コンピュータビジョンと
イメージメディア 106－14
（1997. 7. 25）

Determining Optical Flow under Non-uniform Illumination

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Abstract. In actual scene analysis, the influence of non-ideal conditions such as non-uniform illumination should be taken into account. The conventional methods for the estimation of optical flow are violated in this situation. In this study, two approaches are carried out to extract reliable optical flow under non-uniform illumination. These are an extended constraint equation and a pixel-based temporal filtering. A raw image sequence is first convolved with the temporal filter, then an extended constraint equation as well as additional constraints can be applied to the filtered image sequence. Experiments have been made to confirm the reliability of the proposed method.

Keywords: Optical flow, Non-uniform illumination, Spatio-temporal local optimization, Temporal filtering

1. Introduction

In the Computer Vision[1] fields, many studies have been carried out with the aim of obtaining information on the three dimensional (3D) environment from image sequence. One of the most important problems is to determine optical flow which is the distribution of apparent velocities of moving brightness patterns in an image sequence([2, 3]). Optical flow results from relative motion between a camera and objects in the scene.

A number of different approaches to determine optical flow have been proposed including gradient-based, correlation-based, energy-based, and phase-based methods. A recent survey is due to Barron[5] et al. (1994) where the different approaches were compared on a series of synthetic and real images. In the actual scene analysis, however, the performance of conventional methods is not satisfactory. There exists the influence of non-ideal conditions in the actual scene. For example:

Non-uniform illumination[8],
Occlusions[9],
Multiple optical flow[10, 11],
Non-rigid motion of object[12], and
Diffusion of motion[13].

If we want to obtain a reliable optical flow, we should take into account such problems. Recently, our research group have proposed two methods for determining motion fields from sequential images under spatially or temporally non-uniform illumination[8, 14]. The methods are based on the extended conservation equation which is obtained by observing the total brightness change in a fixed local closed area. One of the methods assumes spatially non-uniform illumination and a stationary motion field. The other one assumes temporally non-uniform illumination and local constancy of motion vectors. With this method, we can determine 2D motion fields of fluid flow under spatially or temporally non-uniform illumination [8].

On the other hand, in the ordinary approach, noise reduction and contrast enhancement of images are based on two-dimensional (2-D) space filtering [4]. For these purposes, we can introduce frequently digital filtering with 2-D fast Fourier transform (FFT) and non-linear filters such as median filter. These space domain approaches are effective for static image processing, however, it is difficult to remove the influence of non-uniform illumination in a dynamic image sequence.

In this paper, we develop a new algorithm to fuse two conditions of non-uniform illumination. We introduce the extend constraint equation with spatio-temporal local optimization. And we propose a new method of temporal filtering which enables to reduce the influence of non-uniform illumination. The effectiveness of the proposed method is confirmed by use of simulation image sequence.

2. Background of extended constraint equation

An extended constraint equation is derived from a conservation law[16] of total brightness in a fixed small region δS as illustrated in Fig.1.

$$\frac{\partial}{\partial t}\int_{\delta S} f dS = -\oint_{\delta C} f\vec{v}\cdot\vec{n}dC + \int_{\delta S}\phi dS \ , \quad (1)$$

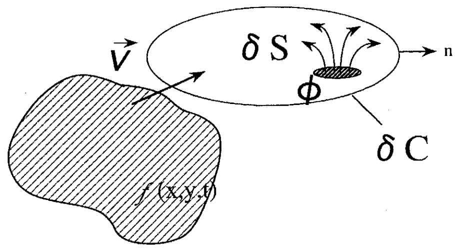

Fig.1: A schematic explanation of variables appeared in the conservation equation.

where $f(x,y,t)$ is a spatio-temporal brightness distribution of a sequential image, δS is a fixed local observation area, δC is the contour surrounding of δS, $\vec{v}=(v_x,v_y)$ is the velocity of optical flow to be determined, $\vec{n}$ is the unit vector normal to δC which pointing outwards, and ϕ is the rate of creation (or annihilation) of brightness at a pixel in δS. The creation term includes increasing or decreasing brightness on the image plane under influence of non-uniform illumination. Equation(1) is reduced to a differential formula[14]:

$$\frac{\partial f}{\partial t} = -fdiv(\vec{v}) - \vec{v}\cdot grad(f) + \phi \ . \quad (2)$$

Under the assumption $div(\vec{v}) = 0$ [16] and $\phi = 0$ [17], Eq.(2) coincides with the basic constraint equation of the gradient-based method[7].

