International Journal of Research and Engineering
ISSN: 2348-7860 (O) | 2348-7852 (P) | Vol. 6 No. 1 | January 2019 | P.547-555
Digital Object Identifier DOI® http://dx.doi.org/10.21276/ijre.2019.6.1.1

ORIGINAL ARTICLE

Disparity Map Computation from Stereo Images Using Hill-Climbing Segmentation

Author(s): *[1]Tin Tin San, [2]Kay Thi Win
Affiliation(s): [1]Image Processing Lab, [2]Faculty of Information Science, University of Computer Studies, Mandalay, Myanmar
*Corresponding author: tintinsan@ucsm.edu.mm

Abstract— Stereo matching is one of the most active research areas in computer vision for decades. The task of stereo matching is to find the point correspondence between two images of the same scene taken from different viewpoints. This paper presents a segment-based stereo matching algorithm. Firstly, the reference image is segmented using hill-climbing algorithm and local stereo matching is performed Scale Invariant Feature Transform (SIFT) feature points with Sum of Absolute Differences (SAD) block matching. Secondly, a set of reliable pixels is constructed by comparing the matching cost and the mutual cross-checking consistent between the left and right initial disparity maps, which can lead to an actual disparity plane. Thirdly, a set of all possible disparity planes are extracted and then plane fitting and neighboring segment merging are performed. Finally, the disparity planes are set in each region using graph cuts to obtain final disparity map. The evaluation of proposed algorithm on the Middlebury data set result shows that the proposed algorithm is competitive with state-of-the-art stereo matching algorithms.

Keywords: *Stereo Matching; Hill-Climbing; SIFT; SAD; Graph Cuts*

I. INTRODUCTION

This paper is an extension of work originally presented in 15th IEEE/ACIS International Conference on Software Engineering Research, Management and Applications (SERA) [1]. Stereo matching solves the correspondence problem between stereo image pairs, which for a long time has been one of the most fundamental and challenging computer vision tasks. A large number of algorithms have been proposed to solve the stereo correspondence problem. However, since the problem is an ill-posed, a satisfying solution has not been found yet [2].

The main challenge of stereo matching is to generate accurate disparity map by comparing corresponding pixels of the same scene taken from different viewpoints. It is challenging, as individual pixels contain only color and spatial information, and hence, these represent low level image features [3]. Therefore in order to effectively compare a pair of stereo images, it is necessary to develop an efficient way to identify appropriate high level image features and compare them with reasonable accuracy and speed.

According to the taxonomy developed by Scharstein and Szeliski [2], the stereo algorithms can be classified into two broad categories: local and global algorithms. The local algorithms [3, 4], also referred to as window-based algorithms only consider the intensity or color value of pixels in a square window for correspondence matching. These algorithms make cost aggregation and consider implicit smoothness assumption. Cost aggregation is typically performed locally by summing corresponding cost in the constant disparity window. However, global algorithms [5, 6] are based on assumption of an explicit smoothness and exclude cost aggregation step, but consider the disparity solution based on minimization of the global cost function taking into account the entire image. These algorithms generally provide accurate and dense disparity measurements but the computational cost is very high.

Segment-based stereo matching methods generally perform four consecutive steps. First, the homogeneous color regions are located by applying a color segmentation method. Second, a local window-based matching method is used to determine the disparities of reliable points. Third, a plane fitting technique is used to obtain disparity planes that are considered as a label set. Finally, the optimal disparity plane assignment is approximated using belief propagation or graph cuts optimization method. Segmentation based stereo correspondence algorithms work well in textureless regions because they assume that the depth varies smoothly within homogeneous color regions, and the depth discontinuity coincide with the depth boundary.

The disparity map computation from a pair of stereo images is presented in this paper. The image is segmented using hill-climbing algorithm. The image segmentation results are used as input for stereo matching. SIFT feature points are extracted from the image and SAD block matching is performed on these feature points. A set of disparity planes for each segment are extracted. And then plane fitting and neighboring segments are merged. Finally, disparity plane assignment and refinement are done by graph cuts energy minimization. The proposed stereo matching algorithm is intended to reduce errors in disparity discontinuous, textureless and nonocclusion areas. The experimental evaluation with standard stereo image pairs shows the effectiveness and robustness of proposed algorithm compared to other methods.

The rest of the paper is organized as follows: In Section 2, overview of related work is presented. Section 3 explains proposed stereo matching algorithm in detail with different subsections. Section 4 demonstrates experimental results with its discussions and shows the performance of proposed algorithm. Finally, Section 5 concludes this paper.

