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EXPO 2012 Yeosu Korea (Click here)

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Important Dates +

- Submission Deadline for Tutorial Proposals — Extended to September 23, 2011

Monday, May 21, 2012

A3L-H	**3D Visual Signal Acquisition and Rendering**
Time:	Monday, May 21, 2012 (15:30 - 17:00)
Place:	Room 307B
Chair(s):	Shao-Yi Chien, *National Taiwan University*
	Lap-Pui Chau, *Nanyang Technological University*

15:30
A3L-H.1 **A Theoretical and Empirical Error Analysis of Mobile 3D Data Acquisition System**
Yiyi Ren, Wenshou Chen, Xiang Xie, Yangdong Deng, Kai Zhao, Enbo Shi, Zhihua Wang, Guolin Li, *Tsinghua University*

15:48
A3L-H.2 **Disparity Map Acquisition with Occlusion Handling Using Warping Constraint**
Woo-Seok Jang, Yo-Sung Ho, *Gwangju Institute of Science and Technology*

16:06
A3L-H.3 **Texture-Assisted Kinect Depth Inpainting**
Dan Miao, *University of Science and Technology of China;*
Jingjing Fu, Yan Lu, Shipeng Li, *Microsoft Research Asia;*
Chang Wen Chen, *State University of New York at Buffalo*

16:24
A3L-H.4 **Low Latency Design of Depth-Image-Based Rendering Using Hybrid Warping and Hole-Filling**
Shen-Fu Hsiao, Jin-Wen Cheng, Wen-Ling Wang, Guan-Fu Yeh, *National Sun Yat-sen University*

16:42
A3L-H.5 **Keyframe Selection for Motion Capture Using Motion Activity Analysis**
Ming-Hwa Kim, Lap-Pui Chau, *Nanyang Technological University;*
Wan-Chi Siu, *The Hong Kong Polytechnic University*

Disparity Map Acquisition with Occlusion Handling Using Warping Constraint

Woo-Seok Jang and Yo-Sung Ho
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***Abstract*—In this paper, we propose a stereo matching algorithm with occlusion handling. In order to detect occlusion, we obtain an initial disparity map via optimization based on modified constant-space belief propagation (CSBP). Such a method is advantageous due to its low complexity. The initial disparity maps provide clue for occlusion detection. From such clue, an energy function for occlusion detection is defined and optimized by energy minimization framework. We classify occlusion into two types from the obtained occlusion map and apply suitable occlusion handling process, respectively. The proposed occlusion handling method based on the potential energy function extends disparity values of visible pixels to occluded pixels. Experimental results show that generated disparity map of the proposed method has satisfactory quality.**

I. INTRODUCTION

Stereo matching which is widely researched topic in computer vision is one of the most useful ways for acquiring three dimensional (3D) data from two images. Stereo matching acquires 3D data by finding the corresponding points in other images for pixels in one image. The correspondence problem is to compute the disparity map which is a set of the displacement vectors between the corresponding pixels. For this problem, two images of the same scene taken from different viewpoints are given and it is assumed that these images are rectified for simplicity and accuracy of the problem. From this assumption, corresponding points are found in same horizontal line of two images.

Since two images are captured from different positions, occluded pixels exist in stereo images. The occluded pixels are only visible in one image, so accurate estimation of disparity value in these pixels is difficult. Figure 1 illustrates the case of occlusion. Occlusion is an important and challenging in stereo matching. Works that detects occluded pixels and assigns reasonable disparity values to the occlusion pixels is needed for reliable disparity map. The simplest method that detects occluded pixels and estimates disparities of occluded pixels is to use cross-checking [1] and extrapolation. Cross-checking tests that disparity value from the left and right disparity maps are consistent for each pixel. This determines occluded pixels. The disparities of visible pixels are extended into occluded pixels by extrapolation.

In this paper, we propose a stereo matching method with occlusion handling of better performance. We consider the low complexity optimization algorithm for practical application. We use warping constraints to detect occlusion accurately. The obtained occlusion is handled by potential energy function, stochastically.

