Local disparity refinement with disparity inheritance

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***Abstract*—It is well known that it is difficult for local stereo algorithms to obtain correct disparities at occluded regions and depth discontinuities. In order to increase matching accuracy, current algorithms always use some disparity refinement measures. An adaptive algorithm to refine disparities based on color and distances has got good results but still not satisfactory. This paper proposes a simple and novel method which employs disparity inheritance within above algorithm, further improving the accuracy and robustness of stereo correspondence. According to our experimental results on Middlebury images, disparity inheritance can connect regions at different depths, and implement the diffusion of initial disparities from accurate areas to less accurate areas. Disparities are obviously improved especially at occlusion areas and depth discontinuities, and we get disparity maps with sharper edges.**

Keywords:stereo matching; disparity refinement; occlusion detection; disparity inheritance.

I. Introduction

Given two or more images of the same scene taken from different viewpoints, stereo matching is the process of finding all the corresponding points in these images. It is a fundamental and crucial problem in computer vision. Stereo algorithms can be classified into local and global methods[1]. Global approaches treat the stereo problem as an energy minimization problem, and many of them get excellent results such as dynamic programming[2], graph cut[4], belief propagation[3]. Global methods have some disadvantages, they are always hard to implement and computationally expensive. Compared with them, local methods have simpler structures and higher efficiency, but poorer results.

Dense disparities maps generated by the state-of-art local algorithms have higher accuracy than before. Among them some local methods[5][6][7][8][9] based on adaptive support-weight can even produce results comparable to lots of global methods. Adaptive-weight approaches use matching windows with fixed shape and size, and assign high weights to points lying on the same depth plane with the center point. Weight of a pixel denotes its importance in the aggregation process. In general, two pixels that are near and have similar colors are more likely to share the same depth[5][8]. After segmenting input images, pixels belong to the same color segment are more likely to have similar depth[6][7]. GeoSup[9] considers that it is more likely for two pixels which have small geodesic distance to share the same disparity.

However, matching algorithms without global optimization are difficult to get correct disparities at low-textured areas, occluded areas and depth discontinuities. Thus, disparity refinement is often applied afterwards to improve initial disparities. The most popular measure is performing a left-right consistency check on the initial disparities and then computing the disparities of occlusions by disparity interpolation. Effectiveness of this measure largely depends on the accuracy of initial disparities and horizontal streaks often occur. Many researchers use another refine measure which is based on color image segmentation, and all pixels within one segment are consumed sharing the same depth. But it is hard to find appropriate segmentations that are strictly along the depth boundaries, and the above assumption is false in many situations, such as slant surfaces. Besides, segmentation brings many extra calculations.

AdaptDispCalib[8] used adaptive weights based on color and distance to refine disparities, in this algorithm image segmentation is not necessary and matching accuracy is highly increased. According to the its results of AdaptDispCalib, there are still many errors around occluded regions and untextured areas. OccWeight[10] is an add-on of AdaptDispCalib, it pays more attention to occlusions while computing weights. Generally, occlusion information is known as output, in OccWeight occlusion information is used as the input of matching. Within each part of disparity computation, occlusion information is used to improve the matching accuracy. OccWeight[10] performs better than AdaptDispCalib[8], but still can't solve the problem of foreground-fattening well. Disparity edges are unsharp and the high accuracy largely benefits from post-procesing measures.

So we consider employing disparity inheritance, in this way those refined disparities can take part in the refine-process of the points whose disparities are to be refined. Using disparity inheritance makes it easier to assign correct disparity values to the occluded points and mismatched points. In addition, edges in depth map will be much sharper because occlusions always locate close to the depth discontinuities.

For all the disparity-refining methods, the accuracy of initial disparities plays a critical role. In our method, initial disparities are computed as in [10]. We introduce our approach of refining disparities in section II. In section III, experimental results are analyzed. Then we conclude our approach in section IV.

