DOI: 10.2352/ISSN.2470-1173.2016.21.3DIPM-402

Temporal Domain Stereo Matching based on Feature Points for Restriction of Error Propagation

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Abstract

Depth estimation from captured video sequence needs a high time complexity. If we select a large size of window kernel for depth estimation, it will also affect to the computational time. Especially, in case of the depth estimation from sequential images, time complexity is a critical problem. In this paper, we propose a temporal domain stereo matching method for real-time depth estimation. Since the sequential image has a many similar region between neighboring frames, we use that properties for restricting a disparity search range. Even the relationship exists between the neighboring frames, following frame depth estimation result includes a small part of error. Eventually, the propagated error affect to accuracy of estimated depth value. Compensation method of error propagation is proposed based on the feature point in stereo image. Depth values are periodically estimated with maximum disparity search range. Since computing a cost value for all disparity search range needs a high time complexity, we restrict the disparity map renewal frequency. Experiment results show that the proposed depth estimation method in sequential image can derive more accurate depth value than conventional method.

1. Introduction

Nowadays many kinds of 3D video contents are used for providing a realistic to viewers. Especially, to express the 3D image, depth information is used in 2D image coordinate. To display the 3D image on a screen, we need depth information which can provide a location of object in a 3D world coordinate. Even a human eyes can feel the perspective and velocity of objects without any additional information, but 2D image plane has a limit in terms of shortness of geometrical information. After the 3D movies attract interest of people, the invention of 3D video technology was boosted.

Since the depth information is essential part of 3D video technology, many kinds of depth image acquisition methods are developed. Basically depth image acquisition methods can be divided into two types. The first method usually called active depth sensing method [1]. Active sensing method mainly use optical devices for depth image acquisition. ToF (time of flight) technique based depth image capturing camera has been invented from many companies. The Kinect V2, which developed by Microsoft and SR4000, which developed by Mesa Imaging AG can provide a depth information from the captured image. The infrared ray was shot from emitter and receiver take the reflected infrared ray, so that the flight time of infrared is exchanged to real distance between object and camera. The other depth image acquisition method is called passive depth sensing method [2]. Contrary to active sensing method, this method use stereo images for estimation of depth value.

Depth estimation using stereo matching method is composed of local and global type. Local stereo matching method uses window kernel for computation of cost value. Overall cost computational time changed depending on the window size. If we apply the large size of window for cost evaluation, then it take a more time than small size of window. The large size of window can estimate depth value without a noise effect, however, it did not consider the edge or complex region of objects. Contrarily, computation time of small window size is shorter than large window size method, it generates a noise affected depth image. Global stereo matching method does not uses the window kernel for depth estimation. Instead using a window kernel, global matching method consider all of image pixels for depth estimation. Since this method considers all of pixel values for cost evaluation, it needs a more time than local stereo matching method. Although global matching method takes amount of time, the result of estimated depth map accuracy is better than local method. Usually, to optimize the cost value in global matching method, graph cuts [3] and belief propagation [4] techniques are used.

Although the depth image is extracted by using the active or passive sensing method, it still has a problem in terms of real-time stereo matching. To improve the efficiency of computational time, many kinds of acceleration methods have been developed for real-time stereo matching. *Zhang et al*. [5] propose the GPU acceleration method to boost the computation time. Parallel computation using GPU can efficiently compute the cost value for each pixel value, so that they can impressively reduce the time complexity than conventional method. *Qingqing Yang et al*. [6] use guide image filter for fast stereo matching. They propose weight propagation method to compute support weight with guide image filter.

In this paper, we basically use temporal domain stereo matching method with sequential image frames. Since this method propagates an error to following frames stereo matching result, we need to restrict the error propagation problem. While performing the temporal stereo matching, to renew a reference disparity image, firstly we extract feature points using a FAST method. The feature points represent a characteristic of object in the image, we search maximum disparity range at those feature points. If we search the maximum range for all pixel values, then it takes more time than general temporal matching method. Also, frequent reference disparity map renewal increases the time complexity in terms of workload. Extracted feature points between stereo images are not matching each other, since we propose a constraint condition with Kalman filter to find out a correctly matched feature point. Based on the correctly matched feature point, we renew the reference disparity map.

