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Error Sources and Error Reduction in Gradient-Based Method with Local Optimization

Atsushi Osa * Lin Zhang Hidetoshi Miike

Faculty of Engineering
Yamaguchi University

Abstract

The purpose of this study is to establish the technique for estimating optical flow with high accuracy and robustness using gradient-based method with local optimization. To obtain high accuracy, we should understand error sources and how to reduce the errors. We proposed error reduction techniques for gradient measurement error which are a spatio-temporal median filter to reduce sensor noise and a spatio-temporal derivative filter to estimate gradients of image function. The result shows that the spatio-temporal median filter can reduce the sensor noises very well, both of white noise and thermal noise of CCD camera. Furthermore, the best performance is achieved by the successive filtering of the Gussian filter and the spatio-temporal median filter. We also confirmed that estimation of partial derivatives of image function using the spatio-temporal derivative filter improved the accuracy of optical flow. The proposed methods are hopeful for the detection of optical flow with high accuracy and good robustness from image sequence.

1 Introduction

Recently, sequential image processing have been attracted an increasing attention from the viewpoints of computer vision and physical measurement. Determining optical flow is one of the most important problems of image sequence processing. In the early study, however, only the calculation cost was picked up especially to realize a real time processing of instantaneous optical flow for robotic vision. Under the development of computer technology, several authors have discussed the accuracy of estimated optical flow[1]. For measuring physical parameters, the accuracy of estimated values becomes more important than the calculation cost. In our recently study, we developed an evaluation technique of body motion using gradient-based method with spatio-temporal local optimization[2], which aimed at medical treatment at home[3]. A person on bed is captured by video camera under low intensity illumination, and the heart rate and the breath can be countered without any physical constraints. For more quantitative evaluation of body motion, the optical flow analysis is required to have robustness and high accuracy.

The purpose of this study is to explore any error sources and to reduce the error in gradient-based method with local optimization. Kearney et.al.[4] classified the sources of error in local estimates of optical flow into three types, 1.gradient measurement error, 2.non-constant flow, 3.ill-conditioning . In this study, we pay our attention to gradient measurement error under low intensity illumination. Several approaches to reduce the error are demonstrated, and we propose a new method to improve the accuracy.

2 Gradient-based Method with Local Optimization

The following equation (1) shows the basic relationship between motion parameters and image derivatives.

$$I_x u + I_y v + I_t = 0, \tag{1}$$

where I represents the image intensity, and I_x, I_y, and I_t are partial derivatives with respect to position x, y, and time t. Motion parameters u, v are x and y components for the motion vector. In a small volume δV, if it is assumed that every point has the same velocity, the least square method can evaluate the motion parameters u, v. In this study, a spatio-temporal small volume (spatial size is 3×3 pixels and temporal size is 3 frames) is utilized to determine optical flow field. This can be called spatio-temporal local optimization technique[2].

3 Sources of gradient measurement error and error reduction techniques

Sources of gradient measurement error are made up of 1) sensor noise, 2) quantization noise, 3) nonlinearities in the brightness function in the direction of optical flow, and 4) optical flow magnitude[4]. 1)

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*Address: 2557 Tokiwadai, Ube, Yamaguchi 755-8611 Japan. E-mail: `osa@kde.yamaguchi-u.ac.jp`

-1/8	0	1/8
-2/8	0	2/8
-1/8	0	1/8

Figure 1: Sovel's derivative spatial filter (x axis).

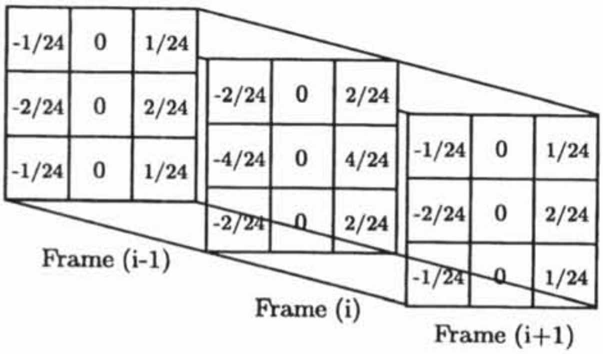


Figure 2: Spatio-temporal derivative spatial filter (x axis). The frame (i) is the target frame.

and 2) are random error, and 3) and 4) are systematic error. Determining optical flow under low intensity illumination, the random error 1) and 2) are very important. Therefore, techniques to reduce the sensor noise and quantization noise are required.