II. The Proposed Algorithm

The core of OccWeight is simple, for every point in the reference image, construct a window around it, each point within the window is assigned a disparity value after the initial disparity computation. Then among all disparity values within the window, the disparity which is most likely to belong to the center pixel is chosen to replace its initial disparity. Here, the possibility is also represented by weights based on colors and distances. Besides, detected occlusion points are now allowed to participate in the disparity-refinement step. Suppose p is the pixel to match in the reference image, q is a certain point within the window, the weight of q $r(p,q)$ is expressed as

$$r(p,q) = \begin{cases} 0 & if\ occ(q) = 1 \\ exp(-(\Delta c_{pq}/\gamma_i + \Delta g_{pq}/\gamma_p)) & otherwise \end{cases} \tag{1}$$

where γ_i and γ_p are control parameters, occ is the occlusion map of reference image(details of adaptive weights are shown in [10]).

The refined disparity $d_2(p)$ is computed as follows:

$$d_2(p) = \underset{d \in disp}{\arg\max} \left(\sum_{q \in W_p} r(p,q) \times m \right) \tag{2}$$

$$m = \begin{cases} 1 & if\ d_1(q) = d \\ 0 & otherwise \end{cases} \tag{3}$$

where W_p is the support window around p, $disp$ is the set of all candidate disparities, and $d_1(p)$ is the initial disparity of p.

We can easily find that, in the whole process above, there are not any connections among the refinement process of each disparity. So we propose the concept of disparity inheritance to construct the connections. While updating disparities, every disparity after refinement immediately takes part in the refinement of all disparities afterwards. Because refined disparities are generally more reliable than before, they have a positive impact on subsequent refinements.

Occluded and non-occluded points are handled in different ways in OccWeight's disparity refinement. Occluded points' initial disparities are not computed at all, but estimated from the disparity values of non-occluded pixels. As to disparity inheritance, for every pixel p to refine in the reference image, if p is not occluded, inheritance means using $d_2(p)$ which is just computed to replace $d_1(p)$; if p is in the occluded area, disparity inheritance refers to using $d_2(p)$ to replace $d_1(p)$ and set p non-occluded in the following steps.

The effectiveness of disparity-inheritance is reasonable theoretically. In general, the reliabilities of many initial disparity values are low, especially in occlusion areas. The newly computed disparity $d_2(p)$ is more likely to approximate ground truth than the initial disparity $d_1(p)$. Moreover, p lies in support windows of many points, among them there are some points to refine after p , using $d_2(p)$ instead of $d_1(p)$ should exert positive influence over their matching. In this way, many points are more likely to get precise disparity values through the refinement process.

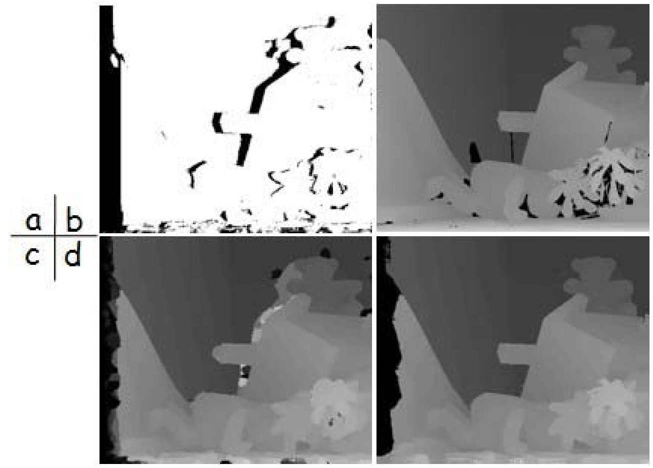

Fig. 1. Comparison between refinement results before and after employing disparity-inheritance. (a)Occlusion map (b)Ground truth (c)Disparity map without disparity-inheritance (d)Disparity map with disparity-inheritance

Thus, by the means of disparity-inheritance, disparity values can propagate layer by layer. The connection between points is established, and regions at different depths are connected. Meanwhile, correct disparity values diffuse from reliable areas to less reliable areas, thereby improving accuracy of the whole disparity map.

