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A Difference-Based Feature Description Method of Image Target

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Abstract

This paper proposed a new method of feature description for target recognition and matching. Firstly, a method of calculating the difference was defined. The gray value matrix of an image was converted to a difference value matrix. Then the difference value, shape, angle and other features of a region and the combined features between regions were described. Finally, the method was applied to identify traffic signs. Experiments showed that the proposed method can represent multiple features of image such as the gray differences, the shape changes, and so on. Through theoretical and simulation analysis, even under rotation, shift or scale transformation, new features description method still can correctly recognize the target.

Keywords: *difference, membership, region, combined features description, traffic signs*

1. Introduction

Overall, the image features can be divided into global and local features two categories. Global features look objects as a whole one. Each feature vector contains all parts (or even all of the pixels) information reflecting the overall properties of the image. Now there are a large number of image description and recognition methods based on global features [1-4]. But these global features don't have clearly mathematical definitions. Therefore, the extracted features and images don't have bidirectional uniqueness. In addition, these features can only apply to a certain type of image.

Compared with the global features, local features focuses on extraction of detail features and have a rich number in the image, the correlations between the features are small. For occlusion case, the detection and matching of other features will not be affected by the disappearance of some features. Because of these advantages, studies of local features are very active; a large number of methods are proposed [5-8]. But many of these methods use feature points to represent the image that don't have actual physical meanings. The amounts of calculation and feature points are large, and the performance of real-time is poor. So a number of improved methods are needed [9-11].

It has shown that a variety of feature description methods have their pros and cons. This paper mainly introduces a theory of difference measure for feature description. Then build a new vector descriptor to represent the image. Meanwhile, the feasibility and effectiveness of this description method was verified.

2. Image Feature Description Method Based on the Difference

2.1. Definition of Difference Measure Formula

Note: Let $u \in [0,1]$ be the membership degree that an object belongs to a grade, D be the difference between the object and the grade. Rules between u and D are as follows:

a) $D = f(u)$, The difference (D) is a function of the membership degree (u).

b) The difference (D) is monotone decreasing function of the membership degree (u). The membership degree that an object belongs to a grade is bigger; the difference between the object and the grade is smaller, and vice versa.

c) If $u(x,y) = u(x) \cdot u(y)$, $D(x \cdot y) = D(x) + D(y)$.

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d) Attributes of D include fuzziness, additivity, monotonicity and non-negativeness.
Lemma: [12] Let $x \in [1,\infty)$, $f(x)$ is a real function of x, which satisfies following:
a) $f(x) \geq 0$;
b) $f(x)$ is the strictly monotone decreasing function , $x > y \Rightarrow f(x) > f(y)$;
c) $f(x \cdot y) = f(x) + f(y)$.
Then:

$$f(x) = c \log_a x \tag{1}$$

Definition: Let $u \in [0,1]$ be the membership degree of a particular grade (excellent, good, moderate, etc.), $D \in [0,+\infty]$ be the difference between the object and its grade, $c(c \in R)$ be the coefficient, $a(a > 1)$ be the base number. The relationship between difference and membership value is:

$$D = c \cdot \log_a \left(\frac{1}{u}\right) = -c \log_a u \tag{2}$$

When the coefficient $c = 1$, the base number $a = 10$, the unit of the difference is “step”:

$$D = lg\left(\frac{1}{u}\right) = -lg\, u \tag{3}$$

2.2. Gray Matrix Transformation

The sensitivity of the human eye to gray level is non-linear. When the gray value is relatively low, the resolution is very strong. When the difference of gray levels is big to a certain extent, the human eye can easily distinguish them [13]. This paper uses the difference concept based on fuzzy membership to change the gray value matrix of image into a difference value matrix. By doing this, extends low gray area and compresses high gray areas, which means the understanding and identification of human eye to image.

How to determine the membership function is a key issue. According to the monotonic relationship between difference value and membership degree, we choose Z-type membership degree function [14], namely:

$$u(x) = \begin{cases} \dfrac{1}{1+(a(x-c))^b} & x > c \quad a > 0, b > 0 \\ 1 & x \leq c \end{cases} \tag{4}$$

In this paper, $a = 1, b = 3, c = 0$.

