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Guided Image Filtering based Disparity Range Control in Stereo Vision

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Abstract

Generating a disparity map has been a challenging issue for several decades. To improve the quality of estimated disparity map and reduce the computational complexity, efficient cost matching functions and cost aggregation methods have been developed. Especially, in case of sequential stereo matching procedure, computational complexity causes a problem in terms of the real time processing. To overcome this problem, we propose a temporal domain stereo matching method using the guided image filtering. The advantage of temporal stereo matching method is restricting a disparity search range while calculating a matching cost value along the horizontal pixel line. Additionally, we adopt the guided image filtering to improve the quality of estimated disparity map in updating procedure. Since the guided image filtering aggregates the cost value by considering object boundary region, the result of stereo matching accuracy is improved than conventional temporal stereo matching method. From the experiment results, we check that the proposed method generates the most accurate disparity map than conventional method.

1. Introduction

Generating a dense disparity map from stereo image pairs are critical issue in many computer vision applications, because it plays an important role in many applications. 3D image reconstruction, image tracking, 3D printing and automatic driving system basically use a depth information. To efficiently perform that kinds of applications, correctly estimating a correspondence from stereo image pairs is a critical issue. Especially, many applications need a real time processing to build a system for specific purpose. Estimating a disparity map with a high accuracy and low computational complexity is a final goal of all stereo matching methods.

The basic concept of stereo matching method and extensions are quite well defined in [1]. According to [1], stereo matching method is divided into local and global approach. Global stereo matching method uses a concept of energy function and optimization about cost function by using optimization techniques such as belief propagation (BP) or graph cut (GC) method. On the other hand, local stereo matching meth-od uses pre-defined window kernel to compute a matching cost through the overall stereo images. The global method generates a disparity map with high accuracy at the risk of complex computational time. However, the local method takes less computation time than global method, instead of the dis-parity value accuracy is lower than global method result.

The emergence of powerful graphic processing units (GPUs) based accelerated computing engine and multi-core processing enabled the implementation of high accuracy real time stereo matching methods even though the global method. The parallel computing is possible through the compute unified device architecture (CUDA) programming interface which developed by NVIDIA. CUDA based parallel computation is one of the most powerful equipment used by researcher to implement real time stereo matching algorithms [2]. Most of the computation complexity bottle neck problem happens in matching cost calculation and cost aggregation step. Even the parallel computing solves the bottle neck problem, it is not proper to implement on the real system such as outdoor cam-eras or automatic vehicles.

In this paper, we propose a real-time stereo matching algorithm using temporal relationships. The sequential image frames have very similar relation with neighbor frames, since we focusing on this characteristic. Previously generated dis-parity map provides an information which related to disparity search range in following frames stereo matching procedure. Since the moving difference area is small between current and neighbor frame, we restrict the disparity search range while performing the stereo matching of sequential frames. If the accuracy of previously estimated disparity map is reliable then disparity search range restriction method is efficient. However, when the previous disparity map is not reliable, the restricted disparity search range will cause an error propagation problem.

To prevent the inaccurate disparity value affect to a sequential disparity map quality, we adopt the guided image filtering in cost aggregation procedure. Before aggregating a cost value, we compute a matching cost value by combining sum of absolute differences (SAD), gradient information and improved census transform terms. The mixed matching cost function increase the accuracy of estimated disparity value. The cost aggregation is operated after generating a cost volume about each disparity search range. Since the guided image filtering considers object boundary region using guidance image, we select an optimal matching cost value for fine dis-parity map. The pipeline of proposed method is indicated in Figure 1.

