

## A Small Baseline Stereo Matching Method Based on Adaptive Weight

Jilong Bian<sup>1</sup>, Jinfeng Li<sup>2</sup>, Nana Wang<sup>3</sup> and Liu Yang<sup>2</sup>

<sup>1</sup>*College of Information & Computer Engineering, Northeast Forestry University, Harbin, China*

<sup>2</sup>*Engineering Institute, Mudanjiang Normal University, Mudanjiang, China*

<sup>3</sup>*College of Computer Science and Technology, Harbin Engineering University, Harbin, China*

*bianjilong@hrbeu.edu.cn, allylili0453@163.com*

*Corresponding author: Jilong Bian*

### Abstract

*Due to a high percentage of the bad pixels in small baseline stereo matching method, a small baseline stereo matching method based on adaptive weight is proposed. Firstly, the size of reference window is adaptively calculated for each reference point and then matching costs is evaluated according to adaptive weights and reference window size. Secondly, winner take all is used to evaluate initial disparities and unreliable matches are refused by using reliability constraints. Finally, disparity post processing method based on iterative diffuse using a new cost function is used to obtain a dense disparity map. A small baseline stereo image pair of Toulouse and stereo image pairs provided by the benchmark Middlebury database are used to test the proposed method. The experimental results show that this method can effectively reduce a percentage of the bad pixels of depth discontinuity areas, improve the overall disparity matching accuracy and meet the requirements of small baseline three-dimensional reconstruction.*

**Keywords:** *stereo matching; small baseline; disparity; adaptive window; adaptive weight; disparity post processing*

### 1. Introduction

Stereo matching is one of the extensively researched topics in computer vision. It can determine Three-Dimensional (3D) depth information of objects by finding corresponding points in stereo images taken from different points of view and find a wide range of applications in robotic vision, stereo mapping and automated systems. Stereo matching algorithms can be classified into local and global methods by Scharstein and Szeliski [1]. In local methods, the state-of-the-art technologies, such as Non-Local Cost Aggregation [2], adaptive guided filtering [3] and iterative refinement method for adaptive support-weight, were proposed to obtain the matching accuracy in close to global methods. In global methods, an energy function is solved to obtain a disparity map by optimization algorithms, such as Dynamic Programming [5], Belief Propagation [6] and Graph Cut [7]. Global methods have high matching accuracy and avoid the foreground fattening problem generated by local methods. However, its speed is lower than local methods. Neither local methods nor global methods can effectively resolve occlusions, differences in radiometry and geometrical deformations in stereo images. Therefore, small baseline stereo matching is proposed to overcome these problems. In small baseline stereo matching method, small baseline can generate less occlusion, less differences in radiometry and smaller geometrical deformations, which help improve matching accuracy. For now, small baseline stereo matching method is divided into two stages: pixel level matching stage[8-

[11] and subpixel level matching stage[12-14]. Since subpixel level matching is founded on pixel level matching, the accuracy of pixel level matching have an impact on the accuracy of subpixel level matching. So, pixel level matching with high accuracy is still one of the key problems in small baseline stereo matching. References [9-11] are mainly devoted to the solution of the foreground fattening problem to improve the accuracy of pixel level matching, thereby improving the accuracy of subpixel level matching. In [9], adaptive window and barycentric correction were proposed to reduce the foreground fattening problem. In [10], the Central Equation of Correlation was solved according to the variational principle to reduce the foreground fattening problem, but its effect is not obvious. In [11], an automatic low baseline stereo based on a piecewise affine representation was proposed to reduce the foreground fattening problem. This method is superior to the references [9-10], but its time complexity is high.

In order to improve the accuracy of pixel level matching to lay a good foundation for sub-pixel matching, this paper presents a small baseline stereo matching method. The main contributions in this paper were the following: (1) an adaptive weight method is proposed and is combined with a adaptive window for aggregating matching cost to reduce the foreground fattening problem; (2) disparity post processing method based on iterative diffuse using a new cost function is used to produce a dense disparity map.

This paper is organized as follows. In Section 2, we describe the fundamental principle of small baseline stereo matching in detail. In Section 3, we give a full account of adaptive support-weight, adaptive window, reliable constraints and disparity post processing. Section 4 demonstrates the effectiveness of the proposed algorithm in experimental results. This paper is summarized in Section 5.

