A Robust Stereo-Matching Algorithm Using Multiple-Baseline Cameras

Jeonghee Jeon*, Kyungsu Kim*, Choongwon Kim**, Yo-Sung Ho*

* Kwangju Institute of Science and Technology (K-JIST)
1 Oryong-Dong Puk-Gu, Kwangju, 500-712, Korea
Email: {jhjeon,arieskim,hoyo}@kjist.ac.kr

** College of Electronics and Information Engineering, Chosun University
375 Seosuk-Dong Dong-Gu, Kwangju, 501-759, Korea
Email: cwkim@chosun.ac.kr

ABSTRACT

Calculating the distance of various points in the scene relative to the camera position is one of the important tasks in stereovision systems. A fundamental problem in stereovision is to find corresponding pixels, points, or other features in both the left and right images that are taken from stereo cameras. For precise measurement and correct matching of repetitive patterns, a multiple-baseline stereo (MBS) algorithm has been proposed. In this paper, we develop a robust multiple-baseline stereo (RMBS) algorithm to solve continuous as well as repetitive multiple local minima through an adaptive window. Experimental results with both synthetic and natural scenes demonstrate that RMBS is faster in the processing speed than MBS by 24.1%. In addition, the proposed RMBS algorithm is robust to different types of multiple local minima.

1. INTRODUCTION

A common method for extracting depth information from intensity images is the stereo vision, which acquires a pair of images using two cameras displaced from each other by a known distance, solves the correspondence problem and then computes the distance of various points using triangulation [1,2]. Stereo correspondence is the problem of finding points in two or more images of the same scene, usually assuming known camera geometries. However, a critical issue in the stereovision is to find corresponding pixels, points, or other features both in stereo images taken from two cameras.

Various algorithms with certain constraints have been proposed to reduce possibility of false matches, but many problems still remain in stereo correspondence. Some of these problems include occlusion, depth discontinuity, and repetition. The depth information from corresponding points is more precise if we set the two cameras further apart from each other, which means a longer baseline. However, it poses its own problem. Since we need to search a larger disparity range, there is more possibility of a false match.

A multiple-baseline stereo (MBS) algorithm using the sum of sums of absolute differences function has been proposed to overcome this dilemma [3,5]. MBS processes several images taken from multiple cameras, which provide different baselines relative to the base camera. While stereo matching with a shorter baseline ensures correctness of matching, stereo matching with a longer baseline provides more precise depth. Therefore, the stereo matching operation using several images of different baselines can improve the performance. If there are continuous multiple local minima in stereo images, it is difficult to find correct matching by MBS. These multiple local minima usually occur in the shinning area of images by illumination.

In this paper, we develop a robust multiple-baseline stereo (RMBS) algorithm that can deal with continuous and repetitive multiple local minima using an adaptive window.

2. THE RMBS ALGORITHM

2.1 Multiple-Baseline Stereo

A simple but elegant multiple-camera matching method was suggested using all pictures at the same time [4]. Assuming that stereo images are rectified, they replace search for correct disparities by search for the correct depth, or rather its inverse. Although disparity varies from camera to camera, the inverse depth is proportional to the disparity for each camera; therefore, the inverse depth can be used as the common search index.

$$z = \frac{BF}{d} \tag{1}$$

or

$$d = B \cdot F \frac{1}{z} \tag{2}$$

where B represents the baseline from the base camera, F is the focal length of the camera lens, and d is the disparity. For multiple baselines, we calculate

$$\frac{d}{B} = F\frac{1}{z} = \zeta \tag{3}$$

where ζ is a constant. After selecting the left-most image as the reference image, they add up the sums of absolute differences (SAD) associated with all other cameras into a global evaluation function [3].

Fig. 1 shows the sums of SADs (SSAD) as a function of the inverse depth for all images included in the calculation.

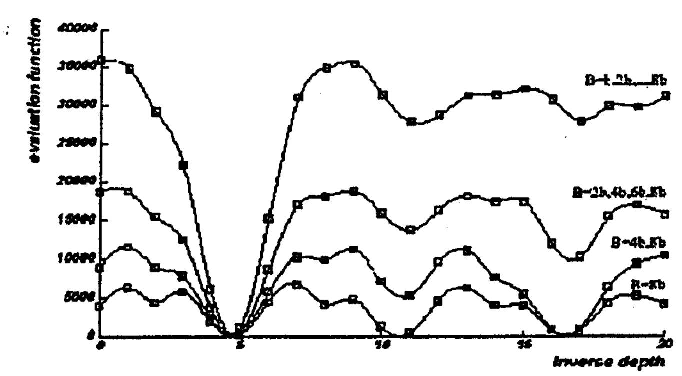


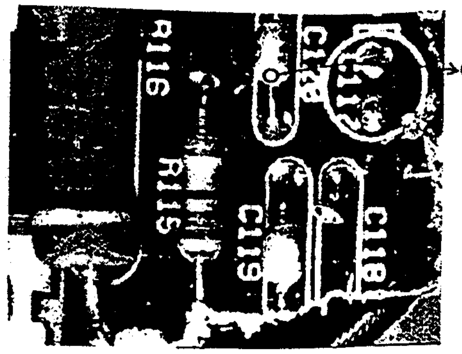
Figure 1. Sum of the Sums of Absolute Differences

