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A Novel Stereo Matching Method based on Rank Transformation

Wenming Zhang , Kai Hao* , Qiang Zhang, Haibin Li

Key Lab of Industrial Computer Control Engineering of Hebei Province, Yanshan University
Qinhuangdao, Hebei /066004, China

Abstract

For the problems that the traditional local SAD algorithm is affected by the central pixels largely and noise easily, this paper puts forward a new Rank-transform stereovision matching algorithm based on window weighted function. Firstly, the traditional nonparametric Rank transformation is used for left and right gray images to suppress the noise; meanwhile, the weighted window function is added to Rank transformation to keep the detail information of the scene as integral as possible; the match based on SAD algorithm is applied in gray space and the second match on the exponent constraint of color difference is applied in color space to remove mistake matching points; finally a dense disparity map can be obtained. Experimental results show that the proposed algorithm can suppress the noise much better than the traditional SAD algorithm. At the same time, the accuracy rate is nearly improved by 5.6%.

Keywords: *Stereo matching, SAD, Rank transformation, weighted window function, color difference.*

1. Introduction

Stereo vision is an important part of the computer vision, which researches how to get an object's three-dimensional information in a certain scene from an image by imaging principle. The basic method of the binocular vision is to observe the same scene from the two viewpoints and obtain a group of images in different perspectives. According to the triangulation principle, corresponding pixel disparity between two images can be obtained. And it provides deep information. Stereo matching technology is widely applied in various fields, such as robot vision navigation, medical imaging, aerial surveys, virtual reality, and so on. It is the most important and difficult part among in the stereo vision algorithms. Currently, there is no perfect way to solve the problem about matching two images corresponding points. Therefore, the research about how to achieve imagines' real-time and accurate matching is meaningful.

The common stereo matching algorithms usually include the matching algorithms that based on the features and the areas. The first one utilizes some image's features, such as edge, corner, and so on. And this way can produce sparse disparity map [1]. For example, the main idea of an expressing stereo matching methods based on the SIFT feature, which is mentioned by David G. Lower[2], is to look for the extreme point in the scale space, extract the location, scale and rotation invariant, and build the key point feature descriptors. The matching can be achieved by the Euclidean distance in the eigenvectors and invariant constraint. Even this method has a powerful matching capability and can get a better result, it is not applicable to the image, owning a large number of single features; and its results are not effective enough.

The matching method based on region can produce a dense disparity map. The point matching based on gray level is the most directly and commonly used for this method. Common matching similarity measure function includes three aspects, SAD (the Sum of absolute difference), SSD (Sum of squared difference) and NCC[3]. The NCC algorithm is to search the similarity measure function when it values the maximum corresponding disparity; And SAD and SSD algorithms are to search the similarity measure function when they take the minimum corresponding disparity; the algorithm is simple and easy to realize, but it is very sensitive to noise and light. In order to reduce negative factors, such as noise, [4] and [5] introduce the nonparametric transformation into the idea of stereo matching, and it also can get a good disparity map in case of noise and deformation. But its transformation process is just a single comparison between the neighborhood pixel gray value and center pixel gray value. If the center pixel gray value is largely disturbed by the noise interference, the stereo matching robustness will abate. So in order to improve the robustness of the algorithm, the literature [6] and [7] use neighborhood information and bilinear interpolation to improve the

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traditional nonparametric transformation to obtain better results. However, because of its fixed matching window, if the window is too big, the image's detailed information will lose. Though using the constant iterative of adaptive window [8],[9] can get good results, its computing complexity will increase much more. Compared with grayscale, color image can provide more abundant information. With the color camera and related hardware prices becoming cheaper, the color image attracts more and more attention.

In view of the limitation that traditional regional matching algorithm SAD is susceptible to noise and light, this paper firstly applies the traditional nonparametric Rank transformation to the image based on SAD algorithm, and matches it with the weighted window function defined in this paper. At the same time, color information is used and the exponent constraint of color difference is introduced into the algorithm to eliminate the ambiguity point to get a more accurate dense disparity map. Experimental results show that with the same standard of image matching the matching accuracy of our method is nearly 5.6% higher than that of SAD method.