We transform the image gray value matrix $I(x,y)$ to the difference value matrix $D(x,y)$:

$$D(x,y) = \begin{cases} \left| \log \dfrac{1}{1+I^3(x,y)} \right| & x > 0 \\ 1 & x \leq 0 \end{cases} \tag{5}$$

The difference value of each pixel in image (except boundary points) is compared with that of eight pixels of the neighborhood. Put the direction of this point changes to the maximum difference value point as the direction of the point. Then the image direction matrix $A(x,y)$ is constituted.

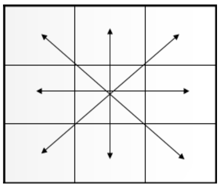

Figure 1. Determining a direction

2.3. Image Segmentation

This method is for gray images, so first need to do gray image processing. Next is the image region segmentation. This paper used a method of region growing. The basic idea is to set the pixels having similar properties together to form regions. Different with the usual gray-based threshold, here we use the difference value as the criterion. Transform the range of difference value matrix of the image to 0~255 and make the Figure 2. The figure shows that, after transforming to the difference value, the difference between low-gray pixels of image is enlarged. The segmentation results of these parts will be more clear and detailed than the gray value segmentation.

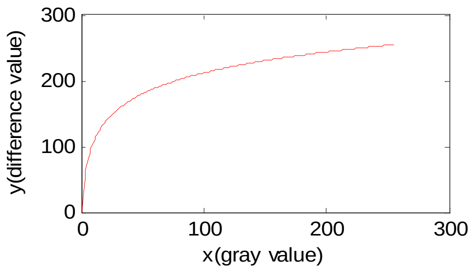

Figure 2. Conversion of gray value and difference value

2.4. Regional Features Description of Image

After each image is divided into regions, the features of each region can be obtained. A single feature tends to cause errors and affect subsequent image matching and recognition. This paper combined the mean of image represent matrix and the shape coefficient, constituted a new regional features vector, namely:

Modulus:

$$R = S \cdot \frac{1}{N} \sum D(x, y) \tag{6}$$

Direction angle:

$$O = \frac{1}{N} \sum A(x, y) \tag{7}$$

Where, N is the number of all pixels in the region, S is the shape coefficient:

$$S = 4\pi \cdot \frac{E}{E_1^{\,2}} \tag{8}$$

E is the area of region, E_1 is the perimeter of region.

Good local features should have variety of properties. The features corresponding to the image obtained by the same object or scene at different viewing angles should be the same.

Currently used invariance is: translation invariance, rotation invariance and scale invariance. The following formulas are derived to verify the invariance of the new regional descriptor.

Let B' be the region B transformed by translation, rotation and scaling. $k(k>0)$ is the amount of scaling, β is the angle of rotation, Tx and Ty are respectively the shift amounts of the x-axis and y-axis direction. $(x',y')\in B'$ is the point $(x,y)\in B$ transformed by translation, rotation and scaling. $I_{B'}(x',y')=I_B(x,y)$, $D_{B'}(x',y')=D_B(x,y)$. The relationship as follows:

$$[x',y',1]=[x,y,1]\cdot\begin{bmatrix} k\cos\beta & k\sin\beta & 0 \\ -k\sin\beta & k\cos\beta & 0 \\ -kTx & -kTy & 1 \end{bmatrix} \text{ [15]} \tag{9}$$

Namely: $x'=k(x\cos\beta-y\sin\beta-Tx)$, $y'=k(x\sin\beta+y\cos\beta-Ty)$

1) Strike the areas (E, E') and perimeters (E_1, E_1') of two regions, respectively:

$$E=\sum_{regionB}D(x,y)=\iint_{regionB}D(x,y)dxdy \tag{10}$$

$$E_1=\sum_{outlineB}D(x,y)=\iint_{outlineB}D(x,y)dxdy \tag{11}$$

$$E'=\sum_{regionB}D(x',y')=\iint_{regionB}D(x,y)d[k(x\cos\beta-y\sin\beta-Tx)]\cdot d[k(x\sin\beta+y\cos\beta-Ty)]=k^2E \tag{12}$$

