Hybrid Tree Guided Patch Matching

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***Abstract*—Either any of the current global or non-local stereo matching algorithms cannot be good enough to show both matching accuracy and calculation efficiency during the matching processing, especially while there are less texture regions or the images are captured from real scene. Therefore, the goal of our research is to break current bottleneck of stereo matching in aspects of the precision and speed, then get a relatively perfect method compared with other current stereo matching algorithms. Based on this ambitious goal, we proposed hybrid tree guided patch matching algorithm to get a dense and accurate depth image in fast processing speed. We utilize (1) pixel-level and region-level minimum spanning tree to achieve an initial disparity value searching constraint by using hybrid tree cost aggregation, and then (2) apply a robust guided patch matching method to calculate the final accurate disparity of each pixel efficiently by using a cost aggregation restricted through the hybrid tree generated disparity value. In the experience, we demonstrate that our proposed algorithm can generate a high quality depth images and better efficiency compared with recent new stereo matching algorithms. In the Middlebury evaluation, our algorithm also got top ten ranking and better performance among the most of the global stereo matching algorithms in both accuracy and efficiency.**

***Keywords*-stereo matching; hybrid tree; patch matching; cost aggregation; depth estimation**

I. Introduction

Stereo matching has always been one of the most important research problems in computer vision. Because the depth estimation has played a crucial role in most computer vision applications, such as depth of field rendering, consistent segmentation, object extraction, depth manipulation, and view synthesis, allowing for more creative and meaningful expressions of image contents, the researching of depth information acquisition methods become the timeless topic in computer vision and continues to attract more and more attention from researchers.

Given two rectified images of the same scene, the goal of stereo matching is to find the correspondence of pixels in the two images to calculate dense disparity and finally estimate the depth information. Especially in the 1980s, Marr in MIT proposed one famous theory and applied it on the binocular stereo matching to get a stereo image from two plan images with disparity, which laid the theoretical foundation of stereo vision development. Up to now, due to the uncertainty of matching, stereo matching problem still has no unified solution, in which many researchers have done lots of contributions. Examples of recent proposed methods including: Yang [1] proposed a new bilateral filtering method specially designed for practical stereo vision systems, which can be very effective for high-quality local stereo matching and estimate the depth of a scene. Takuya et al. [2] proposed an efficient method by using edge-preserving filter for cost aggregation processing to estimate depth information. Sinha et al. [3] presented a stereo matching system by using local slanted plane sweeps to propose disparity and get the depth information. Recently, researchers seem more like to use tree structure theory to help solve the matching problem, such as, Cheng [4] proposed a novel cross-trees structure to perform the non-local cost aggregation strategy, and the cross-trees structure consists of a horizontal-tree and a vertical-tree to get a better depth information from stereo image pair. Vu et al. [5] proposed a hybrid tree method to estimate the depth information by using pixel and region level minimum spanning tree.

Though there are many algorithms being developed to do their best to strike the balance of the processing efficiency and depth estimation accuracy. But the fact is that he balance is difficult to break and the challenges are still remain. Most current stereo matching algorithms exist more or less inadequate. There is no one method can be perfect in all aspects of stereo matching. A perfect algorithm must not only handle the imperfections of real-world images but also possess their qualities including accuracy (degree of a correct matching), complexity (cost of equipment and calculation amounts), reliability (degree of errors removing) and commonality (ability to match different scenes).

Therefore, to achieve better estimation results than other current research, we propose a more accuracy and low complexity stereo matching algorithm that can estimate depth information more robustly and reliably. Our proposed depth acquisition algorithm is both based upon the recently popular hybrid tree [5] algorithm that is mentioned in the previous paragraph and the accuracy patch matching algorithm [19]. We first get the cost aggregation value of each node from pixel and region level of MST (Minimum Spanning Tree) by using a novel adaptive aggregation function. Then we can

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get a set of initial disparity value, and we will treat these values as a constraint on disparity searching. Finally, we proposed a new patch matching method to estimate the depth information, which the searching range of initial disparity and normal is under the searching constraint previous mentioned. As a result, our proposed method greatly reduces the searching scope and improves the depth acquisition speed indirectly. On the issue of accuracythe pixel level disparity from MST naturally converts to sub-pixel level disparity. Obviously, our proposed method can simultaneously enhance the accuracy and speed. Through lots of experiments, our algorithm was proved to be suitable in many kinds of scene. It is also worth noting that our algorithm has no limitations for input images and image capture devices, such as personal computer, mobile devices, web camera and so on. Therefore, commonality of our algorithm also has been guaranteed. The paper structure is organized as follows. Section II will explain current successful stereo matching algorithms. Section III will discuss every parts of our algorithm and meaning of each aspect. Section IV will show the experimental results of our algorithm running on image pairs captured using different devices. Section V will give a conclusion and present the future enhancement of our proposed method.