## 2. Fundamental Principles

Suppose that an image pair  $u(x)$  and  $\tilde{u}(x)$  satisfy the classical model:

$$\tilde{u}(x) = u(x - \varepsilon(x)) + g_b(x) \quad (1)$$

Where  $\varepsilon(x)$  denotes a disparity function between  $u$  and  $\tilde{u}$ , and  $g_b(x)$  denotes the convolution  $g * b$  between a Gaussian noise  $b$  of standard deviation  $\sigma_b$  and the function  $g$ . This model is false if the angle between the snapshots is too large, but is quite reasonable if this angle is small. Indeed, the model assumes that the differences between  $u$  and  $\tilde{u}$  are purely geometrical and that almost no occlusion and radiometric change occurs. Ultimately, the model is more and more accurate when the baseline becomes small. A new correlation-based method for small baseline stereo vision known as the Multi resolution Algorithm for Refined Correlation (MARC) is introduced in [9], which computes disparities between  $u$  and  $\tilde{u}$  by maximizing a local similarity coefficient between images(the normalized cross correlation):

$$m(x_0) = \arg \max_m \frac{\langle \tau_m u, \tilde{u} \rangle_{\varphi_{x_0}}}{\|\tau_m u\|_{\varphi_{x_0}} \|\tilde{u}\|_{\varphi_{x_0}}} \quad (2)$$

where  $m(x_0)$  is a evaluated disparity of the pixel  $x_0$  of interest,  $\varphi_{x_0} = \varphi(x_0 - x)$  denotes a support window centered at  $x_0$ ,  $\tau_m u$  denotes the shifted image  $u(x - m)$ ,  $\langle \cdot, \cdot \rangle_{\varphi_{x_0}}$  denotes the corresponding scalar product  $\langle \tau_m u, \tilde{u} \rangle_{\varphi_{x_0}} = \int \varphi_{x_0}(x) \tau_m u(x) \tilde{u}(x) dx$ , and  $\|\cdot\|_{\varphi_{x_0}}$  denotes weighted norm. Let  $m(x_0)$  be the

shift which maximizes the normalized cross correlation, the derivative of the normalized cross correlation at  $m(x_0)$  equals zero. Under the assumption that  $|\varepsilon(x) - m(x_0)|$  is small enough, this equation gives

$$m(x_0) = \frac{\langle d_{x_0}^{\tau_m u}, \varepsilon(x) \rangle_{\varphi_{x_0}}}{\langle d_{x_0}^{\tau_m u}, 1 \rangle_{\varphi_{x_0}}} + \langle \omega^m, g_b \rangle_{\varphi_{x_0}} \quad (3)$$

Where

$$\omega^m(x) = \frac{\|\tau_m u\|_{\varphi_{x_0}}^2 \tau_m u'(x) - \tau_m u(x) \langle \tau_m u, \tau_m u' \rangle}{\|\tau_m u\|_{\varphi_{x_0}}^2 \langle \tau_m u', \tau_m u' \rangle_{\varphi_{x_0}} - \langle \tau_m u, \tau_m u' \rangle^2} \text{ and}$$

$$d_{x_0}^u : x \rightarrow \frac{\|u\|_{\varphi_{x_0}}^2 u'^2(x) - \langle u, u' \rangle_{\varphi_{x_0}} u(x)u'(x)}{\|u\|_{\varphi_{x_0}}^4}.$$

As shown in (3), the disparity at  $x_0$  is not true disparity, but the sum of the true disparities weighted by its correlation density in the window and the noise term. Hence, matching error is divided into two parts: one part is caused by the violation of the fronto-parallel plane assumption and the other part is caused by image noise. In matching process, two errors can be decreased to improve matching accuracy.

