SAR Target Recognition Based on Modified Sparse Representation for Ground Safety

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Abstract. Recognition of synthetic aperture radar (SAR) targets is a hot topic in pattern recognition field. In the previous works, the sparse representation-based classification (SRC) is successfully used in SAR target recognition with high performance. The traditional SRC is performed on the global dictionary from the training classes. As a result, the representation capability of an individual class is not fully considered. This paper modifies the traditional SRC by performing the sparse representation over the local dictionaries formed by individual classes. In this way, the reconstruction error from one class can better reflect its representation capability as for describing the test sample. By comparing the reconstruction errors of different training classes, the target label of test sample can be classified finally. In the experiments, the MSTAR dataset is used to test the proposed method, which show the good results of the proposed method.

1. Introduction

Recognition of synthetic aperture radar (SAR) targets has long been studied because of the extensive advantages [1]. For a concrete SAR target recognition algorithm, it often comprises of feature extraction and classifier. In the previous works on SAR target recognition, many feature extraction and classifier algorithms were designed. Features like geometrical ones [2][3], scattering centers [4][5], and projection ones [6][7] are designed or employed. Classifiers like K-nearest neighbour (KNN) [6], support vector machine (SVM) [8] are used. It is assumed that both the features and classifiers are important to the final recognition performance.

In recent years, the compressive sensing theory has drawn intensive attentions in signal processing and pattern recognition fields. Specifically, the sparse representation-based classification (SRC) is a typical application, which was used for face recognition [9], SAR target recognition [10][11], etc. However, the traditional SRC performs linear presentation on the global dictionary from the training classes. As a result, the representation capability of an individual class can not be fully exploited. Therefore, in this paper, the representation about the test sample is conducted in the local dictionary formed by each training class. Then, the reconstruction errors from different training classes are compared equally to determine the target label. In the experiments, MSTAR dataset is used to set some conditions to examine the proposed method. Based on the comparison, the performance of the proposed method is confirmed.

2. Method Description

2.1. Modified SRC
Traditionally, SRC is performed over the global dictionary for target classification. Denote $A = \{A^1, A^2, \ldots, A^C\} \in \mathbb{R}^{d \times N}$ as the dictionary from $C$ different training classes, the test sample $y$ is linearly represented by the dictionary as equation (1).

$$\hat{\alpha} = \min \| \alpha \|_0$$

s.t. $\| y - A \alpha \|_2^2 \leq \varepsilon$ (1)

where $\alpha$ contains the sparse coefficients and $\varepsilon$ is the error.

The above optimization problem can be smoothly solved via orthogonal matching pursuit (OMP) or $\ell_1$ norm approximation. After solving the sparse coefficients, equation (2) can be used to calculate the reconstruction errors from different training classes thus determining the target label of $y$.

$$r(i) = \| y - A(i) \|_2^2 (i = 1, 2, \ldots, C)$$

class($y$) = $\min(r(i))$ (2)

As a modification, this paper performs the linear representation about the test sample over the dictionary of each training class, i.e., $A(i) (i = 1, 2, \ldots, C)$ . Then, the sparse coefficients and reconstruction errors are obtained using the same way as equation (1) and equation (2). And the target label is also decided as the class with minimum reconstruction error.

2.2. Target Recognition

The detailed procedure of the proposed method can be illustrated as Fig. 1, which can be implemented as followings:

Step 1: Form the individual dictionaries from different training classes;

Step 2: Solve the sparse coefficients of the test sample over different local dictionaries;

Step 3: calculate the reconstruction errors;

Step 4: determine the target label based on the minimum reconstruction error.

Specifically, PCA is used for feature extraction during the whole recognition process.

Fig. 1 Procedure of modified SRC for target recognition.

3. Experiments

3.1. MSTAR Dataset

The experiments are implemented with the MSTAR dataset, which includes volumes of SAR images from ten classes of targets. A typical experimental setup is given in Table 1, where images from $17^\circ$ and $15^\circ$ depression angles are adopted for training and testing, respectively. Some other methods are compared during the experiments. They are Method 1 from [8], Method 2 from [9], and Method 3 from [10].
### Table 1. Training and test samples used.

| Depr. | BMP2 | BTR70 | T72 | T62 | BDRM2 | BTR60 | ZSU23/4 | D7  | ZIL131 | 2S1 |
|-------|------|-------|-----|-----|-------|-------|---------|-----|--------|-----|
| 17°   | 233(Sn_9563) | 233   | 232(Sn_132) | 299  | 298   | 256   | 299     | 299 | 299    | 299 |
| 15°   | 195(Sn_9563) | 196   | 196(Sn_9566) | 273  | 274   | 274   | 274     | 274 | 274    | 274 |
|       | 196(Sn c21)  |       | 191(Sn s7)   |       |       |       |         |     |        |     |

### 3.2. Results and Analysis

By training and the testing the proposed method using the data in Table 1, the ten classes of targets are classified as the confusion matrix in Fig. 2. Each of the ten targets is with a recognition rate over 95% and the average recognition rate is 97.52%. Table 2 gives the performance comparison under the same condition. With a higher recognition rate, the performance of the proposed method is validated. Fig. 3 shows the performance of different methods under noise corruption. It is normal that the performance of all the methods degrades with the decrease of the signal-to-noise ratio (SNR). In comparison, better robustness to noise corruption can be achieved by this method.

![Confusion Matrix](image)

**Fig. 2** Confusion matrix of the proposed method.

### Table 2. Performance comparison on ten classes of targets.

| Method  | Average recognition rate (%) |
|---------|------------------------------|
| Proposed| 97.52                        |
| Method 1| 95.82                        |
| Method 2| 96.23                        |
| Method 3| 97.04                        |
4. Conclusion
A modified SRC is designed in this paper for SAR target recognition. The sparse representation is performed over the local dictionaries formed by individual training classes. Therefore, the absolute representation capabilities of different training classes as for describing the test sample can be equally compared. According to the experiments on the MSTAR dataset, the good performance of this method to noise corruption can be validated.

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