II. Related works

Despite a long history of research in stereo matching, the significance of depth information acquisition has been demonstrated by many researchers' active search for better, faster and more accurate matching methods. But there are still many challenges remained for acquiring accurate depth image in a computationally efficient manner. To make these methods come true and practical, researchers are still keeping on searching better ways to solve the problems. As previous mentioned, in stereo matching aspects, there have been born a number of creative and outstanding effect algorithms. Before we deeply explain our proposed method, we need to provide a more through consideration.

Based on different characteristics of stereo matching methods framework, Scharstein et al. [6] made a detailed classification and evaluation for different stereo matching algorithms, which can generate dense disparity from two images. They pointed out that the existing stereo matching algorithms generally consist of four independent modules: matching cost calculations, cost or support aggregation, disparity calculation or optimization and disparity correction. And the current varieties of stereo matching algorithms are the results of the relative changing of the modules. What is more, the specific impact of algorithm performance from variable factors through the four independent modules performance especially the performance of matching cost and cost aggregation. Therefore, following this theory, we generally divided the current matching stereo technique into two categories: local and global stereo matching algorithms.

Local algorithms calculate by utilizing local region information of interesting points. Their calculation involves less information and lower computational complexity. Most of recent new researching stereo matching algorithms are refer to this theory. Such as, Xing et al. [7] proposed a local stereo matching algorithm to estimate disparity by using rotation-skeleton based region (RSBR). They developed adaptive local regions to generate more accurate regions for depth estimation. Cao et al. [8] proposed a constant time spatiotemporal local stereo matching based on the information permeability method. They proved that their algorithm improves the disparity consistency compared to the traditional methods. Jiao et al. [9] proposed an improved method that uses a non-parametric transform in the pre-processing and an edge-preserving filter in the post-processing during stereo matching processing. Their method can get depth more robust from pairs of image in different light sources or devices. Xia et al. [10] proposed an effective local stereo matching method based on extended triangular interpolation. They cover the whole image with a triangular mesh and formulate a new matching model based on the Bayesian rule to achieve dense accuracy disparity estimation. And some recent local stereo matching methods have already achieved comparable performance with global methods. Jiao et al. [11] showed their performance of proposed algorithm could be compared with global methods. They employed a new combined cost approach and a secondary disparity refinement to remove the outliers remained in disparity image. It seems that the current local algorithms had solved the some accuracy problems.

But most of the local algorithms are still sensitive to noise, textureless area, depth discontinuities area and blocked area, furthermore, the effects of using local stereo matching on such areas are still not ideal. Global algorithms calculate by utilizing entire image information or corresponding scanning lines. They focus on solving the problem of matching uncertain or textureless regions and get a global optimal result. The nature of global algorithms is to convert the corresponding points matching problems into finding a global optimum energy function. It always directly skips the cost aggregation to calculate the disparity values. Typical examples of recent proposed methods such as, Atlanta et al. [12] proposed a new segment-based stereo matching algorithm that provides a fast denoising technique with an edge preserving property in the initial disparity map estimation and globally on graph cuts for the disparity plane. They improved the quality of the disparity values but ignore the complexity of the method. Yang [13] re-examined cost aggregation problem and proposed a non-local algorithm. The matching cost values are aggregated adaptively based on pixel similarity on a tree structure. The proposed non-local solution outperforms all local cost aggregation methods on the standard Middlebury benchmark. The great advantage of the method is its extremely low computational complexity.

But the accuracy of the disparity is not enough for estimate good quality depth information. Chen [14] proposed a new weight function includes the color cues and the boundary cues of the reference color image. The experimental results proved that this method improves the efficient of stereo matching calculation but the accuracy of disparity value is not satisfied. Yang [15] proposed a non-local method as every node receives supports from all other nodes on the tree. This method totally reduced the complexity of the algorithm. Unfortunately, disparity value accuracy is in pixel level that cannot provide accuracy depth estimation.