II. RELATED WORK

Stereo matching is one of the important topics in computer vision and a heavily researched problem. The main purpose of stereo matching is to find the estimate of depth information in the scene. The depth estimate can be utilized for 3D image reconstruction and virtual view rendering. Mobile robots can take advantage of a stereo vision system as a reliable and effective way to extract 3D data from the environment. Another device that is used to acquire depth information is a Time-of-Flight (ToF) or structured light sensor. Such a device is a type of active sensor, unlike a classic stereo vision camera. Devices of this type such as the Microsoft Kinect are cheap and have led to increased interest in computer vision applications. The stereo matching framework includes four main steps: matching cost computation, cost aggregation, disparity computation and disparity refinement to get dense disparity map.

The fast stereo vision system [4] was developed that analyzes the grayscale or color images to estimate the disparity map for 3D scene reconstruction. To deal with additive noise, a robust and novel approach capable of fast estimation of stereo correspondence is proposed. A fuzzy rule-based filtering is employed for noise elimination which can remove the non-interesting points from the stereo images. They have reconstructed 3D information of real images from the estimated disparity fields and camera parameters.

Alagoz [5] presented to integrate color information into regional stereo correspondence and made it possible to make the better use of information of each channel. The global error energy minimization by smoothing functions method is more reliable but more time consuming. The line growing method is more convenient for the sequential computing architectures because of promising higher speed. The reliability of disparity map has been increased by filtering unreliable disparity estimation with average error thresholding.

Mukherjee et al. [6] proposed a region and block based stereo matching algorithm. A dense disparity map is generated by using only 18% pixels of either left or right image of a stereo image pair. First, it segments the lightness values of left image pixels using K-means clustering. Then, a boundary map is generated which contains false identification of pixels at the segmented boundaries. So, it refines these segmented boundaries using morphological filtering and connected components analysis. SAD cost function is used to determine the disparities of boundary pixels. The disparity map is reconstructed using disparity propagation and then pixels whose disparity has not yet been determined the values of the neighboring pixels are used to estimate the disparity. The main advantage of this algorithm is that it estimates the disparity of refined boundary pixels only, thus reducing the number of computations needed.

The algorithm in [7] is a semi-global algorithm which uses mutual information for pixel-wise matching. The calculation of mutual information is performed hierarchically. A global cost calculation is approximated and can be performed at a time that is linear in the number of pixels. In [8], an extension of semi-global matching is used to solve stereo correspondence in a structured environment. In order to handle untextured areas, intensity consistent disparity selection is proposed. Holes caused by filters are filled in by discontinuity preserving interpolation. One of the main advantages of this algorithm is its low complexity and runtime.

Lee et al. [9] combined the CT and gradient difference approaches to achieve a higher matching cost quality. However, according to them, matching ambiguities can occur in certain regions as a result of similar or repetitive texture patterns. The authors in [10] presented the probability based rendering method for the robust reconstruction of intermediate view using the steady state matching probability density function. Rhemann et al. [11] formulated the aggregation step as a cost filtering problem. By using guided filter to smooth out each cost slice, they can get good disparity results.

In [12], the disparity estimation is done on per-pixel basis instead of general methods that estimate disparities on per-segment basis. First of all the initial disparity map is generated using any local or global algorithm. Then color segments are generated using mean-shift segmentation. And then initial set of planes is determined. Pixel-wise cost volume is computed and minimum spanning tree (MST) is used to compute aggregated cost. To generate more accurate disparity map plane filtering is done followed by re-labeling. The result can be enhanced by repeating the plane estimation and assignment steps. The accuracy improves with increase in iterations. The main advantage of this algorithm is that even if the initial disparity map is poor, good results can be acquired.

Ploumpis et al. [13] developed a new stereo matching approach based on particle filters and scattered control landmarks. The proposed method consists of three steps. First multiple disparity maps are used to acquire a set of features or landmarks and then segment the images. Afterward, to estimate the best disparity values, scan line particle filtering is applied. In the last step, a Markov chain model is employed to reduce the computational redundancy of the particle filtering process. Using this method, high quality disparity maps can be produced.

The work in [14] proposed stereo matching with reliable disparity propagation. The initial disparity estimation is performed with pixel wise line segment matching and absolute difference on census measure. The seed pixels with reliable disparities are detected with left right consistency checking. The disparity map is generated with 1D scanline propagation. Finally disparity map is refined with vertical voting and bilateral filtering.