To reduce the sensor noise, three digital image filters are tested. These are the ordinary spatial median filter (spatial size is 3×3 pixels), the Gaussian filter (spatial size is 3×3 pixels) and the spatio-temporal median filter (spatio-temporal size is 3×3 pixels and 3 frames) which we introduced as a new trial. We call the new filter by ST median filter. The ST median filter selects a median intensity from image function having a spatio-temporal local volume (3×3 pixels and 3 frames). The ordinary spatial filters (such as median filter and the Gaussian filter) are known as popular technique to reduce noise on image.

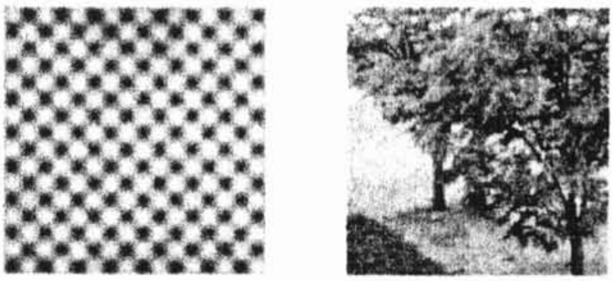
In gradient based method, space and time derivatives are very important factor, because the space and time derivatives affect gradient measurement error. The most popular derivative spatial filter is Sovel's filters (Fig.1). We propose an extended filter of Sovel's filters. It is called spatio-temporal derivative filter which has a spatio-temporal size of 3×3 pixels and 3 frames (Fig.2).

4 Error Measurement

Following Barron et.al.[1] we use an angular measure of error. The angular error Ψ_E between the correct velocity $\mathbf{v_c}$ and an estimate $\mathbf{v_e}$ is defined by

$$\Psi_E = \arccos\left(\mathbf{v_c} \cdot \mathbf{v_e}\right). \tag{2}$$

A large Ψ_E means bad accuracy.



(a) Sinusoidal image (b) Tree image

Figure 3: One frame of synthetic images.

5 Synthetic Image Sequence

Two synthetic original image sequences are prepared. The first sequence represents a clockwise rotation of a simulation image (sinusoidal wave) (see Fig.3(a)). The second one shows a clockwise rotation of a tree image (see Fig.3(b)). Both image size is 64 × 64 pixels. The rotation speed of both sequences is 0.04 radian/frame. The first sequence of rotated sinusoidal image has a character that did not include the third error source, ill-conditioning problem, classified by Kearney et.al.[4]. On the other side, the second sequence includes ill-conditioning problem area.

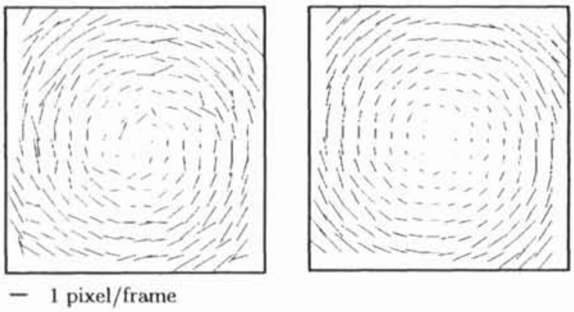
Then, five kinds of noises were added to the sequences. Noise (a) and (b) were the white noise, whose rates were 1% and 5%, respectively. Noise (c), (d), and (e) were extracted noises from a real image sequence that were captured under low intensity illumination (240 lx), (40 lx), and (40 lx) respectively by a CCD camera (KY-F57, Victor) with automatic gain control (AGC) function. Where, Noise (e) was amplified twice as much as Noise (d). We call tentatively these noises by AGC noise. Twelve synthetic image sequences were made in all by the combination of two synthetic original images and five noises (see Table 2, 3).

