

# An Efficient Relative Gradient Based Radiometric Invariant Stereomatching Using Guided Filter

Sarika S, Deepambika V. A, M. Abdul Rahman

**Abstract** — Stereomatching algorithms provide a better disparity map only when the stereo image pairs under consideration are under similar radiometric conditions, but under real world scenarios this condition may not hold. As a result of this corresponding pixels in the left and right image will be at different intensities and most of the state of the art stereomatching algorithm fails to provide a better disparity map. To overcome this issue this paper proposes a relative gradient based approach. Also in order to have better edge preservation and faster result guided filter based cost aggregation is used. The result shows that the proposed method performs well under varying radiometric conditions where the conventional state of the art stereomatching algorithms fail.

**Index Terms**— Stereomatching, Radiometric variations, Relative gradient, Guided filter

## I. INTRODUCTION

The performance of stereomatching algorithms are based on the pixel intensity values so only when the corresponding pixels in the left and right images are at similar intensities it performs well. The most challenging task of this field is the stereo correspondence which aims at finding the corresponding matching pixels between 2 images. Many stereocorrespondence algorithms have been developed in recent years for getting an accurate disparity map and in most of the cases satisfactory results have been obtained. Stereocorrespondence algorithm can be basically classified into two types, global and local methods<sup>1</sup>. Global methods can produce accurate disparity map comparable to local methods, but computationally it is very expensive and time consuming. On the other hand local methods achieve satisfactory results quickly and is very appropriate for real time applications, However this method does not produce accurate results in the textureless areas and near depth discontinuities and researches are still going on to solve these issues in local methods. Stereocorrespondence method consists of four steps<sup>1</sup>: (1) matching cost computation (2) cost aggregation (3) disparity computation/optimization (4) disparity refinement. Global methods do not involve step 2. Matching cost can be pixel based like absolute difference (AD), squared intensity difference (SD) etc. In local methods cost aggregation step involves the aggregation of matching cost over a window which depends on the intensity values of images and usually makes some implicit smoothness assumptions. Most of the local stereo algorithm works well only when the input image pairs are under similar radiometric conditions.

It is based on the assumption that pixel intensity value in the left image and right image is the same. But in real world scenario this may not hold, there may be variations in the intensity values between the two images due to radiometric conditions. The radiometric variations include illumination variations and exposure changes. Due to these variations stereocorrespondence search becomes very difficult. In related works to compensate for radiometric variations several algorithms and matching cost that are invariant to radiometric variations have been proposed. Hirschmuller and Scharstein<sup>2</sup> evaluated the performance of several cost values that is insensitive to radiometric variations. Heo<sup>3</sup> used adaptive normalized cross correlations as a radiometric invariant cost value. Cumulative Distribution of gradient values<sup>4</sup> which is based on the ordering of pixels and Rank transform<sup>5</sup> which depends on the rank intensity values of the pixels are another popular methods to overcome radiometric issues. For cost aggregation to avoid edge fattening Veksler<sup>6</sup> adopted an adaptive window based approach and Kang *et.al*<sup>7</sup> adopted a multiple window based method. Both these approaches improve the matching result to a certain extent but the size and shape of the window are restricted in these approaches. Yoon and Keon<sup>8</sup> proposed an adaptive support weight aggregation which is actually bilateral filtering where the window size is fixed, but the pixels in the window have different weights depending on the colour proximity and similarity compared to the center pixel and Gestalt law. Even though it provides good result near depth discontinuities the execution time is very long and hence not apt for real time applications. Guided filtering<sup>9,10</sup> based cost aggregation proved to be the better performing local correspondence method. It is very fast compared to bilateral filtering and hence is suitable for real time applications. In this paper, to compensate for radiometric variations, Relative Gradient<sup>11</sup> based approach is used. The matching cost computation is based on Absolute difference value. For cost aggregation Guided filter weight is adopted. The disparity value is then computed using winner-take all optimization (WTA) and left-right consistency check. Finally median filtering is performed as a post processing step to get the final disparity map. The rest of the paper is organized as follows, the proposed algorithm is described in section 2. In section 3 experimental results of the proposed algorithm is compared with conventional SAD based stereomatching algorithm. Section 4 provides the conclusion.

## II. PROPOSED METHOD

In order to compensate for radiometric variations like exposure and illumination changes, first relative gradient of pixels are found out as a pre-processing step. Absolute difference (AD) is taken as the matching cost which is used to find out the pixel correspondence. For getting an accurate disparity map the cost value is aggregated over a window

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using guided filter. Finally the disparity value is selected by choosing the minimum aggregated cost value corresponding to every pixel using winner take all optimization (WTA).