$$E_1'=k^2E_1 \tag{13}$$

The feature vector of these two regions were (R,O) and (R',O'). Then:

$$R=S\cdot\overline{D}=4\pi\cdot\frac{E}{E_1^{\,2}}\cdot\frac{1}{N}\sum D(X,Y)=\frac{4\pi}{N}\cdot\left(\frac{E}{E_1}\right)^2 \tag{14}$$

$$R'=S'\cdot\overline{D'}=\frac{4\pi}{N}\left(\frac{E'}{E_1'}\right)^2=\frac{4\pi}{N}\left(\frac{k^2E}{k^2E_1}\right)^2=R \tag{15}$$

The modulus values of two regions are the same. This indicates that the modulus of this descriptor has the invariance of translation, rotation and scaling.

2) Let $A(x,y)$ be the direction matrix of the original region, $A'(x',y')$ be the ones of the region after translation, rotation and scaling. Let (x_0,y_0) be the center of a 3*3 pixel unit of original region, (x,y) be the point that has maximum difference value of the 9 points ($x-x_0\neq 0$), the direction angle of the center is:

$$a(x_0,y_0)=arc\tan\frac{y-y_0}{x-x_0} \tag{16}$$

The point (x_0,y_0) is changed to (x_0',y_0') after transformation:

$$x_0'=k(x_0\cos\beta-y_0\sin\beta-Tx),\quad y_0'=k(x_0\sin\beta+y_0\cos\beta-Ty)$$

Because the difference value of each point is unchanged, only the coordinate is changed, so that the maximum difference value point is changed from (x,y) to (x',y'), calculate the direction angle of the center point:

$$a'(x_0', y_0') = arctan\frac{(x-x_0)\sin\beta + (y-y_0)\cos\beta}{(x-x_0)\cos\beta - (y-y_0)\sin\beta} \quad (17)$$

It can be seen that $a'(x_0', y_0') \neq a(x_0, y_0)$, that means the direction matrix $A_{B'}(x', y') \neq A_B(x, y)$, The relationship between the two direction matrixes only related with the rotation angle. So the direction of the vector described the two regions has invariance of translation and scaling, but doesn't have rotation invariance.

2.5. Combined Features Description of the Image

If a target is constituted by a plurality of regions, a series of two-dimensional vectors will be used to describe its features. While the relationships between each of these regions are in the range of features of the target, they also need to be considered. By feature extraction, we can use a feature point at the center of the region to describe each region. Connect the feature points of each adjacent region of target to structure triangular meshes. The side lengths and angles of each triangle can represent the relationship between regions.

Let a simple triangle consisting of three points be an example to verify the performance. Original target consists of three regions, their centroids are (x_1, y_1), (x_2, y_2) and (x_3, y_3). Connecting the three points to structure a triangular, its side lengths and angles are: l_1, l_2, l_3, A, B, C. After transformation, the centroids are changed to (x_1', y_1'), (x_2', y_2') and (x_3', y_3'), Each value corresponds to the triangle is: $l_1', l_2', l_3', A', B', C'$.

$$l_1 = \sqrt{(x_1 - x_2)^2 + (y_1 - y_2)^2} \quad (18)$$

$$l_1' = \sqrt{(x_1' - x_2')^2 + (y_1' - y_2')^2} = kl_1 \quad (19)$$

Similarly available: $l_2' = kl_2$, $l_3' = kl_3$.

$$A = arccos\frac{l_1^2 + l_2^2 - l_3^2}{2 \cdot l_1 \cdot l_2} \quad (20)$$

$$A' = arccos\frac{l_1'^2 + l_2'^2 - l_3'^2}{2 \cdot l_1' \cdot l_2'} = A \quad (21)$$

Similarly available: $B' = B$, $C' = C$.

It can be seen that, the side lengths of triangular have translation and rotation invariance, but will vary with changes in scale, but if normalized, they will be unchanged; the angles of triangle have invariance of translation, rotation and scale.