From the previous research, no matter it is a local or global algorithm; it is true that to achieve a coexisting of method complexity and disparity accuracy in one method is not an easy work. Current year, more and more researchers begin to look for a suitable way to solve the coexisting problem and there comes a lot of pretty good ideas. Huang [16] proposed a fast non-local disparity refinement method based on disparity belief propagation. Performance evaluation on standard Middlebury data sets shows the proposed method performs stereo matching both in accuracy and speed. Atlanta, et al. [17] proposed a hybrid local-global stereo matching techniques. New adapting similarity measure with new Bilateral is getting from non-local adaptive cost aggregation techniques. It tries to make the top benefit from the local stage and takes both advantages of local and non-local methods. Xing [18] proposed a novel segment-tree based cost aggregation method for dense stereo matching. Experimental results on the Middlebury dataset demonstrated that the method could provide better stereo matching performance both in disparity accuracy and processing speed.

These methods still need to do the further enhancement before they might be ready for widespread use. Our stereo matching method is designed to generate a dense accuracy depth with in fast speed. The next section we will give our novel algorithm and we will explain its charm in details.

III. Proposed method

This section will deeply explain our method for depth information acquisition from calibrated images. Our goal is to get a dense and good quality depth map from general input image pairs, while taking both accuracy and efficiency into account. The core of our proposed stereo matching algorithm is mainly based on recent years' popular patch matching method with slanted support windows technique [19].

According to the computation principle of original patch matching algorithm, the researchers add an estimation of individual 3D planes at each pixel to overcome bias problems during reconstructing fronto-parallel surfaces and extend to find an approximate nearest neighbor according to a plane in order to get a pixel's optimal 3D plane among all possible planes whose number is infinite. It is clearly that this method successfully increases the disparity values from pixel level up to sub-pixel level. And they also reconstruct highly slanted surfaces and achieve impressive disparity details with sub-pixel precision. But when we take a closer scrutiny of this algorithm, which has been almost approach to perfect, we found a un- perfect aspect in its algorithm, which will seriously affect its calculation speed. In their proposed method to compute a random plane for each pixel, they first select a random disparity in a huge range of disparity estimation set then they do iteration process to calculate each pixel's true disparity. Obviously, it make the disparity searching waste too much time. So according to this defect, we reference the results of recent new technique hybrid tree [5] as a searching range and cooperated with patch matching, then finally build our new stereo matching algorithm.

A. Initial Disparity Set from Hybrid Tree

Here, given a pair of images I_0 and I_1 from left and right viewpoints. The $I_0(p)$ represents as the intensity of pixel p in image I_0, and $I_1(p_d)$ is the intensity of pixel p_d in image I_1, what is more, we assign $p_d = p + (d, 0)$, where d is the corresponding disparity value, and cost volume D is a discrete disparity range which can be defined from the focal length of the cameras, the baseline between the stereoscopic images and the desired depth resolution. Finally, according to the hybrid tree algorithm [5], we can get the initial disparity set as bellow.

1) Pixel Level Cost and MST Construction: The matching cost between I_0 and I_1 on pixel level for each disparity is depended on cost volume D. We defined the pixel level matching cost $C_d(p)$ as the dissimilarity of pixel p and pixel p_d, which is given by linear combination of the color dissimilarity e_i and the gradient difference e_g as

$$C_d(p) = \beta e_i(p, p_d) + (1 - \beta) e_g(p, p_d) \tag{1}$$

Where

$$e_i(p, p_d) = min(|I_0(p) - I_1(p_d)|, T_i) \tag{2}$$

$$e_g(p, p_d) = min(|I_0^{'}(p) - I_1^{'}(p_d)|, T_g) \tag{3}$$

In order to reduce the affect of noise in pixel based stereo matching to get the lowest cost, we get the good quality disparity by cost aggregation on a special MST. Without the computationally expensive calculation of adaptive windows as common methods, we convert each image into a structure of graph and each vertex represents a pixel and is connected via edges to its eight neighboring pixels with weight. The weight is defined as

$$\omega(p, q) = |I(p) - I(q)| \tag{4}$$

Where pixel p and pixel q are two connected vertices. We finally generate the pixel level MST by using Kruskal's algorithm [20]. However, we don't stop to further estimate the depth information, because the pure pixel level MST will still not get reliable disparity. Therefore, we defined a region level MST to void the drawback as bellow.