We use 4 different test video sequences, to verify the performance of the proposed error restriction method. The estimated depth images are compared with the provided ground truth image. In our experiments, we found that the proposed temporal stereo matching method can efficiently restrict the error propagation in later image frames matching result, but time complexity is somewhat increased than conventional temporal domain stereo

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DOI: 10.2352/ISSN.2470-1173.2016.21.3DIPM-402

matching method. Even the time complexity is increased it still possible to use as a real-time stereo matching.

2. Background

The problem of local and global stereo matching method is time complexity when performing the real-time depth estimation. Especially, time complexity of conventional methods are very dependent to predefined parameter value. In case of local stereo matching method, window kernel size affects to computation time for each pixel cost value. Also, global stereo matching method affected by optimization technique [3, 4].

Previously studied temporal stereo matching method uses block matching in video domain to assist disambiguate spatially similar candidates [7]. The advantage of temporal domain stereo matching is finding a relationship between single pair of images. *J. Kowalczuk et al*. propose temporal stereo matching method by passing an iterative support weight value with GPU implementation.

The hardware assistance and block matching based stereo matching methods can efficiently estimate depth image. The proposed temporal domain stereo matching method in sequential image uses an estimated disparity image, which is computed in previous image frames. Although, we adopt the previously estimated disparity image, the quality of estimated depth information is not perfect to real distance. To improve the estimated depth value correctness, we apply different type of initial disparity image. Differently obtained initial disparity images are related to three proposed stereo matching types.

2.1 Temporal Stereo Matching

2.1.1 General Approach

Generally used temporal domain stereo matching method just uses the previously estimated disparity image for restriction of disparity search range in following image frames. Figure 1 indicates that temporal domain stereo matching work flow.

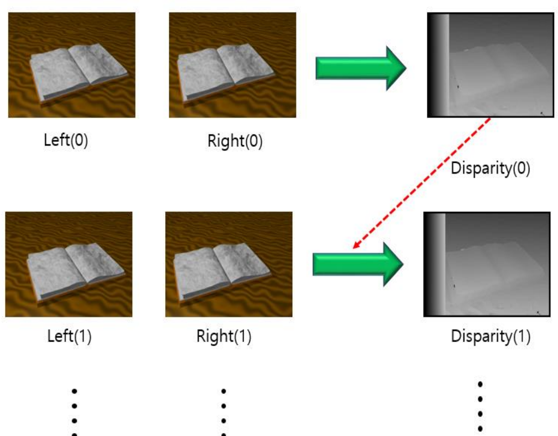

Figure 1. General temporal domain stereo matching structure

Temporal domain stereo matching method use the pre-obtained disparity image from Left(0) and Right(0). Since in sequential video images has similarity of objects in the image, we can restrict the disparity search range in following image frames. For example, if previously estimated disparity value is '75' at the same coordinate in following image matching, then we search ±3 or ±5 pixel range. Depth estimation with restricted disparity search range can efficiently reduce the time complexity when computing a cost value within the defined window kernel. We define disparity search range $\mathrm{Min}_{\mathrm{disparity}}$ and $\mathrm{Max}_{\mathrm{disparity}}$ in (1).

$$Min_{disparity} = disp_{pre} - n$$
$$Max_{disparity} = disp_{pre} + n \quad (1)$$

Where $disp_{pre}$ represents the previously estimated depth value from image pair and n indicate the additional disparity search range like 3 or 5. In general temporal domain stereo matching method, we use local stereo matching method. Usually, in local stereo matching method SAD (sum of absolute differences), SSD (sum of squared differences) and NCC (normalized cross correlation) cost computing functions are used. In case of this general stereo matching method, we apply the SAD cost calculation method for defining a disparity cost value comparison within the window pixels. NCC cost function can derive more accurate disparity value than other cost computing functions, however, it need more computation time for cost evaluation. Our objectives is reducing a time complexity, so that we did not use the NCC cost function.

2.1.2 Initial disparity changing

General proposed method use the local stereo matching result at second frames stereo matching. Since the reference disparity image affects to sequential image frames stereo matching result, the accuracy of reference disparity value is important. To improve the quality of disparity value while conducting a temporal domain stereo matching, we use different type of initial disparity value.