### 3. Key Steps of the Proposed Algorithm

#### 3.1. Adaptive Support-Weight

The first part of the matching error for evaluated disparities is generated by the true disparities weighted by its correlation density  $d_{x_0}^u(x)$  in the window centered at  $x_0$ :

$$\frac{\langle d_{x_0}^{\tau_m u}, \varepsilon(x) \rangle_{\varphi_{x_0}}}{\langle d_{x_0}^{\tau_m u}, 1 \rangle_{\varphi_{x_0}}} = \frac{\int d_{x_0}^{\tau_m u}(x) \varepsilon(x) \varphi_{x_0}(x) dx}{\int d_{x_0}^{\tau_m u}(x) \varphi_{x_0}(x) dx} \quad (4)$$

Suppose that all pixels within the support window have constant disparity  $c$ , equation (4) is rewritten as:

$$\frac{\langle d_{x_0}^{\tau_m u}, \varepsilon(x) \rangle_{\varphi_{x_0}}}{\langle d_{x_0}^{\tau_m u}, 1 \rangle_{\varphi_{x_0}}} = \frac{\int d_{x_0}^{\tau_m u}(x) \varphi_{x_0}(x) c dx}{\int d_{x_0}^{\tau_m u}(x) \varphi_{x_0}(x) dx} = c \quad (5)$$

Equation (5) shows that if an image pair meets the fronto-parallel plane assumption, then the first part of the matching error is removed. However, if some parts of an image pair can't meet the assumption, then the foreground fattening problem occurs. In order to reduce this error, this paper presents the matching cost aggregation based on adaptive support weight. In this method, the adaptive support weight is modified by adding the correlation density  $d_{x_0}^u(x)$ :

$$\varphi(x_0 - x) = \frac{\rho(x_0 - x)}{d_{x_0}^{\tau_m u}(x)} \quad (6)$$

Substituting equation (6) into equation (4), equation (4) is reduced to

$$\frac{\langle d_{x_0}^{\tau_m u}, \varepsilon(x) \rangle_{\varphi_{x_0}}}{\langle d_{x_0}^{\tau_m u}, 1 \rangle_{\varphi_{x_0}}} = \frac{\int \varepsilon(x) \rho(x_0 - x) dx}{\int \rho(x_0 - x) dx} \quad (7)$$

Suppose that window function  $\rho$  is a smooth, positive, normalized and compactly supported function:

$$\int \rho(x_0 - x) dx = 1 \quad (8)$$

Substituting equation (8) into equation (7), equation (7) is given by

$$\frac{\langle d_{x_0}^{\tau_m u}, \varepsilon(x) \rangle_{\varphi_{x_0}}}{\langle d_{x_0}^{\tau_m u}, 1 \rangle_{\varphi_{x_0}}} = \int \varepsilon(x) \rho(x_0 - x) dx \quad (9)$$

Equation (9) shows that the first part of an evaluated disparity becomes the true disparities weighted by the corresponding window function, not including correlation density  $d_{x_0}^u(x)$ . This can effectively weaken the foreground fattening problem and improve matching accuracy. To avoid too small correlation density due to noise, we shall use the following weight function:

$$\varphi(x_0 - x) = \frac{\rho(x_0 - x)}{\max(d_{x_0}^{\tau_m u}(x), \gamma)} \quad (10)$$

Where  $\gamma$  is the normalized constant. Considering the symmetry, correlation density functions of the left and right images are added to the support weight function:

$$\varphi(x_0 - x) = \frac{\rho(x_0 - x)}{\max(d_{x_0}^{\tau_m u}(x), \gamma) \times \max(d_{x_0}^{\hat{u}}(x), \gamma)} \quad (11)$$

In order to reduce the foreground fattening problem, this paper presents a new adaptive support weight, in which correlation density functions are added to adaptively adjust matching costs to achieve this purpose.

### 3.2. Adaptive Window

The second part of the matching error for evaluated disparities is produced by random noises in images. Since the analytic expression of this error is a function with respect to a support window, the support window is resized to make this error less than a given threshold to improve matching accuracy. Because the random noises in images are unknown, the analytical expression of the error can not be obtained. However, we can get an analytical expression of the upper bound of the error, which can be used to limit this error and calculate window size. According to the Cauchy–Schwarz inequality, we have

$$\langle \omega^m, g_b \rangle_{\varphi_{x_0}} \leq \|\omega^m\|_{\varphi_{x_0}} \|g_b\|_{\varphi_{x_0}} = \frac{\|g_b\|_{\varphi_{x_0}}}{\|\tau_m u\|_{\varphi_{x_0}} \sqrt{\langle d_{x_0}^{\tau_m u}, 1 \rangle_{\varphi_{x_0}}}} \quad (12)$$

