A Stereo Feature Matching Technique Using Feature Window

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Abstract—**This paper proposes a novel stereo matching technique which is based on feature window. The proposed method uses the FAST feature detector to find features in stereo images and determines their correspondences by matching feature windows. We define a feature window which is an image region containing several image features. Compared to conventional feature-based matching techniques, the proposed technique yields better matching accuracy. In the experimental results, we evaluate the accuracy of two matching techniques by comparing with the ground truth images of the Middlebury stereo datasets.**

Keywords-Stereo Matching, Feature Matching, Feature Window

I. INTRODUCTION

Stereo vision is one of the fundamental techniques in computer vision. Since the stereo vision technique is to solve the inherent problems of the human visual system, there are many applications such as 3D scene reconstruction, object recognition, robot vision, etc. Stereo vision is to determine the correspondences of an object between stereo images. Then the correspondence is commonly represented by disparity which is the difference of the image position of the correspondences in the stereo image.

Stereo matching techniques are generally divided into two categories: area based and feature based methods [1]. The area based method decides the disparity of an entire image. Thus, we can obtain a dense disparity map. However, the area based method needs high computation time. Another method is the feature based method. This method utilizes image features which are relevant subjects in an image such as corner or edge.

In the feature based method, it is additionally used an interpolation or diffusion method from the disparity of sparse features in order to obtain a dense disparity map [2]. For this reason, it is important to determine the accurate disparity of image features and this procedure is called stereo feature matching. Thus, the result of stereo feature matching is a sparse disparity map. Generally, a stereo feature matching has high accuracy and low computation time. Besides, a stereo feature matching technique can be applied for real-time system such as navigation and autonomous driving [3]. Besides, additional geometric information of image features such as distance or angle between features can be used for increasing the matching accuracy of features [3,4,5].

It is also important to measure the correlation between stereo images. Defining a cost function generally falls into two parts. First one is a window method. The window matching algorithms calculate correlations of neighboring pixels between stereo images [1,2,3]. Examples are SAD (Sum Absolute Difference), SSD (Sum Squared Difference) and NCC (Normalized Cross Correlation). This method is simple and has low computation time.

Another method is to minimize an energy function [6,7]. An energy function consists of data and continuity term. Then, disparity is determined by comparing with entire costs through an iterative scheme. This method produces very an accurate disparity map. However, high computation cost is needed. Examples are Graph cuts [6] and BP (Belief Propagation) [7].

In this paper, we propose a new stereo feature matching algorithm which is based on matching of feature windows. A feature window refers an image region containing several features. The proposed method generates feature windows in both standard and reference images. Then, the correspondence of each feature in stereo feature windows is determined. If some features fail to determine their disparities in the feature window, they are interpolated by the disparity sets of the feature window.

This paper consists of following sections. In section 2, we describe the feature window matching. Section 3 presents experimental results with performance evaluation through the comparison of matching accuracy using ground truth stereo images from the Middlebury stereo data. In addition, we compare computation cost between two matching algorithms. Finally, conclusion and future work are presented in Section 4.

II. FEATURE WINDOW MATCHING

To obtain a sparse disparity map from a stereo image pair, we present a novel stereo feature based matching algorithm which is called Feature Window Matching (FWM). Among stereo feature matching algorithms, a simple feature matching algorithm can find correspondences by searching feature pairs using only cost function. On the other hand, the proposed method uses a feature window which is defined as a square window in stereo images. The size of a feature window equals the disparity search range in pixel. Therefore, the search range of features in stereo images is determined between the minimum and maximum disparity. The procedures of the

FWM algorithm are as follows. First, we decide a feature window in the standard image. Second, we choose the corresponding feature window in the reference image. Third, features at the feature window are used to determine the feature disparity. Finally, the disparity of undetermined features is interpolated by known disparity sets.

A. Matching Constraints

Many stereo matching techniques use some constraints for increasing matching accuracy. Among many constraints, we choose three matching constraints. First, the *epipolar* constraint is widely used [1,2,3,4]. It is assumed that two corresponding features in stereo images are located in the same *epipolar* line. Using the *epipolar* line, computation time can be reduced and matching accuracy can be increased. Second, the ordering constraint which determines the order of neighboring correspondences is used [8]. Third, we use the disparity constraint such that the disparity value of a stereo image feature is determined between the minimum and maximum disparity ranges [9]. Using three constraints, we can increase matching accuracy.