The side lengths and angles of triangles structured by feature points, the modulus and direction angles of each feature points are all the important features of the target. They need to be combined to describe the features.

3. Image Recognition Process of this Paper

The image recognition process in this paper can be divided into three major steps: Firstly, create a difference vector matrix of image (i.e., the difference matrix and the direction matrix). Divide the image regions according to the difference value and extract the features. Secondly, features of each region and combined features of them are described. If the target can be represented by a single region, just a step of feature points matching can be used to find the target in the image. If the target is constituted by a plurality of regions, connecting the feature points matched with the target to structure the triangular meshes in the test image. If the side lengths and angles matrixes of triangle mesh can be matched with the target too, it will be proved that the target can be found in the test image.

The following three vector matrixes are structured for features description:

$$M_1 = \begin{bmatrix} R_1 & O_1 \\ R_2 & O_2 \\ R_n & O_n \end{bmatrix} \qquad M_2 = \begin{bmatrix} l_{11} & l_{12} & l_{13} \\ l_{21} & l_{22} & l_{23} \\ l_{m1} & l_{m2} & l_{m3} \end{bmatrix} \qquad M_3 = \begin{bmatrix} A_1 & B_1 & C_1 \\ A_2 & B_2 & C_2 \\ A_m & B_m & C_m \end{bmatrix}$$

Each row of M_1 are vector values (i.e., the modulus and angles) of the feature point for each region. Each row of M_2 are the three normalized side lengths of a triangle. Each row of M_3 are the three angles of the triangle.

4. Experimental Results and Analysis of Traffic Signs Recognition

In order to verify the correctness and validity of this method, we use a series of traffic sign images for target recognition, and analyze its performance by experimental results.

4.1. Recognition of a Single Regional Target

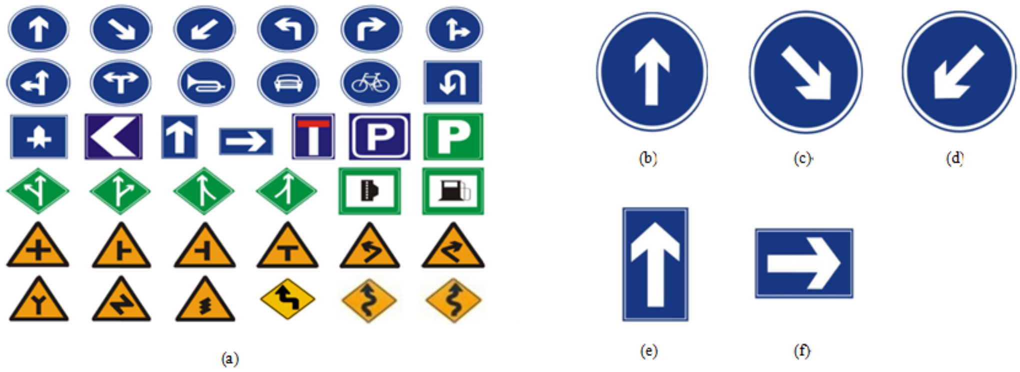

Figure 3. Simple traffic signs

Figure 3(a) are some examples of simple traffic signs. Because they are all easy to distinguish from the background, so the pretreatment process and background region are not considered. It can be seen that every target to be recognized consists of only a region. Take one of the arrow sign to be explained in detail. Compare the five images from (b) to (f), (c) and (d) can be seen as obtained by rotation of (b), so their features modulus are almost same, only the angles change. (e) looks the same with (b), but its size is bigger, it can be seen as obtained by scaling of (b). We can see their features from the following specific values:

$$M_{1b} = [21684.03 \quad 75.68] \quad M_{1c} = [21752.65 \quad 298.45] \quad M_{1d} = [21265.03 \quad 210.03]$$
$$M_{1e} = [21345.67 \quad 68.19] \quad M_{1f} = [21401.04 \quad 320.74]$$

Select the appropriate threshold of modulus (in this case is 500). It can be found that the five target regions are the same traffic sign; only the angles are changed with rotation. We can get all the feature values of traffic signs in Figure 3(a) under the same operation, thus achieving recognition.

