A METHOD FOR ADJUSTING ADAPTIVELY THE WEIGHT OF FEATURE IN MULTI-DIMENSIONAL FEATURE VECTOR MATCHING

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ABSTRACT : Muilti-dimensional feature vector matching algorithm uses multiple features such as intensity, gradient, variance, first or second derivative of a pixel to find correspondence pixels in stereo images. In this paper, we proposed a new method for adjusting automatically the weight of feature in multi-dimensional feature vector matching considering sharpeness of a pixel in feature vector distance curve. The sharpeness consists of minimum and maximum vector distances of a small window mask. In the experiment we used IKONOS satellite stereo imagery and obtained accurate matching results comparable to the manual weight-adjusting method.

KEY WORDS: Muilti-dimensional feature vector, sharpeness measure, feature vector distance

1. INTRODUCTION

The interest on high resolution satellite imagery has been increased for earth observation in many applications. The high resolution satellite imagery can provide useful information especially for the observation of urban areas. In urban area analysis, however, high resolution satellite imagery has not been widely used to extract the information of man-made objects. First of all, the extraction process such as building detection and reconstruction is very difficult in high resolution satellite imagery. To obtain good extraction result, it is necessary to develop robust stereo matching method.

In stereo matching, pixel's intensity is usually used for finding correspondence pixels between stereo pair images. Other features such as gradient, derivative and texture of a pixel can also be used for stereo matching. In multiple dimensional feature vector matching (Jawahar and Narayanan, 2002a, 2002b), some features are combined to calculate similarity between stereo pair images. The combined multiple features give better matching result than one feature does.

In this paper, we propose a new method for adjusting adaptively weights of features considering relative importance of each feature in stereo matching.

2. MULTI-DIMENSIONAL FEATURE VECTOR

2.1 Feature elements of multi-dimensional feature vector

A feature of multi-dimensional feature vector is a value representing local property of a pixel such as mean, variance and gradient value within small window mask of the pixel. A feature image is generated by calculating feature values of all pixels in an image. Then the feature vector consists of all feature values of the pixel with the same coordinate in the feature images.

2.2 Estimation of feature weight

To find correspondence pixels, we calculate feature vector distance between stereo images as follows:

$$D(\vec{r},\vec{s}) = \min \sum_{k} \omega_k \cdot \left| f_k - g_k \right| \qquad (1)$$

where $\vec{r}$ and $\vec{s}$ are feature vectors in reference and target image respectively, f_k and g_k are kth feature values of $\vec{r}$ and $\vec{s}$ respectively, ω_k is weight of kth feature in stereo matching. The weight ω_k represents relative importance of feature and can be obtained by imposing the following constraint on the weight ω_k (Jawahar and Narayanan, 2002a):

$$\sum_{k} \omega_k = 1 . \qquad (2)$$

Finally the weight ω_k is inversely proportional to the feature vector distance.

In a heuristic method, the weight ω_k is determined by estimating the sharpeness of partial correlation function, in which a strong peak indicates a good match (Jawahar and Narayanan, 2002b). In the above method, the sharpeness is obtained by convolving the partial correlation function with the mask [-1, -2, 6, -2, -1] and then average sharpeness is computed within all pixels in search range. The average sharpeness, however, does not fully represent the characteristic of the sharpeness of partial correlation function.

3. DETERMINATION OF ADAPTIVE FEATURE WEIGHT BY USING LOCAL SHARPENESS MEASURE

3.1 Feature vector distance curve

Many stereo matching methods define a dissimilarity function of the pixels in a small window patch, for example, sum of difference (SD), normalized cross correlation(NCC) and etc. As a matched pixel, we choose the pixel with smallest dissimilarity value in disparity range. Similarly, we compute feature vector distances between reference pixel and all candidate pixels within disparity ranges $[d_{\min}, d_{\max}]$. The good dissimilarity function or feature vector distance curve needs to have the property to distinguish easily the matched pixel having smallest dissimilarity value and other pixels around the matched pixel. In this context, the feature vector distance curve of feature 1, for example, has more sharper slope near the location with smallest distance than that of feature 2 in Figure 1.

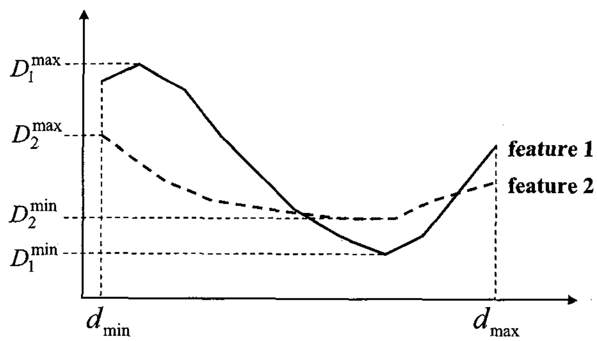


Figure 1. Feature vector distance curve.

