Color image optical flow estimation algorithm with shadow suppression

Guojian Wei, Zhiqiang Hou, Wu Li, Wangsheng Yu
School of Information and Navigation
Air Force Engineering University
Xi'an, China
guojian26@qq.com, hou-zhq@sohu.com, liwu19890411@qq.com, xing_fu_yu@sina.com

Abstract—A new optical flow estimation algorithm for color image is proposed to overcome the influence of shadows and improve the accuracy of optical flow estimation. Its idea is to compute optical flow of the color invariant space and then fuse the result with optical flow of the RGB space. Firstly, it computes edge strength from color invariants of two adjacent frames to build three-channel color images, and then computes optical flow of the images we have built before, finally, fuses the result of color invariant optical flow with RGB image optical flow through L_∞ norm. The experimental results demonstrate that the target regions detected by this method are more robust and accurate under shadow and illumination conditions. Compared with some methods proposed recently, it performs better.

Keywords-optical flow estimation; color image optical flow; color invariants; IRLS

I. Introduction

Optical flow is the distribution of apparent velocities of movement of brightness patterns in an image [1]. Not only does it contain rich 2D motion cues, but contain 3D scene structure information [2]. Recently, optical flow estimation has been the foundation of many technologies for motion estimation, tracking, image segmentation and compression [3], which can acquire motion cues of targets under camera moving[4], and gain target's zoom and rolling cues if deeper analysis is done.

Classical optical flow algorithms [1, 5, 6] use pixel value (brightness or gradient) to build targets, compute optical flow under brightness constancy assumption and smoothness restriction. But in real motion analysis, the brightness constancy assumption that pixel values are invariant from one frame to another along with the motion, often breaks because of illumination changes and noise [7], namely it is difficult to acquire accurate motion information of targets from pixel value only.

Compared with gray image, color image contains more optical information, which could deal with the aperture problem of optical flow computation for gray images [8]. Ohta [9] firstly proposed an optical flow algorithm making use of color information, subsequently, many scholars made research on optical flow computation for color image. Nevertheless, those algorithms compute optical flow mostly under RGB, normalized RGB or HSV color models et al. [10]. [13] proposes a variational optical flow computation algorithm based on segmentation, which combines with RGB image segmentation and optical flow computation, and improves accuracy of optical flow estimation. In recent years, some researchers have proposed optical flow algorithms combined with histogram or edge features et al to cope with moving object detection [14]. Lately, many other flow algorithms have been proposed starting off with restriction equations of optical flow, such as SIFT Flow in [16], which could handle scene alignment and face recognition of higher level; Different from global optimization, SimpleFlow in [17] computes the mean value of local probability distributions from standard color differences, and uses a sparse set of samples to estimate the flow in image regions where the motion is smooth. Its running time grow sublinearly with the frame resolution, thus enhances algorithm's timeliness vastly.

However, without full consideration of the influence of illumination changes on target description and follow-up results, aforementioned methods may result in problems like streaking effect, target's being obscured by other surroundings, seriously affecting further processing.

In [18], the author exploits the Gaussian scale-space paradigm for color images to define a framework for the robust measurement of object reflectance from color images. Object reflectance is derived from a physical reflectance model. Inspired by this work, a new optical flow estimation algorithm for color images via computing optical flow of the color invariant space and then fusing with optical flow of the RGB space is proposed to overcome illumination's effects and improve the accuracy of optical flow. We introduce how to build the model of color invariants and take experiments to validate it. We also import iterative reweighted least square (IRLS) into variational optical flow algorithm.

The rest of the paper is organized as follows: Section 2 introduces color invariants, and confirms the suppression of illumination and shadow; In Section 3, we propose a new optical flow estimation algorithm for color images fused with color invariants; Experiments and analysis are presented in Section 4; we conclude this paper in Section 5.