Let Figure 4(b) be an image to be identified. It can be divided into three regions after removing small regions. Specific features values are as follows. According to the modulus and angles values, the straight arrow (the second region) can be recognized.

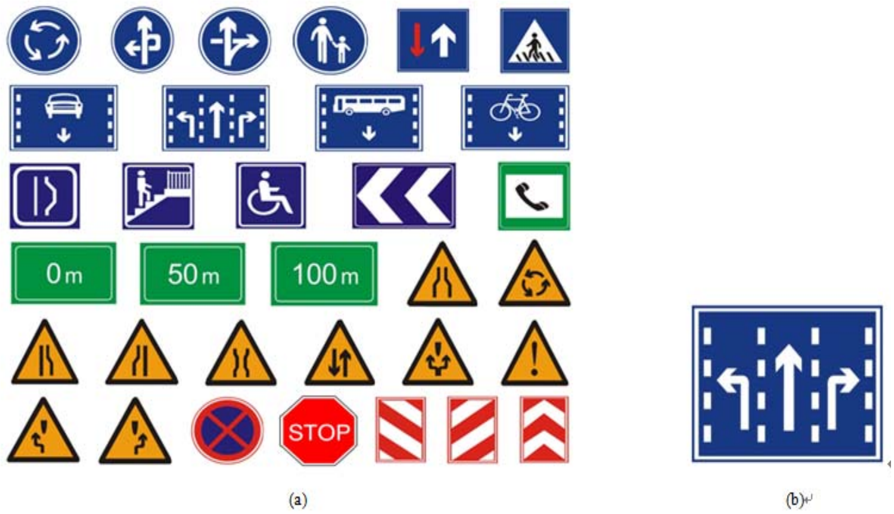

Figure 4. traffic signs combined multiple regions

$$M_1 = \begin{bmatrix} 18119.86 & 80.99 \\ 21862.66 & 83.21 \\ 18279.79 & 92.37 \end{bmatrix}$$

4.2. Recognition of Target Combined Multiple Regions

If Figure.5(a) is taken as a whole target constituted by three small regions, (b) is obtained by rotating 90 degrees of (a), (c) is a double expansion of (a). Then the combined features description of the image mentioned in 2.5 will be needed. Get the feature matrixes through the above steps. (d), (e) and (f) are the corresponding triangular meshes respectively.

$$M_{1a} = \begin{bmatrix} 18119.86 & 80.99 \\ 21862.66 & 83.21 \\ 18279.79 & 92.37 \end{bmatrix} \quad M_{2a} = \begin{bmatrix} 0.25 & 0.50 & 0.25 \end{bmatrix} \quad M_{3a} = \begin{bmatrix} 0.18 & 2.79 & 0.18 \end{bmatrix}$$

$$M_{1b} = \begin{bmatrix} 21862.66 & 168.56 \\ 18279.78 & 181.77 \\ 18120.38 & 172.05 \end{bmatrix} \quad M_{2b} = \begin{bmatrix} 0.25 & 0.25 & 0.50 \end{bmatrix} \quad M_{3b} = \begin{bmatrix} 2.79 & 0.18 & 0.18 \end{bmatrix}$$

$$M_{1c} = \begin{bmatrix} 17456.07 & 90.38 \\ 22655.39 & 88.97 \\ 18219.40 & 90.01 \end{bmatrix} \quad M_{2c} = \begin{bmatrix} 0.25 & 0.50 & 0.25 \end{bmatrix} \quad M_{3c} = \begin{bmatrix} 0.17 & 2.80 & 0.17 \end{bmatrix}$$

Figure 5(b) and (c) are compared with (a). The order of the feature points in (b) is changed, but the modulus of each feature point are almost the same, and the angle is changed about 90 degrees. While the angles and side lengths of each triangle structured by the feature points are constant. All the feature values of (c) are the same as (a). The experimental results are just like the theoretical derivation of chapter 2. Combine these conclusions, the changed target can also be recognized in the test image as long as the appropriate judgment criteria is selected.