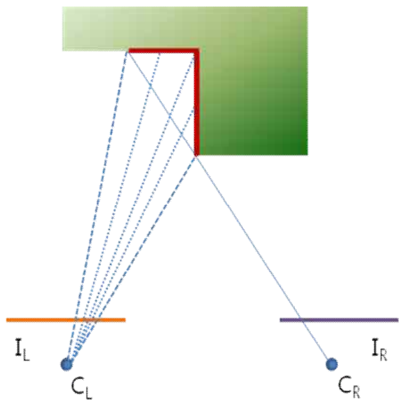


Figure 1. Occurrence of occlusion

II. OCCLUSTION CONSTRAINTS

In general, two constraints have been typically used for occlusion handling in stereo matching: ordering and uniqueness. The former preserves the order of matching along the scanline in two input images [2]. The ordering constraint provides clues for accurate occlusion handling. However it has limitation which violates in image that contains thin objects or narrow holes. Figure 2 shows an example of violation for ordering constraint. The circled stick in the left image is to the left of the letter ‘u’. However, the circled stick in the right image is to the right of the letter ‘u’. The uniqueness constraint uses the fact that the corresponding points between two input images are one-to-one mapping. Several stereo matching methods using uniqueness constraint alternate between occlusion estimation using the estimated disparity map and disparity estimation using the estimated occlusion map [3]. However, in these cases, the complex rate increases with the amount of iterations.

(a) Left image (b) Right image

Figure 2. Violation of ordering constraint.

III. PROPOSED OCCLUSION HANDLING

Figure 3 represents the overall framework of the proposed algorithm. First, initial disparity maps are obtained for the left and the right images. Constant-Space Belief Propagation(CSBP) [7] is used for optimization of the initial disparity map. Occlusion is detected using both disparity maps. Estimation of disparity values is performed for occluded pixels. Finally, the final disparity map with occlusion handling is generated.

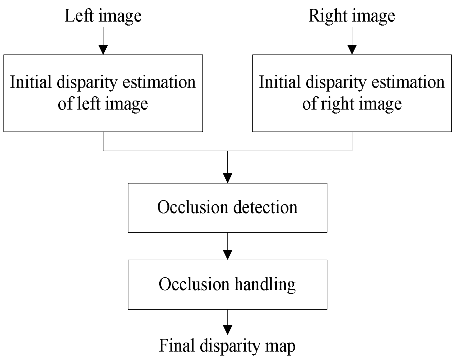


Figure 3. Overall framework of our proposed method

A. *Initial Disparity Based on Modified CSBP*

Many stereo matching algorithms define an energy function and solve it through several optimization techniques such as graph cut [4] and belief propagation [5]. The energy function by MRF is defined as

$$E(f)=\sum_{s} D_s(f_s)+\sum_{s,t\in N(s)} S_{s,t}(f_s,f_t) \tag{1}$$

where $D_s(\cdot)$ is the data term of node s. $S_{s,t}(\cdot)$ is the smoothness term between node s and t. f_s represents the state of each node s. $N(s)$ is the neighbor of the node s. In stereo matching, a node represents a pixel and the data term is generally defined by intensity consistency of pixel correspondences for hypothesized disparity. We use the luminance difference between two pixels as the matching cost. The matching cost as a data term of MRF is defined as

$$D_s(d_s)=\min(|I_L(x_s,y_s)-I_R(x_s+d_s,y_s)|,T_d) \tag{2}$$

where I_L and I_R are left image and right image, respectively. x_s and y_s are horizontal and vertical coordinates of pixel s in the image. d_s is disparity of pixel s. T_d controls the limit of the data cost. The smoothness term in stereo matching is based on the degree of difference among disparities of neighboring pixels. In our method, the smoothness term is defined as