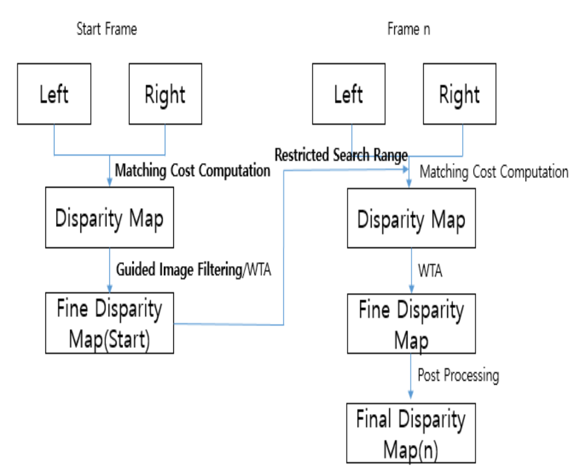

Figure 1. Pipeline of proposed method

2. Background

To get a disparity map of a stereo image sequences in real time, a temporal domain based matching algorithm is pro-posed. Figure 2 shows the brief illustration of fast disparity estimation procedure.

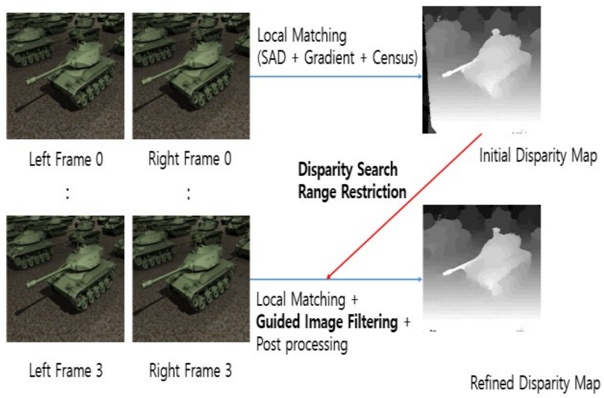

Figure 2. Simple diagram of temporal domain stereo matching

Disparity search range restriction information is extracted from the initial disparity map as indicated in Figure 2. Generally, local stereo matching method uses SAD, sum of squared differences (SSD) and normalized cross correlation (NCC) matching functions. We adopt the SAD matching cost function to compute a texture stereo image pair cost value. Additionally, to improve the accuracy of matching cost value gradient information and census transform result are considered simultaneously.

Based on the initially estimated disparity map, we restrict the disparity search range in sequential stereo matching procedure. By restricting a search range the number of matching computation is reduced. If we continuously restrict the disparity search range, a small error is accumulated as the frame number is grown. To prevent the error propagation problem, we periodically aggregate cost volume using the guided image filtering. At the same time, the quality of disparity map is improved by performing post processing.

3. Fast Sequential Stereo Matching

The conventional temporal domain stereo matching method [3] directly uses raw image pairs to generate an initial disparity map. Since the initial disparity value affect to the disparity search range condition, we have to generate quite accurate initial disparity map. Because of this reason, we combine gradient and census transform image for computation of matching cost function. The guided image filtering is operated based on that cost volume images.

3.1 Improved Gradient Model

Image gradient contains plentiful structural information such as feature points and edges. Additionally, it is not sensitive to variant luminance condition, so gradient information is widely used for stereo matching cost function [4]. Many stereo matching algorithms extract the gradient information from raw image intensity value which is transformed from RGB to gray space. While converting a color space from 3D to 1D, an important structural information is removed.

To overcome this problem, we generate gradient information from raw RGB image and filtered image. In this work, we adopt the bilateral filter before extracts the gradient information. Bilateral filter efficiently removes a noise factor which originally contained in raw image. By combining those two gradient information, we compensate an information missing problem when image gradient is extracted. Assume that there is a pixel coordinate $p(x, y)$ and raw image RGB vector space I_R, I_G, I_B. The gradient information is extracted in terms of x and y direction respectively as indicated in (1).

$$\nabla I(x, y) = (\nabla_x I, \nabla_y I) \tag{1}$$

where ∇_x and ∇_y indicate the derivative of x and y direction. The raw image and filtered image are operated using (1) to extract a two directional gradient information. For each RGB channel and x and y directional information are combined with filtered image x and y directional information for gradient model. Figure 3 shows the extracted gradient results from raw image and filtered image. Since the bilateral removes the small scale factor or noise information from raw images, the filtered image based gradient results have a simple object contour region.