As indicated in Fig. 1, if corresponding images contain any repetitive patterns, it is difficult to find a single well-defined minimum SAD value using only two or three cameras. If we include more cameras in the SSAD calculation, we can increase the chance to find a clear minimum SAD value corresponding to the correct match.

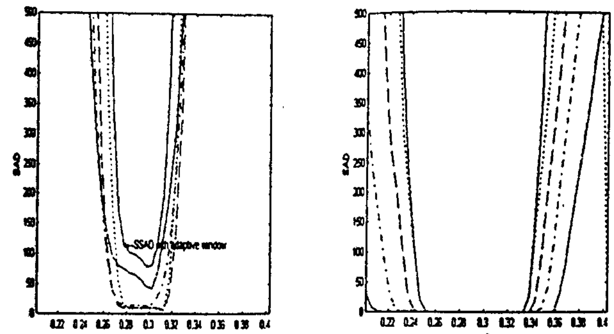
For the case of continuous multiple local minima, however, we cannot determine the correct match by MBS because all SADs of each baseline image become zero, i.e., MBS does not work well in regions of continuous patterns. In addition, MBS needs some processing time to interpolate ζ.

If all stereo image pairs are the same, values of ζ should be the same because distances from cameras to the point in the scene are equal, which means $\zeta_1 \fallingdotseq \zeta_2 \fallingdotseq \zeta_3 \fallingdotseq \ldots \fallingdotseq \zeta_n$.

In order to solve the problems of MBS, we propose a robust MBS (RMBS) algorithm using an adaptive window [5]. Fig. 2(a) shows one of the multiple-baseline stereo images acquired by a single camera with four baselines. Fig. 2(a) contains continuous multiple local minima at (388,85) due to the illumination. We assume that the stereo cameras are set up in parallel and camera parameters are known. Fig. 2(b) and Fig. 2(c) plots the SAD values by MBS with and without using an adaptive window, respectively. The adaptive window used for Fig. 2(b) is decided according to the number of local minima.



(a) Reference Image



(b) MBS with Adaptive Window (c) MBS

Pixel Coordinate: 388, 85

B: Baseline

___ : B1=2.0mm,	-·- : B2=2.5mm	-- : B3=3.0mm
··· : B4=3.5mm	-- : Sum of SAD	

Figure 2. Stereo Matching by MBS

Since distances from all the cameras to the point in the scene are the same, we can compute the disparity of a matching point by RMBS using the average of ζ_i's obtained from all stereo image pairs. The disparity d is obtained from the average value ζ by

$$d = B \cdot \zeta \tag{4}$$

2.2 The Robust MBS Algorithm

In this paper, we devise the RMBS algorithm to solve not only repetitive but also continuous multiple local minima, and determine ζ without any interpolation operations. In the RMBS algorithm, we can locate regions of unreliable disparity from the variance image.

The procedure of the RMBS algorithm is described in Fig. 3. We begin the stereo matching operation with a window size of 3x3 pixels. In general, we can adjust the window size according to local variations of intensity values or the disparity distribution. However, since we do not know the disparity distribution, we can use the number of multiple local minima of intensity variations to decide the window size. We can increase the window size until the number of local minima becomes one. Owing to the adaptive window size, we can avoid projective distortion and invalid stereo matching in RMBS.

