An Efficient Stereo Disparity Estimation Method Based on Region Information

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Abstract: - An efficient algorithm addressing robust disparity estimation based on region information is proposed. In the proposed method, a new adaptive-size window approach is introduced to stereo matching in order to overcome problems with fixed-size window. The reliability of disparity estimation is then measured with a criterion based on uniqueness and smoothness constrains. In occluded areas and image points with unreliable disparity assignments, region-based interpolation strategy is applied to compensate the disparity values. Experimental results with natural stereo pairs show that the proposed algorithm provides good disparity map and can be used for synthesizing intermediate views with high quality.

Key-Words: - Disparity estimation, region information, adaptive-size window, reliability measurement, region-based interpolation

1 Introduction

Most research efforts in stereo vision have been focused on an accurate disparity estimation, and there have been various estimation algorithms that can be mainly classified into two categories: feature-based and area-based approaches. Feature-based methods use zero-crossing points, edges, corner points, etc as matching primitives. Therefore, they can only obtain sparse disparity map. In area-based approaches, pixels or regions are used to measure the similarity between stereo pair. They yield dense disparity maps but tend to fail because of local ambiguities in the correspondence. In the stereo matching, window size must be large enough to reduce noise-sensitive distortion. However the position of maximum correlation or minimum sum of squared differences (SSD) may not represent correct matching due to different projective distortions if the window size is too large. On the other hand, if the window size is too small, it gives a poor disparity estimate when the signal-to-noise ratio of the stereo images is low. In addition, no fixed window shape works well for all pixels. Therefore, the adaptive window method [1,2,3,4] had been proposed to overcome problems with fixed window. Kanade and Okutomi [1] developed an adaptive technique with different window size for each pixel, which selects an appropriate window by evaluating the local variation of the intensity and the disparity. Veksler [2] proposed an algorithm, which chooses an appropriate window shape by optimizing over a large class of "compact" windows. The multiple window approach in the simplified version was used in method [3], where nine different windows are used to correspondence estimate. Izquierdo [4] calculated the size and shape of the matching window according to the degree of reliability of disparities estimated previously.

In practice, due to camera noise, occluded areas, and lack of image texture, stereo matching algorithm generally cannot provide a reliable disparity estimate for every image point. It occurred to us that it might be useful to measure the reliability of disparity estimates and compensate them. Uniqueness constraint is mostly used to assess the reliability of disparity estimates [5,6]. In addition to uniqueness constraint, stereo-motion consistency and the analysis of the curvature of the correlation are also employed to the reliability measure [7]. In method [8], a criterion is proposed based on a-posteriori probability taking displaced image intensity differences and the variation of disparity estimates into account. Method [5] extracts objects and performs a bilinear interpolation for dense disparity field. Method [6] handles occluded areas by making reasonable assumptions of depth constant. Methods [7] apply an edge-assisted disparity interpolation method to the occluded areas and image points with unreliable disparity assignments.

In this paper, an efficient adaptive-size window algorithm is proposed, which differents from the adaptive window searching methods [1,2,4] that require high computational costs. The proposed algorithm firstly determines the matching window size for every pixel, and then performs disparity estimate with the window. For this purpose, the region growing technique is employed. To measure the reliability of disparity estimates, we propose to use a criterion based on uniqueness and smoothness constrains. Region-based interpolation is applied to handle the occluded areas and image points with unreliable disparity assignments.

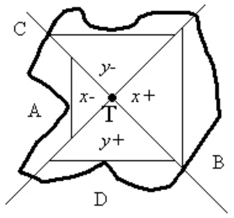
This paper is organized as follows. In Section 2, the algorithm for reliable disparity estimation is described. Section 3 gives some experimental results with natural stereoscopic image pair. Conclusions are drawn in Section 4.

2 Disparity Estimation Algorithm

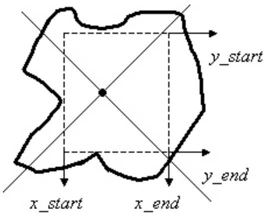
Throughout the paper, a setup where the cameras have parallel optical and vertical axes and coplanar plans is assumed. This means that only a one-dimensional search along the scan lines is necessary for disparity estimation. In addition, several suitable constraints such as uniqueness and smoothness can be applied in disparity estimation in order to enhance efficiency and accuracy.