$$S_{s,t}(d_s,d_t)=\min(\lambda\,|d_s-d_t|,T_s) \tag{3}$$

where T_s is the constant controlling to stop increasing of the cost. λ represents the smoothness strength and is generally represented by a scalar constant. However, this smoothness strength is very sensitive. Thus, we adaptively refine smooth strength to make our method more practical. First, color differences between pixel s and its neighboring pixels are calculated. High color difference means edges in the color image. We assume that the color edge in the color image is remarkably consistent with the depth edge in the depth image. The smoothness strength should be small in the depth edge. On the other hand, the smoothness strength can be high in non-edge. The color difference is defined as

$$diff_{s,t}=\sum_{c\in\{R,G,B\}}|I_c(s)-I_c(t)| \tag{4}$$

The sum of absolute difference (SAD) is used as a difference measure and each color channel of R, G, B components is used for color difference. After obtaining the color difference, the scale of the color difference is controlled to set the average of the color difference to ‘1’. New color difference scale is defined as follows.

$$diff_{scale}=1-(diff_{s,t}-diff_{mean})/diff_{\max} \tag{5}$$

where $diff_{mean}$ is the mean of the color difference and $diff_{\max}$ is the maximum value of the color difference in the whole image. We replace λ value in (3) with λ' value for suitable smoothness strength.

$$\lambda'=\lambda\cdot diff_{scale} \tag{6}$$

The energy function is completed. A global optimization method is used to find a disparity value which minimizes the energy at each pixel. Belief propagation as an optimization method provides good results. However, general belief propagation is too complex for reasonable results, since the cost is converged after numerous iterations. In practice, when image size is N, the number of disparity levels is L, and the number of iterations is T, the computational complexity is originally O(TNL^2) in standard belief propagation [5]. Thus, it is not good to apply standard belief propagation in real applications. A low complexity algorithm is needed, even if its quality is a little low. One of the fast belief propagation algorithms reduces the complexity to O(TNL) by using hierarchical coarse-to-fine manner [6]. This algorithm facilitates real-time computation if it uses GPU implementation. However, we want a lower complexity algorithm. CSBP [7] is one of the fastest algorithms. Its complexity depends on only constant space, that is O(1). However, CSBP cannot make enough quality. In the proposed method, we use CSBP with remarkable fast speed and refine the result of CSBP sufficiently.

B. Occlusion Detection

We present warping constraint for occlusion detection. In the warping constraint, all pixels in the left image are projected to the right images using the left disparity map for the left occlusion map. If multiple pixels in the left image are projected on only one pixel in the right image, all but one pixel are occluded pixels. In this case, if the disparity map is reliable, the pixel which has the largest disparity value among the multiple matching pixels is visible, and the rest of the pixels are the occluded pixels. However, our initial disparity map based on the modified CSBP is not perfect. Thus, we consider all multiple matching pixels as candidates of the occluded pixels. Figure 4 illustrates the warping constraint. The dark pixels can be regarded as candidates of the occluded pixels.

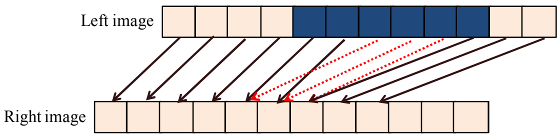


Figure 4. Warping constraint

We define an energy function for warping constraint considering above characteristics.

$$E_G(D_L) = \sum_{s} w_b \,|\, o_s - G_L(s, D_L) \,| \tag{7}$$

where $G_L(s, D_L)$ is a binary map by the warping constraint. Multiple matching pixels in the left image are set to '1'. o_s is the occlusion value. When pixel s is supposed to the occluded pixel, the occlusion value o_s is set to '1'. w_b is the weighting factor which is applied to the pixel of the largest disparity value and the other pixels, differently. The final energy function for occlusion detection is defined as

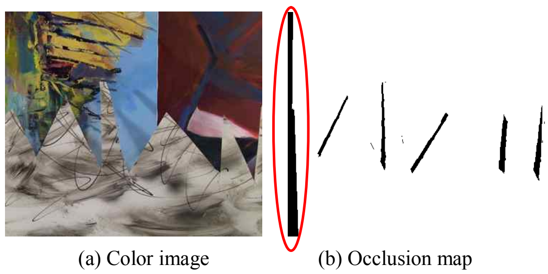
$$\begin{aligned} E_O = &\sum_{s} (1 - o_s) D_s(d_s) + \lambda_O o_s \\ &+ \lambda_G E_G(D_L) + \sum_{s,t \in N(s)} \lambda_s \,|\, o_s - o_t \,| \end{aligned} \tag{8}$$