Woodford et al. [15] maintain the scalar disparity labels while using triple-cliques to penalize second derivatives of the reconstructed surface. This encourages near planar smooth disparity maps. The optimization problem is however made substantially more difficult due to the introduction of non submodular triple interactions. The authors of [16] proposed a new 3D label stereo algorithm that encodes the second order smoothness of the disparity map with pairwise interactions. They show that the representation of second order surface smoothness with 3D labels leads to simpler optimization problems with nearly submodular pairwise interactions.

III. PROPOSED APPROACH

The disparity map computation is one of the key problems in stereo vision. The disparity map or depth map represents the mapping of each pixel of an image to its corresponding pixel. The disparity of a pixel is inversely proportional to the distance of a point in the scene from the camera. The reconstruction of disparity map from the left and right stereo images is referred to as a stereo matching algorithm. A pair of rectified stereo images are given as input to the proposed algorithm. In the rectified stereo images the rows of pixels are aligned parallel to the baseline which makes matching efficient. The rectified images satisfy the epipolar constraint, which can reduce the search along the corresponding row.

Image segmentation and detection of feature points in stereo images plays a very important role in stereo vision. First, the image is segmented using hill-climbing algorithm. The purpose of image segmentation is to simplify the representation of image in a form that is more suitable for analysis and further processing, resulting in an accurate disparity estimate. Second, the image segmentation results are used as an input to the SIFT-SAD algorithm to estimate the initial disparity. Next, the initial disparity map is improved with RANSAC based plane fitting technique which depends on the disparity accuracy of the pixels in the homogeneous color region. Finally, the disparity map is further enhanced by incorporating energy constraints on smoothness between neighboring regions using graph cuts. As a result, improving the initial estimate of disparity has a direct impact on the final disparity estimation. This methodology has been tested on Middlebury test set and the results indicate that the proposed method is compatible with current stereo matching algorithms. Figure 1 shows the framework of proposed stereo matching algorithm.

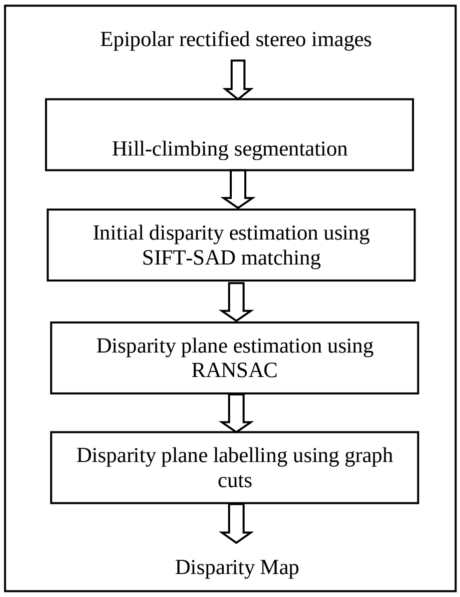
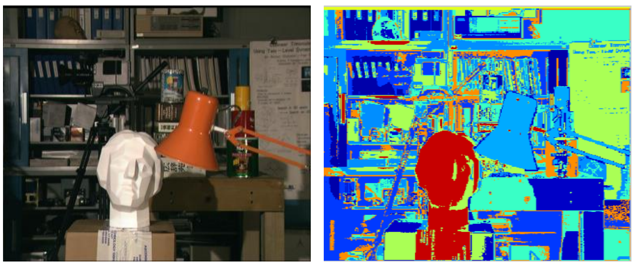


Fig. 1. Framework of Proposed Approach.

A. *Image Segmentation*

The image can be segmented using a large number of available segmentation techniques and further processing is performed on this segmented image after the segmentation step. Segment-based methods [15-17] are popular because of the superior performance on managing boundaries, textureless areas and enhancing noise tolerance. Stereo matching becomes easier even in the presence of outliers, intensity variation and minor deviation in the segmented region. They are based on the assumption that the structure of scene is estimated by a set of non-overlapping planes in the disparity space and that each plane of target image matches with at least one uniform color segment in the image. Larger segments lead to much reduced computational complexity. Instead of assigning accurate disparity cost to every pixel in the local matching method, the segmentation based algorithm assigns the disparity plane to uniform color segment in the image. Therefore, the robustness of the algorithms is improved against outliers or noise in the image.