In this study, we adopt the following relationship for the determination of *image flow*[18]:

$$\frac{\partial f}{\partial t} = -\vec{v}\cdot grad(f) + \phi \ . \quad (3)$$

This relationship is reduced from Eq.(2) under the assumption of $div(\vec{v}) = 0$. This assumption requires a rigid object motion perpendicular to camera optical-axis. Since this conservation equation contains the creation term of brightness, it is possible to remove the effects of non-uniform illumination for the detection of image flow.

Nomura [8] et al. (1995) introduced an assumption of separability of non-uniform illumination. For the first situation, the illumination is assumed only spatially non-uniform and constant with respect to time($r = r(x,y)$). The reduced relationship is

$$\frac{\partial f}{\partial t} + \vec{v} \cdot grad(f) = fq\sqrt{v_x^2 + v_y^2} \ , \qquad (4)$$

where $q(x,y)$ is an unknown constant. If the velocity field is constant with respect to time, image flow $\vec{v}$ and the unknown constant $q(x,y)$ are determined by minimizing the following error function (with temporal local optimization[14]) with the non-liner least squares method (for example the *Newton-Raphson method*):

$$E = \sum_{t=t_0}^{t_0+n} (f_t + v_x f_x + v_y f_y - fq\sqrt{v_x^2 + v_y^2})^2 . \ (5)$$

As the second situation, we assume the case of temporally non-uniform illumination and local constancy of motion vectors ($r = r(t)$, $grad(r) = 0$). The reduced relationship is

$$\frac{\partial f}{\partial t} + \vec{v} \cdot grad(f) = f \cdot \frac{\partial r(t) / \partial t}{r(t)} = fw(t) \ , \qquad (6)$$

where $w(t)$ is as an unknown constant. If the velocity field is constant with respect to space, image flow $\vec{v}$ and the unknown constant $w(t)$ are determined by minimizing the following error function with the liner least squares method (with spatial local optimization[15]):

$$E = \sum_{x=x_0-l}^{x_0+l} \sum_{y=y_0-m}^{y_0+m} (f_t + v_x f_x + v_y f_y - fw)^2 . \quad (7)$$

Here, the parameters l and m represent the width of the local neighborhood δS in x and y direction.

3. Proposed method

The extended constraint equation for gradient-based method contains the creation term of brightness. Nomura[8] et al. (1995) separated the term into two different conditions of illumination (spatially non-uniform illumination or temporally changing illumination) and determined this term under respective conditions.

In actual scene, however, there is the case coexisting two conditions of non-uniform illumination. In this section, we propose new model which fuses two conditions of non-uniform illumination. We introduce the extended constraint equation with spatio-temporal local optimization[19].

3.1 A spatio-temporal local optimization

The parameter $\phi(x,y,t)$ of Eq.(3) represents the non-uniform illumination. Under the assumption that the illumination is only spatially non-uniform, $\phi_1 = f\sqrt{v_x^2 + v_y^2}q(x,y)$. On the other hand, $\phi_2 = fw(t)$ when we can assume that the illumination is only temporally non-uniform. Here, $q(x,y)$ represents spatially non-uniform illumination and $w(t)$ represents non-stationary illumination. Now we assume the case that $\phi(x,y,t)$ is represented by the following equation:

$$\phi(x,y,t) = \phi_1(x,y,t) + \phi_2(x,y,t) = f(\sqrt{v_x^2 + v_y^2}q(x,y) + w(t)) . \quad (8)$$

When the unknown variables v_x, v_y are assumed to be constant in a local spatial-temporal neighborhood $\delta V = \delta x \cdot \delta y \cdot \delta t$, Eq.(8) can be reduced:

$$\phi = f(x,y,t)(cq(x,y) + w(t)) ,$$

where $c = \sqrt{v_x^2 + v_y^2} = const$. We also assume that the image function $f(x,y,t)$ varies rapidly with respect to time and space compared to the effect of non-uniform illumination $q(x,y)$ or $w(t)$. Thus, we obtain a simplified relationship:

$$\frac{\partial f}{\partial t} = -\vec{v} \cdot grad(f) + fw', \qquad (9)$$

where $w' = cq(x,y) + w(t)$ is a constant in the local volume δV. Since this equation contains both effects of spatially non-uniform illumination and non-stationary illumination, it seems possible to manipulate the effects of every conditions of non-uniform illumination under above assumptions.