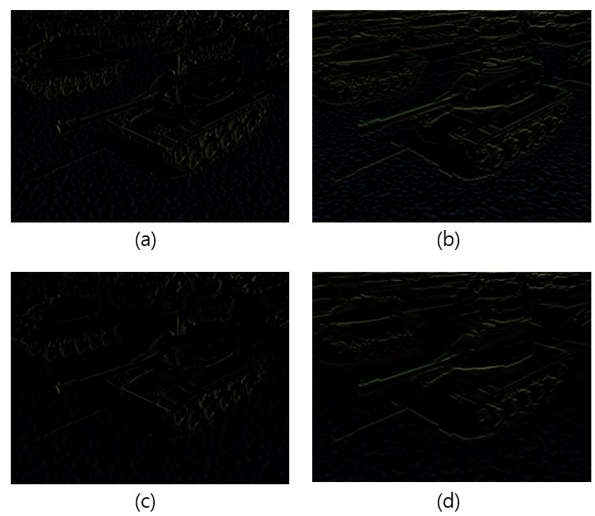

Figure 3. Extracted gradient results, (a) and (b) x/y-direction gradient from raw image, (c) and (d) x/y-direction gradient from filtered image

Since improved gradient model contains full detailed local and global information, we use this information to compute a stereo matching cost value for initial disparity map. As a basic matching cost computation method, SAD is adopted to measure the cost value. SAD is very widely used matching cost function since it has low computational complexity and simple structure. The improved gradient model based matching cost equation is defined in (2)

$$C_{SAD,grad} = |\nabla I_{Ref}(x, y) - \nabla I_{Mat}(x, y)| \tag{2}$$

Each variable ∇I_{Ref} and ∇I_{Mat} contain RGB channel and raw/filtered image gradient information. The subscript *Ref* and *Mat* indicate the matching comparison image pairs. The majority of improved gradient model is computing a gradient value for each x, y direction and raw, filtered image. This procedure is concluded with low computational complexity.

3.2 Weighted Census Transform

Conventional census transform is developed to diminish the effect of luminance variation problem when operating a stereo matching. Census transform compares current pixel and neighbor pixels within a pre-defined window kernel. If the neighbor pixel value is higher than current pixel values, then we assign 1, otherwise assign 0 for each pixel as indicated in (3).

$$C_{SAD,census} = \otimes_{p' \in M(p)} \xi(p, p')$$
$$\xi(p,p') = \begin{cases} 1, if\ I(p') > (I(p) \\ 0, \quad\quad o/w \end{cases} \quad (3)$$

where ξ indicates a computation function between current and neighbor pixels. p and p' represent current pixel value and neighbor pixel value respectively. After the comparison procedure is completed within the window kernel, we obtain a binary bit array which related to pixel intensity variation. However, conventional census transform result does not provide how the current pixel and neighbor pixel has different intensity [5].

In our work, we express the census transform result by using an adaptive weight value. If one neighbor pixel has bigger difference value with current pixel than the other neigh pixel, then we adaptively assign a different weight value for census transform. Firstly, we divide a pre-defined window kernel into small number of sub-windows. Each sub-windows computes an average pixel value and compares the pixel differences with current pixel value. Based on that sub-windows, we assign a different weight value to each neighbor pixels.

Generally, window kernel of homogeneous region or similar pixel region has more change to obtain inaccurate census transform result than other window kernel region. Since the conventional method only considers whether the neighbor pixel is big or not comparing with current pixel, the census transform result is not fully informative when computing a matching cost value. Conventional census transform derives an inaccurate disparity value especially on the similar pixel intensity region.

To represents the census transform results along the steady status of luminance variation condition, we define 4-steps (0 to 3) weight function (4). Adaptive weight concept is coming from characteristics which different pixel values derive accurate stereo matching cost result [6].

$$\xi(\overline{I_p}, I_q) = \begin{cases} 3, when\ I_q = Max \\ 2, when\ I_q \geq \overline{I_p} + \alpha \\ 1, when\ I_q \geq \overline{I_p} - \alpha \\ 0, when\ I_q = Min \end{cases} \quad (4)$$
$$\alpha = \frac{1}{n}\sum_{p \in q} |\overline{I_p} - I_q|$$

where ξ is the same function indicated in (3). $\overline{I_p}$ represents the average value of sub-window and I_q indicates a current pixel value. If the difference of luminance value has maximum then assign 3 for weight value, and the difference of luminance variation is minimum then assign 0 for weight value. To adjust the weight value between maximum and minimum range, we computes α by using an difference of current pixel value and average of sub-window kernel value. The role of variable α is assigning a different weight value based on the sub-window average value. If the current pixel value is higher than the summation of average of sub-window and α then assign 2. But, current pixel value is higher than difference of average of sub-window and α, then assign 1. Figure 4 presents the result of weighted census transform result with different test sequences.