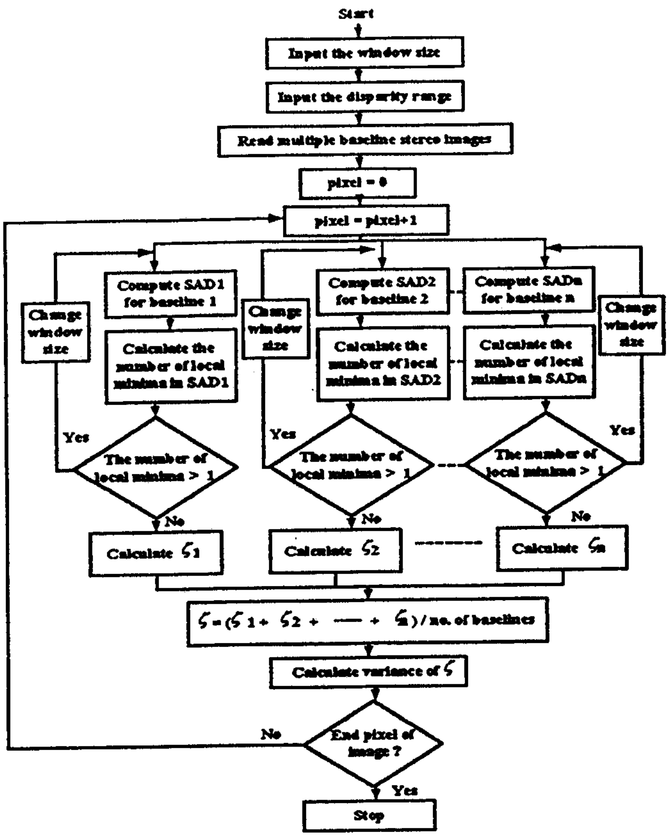


Figure 3. The RMBS Algorithm

3. EXPERIMENTAL RESULTS

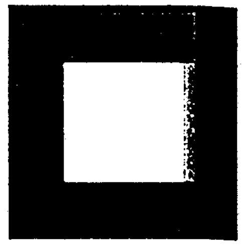
We have applied the RMBS algorithm to synthetic and natural images. Since the synthetic scenes are generated by Photoshop graphic tool, we know the depth information. The natural scenes are circuit-board images acquired at baselines of 0, 2.0, 2.5, 3.0, and 3.5 mm by a single camera equipped with the x-y-z axis robot. It should be noted that the baselines are very narrow. The object is located at about 75 cm away from the camera. The focal length of the camera lens is 10 mm. The disparity ranges and image sizes are shown in Table 1.

Table 1. Disparity Range and Image Size

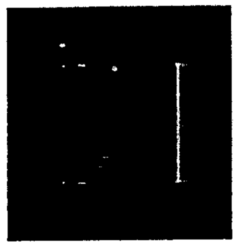
	Disparity Range	Image Size
Synthetic Image	4-10	256×256
Board Image	54-66	320×240

Fig. 4 and Fig. 5 display disparity and variance maps of the synthetic and natural images, respectively. From Fig. 4 and Fig. 5, we know that disparity maps by RMBS are similar to those by MBS. However, RMBS can locate regions whose computed disparity is not very reliable, as shown in Fig. 4(c) and Fig. 5(c).

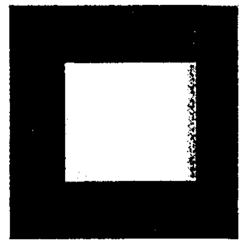
(a) Synthetic Image



(b) Disparity Map (RMBS)

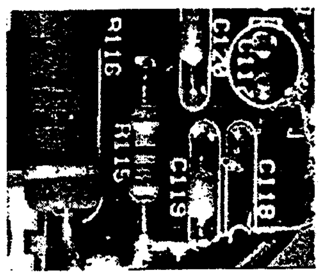


(c)Variance Image (RMBS)

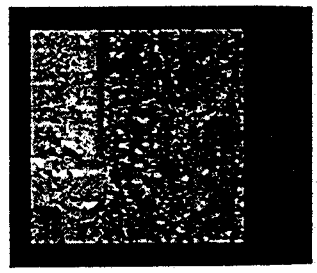


(d) Disparity Map (MBS)

Figure 4. Disparity Maps of Synthetic Image

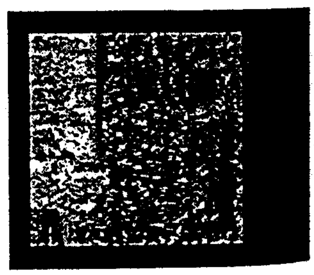


(a) Board Image



(b) Disparity Map (RMBS)

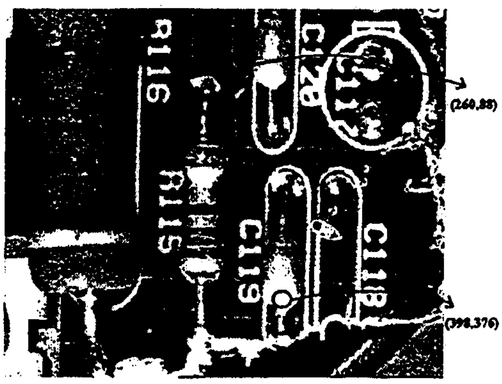
(c) Variance Image (RMBS)