As well as in [17], proposed approach is built upon the assumption that disparity values vary smoothly in the homogeneous color segment and disparity discontinuities only occur on the boundaries of segments. The color image segmentation are performed with hill-climbing algorithm to handle disparity estimation in large textureless region. The basis of hill-climbing segmentation is simple and fast nonparametric algorithm used to discover cluster peaks in global three dimensional color histogram of images. The histogram bins instead of the pixels themselves to find the peaks of clusters thus the algorithm can efficiently find the peaks. And then, the algorithm associates the pixels of a detected cluster based on local structure of the cluster [18]. Figure 2 shows an example of color image segmentation for tsukuba where left image is the original image and right image is the segmented one.



(a) (b)

Fig. 2. An example of segmentation. (a) reference image (b) segmented image

B. Initial Disparity Estimation

The SIFT-SAD stereo matching algorithm improves the accuracy of disparity calculation. Lowe introduced SIFT for extracting distinctive invariant features from images that can be invariant to image noise, rotation, illumination, scaling and viewpoint changes. The SIFT features are features extracted from images that can provide reliable matching between different views of an object or scene [19]. The SIFT algorithm has four main steps: scale-space extrema detection, key point localization, orientation assignment and generating key point descriptor. The disparities of corresponding SIFT feature points are calculated with SAD matching cost as in [20]. The SIFT descriptor provides most of the local gradient information and SAD provides local intensity information. The SIFT-SAD consists of two parts. Firstly, the L1 distance of SIFT descriptor between pixel p in the left image and $p+d_p$ in the right image is calculated.

$$D_{SIFT}(d_p) = \|x_L(p) - x_R(p + d_p)\| \quad (1)$$

where d_p is the disparity of pixel, $||x_L(p) - x_R(p+d_p)||$ is the L1 distance. Next, SAD for matching cost of pixel intensity is computed. SAD is the simplest and effective dissimilarity measures between stereo image pairs.

$$D_{SAD}(d_p) = exp(-SAD(p, p + d_p)) \quad (2)$$

where $SAD(p, p + d_p)$ is the SAD score between p and $p + d_p$ in square neighborhood searching window. The disparities for all pixels are computed with 9x9 square window sizes. Finally, one dimensional standard Gaussian weight with the scale factor s is used to get the matching cost. The disparity of SAD matching cost calculates horizontal distance between the centers of frame in the image based on predefined disparity range. The best matching pixel have minimum difference value and the position defines the disparity of the actual pixel. Figure 3-6 shows the initial disparity estimation results on Middlebury test set in comparison with standard stereo method SAD. It can be shown that the results of proposed approach are better than the results obtained by using SAD.

C. Disparity Plane Estimation

After initial disparity estimation, the plane parameters are estimated to represent the structure of scene. A set of all possible disparity planes inside the scene from reliable correspondences are estimated. Then the initial plane parameters from each segment are calculated using a robust disparity plane fitting and refinement.

1) *Robust Plane Fitting*: According to Tao et al. [21], the general form of plane fitting from the initial disparities in a segment as

$$d(x, y) = ax + by + c \quad (3)$$

where a, b and c are disparity plane parameters and $d(x,y)$ is the corresponding disparity of the image pixel (x,y). The reliable pixels and their disparities are used to fit a planar surface to the segment. The RANSAC robust plane fitting method is used to estimate the parameters of the plane.

2) *Disparity Plane Refinement*: This step is designed to improve the accuracy of the disparity plane set by refining the plane fitting on each grouped segments. As in [10], the following steps are processed: First, segment matching costs are calculated for each disparity plane assignment. This is calculated as the sum of the matching costs for each pixel in the segment S:

$$C(S, P) = \sum_{(x,y)\in S} c(x, y, d) \quad (4)$$

where P is a disparity plane and d defines disparity. Second, each segment is assigned disparity plane with the minimum matching cost. Third, segments that have the same disparity plane are grouped. Finally the plane estimation process is repeated to each grouped segment.