2. Stereo Matching of Rank Transformation of Traditional Non-parametric

The traditional Rank transformation regards the relative values of the gradation as the matching similarity primitives, and the conversion reflects the size relationship of gradation value of each neighbor pixel and center.

2.1 Principle of Rank Transformation

Conventional non-parametric Rank transformation [10] sets a pixel of the matching window as a center, takes a rectangular transformation window, and calculates R(T) which is a number that the pixel gray value less than the center pixel gray value in the window after Rank transformation, i.e. the value of the Rank transformation. Defined as follows:

Here, we set that I (x, y) is the gradation value of the pixel T(x, y), N(T) represents the set of pixels of a rectangular transformation window within the pixel T(x, y) as the center, and R (T) represents a number that the pixel gray valuing less than the center pixel gray value in the rectangular window N (T).

$$R(T) = \sum_{(i,j)\in N(T)} \sigma[I(x+i, y+j), I(x,y)] \tag{1}$$

where

$$\sigma(x,y) = \begin{cases} 1, x_2 > x_1 \\ 0, x_2 \le x_1 \end{cases}.$$

2.2 Realization of Stereo Matching of Traditional Nonparametric Rank Transformation

Suppose to test the similarity measure of a pixel in the two images. Set the point of the pixel as the center and take 3*3 Rank transformation rectangular window N(T) and N(T')respectively, which are shown as formula (2), (3) below.

$$N(T) = \begin{matrix} 111 & 118 & 123 \\ 124 & 121 & 119 \\ G & 120 & 135 \end{matrix} \tag{2}$$

$$N(T') = \begin{matrix} 110 & 119 & 134 \\ 125 & 121 & 116 \\ H & 118 & 129 \end{matrix} \tag{3}$$

where $0 \le G \le 255$, $0 \le H \le 255$.

After Rank transformation, formula (2) is transformed into formula (4) and formula (3) is transformed into formula (5).

$$\sigma(x,y) = \begin{matrix} 1 & 1 & 0 \\ 0 & 0 & 1 \\ g & 1 & 0 \end{matrix} \tag{4}$$

$$\sigma'(x,y) = \begin{matrix} 1 & 1 & 0 \\ 0 & 0 & 1 \\ h & 1 & 0 \end{matrix} \tag{5}$$

There are two cases that both g and h are less than 121 and not less than 121 correspondingly. If both g and h are less than 121, $\sigma(x,y)$ and $\sigma'(x,y)$ would be 5; otherwise they would be 4. Therefore, though the pixel gray value may change a lot due to noise, the corresponding difference value is just 1 after Rank transformation. The robustness of stereo matching has been improved.

3. Stereo Matching Algorithm of Rank Transformation Based on the Weighted Window Function

If the algorithm doesn't do the non-parametric Rank transformation before matching but just uses the pixel gray values as the criterion to match directly, the gradation

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value is easily influenced by both luminance and noise of the left and right image. Traditional non-parameter transformation also relies on the cost function based on the region matching. If the window is too large, even if the noise can be well reduced, it also can cause the loss of a large number of details in the image, which makes the disparity map obscure. Therefore, an improved algorithm for the traditional non-parametric Rank transformation is put forward in this paper.

3.1 Rank Transformation Based on the Weighted Window Function

For the determined size of the matching window, the support weight can be adjusted based on the geometric relationship between the pixels of the neighboring pixels and the matching pixels in the window. Therefore, the weighting function is proposed in this paper.