The first type for initial disparity image uses a provided ground truth image. Although we effort to estimate the correct disparity value, the ground truth image is the most accurate value compare to other stereo matching methods. Figure 2 represents the temporal domain stereo matching method with ground truth image.

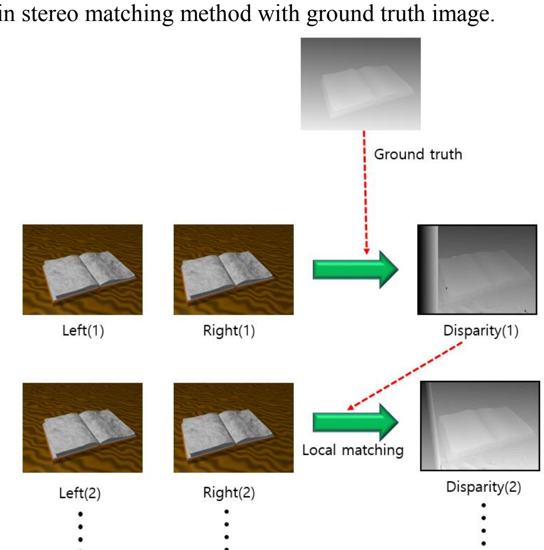

Figure 2. Temporal domain stereo matching using ground truth

Ground truth based temporal domain matching method also restrict the disparity search range in sequential image frame stereo matching procedure. Since the initial disparity image(ground truth) has an accurate disparity value, so that we use minimum disparity search value. Even we can get an accurate depth image using a

DOI: 10.2352/ISSN.2470-1173.2016.21.3DIPM-402

ground truth image as an initial disparity information, the ground truth image is not obtained in real situation.

The ground truth based temporal domain stereo matching method has a limit when performing the stereo matching without provided ground truth image. To treat that kind of problem, we adopt different initial disparity image using global stereo matching method. Instead of the ground truth image in initial image frames matching, global stereo matching is adopted. Figure 3 indicates a temporal domain stereo matching method with global stereo matching method.

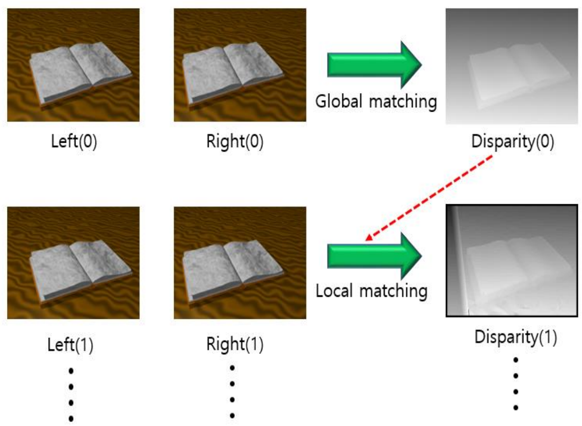

Figure 3. Global matching in temporal domain stereo matching

Contrary to ground truth image based method, the global matching result disparity needs a computation time for initial disparity image. Additionally global matching result has some error in estimated image. Although the global matching result has error, that method is more proper to real situation. The global matching used in Figure 3 is proposed by Jang et al. [8], and they propose an occlusion handling method while depth estimation. The occlusion area is occurred by shaded area between two objects, as a result of that the estimated depth image quality is degraded. Using those occlusion handling method we can get a non-occluded disparity image, and adopt that image as an initial disparity image in temporal domain stereo matching. Since to get a global stereo matching result at initial image frames we need time for computation of cost value, so this method takes more time than ground truth based method.

2.1.3 Motion detection based Matching

Previously explained methods use ground truth image and global stereo matching at initial image frames to improve the accuracy of disparity value in sequentially estimated image frames. Motion detection based method considers the sequential image frames in same view point. For example, to detect the motion between different time, we consider a Frame(n) left image and Frame(n+1) left image. Figure 4 shows the overall structure of motion detection based temporal domain stereo matching method. Where Moving differences represents the subtraction result between Left(0) and Left(1). Instead, only using the initial disparity image for restriction of disparity search range, we added a difference information of neighbor frames in same view point. At the edge of the object in the image, it has critical characteristics of object in terms of accuracy of disparity. Since the edge has many information in the image, so that Canny and Sobel introduce the edge detection method. In this paper, we just subtract neighbor image frames for extraction of moving area of image. However, if we set a small number of threshold value for motion detection, then non-important region also detected as a moving area. For this reason, we control the threshold value to properly detect the moving area between two image frames.