The above assumption seems to be valid in a small spatio-temporal neighborhood $\delta V = \delta x \cdot \delta y \cdot \delta t$. For the determination of three unknown variables in Eq.(9), $\vec{v} = (v_x, v_y)$ and w', we propose the assumption that the components of image flow and unknown variables are constant with respect to time and space in a local volume of $\delta V = \delta x \cdot \delta y \cdot \delta t$:

$$\begin{cases} w' = const \\ v_x = const \\ v_y = const \end{cases} \quad \text{in } \delta V. \qquad (10)$$

Image flow $\vec{v}$ and the unknown constant w' can be determined by minimizing the following error function.

$$E = \sum_{\delta x}\sum_{\delta y}\sum_{\delta t}(f_t + v_x f_x + v_y f_y - fw')^2. \qquad (11)$$

We call this approach "the spatio-temporal local optimization" (**STO**) tentatively. Since this method can manipulate many equations effectively compared with SLO and TLO, it is expected to determine more accurate image flow. It is also possible to introduce smoothness constraints or regularization approach to solve Eq.(9).

3.2 The pixel-based temporal filtering

In this paper, we also introduced a new approach based on a pixel-based image sequence processing [20]. With a temporal trace of brightness intensity at each pixel site, a band-pass or a low-pass filtering is carried out in a local time window. By shifting the time window step by step, we can create filtered image sequences. From raw image sequence, a sequential image is created to enhance the brightness of moving object and expected to reduce the influence of non-uniform illumination.

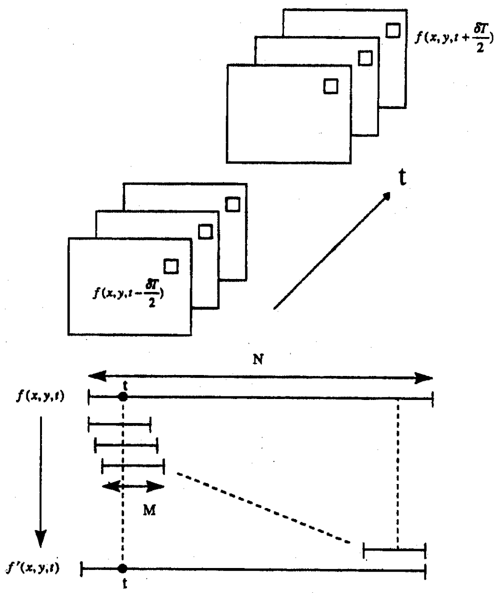

Fig.2: A schematic explanation of a pixel-based temporal filtering. The reduced instantaneous spectrum $F(x,y,t;\omega_K)$ can be represent by

$$F(x,y,t;\omega_K) = \sum_{t-\delta T/2}^{t+\delta T/2} f(x,y,t)\exp(-i\omega_K t),$$

where $\omega_K = 2\pi k / \delta T$. After a digital filtering of the spectrum, inverse transformation is carried out at each pixel site to create filtered images:

$$f'(x,y,t) = \sum F_{ac}(x,y,t;\omega_K)\exp(i\omega_K t),$$

where $F_{ac}(x,y,t;\omega_K) = F(x,y,t;\omega_K \neq 0)$.

For sequential image, temporal change of the brightness at each pixel is regarded as a time series. The method is based on digital Fourier transform and digital filtering under the assumption of local constancy of statistical characteristics of the time series. We evaluate temporal development of the spectrum within a finite time at each pixel by fast Fourier transform. After a digital filtering of the spectrum, inverse transformation is carried out at each pixel site to create filtered image sequences (see Fig. 2).

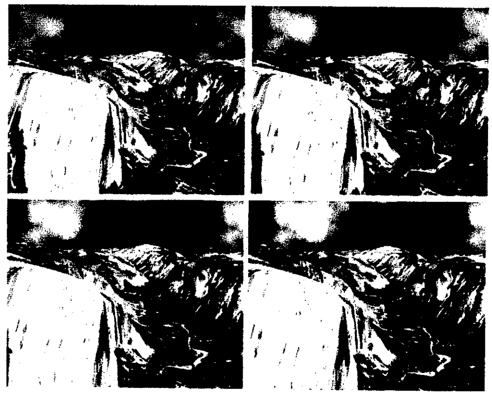

Fig.3: A simulation image sequence (Yosemite sequence).

