SAR Image Target Recognition via Dynamic Kernel Dictionary Learning

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***Abstract*—a novel algorithm for target recognition in synthetic aperture radar (SAR) based on dynamic kernel dictionary learning is proposed to enhance the ability of sparse representation by extracting non-linear feature information. Firstly, each SAR image which contained the nonlinear information is mapped into kernel feature space with a kernel function, and dimensionality reduction method is applied to the feature space. Secondly, the dictionary is learned by optimization method. At the same time, the sparse coefficients are dynamically calculated according to the information of each dictionary updating. Finally, the classification result of SAR target is obtained by minimizing the error between the original and reconstructed samples. Experimental results on MSTAR dataset prove that the efficiency of the proposed approach in target recognition of SAR imagery. Moreover, the robustness to low signal-to-noise ratio (SNR) is also demonstrated, which proves the better performance of our proposal.**

Keywords—SAR image; target recognition; sparse representation; dictionary learning; kernel method.

I. INTRODUCTION

Synthetic aperture radar (SAR) target recognition has played a very important role in military and homeland security. A number of works have been done in the past decade [1-3]. However, there are still some problems in the existing SAR target identification methods. The extraction and processing of feature information is the key of SAR target recognition. Different feature information processing methods will affect the final recognition result. At present, there are many different methods of SAR image recognition. For example, Zhou [4] extracted the scattering center features from different poses by using the scattering center model and realized the recognition of SAR targets. The size-related features and clutter-free features of SAR images were used to distinguish between targets and interferences, and the classical classification method was used to identify SAR targets in [5].

Sparse representation (SR) [6] has attracted considerable attention recent years, and has been applied successfully in wide-range fields, including visual saliency, image processing [7-8] and so on. The dictionary is crucial in the sample reconstruction process. Dictionary learning (DL) is a basic element to sparse representation. Learning an optimal dictionary from data instead of using a set of predefined bases has achieved a big success in various practical tasks, such as face recognition [9], image classification [10], image and speech denoising [11-12]. Recently, the study of dictionary learning method applied to SAR target recognition is becoming more established.

The amplitude and scale invariant features of SAR images were trained through the DL method and classified according to the principle of feature [13]. A local adaptive dictionary was established to use sparse representation and realize the SAR image recognition by combining multi-objective information in [14]. Ding [15] used the dictionary learning method to extract the features of SAR images and used the nearest neighbor classifier to classify the targets. Xiang [16] used multiscale Gabor methods to extract features and used the dictionary learning model to achieve SAR target recognition. A multi-layer and multi-core model was constructed through a combination of deep learning and kernel methods to achieve SAR target identification in a layer-by-layer optimized manner in [17]. Discriminating kernel edge samples is proposed in [18], which enhances the discriminant performance of SAR images by using the advantages of kernel method and manifold learning. A structured kernel dictionary was proposed to realize SAR target recognition by constraining the correlation between different discriminants [19]. However, the recognition performance in these methods is not very prominent.

The main contribution of this paper is the proposed a novel dynamic kernel dictionary learning (DKDL) approach to extract nonlinear feature with limited SAR data. First of all, the method maps the non-linear data to the kernel space for sparse representation and performs dictionary training. Then, it adaptively calculates the sparsity by dynamic calculation to enhance the flexibility of nonlinear feature extraction and enhance the overall classification performance. Experimental results show that the DKDL has high classification performance.

The remainder of the paper is organized as follows. In Section II, we briefly review the dictionary learning and kernel sparse representation. The proposed dynamic kernel dictionary learning method and the design of its objective function, moreover, its application for SAR target recognition are discussed in detail in Section III. Experimental results on three public databases are reported in Section IV. Finally, and the paper concludes in Section V.

II. DICTIONARY LEARNING IN THE KERNEL SPACE

A. Dictionary Learning

Through the dictionary learning, the goal is to find the best representation of the training samples. By best representation, we mean the one that leads to the least reconstruction error. The optimization problem for achieving this goal is as follows:

Suppose there is a set of training samples, $\boldsymbol{Y} \in \mathrm{R}^{m\times n}$, it can be expressed by a linear equation. The linear equation is $\boldsymbol{Y} = \boldsymbol{DX}$, the dictionary is $\boldsymbol{D} \in \mathrm{R}^{m\times p}$, $\boldsymbol{D} = [\boldsymbol{d}_1, \boldsymbol{d}_2, ..., \boldsymbol{d}_p]$; the sparse coefficient matrix $\boldsymbol{X} \in \mathrm{R}^{p\times n}$ ($\boldsymbol{X} = [\boldsymbol{x}_1, \boldsymbol{x}_2, ..., \boldsymbol{x}_n]$) with maximum number of k non-zero entries. Use (1) to get the $\boldsymbol{D}$ and $\boldsymbol{X}$.

$$\arg\min_{D,X} \|\boldsymbol{Y} - \boldsymbol{DX}\|_F^2 \quad \text{s.t.} \quad \|\boldsymbol{x}_i\|_0 \le k \tag{1}$$

where $i = 1,2,...,n$; k is the sparsity of coding coefficients. Two well-known algorithms for solving the above problem are the method of optimal direction (MOD) [20] and the KSVD algorithm [21].