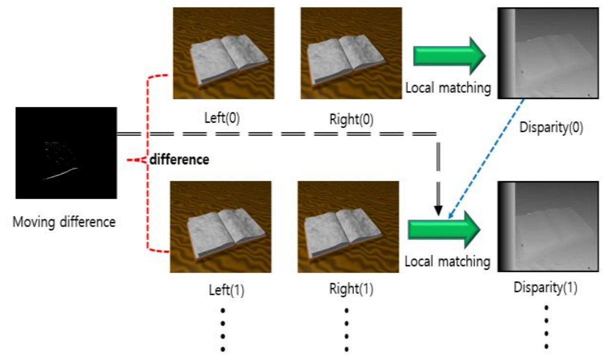

Figure 4. Motion detection based temporal domain stereo matching

We determine the threshold value for motion detection as indicated in Figure 5.

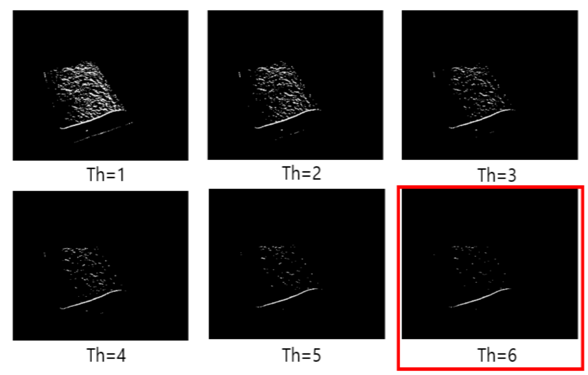

Figure 5. Differently detected motion area depending on Th value

As we can check in Figure 5, small threshold(Th) value detect many motion area between the image frames. As the threshold values are increased, motion areas is intensively detected on the edge of object. From that experiments, we determine the threshold value as 6, and applying this threshold value. Our goal is reducing the computational time while conducting a stereo matching with sequential images, since as indicated in Figure 4, we do not use the global stereo matching method in initial stereo matching procedure. Similarly, estimation of sequential image pair uses the local stereo matching method. If we conduct the global stereo matching method for depth estimation in that case, it will increase the time complexity. Since the motion detection based method find a difference between neighbors frames, that procedure also need a time for calculation even a millisecond.

While conducting a stereo matching in sequential image, at the detected motion region we search the minimum and maximum disparity range for depth estimation. Since the motion detected region represents the edge of object, full disparity search can improve the accuracy of estimated depth value, and simultaneously preserving the overall depth image quality.

3. Problem Setup

In temporal domain stereo matching, we can treat the time complexity problem, however, the estimated depth image quality is

DOI: 10.2352/ISSN.2470-1173.2016.21.3DIPM-402

not better than our expectation. While conducting the temporal domain stereo matching, since the restriction of disparity search range, the estimated depth value is not accurate than full disparity search result. Moreover, as a frame numbers are increased, the error which occurred by previous frame was propagated. The propagated error effects are indicated in Figure 6.

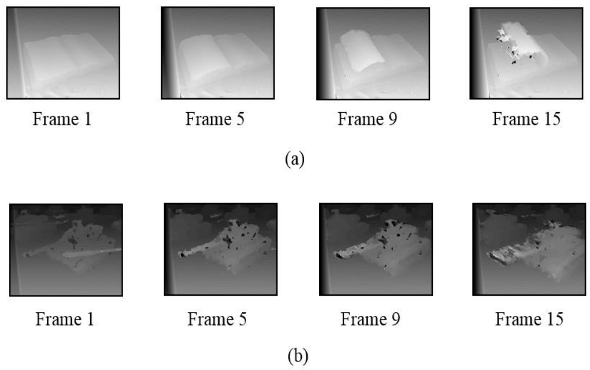

Figure 6. Error propagation effect in temporal domain stereo matching, (a) Book, (b) Tank

As represented in Figure 6, prior image frame disparity results are similar to local stereo matching result, however error was propagated in disparity result of later image frames. That problem is caused by restriction of disparity search range. To solve error propagation effect in sequential image stereo matching, we propose the feature point based matching method.