### A. Relative Gradient

Relative gradients, consider both the view independent and view dependent colors, so it can deal with both color and gray scale images. There are basically two lighting models:

The first model is represented as:

$$C = \epsilon b \quad (1)$$

The second model is represented as:

$$C = m_b \epsilon b + m_s \epsilon \quad (2)$$

Relative gradient approach is based on the following complete lighting model

$$C = m_b \epsilon b + a + m_s \epsilon \quad (3)$$

Where  $m_b \epsilon b + a$  is the view independent term which deal with body reflection and  $m_s \epsilon$  is the view dependent term which deals with the surface reflection.  $m_b$  is the weight coefficient for view independent term and  $m_s$  is the weight coefficient for view dependent term and  $\epsilon$  is the illumination energy. The relative gradient of a pixel can be expressed as:

$$R(i,j) = \text{gradient}(i,j) / \text{maximalgradient}(i,j) + 1 \quad (4)$$

Considering the lighting conditions are same in local window under consideration the gradient operation compensates for the view dependent information. After performing the gradient operation the images will differ in the illumination energy so normalization is performed after gradient operation in order to eliminate the effect of illumination energy.

### B. Matching Cost Value.

After computing the relative gradient of each pixels corresponding point is matched using absolute difference value to extract the disparity value since it is the fastest approach. The cost value using absolute difference (AD) is given by:

$$AD = |I_1(i,j) - I_2(i + d, j)| \quad (5)$$

Where  $d$  is the disparity range.

### C. Cost Aggregation Using Guided Filter

In this step the matching cost value computed is aggregated over a window. In order to get satisfactory result near depth discontinuities and textureless region, matching cost is aggregated using guided filter. The advantage of using guided filter is that it has better edge preserving property and is very fast compared to the bilateral filtering. The aggregated cost value with guided filter is given by:

$$C_{agg}(p, d) = \sum_q W_{p,q}(I) C_{reensus}(p, d) \quad (6)$$

where  $C_{agg}(p, d)$  is the filtered cost value of the pixel  $p$  for each slices of  $d$ .  $W_{p,q}(I)$  is the weight of the guided filter which depends on  $I$ , which is the reference image. Here the guidance image is the left image which is used to filter the guided image which is the  $(x, y)$  slices of the cost volume<sup>10</sup>. For a gray scale guidance image  $I$  the filter weight can be simply given by:

$$W_{p,q}(I) = \frac{1}{|w|^2} \sum_w \mathbf{1} + \frac{(I_p - \mu_k)(I_q - \mu_k)}{\sigma_k^2 + \epsilon} \quad (7)$$

where  $\mu_k$  and  $\sigma_k^2$  are mean and variance of the guidance image over the window  $w$  centred at pixel  $k$  with dimension  $\gamma \times \gamma$ .  $\epsilon$  is the smoothness parameter. For colour images filter weights can be given by:

$$W_{p,q}(I) = \frac{1}{|w|^2} \sum_{k \in p, q \in w} \mathbf{1} + \frac{(I_p - \mu_k) - (\epsilon_k - \epsilon U) - (I_q - \mu_k)^T}{\epsilon_k - \epsilon U} \quad (8)$$

where  $I_p, I_q$  and  $\mu_k$  are the  $1 \times 3$  vectors,  $U$  is a  $3 \times 3$  identity matrix and  $\epsilon_k$  is the covariance matrix.

### D. Disparity Optimization and Disparity refinement

After the cost volume filtering, final disparity value for each pixel is fixed by selecting the minimum value from the aggregated cost value using winner take all optimization (WTA). In disparity refinement stage the disparity of the right image is computed in the same way as the left image (reference image). Then a left right consistency check is performed to detect the occluded areas and then the holes due to occlusion are filled by the disparities of the neighbouring pixels. Finally a median filter is applied as a post processing step to get the final dense disparity map.

## III. EXPERIMENT RESULT

The performance of the algorithm is evaluated on Middlebury dataset<sup>12</sup>. The experiments are conducted on both radiometrically clean and radiometric invariant images in order to find out the robustness of the method to radiometric variations. The experiment is performed on the windows 8 operating system with Intel core i5 processor. The parameters used are  $\{\epsilon, \gamma\} = \{0.0001, 9\}$ . To quantitatively evaluate the performance of algorithm on radiometrically clean images, percentage of bad pixels<sup>1</sup> is calculated in Non-occluded regions with error threshold greater than 1. The test is conducted on standard stereo pair Cone, Teddy and Venus. The results are shown in Table 1. The data shows that proposed method is much better than the most commonly used conventional stereomatching algorithm SAD. The result of applying gradient on radiometric variant images are shown in fig (3) and fig (4). The results shows it overcome the variations in the image.

**Table 1: Percentage of bad pixels for non-occluded pixels**

Method	Teddy	Cone	Venus
SAD	20	12	4.2
Proposed Method	12.6	8.2	3.8



**Fig. 1. Aloe (left)**



Fig. 2. Aloe (right).