B. Kernel K-SVD

The There are several known algorithms for dictionary learning. Among them the K-SVD algorithm is widely used due to its effectiveness in practical applications. In the K-SVD algorithm, the feature vectors extracted from a training data set are linearly combined in order to design the dictionary. However, because of the non-linear structure of some real world data, such a linear combination is not always efficient. Nonlinear transformation using kernel methods is a well-known technique widely used for generalization of linear methods.

In the non-linear version of the K-SVD algorithm, the Kernel K-SVD (KK-SVD) algorithm [22], the data points are implicitly mapped into a new high dimensional feature space. The sparse coding and dictionary learning steps are then performed in this new feature space to realize the linear analysis of the nonlinear data. As known, a kernel function computes the inner product of the samples in the related feature space (high-dimensional space), that is:

$$\kappa(\boldsymbol{x}, \boldsymbol{y}) = <\Phi(\boldsymbol{x}), \Phi(\boldsymbol{y})> = \Phi(\boldsymbol{x})^{\mathrm{T}}\Phi(\boldsymbol{y}) \tag{2}$$

where $<,>$ is the dot product operator. Kernel trick proposes that any dot product in a projected feature space can be computed with much lower computational burden using an appropriate nonlinear function.

Common kernel functions are mainly Gaussian kernel function $\kappa(\boldsymbol{x}, \boldsymbol{y}) = \exp(-\|\boldsymbol{x} - \boldsymbol{y}\|^2 / c)$, polynomial kernel function $\kappa(\boldsymbol{x}, \boldsymbol{y}) = (\alpha < \boldsymbol{x}, \boldsymbol{y} > + c)^d$, logarithmic kernel function $\kappa(\boldsymbol{x}, \boldsymbol{y}) = -\log(\|\boldsymbol{x} - \boldsymbol{y}\|^d + 1)$, Cauchy kernel unction $\kappa(\boldsymbol{x}, \boldsymbol{y}) = 1/(1 + \|\boldsymbol{x} - \boldsymbol{y}\|^2 / c)$. The α, c, d are parameters.

III. DYNAMIC KERNEL DICTIONARY LEARING METHOD

A. Dynamic Kernel Dictionary Learning Algorithm

In the dictionary learning, the kernel function is used to transform the sample data into the kernel space by using the kernel function, and a sparse representation algorithm of the kernel dictionary is obtained and the dynamic feature extraction of the nonlinear features is realized by using the sparsity dynamic transformation. Through dynamic dictionary learning in kernel space, more comprehensive feature information can be obtained and the feature information can be flexibly learned.

The sparse representation formula by kernel function transformation is

$$\arg\min_{X} \|\Phi(\boldsymbol{Y}) - \Phi(\boldsymbol{D})\boldsymbol{X}\|_{\mathrm{F}} \quad \text{s.t.} \quad \|\boldsymbol{x}_i\|_0 < k \tag{3}$$

The cross-correlation function of dictionary $\boldsymbol{D}$ can be solved by

$$\begin{aligned}\mu(\Phi(\boldsymbol{D})) &= \max_{1\le i,j\le \mathrm{N}, i\ne j} \frac{\Phi(\boldsymbol{d}_i)^{\mathrm{T}}\Phi(\boldsymbol{d}_j)}{\|\Phi(\boldsymbol{d}_i)\|_0 \|\Phi(\boldsymbol{d}_j)\|_0} \\ &= \max_{1\le i,j\le \mathrm{N}, i\ne j} \frac{\kappa(\boldsymbol{d}_i, \boldsymbol{d}_j)}{\kappa(\boldsymbol{d}_i, \boldsymbol{d}_i)\kappa(\boldsymbol{d}_j, \boldsymbol{d}_j)}\end{aligned} \tag{4}$$

According to the unique solution theorem of linear equations, we can be obtained:

$$\|\boldsymbol{x}_i\|_0 < \mathrm{spark}(\Phi(\boldsymbol{D}))/2 \tag{5}$$

There is a connection between $\mu(\Phi(\boldsymbol{D}))$ with $\mathrm{spark}(\Phi(\boldsymbol{D}))$.

$$\mathrm{spark}(\Phi(\boldsymbol{D})) \ge 1 + 1/\mu(\Phi(\boldsymbol{D})) \tag{6}$$

The k can be donated as:

$$k = \frac{1}{2}(1 + 1/\mu(\Phi(\boldsymbol{D}))) \tag{7}$$

The intrinsic characteristics of data in kernel space are not changed, the residual values of the sparsely expressed data in kernel space are the same as the residual values before the conversion, and the sparse coefficients are the same. The residual matrix can be expressed as:

$$\boldsymbol{E} = \Phi(\boldsymbol{Y}) - \Phi(\boldsymbol{D})\boldsymbol{X} \tag{8}$$