4. Feature based Temporal Stereo Matching

Many kinds of feature points detection method have been developed like SIFT (scale invariant feature transform), FAST (features from accelerated segment test) and Harris corner detection. Among them, we adopt the FAST feature detection method, since literally the FAST feature detection method is developed to find out the feature point in a short time. FAST feature detection can control the number of detected feature points using a parameter value. Figure 7 represents the extracted feature points with different parameter value.

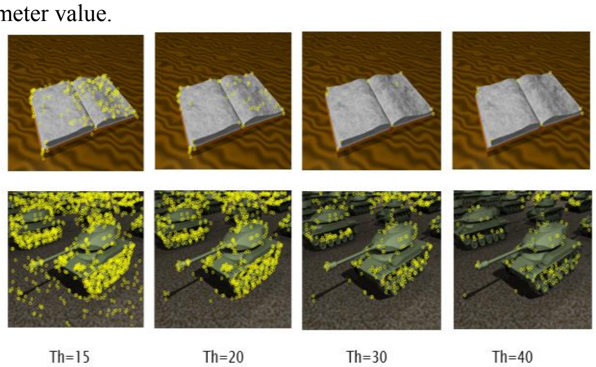

Figure 7. FAST feature detection result with different threshold value

Smaller threshold value for FAST feature detection extracts many feature point on the object, however higher threshold value extracts small part of feature points. Even the extracted feature points represent a characteristic of object in the image, unnecessarily extracted feature points do not help to find a proper disparity value. Our interest is corner points of object, since we control the threshold value for feature extraction.

Between the extracted feature points left and right images, that points coordinates are always correctly correspond to each other. Since the difference of view point in pair of images, the extracted feature coordinates are different. To identify the correctly matched feature points, we use feature points constraint conditions.

The first constraint condition is epipolar constraint. Basically we compare the feature points on the same baseline, since the stereo matching is conducted with a rectified image. If we compare the same baseline feature points, then correctly matched feature points are detected between image pairs.

The second constraint for matched feature points is ordering constraint, which consider the order of extracted feature points in stereo image. Even the feature points exist on the same base line, the feature points have different pixel coordinate. To reduce the time complexity and improve the quality of disparity image, the ordering constraint is essential part.

Lastly, we use linked length constraint condition. Between the feature points on the same base line on stereo image, the distance of two feature points are considered for feature matching. As indicated in Figure 8, we consider the two feature points.

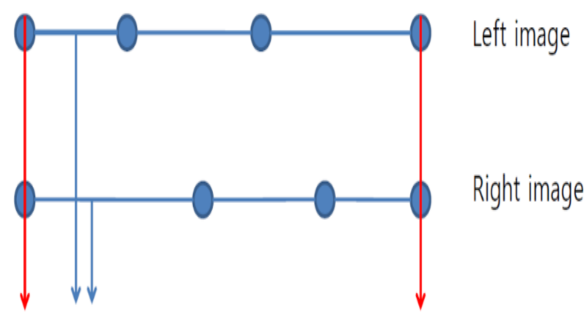

Figure 8. Linked length constraint between stereo image

Where the vertical red line indicate the feature link, and other vertical lines represent not correctly matched linked line. From the left feature point in left and right image, we consider the distance of sequential feature point on the same base line. If the distance between two feature points is same on left and right image, then we determine that points are correctly matched feature points.

Iteratively using those feature matching constraint conditions with Kalman filter [11] for removing incorrectly matched feature points, we efficiently find out the correctly matched feature points. Updating a measurement for removing error among the extracted feature points, Kalman filter gradually finds a correctly matched feature point. Based on the matched feature points, we conduct the temporal domain stereo matching for depth estimation. Additionally, we use the feature point information while performing the stereo matching.

In this paper, the remaining errors after applying the constraint condition are treated using Kalman filter. Kalman filter was generally used for removing a noise, which included in an observed data. In our case, the noise represents an incorrectly matched feature points between stereo images. Since the noise model used in Kalman filter has a normal distribution. The multiplication of two normal distribution can iteratively derive a new normal distribution model, so that we apply this characteristics in our feature matching model.