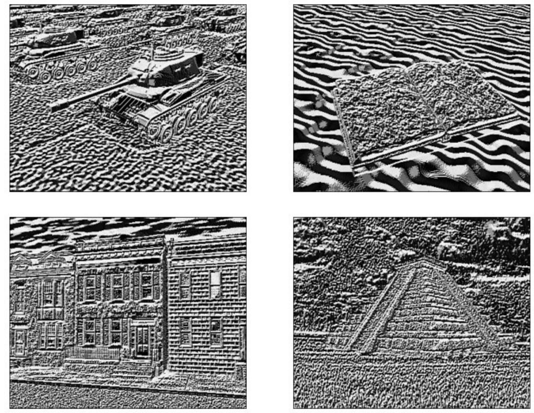

Figure 4. Weighted census transform results

3.3 Color image Model

Color image based absolute differences (AD) measuring between two corresponding pixels is easy to implement and also has low computational complexity. AD computation of color image help to reduce the matching ambiguities in some homogeneous region or repetitive texture region, so many stereo matching algorithms adopt color image based AD matching cost function. In our work, we also adopt the AD measurement method and cost value is directly computed from stereo image pairs. The matching cost function is defined in (5).

$$C_{ADcolor}(p,d) = |I_i^{Ref}(p) - I_i^{Mat}(p+d)| \quad (5)$$

where I_i^{ref} and I_i^{Mat} indicate a stereo image pairs for evaluation of matching cost. Since we use color image for cost computation, matching cost is evaluated in three channels. Figure 5 shows the color image model based disparity estimation results.

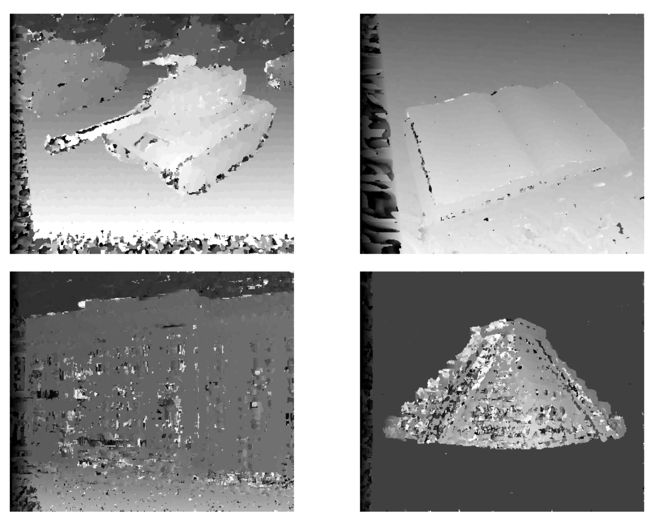

Figure 5. SAD based matching results.

3.4 Prevention of error propagation

Based on previously defined matching cost functions, we iteratively estimate a disparity map by restricting a disparity search range. Assume that we use fixed window size to operate a census transform and SAD, then census transform need 9 comparisons and SAD need 27 comparisons with RGB channel. Then, we need to operate 36 comparisons for each disparity search range. However, if we restrict the disparity search range depending on a pre-estimated disparity map which generated by previous frame, the number of comparison operation is diminished. For example, if estimated disparity value from previous frame is 60 on the same coordinate at following matching procedure, then we just search around ± 3 or ± 5 pixels for disparity search area. Instead of 27×60 number of comparison 27×3 or 27×5 comparison is needed for matching cost computation.

The advantage of disparity search range restriction is only focusing on the reduced computational complexity. As frame number is growth an error information is steadily propagated in sequential disparity map. Figure 6 exhibits error propagation phenomenon in sequential stereo matching procedure.