2.1 Block-based Disparity Estimation by Adaptive-size Window

Basically, we select window size such that the region within the window has similar gray values. Variance of an object boundary is apt to change abruptly. If search window includes the abruptly change region, disparity errors can be produced because there is much depth difference. Therefore, the first step is to locate the boundary of each object region in the image. For this, the region growing technique [9] is performed to segment the intensity image. Fig.1 shows an example of window size decision. The thick lines are object region boundaries, and point T is a target point for disparity estimation. A left image of stereo pair is diagonally divided into four parts centered at the target point. For the four divided parts, the window size is expanded from center to each direction (x^-, x^+, y^-, y^+). While the window size increases to each direction, if a pixel within the window belongs to a different object with target point, then we stop expanding the window to such direction. This means that a certain disparity discontinuous points such as an object boundary is encountered. In Fig.1, increase of window size in the x^- direction stops at the point A, x^+ at the point B, y^- at the point C, and y^+ at the point D. Thus, the points of A, B, C, D define the *x_start*, *x_end*, *y_start*, *y_end*, respectively, of a rectangular window (dotted rectangle in Fig.1 (b)). In this paper, we define the maximum window size as 13×13, and minimum as 5×5.



(a) Window size growing



(b) Final window of the rectangle

Fig.1 Procedure to determine adaptive-size window

Disparity estimation is performed by using the adaptive-size window. The SSD function is used as a matching cost as follows:

$$S(x,y,d)=\sum_{y'=-N/2}^{y'=N/2}\sum_{x'=-M/2}^{x'=M/2}[I_L(x+x',y+y')-I_R(x+x'+d,y+y')]^2 \quad (1)$$

where $I_L(x,y)$ and $I_R(x,y)$ are the gray-level intensities of the left and right image respectively, window size is $M\times N$, and d is the disparity. Once we have computed the costs, we need to determinate which discrete set of disparities is best. The conventional way is to fix a point and vary d in the disparity range to calculate the matching costs, then simply picks d with the smallest matching cost as the final disparity at this point. This method is also called winner-take-all (WTA), which is sensitive to noise. So in our algorithm, we first fix one particular d on all the points and calculate the matching costs for each image row. Then we vary d, repeat the process of costs calculation until the value of d has gone through the whole disparity range. So we can obtain a two-dimensional matrix containing the SSD value for each image row. The width of the matrix is the same as the length of image row, and the height of the matrix is the disparity range. Finally, we find a best path through the matrix using DP technique [10], and the path indicates the best disparity for this image row.

2.2 Reliability Measurement of Disparity Estimation

By the method mentioned above, we get both the left to right disparity map (d^{LR}) and right to left disparity map (d^{RL}). Note that d^{LR} and d^{RL} have different signs. In order to obtain more accuracy disparity estimates, we propose using a criterion based on the uniqueness constraint together with the smoothness constraint to measure the reliability of disparity estimation. According to the uniqueness principle, each image point may be assigned at most one disparity value. Using the relation

$$\delta = | d^{LR}(x,y) + d^{RL}(x + d^{LR}(x,y), y) \qquad (2)$$

the uniqueness condition can be test for each sampling position (x,y). The deviation δ can be seen as a measure of the estimate perturbation and it describes the difference given by the relation (2). In order to consider how much input image satisfy the uniqueness constraint, the following reliability function is employed

$$f_1 = \begin{cases} e^{-C\delta}, & if \quad 0 \le \delta \le A \\ 0, & else \end{cases} \qquad (3)$$

where A is an upper bound for the δ and C is a dampening parameter to control the decreasing velocity of f_1. The smoothness constraint describes that disparity values vary smoothly in neighborhood region. So we calculate the disparity change

$$\Delta(x,y) = | d(x+L,y) - d(x-L,y) | \qquad (4)$$

where d(x,y) is the disparity of position (x,y) and L is window length. We define the smoothness reliability

$$f_2 = \begin{cases} \dfrac{T - \Delta(x,y)}{T}, & if \quad 0 \le \Delta(x,y) \le T \\ 0, & else \end{cases} \qquad (5)$$

where T is a threshold. We define final reliability function f as a linear combination of f_1 and f_2

$$f = \lambda_1 f_1 + \lambda_2 f_2 \qquad (6)$$

where λ_1 and λ_2 are weigh coefficients satisfying the relation $\lambda_1 + \lambda_2 = 1$. The function values of f are larger if the reliability is higher, whereas f will take small values for lower reliability.

2.3 Region-based Interpolation

It is assumed that each region in the image has smooth disparity values. Therefore, the above regions acquired by intensity-based segmentation are used again. For those image points with low reliability, region-based interpolation is introduced to compensate these disparity values using the correctly estimated disparity values within the individual region. Let l_k denote the distance between the position of the disparity value d to be interpolated and the position of the known disparity value d_k for $1 \leqslant k \leqslant 4$. The region-based interpolator presented in [11] is employed