II. Color invariants model

In Gaussian Color Model, the relationship between spectral components and RGB components can be expressed as follows:

$$\begin{pmatrix} E \\ E_\lambda \\ E_{\lambda\lambda} \end{pmatrix} = \begin{pmatrix} 0.06 & 0.63 & 0.27 \\ 0.3 & 0.04 & -0.35 \\ 0.34 & -0.6 & 0.17 \end{pmatrix} \begin{pmatrix} R \\ G \\ B \end{pmatrix} \tag{1}$$

978-0-7695-5050-3/13 $26.00 © 2013 IEEE
DOI 10.1109/ICIG.2013.91

[19] use $H = \left(\frac{E_\lambda}{E_{\lambda\lambda}} \right)$ as color invariant to build a new image, but owing to linear transform, there are many negatives in the image, which doesn't agree with the physical meaning of pixel values and makes further video analysis unreasonable. Therefore we select edge strength of color invariants under the idea of illumination invariance [18]. Besides, [18] provides five edge strength measures for color invariant sets. But after abundant experiments, we find that Cw has the best performance in estimating optical flow. The formula is given by

$$C_w = \sqrt{C_{\lambda x}^2 + C_{\lambda\lambda x}^2 + C_{\lambda y}^2 + C_{\lambda\lambda y}^2} \quad (2)$$

Middle variables can be seen in Table 1:

TABLE I. MIDDLE VARIABLES FOR EDGE STRENGTH OF COLOR INVARIANTS

C_λ	$C_{\lambda\omega} = \sqrt{C_{\lambda x}^2 + C_{\lambda y}^2} = \frac{1}{E^2}\sqrt{(E_{\lambda x}E - E_\lambda E_x)^2 + (E_{\lambda y}E - E_\lambda E_y)^2}$
$C_{\lambda\lambda}$	$C_{\lambda\lambda\omega} = \sqrt{C_{\lambda\lambda x}^2 + C_{\lambda\lambda y}^2} = \frac{1}{E^2}\sqrt{(E_{\lambda\lambda x}E - E_\lambda \lambda E_x)^2 + (E_{\lambda\lambda y}E - E_{\lambda\lambda} E_y)^2}$
E	$E_w = \sqrt{E_x^2 + E_{\lambda x}^2 + E_{\lambda\lambda x}^2 + E_y^2 + E_{\lambda y}^2 + E_{\lambda\lambda y}^2}$

In Table 1, E is spectral components, E_x、E_y are spatial derivatives of E in the x-direction and y-direction, the others can be deduced similarly.

To test and verify their suppression of shadow, we select one image[1] with shadows, and compute the edge strength of color invariants, the results are shown in Fig. 1.

As we can see, the edge strength Ew can't overcome the influence of illumination, and all boxes have shadows; Cw is able to overcome the influence of illumination and eliminate shadows effectively.

III. COLOR IMAGE OPTICAL FLOW ESTIMATION FUSED WITH COLOR INVARIANTS

A. Main idea

SIFT Flow [16] is an excellent example of computing optical flow of 2D image in feature subspace. It adopts the computational framework of optical flow, but it extracts SIFT descriptor at each pixel (pixel-level) instead of raw pixels, and describes target's motion filed through dense and pixel to pixel correspondences between two images. CSIFT [19] put forward an idea that describing input image by building SIFT descriptors in the color invariant space instead of gray space.

[1] The image and code of color invariance are available at http://staff.science.uva.nl/~mark/downloads.html#colinv

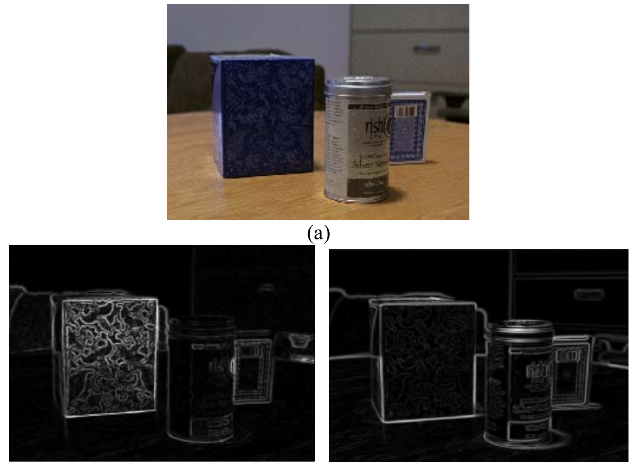

Figure 1. Edge image of color invariants. (a) Source image. (b) Cw image. (c) Ew image.

