Sharp and Dense Disparity Maps Using Multiple Windows

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Abstract. In order to minimize boundary overreach, we propose a new stereo matching algorithm for sharp and dense disparity maps for color and gray-level stereo images using adaptive multiple windows. In the proposed method, we consider left-right consistency and unique constraint. Experimental results demonstrate that our algorithm produces sharp and dense disparity maps for color and gray-level stereo image pairs. We point out the disposition order problem of multiple windows and introduce window maps to indicate which window is selected among multiple windows.

1 Introduction

Quality of depth information in stereo images is usually determined by finding corresponding points the same point in two images of the same scene. For this purpose, most stereo matching algorithms use square or rectangle windows of the same size in different images.

Kanade et al. [1][2] proposed an adaptive window for choosing the right support region and also presented a multiple-baseline stereo to determine a single match point in the region of repetitive patterns. Their window has the shape of a square or rectangle according to the local intensity information. Fusiello et al. [3] proposed a method to choose the right support region by the multiple window approach. For each pixel, they perform the correlation operation with nine different windows, and obtain the disparity from the window of the smallest sum of square differences (SSD). The basic idea of this scheme is that a window yielding a smaller SSD is more likely to cover a constant depth region. Klette et al. [4] shows that stereo matching using color information instead of gray-level improves the performance around 25%. Mühlmann et al. [5] presented an efficient implementation method using the RGB information of color stereo images.

However, most window-based stereo techniques have the boundary overreach problem, which is caused by an unsuitable window shape or size [6][7]. In this paper, we introduce special multiple windows to minimize the boundary overreach. We also develop a stereo matching algorithm using left-right consistency, uniqueness constraint, and multiple windows, and point out the disposition order problem.

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After Section 2 describes conventional stereo matching techniques and similarity measure, a new algorithm using multiple windows to estimate sharp boundaries of objects is explained in Section 3. Section 4 presents experimental results using natural and synthetic, color and gray-level stereo images. Finally, Section 5 summarizes our contributions.

2 Stereo Matching Techniques

In order to measure similarity in stereovision, we usually employ SSD, defined by

$$SSD(x,y,d)=\sum_{(i,j)\in w}\{I_L(x+i,y+j)-I_R(x+i+d,y+j)\}^2 \tag{1}$$

$$\begin{aligned} SSD(x,y,d)=\sum_{(i,j)\in w}\{&\{R_L(x+i,y+j)-R_R(x+i+d,y+j)\}^2\\ &+\{G_L(x+i,y+j)-G_R(x+i+d,y+j)\}^2\\ &+\{B_L(x+i,y+j)-B_R(x+i+d,y+j)\}^2\ \}\end{aligned} \tag{2}$$

where I_L and I_R mean left and right images, respectively. d and w are disparity and cells within a window, respectively. In Eq. (2), R, G, and B are color components of each pixel. In Eq. (1) and Eq. (2), matching points can be found at scan line, assuming that stereo images are rectified. The best match for a point in one image can be determined by comparing similarity measures of square windows centered at points that lie on the corresponding scan line in the other image. The location of the smallest measure is selected as the best matching point and is stored as disparity.

In order to detect occlusions, Fua proposed a technique of left-right consistency [8], which is described by Eq. (3) and illustrated in Fig. 1.

$$d_{LR}(x+i,y+j)=-d_{RL}(x+i+d,y+j) \tag{3}$$

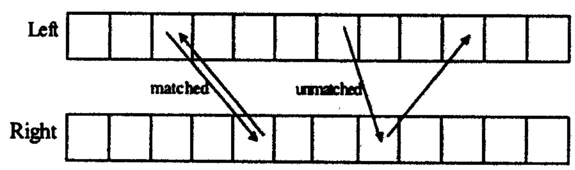


Fig. 1. Left-right Consistency Checking

The principle of the left-right consistency checking is that a valid match point should be equally matched in both left-right and right-left directions. Each point in one image can match at most one point in the other image, and the matched points should have the same disparity in both directions. Therefore, we can easily predict an occluded pixel or region by checking left-right consistency.