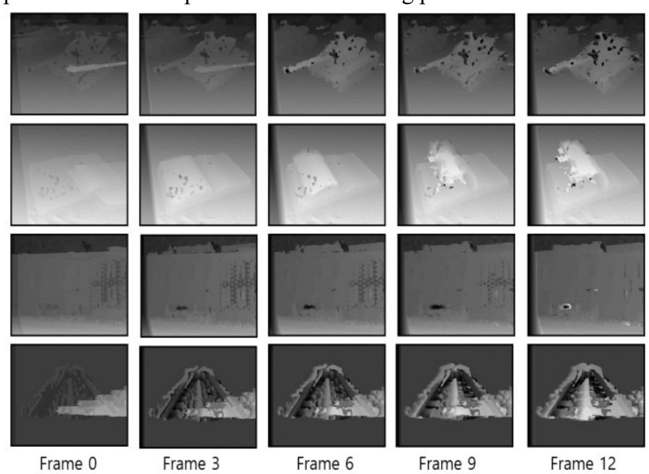

Figure 6. Error propagation problem in sequential stereo matching

To solve the error propagation problem, conventional method uses disparity map refresh technique [3]. It extracts the feature points and find out correctly matched feature points between reference image and matching image. Based on matched feature points, matching cost is computed within full disparity search range. The performance of disparity refresh technique is varying depending on the extracted number of feature points. In our work, we propose the guided image filtering based disparity map updating method.

Instead of refresh the disparity map for search range restriction, we totally update the disparity map frequently. The conventional method improves the accuracy of disparity value especially near the object boundary region. However, the proposed scheme enhances the reliability of estimated disparity map by updating disparity map. The guided image filtering is used to aggregate disparity image volumes which generated by local matching function.

The guided image filtering has very similar structure with bilateral filter in terms of considering pixel intensity and distance. Recently, instead of bilateral filter, the guided image filtering is widely used to aggregate the matching cost in filter based cost aggregation procedure. Contrary to the bilateral filter, the guided image filtering uses a linear equation to perform the object boundary preserving filtering in a short time. The other main difference is usage of guidance image. The guided image filtering uses input image as a guidance image for filtering. Because of that reason, the guided image filtering has better edge preserving performance than bilateral filter result. As indicated in (6), the guided image filtering uses a raw input image and reference image.

$$W_{ij}(I) = \frac{1}{|\omega|^2} \sum_{k(i,j)\in\omega_k} \left(1 + \frac{(I_i - \mu_k)(I_j - \mu_k)}{\sigma_k^2 + \epsilon}\right) \tag{6}$$

In (6), μ_k and σ_k are mean and variance of I respectively in a squared window ω_k with dimensions $r \times r$ centered at pixel k. The number of pixels in this window is defined ω and ϵ is a smoothness parameter value. Since the general guided image filtering method aggregates the initial matching cost within the pre-defined window kernel, the object boundary region is not quite well preserved even though the guidance image is adopted. To improve the performance of edge preserving characteristics in cost aggregation step, we propose an adaptive weight filtering method which enhance the object boundary region from the extracted edge region information.

4. Improved guided image filtering

In our work, the original purpose of guided image filtering enhances the matching cost volumes which generated by local matching procedure. However, the performance of the conventional guided image filtering is changed by user defined window size. To overcome this limitation, we propose an adaptive weighting guided image filter method. Assigning a weight value is determined by extracted edge information from noise removed image.

4.1 Noise removal from input image

The raw input image has a high chance to contain noise factor which prevents obtaining a high accurate matching results. The image noise is sometimes called small scale factor. The small scale factor and unsteady pixel intensity value are main problem when performing a stereo matching. Especially, the fluctuated frequency of small scale factors mainly affects to stereo matching result. As displayed in Figure 7, the small scale factors appear near the homogeneous region or inside of object area.