Compared with conventional SIFT, the built Colored SIFT (CSIFT) is more robust respect to color and photometrical variations. Inspired by [16] and [19], we can improve the accuracy of optical flow estimation by three steps. Firstly, compute the optical flow by mapping the RGB image space to the color invariant space so as to overcome the illumination influence, and then compute the optical flow in the RGB space, finally, fuse the two results to make up the optical flow deviation caused by information shortage in color invariant space.

B. Arithmetic procedure

Fig. 2 is the flow chart of color image optical flow algorithm. (a) stands for two adjacent image frames; (b) computes optical flow in the RGB space; (c) computes optical flow in the color invariant space; (d) fuses the color invariant optical flow with RGB image optical flow through L_∞ norm ; (e) the result of fused optical flow. The detailed arithmetic procedures are as follows:

Step 1: Algorithm initialization

Read two adjacent color image frames, filter or do down sampling to wipe off image noise and downsize the image as necessary.

Step 2: Compute optical flow in RGB space

Variational methods are predominant ways to estimate dense optical flow in today's computer vision literatures [21]. Such methods compute dense displacement field $\mathbf{u} = (u, v)^T$ between two images I_t and I_{t+1} by minimize a suitable energy functional. Under the assumption of brightness constancy, the pixel value should be consistent along with the flow field, and the flow field should be piecewise-smooth. This results in an objective function in the continuous spatial domain:

$$E(u,v) = \int \psi(|I(\mathbf{p}+\mathbf{w}) - I(\mathbf{p})|^2) + \partial\phi(|\nabla u|^2 + |\nabla v|^2) d\mathbf{p} \quad (3)$$

Where $\mathbf{p} = (x, y, t)$ is image lattice, $\mathbf{w}(\mathbf{p}) = (u(\mathbf{p}), v(\mathbf{p}), 1)$ is underlying flow field, $u(\mathbf{p})$ and $v(\mathbf{p})$ denotes the horizontal and vertical components of the flow field, respectively. $\psi(\cdot)$

and $\phi(\cdot)$ are robust functions (We use L1 norm, $\psi(x)=\sqrt{x^2+\varepsilon^2}$, $\phi(x)=\sqrt{x^2+\varepsilon^2}$, $\varepsilon=0.001$ in this paper), $|\nabla u|^2 = u_x^2 + u_y^2$ ($u_x = \frac{\partial}{\partial x}u, u_y = \frac{\partial}{\partial y}u$), ∂ weights the regularization.

Optical flow components could be estimated by minimizing Eq. (3). Although the mathematical derivation appears complicated, the IRLS method can make it easier and more straightforward [7]. As pointed out in literature [7], compared with traditional Euler-Lagrange method, IRLS has no limit to derivative filters and is easier to handling the large magnitude flows, moreover IRLS is equivalent to the variational method when optimizing a nonnegative, monotonic function. Aiming at color images, we use multi-channel IRLS optical flow method, see more detailed derivation process in [7].

Step 3: Compute optical flow in the color invariant space

Firstly, build color invariant channel images. We use single color invariant to build three channel color images, and then compute color invariant optical flow by using multi-channel IRLS method. Using three channel color image, on the one hand can utilize the combination of multiple color invariants so as to increase the accuracy of optical flow estimation, on the other hand it guarantees the unify and convenience of optical flow computation, and is easier to fuse with RGB optical flow. It should be noted that the data of the color invariant edge image acquired from Table 1 and Table 2 is between (0,1), we map them to (0,255), and then build a multi-channel color image so as to expand the scope of data, and take full advantages of image information.

