (Matlab)	
Anonymous submission										
9	eFolki		22.01 %	31.50 %	5.2 px	10.8 px	100.00 %	0.026 s	GPU @ 700 Mhz (C/C++)	
Anonymous submission										
10	HS		22.02 %	31.18 %	5.8 px	11.7 px	100.00 %	3 min	1 core @ 2.5 Ghz (Matlab + C/C++)	
Berthold K. P. Horn and Brian G. Schunck. Determining optical flow: A Retrospective. AI 1993.										
11	RSRS-Flow		22.68 %	31.81 %	6.2 px	12.1 px	100.00 %	4 min	1 core @ 2.5 Ghz (Matlab)	
Pratim Ghosh and B.S. Manjunath. Robust Simultaneous Registration and Segmentation with Sparse Error Reconstruction. IEEE Transactions on Pattern Analysis and Machine Intelligence 2012.										
12	GC-BM-Bino	ms	23.07 %	33.10 %	5.0 px	12.0 px	83.73 %	1.3 s	2 cores @ 2.5 Ghz (C/C++)	
Bernd Kitt and Henning Lategahn. Trinocular Optical Flow Estimation for Intelligent Vehicle Applications. Proceedings of the IEEE International Conference on Intelligent Transportation Systems 2012.										
13	ALD		24.28 %	33.63 %	10.9 px	16.0 px	100.00 %	110 s	1 core @ 2.5 Ghz (C/C++)	
M. Stoll, S. Volz and A. Bruhn. Adaptive Integration of Feature Matches into Variational Optical Flow Methods. ACCV 2012.										
14	LDOF		24.43 %	33.87 %	5.5 px	12.4 px	100.00 %	1 min	1 core @ 2.5 Ghz (C/C++)	
T. Brox and J. Malik. Large Displacement Optical Flow: Descriptor Matching in Variational Motion Estimation. PAMI 2011.										
15	GC-BM-Mono	ms	24.79 %	34.59 %	5.0 px	12.1 px	84.33 %	1.3 s	2 cores @ 2.5 Ghz (C/C++)	
Bernd Kitt and Henning Lategahn. Trinocular Optical Flow Estimation for Intelligent Vehicle Applications. Proceedings of the IEEE International Conference on Intelligent Transportation Systems 2012.										
16	C+NL		26.42 %	35.28 %	9.0 px	16.4 px	100.00 %	3 min	1 core @ 2.5 Ghz (C/C++)	

Fig. 4. Evaluation table for 2 pixel error threshold (data from [15])

Rank	Method	Setting	Out-Noc	Out-All	Avg-Noc	Avg-All	Density	Runtime	Environment	Compare
9	C+NL-M		19.17 %	26.35 %	7.4 px	14.5 px	100.00 %	5 min	2 cores @ 2.5 Ghz (Matlab)	
16	C+NL		24.64 %	33.35 %	9.0 px	16.4 px	100.00 %	3 min	1 core @ 2.5 Ghz (C/C++)	

Fig. 5. Evaluation table for 3 pixel error threshold (data from [15])

4 Conclusions

We explore and realized that the state of the art optical flow methods does not necessarily perform well for driving scenarios. Towards this, in this paper we propose a modification of the regularization term in a state of the art method. The derivative of flow components are changed to Laplacian from gradient. The experimental results are performed on a standard benchmark data set (KITTI) that contains real image pairs of a driving scenario with challenging characteristics. The evaluation shows that the proposed modification performs better. We envisage that the KITTI dataset will lead research to the development of new approaches that can perform in very complex scenarios and our future work concentrates on this line.

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