The norm of the noise function in equation (12) can be approximated by

$$E\left(\|g_b\|_{\varphi_{x_0}}^2\right) = E\left(\int_{\varphi_{x_0}} \left(\int g(x-t)b(t) dt\right)^2 dx\right) \leq \int \varphi_{x_0}(x) \|g_b\|_{L^2}^2 \sigma_b^2 dx = \sigma_b^2 \|g_b\|_{L^2}^2 \quad (13)$$

Substituting equation (13) into equation (12), the analytical expression of the upper bound of the error can be approximated by

$$N(\tilde{u}, g, \sigma_b, \varphi, x_0) = \frac{\sigma_b \|g\|_{L^2}}{\|\tilde{u}\|_{\varphi_{x_0}} \sqrt{\langle d_{x_0}^{\tilde{u}}, 1 \rangle_{\varphi_{x_0}}}} \quad (14)$$

Equation (14) shows that for a given amount of noise, the larger the correlation density, the smaller the error induced by the noise bias at  $x_0$ . So, more reliable matches can be obtained. In the predefined window range, the window size is chosen to make equation (14) less than the predefined amount of noise. At the same time, this size must be as small as possible if we want the computed disparity  $m(x_0)$  to be a good approximation of the true disparity  $\varepsilon(x_0)$ . Hence, the support window size can be chosen as the smallest size such that

$$W_{opt}(x_0) = \min \left\{ \varphi_{x_0} \left| \frac{\sigma_b \|g\|_{L^2}}{\|\tilde{u}\|_{\varphi_{x_0}} \sqrt{\langle d_{x_0}^{\tilde{u}}, 1 \rangle_{\varphi_{x_0}}}} < \alpha \right. \right\} \quad (15)$$

Where  $\alpha$  is the desired precision. Points where this inequality can be met for a given window size are called reliable points, otherwise called unreliable points. We can expect the chosen size to be small at informative points and larger in flat zones. In matching process, only disparities of reliable points are evaluated, and disparities of unreliable points are filled in the disparity post processing stage.

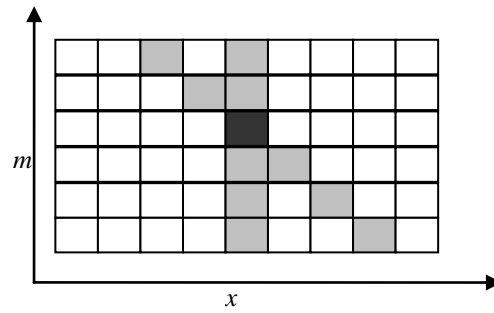
### 3.3. Reliable Constraints

In order to remove mismatches, reliable constraints are imposed on the matching process:

$$C(p, m_p^{best}) \geq \lambda C(p, m'), \forall m' \neq m_p^{best} \quad (16)$$

$$C(p, m_p^{best}) \geq \lambda C(p', m'), \forall p' + m' = p + m_p^{best} \quad (17)$$

Where  $C(p, m_p^{best})$  is the normalized cross correlation for assigning the disparity  $m_p^{best}$  to the pixel  $p$ , and  $\lambda \geq 1$  denotes confidence level. Equation (16) works on the vertical gray cells corresponding to possible candidate matches of the pixel  $p$  in the right image shown in Figure 1, which shows that the matching cost  $C(p, m_p^{best})$  is significantly larger than other matching costs on vertical gray cells, so the disparity  $m_p^{best}$  is reliable. Equation (17) works on the left-slanted gray cells corresponding to possible candidate matches of the pixel  $p + m_p^{best}$  in the left image shown in Figure1, which shows that the matching cost  $C(p, m_p^{best})$  is significantly larger than other matching costs on the left-slanted gray cells. The constraint is stronger than the left-right consistency. Those matches meeting these constraints are more reliable, and most of mismatches can be removed.



**Figure 1. Reliable Constraints**

### 3.4. Disparity Post Processing

In the adaptive window stage and the matching stage, this proposed small baseline stereo matching method produces some unreliable points, the disparities of which not are computed. Hence, the proposed method gives a sparse disparity map. In order to obtain a dense disparity map, the disparities of unreliable points are calculated based on those disparities of reliable points. To this end, this paper presents a disparity post processing method based on iterative diffuse using a new cost function to obtain a dense disparity map.