Step 4: Compute optical flow in the RGB space

As we indicated, color invariant optical flow can eliminate the effect of illumination and shadow, while some image information will be lost in the color invariant space, which leading deviation of optical flow (e.g. some data are small), while the RGB optical flow in these place may reserve more information. Therefore we use L_∞ norm ($\|\mathbf{x}\|_\infty = \max_i |\xi_i|$, where $\mathbf{x}=(\xi_1,\xi_2,\cdots,\xi_n)\in C^n$) to fuse two kinds of optical flow， so as to correct the results.

C. *The visualization of flow fields*

We adopt the method in [22] to visualize the flow field. As shown in Fig. 3: Each pixel denotes a flow vector where the orientation and magnitude are represented by the hue and saturation of it, respectively. e.g. the still points of the image are white, objects moving toward left are blue, bottom left are green, the deeper the color is, the greater the range is.

IV. EXPERIMENTS

A. *Experimental method*

Using image sequences in Middlebury optical flow benchmark [23] and [12] to compare the proposed method with RGB optical flow [24] and SIFT Flow [16].All the experiments are carried out on a 2.6GHz PC with 2GB memory. The simulation software is Matlab R2011a.

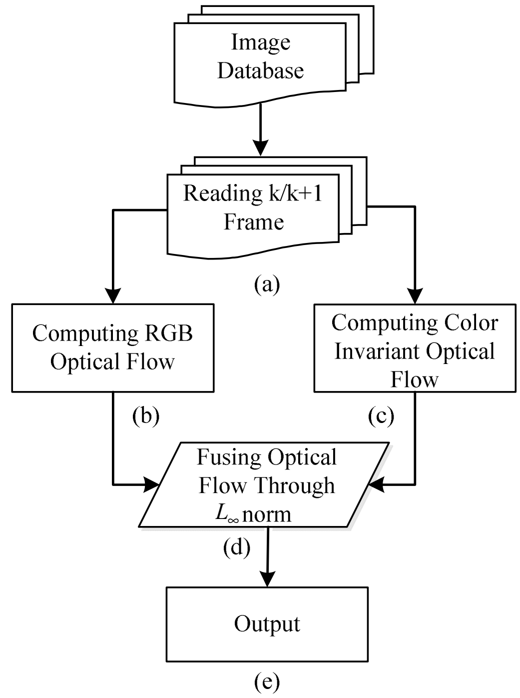

Figure 2. Color image optical flow estimation fused with color invariants. (a) Read two adjacent image frames from image database. (b) Compute RGB optical flow. (c) Compute color invariant optical flow. (d) Fuse optical flow. (e) Final result.

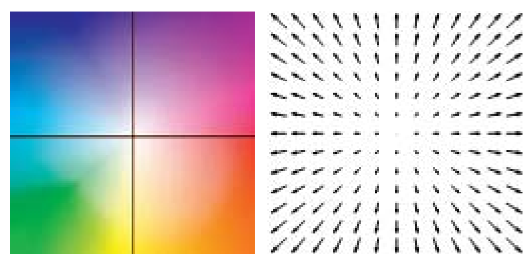

Figure 3. The visualization of flow fields

B. *Results comparison*

The result of Table sequences is shown in Fig. 4, there is visual angle change in the sequences (approximately clockwise running in horizontal direction, namely the upper part of the image goes right, and the lower part of the image goes left). As we can see, the result of RGB optical flow is much smoother and more uniform, while shadows make the interface of the boxes and the table highly blurry; SIFT Flow uses SIFT feature points instead of RGB value or gradients to estimate optical flow, the result also combine the table and the boxes as a whole, and there are many patches. The optical flow acquired only from Cw can distinguish the boxes and the table very well, and the interface is much clearer. But the deviation can be seen from the upper part color of the boxes. Nevertheless, the result acquired by fusing color invariant optical flow and RGB optical flow can overcome the shortage of both, and contains much more accurate information, shows better performance especially in shaded area. This experiment indicates the necessity of optical flow fusing.