D. Disparity Plane Assignment

In the final step of the algorithm, the disparity plane label is assigned to each image segment by minimizing the energy function with smoothness constraint. The energy minimization problem is solved using a graph cut approach in which each node corresponds to a segment. Therefore, the stereo matching is formulated as an energy minimization problem for the labeling f that assigns each segment $s \in R$ a corresponding plane $f(s) \in D$ that minimizes:

$$E(f) = E_{data}(f) + E_{smooth}(f) \quad (5)$$

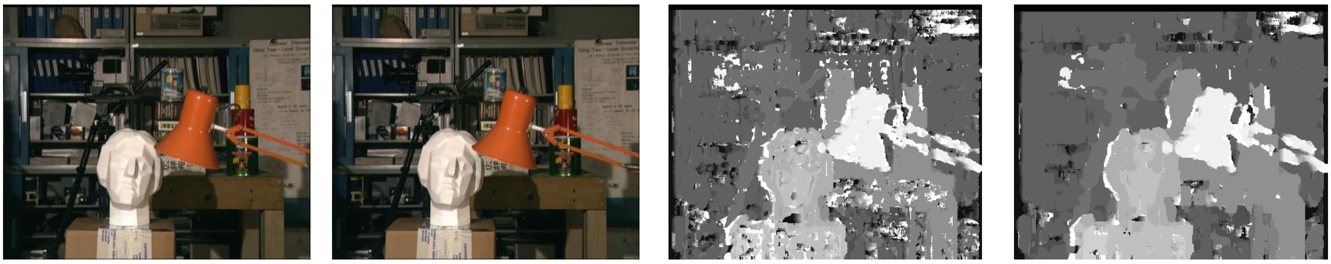
where

$$E_{data}(f) = \sum_{S \in R} C(S, f(S)) \quad (6)$$

And

$$E_{smooth}(f) = \sum_{(S,S')} u_{S,S'} . \delta(f(S) \neq f(S')) \quad (7)$$

where *S and S'* are neighboring segments, *uS,S'* is proportional to the common border length between segment *S* and *S'*, and $\delta\,(f(S) \neq f(S'))$ has value 1 if $f(S) \neq f(S')$, otherwise 0.



(a) (b) (c) (d)

Fig 3. Initial disparity estimation results of Tsukuba image pair (a) left image (b) right image (c) initial disparity map generated by SAD (d) initial disparity map generated by proposed approach.

(a) (b) (c) (d)

Fig 4. Initial disparity estimation results of Venus image pair (a) left image (b) right image (c) initial disparity map generated by SAD (d) initial disparity map generated by proposed approach.

(a) (b) (c) (d)

Fig 5. Initial disparity estimation results of Teddy image pair (a) left image (b) right image (c) initial disparity map generated by SAD (d) initial disparity map generated by proposed approach.

(a) (b) (c) (d)

Fig 6. Initial disparity estimation results of Cones image pair (a) left image (b) right image (c) initial disparity map generated by SAD (d) initial disparity map generated by proposed approach.

IV. EXPERIMENTAL RESULT AND ANALYSIS

The author [22] provides many stereo datasets with ground truth disparity for the performance evaluation of stereo matching algorithm. The Middlebury stereo benchmark dataset is used to evaluate the results of the proposed algorithm. The image pairs like Tsukuba, Venus, Teddy and Cones used for the evaluation purpose are popular and widely used in the stereo vision community. These stereo image pairs are well known for the combining objects with different characteristics and are challenging for stereo matching. The proposed algorithm is evaluated by using the quantitative measures where the percentages of pixels with absolute disparity error greater than one pixel are shown for different regions: nonoccluded pixels only (nonocc), all pixels (all) and pixels near discontinuities (disc).

$$B_r = \frac{1}{N_r}\sum_{(x,y)\in r}\left(\left|d_C(x,y) - d_T(x,y)\right| > \delta_d\right) \qquad (8)$$

Where B_r is the percentage of bad matching pixels, Nr is the number of pixels in region r, $d_C(x,y)$ is the computed disparity map, $d_T(x,y)$ is ground truth disparity map and δ_d is disparity error tolerance ($\delta_d = 1.0$).

Table 1 compares the quantitative results of the proposed stereo matching with state-of-the-art algorithms. The same experiment is conducted as that mentioned in [2] and used the same evaluation methodology. For comparison, some reported algorithms are also tested on these datasets using the source code provided by the authors. The proposed algorithm get least error rate in teddy and cones image pair. On the average percentage of bad pixels greater than one over all four stereo images, the proposed algorithm obtained 5.63%. Figure 7 shows the result of disparity map of the four stereo images obtained by the proposed algorithm. Experimental result shows that the proposed stereo matching algorithm obtains good performance in disparity discontinuous, textureless and nonocclusion areas.