The Kalman filter composed of two update stages. First update stage is *Prediction*, which predicts an initial parameter value of state

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and error covariance. Those prediction procedure can express like (2).

$$\hat{x}_k^- = A\hat{x}_{k-1}^- + Bu_k \tag{2}$$

Where $\hat{x}_{k-1}$ is estimated from k-1 time, and $\hat{x}_k^-$ represents not yet refined value, which coming from k-1 time. Furthermore, we need an initially estimated error covariance value, since the error model dependent to the normal distribution. The initial error covariance model is indicated in (3).

$$P_k^- = AP_{k-1}A^T + Q \tag{3}$$

The P_{k-1} represents the covariance matrix, which based on a measured value. In the *prediction* step, we generate an error and covariance model of incorrectly matched feature points after finishing the constraint conditions. Based on those initial model, we compensate the estimated value to find a correctly matched feature points.

The compensation stage is called *correct* step. In this step, we compute a Kalman gain and update estimated state with error covariance value. Kalman gain is normalized value within a 0 to 1, since this value working as a weight between estimated and measured value. The optimized Kalman gain is computed using (4).

$$K_k = P_{k|k-1}H_k^T S_k^{-1} \tag{4}$$

Using computed gain value, we update estimate with measurement value with respect to previously estimated value. The update of estimation value can express like (5)

$$\hat{x}_k = \hat{x}_k^- + K_k(z_k - H\hat{x}_k^-) \tag{5}$$

If we assume H matrix as an identity matrix I, then Kalman gain factor is evenly multiplied to estimated and measured value as in (6).

$$\hat{x}_k = K_k z_k + (1 - K_k)\hat{x}_k^- \tag{6}$$

As we can check in (6), Kalman gain value K_k properly control the value for updated value between estimated and measured value. In this equation, the estimated value is $\hat{x}_k^-$ and z_k represents the measured value. In our case, the measured value is extracted feature points using FAST and estimated value is obtained by constraint condition. Since the estimated value has more reliable value than measured value, we applying more weight value to estimated result. The covariance of error also updated while performing an iterative procedure, so that the updated error covariance value can be expressed like (7)

$$P_k = (I - K_k H)P_k^- \tag{7}$$

Where P_k^- indicates estimated error covariance value without compensation and H is relative matrix, which value is dependent on a time of measurement. Based on those *prediction* and *correct* step in Kalman filter, the remaining a small part of incorrectly matched feature points are removed between stereo images. RANSAC method usually used for noise removing between two extracted feature points, but this method is non proper to our method in terms of time complexity problem.

Figure 9 demonstrates the correctly matched feature points based temporal stereo matching method. The extracted feature points help to restrict the error propagation in sequential image stereo matching results. Since the error was propagated in later image frame disparity result, the reference disparity image is periodically refreshed based on the feature points. In our experiment we refresh the reference disparity image 1 per 3, 5 and 10 frames. If we refresh the disparity image frequently, then the time complexity also increased.

Disparity map renewal is depending on the number of extracted feature points. As we checked in Figure 7, a proper threshold value was adopted for feature extraction. If we assume that, the feature points are properly extracted on the edge of object, then we search the minimum and maximum disparity range for disparity map renewal. Since the feature points indicate the distinctive character of object, we performing full disparity search for the disparity map renewal instead of whole image pixels.

Feature detection and finding a corresponding feature points take a time for computation, so that will increase the time complexity. FAST feature detection can find feature points in a millisecond and also the work load of constraint conditions has small for feature based stereo matching, so that those procedure does not cause a critical time complexity problem.

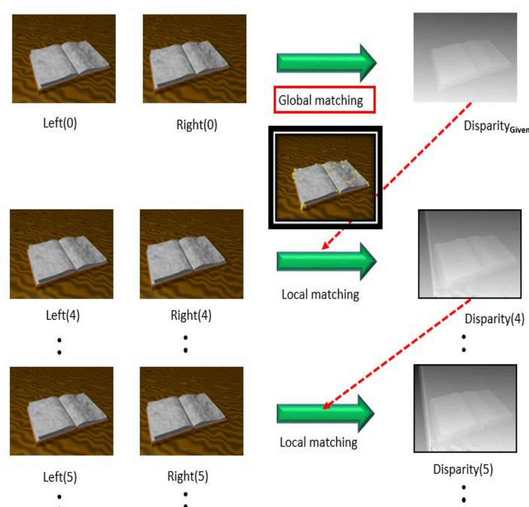

Figure 9. Feature points based restriction of error propagation in temporal domain stereo matching