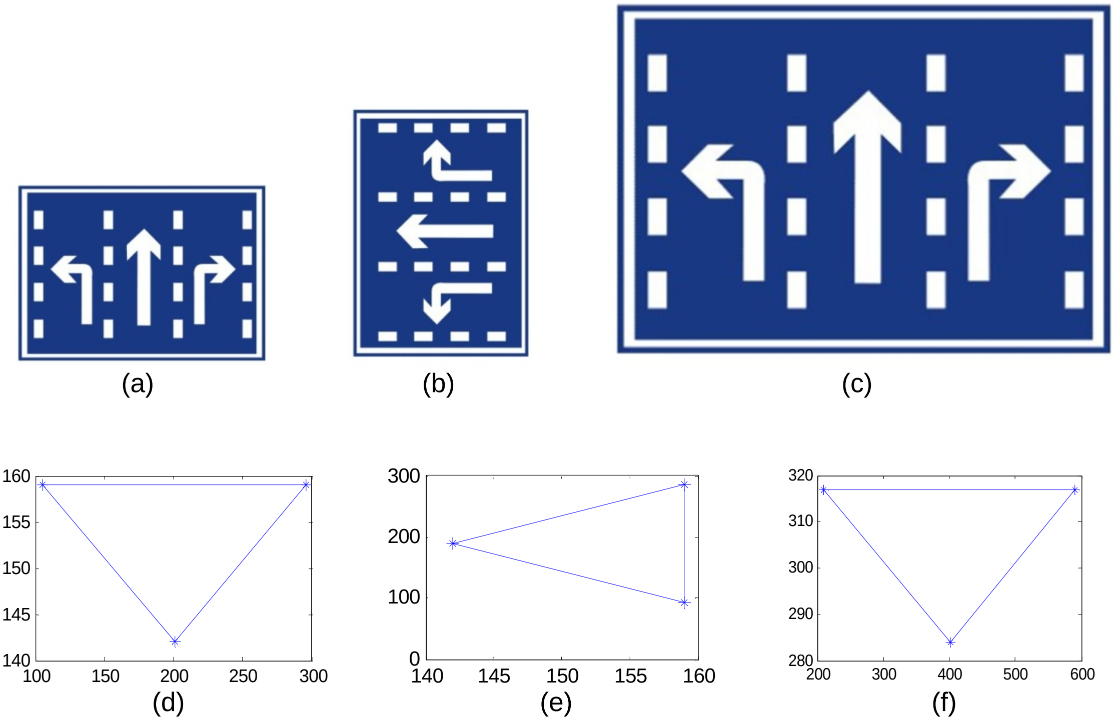

Figure 5. Research the invariance of features description

Similarly, we can recognize all the traffic signs in the Figure 4(a) with features values and combined features. In many actual cases, the measured targets will have different variations of size, location, etc. Changed target also need to be recognized. Therefore, analysis the invariance of this description method is necessary. Figure 6(a) and (b) are two sign images shot on the actual road. Features matrixes and meshes can be obtained through a series of processing as below. It can be found the two images are the same sign after matching. We can recognize the sign easily as long as the species of pre-established template library is enough to complete.