2) Region Level Cost and MST Construction: We first find the super pixel segment I_{S0} and I_{S1} from images I_0 and I_1 by using SLIC (simple linear iterative clustering) methods. The super pixel from SLIC can well adhere to image boundaries, so we can get relative reliable disparity in texture less regions and texture with large boundaries. The region level cost for super pixel S under each disparity level is given as follow

$$C_d(S) = \sum_{p \in S} C_d(p) \tag{5}$$

We can find that the super pixel S likes a region that contains a set of connected pixels p. So if we present the images as a graph and each super pixel as a vertex, the problem is connections between nodes that are not truly "neighbors". So how to build its MST under the traditional theory is the mainly problem we face.

To construct the MST for super pixel graph. We consider two super pixels are neighbor only when their contained pixels are neighbor. We select the neighbor nodes by penalizing the connections to set not connection edge weights to the maximum. We calculate the edge weight by using the difference of the dominant color between two neighboring super pixel nodes S_0 and S_1. The weight of the edges is

$$W_R(S_0, S_1) = |I(S_0) - I(S_1)| \tag{6}$$

Finally, we also simply use traditional Kruskal's algorithm [20] to construct the region level MST.

3) Adaptive Fusion of Both Level Costs: After we construct both pixel level and region level MST, we need to aggregate the matching cost for each node from MST to estimate the depth maps. We define the MST structure as $T(V, E)$, which $V_i \in V$ is a node and $E_i \in E$. For each node V_i, we get the cost aggregation $C_d^A(V_i)$ with weighted support from every node in the tree.

$$C_d^A(V_i) = \sum_{V_i \in T} W(V_i, V_j) C_d(V_j) \tag{7}$$

Where the weight is made up of exponential function of edges weights summary between V_i and V_j.

$$W(V_i, V_j) = e^{-(D(V_i, V_j))/\sigma} \tag{8}$$

$$D(V_i, V_j) = \sum_{\omega_E \in P(V_i, V_j)} \omega_E \tag{9}$$

The parameter σ will control the cost aggregation. When we process a low texture region we can increase the parameter then the long distance nodes will provide a larger contribution. But we find that it will create error in sharp edges and thin objects if we only define the aggregation by only using pixel level MST. Luckily, the region level MST outperforms the pixel level MST in texture less region. So we combine the two MST together to fully use of each advantage. In texture less region the region level MST should dominate the cost aggregation and in a region of rich texture the cost aggregation should relay more on the pixel level MST. Then the pixel level and region level aggregated costs are adaptively blended in an unsupervised fusion:

$$C_d^{FA}(s) = \alpha_R C_d^A(p) + (1 - \alpha_R) C_d^A(R) \tag{10}$$

Where $C_d^{FA}(s)$ is the new fusion cost aggregation, S is super pixel, $C_d^A(p)$ is pixel level cost aggregation and $C_d^A(R)$ is region level cost aggregation. Here the parameter of α_R we defined is an edge density of the region R. To get the density first we run the Canny detector to find edges and calculate the number of edges pixels. Then edge density is defined as a ratio of the number of edge pixels N_e to the total number of related region pixels N_R:

$$\alpha_R = N_e / N_R \tag{11}$$

After calculate the cost aggregation from the hybrid tree we finally get true minimum cost and then get the optimal initial disparity value set D_{hybrid} for each pixel.

B. PatchMatch with Disparity Constraint

After we got the optimal initial disparity value set, we still cannot treat them as the final result of disparity. All the processing that previous mentioned is to help get a disparity guessing range to serve the current patch mating method that we will explain in this section.

Based on the optimal initial disparity value $d \in D_{hybird}$ for each pixel, we first compute the reliable disparity searching range for matching all pixels. This is accomplished by setting a minimum allowed disparity $mindisp := d - 0.5$ and a maximum allowed disparity $maxdisp := d + 0.5 - eps$, where eps is a very small value. We then compute the reliable normal searching range from current normal vector defined on the initial disparity values of pixels, and the allowed rotation is constrained in $[-30°, 30°]$. Finally, we run the global PatchMatch algorithm as bellow.