The final energy function includes the difference of luminance component for data term in addition to the warping constraint. This comes from the assumption that the large difference of luminance makes wrong matching, even if a particular pixel is regarded as a visible pixel by two constraints. The last term represents the smooth term for energy function of occlusion detection and it uses the sum of absolute difference among the neighboring pixels of pixel s. This final function is optimized by belief propagation.

C. Disparity Assignment for Occlusion

After detecting occlusion, the reasonable disparity value should be assigned to the occluded pixel. Occlusion is only visible in one image. Thus, it is impossible to determine the accurate disparity value by conventional stereo matching. If we use the disparity values from neighboring pixels in the non-occlusion region, estimation of the disparity value in the occlusion region is possible. Generally, disparity values in occluded pixels are similar to the disparity values of visible pixels in the background. In our proposed method, we try to propagate the disparity values of visible pixels to occlusion.

First, we classify occlusion regions into two parts: left-side and general. Figure 5 shows the left image and the corresponding occlusion map. The circled part in Fig. 5 (b) is the left-side part and the rest of the occlusion is the general part. Occlusion in left-side part is generated due to the non-existence of left-side occlusion region in the leftmost of a right image. In this part, it is useless to estimate the disparity value using disparity values of the neighboring pixels, since our algorithm does not use iterative optimization. Thus, we extend the disparity of the leftmost visible pixels to the left-side part for each horizontal line.



(a) Color image (b) Occlusion map

Figure 5. Two kinds of occlusion

For the general part, we define a potential energy function. Let *L(s)* be the neighboring pixels whose distance from occluded pixel s is smaller than predefined distance and $C = \{s, t \,|\, s > t, t \in L(s)\}$ be the set of all nearby pixels which affect pixel s. The potential energy function for occlusion handling is defined as

$$E_{OH}(s, d_s) = \sum_{t \in C \setminus B} (1 - o_t) \frac{1}{dist(s,t)} \exp\left(-\frac{diff_{s,t}}{\sigma^2}\right) \tag{9}$$

where $B = \{s, t \,|\, d_s \neq d_t, t \in C\}$, o_t is the occlusion value from the obtained occlusion map. $dist(s,t)$ is the distance between occluded pixel s and visible pixel t. $diff_{s,t}$ is the color difference defined in (4). The disparity value, which has the maximum value of (9), is determined as the disparity value for the pixel s. This process works at only occluded pixels which are near visible pixels. Thus, it completely handles thin or small occlusion. However, wide and large occlusion is processed at only near visible pixels. In order to solve this problem, we apply potential energy function for occlusion handling one more time. At this time, we do not consider only visible pixels to assign the disparity value to occluded pixel, since visible pixels are sufficiently propagated to the occluded pixels until previous process. The proposed occlusion handling process assigns disparity values which have maximum value of the potential energy function for occlusion handling without complex optimization methods. Thus, its complexity is much lower than other algorithms which optimize the energy function iteratively.