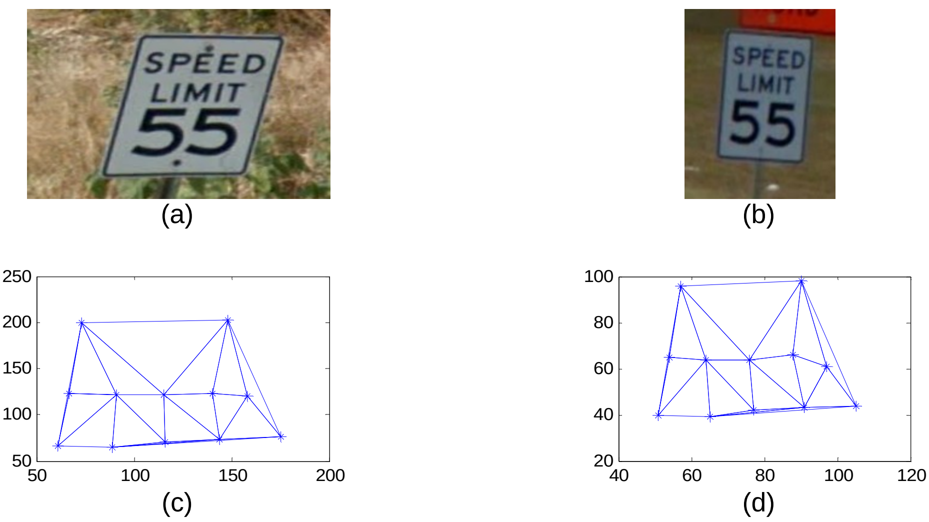

Figure 6. A practical example

$$M_{1a} = \begin{bmatrix} 2619.65 & 177.37 \\ 10230.53 & 173.87 \\ 13695.33 & 186.56 \\ 20515.60 & 195.15 \\ 17745.12 & 221.09 \\ 7883.77 & 203.84 \\ 2606.75 & 171.27 \\ 8872.65 & 177.92 \\ 17976.62 & 218.89 \\ 10193.09 & 173.16 \\ 13427.30 & 211.33 \\ 23743.23 & 191.61 \end{bmatrix} M_{2a} = \begin{bmatrix} 0.21 & 0.50 & 0.29 \\ 0.19 & 0.42 & 0.39 \\ 0.17 & 0.43 & 0.30 \\ 0.45 & 0.13 & 0.42 \\ 0.32 & 0.18 & 0.50 \\ 0.40 & 0.20 & 0.40 \\ 0.50 & 0.25 & 0.25 \\ 0.50 & 0.18 & 0.32 \\ 0.38 & 0.37 & 0.25 \\ 0.10 & 0.44 & 0.46 \\ 0.42 & 0.42 & 0.16 \\ 0.38 & 0.41 & 0.21 \\ 0.38 & 0.43 & 0.19 \\ 0.43 & 0.18 & 0.39 \\ 0.13 & 0.46 & 0.41 \\ 0.30 & 0.35 & 0.35 \\ 0.42 & 0.46 & 0.12 \end{bmatrix} M_{3a} = \begin{bmatrix} 0.02 & 3.11 & 0.01 \\ 1.13 & 1.54 & 0.47 \\ 1.14 & 1.60 & 0.40 \\ 1.26 & 0.31 & 1.58 \\ 3.04 & 0.04 & 0.06 \\ 1.32 & 0.50 & 1.32 \\ 0.06 & 0.05 & 3.03 \\ 0.16 & 0.09 & 2.90 \\ 0.66 & 1.21 & 1.27 \\ 1.64 & 1.28 & 0.22 \\ 0.38 & 1.44 & 1.32 \\ 0.53 & 1.48 & 1.12 \\ 0.47 & 1.57 & 1.10 \\ 1.11 & 0.44 & 1.59 \\ 1.11 & 1.75 & 0.28 \\ 1.13 & 1.13 & 0.88 \\ 0.27 & 1.80 & 1.08 \end{bmatrix}$$