The uniqueness constraint means that a given pixel or feature from one image can match only one pixel or feature from the other image [9]. However, if the number of pixels having the same minimum value is two or more, we cannot determine disparity exactly. It could happen in image regions of regular patterns or uniform intensity values. We have described a new method to estimate the single disparity at a region of uniform intensity by expanding the window size [10]. Our method simply expands the window size in four directions to include more pixels if there are multiple local minima within the search range. With the operation, a bulk of multiple local minima is disappeared as the sum of SSD function of multiple-baseline stereo [2].

3 Multiple Windows

The main advantage of using multiple windows is to choose a special window to extract sharp boundaries and estimate more accurate similarity measure compared to the case using a single window [3][11]. The former implies that we can use a pattern of special form, not square or rectangle. In order to detect clear boundaries, we have designed eight windows with characteristics of edges, as shown in Fig. 2.

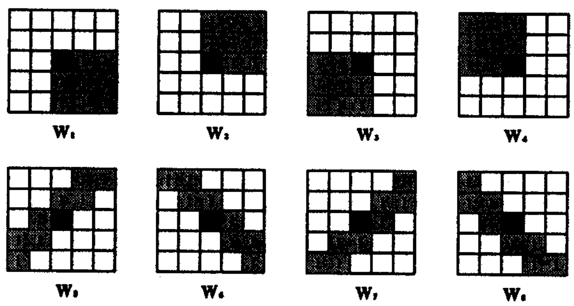


Fig. 2. Multiple Windows

Fig. 2 shows four windows W_1~W_4 to detect horizontal, vertical, and corner edges [3][11]. Windows W_5~W_8 for diagonal edges are newly introduced. All windows shown in Fig. 2 can be regularly expanded for stereo matching. We notice that the multiple windows have the same number of gray cells if their sizes are the same. All gray cells are considered to calculate similarity of each window and the darker gray cells are pixels that we want to find in other images. The later implies that similarity measure can be calculated as follows.

$$S(x, y, d) = \arg\min_{W=1}^{8} SSD_W(x, y, d) \quad (4)$$

where $S(x, y, d)$ is a similarity function and W is the window index in Fig. 2.

3.1 Disposition Order of Multiple Windows

In Fig. 3(a), the disparity can be easily estimated as d if the minimum of SSD in each window is different. However, as shown in Fig 2(b), we cannot uniquely determine the disparity of the window with the smallest SSD. We call this difficulty as the disposition order problem, which means the priority of windows to estimate a disparity from SSDs. Thus, it should be carefully determined to estimate the right disparity. We have selected the disposition order in Fig. 1. This selection is made from the assumption that boundaries of object in the scene of real world have mostly vertical and horizontal lines.

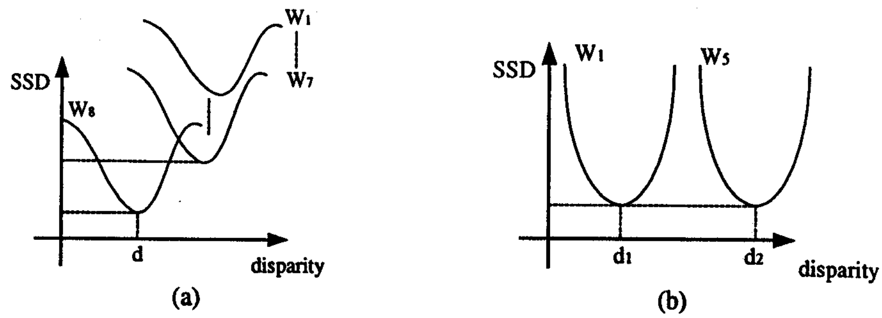


Fig. 3. Disparity in Multiple Windows

3.2 Boundary Overreach

Most window-based stereo matching algorithm have problem of low reliability in occluded areas or poorly textured regions, which generate fattening or thinning of the object along the object boundary. The window can contain both foreground and background surfaces with different disparities, which causes a boundary overreach problem. This affects segmenting objects using depth information [1][11][12]. However, the proposed windows have some possibilities to minimize boundary overreach because they can detect not only horizontal and vertical edges but also diagonal edges in the image and find a disparity using the window with the smallest similarity measure. We show that our algorithm minimizes boundary overreach in spite of expansion of the window size and that the disparity map retains clear boundaries.