5. Experiment Results

In this paper, we took test video image sequences [9], which provided by Cambridge computer laboratory for testify the performance of proposed method in temporal domain. We processed the sequences on a desktop computer with Intel Xeon CPU (8-core), 32GB memory and Visual studio was used for compile. Whole test sequences are 4 different images and have a same resolution as 400

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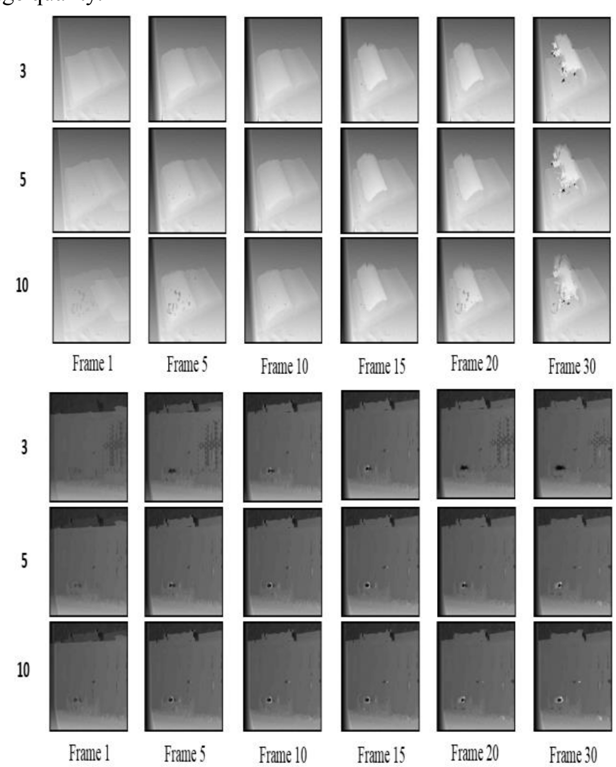
× 300. Since the feature based temporal stereo matching is conducted within whole given image frames, we use 30frames for testify. Figure 10 shows test video sequences for our experiments.

Figure 10. Cambridge video sequences test sets,
(a) Book, (b) Street, (c) Tank, (d) Temple

For the comparison of proposed method performance with different disparity map renewal period, we use given ground truth images. To restrict the error propagation to sequential image frames, feature points are extracted with fixed threshold value 30. Disparity map renewal is performed with different period as 10, 5 and 3. When we frequently perform the disparity map renewal, the time complexity was increased than lower frequency.

To compare the time complexity of proposed method, we use small resolution test image, however if we use larger size of image then time complexity also increase than our test results. For depth image estimation, we use local stereo matching method with fixed window size 7×7.

In Figure 11, experiment results are represented with different disparity map renewal period. Where the column indicates the frame number and row represents different renewal frequency of disparity image. As we can check in Figure 11, frequent disparity map renewal results has more proper result than lower frequency. In prior image frames, restricted error propagation method does not shows a remarkable effect on the result disparity image. However, as frame numbers are increased, proposed method derive noticeable disparity image quality.