The result of Mequon sequences is shown in Fig. 5, the motion information of behind the people in RGB optical flow is mixed up; the result of SIFT Flow is not smooth enough though it doesn't mix up the head with the background. Optical flow fused with color invariants removes patches behind the head, distinguishes foreground and background well.

The result of Stelae sequences is shown in Fig. 6, RGB optical flow has shadows; SIFT Flow mixes up some motion information; Our method distinguishes every object very well, especially it eliminates shadows effectively.

V. CONCLUSION

In this paper we propose a new color image optical flow estimation algorithm, which firstly computes optical flow in the color invariant space, and then fuses with RGB optical flow. We confirm its suppression of shadows by series experiments, and make multi-channel image optical flow much more succinct by introducing the IRLS method. Compared with other two algorithms, ours can overcome the illumination effect and improve the accuracy of optical flow. In addition, future work will also aim at combining other image features with color invariants in order to segment moving targets more completely.

ACKNOWLEDGEMENTS

The authors would like to thank the editors for their time and effort. This work is supported by NSF of China (No. 61175029) and Natural Science Foundation of Shaanxi Province of China (No. 2011JM8015).

REFERENCES

[1] B. Horn and B. Schunck. Determining optical flow[J]. Artificial Intelligence. 1981,17(1):185-203

[2] Liu T. The study and application of video vehicles detection and tracking based on optical flow field [D]. Wuhan University of Science and Technology, 2011.

[3] Yan N, A Dick, M Brooks. Locally oriented optical flow computation[J]. IEEE Transactions on Image Processing, 2012,21(4):1573-1586

[4] Hou Z Q, Han C Z. A background reconstruction algorithm based on pixel intensity classification[J]. Journal of Software, 2005,16(9):1568-1576

[5] B. Lucas and T. Kanade, An iterative image registration technique with an application to stereo vision[J]. in Proc. IJCAI,1981:674-679

[6] T. Brox, A. Bruhn, N. Papenberg, et al. High accuracy optical flow estimation based on a theory for warping[J]. in Proc. ECCV, 2004:25-36

[7] Ce Liu. Beyond pixels: exploring new representations and applications for motion analysis[D]. Massachusetts Institute of Technology, 2009

[8] Xiang X Z, Zhao C H. An estimation arithmetic for improving optical flow estimation of color imagery based on HSV[J].Journal of Projectiles, Rockets, Missiles and Guidance, 2008, 28(2):197-201

[9] N. Ohta. Optical flow detection by color images[C]. Proceedings of IEEE International Conference on Image Processing , 1989:801-805

[10] P Golland, A M Bruckstein. Motion from color[J]. Computer Vision and Image Understanding, 1997, 68(3):346-362

[11] Y Mileva, A Bruhn, J Weickert. Illumination-robust variational optical flow with photometric invariants[C]. Proceedings of the 29th DAGM conference on Pattern recognition, 2007, 152-162

[12] H Zimmer, A Bruhn, J Weickert. Optic flow in harmony[J]. International Journal of Computer Vision, 2011, 93:368-388

[13] Xu L, Chen J N, Jia J Y. A segmentation based variational model for accurate optical flow estimation[J]. ECCV, 2008,5302(1):671-684

[14] R. Chaudhry, A. Ravichandran, G. Hager, et al. Histograms of oriented optical flow and Binet-Cauchy kernels on nonlinear dynamical systems for the recognition of human actions[J]. IEEE Computer Society Conference on Computer Visio-n and Pattern Recognition Workshops, 2009:1932-1939

[15] Naito T, Ito T, Kaneda Y. The obstacle detection method using optical flow estimation at the edge image[C]. Proceedings 2007 IEEE Intelligent Vehicles Symposium. 2007:817-822

[16] C Liu, J Yuen, A Torralba. SIFT Flow: dense Correspondence across scenes and its applications[J]. IEEE Transactions on Pattern Analysis and Machine Intelligence, 2011, 33(5):978:994

[17] M. Tao, J. Bai, P. Kohli, et al. SimpleFlow: A non-iterative, sublinear optical flow algorithm[J]. EUROGRAPHICS, 2012,31:345-353

[18] J. M. Geusebroek, R. van den Boomgaard, A. W. M. Smeulders, et al. Color invariance[J]. IEEE Transactions on Pattern Analysis and Machine Intelligence. 2001, 23(12):1338–1350.

