Feature-Based Optical Flow Computation

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Abstract

Visual servo can be achieved by extracting motion information from the optical flow, defined as the apparent motion of brightness patterns of an image. Control performance using this technique fully depends on accurate estimation of the flow velocities. It appears that most correct values of the optical flow usually locate at the regions with image features. In this paper, feature-based optical flow computation methods are presented. The approaches of scatter of brightness, edge acquisition, and feature orientation are developed. Simulation studies on six test images were conducted to demonstrate accuracy improvement of the estimated optical flow.
Keyword: Image features, Machine vision, Optical flow, Visual flow.

I. Introduction

Typical visual servo controls can be classified into two categories, the position-based visual servo and the feature-based visual control [1]. The position-based methods determine relative movement between an image sensing device and its environment by extracting motion information from the image. However, the feature-based approaches solve the motion of a viewed object based on variation of the object's features on the image plane. The major difference between these two types of visual servo is that the feature-based approaches need to have good knowledge of features of the viewed object in advance. Since the position-based methods only manage pixels information of an image in spite of their physical indications, this category is suitable for general control purposes and unknown images.

Optical flow, caused by relative motion of objects and the viewer, is the distribution of apparent velocities regarding movement of brightness patterns in an image. The optical flow obviously stores useful information of the relative motion. If the movement is extracted, appropriate actions for relative positioning can thus be generated for control purposes. Besides, this approach does not need to define features of the viewed object at the beginning. Hence the optical flow has been playing an important role in the field of the position-based visual servo.

The computation of the optical flow stems from the concept of brightness constancy [2], which reasonably assumes that brightness of a particular point in an image pattern is constant for steady lighting condition. But the flow velocity owns two components, which cannot be solved by just one equation. Therefore, a global smoothness assumption, the apparent velocity of the brightness pattern varying smoothly, was also raised at the same time to establish another constraint equation.

However, in order to prevent the computation process of determining the optical flow from recursive calculations, the idea of the same optical flow in local regions was introduced [3][4]. The weighted least-squares method is usually applied to obtain the solution of the flow velocities. This strategy is based on image brightness derivatives with respect to both time and space and belongs to the gradient-based approach. Another strategy, the correlation-based approach, relies on corresponding relationships between image regions at different moments to obtain the optical flow, instead of solving the brightness constancy constraint [5][6]. Furthermore, a nice work [7] was conducted on performance comparison using different optical flow estimation techniques. Their results can be used as a preliminary criterion for choosing an appropriate algorithm to solve the optical flow.

Tracking controls of robots and underwater vehicles have been popular topics for employing the visual servo technique [8][9][10]. Nevertheless, satisfactory control performance can only be expected under the circumstance of accurate estimation of the optical flow. Unfortunately, consistently accurate estimation of the optical flow for a variety of images still cannot be easily achieved. To improve estimation performance of optical flow, parametric models of optical flow from image sequences was therefore presented [11]. In this paper, it will be shown that most correct values of the optical flow occur at the boundary of features of the image. As a result, the estimation accuracy of the optical flow will be enhanced, if the feature acquisition can be incorporated into the computation algorithm of the optical flow.

II. The Optical Flow

An object in an image consists of brightness patterns. As the object or the camera moves, the brightness patterns in the image move simultaneously. If the motion is relatively small and illumination of the scene maintains uniform in space and steady over time, it can be assumed that the brightness of a particular point remains relatively constant during the motion. In other words, the classical brightness constancy constraint equation can be established as

$$E(x+\Delta x, y+\Delta y, t+\Delta t) = E(x, y, t) \tag{1}$$

where $E(x, y, t)$ represents the brightness of a point (x, y) on the image plane at time *t*. Expanding the left-hand side and ignoring high-order terms, the above equation reduces to

$$E_t + E_x u + E_y v = 0 \tag{2}$$

where u and v are components of the optical flow along the x and y axes, respectively.

Since the classical smoothness constraint needs recursive computations for the optical flow, an alternate approach will be applied. Assume an identical optical flow exists for every pixel in an image. A cost function of the sum of squares of the brightness variation can be formulated. Hence the optimal solution of the optical flow (u, v) that causes the cost function to be a minimum can be easily determined by the standard least-squared method.

Nevertheless, the above point-based calculation may result in deviations of the optical flow due to possible noises on real images. Therefore, if the above equation is extended to a patch-based formulation, the estimation error can be significantly reduced by the effect of averaging. Assume pixels in an image patch Ω own a similar optical flow. A patch-based brightness constancy equation is then expressed as

$$\sum_{\Omega}(E_t + E_x u + E_y v) = 0 \tag{3}$$

In the above equation, *u* and *v* represent the values of the optical flow for the whole small image patch Ω. The patch-based approach not only enhances accuracy of the calculated optical flow, but considerably improves computational efficiency.