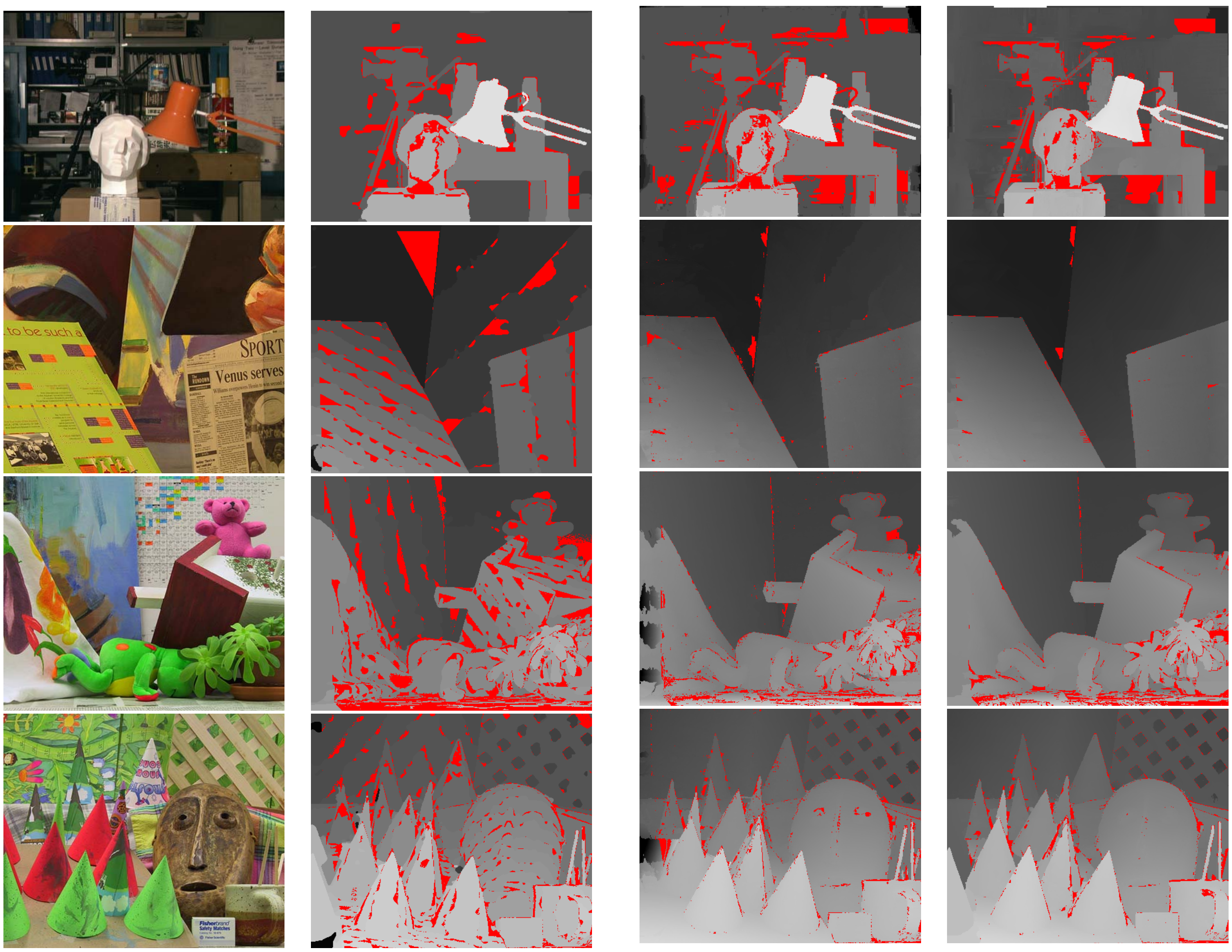
For each pixel p of image pair, we hope to find a plane f_p, which is one of the minimum aggregated matching costs among all possible planes in the reliable ranges:

$$f_p = \text{arg min } m(p, f) \tag{12}$$

We calculate the pixel matching aggregation costs according to plane f as

Table I
OBJECTIVE EVALUATION FOR THE PROPOSED METHOD WITH THE MIDDLEBURY BENCHMARK IN SUB-PIXEL ACCURACY.