Define M(x, y) as the weighted window function, which is shown as Eq. (6).

$$\lg M(x,y) = [\max(\tfrac{1}{2}u, \tfrac{1}{2}v) - \max(|x-\tfrac{1}{2}u-1|, |y-\tfrac{1}{2}v-1|)] \times \lg w \quad (6)$$

where u and v are the length and width of the neighborhood window of pixels, max() is the maximum operator, w (omega) is weight base, with the changing of w, the neighboring pixels' effects on the center pixels are different in the different positions of the window. It may be possible to maintain the details of the object by adjusting the value of w. This paper set w as 1.2 during the simulation. In order to overcome the limitations of traditional non-parametric Rank transformation, the weighted window function is introduced into Rank transformation. Substitute formula (6) into (1); then we have the conversion formula (7).

$$R'(T) = \sum_{x=1}^{k}\sum_{y=1}^{h} \sigma[I'(x,y) \times M(x,y), I(x,y) \times M(x,y)] \quad (7)$$

where $\sigma(x,y) = \begin{cases} 1, x_2 > x_1 \\ 0, x_2 \le x_1 \end{cases}$.

3.2 Realization of the Algorithm

The similarity of neighborhood is usually used as matching strategy in region matching algorithm, and the SAD (Sum of Absolute Differences) is a representative algorithm strategy, which has simple structure, fast speed and is able to obtain the dense disparity map, as shown in Eq. (8).

$$SAD(x,y,d) = \sum_{i,j \in win} |I_l(x+i, y+j) - I_r(x+i+d, y+j)| \quad (8)$$

where I_l and I_r denote the left and right grayscale images, win represents the matching window, and d represents the range of disparity searching. These two corresponding left and right pixels are the best matching pair when the SAD (x, y, d) values the minimum and d is the disparity value. The following Eq.(9) can be obtained by applying this algorithm to the matching strategy.

$$SAD(x,y,d) = \sum_{i=1}^{u}\sum_{j=1}^{v} |\sigma_l(x,y) \times M(x,y) - \sigma_r(x,y) \times M(x,y)| \\ = \min(S_1, S_2, \ldots\ldots S_d, \ldots\ldots S_z) \quad (9)$$

Similarly, we still take the minimum value of the SAD and the corresponding d is the disparity value. The problem that the outline of disparity map is becoming vague due to choosing the larger window based on area matching algorithm is solved effectively by using the algorithm which is proposed in this paper, and the matching accuracy has been improved.

4. The Second Matching Based on the Color Information

The colorful image contains more necessary information. Based on the traditional gray information matching, the color information of the image is brought during the matching process, in order to obtain more accurate matching results. At present, the color image files are mostly stored in RGB format, so the color similarity measure is tested in RGB space.

4.1 RGB Color Model[11]

In order to conduct the color image correctly, it is necessary to set up the right color model. In the RGB model, each color has red (R), green (G) and blue (B) components. This model is based on the cartesian coordinate system, whose three axes are R, G and B. The forming subspace is shown as figure 1. In this model, the grey level goes from black to white along the black point and white point extension. The other colors are indicated by the points on the cube or inside the cube as well as the vector from the origin to extend. For convenience, assume that all the color values are normalized. Then the cube in figure 1 is a unit cube. That is to say that all R, G and B range between [0, 1].

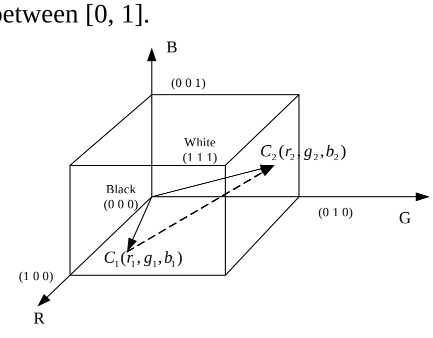

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Fig.1 RGB color space model

Fig.2 Situation of many to one ambiguous point

In Fig.1, C_1 and C_2 indicate two different colors of the corresponding color vector respectively.

4.2 Similarity measure of the color information

Compared with the gray image, the colorful image contains more information. Colors of any colorful image can be regarded as a color space vector set, and any color can be shown as a vector. So the similarity of two kinds of colors can be judged by the comparison between the corresponding vectors in two images. In [12], 12 different kinds of color similarity calculation methods are compared, and the optimal one is the absolute value exponent method.