The experiment is carried out in Matlab on a PC with Intel Core i7 processor (3.40 GHz) and 4GB of memory. The proposed algorithm is applied to each stereo image pair and calculates the disparity result. In each case, the computational time is recorded. The time analysis in seconds of state-of-the-art stereo matching algorithms and proposed algorithm is tabulated in Table 2. Runtimes of the competing methods SMPF [13], RDP [14] and GlobalStereo [15] are taken from their paper. Times is measured on different machines but still give a good indication of the computational complexity. The computation time of proposed algorithm for tsukuba, venus, teddy and cones images are 41.22, 58.99, 63.61 and 56.91 seconds respectively.

V. CONCLUSION

The disparity map computation from stereo image pair is presented in this paper. The segment based stereo matching methods are popular for its excellent performance in dealing with textureless areas, edges and noise. The chances of making a wrong selection of disparity upon a segment is significantly lessen as segments enclose a large amount of information compared to individual pixels. It is shown that the segmentation based algorithm makes it possible to match the excellently large textureless region which is a major issue with standard area-based stereo matching techniques. So in this paper, stereo matching is performed with hill-climbing segmentation and SIFT-SAD matching. The proposed stereo matching algorithm was evaluated on Middlebury stereo dataset and the result indicates that the proposed algorithm obtained good performance in challenging image regions such as textureless, disparity discontinuous and nonocclusion regions. The optimization in reducing computational complexity and further assessment will be studied in future work.

TABLE I. PERCENTAGE OF ERRONEOUS DISPARITY VALUES OF PROPOSED STEREO MATCHING ALGORITHM WITH STATE-OF-THE-ART ALGORITHMS

Stereo Matching Algorithm	Tsukuba			Venus			Teddy			Cones			Average
	nonocc	all	disc	nonocc	all	disc	nonocc	all	disc	nonocc	all	disc	
RDP [15]	0.97	1.39	5.00	0.21	0.38	1.89	4.84	9.94	12.60	2.53	7.69	7.38	**4.57**
SSMP [11]	1.60	1.97	6.44	0.20	0.38	2.51	6.15	11.50	15.80	2.60	7.92	7.48	**5.38**
CostFilter [12]	1.51	1.85	7.61	0.20	0.39	2.42	6.16	11.80	16.00	2.71	8.24	7.66	**5.55**
Proposed	2.62	3.71	13.63	0.70	1.44	10.00	4.28	12.01	2.09	6.60	10.25	0.25	**5.63**
3DLabelStereo [17]	3.18	4.37	12.05	0.38	0.70	4.40	8.58	14.23	4.22	10.98	15.56	6.15	**7.07**
SMPF [14]	0.98	1.53	5.31	0.25	0.69	2.60	9.93	14.50	22.60	6.51	13.10	14.80	**7.73**
GlobalStereo [16]	2.91	3.56	7.33	0.24	0.49	2.76	10.90	15.40	20.60	5.42	10.80	12.50	**7.74**
ARW [10]	4.90	6.70	19.42	4.83	4.71	28.04	10.22	17.80	3.14	8.09	15.38	3.33	**10.55**
StereoDisp [7]	21.83	23.10	26.66	22.57	19.04	38.35	31.67	36.93	26.24	31.75	36.84	23.57	**28.21**
StereoRegion [5]	45.86	46.43	71.88	48.50	47.35	58.59	48.09	50.53	40.66	43.67	47.77	32.53	**48.49**

TABLE I. TABLE II. COMPARISON OF COMPUTATION TIME OF PROPOSED STEREO MATCHING ALGORITHM WITH STATE-OF-THE-ART ALGORITHMS.

Stereo Matching Algorithm	Tsukuba	Venus	Teddy	Cones	Average Computation Time
ARW [10]	1.52	1.88	2.00	1.91	**1.83**
StereoDisp [7]	3.74	4.88	5.15	5.62	**4.85**
RDP [15]	2.50	3.80	8.70	8.60	**5.90**
StereoRegion [5]	8.64	13.13	13.31	13.50	**12.15**
Proposed	41.22	58.99	63.61	56.91	**55.18**
3DLabelStereo [17]	52.77	59.64	58.35	56.56	**56.83**
SSMP [11]	26.80	48.05	89.92	90.24	**63.75**
SMPF [14]	36.10	69.04	101.30	107.20	**78.41**
CostFilter [12]	29.72	82.99	132.31	144.06	**97.27**
GlobalStereo [16]	106.00	139.00	143.00	181.00	**142.25**