3.2 Sharpeness measure

The sharpeness measure S_k of feature vector distance curve is given by

$$S_k = \frac{D_k^{\max} - D_k^{\min}}{D_k^{\max}} \tag{3}$$

where $D_k^{\max}$ and $D_k^{\min}$ are maximum and minimum vector distances of kth feature in disparity range $[d_{\min}, d_{\max}]$ respectively. This sharpeness measure has the following properties. First, if $D_k^{\min}$ is ralatively much smaller than $D_k^{\max}$, sharpeness measure S_k becomes high and this ensures that the feature with smaller $D_k^{\min}$ than other features has higher sharpeness measure. If $D_k^{\max}$ is high, for example, then the feature with smallest $D_k^{\min}$ has highest sharpeness measure. Second, if $D_k^{\min}$ is constant, then sharpeness measure S_k becomes low and less sharper when $D_k^{\max}$ gets small. In other words, sharpeness measure S_k becomes low when the difference value of $D_k^{\max}$ - $D_k^{\min}$ gets small. In Figure 1, for example, feature 1 has higher sharpenss measure than feature 2 because both $D_1^{\max} - D_1^{\min}$ and $D_1^{\max}$ are larger than $D_2^{\max} - D_2^{\min}$ and $D_2^{\max}$ respectively.

3.3 Feature vector distance calculation

We calculate feature vector distances of each feature within disparity range $[d_{\min}, d_{\max}]$ using 3x3 window mask as bellows :

$$D_k(p, q+d_i) = \sum_{m=-1}^{1}\sum_{n=-1}^{1}(f_k(p+m, q+n) - g_k(p+m, q+n+d_i))^2, \quad d_i \in [d_{\min}, d_{\max}] \tag{4}$$

where $f_k(p+m, q+n)$ is a value of kth reference feature image at location $(p+m, q+n)$ and $g_k(p+m, q+n+d_i)$ is a value of kth target feature image at location $(p+m, q+n+d_i)$. After computing feature vector distances of all feature, we compute sharpeness measure of each feature using the above equation (3). The feature takes the sharpeness measure as feature weight used in next stereo matching as shown in Figure 2.

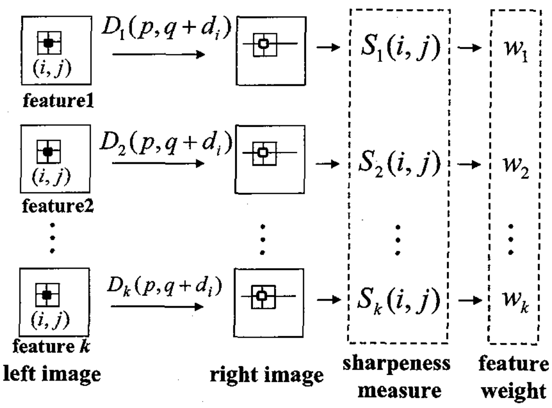


Figure 2. Determination of feature weight and sharpeness measure from feature vector distance.

4. FEATURE VECTOR MATCHING WITH ADAPTIVE FEATURE WEIGHT

The proposed stereo matching consists of the following two steps. In the first step, we determine feature weights of all pixels in reference feature images using the sharpenenss measure proposed above. In the next step, for each pixel in reference image, we find the corresponding pixel with minimum vector distance within disparity range in target image using the feature weights determined in the first step.

5. EXPERIMENTAL RESULTS

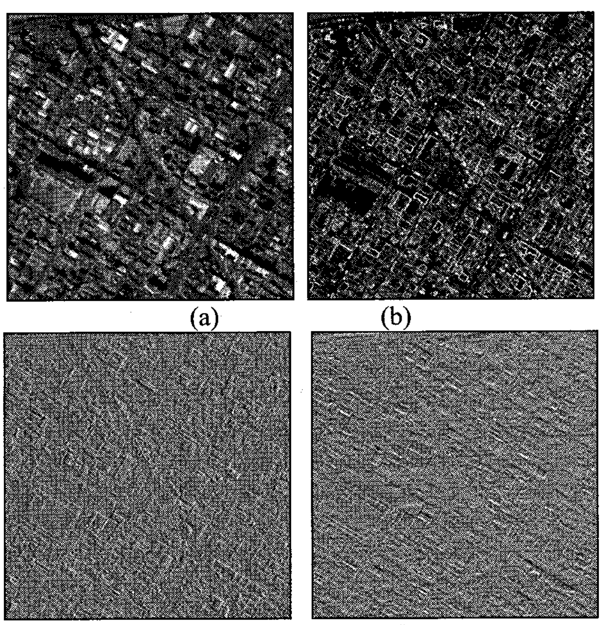
We used ikonos stereo imagery with the size of 512 x 512 pixels acquired over Daejeon in 2002 (Figure 3).

The image contains many small and complex buildings including regions of shadow. Multi-dimensional feature images were generated by convolving original image with the six kernels listed in Table 1, where the size of window mask is 3x3. Figure 3 shows the feature images generated by the six kernels.

Figure 3. Ikonos sample image (Daejeon).