B. Cost Function

There are many cost functions to determine correspondence between stereo images. Among them, the template matching method is simple and fast. Most of window matching methods use grey level intensity. However, grey level intensity is difficult to find correct correspondence between stereo images. For this reason, we use a correlation function using color information [2,7]. Using color information, the matching accuracy is more increased.

We choose a MSE (Mean Square Error) algorithm and RGB color space to find feature correspondence [2]. A MSE function is defined as:

$$f(x,y)=\frac{1}{n^2}\sum_{i=-n/2}^{n/2}\sum_{j=-n/2}^{n/2} dist_c(Right(x+i,y+j),Left(x+i+d,y+j)) \tag{1}$$

$$dist_c(u,v)=(u-v)^2 \tag{2}$$

$$Right(u,v)=(R(u,v),G(u,v),B(u,v)) \tag{3}$$

$$Left(u,v)=(R(u,v),G(u,v),B(u,v)) \tag{4}$$

In Equation 1, d means the disparity of a pixel in the standard image, n means the window size.

C. Feature Detection

In this paper, we propose a stereo feature matching technique. Therefore, it is necessary to use a feature detector. Among many feature detectors, we choose the FAST (Feature from Accelerated Segment Test) feature detector [10]. Features are determined by comparing the brightness with some neighboring pixels using a certain threshold value. This detector is faster than other feature detectors and provides reasonably high quality image features. Actually, it is possible for the FAST detector to determine image features which are sorted in a descending ordering in milliseconds. Therefore, using the FAST detector, the disparity constraint is simultaneously satisfied.

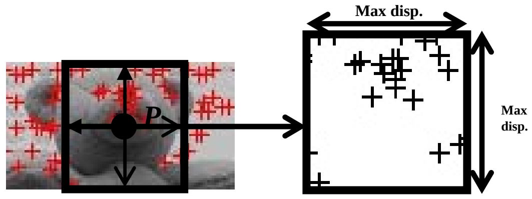

Figure 1. The procedure of a feature window at certain point ***P***.

D. Feature Window Matching Algorithm

In this section, we describe the proposed feature window matching algorithm. The FWM algorithm consists of four parts.

1) Feature Window Decision

In order to run the FWM algorithm, we first decide a feature window. A feature window is a square box and the size of a window is equal to the size of disparity range. In a standard image, we construct a feature window with a center feature point of pixel ***P*** as shown in Fig. 1. If there are enough features in the current feature window, we choose this feature window for stereo matching.

Besides, a feature in a feature window is defined by a two-dimensional vector with respect to the left top of the feature window. The feature window is a basic unit in the proposed method. In the proposed method, the standard image is scanned and matched in every scan line.

To use a feature window, we should consider about the moving distance of a feature window. If the moving distance is smaller than the size of window size, features are possible to match repeatedly. In other words, the moving distance of a feature window is an important factor to matching accuracy. Besides, features which fail to determine disparity are possible to decide disparity because of the error of the corresponding feature window. For this reason, the smaller moving distance is, the higher the matching accuracy is. However, it is necessary to additional computation time is needed for increasing the matching accuracy.

2) Feature Window Matching between Standard and Reference Images

After deciding a feature window at the standard image, we should find the corresponding feature window at the reference image. If the feature window is decided at *(x, y)* in the standard image, we consider the corresponding feature window between $(x+d_{min}, y)$ and $(x+d_{max}, y)$. Here, d_{min} means the minimum disparity and $d_{\max}$ means the maximum disparity.

In order to decide the corresponding window, we use the Principal Component Analysis (PCA) algorithm. The PCA algorithm is widely used for characteristic expression about a data set. Using PCA, it is possible to transform a two-dimensional feature vector set into an eigenvalue. Deciding the corresponding feature window at the reference image is equal to finding the window of the most similar eigenvalue in search ranges.