The effectiveness of disparity diffusion is most remarkable in pre-detected occlusion regions. In fact, detected occlusions comprise real occluded points and mismatched points. For areas full of mismatches, disparity-inheritance makes disparities propagate from non-mismatches to mismatches gradually. Thus, areas of mismatches are devoured at last. For real occluded points which often locate at background regions next to foreground, our disparity-inheritance measure ensures that correct disparities diffuse from background to foreground layer by layer. In this way, we provide a novel and effective method to implement occlusion filling.

From the comparison between the disparity-refining results before and after using disparity-inheritance, it is clear that with the help of disparity inheritance, we can obtain disparity maps more accurate. According to Fig. 1(d), positive disparity diffusion is very obvious. Reliable disparity values propagate from white regions to black regions in Fig. 1(a). As a result, points at black regions get assigned more reliable disparities. The final disparity map is closer to the ground truth, with accuracy greatly enhanced.

III. Experimental Results

We evaluate the performance of our algorithm using the Middlebury benchmark[11] with ground truth, which is often used for the performance comparison of various algorithms. The proposed approach is run with constant parameters across all image pairs. The window size is 21×21, γ_p=10.5, γ_i=15.0.

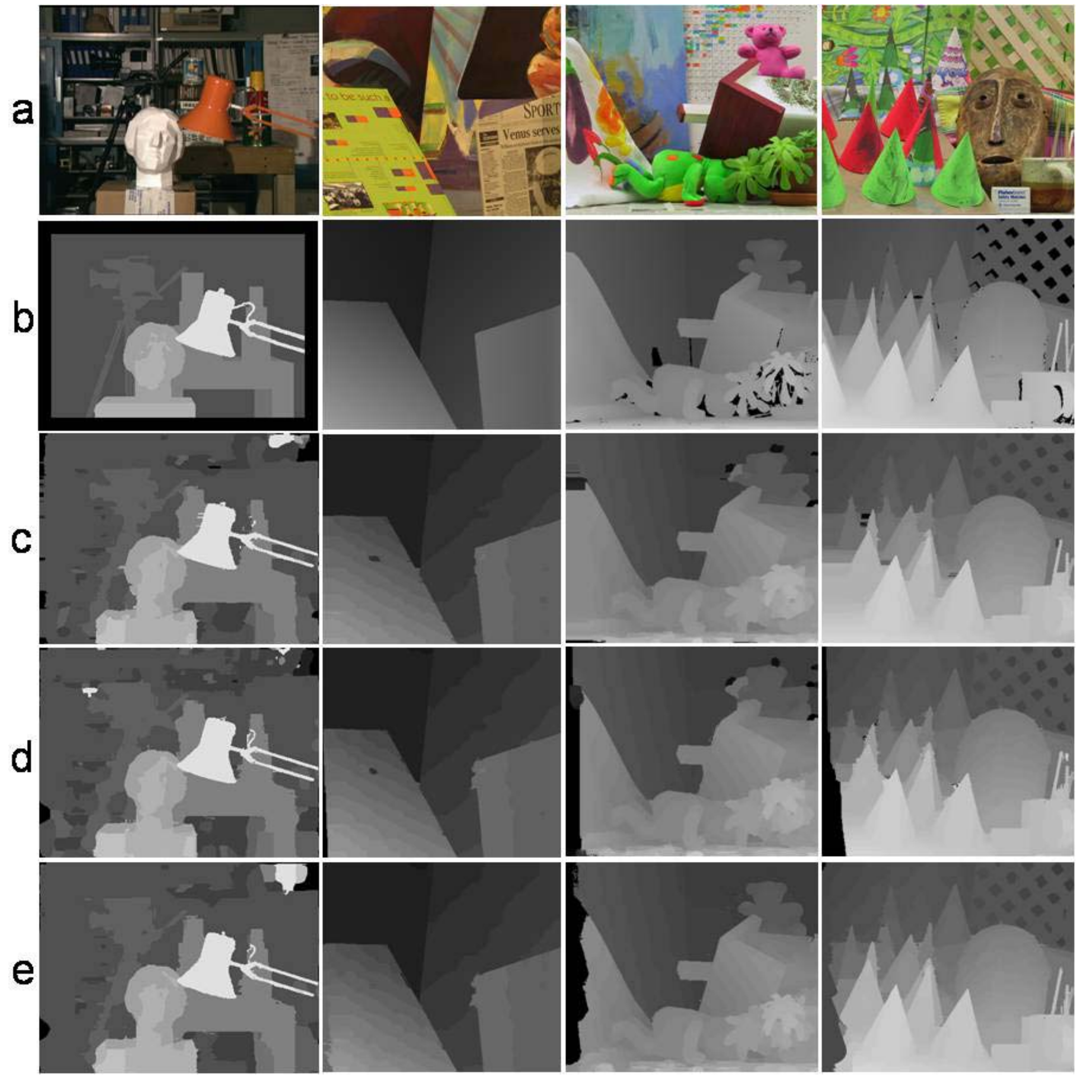

Fig. 2. Result comparison of three disparity refinement methods. (a)Reference image (b)Ground truth (c)Method 1 (d)Method 2 (e)Method 3

In order to illustrate the advantages of our method, we compare the following common disparity-refining methods. To make it fair, the same initial disparities are used for three methods. In addition, all of them are raw results without post-processing steps such as median filtering.