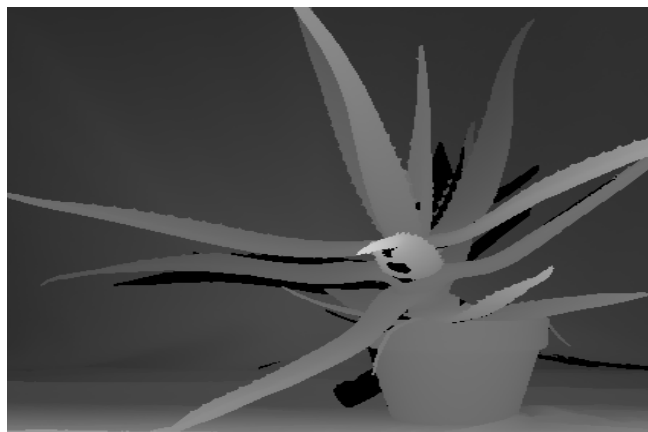


Fig. 5. Groundtruth Aloe

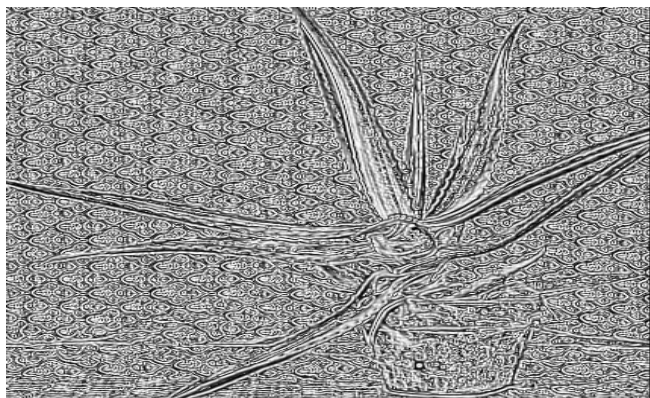


Fig. 3. Relative gradient Of Aloe(left)

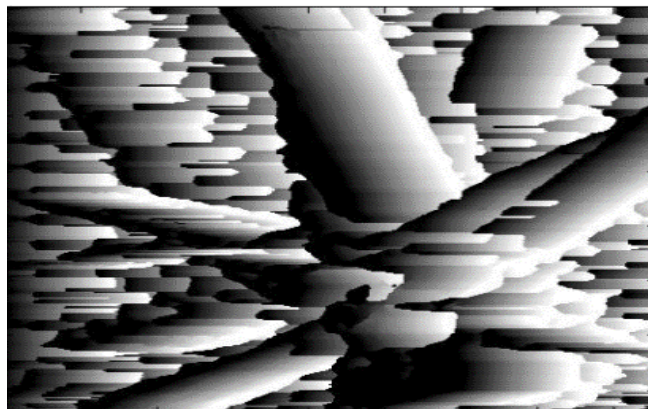


Fig. 6. SAD result

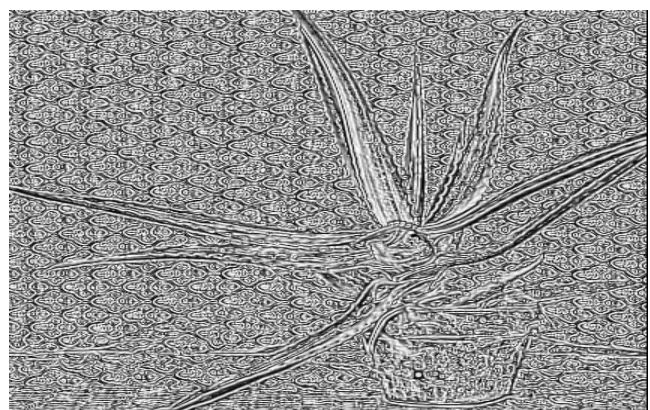


Fig. 4. Relative gradient of aloe(right)