6 Experimental Results

At first, to compare between ordinary Sovel's derivative filter and spatio-temporal derivative filter, optical flow fields of the synthetic image sequences were estimated without any filter to reduce sensor noise. The mean angular measures of error are shown in table 1. The proposed filter achieves better accuracy of optical flow than ordinary Sovel's

Table 1: Mean angular measures of estimated optical flow error

Image type	Sovel's derivative filter	Proposed derivative filter
Sinusoidal image	2.21 °	2.06 °
Tree image	9.36 °	3.32 °

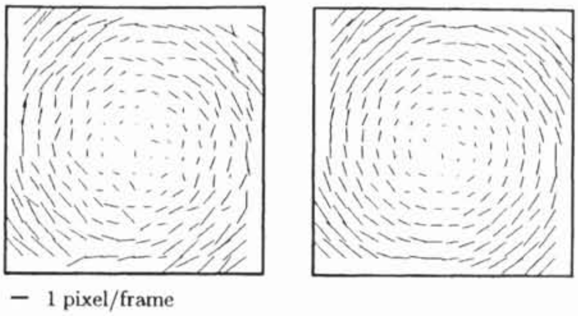


(a) Sovel's derivative filter (b) Proposed derivative filter

Figure 4: Estimated optical flow fields of the tree image introduced by Sovel's derivative filter and the proposed filter.

filter. The performance of the proposed filter is represented more effectively in a synthetic image sequence obtained by a tree image (see Fig.4).

Then, five kinds of image filtering to reduce senser noises were introduced for twelve image sequences, as a preprocessing tool for the estimation of optical flow. Spatio-temporal derivative filter was also introduced to estimate optical flow. Table 2 shows the relationship between averages of error of optical flow estimation for sinusoidal image sequences (image sequence 1~6) and the types of image filters. On the image sequence 1 there is no noise, the Gaussian filter was effective to reduce the error. However, introduction of the ST median filtering before the Gaussian filtering achieved the best accuracy for all noise image sequences. A typical result of the filtering is shown in Fig.5(b). The ordinary spatial median filter can not achieve the same accuracy. We confirmed almost the same results in the evaluation of optical flow from the synthetic image sequence obtained by the tree image (see Table 3). The ST median filter is hopeful for the estimation of optical flow with high accuracy and good robustness.



(a) Without filtering (b) With ST median and Gaussian filtering

Figure 5: Estimated optical flow fields of image sequence 6.

7 Summary

Karney et. al.[4] pointed out the effectiveness of the smoothing technique to reduce error of optical flow using gradient-based method with local optimization. The smoothing technique corresponds to the Gaussian filter in this study. We tested the performance of the ST median filter. The results of this study indicate that the error of estimated optical flow was decreased by the ST median filtering before the Gaussian filter compared to using only the Gaussian filter. Spatio-temporal derivative filter also decreased the error effectively. The combinations of those proposed techniques are very useful to determining optical flow under low intensity illumination. In order to expect higher accuracy and robustness, it is necessary to study the relationship between the other error sources and the error reduction methods.

References

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Table 2: Mean angular measures of estimated optical flow error for sinusoidal image.

Filter type	Image 1 Sin. Image (no noise)	Image 2 Sin .image + Noise (a)	Image 3 Sin. image + Noise (b)	Image 4 Sin. image + Noise (c)	Image 5 Sin. Image + Noise (d)	Image 6 Sin. image + Noise (e)
No filtering	2.06°	6.29°	17.14°	3.14°	4.34°	8.42°
Median filter	2.12°	2.50°	4.09°	3.08°	3.99°	7.00°
ST median filter	2.13°	2.31°	3.07°	2.53°	3.00°	4.41°
Gaussian filter	2.04°	4.98°	12.68°	2.80°	3.63°	6.63°
Median filter and Gaussian filter	2.06°	2.36°	3.72°	2.89°	3.65°	6.31°
ST median filter and Gaussian filter	2.07°	2.20°	2.78°	2.40°	2.76°	3.92°

* Underline means the best accuracy in the image sequences.

Table 3: Mean angular measures of estimated optical flow error for tree image.

Filter type	Image 7 Tree Image (no noise)	Image 8 Tree image + Noise (a)	Image 9 Tree image + Noise (b)	Image 10 Tree image + Noise (c)	Image 11 Tree Image + Noise (d)	Image 12 Tree image + Noise (e)
No filtering	3.32°	11.73°	28.50°	5.06°	7.01°	13.36°
Median filter	5.12°	5.78°	8.14°	7.45°	9.35°	15.63°
ST median filter	4.40°	4.79°	6.19°	5.89°	6.81°	11.16°
Gaussian filter	2.92°	11.94°	27.61°	4.80°	6.80°	12.84°
Median filter and Gaussian filter	4.74°	5.33°	7.83°	7.29°	9.08°	15.87°
ST median filter and Gaussian filter	4.15°	4.48°	5.92°	5.47°	6.32°	10.67°

* Underline means the best accuracy in the image sequences.