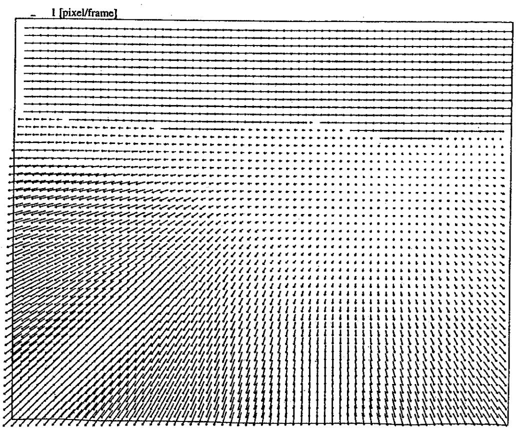

Fig.4: Theoretical motion fields of Yosemite sequence

4. Simulation

In this section, we try to apply the proposed method to determine motion vector fields under non-uniform illumination (containing non-stationary illumination with respect to time and non-uniform illumination with respect to space). We compare the proposed method with the conventional methods and discuss the usefulness of the proposed method.

4.1 Simulation image analysis

Fig.3 shows a snap shot of simulation image sequence (*Yosemite sequence*[1]). The image sequence has a resolution of 316×252 pixels. The brightness is quantified into 256 steps. The Yosemite sequence is a complex test case. In the scene, the cloud has a translational motion with a speed of 2 pixels/frame, while speed in the lower left is about 4-5 pixels/frame. However, the brightness of cloud changes with respect to time and space. The landscape (mountains, river, etc. ...) moves against depth direction. Then, motion fields expands. This sequence is challenging because of the range of velocities and occluding edges between the mountains and at the horizon, divergence, non-uniform illumination. Fig.4 represents the theoretical motion fields of Fig.3.

4.2 Comparison of conventional method with the proposed method

We try to determine motion field of this image sequence by use of the following methods.

First, we use the conventional gradient-based method [7].

Spatio-Temporal Local Optimization (STO):

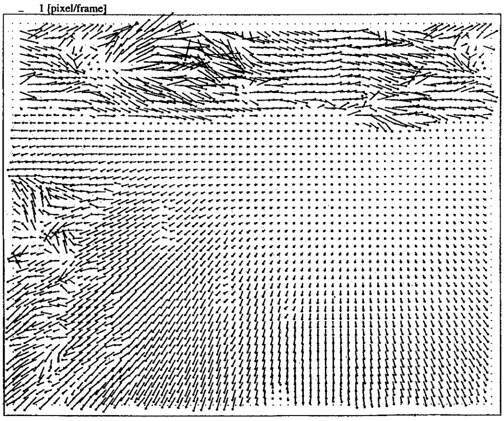

Fig.5: Motion fields determined by STO
(conventional gradient-based method).

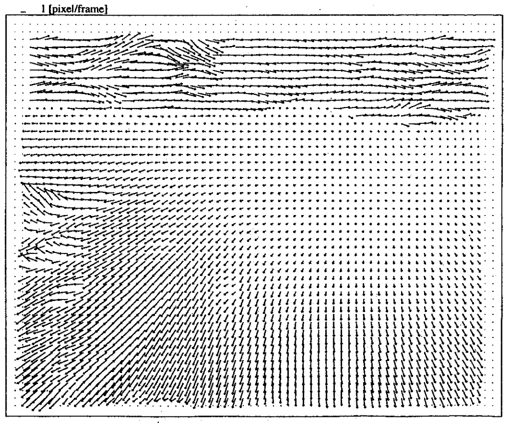

Fig.6: Motion fields determined by
the proposed method.

We assume that optical flow is constant with respect to time and space in a local volume of 5×5 pixels and 8 frames. The result of obtained motion fields is shown in Fig.5.

Second, we use the proposed method in Eq.(9). We assume that the image flow $\vec{v}$ and ϕ are constant in a local volume of 5×5 pixels and 8 frames. The result of obtained motion fields is shown in Fig.6.

The motion fields obtained by the conventional gradient-based methods (with STO) have serious errors at the place of foreground mountain surface and cloud position where the brightness changes temporally and spatially. When we apply the extended constraint equation under the assumption of Eq.(9), motion fields at these places are apparently improved. However, reduction of the error at foreground mountain surface is not satisfactory. Because that the texture of foreground mountain surface has only pinstriped, it is easy to encounter the aperture problem. When we try to determine image flow by the gradient method, we have to consider the aperture problem. If the pinstriped texture area is larger than observation area, it is hard to obtain the correct image flow. With the local frame of the aperture, we cannot determine the moving direction and velocity of the pinstripe. In general, it is not possible to compute true velocity and direction by the observation within a small neighborhood (a local area). In order to overcome the shortage, it seems to be considerable to introduce a spatial filtering(e.g. Gaussian filter) based on the image sequence(see Fig.8), we also can introduce the global optimization techniques [7] and hierarchical approaches [6]. It is possible to introduce such a global approach in the proposed method.