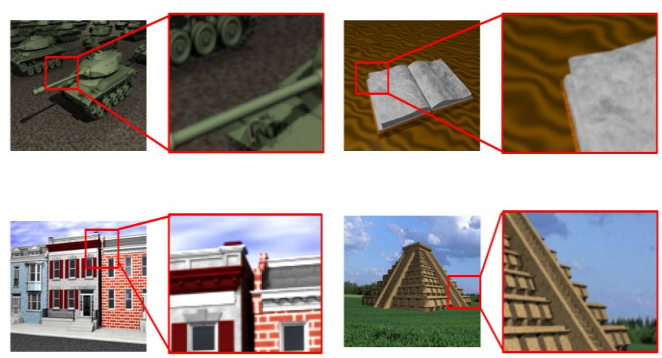

Figure 7. Small scale factors in raw input images

Many filtering methods have been invented to weaken the effect of noise factor in stereo matching such as anisotropic diffusion [7] or bilateral filter [8]. However, they do not preserve an object boundary region quite well. To smooth the image while preserving edge area, we propose the guided image filter based iterative method.

Firstly, the raw image is filtered through the Gaussian filtering. Since Gaussian filtering not only remove a noise area but also demolish the crucial information area. To recover the damaged Gaussian filtering result image, we apply the guided image filtering. Since the guided image filtering enhances the accuracy of object boundary region by using a guidance image, the damaged image is changed to sharpen. Only a single iteration of guided image filtering is insufficient in terms of image recovery. Because of that reason, we iteratively filter the damaged image. The iterative filtering method for noise removal method is indicated in Figure 8.

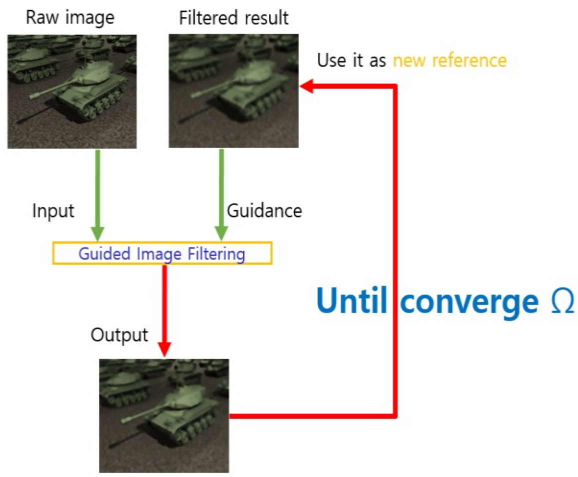

Figure 8. Small scale factors in raw input images

The number of overall filtering operation is determined by Ω value. A fixed number of iteration derives acceptable results about some images, but it also has chance to make an improper result. To prevent this problem, we compute a structural similarity (SSIM) value to determine the criterion of iteration. SSIM compares the filtered image and raw image how they are related. If we have SSIM value which very close to 1, then it means that the filtered image is very similar to raw image.

Figure 9. SSIM results

By considering a noise factor in raw image, we set a Ω value 0.75. Figure 8 express the SSIM computation results. In Figure 9, each column indicates the filtered result from 1 to 4 iteration. As indicated in the box, the dissimilarity region is shrunk in the 4th iteration result than 1st result.

4.2 Edge detection for adaptive weight

To assign a weight in guided image filtering based cost aggregation, we extract the edge region from noise removed image. The edge region is extracted by Canny edge detection method which widely used in many computer vision field. Figure 10 shows the comparison result of extracted edge region from raw and smoothed image. From the extracted edge region, we notice that the filtered image provides more accuracy object boundary information than raw image.

Figure 10. Edge detection results from raw and smoothed image

4.3 Adaptive weighted cost aggregation

The matching cost volumes which generated by local matching function is aggregated through the guided image filtering. We enhance this procedure by assigning a weight value especially on the extracted edge region. The center pixel of guided image filtering window match with extracted edge region, the Gaussian filter is applied at that pixel. Demolished edge neighbor region provides improper cost value than edge pixel. In (7), we define the adaptive weight function using control parameter α.

$$W_{Agg} = \sum_{i=1}^{disp} [\alpha \cdot G(I, C_{vol(i)edge}) + (1-\alpha) \cdot G(I, C_{vol(i)})] \qquad (7)$$

where $C_{vol(i)edege}$ indicates the extracted edge map for each cost volume, and $C_{vol(i)}$ represents the initially generated cost volumes by local matching function. The weight control parameter α adjusts the balance between edge cost volume and initial cost volumes. Function G(•) represents the guided image filtering function using reference and guidance image. As a guidance image, raw input image was adopted and reference image is obtained by Canny edge detection and initial matching cost respectively. In this paper, we set a control parameter value α as 0.6, because the edge region provides an important information while performing the cost aggregation.