[19] Alaa E. Abdel-Hakim, Aly A. Farag. CSIFT: A SIFT descriptor with color invariant characteristics[C]. IEEE Computer Society Conference on Computer Vision and Pattern Recognition, 2006, 2:1978-1983

[20] Zhou P, Luo X L. A robust feature matching algorithm based on CSIFT descriptors[C]. IEEE International Conference on Signal Processing, Communications and Computing (ICSPCC), 2011

[21] T Brox, J Malik. Large displacement optical flow: descriptor matching in variational motion estimation[J]. IEEE Transactions On Pattern Analysis and Machine Intelligence, 2011, 33(3):500-513

[22] P. Meer. Robust techniques for computer vision[C]. Emerging Topics in Computer Vision, 2004, 107-190

[23] Baker et al. 2009, http://vision.middlebury.edu/flow/eval/

[24] Optical Flow Matlab/C++ Code (2011-08-01). http://pe ople.csail.mit. edu/celiu/OpticalFlow/

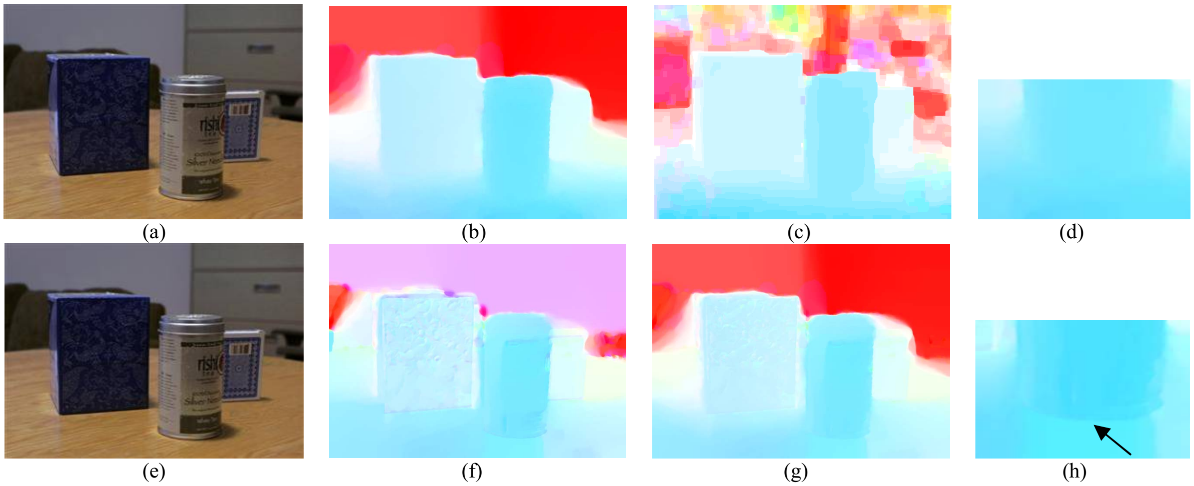

Figure 4. Table sequences optical flow. (a) and (e) Two input frames. (b) RGB optical flow. (c) SIFT Flow. (d) Close-up of (b). (f) Cw optical flow. (g) fused optical flow with (b) and (f). (h) Close-up of (g).