$$M_{1b} = \begin{bmatrix} 2506.70 & 169.80 \\ 10315.17 & 169.15 \\ 13487.47 & 143.11 \\ 20244.80 & 178.39 \\ 17950.72 & 195.00 \\ 7608.86 & 182.85 \\ 2760.33 & 173.60 \\ 8913.35 & 181.42 \\ 17724.08 & 225.00 \\ 10303.83 & 174.73 \\ 13695.17 & 198.19 \\ 23151.78 & 186.79 \end{bmatrix} M_{2b} = \begin{bmatrix} 0.21 & 0.41 & 0.38 \\ 0.33 & 0.17 & 0.50 \\ 0.44 & 0.40 & 0.16 \\ 0.28 & 0.22 & 0.50 \\ 0.44 & 0.14 & 0.42 \\ 0.40 & 0.20 & 0.40 \\ 0.50 & 0.23 & 0.27 \\ 0.50 & 0.17 & 0.33 \\ 0.40 & 0.47 & 0.13 \\ 0.37 & 0.36 & 0.27 \\ 0.20 & 0.36 & 0.44 \\ 0.36 & 0.42 & 0.22 \\ 0.38 & 0.42 & 0.20 \\ 0.43 & 0.20 & 0.37 \\ 0.15 & 0.45 & 0.40 \\ 0.31 & 0.34 & 0.35 \\ 0.45 & 0.15 & 0.40 \end{bmatrix} M_{3b} = \begin{bmatrix} 1.15 & 1.46 & 0.54 \\ 3.06 & 0.03 & 0.05 \\ 0.38 & 1.17 & 1.59 \\ 3.12 & 0.01 & 0.01 \\ 1.26 & 0.31 & 1.57 \\ 1.28 & 0.49 & 1.37 \\ 0.09 & 0.08 & 2.97 \\ 0.17 & 0.08 & 2.89 \\ 0.25 & 2.02 & 0.88 \\ 0.76 & 1.18 & 1.20 \\ 1.75 & 0.93 & 0.45 \\ 0.57 & 1.54 & 1.02 \\ 0.49 & 1.54 & 1.12 \\ 1.04 & 0.49 & 1.62 \\ 1.02 & 1.80 & 0.32 \\ 1.12 & 1.10 & 0.92 \\ 1.04 & 0.32 & 1.79 \end{bmatrix}$$

5. Conclusion

This paper mainly defined a method of calculating the difference based on the knowledge of fuzzy membership and a new method of feature description for target recognition and matching. Both the features of each image region and the relationship between regions can be described. Theoretical analysis and experiments verified the feasibility and effectiveness of this description method, and it has a better robustness.

References

[1] Linde O, Lindeberg T. Composed complex-cue histograms: An investigation of the information content in receptive field based image descriptors for object recognition. *Computer Vision and Image Understanding*. 2011; 116(4): 538-560.

[2] Clausi DA, Zhao YP. Grey level co-occurrence integrated algorithm (GLC IA): A superior computational method to determine co-occurrence probability texture features. *Computers & Geosciences.* 2003; 29(7): 837-850.

[3] Wang Y, Liang D, Wang B. Daubechies wavelet construction using homotopy method. *Chinese Journal* of *Electronics*. 2007; 16(1): 93-96.

[4] Clausi DA, Huang D. Design-based texture feature fusion using Gabor filters and co-occurrence probabilities. *IEEE Transactions on Image Processing*. 2005; 14(7): 925-936.

[5] Moravec HP. Proceedings of the 6th International Joint Conference on artificial Intelligence. *Visual mapping by a robot rover*. 1979; 599- 601.

[6] Harris C, Stephens M. Proceedings of the 4th Alvey Vision Conference. *A combined corner and edge detector.* 1988; 147-151.

[7] Smith SM, Brady M. SUSAN-a new approach to low level image processing. *International Journal of Computer Vision*. 1997; 23(1): 45-78.

[8] Lowe DG. Distinctive image features from scale-invariant key points. *International Journal of Computer Vision*. 2004; 60(2): 91-110.

[9] Ke Y, Sukthankar R. Proceedings of the Conference on Computer Vision and Pattern Recognition. *PCA-SIFT: a more distinctive representation for local image descriptors.* 2004; 511-517.
[10] Herbert B, Andreas E, Tinne T, et al. Speeded-up robust features (SURF). *Computer Vision and Image Understanding.* 2008; 110(3): 346-359.
[11] Zhu YX, Cheng S, Stankovic V, et al. Image registration using BP-SIFT. *Journal of Visual Communication and Image Representation.* 2013; 4(24): 448-457.
[12] Saff EB, Snider AD. Fundamentals of complex analysis with applications to engineering, science, and mathematics. London: Prentice Hall. 2003.
[13] Hao YX, Chen XJ, Zhang BZ. Photometry. Beijing: Beijing Normal University Press. 1997.
[14] Zhang X, Xiao XL, Xu GY. Determination and analysis of fuzzy membership for SVM. *Journal of Image and Graphics*. 2006; 8(11): 1188-1192.
[15] Zhang XQ, Guo MM, Tang Y, et al. New geometric feature shape descriptor. *Computer Engineering and Applications*. 2007; 43(29): 90-92.