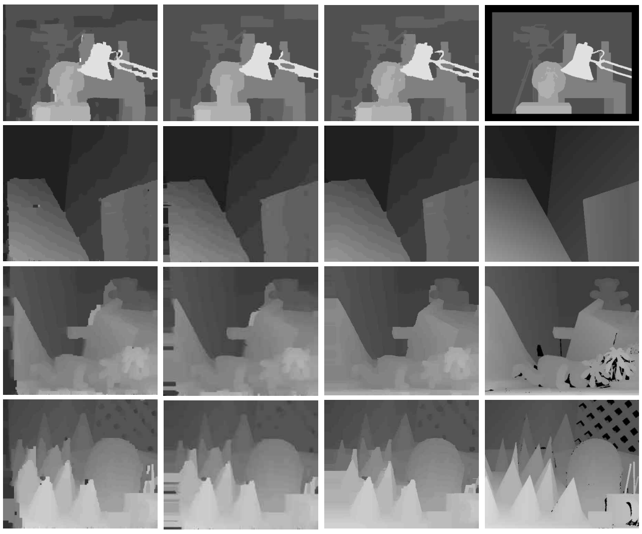
IV. EXPERIMENTAL RESULT

Table 1 lists the values for the parameters used in the proposed method. These parameters are acquired by experiments to balance energy terms. As I presented before, the smoothness strength (λ) is adaptively set.

TABLE I. Parameters for experiment

T_d	T_s	λ_o	λ_G	λ_s
30	105	7.5	3	4.2

In order to evaluate the performance of our proposed method, we follow the methodology which measures the percentages of bad matching pixels [8]. Figure 6 illustrates the visual comparison of our disparity maps with other methods.



(a) CSBP[9] (b) Uniquness[9] (c) Proposed (d) Ground truth
Figure 6. Result of final disparity map

Objective evaluation is presented in table II. Table II shows the percentage of the mismatching pixels between the proposed method and ground truth. When the absolute disparity error is greater than 1 pixel, the pixel is regard as the bad matching pixel. The result shows that proposed method improve quality of a CSBP based disparity map.

TABLE II. Evaluation for disparity map (error rate, %)

Image	CSBP	Uniqueness [9]	Proposed method
Tsukuba	4.17	3.10	2.63
Venus	3.11	2.79	1.35
Teddy	20.20	18.02	14.82
Cone	16.50	15.49	13.45

V. CONCLUSION

In this paper, we proposed the stereo matching method considering occlusion. Initially, we applied CSBP for an initial disparity map optimization. We modified the algorithm to achieve better result. Warping constraint controlled occlusion detection. The proposed occlusion handling method assigned reasonable disparity values to the occluded pixels. The proposed method led to efficient computation since iterative global optimization technique at occlusion handling was not used. The experimental results demonstrate high quality performance for stereo images.

ACKNOWLEDGEMENT

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REFERENCES

[1] G. Egnal and R. Wildes, "Detecting binocular halfocclusions: empirical comparisons of five approaches," IEEE Transactions on Pattern Analysis and Machine Intelligence, vol.24 no. 8, pp. 1127-1133, Aug. 2002.

[2] A. Bobick and S. Intille, "Large occlusion stereo," International Journal of Computer Vision, vol.33, no. 3, pp. 181-200, Sep. 1999.

[3] V. Kolmogorov and R. Zabih, "Computing visual correspondence with occlusions using graph cuts," IEEE International Conference on Computer Vision, pp. 508-515, 2001.

[4] Y. Boykov, O. Veksler, and R. Zabih, "Fast approximate energy minimization via graph cuts," IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 23, no. 11, pp.1222-1239, Nov. 2001.

[5] J. Sun, N. N. Zheng, and H. Y, Shum, "Stereo matching using belief propagation," IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 25, no. 7, pp. 787-800, July 2003.

[6] Q. Yang, L. Wang, R. Yang, S. Wang, M. Liao, and D. Nister, "Real-time global stereo matching using hierarchical belief propagation," British Machine Vision Conference, pp. 989-998, 2006.

[7] Q. Yang, L. Wang, N. Ahuja, "A constant-space belief propagation algorithm for stereo matching," IEEE Computer Society Conference on Computer Vision and Pattern Recognition, pp. 1458-1465, 2010.

[8] D. Scharstein and R.Szeliski, "A taxonomy and evaluation of dense two-frame stereo correspondence algorithms," International Journal of Computer Vision, vol. 47, no. 1, pp. 7-42, April 2002.

[9] W. S. Jang and Y. S. Ho, "Disparity Map Refinement using Occlusion Handling for 3D Scene Reconstruction," International Conference on Embedded Systems and Intelligent Technology, pp. 213-216, 2011.