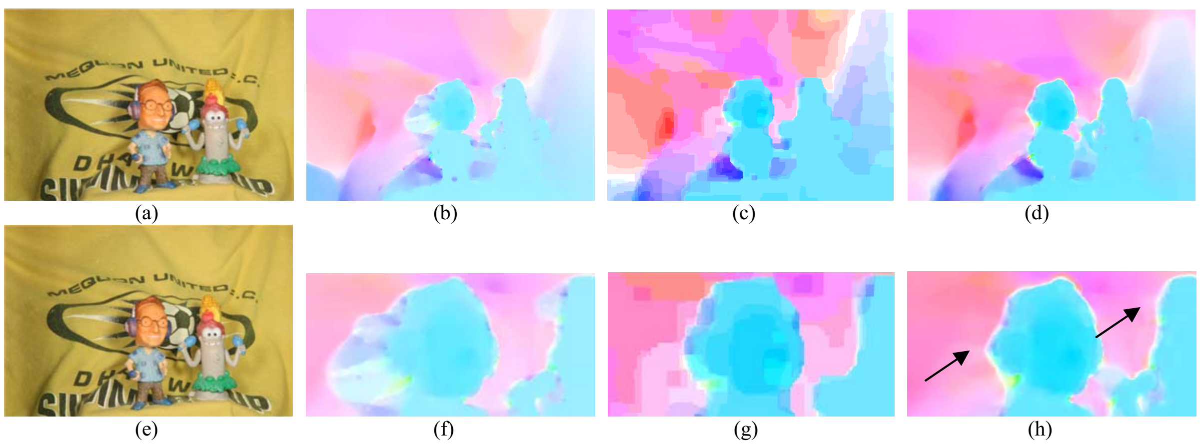

Figure 5. Mequon sequences optical flow. (a) and (e) Two input frames. (b) RGB optical flow. (c) SIFT Flow. (d) Proposed method. (f)-(h) Close-ups of (b)-(d).

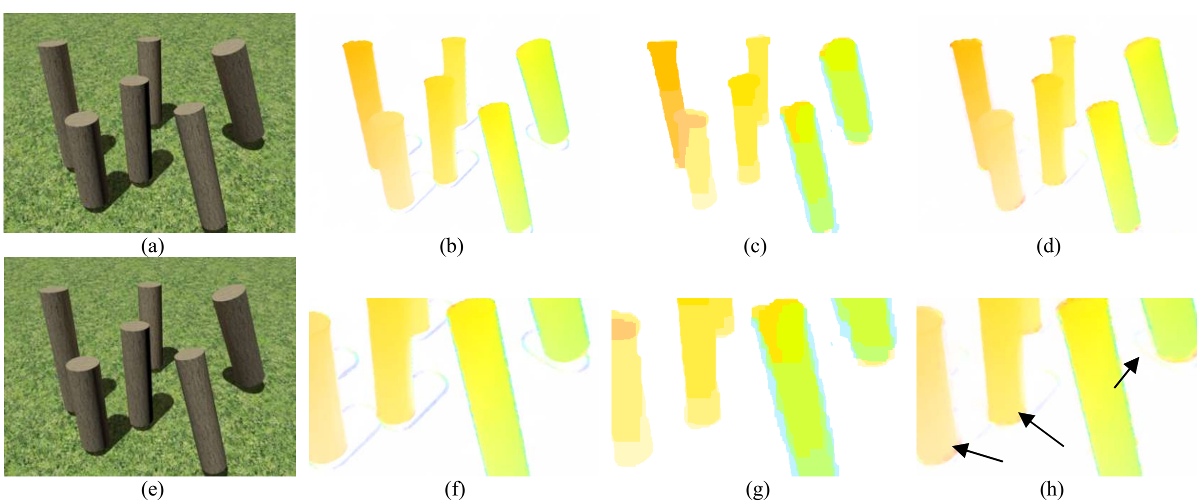

Figure 6. Stelae sequences optical flow. (a) and (e) Two input frames. (b) RGB optical flow. (c) SIFT Flow. (d) Proposed method. (f)-(h) Close-ups of (b)-(d)