5. Experiment results & analysis

To verify the performance of proposed method, we use Cambridge computer laboratory test sequences [9]. We processed the sequences on a desktop computer with Intel Xeon CPU (4.0GHz, 8-cores), 32GB memory. The proposed method is implemented using MATLAB. All test sequences have a same resolution as 400×300.

By combining a local matching cost functions which defined in chapter 3, we generate a mixed local matching function as (8). The mixed cost function is composed of multiplication with β, γ and δ. In this paper, we set each β, γ and δ parameter value as 0.45, 0.25 and 0.3 respectively. Since the gradient map contains important information than other matching cost function in terms of object boundary accuracy, we assign a highest weighting value.

$$C_{mix} = \beta \cdot C_{SAD,grad} + \gamma \cdot C_{SAD,census} + \delta \cdot C_{AD,color} \quad (8)$$

From the combined equation (8), we generate initial matching cost volumes. The number of matching cost volume is determined by the disparity search range of input image. For example, the test sequence has a disparity search range from 0 to 63, then generated cost volume number is 64. The generated matching cost volume is expressed in Figure 11.

The matching cost is computed along the disparity search range, so different kind of initial disparity maps are generated. The purpose of disparity search range restriction is reducing a number of matching cost volumes. If we have small number of matching cost volume, the temporal stereo matching method is possible to operate in real time.

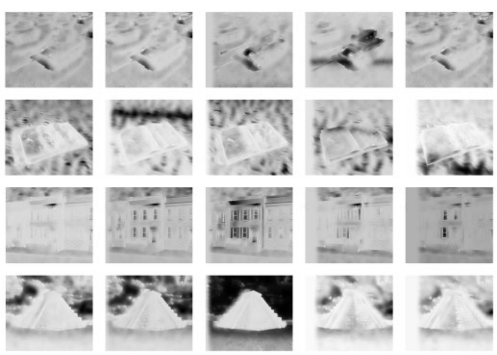

Figure 11. Initially computed matching cost volumes

The conventional method just applies the winner-takes-all (WTA) algorithm on the matching cost volume to find an optimal matching cost value.

Since the guided image filtering requires higher computational time complexity than WTA method, we do not apply the guided image filtering for cost aggregation for each frames. Instead of that, the proposed method periodically updates the reference disparity map using guided image filtering. Additionally, to reduce the time complexity of guided image filtering based cost aggregation, multi-thread method is adopted. The multi-thread method calculates the (6) about each disparity search range.

In our work, the disparity search range is restricted within ± 3 around the current pixel location in case of non-updating procedure. If the disparity map is not updated using guided image filtering the computational complexity has to maximally reduced. However, in an updating procedure, we provide many pixel intensity information to guided image filter function around ± 5 range. Based on that pixel values the guided image filtering aggregates a stereo matching cost value for accurate disparity map generation.

After generating a disparity map using WTA algorithm, the disparity map contains some error or occlusion area. To handle that problem, we use a cross-check and weighted median filtering. The cross-check detects an occlusion area as indicated in Figure 12. The detected occlusion area and remaining error is removed by using a weighted median filter.

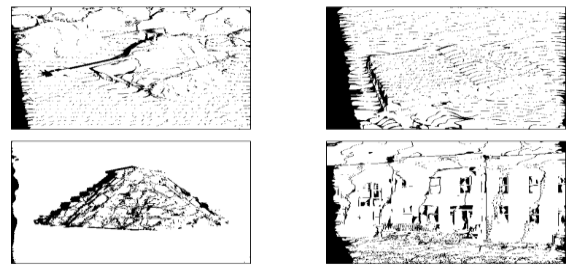

Figure 12. Occlusion area detection results

Since the guided image filtering takes most of the processing time in overall procedure, we use multi-threading scheme while computing the guided image filtering. Figure 13 shows the experiment results with other filter based cost aggregation methods. We update the disparity maps for every 4 frame to prevent the error propagation problem.

