APPLICATION OF 3D-ZERNIKE DESCRIPTORS IN REMOTE SENSING TARGET RECOGNITION

Zhang Ye, Yan Yiming, Chen Hao

School of Electronics and Information Engineering, Harbin Institute of Technology

1. INTRODUCTION

In remote sensing (RS) recognition, researchers usually utilize 2D image features to recognize different targets. However, it is always difficult to distinguish targets that have similar image contour but different height. It is because that 2D image contains only 2D contour information, while height information of a target has lost during the imaging process. In this paper, 3D-Zernike descriptors are proposed as a 3D feature to solve this RS recognition problem. 3D-Zernike descriptors have good performance in the field of computer vision [1] and medical image processing [2], however, little work is done in RS field. We tested the characteristics of the feature when working on RS 3D images. Besides, groups of test samples were recognized by using this feature.

2. METHODOLOGY

2.1. 3D-Zernike Descriptors

3D-Zernike descriptors are based on 3D-Zernike functions and 3D-Zernike moments. N. Canterakis [3] demonstrates the invariance of spherical harmonics in a unit sphere and utilize the invariance of spherical harmonics to define 3D-Zernike functions Z_{nl}^{m} as:

$$Z_{nl}^{m}(\mathbf{x}) = R_{nl}(r) \cdot Y_{l}^{m}(\theta,\varphi) \tag{1}$$

where $Y_{l}^{\mathbf{m}}(\theta,\varphi)$ is spherical harmonics, $R_{nl}(r)$ is radial polynomials, $\mathbf{x}$ is 3D coordinate (x, y, z).

If $f(\mathbf{x})$ is the 3D surface function of target, the definition of 3D-Zernike moments Ω_{nl}^{m} of a target is as:

$$\Omega_{nl}^{m} = \frac{3}{4\pi} \int_{|\mathbf{x}|\le 1} f(\mathbf{x}) \overline{Z_{nl}^{m}(\mathbf{x})} d\mathbf{x} \tag{2}$$

In order to achieve invariance, collecting the moments into $(2l+1)$-dimensional vectors:

$$\Omega_{nl} = \{\Omega_{nl}^{l}, \Omega_{nl}^{l-1}, \Omega_{nl}^{l-2} \ldots\ldots \Omega_{nl}^{-l+1} \Omega_{nl}^{-l}\} \tag{3}$$

The definition of 3D-Zernike descriptors is as norms of vectors:

$$F_{nl} = \left\|\Omega_{nl}\right\| \tag{4}$$

To test the invariance of 3D-Zernike descriptors and its ability to distinguish different targets, select Camberra-Distance [4] as similarity function to measure this difference between features:

$$d(x,y) = \sum_{i=1}^{N} \frac{|x_i - y_i|}{|x_i + y_i|} \tag{5}$$

where x_i, y_i are two feature vectors for comparing.

2.2. 3D-Zernike Descriptors Based Recognition

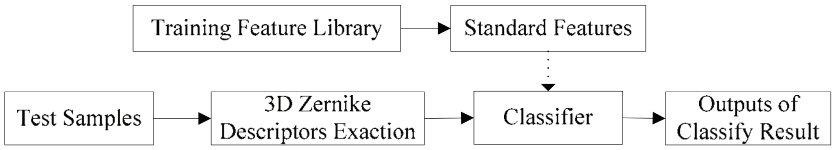


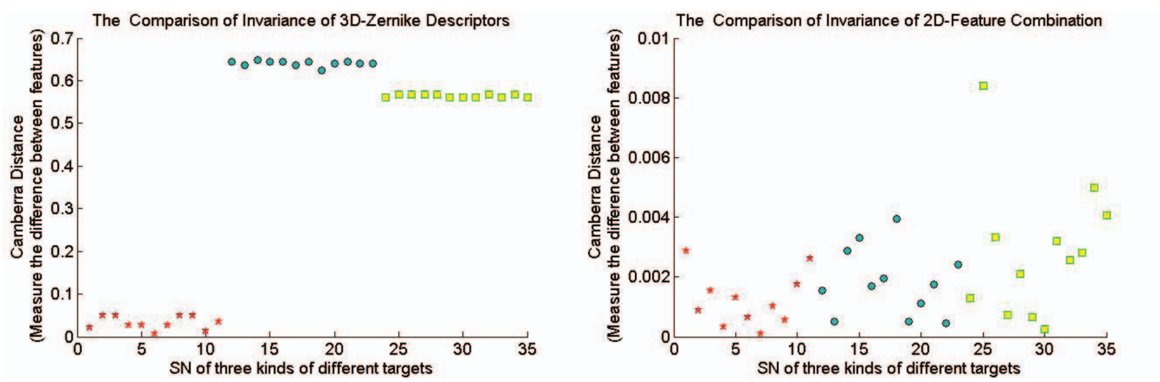
Fig.1 Target Recognition System

In this paper, the flowchart for remote sensing target recognition is shown in Fig.1. Training feature library is done offline to collect the standard features of some certain categories of targets. When starting to work, choose some features from the library as the standard of the classifier. Exact the 3D-Zernike descriptors of all test samples and input them into the classifier. The classifier computes all the Camberra-Distance values (according to Eqn.5) between standard features and the features of test samples. Find the minimum Camberra-Distance between a test feature and a standard feature, and believe the target is the corresponding category.

3. EXPERIMENTS

3.1. Characteristics Test of 3D-Zernike Descriptors

Choose thirty-six targets as test samples, which are from three categories (twelve for each category) and have similar 2D contour but different height. Compute all their 3D-Zernike descriptors. Select one arbitrarily from the first category as a standard. Compute the Camberra-Distance to measure the difference between the standard and other features.



(a) 3D-Zernike Descriptors

(b) 2D Features

Fig.2 Characteristics of Features

Results are shown in Fig.2, same color denotes same category, and the smaller Camberra-Distance means the less difference. As Fig.2 (a) shows, 3D Zernike descriptors of same category are similar, and the Camberra-Distance is large among different categories. But for 2D features showed in Fig.2 (b), all features are hardly distinguished.

3.2. Recognition Results

As Fig.3 shows, the RS images are collected from "Google-Earth". The heights of the four different targets (from 1 to 4) are 33m, 16m, 23m and 33m. 3D-Zernike descriptors could distinguish them but the result is not ideal when using 2D features.

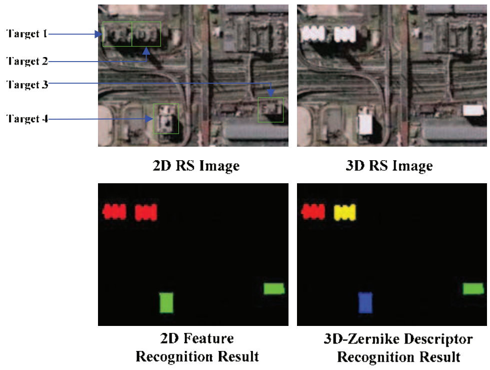


Fig.3 Recognition Results

Besides, other 80 samples are tested with our method, the accuracy is 20% when using 2D features, but with 3D-Zernike descriptors, the accuracy is 82.5%.

4. CONCLUSION

In this paper, 3D-Zernike descriptors are proposed to do recognition in RS field. We tested the characteristics of the feature and showed its performance when working on the targets that are difficult to identify by 2D features. The experimental results indicate that a high recognition rate is obtained by using 3D-Zernike descriptors and the feature could be widely used for RS target recognition.

5. REFERENCES

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