4.3 Comparison of conventional method with raw images and with filtered images

In Fig.8 we demonstrate a different approach to remove the influence of non-uniform illumination in motion analysis. The original image sequence is also *Yosemite sequence* shown in Fig.3. Example of filtered image sequence obtained by temporal filtering described in section 3.2 is shown in Fig.7(a). We applied the

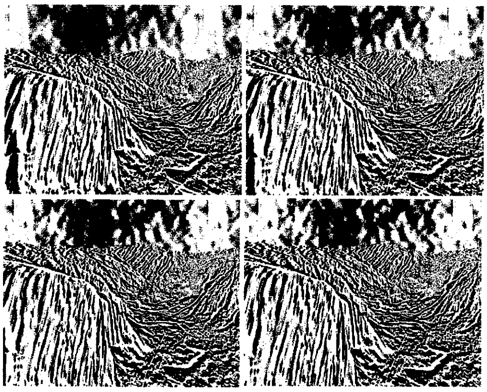

Fig.7(a): A filtered image sequence: DC-cut (Yosemite sequence).

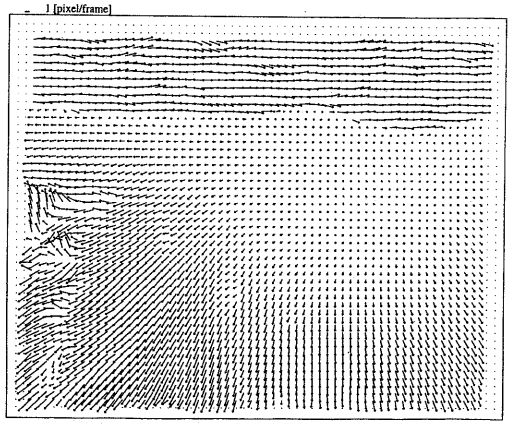

Fig.7(b): Motion fields determined by STO: applied to filtered images(conventional gradient-based method).

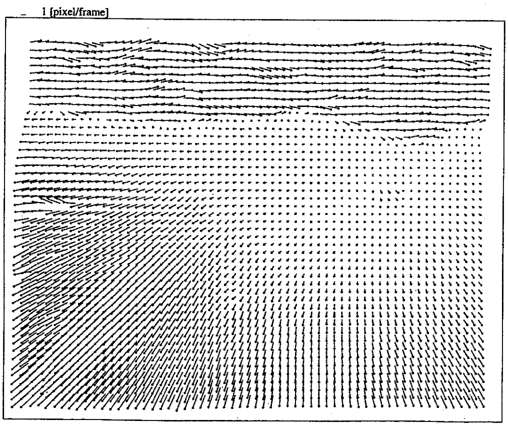

Fig.8: Motion fields determined by STO: applied to temporal filtered and Gaussian spatial filtered images (conventional gradient-based method).

conventional gradient-based method with STO to obtain optical flow fields from the filtered (Fig.7(a)) image sequence. Fig.7(b) shows the analyzed optical flow. By the comparison between the analyzed flows (Fig.5 and Fig.7(b)), the error of optical flow estimation at the cloud place (non-uniform illumination) is reduced in Fig7(b).

5. Conclusions

In this paper, we proposed a method to determine optical flow from an image sequence under non-uniform illumination. The proposed method is based on the extended constraint equation from the conservation law of total brightness in a fixed observation area. Then, it is possible to manipulate the effects of non-uniform illumination. Since we adopted the spatio-temporal local optimization, we obtained high resolution and high reliability of the determined image flow compared to the conventional extended gradient method. The usefulness of the proposed method was confirmed by the analysis of an synthetic image sequence.

In this paper, we also propose a different approach to remove the influence of non-uniform illumination. The algorithm is based on a local temporal filtering. From an original image sequence, a dynamic scenes is created which is defined in a local time domain δT at around t. By the experiment, the reduction of the effect of non-uniform illumination is also confirmed.

However, the obtained motion fields was still not satisfactory. As the cause of this fact, we have to consider the following unsolved problems in future:

· Divergence of the velocity field at the motion boundary and the motion toward depth direction, and

· The aperture problem at the straight contour of object texture or the motion boundaries.

Divergence of the velocity is explicitly given as the term of $div(\vec{v})$ in Eq.(2), however, we always assume $div(\vec{v}) = 0$ in the proposed method. In the future stage, the estimation of this term can be a key step to establish a reliable method to determine more realistic optical flow from a real image sequence.

Notes

1. The image sequence of *Yosemite sequence* is obtained from the ftp-site of ftp.csd.uwo.ca.

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