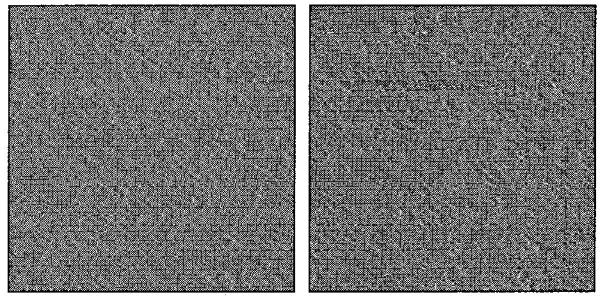
Table 1. Feature kernel used for generating feature image.

Feature	Property	Kernel	Weight
f_1	mean	window mask	w_1
f_2	variance	window mask	w_2
f_3	Horizontal high pass	$\{2,1,0,-1,-2\}$	w_3
f_4	Vertical high pass	$\{2,1,0,-1,-2\}^T$	w_4
f_5	Horizontal band pass	$\{1,0,-1,0,1,0,-1\}$	w_5
f_6	Vertical band pass	$\{1,0,-1,0,1,0,-1\}^T$	w_6



(a) (b)

(c) (d)



(e) (f)

Figure 3. Feature images (a) average (b) variance (c) horizontal high pass (d) vertical high pass (e) horizontal band pass (f) vertical band pass.

After constructing multi-dimensional feature vector from feature images, we calculated the feature vector distance for all pixels in reference feature image. Figure 4 illustrates the computed feature vector distances of a pixel for each feature image within disparity range. The features have smallest vector distances near disparity value of 6 or 7. The two features, f5 and f6, have relatively low maximum vector distances and high minimum vector distances than other features and thus result in poor sharpeness as shown in table 2.

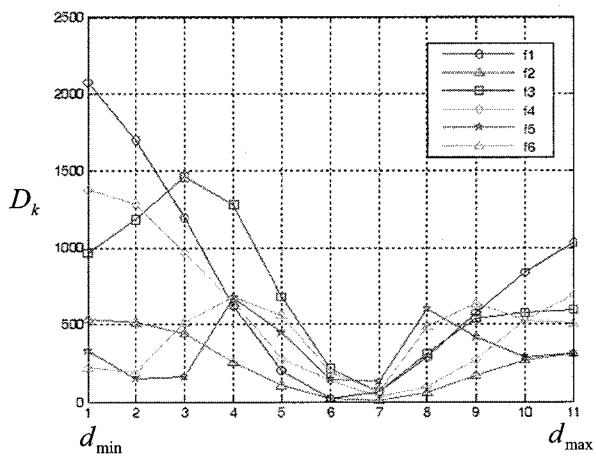


Figure 4. Example of feature vector distance curve.

Table 2. An example of sharpeness measure from the feature vector distance curve in figure 4.

Feature	Sharpeness measure
f_1	0.990
f_2	0.985
f_3	0.955
f_4	0.974
f_5	0.806
f_6	0.899

We compared the proposed method to other two methods. The one method uses as feature weight the inverse of minimum sharpeness within disparity range and the other method uses same feature weights. We normalized all the feature images and set the matching threshold to 0.05, that is, we finally accepted matching result of a pixel only when the minimum vector distance of the pixel to be matched was below the predefined matching threshold. To evaluate the accuracy of each method, we selected manually 100 matched pixels in reference and target image and computed the root mean square error (RMSE) of each matching method (Table 3). The matching result of the proposed method was filtered using median filter with the size of 3x3 and the RMSE of the filtered disparity map was 1.212 (Figure 5).

Table 3. Comparison of the matching results.

Method	RMSE
Proposed method	**1.558**
Inverse of minimum sharpendess	**1.692**
Same weights	**1.638**

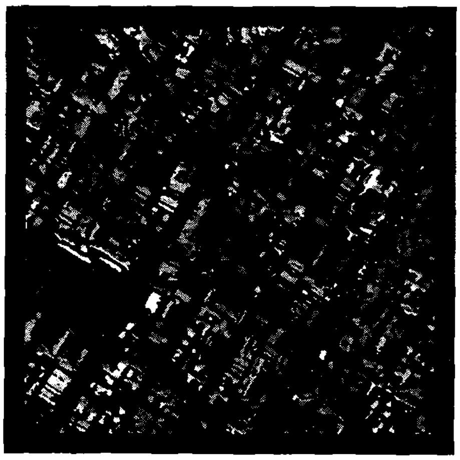


Figure 5. Disparity map of proposed method after median filtering.

6. CONCLUSIONS

In this paper, we proposed a new method for determining adaptively weights of the features used for multi-dimensional feature vector matching, in which each feature weight is automatically determined considering its importance in stereo matching. We developed a new sharpeness measure of feature vector distance curve in disparity range. The weights of features in multi-dimensional feature vector are adaptively determined during stereo matching according to each pixel's sharpeness. In future work, we will explore more appropriate features in urban area stereo matching and how to adjust automatically weights of the features.

REFERENCE

Jawahar, C.V. and Narayanan, P.J., 2002a. An adaptive multifeature correspondonce algorithm for stereo using dynamic programming, Pattern Recognition Letters 23, pp. 549-556.

Jawahar, C.V. and Narayanan, P.J., 2002b. Generalised correlation for multi-feature correspondence, Pattern Recognition 35, pp. 1303-1313.