Therefore, here the absolute value exponent method is introduced for color similarity measure. In RGB color space, any two color vectors C_1 and C_2 are used to indicate two kinds of different colors. Here, we define X as the exponent factor of color difference to show the difference between the two kinds of colors:

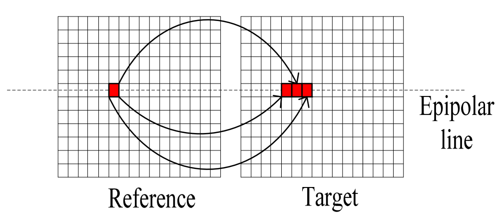
$$X(C_1, C_2) = \exp(|r_1 - r_2| + |g_1 - g_2| + |b_1 - b_2|) \qquad (10)$$

The formula (10) shows that the smaller the two vector difference is, the smaller color difference exponent factor is. So the exponent factor of color difference X can be used as the color similarity measure of two kinds of colors.

4.3 The second sentence of color exponent

In the traditional gray matching, it is necessary to meet some constraint conditions such as polar constraint, disparity range constraint and compatibility constraint. The second sentence using color pictures is the exponent constraint of color difference introduced into this paper. The difference in color between the best matching point and the reference point is smallest in the searching range of disparity. In other words, the exponent factor of color difference is the smallest.

In the gray matching process, there may be ambiguous points between the left and right pictures. That is to say, one point of the reference image (the left picture) and some points of target image (the right picture) will get the same minimum value.



As shown in figure 2, in the disparity search range, as one point of the left picture matches the three points of the right picture, the optimal matching values are the same, which are the minimum value. After the gray image matching, the exponent constraint of color difference is introduced according to these ambiguous points. Then the corresponding point of the minimum exponent factor of color difference can be easily obtained, which is the right matching point. And the color information on matching points of secondary judgment is completed. In this paper the algorithm flow chart is shown in figure 3.

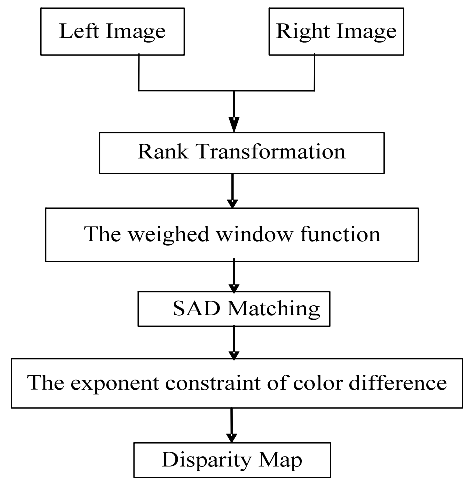
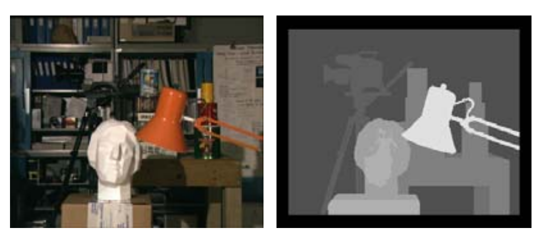


Fig.3 Method flow diagram

5. Experimental verification

In the Matlab R2007a environment, the algorithm in this paper is compared with the SAD matching algorithm. The four pairs of images used here are the standard color stereopair downloaded from the website http://www.middlebury.edu/stereo. They all have been revised through polar correction and are specially used for test stereo matching algorithm to get the final disparity map. The disparity search range of the four pairs of images is: 15,19,59,59. Rank transformation window takes 7 * 7 and the size of matching window takes 17 * 17. Figure 4 and table 1 show the results of the experiment.