III. Feature-based Computations

As a matter of fact, it is not easy to obtain correct enough values of the optical flow for control applications according to the whole image information. The regions, where provide poor estimation of the optical flow, should not be considered in the computation.

Let an image with resolution of 736x556 pixels and 256 gray levels shown in Fig. 1 have a translation motion of (2, 1). The optical flow solved by incorporating 3x3 patches with the classical method was estimated to be (-0.065307, 0.123923), which were far away from the true values. Some image patches where offer correct values of the optical flow are specially marked in the same figure. It can be easily shown that those patches usually occur at features of the image, where have distinguishable variations of brightness.

Fig. 1. Marked image patches denoting correct values of the estimated optical flow

(a) before → after translation (2, 1):

206	213	232		232	236	217
206	213	232	⇒	72	90	81
51	57	72	(2, 1)	72	96	92

(a)

37	18	28		23	32	32
38	23	23	⇒	18	27	33
40	30	18	(2, 1)	18	28	33

(b)

Fig. 2. Two example image patches before and after the translation motion of (2, 1)

Consider two image patches employed in Fig. 1. Fig. 2 illustrates the corresponding brightness information before and after the translation motion. The subfigure (a) clearly owns greater brightness variation than that in subfigure (b). The estimated optical flow velocities were calculated as (1.872073, 1.005517) and (0.418524, -1.563328) for the cases of (a) and (b) respectively. Apparently, the flow velocities obtained from the image region with features of significant brightness difference are close to the true values. In other words, the regions with image features make a contribution to correct estimation of the optical flow.

Therefore, if image features can be quickly extracted from the whole image pattern, better accuracy for the optical flow will be achieved. Three feature-based methods for accuracy improvement of the optical flow are proposed and described as follows:

A. *Scatter of Brightness*

A quick way to judge if an image region owns features of significant brightness difference is to utilize statistical property of its brightness pattern. Assume distribution of brightness in an image region can be formulated as a Gaussian normal distribution. The corresponding standard deviation of the normal distribution actually indicates the property of brightness scatter. A limited standard deviation implies low contrast, which may be unlikely to include image features of significant brightness difference. Hence the standard deviation of the brightness of an image region can be used as an index to justify if the region should be considered for calculation of the optical flow. If an image region contains n pixels, the standard deviation of the image pattern is decided by:

$$\sigma^2 = \frac{1}{n}\sum_{i=1}^{n} E_i^2 - \frac{1}{n^2}\left(\sum_{i=1}^{n} E_i\right)^2 \qquad (4)$$

Once the standard deviation of an image region is greater than a pre-specified threshold value, the image brightness is then wide spread enough to contain image features and the region should be qualified to provide more accurate values of the optical flow.

B. *Edge Acquisition*

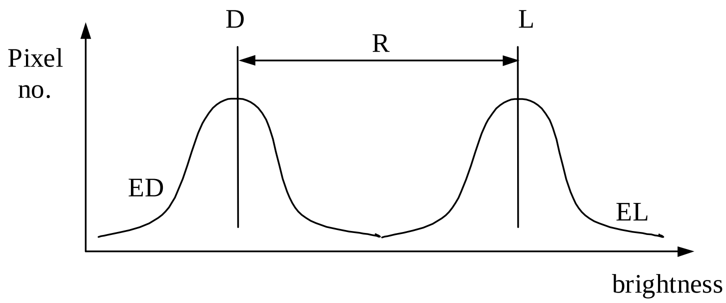

Fig. 3. Brightness distributions of darker pixels and brighter pixels

The approach of edge acquisition fetches possible image edge features by examining if there exists significant difference between groups of darker and lighter pixels. First of all, determine the total mean brightness of the image region. Then, pixels of the region can be divided into two sets, the darker group (ED) and the lighter group (EL) as shown in Fig. 3, based on the total mean value. Whether the image region has boundary of apparent brightness difference can be indicated by the distance R between distributions of those two pixel groups. A simple way is to use the distance R between mean values of those two distributions. If the distance is greater than a pre-determined threshold value, a possible edge of clear brightness contrast is detected. Therefore, the image region should be able to generate correct values of the optical flow. Otherwise, the image region is rejected in the computation algorithm.