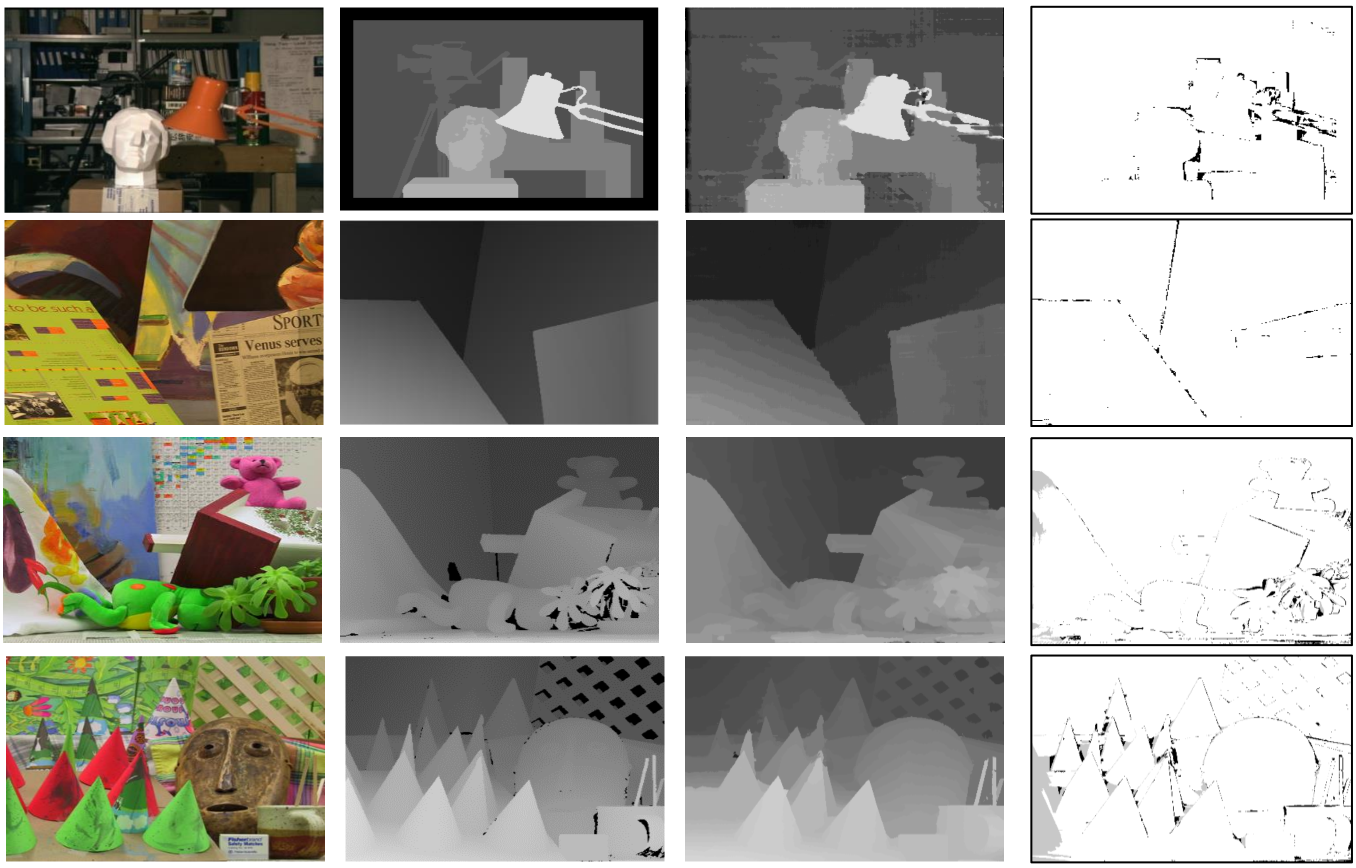


Fig 7. Results on Middlebury datasets. From top to bottom: Tsukuba, Venus, Teddy and Cones. From left to right: reference images, ground truth disparity maps, the results of proposed algorithm and the error images where the black regions represent the erroneous pixels.

DECLARATION

The authors have disclosed no conflicts of interests and the project was self-funded.

ACKNOWLEDGMENT

The authors would like to thank Daniel Scharstein and Richard Sezliski for providing stereo images with ground truth and evaluation results on their Middlebury website.

REFERENCES

[1] T.T. San and N. War, "Feature based disparity estimation using hill-climbing algorithm." In Software Engineering Research, Management and Applications (SERA). IEEE 15th International Conference on, pp. 129-133. IEEE, 2017.

[2] D. Scharstein and R. Szeliski, “A taxonomy and evaluation of dense two-frame stereo correspondence algorithms” International Journal of Computer Vision (IJCV), 47:7–42, 2001.