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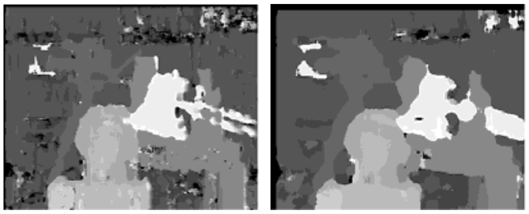
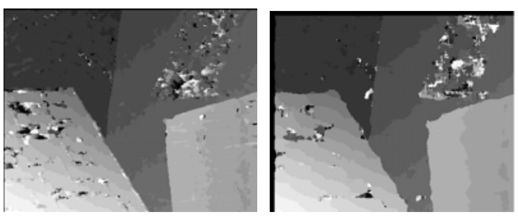
(a) Left image of Tsukuba (b)True disparity map



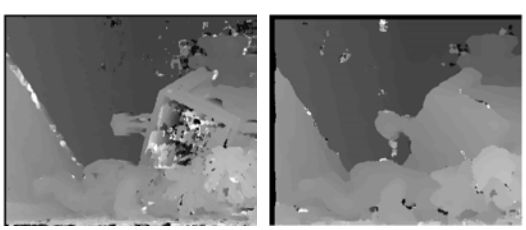
(c) SAD algorithm (d) Our method

(a) Left image of Venus (b) True disparity map



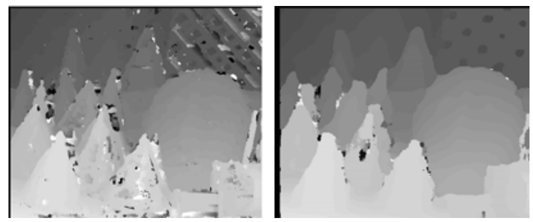
(c) SAD algorithm (d) Our method

(a) Left image of Teddy (b) True disparity map



(c) SAD algorithm (d) Our method

(a) Left image of cones (b) True disparity map



(c) SAD algorithm (d) Our method

Fig.4 Experimental simulation pictures

In figure 4, the first column signifies the left image of the standard image, the second column signifies the real disparity map, the third column signifies disparity map that comes from SAD algorithm and the fourth column signifies the disparity map that comes from the algorithm of this paper. By comparing the third column and the fourth column, we can directly find out that in the picture of Tsukuba, the background region of the result figure, which comes from the algorithm in this paper, is clearer than the result figure of the SAD algorithm. In the picture of Venus, the result figure of the SAD algorithm has much more dark and small areas than the result figure of this paper. This situation is actually caused by mismatching. From the Teddy graph we can see that the disparity continuity of the board and the small house's top area in the result of this paper have been kept better. In the picture of Cones, details in the result figure of this paper like the edge of the cone and the square lattice of the background region and so on, are obtained better.

Table1: False matching contrast

Picture		Tsuk-uba	Venu-s	Tedd y	Cones	Aver-age
Misma-tching Rate	Our method	15.0 %	9.8 %	12.1 %	11.7 %	12.2 %
	SAD Algori-thm	19.9 %	18.8 %	15.0 %	17.3 %	17.8 %

From Table 1, it is obvious to see that the error matching rate of the four pictures from SAD algorithm is higher than the algorithm in this paper; and the average mismatching rate of the algorithm in this paper is 5.6% lower than SAD algorithm. This shows that the correctness of the algorithm in this paper compared with SAD algorithm has increased significantly and the matching effect is better than that of SAD algorithm due to the introduction of the weighted window function and the exponent constraint of color difference.

6.Conclusion

In this paper, a novel matching algorithm, that the weighted window function and the exponent constraint of color difference are introduced into nonparametric Rank transformation based on SAD matching algorithm, is formed. After Rank transformation, grayscale images can choose enough matching window to extremely keep the scene's detailed information. The color information is introduced to augment the amount of effective information. For the second sentence of the exponent constraint of color difference, the matching accuracy is improved. Based on the test results, the following conclusion can be safely drawn: disparity maps obtained by the algorithm in this paper are more accurate and smoother. The algorithm in this paper, which, to some extent, restrains the noise influence on matching results, is a better stereo matching algorithm.

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h was born in 1979. He received the M.Sc. and Ph.D. degrees in Instrument Science and Technology from Yanshan University, China, in 2006 and 2010, respectively. He is currently an instructor in the Electrical Engineering Department at the Yanshan University, China. His research interests include nonlinear system vision and dynamics.

o was born in 1988. He will receive his M.Sc. degree in Electrical Engineering from the Yanshan University, China, in 2014. His current research interests include Machine vision.