Firstly,  $M$  denotes the sparse disparity map generated by the proposed small baseline stereo matching method. The sparse disparity map is made of two kinds of points: one kind is a reliable point, the disparity of which is  $M(p) \neq 0$ ; the other kind is called an unreliable point, the disparity of which is  $M(p) = 0$ . A new cost value is computed for each pixel  $p$  at each disparity level  $m$  as

$$C(p, m) = \begin{cases} |m - M(p)|, & M(p) \neq 0 \\ 0, & M(p) = 0 \end{cases} \quad (18)$$

Note that for all unreliable pixels, the cost value  $C(p, m)$  will be zero for all disparity levels, thus will completely depend on the reliable pixels. If a winner-take-all selection is applied to this new cost volume, then the disparity values of the reliable pixels will be the same as disparity map  $M$ , and the rest zero.

In order to compute disparities of unreliable pixels, the matching costs of reliable pixels are diffused into unreliable pixels. The matching cost is computed for each pixel  $p$  at each disparity level  $m$  as

$$C_n(p, m) = \frac{1}{|N_p|} \sum_{q \in N_p} C_{n-1}(q, m) \quad (19)$$

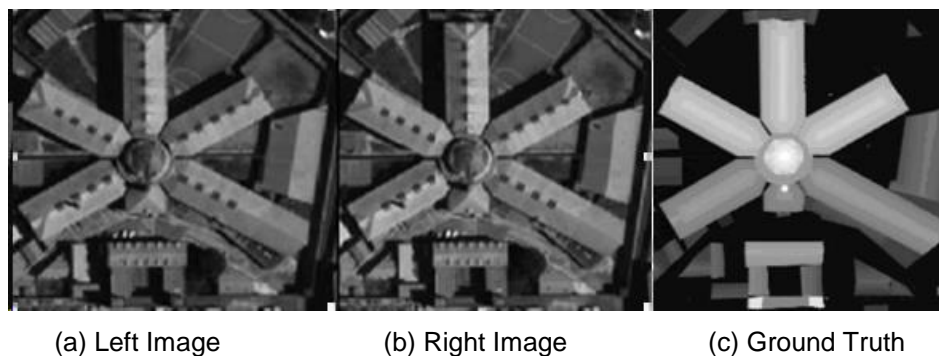
Where  $N_p$  denotes a support window,  $|N_p|$  denote the support window size, and  $C_n(p, m)$  denotes the matching cost at  $n$ th iteration. With a winner-take-all selection, the disparities of unreliable pixels are given by

$$m(p) = \arg \min_m C_n(p, m), p \in \{p | M(p) = 0\} \quad (20)$$

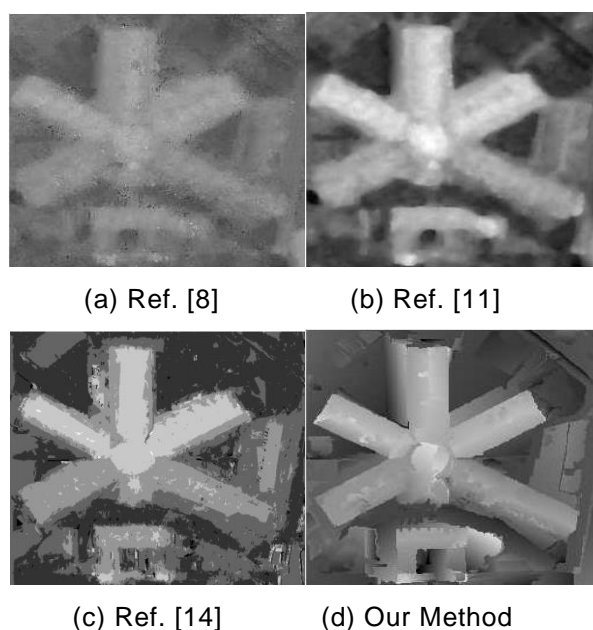
## 4. Experimental Results

### 4.1. Experimental Environments

The proposed algorithm was implemented using C++. Our experiments were conducted on a desktop with Core Intel 2.6 GHz CPU and 4 GB RAM by using the image pair of Toulouse and the stereo image pairs provided by the benchmark Middlebury database.