If the number of feature windows is more than one, features of a feature window are transformed to an eigenvalue

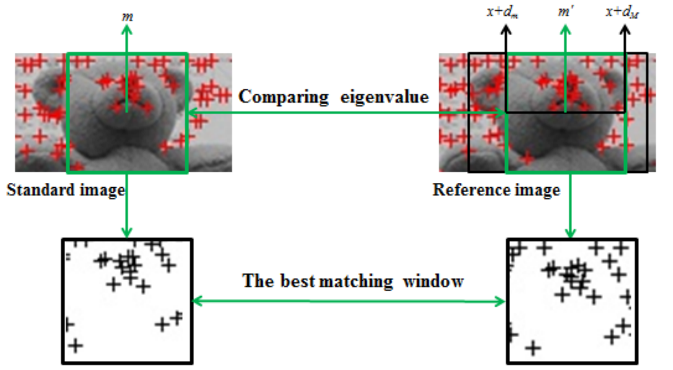

Figure 2. Feature window matching. If the difference of two eigenvalues is the minimum, corresponding window is decided at reference images.

using the PCA algorithm. After getting an eigenvalue, we compare difference of two eigenvalues between the standard and reference image.

$$\lambda_u = PCA\{SV(u,y)\} \tag{5}$$

$$\lambda_v' = PCA\{RV(v,y)\} \tag{6}$$

$$x' = \underset{x+d_m \le k \le x+d_M}{\arg\min} \; |\lambda_x - \lambda_k'| \tag{7}$$

In Equation (5) and (6), SV means feature vectors of a feature window in the standard image and RV means feature vectors of in a feature window in the reference image. Using the PCA algorithm, we obtain an eigenvalue λ_u and λ_v about feature set of each image. By Equation (7), x' is the location of the best corresponding feature window. This procedure is shown as Fig. 2.

3) Feature Matching between Stereo Feature Windows

In this section, we present about determining the disparity of a feature. If the cost of correlation function between two features at two corresponding windows is less than a predefined threshold value, their disparities are determined. If the difference in the vertical direction between two features to determine disparity is less than v, we regard they are similar features because this difference is generated by the error of feature detector. Here, v is called vertical error threshold. In other words, if the difference of two similar features in the vertical direction is inner than v, disparities of two features are determined by a cost function.

4) Disparity Interpolation

If several features fail to determine disparity, these features are interpolated. For disparity interpolation, we first make disparity candidates. Disparity candidate is a set of decided disparities at feature matching. Then, a feature is assigned by each disparity of sets and its correlation value is calculated. If the minimum correlation value of correlation values is less than threshold, disparity of this feature is interpolated.

III. EXEPERIMENT

Experimental results are described using several pairs of stereo images available in the Middlebury stereo data sets. We use tree different stereo images, Venus (2001), Teddy (2002), Aloe (2006) [11]. In order to analyze matching accuracy, we compare the disparity values of features with the ground-truth image from Middlebury stereo data sets. If the difference of disparities between results and the ground truth are less than an error threshold value (ε), we regard they are correctly matching features. Also, a right image is a standard image and a left image is a reference image.

Common parameters are as follows: comparing pixels of FAST detector is 9, vertical error threshold (v) is 2. Moving distance of a feature window is 2, window size of correlation function is 7, and correlation threshold is 500. Besides, error threshold (ε) is set 1.0 and 2.0 pixels and specific parameters are shown in Table 1.

TABLE I. EXPERIMENT CONDITION

	Venus	Teddy	Aloe
Image width	434	450	641
Image height	383	375	555
# of features at the standard image	1025	1000	1029
# of features at the reference image	1066	1016	1156
Maximum disparity	20	53	110
Minimum disparity	1	14	20

The matching algorithm is programmed by using Microsoft visual studio 2008 and OpenCV 2.0 library. The computing environment is Intel i5 750 processor, 4.00 GB RAM, and Microsoft Window 7 OS.

Fig. 3 and Table 2 represent the matching accuracy and the number of matched features about two matching methods. Here, MSE matching method uses only color MSE correlation function to decide disparity. By Table 2, performance of the FWM is better than simple matching algorithm because of increasing not only the accuracy but also matched features.