[3] G. Wang and H. Ju, “A disparity map extraction algorithm for lunar rover BH2” IEEE International Conference on Intelligent Computing and Intelligent Systems (ICIS), vol. 4, pp. 385 – 389, Shanghai, 2009.

[4] M.M. Chowdhury and M.A.A. Bhuiyan, “Fast window based stereo matching for 3D scene reconstruction.” Int. Arab J. Inf. Technol., 10(3), pp.209-214, 2013.

[5] B.B. Alagoz, “Obtaining depth maps from color images by region based stereo matching algorithms”, arXiv preprint arXiv: 0812.1340, 2008.

[6] S. Mukherjee and R.M.R. Guddeti, “A hybrid algorithm for disparity calculation from sparse disparity estimates based on stereo vision.” In Signal Processing and Communications (SPCOM). International Conference on, pp. 1-6. IEEE, 2014.

[7] H. Hirschmuller, “Accurate and efficient stereo processing by semi-global matching and mutual information.” In Computer Vision and Pattern Recognition (CVPR). IEEE Computer Society Conference on Vol. 2, pp. 807-814. IEEE, 2005.

[8] H. Hirschmuller, “Stereo vision in structured environments by consistent semi-global matching.” In Computer Vision and Pattern Recognition (CVPR). IEEE Computer Society Conference on Vol. 2, pp. 2386-2393. IEEE, 2006.

[9] S. Lee, J.H. Lee, J. Lim and I.H. Suh, “Robust stereo matching using adaptive random walk with restart algorithm.” Image and Vision Computing, 37, pp.1-11, 2015.

[10] B. Ham, D. Min, C. Oh, M.N. Do and K. Sohn, “Probability-based rendering for view synthesis.” IEEE Transactions on Image Processing, 23(2), pp.870-884, 2014.

[11] C. Rhemann, A. Hosni, M. Bleyer, C. Rother and M. Gelautz, “Fast cost-volume filtering for visual correspondence and beyond.” In Computer Vision and Pattern Recognition (CVPR), IEEE Conference on, pp. 3017-3024. IEEE, 2011.

[12] V. Muninder, U. Soumik and G. Krishna, “Robust segment-based stereo using cost aggregation.” In Proceedings of the British Machine Vision Conference. pp. 1-11, 2014.

[13] S. Ploumpis, A. Amanatiadis and A. Gasteratos, “A stereo matching approach based on particle filters and scattered control landmarks.” Image and Vision Computing, 38, pp.13-23, 2015.

[14] X. Sun, X. Mei, S. Jiao, M. Zhou and H. Wang, “Stereo matching with reliable disparity propagation.” In 3D Imaging, Modeling, Processing, Visualization and Transmission (3DIMPVT). International Conference on pp. 132-139. IEEE, 2011.

[15] O. Woodford, P. Torr, I. Reid and A. Fitzgibbon, “Global stereo reconstruction under second-order smoothness priors.” IEEE transactions on pattern analysis and machine intelligence, 31(12), pp.2115-2128, 2009.

[16] C. Olsson, J. Ulén and Y. Boykov, “In defense of 3d-label stereo.” In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition. pp. 1730-1737, IEEE, 2013.

[17] L. Hong and G. Chen. “Segment-based stereo matching using graph cuts.” Computer Vision and Pattern Recognition (CVPR), Proceedings of the 2004 IEEE Computer Society Conference on. Vol. 1, pp. 74–81. IEEE, 2004.

[18] T. Ohashi, Z. Aghbari, and A. Makinouchi, “Hill-climbing algorithm for efficient color-based image segmentation”, IASTED International Conference on Signal Processing, Pattern Recognition and Applications, 2003.

[19] D. Lowe, “Distinctive image features from scale-invariant keypoints.” International journal of Computer Vision 60(2): pp.91–110, 2004.

[20] P. Kamencay, M. Breznan, R. Jarina, P. Lukac and M. Zachariasova, “Sparse disparity map computation from stereo-view images using segment based algorithm.” Radioelektronika, 2012 22nd International Conference. IEEE, 2012.

[21] H. Tao, H. Sawhney, and R. Kumar, “A global matching framework for stereo computation.” Computer Vision, ICCV 2001. Proceedings. Eighth IEEE International Conference on. Vol. 1, pp.532-539. IEEE, 2001.

[22] D. Scharstein and R. Szelinski, “Middlebury stereo vision website.” http://vision.middlebury.edu/stereo/.