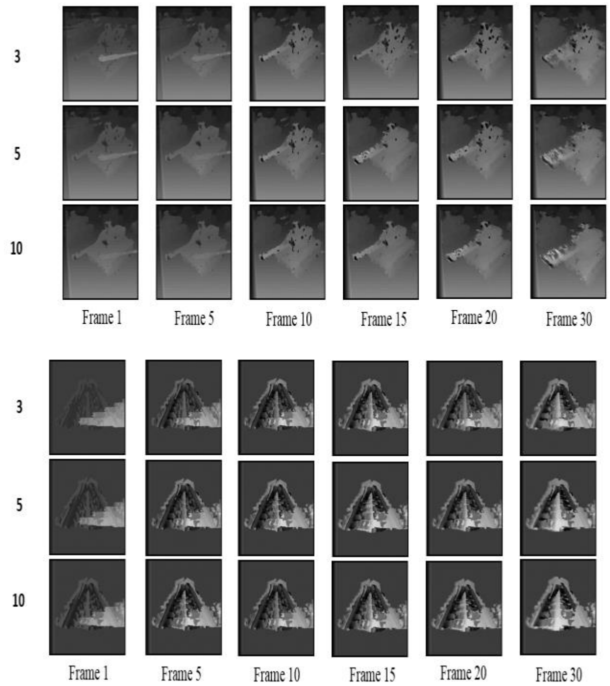


Figure 11. Temporal domain stereo matching results

To compare the performance of proposed method with numerically, we compare the estimated disparity image with provided ground truth image. Table 1 shows the comparison results of estimated depth image quality. Usually, disparity image quality was compared using a BPR (bad pixel rates) value. If compared each pixel between estimated image and ground truth image difference is bigger than 1, then we determine that pixel is bad pixel. Since proposed method renews the reference disparity image, BPR has better result than general temporal domain stereo matching method. Especially, frequent renewal period has exceptional result than lower frequency method. The performance of BPR is improved about 2.3% when compared to general temporal domain stereo matching method.

Table1. BPR comparison results

Method	Sequence	BPR(%)		
		1per10	1per5	1per3
General	Book	11.8		
	Street	13.2		
	Tank	11.3		
	Temple	12.3		
Proposed	Book	10.0	9.8	9.2
	Street	12.8	11.6	11.0
	Tank	11.1	10.7	9.2
	Temple	10.1	9.4	8.1

Additionally, the objective of temporal domain stereo matching method is reducing a time complexity in sequential image stereo matching, so that we compare the time complexity with general method [10] and proposed method in Table 2. Likewise the BPR comparison we compare the time complexity with different disparity map renewal ratio. Overall number of test image sequence images are 30 frames.

Table2. Time complexity comparison results

Method	Sequence	Time complexity(sec)		
		1per10	1per5	1per3
General	Book	4.12		
	Street	4.46		
	Tank	4.48		
	Temple	3,87		
Proposed	Book	3.75	3.84	4.51
	Street	4.15	4.31	4.52
	Tank	4.23	4.38	4.51
	Temple	4.01	4.18	4.24

Since feature extraction and constraint conditions, higher frequency rate takes more computation time than lower frequency rate. Additionally, overall computation time complexity is higher than general method. General method perform the stereo matching with restricted disparity search range, however, proposed method periodically search the full disparity range for depth estimation. From this result we notice that, disparity search range effects to the time complexity in temporal domain stereo matching.

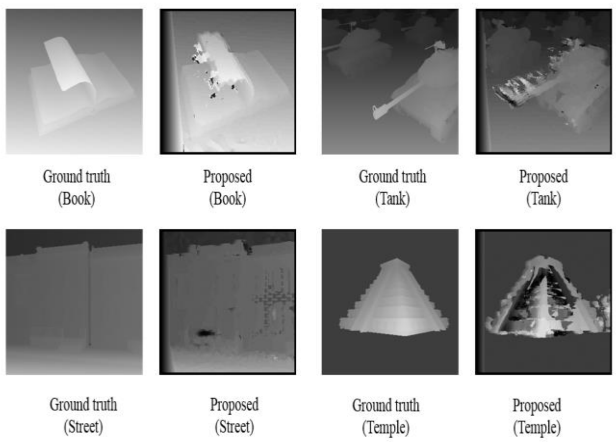


Figure 12. Ground truth and proposed method results

Figure 12 shows the ground truth image and proposed stereo matching result. Even though the error was restricted in later image frames, still some error was occurred near the object boundary regions.

6. Conclusion

In this paper, we have demonstrated the temporal domain stereo matching method with different initial disparity image. Especially our target is restricting an error propagation in any type of temporal domain stereo matching methods. Many temporal domain stereo matching methods are proposed to improve the accuracy of depth value, but error information is constantly propagated to following image frames. To prevent the error propagation effects, we propose feature based temporal stereo matching method. Based on the extracted feature points, reference disparity images are periodically refreshed. From the test results, we notice that more frequent disparity map renewal ratio improves the BPR result than lower renewal ratio. We also compare the time complexity with general method and proposed feature based temporal matching method.

Acknowledgements

This research was supported by the ‘Cross-Ministry Giga KOREA Project’ of the Ministry of Science, ICT and Future Planning, Republic of Korea (ROK). [GK15C0100, Development of Interactive and Realistic Massive Giga-Content Technology]

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