Algorithm	Avg. Rank	Tsukuba nonocc	Tsukuba all	Tsukuba disc	Venus nonocc	Venus all	Venus disc	Teddy nonocc	Teddy all	Teddy disc	Cones nonocc	Cones all	Cones disc	Avg. Error
Our Method	20.0	12.0_{52}	12.5_{49}	19.2_{76}	0.53_{3}	0.91_{7}	4.75_{5}	5.25_{6}	11.3_{9}	15.8_{7}	3.50_{7}	9.58_{9}	9.84_{10}	8.76%
PatchMatch [19]	28.7	15.0_{74}	15.4_{73}	20.3_{91}	1.00_{14}	1.34_{13}	7.75_{17}	5.66_{10}	11.8_{10}	16.5_{10}	3.80_{10}	10.2_{11}	10.2_{11}	9.91%
HybridTree [5]	75.1	9.45_{31}	10.1_{29}	15.4_{24}	8.26_{113}	8.66_{109}	12.0_{56}	17.1_{115}	23.3_{112}	31.5_{106}	9.08_{72}	15.1_{80}	15.6_{54}	14.6%



(a) Stereo Image Pair (b) Hybrid Tree Results (c) PatchMatch Results (d) Our Method Results

Figure 1. Visual comparison with other methods for disparity results and sub-pixel error maps on Middlebury benchmark. From left to right, they are orginal stereo image pair, Hybrid Tree results [5], PatchMatch Results [19] and Our Method Results.

$$m(p,f) = \sum_{q} \omega_{pix}(p,q)\rho(q, q-d_p) \tag{13}$$

Where the function of $\omega_{pix}(p,q)$ is an adaptive weight function, which is used to solve the edge-fattening problem. It is computed by pixel p and q color difference. The function of $\rho(p,q)$ is the pixel dissimilarity between p and q.

$$\omega_{pix}(p,q) = e^{-(|I(p)-I(q))/\gamma} \tag{14}$$

$$\begin{aligned} \rho(p,q) =& (1-\alpha) \min\left(|I(p)-I(q)|, \tau_{col}\right) \\ &+ \alpha \min\left(|\nabla I(p) - \nabla I(q)|, \tau_{grad}\right) \end{aligned} \tag{15}$$

Where $|\nabla I(p) - \nabla I(q)|$ is the absolute difference of gray-value gradients computed at pixel p and q. The parameters τ_{col} and τ_{grad} truncates costs for robustness in occlusion regions.

For optimization we use the α-expansion algorithm. Once we get the related plane f_p , which is corresponded to a minimum aggregated matching costs, then finally we can calculate the disparity of the current pixel as

$$d_p = a_{f_p} p_x + b_{f_p} p_y + c_{f_p} \tag{16}$$

Where a_{f_p}, b_{f_p} and c_{f_p} are the three parameters of plane f_p , p_x and p_y are denoted as the coordinates of pixel p.

IV. Experimental results and evaluations

We use the same parameters as the original PatchMatch stereo matching algorithm [19], which are $\{\gamma, \alpha, \tau_{col}, \tau_{grad}\} = \{10, 0.9, 10, 2\}$, with a larger patch size of 41×41 pixels.

Then, we tested our algorithm on stereo pairs of the Middlebury dataset. We run our hybrid tree guided patch matching algorithm on the full energy and compare it to hybrid tree algorithm [5] and PatchMatch Stereo [19] with no smoothness cost. The results are summarized in Table I and Figure 1. We observe that we are superior to these both stereo matching algorithms in all cases. For the sub-pixel accuracy level, we currently (June 2015) are overall rank ten of all methods. Note that we perform particularly well on the challenging datasets "Venus" and "Teddy", which illustrate the importance of the hybrid tree guidance. As expected, PatchMatch stereo struggles in areas of low textures, a particularly interesting case is marked by the blue rectangle for "Teddy", and the uniform background pattern misleads this pixel level algorithm. Disparity estimation using only the pixel level aggregation further propagates this error, leading to patches of incorrectly estimated disparity around teddy bear. In our algorithm, we apply a hybrid tree guidance (pixel level aggregation and region level aggregation), which can enable the label propagation between small separated regions of the same object and aid disparity estimation to make good candidate labels of the solution without bad local minima, therefore, the integration of hybrid tree guidance for PatchMatch helps to suppress the errors propagation.

V. Conclusion

In this paper, we proposed a hybrid tree guided patch matching algorithm to get a dense and accurate depth image in fast processing speed. We utilize pixel-level and region-level minimum spanning tree to achieve an initial disparity value searching constraint by using hybrid tree cost aggregation, and then apply a robust guided patch matching method to calculate the final accurate disparity of each pixel efficiently by using a cost aggregation restricted through the hybrid tree generated disparity value. In the experience, we demonstrate that our proposed algorithm can generate a high quality depth images and better efficiency compared with recent new stereo matching algorithms. In the Middlebury evaluation, our algorithm got top ten ranking and better performance among most of global stereo matching algorithms in both accuracy and efficiency.

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