1) Method 1: Perform LRC check for the left and right disparity maps, pixels invalidated by the check are regarded as occlusions. For each invalidated pixel, find the first valid pixel left and right of it. Then select the smaller one between the two disparity values to be the new disparity of occluded pixel.

2) Method 2: raw results of OccWeight, not using disparity-inheritance.

3) Method 3: the method we propose using disparity-inheritance.

The results comparison of above methods is shown in Fig. 2:

It can be found through the above contrast that method 1 gets the worst results, and there are many horizontal streaks. The difference between method 2 and method 3 fully reflects the advantages of disparity-inheritance. According to the results, disparity maps yielded by method 3 have sharper edges and are more similar to ground truth than method 2. In images containing fewer depth layers such as teddy, the superiority of disparity-inheritance is especially notable. It is impossible for method 2 to obtain precise disparities at occlusions (for example, left edges of red chest in image teddy); but method 3 solves this problem well, it gets sharp disparity edges along the image edges and achieves effects comparable to occlusion-filling in method 1. On the other hand, when there are serious disparity errors (such as black areas on the top of little teddy), method 2 can't eliminate these errors but magnify the errors sometimes; as to method 3, it lets disparities spread from reliable areas to areas of errors, thereby perfectly eliminating errors.

Through simple disparity inheritance, method 3 can greatly increase the accuracy of initial disparities, especially in mismatched regions and occluded regions. Meanwhile, disparity-

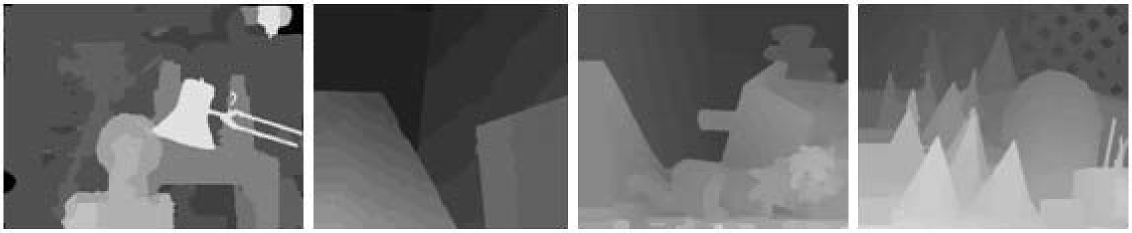

Fig. 3. Final experimental results of the proposed method after post-processing

TABLE I
RESULTS COMPARISON OF THE PROPOSED METHOD AND STATE-OF-THE-ART.