**Figure 2. The Stereo Image Toulouse**



**Figure 3. Results on the Toulouse**

### 4.2. Accuracy Analysis

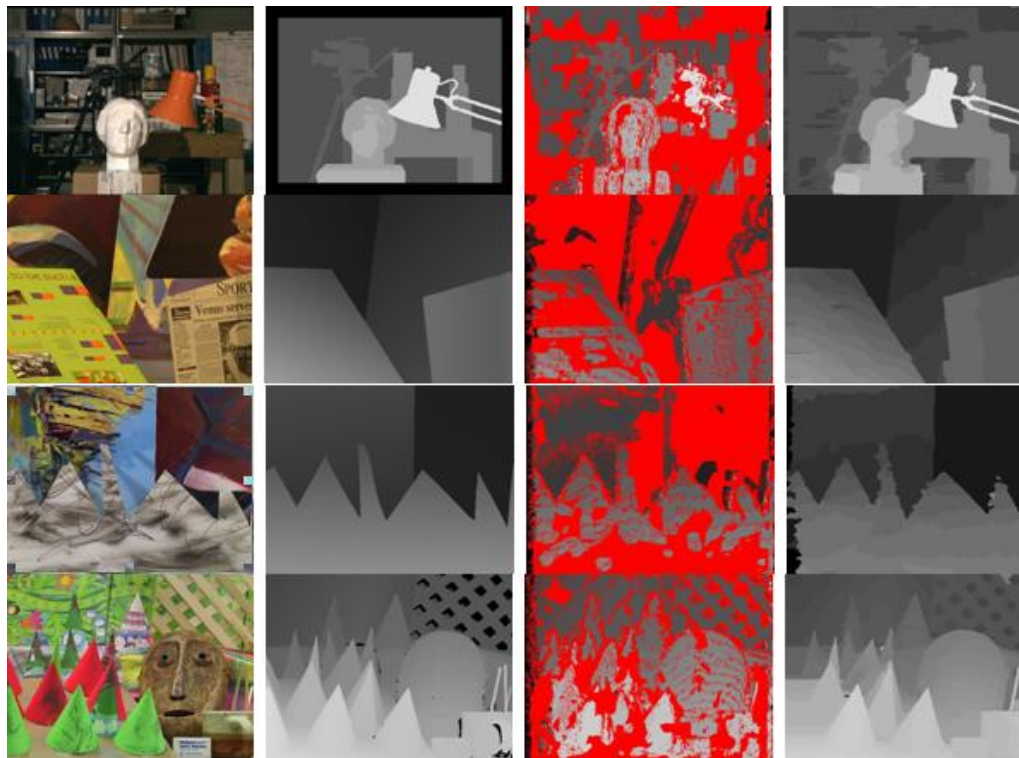
Figure 2 shows a small baseline stereo image of Toulouse with the baseline-to-height ratio of 0.045 and the size  $512 \times 512$ . Figure 3 shows the experimental results of the proposed method and the small baseline stereo matching methods in references [8, 11, 14]. The experimental results show that in the disparity map of the proposed method, the edges of objects in the scene are not fattening and the details of the scene are also evaluated.

In Table 1 we summarize the RMSE measurements of the different methods applied to the data set. The first column indicates the proposed method. In the second to forth columns we report the RMSE for small baseline stereo matching

methods in references [8, 11, 14]. Note that the values of the RMSE are given in pixels. Analyzing the data in Table 1, we observe that the RMSE measures given by the proposed method are smaller than the ones obtained by references [8, 11, 14].

**Table 1. Comparison of the Proposed Method with Ref. [8, 11, 14]**

	our method	Ref.[8]	Ref.[11]	Ref.[14]
RMSE	0.15	0.32	0.26	0.25



(a) Stereo Images (b) Ground Truth (c) Reliable Disparities (d) Computed Disparities

**Figure.4 Results on the Middlebury Dataset**

In this experiment, we evaluate our algorithm on the Middlebury data set and we show the experimental results in Figure4. In Figure4, the stereo images of Tsukuba, Venus, Sawtooth and Cones, and their corresponding true disparity maps, reliable disparity maps and computed disparity maps are displayed from top to bottom. The performance of the proposed method is summarized in Table 2. The Figures shown in Table 3 represent the percentage of the bad pixels with an absolute disparity error greater than one for different regions; they are non-occluded (nocc), whole image (all) and pixels near discontinuities (disc). It is demonstrated that the proposed algorithm outperforms other algorithms in terms of the bad pixels error. Because an adaptive window is combined with an adaptive weight to aggregate matching costs in the proposed algorithm, the foreground fattening problem is reduced, resulting in low percentage of the bad pixels in discontinuity regions. The experimental results show that the proposed method has low percentage of the bad pixels and works well on a variety of scenes. So it is an efficient and reliable small baseline stereo matching method.