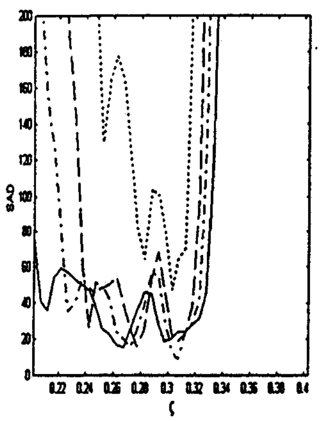
(d) Disparity Map (MBS)

Figure 5. Disparity Maps of Board Image

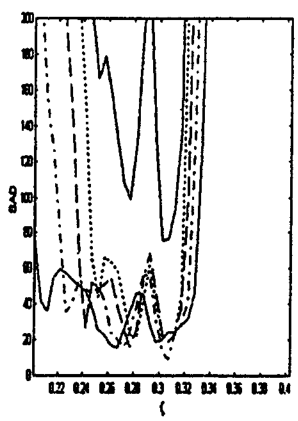
In order to test various types of multiple local minima, we use the same image as Fig. 5(a). Fig. 6(a) shows shinning regions by illumination and repetitive patterns. RMBS produces the correct disparity map, as in Fig. 5(b), but MBS has black holes that miss the correct disparity, as in Fig. 5(d). From Fig. 6(b) and Fig. 6(d), we know clearly that RMBS can solve continuous as well as repetitive multiple local minima by an adaptive window. MBS can find the correct stereo match in repetitive patterns, as in Fig. 6(c); however, it cannot determine the correct stereo match for continuous multiple local minima, as in Fig. 6(d).



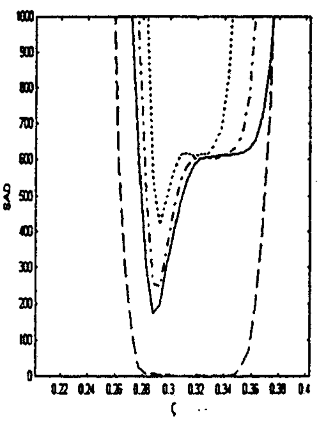
(a) Board Image



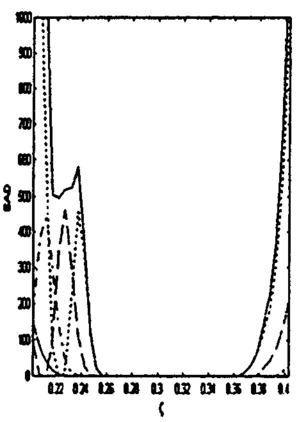
(b) RMBS with Repetition



(c) MBS with Repetition



(d) RMBS with Continuity



(e) MBS with Continuity

—— : B1=2.0mm, -·- : B2=2.5mm -- : B3=3.0mm
··· : B4=3.5mm -- : Sum of SAD

Figure 5. Robust Multiple-Baseline Stereo

For the board image in Fig. 6(a), processing times by MatLab for different image points are listed in Table 2, where we can observe that RMBS is faster than MBS by 24.1% because of no interpolation of ζ. Experimental results demonstrate that the proposed RMBS algorithm is more robust than MBS.

Table 2. Processing Speed (second)

	(x, y)	RMBS	MBS
Image	Global	7.7599e+003	9.8248e+003
Repetitive Pattern	(260,88)	0.12	0.13
Continuous Pattern	(385,88)	2.41	0.13
Single Matching	(200,88)	0.09	0.13

4. CONCLUSIONS

In this paper, we propose a robust MBS algorithm to solve problems of MBS. Experimental results show that RMBS can solve not only continuous multiple local minima but also repetitive ones. RMBS is also faster than MBS because it doesn't need to interpolate for stereo matching. RMBS saves the computing time by 24.1% relative to MBS. RMBS can indicate unreliable regions by the variance image. Although RMBS is robust, it does not consider occlusion and depth discontinuity problems, which need further research in future.

ACKNOWLEDGMENT

This work was supported in part by KOSEF through UFON, and in part by MOE through BK21

REFERENCES

[1] D. Marr and T. Poggio, "Cooperative computation of stereo disparity," Science, vol. 194, pp. 283-287, Oct. 1976.

[2] E. Trucco and A. Veri, Introductory techniques for 3-D computer vision, Prentice-Hall, 1998.

[3] T. Kanade, "Development of a video stereo machine," ARPA Image Understanding Workshop, pp. 549-558, Nov. 1994.

[4] http://www.cs.berkeley.edu/projects/vision/vision_group.htm

[5] J. Jeon, "A robust stereo matching technique using multiple cameras," Ph.D. Dissertation, Chosun University, Korea, Feb. 2001.

[6] T. Kanade and M. Okutomi, "A stereo matching algorithm with an adaptive window: theory and experiment," IEEE Trans. On Pattern Analysis and Machine Intelligence, vol. 16, No. 9, pp. 920-932, Sept. 1994.