$$d = \frac{w_1(l_3 + l_4) + w_2(l_1 + l_2)}{l_1 + l_2 + l_3 + l_4} \qquad (7)$$

where

$$w_1 = \frac{d_1 l_2 + d_2 l_1}{l_1 + l_2} \qquad (8)$$

and

$$w_2 = \frac{d_3 l_4 + d_4 l_3}{l_3 + l_4}. \qquad (9)$$

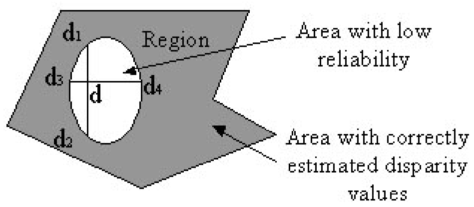


Fig. 2. Region-based interpolation of disparity values

3 Experimental Results

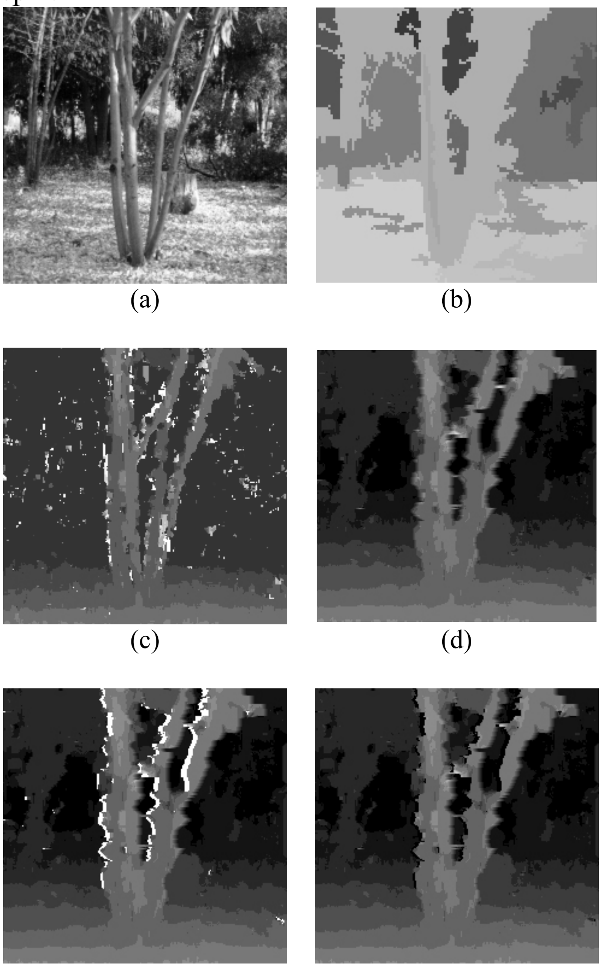
The proposed algorithms have been tested with several natural image pairs. Here, the results of the Tree pair (provided by SRI) are illustrated as an example. Fig. 3(a) and (b) show the original left image and its regions segmented by region-growing technique, where different regions are marked by different intensity values. (c) and (d) are disparity maps pointing from the left image to the right image, which is obtained by using fixed window size 5×5 with WTA and our method respectively. In order to display disparity map better, the disparities are encoded with gray-level. Large disparities are shown light and small disparities are shown dark. In our experiments, some important parameters for reliability measurement of disparity estimation are shown in Table 1. Comparing Fig. 3(c) with (d), clearly our matching algorithm eliminates the influence of noise in quite degree and can obtain better disparity result. Fig. 3(e) shows the disparity reliability measurements of the left image. The white areas mean poor estimates with low reliability. It can be seen that the estimates along boundaries of the objects and the incorrect estimates have low reliability values. This demonstrates that the proposed reliability measurement is effective. Fig.3 (f) is disparity map after compensation. It is clear that the disparities compensation method contributes a lot toward their improvement.

Table 1. Parameters for disparity reliability measurement

A	C	L	T	λ_1	λ_2
3	0.5	2	2	0.6	0.4

To further evaluate the performance of disparity estimation algorithm, an intermediate view synthesis based on the obtained disparity maps was performed with the approach presented in [7]. Fig.4 shows the image quality of synthesized intermediate view (α=0.5) form the Tree pair. It can be seen that the result is good without distinctive defects and can be accepted in visual effect. Moreover, a stereoscopic sequence was created with the synthesized image and two original images. The stereoscopic display of this

3D sequence also exhibits very clean and stable depth.



(a) (b) (c) (d) (e) (f)

Fig. 3 The result for Tree image pair

Fig. 4 Synthesized intermediate view (α =0.5)

4 Conclusions

In this paper, an efficient stereo disparity estimation algorithm using region information was presented. A new adaptive-size window method was proposed to overcome problems with fixed window size. For this purpose, the region growing technique was employed. In the process of disparity estimation, block matching and DP technique are used. The reliability of disparity estimation was measured and region-based interpolation strategy was applied to compensate the disparity values of image points with unreliable disparity assignments. The performance of the presented methods was tested using several natural stereoscopic image pairs. Experimental results show that the proposed method provided good disparity map and can be used for synthesizing intermediate views with high quality.

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