TABLE II. MATCHING ACCURACY COMPARISON

Image			MSE	FWM
Venus	# of matched features		423	661
	Accuracy	ε =1.0	98.1	98.5
		ε =2.0	98.1	98.5
Teddy	# of matched features		178	460
	Accuracy	ε =1.0	88.8	92.4
		ε =2.0	92.7	93.9
Aloe	# of matched features		455	571
	Accuracy	ε =1.0	99.1	95.6
		ε =2.0	99.3	96.7

Accuracy Unit: %

Also, we show the comparison of computation cost of two algorithms in Table III. According to Table III, simple feature matching algorithm needs less computation cost. By Table 3, the FWM algorithm has a limit for utilizing the real-time application. For this reason, we additionally consider the parallel processing such as GPGPU.

TABLE III. COMPTATION TIME COMPARISION

	MSE	FWM
Venus	19.8	106.4
Teddy	19.0	206.3
Aloe	27.4	657.9

Time Unit: msec

IV. CONCLUSION

This paper has presented a novel stereo feature window matching (FWM) algorithm. Results of Middlebury benchmark data sets show that the proposed algorithm is robust and have high accuracy. The performance of the FWM algorithm is generally better than simple feature matching algorithm. However, FWM algorithms are difficult to utilize for real-time application, immediately. Therefore, we consider parallel programming to improve computation time such as GPGPU. Besides, we will research to generate a dense disparity map using propagation or diffusion algorithm.

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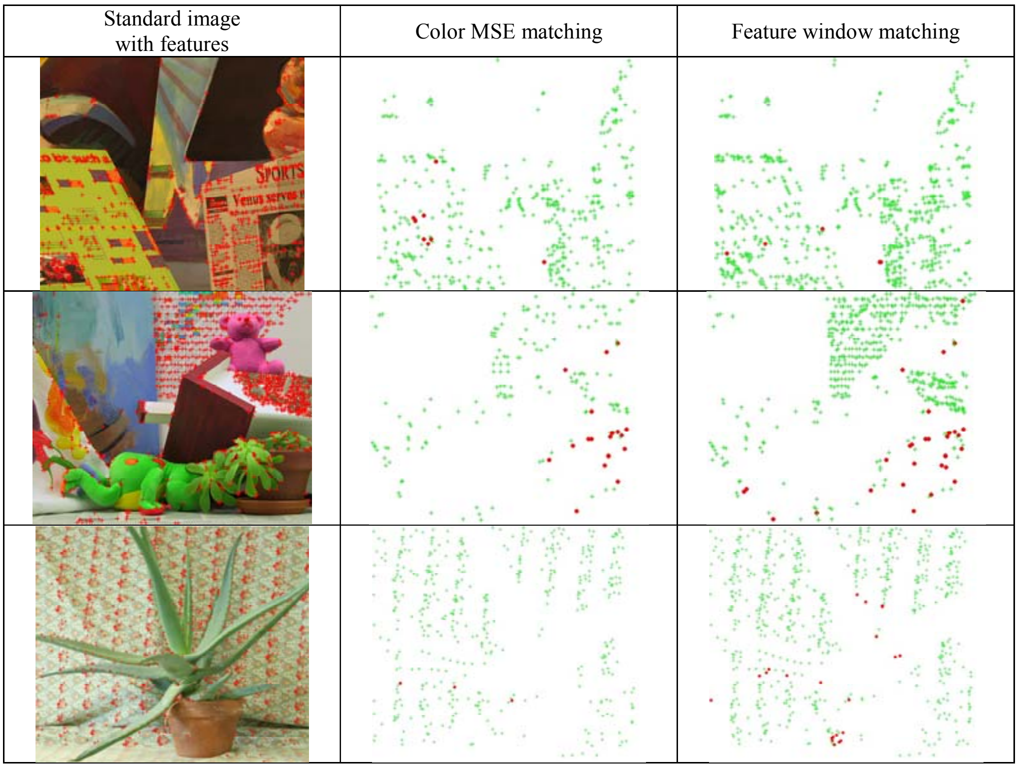

Figure 3. Results of two proposed methods by the Middlebury benchmark datasets. Venus, Teddy, and Aloe. The first column images are standard images. The second and third columns are the sparse disparity maps by each method. Green cross points are correct and red circles are incorrect region at error threshold 1.0.