As indicated in Figure 10, the estimated disparity maps do not contain serious error propagation problem. Contrary to conventional method result exhibited in Figure 5 the error prevented temporal matching results show more accurate disparity value than original ones.

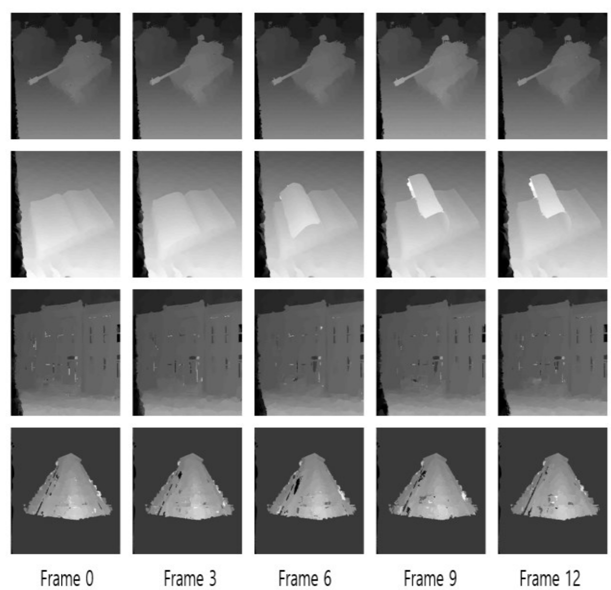

Figure 13. Disparity maps using guided image filtering

Table 1 and Table2 shows the bad pixel rate (BPR) and computational complexity comparison results respectively. To evaluate our performance, we compare the previously invented disparity refresh method in terms of BPR.

Table1. BPR comparison results

Method	Sequence	BPR(%)
		1 per 3 update rate
[3]	Book	9.2
	Street	11.0
	Tank	9.2
	Temple	8.1
Proposed	Book	8.6
	Street	9.8
	Tank	8.5
	Temple	7.7

Table2. Time complexity comparison results

Method	Sequence	Time complexity(sec)
		1 per 3 update rate
[3]	Book	4.51
	Street	4.52
	Tank	4.51
	Temple	4.24
Proposed	Book	5.67
	Street	5.84
	Tank	6.01
	Temple	5.93

As indicated in Table 1, the guided image filtering based updating result derives a better BPR performance than feature based updating method. However, the proposed scheme takes more computational time than feature based method. Because the guided image filtering needs many summation and multiplication than conventional method, the proposed method consume more time as represented in Table 2.

The average time consumption of proposed method is 5.86 sec which derived by multi-threading technique. When we do not apply the multi-threading scheme for temporal disparity estimation, the computational complexity is increased about 13%. If we use CUDA which invented by NVIDIA for computation of guided image filtering, the computational time is possible to reduced efficiently.

Additionally, the computation complexity is affected by resolution of test image. In our experiment, the size of test sequence image is relative lower than other test sequences. So, in our future work, we improve the performance of temporal domain stereo matching algorithm with any test sequences. Especially, to improve the performance in terms of complexity, we have to perform guided image filtering in a short time.

6. Conclusion

In this paper, we propose the guided image filtering based disparity map estimation method in sequential image. Real time disparity value estimation in sequential image stereo matching is nearly impossible. To solve that problem, temporal disparity information is used to restrict a disparity search range. Since disparity search range restriction cause an error propagation problem in sequentially estimated disparity map, we update a reference disparity map periodically. The guided image filtering aggregates initial matching cost volumes and WTA algorithm is adopted to find out an optimal cost value. To improve the accuracy of initial matching cost value, we combine the AD of color, gradient and census transform images. As a post processing, cross-check and weighted median filtering is adopted. From the experiment results, we check that our proposed method generates accurate disparity maps than conventionally used sequential stereo matching method.

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