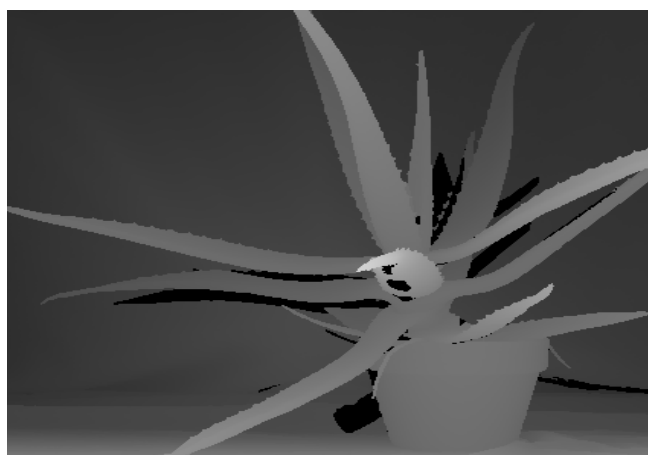


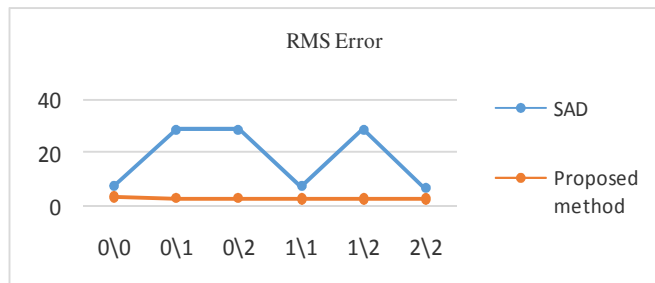
Fig.7. Groundtruth Aloe

Robustness of the method to radiometric variations is tested on image set (Aloe, Baby1). The image set used for the experiments is captured under 3 different exposure conditions(exp0,exp1,exp2)and three different illumination conditions(Illum1,Illum2,Illum3). The disparity maps obtained using SAD and proposed algorithm under varying exposure conditions with illumination condition fixed at Illum1for Aloe and Baby1 are shown in fig(6) and fig(8) respectively. The result shows that the SAD algorithm is very sensitive to radiometric variations while the proposed method yields satisfactory result under varying radiometric conditions and the computational time for the proposed algorithm is 38s.

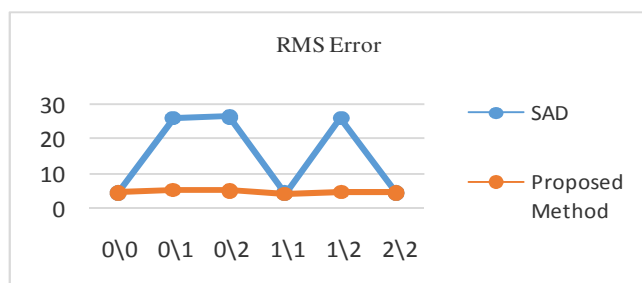


Fig. 8. Proposed Method

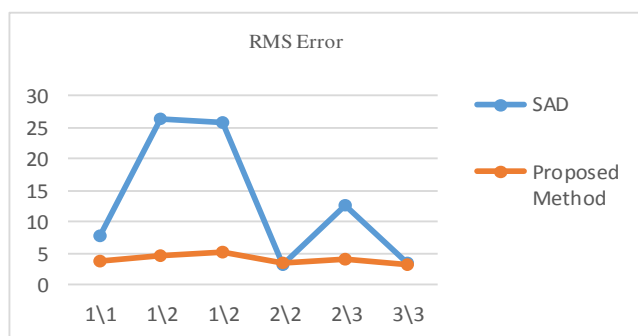
To quantitatively compare the performances of the algorithms, the RMS error<sup>1</sup> of the computed disparity map against the ground truth disparity is calculated. Fig (9) and Fig (10) represent the RMS errors of the algorithms under varying exposure condition with illumination condition fixed at Illum1 and varying illumination condition with exposure condition fixed at exp2 respectively of Baby1 and Aloe images. From the result we can see that the proposed algorithm gives much smaller RMS error than the SAD algorithm, and the computational time for the proposed algorithm is 19secs.



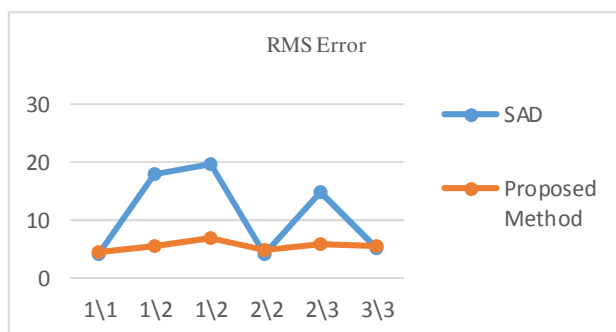
**Fig. 9. a. RMS Error of Baby 1 under different exposure condition**



**Fig. 9. b. RMS Error of Aloe under different exposure condition**



**Fig. 10. a. RMS Error of Aloe under different lighting conditions**



**Fig. 10. b. RMS Error of Aloe under different lighting conditions**

## IV. CONCLUSION

A local stereomatching algorithm for images taken under varying radiometric conditions using Relative Gradient is done. For the transformed image Absolute difference (AD) is considered for the similarity measurement. For cost aggregation guided filtering is adopted. Experimental result gives good result for images under varying radiometric conditions and performs much better than the conventional SAD based stereomatching algorithm.

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