C. *Feature Orientation*

Values of the optical flow are greatly affected by orientation of image features. Apparently, if horizontal features such as horizontal edges exist in an image; serious errors of the horizontal component of the computed optical flow will be resulted. Therefore, to obtain correct values of the optical flow, the feature orientations need to be carefully examined. A straightforward strategy is to neglect a component of the optical flow solved from an image region, if the region owns the corresponding feature orientation.

A simple and quick method to judge the horizontal and vertical edge features of an image patch is proposed here. Assume that the absolute value of the difference between the brightness averages for the *i*-th and the *j*-th columns of an image region is denoted by d_{ij} , i.e., $d_{ij} = \left| c_i - c_j \right|$, where c_i and c_j represent the mean brightness of the *i*-th and the *j*-th columns of the image region. Let max, mid, and min respectively represent functions to determine the maximum, medium, and minimum values from their arguments. Then a vertical edge feature can be easily extracted by applying the following rule:

$$\max(d_{ij}) + \mathrm{mid}(d_{ij}) - 2\min(d_{ij}) > T_d \tag{5}$$

where T_d denotes a specified threshold value. For a 3x3 image patch, d_{ij} includes d_{12}, d_{13}, and d_{23}. If the above expression is satisfied, the vertical edge feature of the image patch should be too significant to be considered for calculation of the vertical component of the optical flow. Based on the same idea, a similar process can be established for extraction of the horizontal edge feature of an image region.

IV. Simulation Studies

To investigate the effectiveness of those proposed feature-based optical flow computation methods, computer simulations were performed on six different images shown in Fig. 4. All images were with resolution of 736x556 pixels and 256 gray levels. The first one (#0) is an image synthesized by two sinusoidal intensity functions and should have the most uniform smoothness. The other five images belong to the category of natural images acquired by an image grabber with a video camera. The next image (#1) contains edges of significant intensity changes. The third one (#2) is full of small regions with clear boundaries. The fourth one (#3) includes a number of straight-line edges and an area with brightness saturation. A number of vertical line edges and curve features are involved in the last two images (#4 and #5), respectively.

The classical error expression between the estimated optical flow and the true one is usually denoted by the angle between those two flow vectors. Nevertheless, this presentation excludes possible magnitude deviation. Since the optical flow is obtained by combining velocity components in both *x* and *y* directions, it should be appropriate to judge accuracy of the components of the computed optical flow individually. Advantage of this approach is that the cause bringing about deviation of the estimated optical flow can be effectively identified. The accuracy of the optical flow will be indicated by the following formulation:

$$accuracy = 1 - \left| \frac{estimated\ velocity - true\ velocity}{true\ velocity} \right| \tag{6}$$

It should be noted that negative values of the accuracy imply incorrect velocity orientation, i.e., the estimated flow velocity and the true flow velocity have opposite directions.

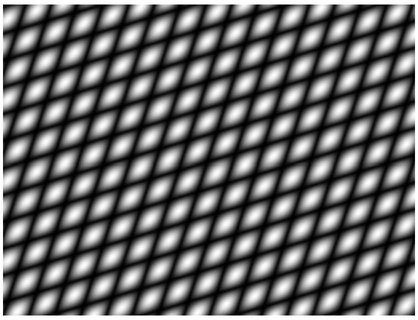

image #0

image #1

image #2

image #3

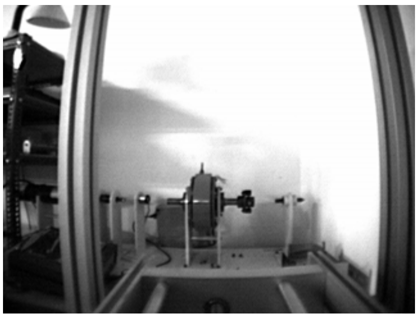

image #4

image#5

Fig. 4. Test images

Simulation studies focus on performance comparison of the estimated velocity components of the optical flow in both *x* and *y* directions using different feature-based computation schemes. The actual optical flow was (2, 1). Fig. 5(a) shows accuracy of the optical flow using the classical computation method. The simply classical method apparently cannot manage effective estimation of the optical flow for all images. Only the synthesized image and the image #2 display satisfactory estimations of the optical flow. Even incorrect flow directions were resulted, e.g., the *x* component for image #1 and the *y* component for image #4.