3.3 The Proposed Algorithm

In order to estimate the unique matching point, we start with a window of 5×5 pixels. The window can be expanded in four directions according to uniqueness constraint and left-right consistency. All pixels are examined whether uniqueness constraint or left-right consistency are satisfied or not. Unless two conditions are satisfied, the window size is enlarged to include more pixels. A pseudo code for the stereo matching algorithm using new multiple windows to minimize boundary overreach is presented.

```
/*Stereo Matching Algorithm Using Multiple Windows (MW)*/
Input: Left and Right stereo images
Output: Disparity map (Dis)
Parameters: Disparity range (dis_max, dis_min),
            Window size (W_size),
            The number of iteration (I_num)
Initialize: Set all points to "FALSE"(Flag)
      Dis.Flag = FALSE;
```

```
Begin ExpandingWindow( )
      for i= (Wsize /2)  to i< Inum  do
            StereoMatching( ); Wsize += 2;
      end for i
End ExpandingWindow( ); Display Dis;

Begin StereoMatching  ( )
   for x=xmin, y=ymin to xmax, ymax do
      if Dis.Flag == FALSE then Left-Right do
          Compute Similarity Measure (SM) of each MW;
          Find a window with the smallest SM;
          Store Left-Right Disparity(L-RD) of the window;
          Check Uniqueness Constraint (UC) on SMs;
      end Left-Right
      if UC then Right-Left do
          Compute SM of each MW;
          Find a window with the smallest SM;
          Store R-LD of the window;
          Check UC on SMs;
          if L-RD == R-LD then
                Dis.Flag = TRUE; Dis = L-RD;
          end
      end Right-Left
   end for y, x
End StereoMatching( )
```

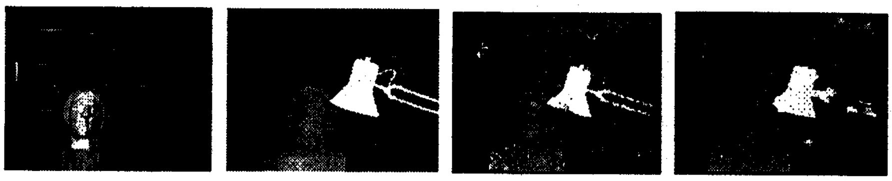
4 Experimental Results

In this section, we perform computer simulations to evaluate performance of the proposed algorithm. Test images, color and gray-level as shown in Fig. 4 and Fig. 5, are downloaded from a web site [13]. After performance is evaluated by disparity maps, we examine effects of the disposition order of multiple windows. Window maps indicate which window is used for searching disparity. Finally, we show that the algorithm minimizes boundary overreach and retains a sharp boundary in disparity maps.

4.1 Disparity Maps in Gray-Level and Color Stereo Images

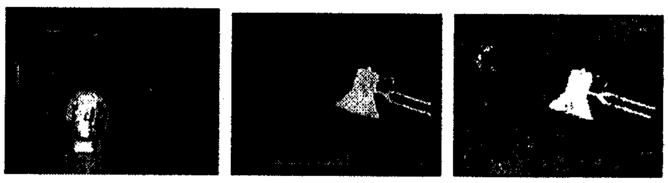
Fig. 4 and Fig. 5 show disparity maps by the proposed algorithm. We use Tsukuba stereo pairs with gray-level and color information. For gray-level images, we compare disparity maps of our algorithm to the symmetric multi-window (SMW) by Fusiello, et al. [3]. The SMW algorithm is an adaptive, multiple windows scheme using left-right consistency to compute disparity and its associated uncertainty. The disparity maps in Fig. 4 show that the proposed algorithm produces improved results in terms of sharp boundaries; however, the SMW algorithm gives a smoother disparity map. The disparity maps of our algorithm assign gray-level values to points of "TRUE" and black to other points of "FALSE". Our disparity maps show steeper boundaries than those of SMW. However, performance of two algorithms cannot be simply compared because the window size of SMW is not known. For the Tsukuba image, by comparing disparity maps of gray-level and color stereo images, we can find that the number of pixels of "FALSE" is reduced and boundaries of narrow objects are improved because of color information.