**Table 2. Comparison of the Proposed Method with Ref. [3,4,9,11]**

algorithm	Tsukuba			Venus			Sawtooth			Cones		
	<i>non-occ</i>	<i>all</i>	<i>disc</i>	<i>non-occ</i>	<i>all</i>	<i>disc</i>	<i>non-occ</i>	<i>all</i>	<i>disc</i>	<i>non-occ</i>	<i>all</i>	<i>disc</i>
Our algorithm	1.19	1.71	4.24	0.20	0.40	2.75	3.20	7.40	10.80	2.36	7.40	6.10
Ref.[3]	1.45	1.99	7.59	0.40	0.81	3.38	4.65	8.30	13.20	3.48	9.34	8.81
Ref. [4]	1.41	1.53	6.83	0.24	0.42	3.02	3.88	8.50	15.10	2.83	7.78	7.50
Ref. [9]	5.17	6.08	21.70	0.95	1.73	12.00	5.04	8.10	19.90	3.59	9.02	10.70
Ref. [11]	1.99	2.84	9.96	1.41	2.10	7.74	12.90	20.90	24.10	10.00	18.30	18.90

## 5. Conclusion and Future Work

In this paper, after we conducted deep analysis of existing small baseline stereo matching methods, we designed and implemented a new small baseline stereo matching method. In the proposed method, an adaptive weight was proposed and combined with an adaptive window to aggregate matching costs for the reduction of the foreground fattening problem. Secondly, reliable constraints were imposed on the disparity computing process to remove mismatches. Finally, a disparity post processing method based on iterative diffuse using a new cost function was proposed to replace those unreliable points. The experimental results showed that this method can effectively reduce the percentage of the bad pixels of depth discontinuity areas, improve the overall disparity matching accuracy and meet the requirements of small baseline three-dimensional reconstruction.

This paper mainly studied the problem of the matching accuracy and the computation of disparities of unreliable points. In the future, the proposed method will be speeded up using GPU. In addition, the shadow in the stereo images is also the main reason for affecting the matching accuracy and we shall solve this problem in future research.

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## Authors

**Jilong Bian**, was born in Nehe, Qiqihaer, China in 1982. He received the Bachelor of Management in Information Management and Information System, Master of Engineering degree in Technology of Computer Application, from the Northeast Forestry University, Harbin, China, in 2005 and 2008 respectively. He is currently a Lecturer in the Department of Information and Computer Science in the Northeast Forestry University. His research interests include Pattern Recognition, Image Processing and Stereo Matching.

**Jinfeng Li**, was born in Fangzheng, Harbin, China in 1981. She received her Bachelor of Engineering degree in Computer Science and Technology from the Mudanjiang Normal University, Mudanjiang, China, in 2003 and the Master of Engineering degree in Technology of Computer Application from College of Information and Computer Engineering, Northeast Forestry University, Harbin, China, in 2008. Her major field of study is Stereo Matching.

She is currently an associate professor in the engineering college in the Mudanjiang Normal University. Her research interests include Image Processing, Computer Vision and Stereo Matching.

**Nana Wang**, received the PhD degree in Computer Applied Technology from College of Computer Science and Technology, Harbin Engineering University, Harbin, China, in 2015. She is now a lecturer of School of Computer Science and Technology, Jiangsu Normal University. Her research interests include fragile watermarking, reversible watermarking, integrity authentication and multimedia security.

**Liu Yang**, was born in Jilin, China in 1969. She received her Bachelor of Engineering degree in Computer Engineering, Master of Engineering degree in Technology of Computer Application, from the Northeast Normal University, Changchun, Jilin, China, in 1992 and 1995 respectively. She is currently a professor in the engineering college in the Mudanjiang Normal University. Her research interests include Wireless Sensor Networks and Operating System.