Algorithm	Tsukuba			Venus			Teddy			Cones		
	nonocc	all	disc	nonocc	all	disc	nonocc	all	disc	nonocc	all	disc
GeoSup	1.45	1.83	7.71	0.14	0.26	1.90	6.88	13.2	16.1	2.94	8.89	8.32
Proposed Method	2.27	2.57	6.44	0.25	0.42	2.89	6.09	11.5	16.1	3.32	8.84	9.07
DistinctSM	1.21	1.75	6.39	0.35	0.69	2.63	7.45	13.0	18.1	3.91	9.91	8.32
SegmentSupport	1.25	1.62	6.68	0.25	0.64	2.59	8.43	14.2	18.2	3.77	9.87	9.77
AdaptWeight	1.38	1.85	6.90	0.71	1.19	6.13	7.88	13.3	18.6	3.97	9.79	8.26
FastBilateral	2.38	2.80	10.4	0.34	0.92	4.55	9.83	15.3	20.3	3.10	9.31	8.59

inheritance provides a novel way to solve the foreground-fattening which is a challenge in stereo correspondence. Besides, disparity-inheritance' fault tolerance to initial disparity is higher, and thus more robust than other refining methods.

After some post-processing measures including disparity estimation of black edges and median filtering, final results are shown in Fig. 3:

In addition, TABLE 1 shows the error percentages with regards to the ground truth which are taken from the Middlebury online table. Three error measures are used: nonocc (image of non-occluded regions), all (image of all regions), disc (image of regions near discontinuities). From the table we can see that the approach with disparity-inheritance yields notable quantitative results. It is among the top performers of local stereo algorithms, surpassing many classic methods such as AdaptWeight[5], SegmentSupport[7], DistinctSM[12].

IV. CONCLUSION

This paper proposes a novel measure used in local disparity refinement. We employ the idea of disparity-inheritance within the refining method based on adaptive weight and occlusion information. We aim to establish the connection between different pixels and areas at different depths while refining disparities. The proposed algorithm handles occluded and non-occluded pixels in different ways. Via the results comparison of the proposed method with lrc check and refinement without disparity-inheritance, it is clear that disparity-inheritance has obvious advantages. Our method is able to increase the accuracy of whole disparity map especially in occlusion regions and depth discontinuities, and it is also good at eliminating mismatched pixels. Our future work is to design a new algorithm based on disparity-inheritance with adaptive diffusion directions. With adaptive directions, disparity-inheritance is more robust and reasonable, and should produce disparities maps with higher accuracy.

REFERENCES

[1] D. Scharstein and R. Szeliski, "A taxonomy and evaluation of dense two-frame stereo correspondence algorithms," IJCV, 47(1/2/3), 7 42, 2002.
[2] C. Lei, J. Selzer, and Y. Yang, "Region-tree based stereo using dynamic programming optimization," CVPR, 2006.
[3] J. Sun, N.N. Zheng, and H.Y. Shum, "Stereo matching using belief propagation," IEEE Trans. PAMI, 25(7), 787 800, 2003.
[4] Y. Boykov, O. Veksler, and R. Zabih, "Fast approximate energy minimization via graph cuts," IEEE Trans. PAMI, 23(11), 1222 1239, 2001.
[5] K.J. Yoon and I.S. Kweon, "Adaptive support-weight approach for correspondence search," IEEE Trans. PAMI, 28(4), 650 656, 2006.
[6] M. Gerrits and P. Bekaert, "Local stereo matching with segmentation-based outlier rejection," In Proc. CRV, 66 66, 2006.
[7] F. Tombari, S. Mattoccia, and L. Di Stefano, "Segmentation-based adaptive support for accurate stereo correspondence," In Proc. IEEE PSIVT, 2007.
[8] Z.Gu, X.Su, Y.Liu, and Q.Zhang, "Local stereo matching with adaptive support-weight, rank transform and disparity calibration," Pattern Recognition Letters 29, 1230 1235, 2008.
[9] A. Hosni, M. Bleyer, M. Gelautz, and C. Rhemann, "Local stereo matching using geodesic weights," ICIP, 2009.
[10] W. Wang and C. Zhang, "Occlusion-Aided Weights for Local Stereo Matching," In Proc. IEEE AVSS, 476 481, 2010.
[11] D. Scharstein and R. Szeliski. Available: http://vision.middlebury.edu/stereo/.
[12] K.J. Yoon and I.S. Kweon, "Stereo Matching with the Distinctive Similarity Measure," ICCV, 2007.