(a) Random dot, ground-truth, and disparity maps by our algorithm and SMW

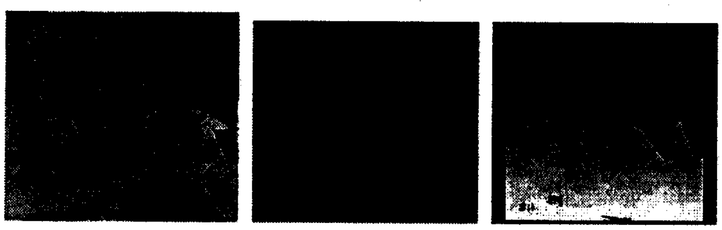


(b) Tsukuba, ground-truth, and disparity maps by our algorithm and SMW

Fig. 4. Gray-level Stereo Images and Disparity Maps



(c) Tsukuba, ground-truth, and disparity maps by our algorithm

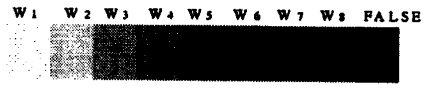


(d) Sawtooth, ground-truth, and disparity maps by our algorithm

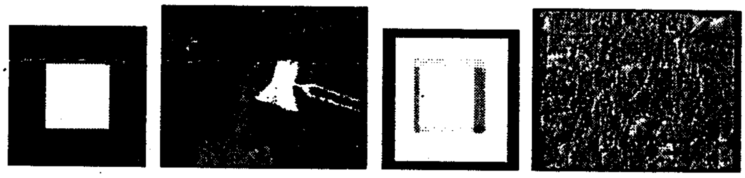
Fig. 5. Color Stereo Images and Disparity Maps

4.2 Effects of Disposition Order

This section describes the effect of disposition order using disparity and window maps. The window map indicates the selected window. The gray-level bar in Fig. 6(a) shows window maps of Fig. 6(b) and Fig. 6(c). As shown in Fig. 6, changing of the disposition order has an effect on quality of disparity maps. The disparity maps and window maps in Fig. 6 demonstrate that our disposition order is correct.



(a) Gray-level bar



(b) Disparity maps and window maps when the priority has order of $W_1 \rangle \ldots \rangle W_8$

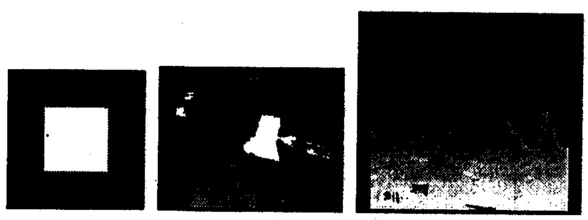
(c) Disparity maps and window maps when the priority has order of $W_1 \langle \ldots \langle W_8$

Fig. 6. Effects of Disposition Order

4.3 Boundary Overreach Problem

In order to experiment boundary overreach, we use two window sizes of 9×9 and 15×15, as shown in Fig. 7, and use only gray-level stereo images. The disparity maps by the proposed algorithm have dense and sharp boundaries irrespective of alteration of window sizes. From Fig. 7, we can observe that our algorithm minimizes boundary overreach.

(a) Disparity maps using window size of 9×9



(d) Disparity maps using window size of 15×15

Fig. 7. Boundary Overreach Problem

5 Conclusions

We have proposed a new stereo matching algorithm using multiple windows, which consider edge features of horizontal, vertical, and diagonal directions and minimize boundary overreach. Experimental results demonstrate that the proposed algorithm displays clear boundaries of objects and dense disparity maps. Left-right consistency checking is employed to estimate the depth of objects in the occluded region and the single matching point is determined by uniqueness constraint. The multiple windows are extended in four directions according to uniqueness or left-right consistency checking. Finally, we have pointed out the disposition order problem of multiple windows.

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