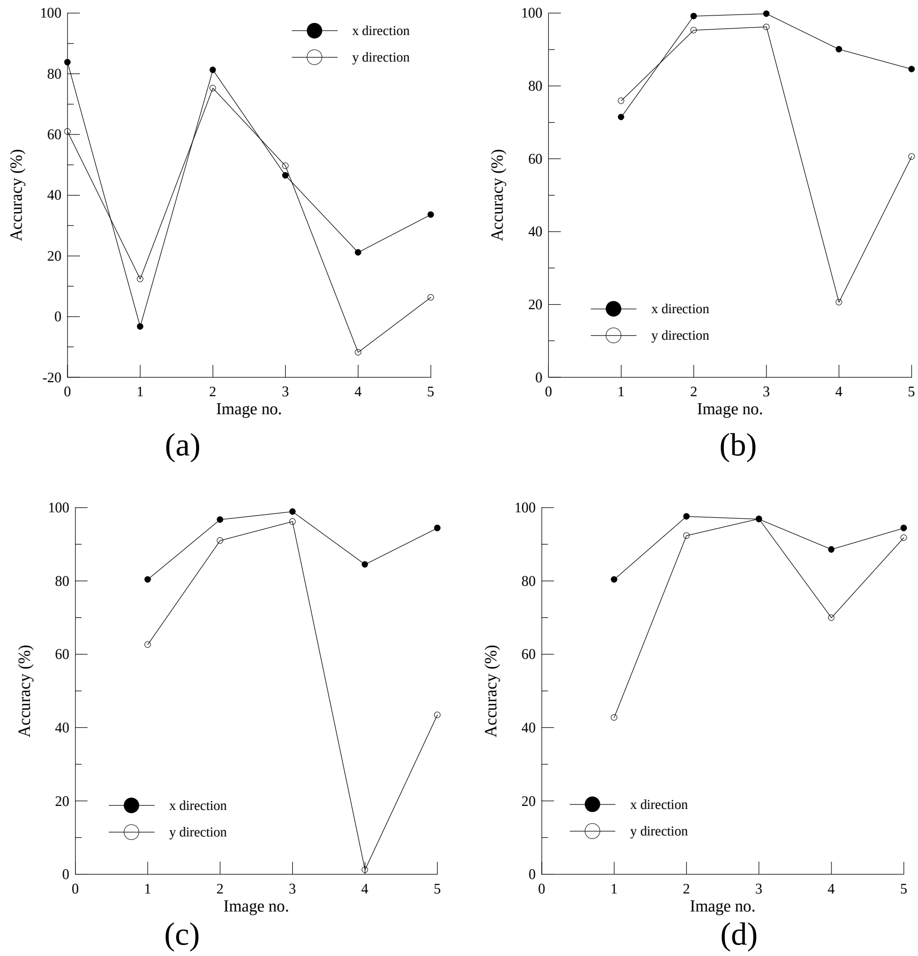

Fig. 5. Estimation performance of the optical flow: (a) using the classical method, (b) by incorporating the scatter of brightness, (c) by incorporating the scatter of brightness and the edge acquisition, (d) by incorporating the scatter of brightness, the edge acquisition, and the feature orientation

Figs. 5(b) to 5(d) demonstrate performance improvement of the optical flow computation by incorporating the proposed feature-based methods. Since the synthesized image always generates excellent computation for the optical flow, this image will not be included in subsequent investigations. Fig. 5(b) depicts the results for the method of the scatter of brightness ($\sigma > 30$). Significant accuracy enhancement of the optical flow is indicated except the *y* component for the image #4. Computational accuracy for the *y* direction in this image seems to be strongly contaminated by existing vertical line features. Performance of the estimated optical flow using both the scatter of brightness ($\sigma > 30$) and the edge acquisition (R > 30) is shown in Fig. 5(c). The edge acquisition did not improve estimation accuracy of the optical flow as expected. This outcome may be due to limited number of image patches meeting both requirements. In addition, the vertical edge feature in the image #4 still strongly limits the resulting performance. Finally, the feature orientation (T_d = 20) was included in extraction of the optical flow and the simulation results are illustrates in

Fig. 5(d). It appears that the filtering for the feature orientation is greatly helpful for the image with clear edge features such as images #3 and #4.

III. Conclusion

It has been shown that most accurate values for the optical flow always exist in image patches with features of significant brightness variation. In this paper, three feature-based computation methods for the optical flow have been proposed to improve accuracy of the estimated flow velocities. Image features can be extracted by using the approaches of the scatter of brightness or the edge acquisition. In order to prevent errors caused by parallel and/or vertical edges, the filtering for feature orientation is also developed. Simulation studies were conducted for a synthesized and five natural images. Promising accuracy enhancement has been demonstrated by using the proposed feature-based computation techniques. Based on such correct values for the optical flow, better control performance of the visual servo using the optical flow approach can be expected.

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