The dictionary $\boldsymbol{D}$ is updated by

$$\boldsymbol{D} = \boldsymbol{E}\boldsymbol{X}^{\mathrm{T}} / \left\| \boldsymbol{E}\boldsymbol{X}^{\mathrm{T}} \right\|_2 \tag{9}$$

The reconstruction error is calculated as:

$$\boldsymbol{r} = \left\| \Phi(\boldsymbol{Y}) - \Phi(\boldsymbol{D})\boldsymbol{X} \right\|_2 / \left\| \boldsymbol{X} \right\|_2 \tag{10}$$

The dynamic kernel dictionary learning algorithm is shown in Algorithm 1.

Algorithm 1: Dynamic kernel dictionary learning (DKDL) Algorithm

Input: Sample data $\boldsymbol{Y}$, dictionary $\boldsymbol{D}$, and maximum number of iterations C.
Output: Updated dictionary $\boldsymbol{D}$, sparse coefficient matrix $\boldsymbol{X}$, reconstruction error $\boldsymbol{r}$.
Initialization: Initialize the iteration counter $\mathrm{t} = 1$. Perform the following steps.
Main Iterations:
1: Choose kernel function from the characteristics of sample data.
2: Calculate $k = \frac{1}{2}(1 + 1/\mu(\Phi(\boldsymbol{D})))$.
3: Calculate $\boldsymbol{X}$ by OMP algorithm.
4: Update $\boldsymbol{D} = \boldsymbol{E}\boldsymbol{X}^{\mathrm{T}} / \left\| \boldsymbol{E}\boldsymbol{X}^{\mathrm{T}} \right\|_2$
5: Compute $\boldsymbol{r} = \left\| \Phi(\boldsymbol{Y}) - \Phi(\boldsymbol{D})\boldsymbol{X} \right\|_2 / \left\| \boldsymbol{X} \right\|_2$.
6: If $\mathrm{t} < \mathrm{C}$, $\mathrm{t} = \mathrm{t} + 1$, repeat 2.
7: Output $\boldsymbol{D}$, $\boldsymbol{X}$, $\boldsymbol{r}$.

B. SAR Target Recognition via Dynamic Kernel Dictionary Learning

When using dynamic kernel dictionary learning algorithm to complete the SAR target recognition, the classification criteria can be described as:

$$i = \arg\min\{\boldsymbol{r}_i\} \tag{11}$$

The main steps of SAR image recognition based on dynamic kernel dictionary learning are shown below:

Step1: Preprocessing stage. Denoising the ground target SAR image and cutting the central area of the SAR image. Each small SAR image block has a size of 64 × 64, and a small SAR image block as a new sample.

Step2: Training phase. Ground target SAR image training sample collection is learned by the dynamic kernel dictionary learning algorithm, and get the sparse coefficient $\boldsymbol{X}$ and update the dictionary $\boldsymbol{D}$.

Step3: Testing phase. The dynamic kernel dictionary learning algorithm is used to learn the test sample collection of ground targets, and the reconstruction errors is calculated, and then classify the testing samples and output the target category.

C. Computational Complexity

This section will discuss the time complexity of the dynamic kernel dictionary learning algorithm. The time of dynamic kernel dictionary learning algorithm is mainly consumed in the processing of OMP algorithm. When the dictionary $\boldsymbol{D} \in \mathrm{R}^{m \times n}$ is used in this algorithm, the iterations of OMP algorithm is s. The complexity of solving phase of OMP algorithm is $\mathrm{O}(sn)$. If the number of iterations in the DKDL algorithm is q, the whole time complexity is $\mathrm{O}(sqmn)$. There is a very small affection of iterations in the real case, so the complexity of the DKDL algorithm can be described as that it is only related to the dimension m and the dictionary atom n.

Meanwhile, the complexity of K-SVD algorithm when performing SVD decomposition is $\mathrm{O}(mn^2)$, the whole complexity is $\mathrm{O}(sqmn^2)$. Compared with the traditional dictionary learning algorithm, the dynamic kernel dictionary learning algorithm is less complex and will be faster in the same hardware environment.

IV. EXPERIMENTAL RESULTS

A. Data Description

To evaluate the performance of the proposed method, we use the Moving and Stationary Target Acquisition and Recognition (MSTAR) three class public dataset. The dataset consists of X-band SAR images with 0.3m × 0.3m resolution of multiple targets, with the polarization mode is HH polarization, and the detection azimuth is 360 °. We uses a typical three classes of ground targets: BMP2 (infantry combat vehicle: SN_9563, SN_9566, SN_C21), BTR70 (armored personnel carrier: SN_C71), T72 (main tank: SN_132, SN_812, SN_S7). The number of images for training and testing in our experiments is summarized in Table 1. The training images are obtained at an elevation angle of 15°, and the testing images are at 17°.

TABLE I. SETUP OF THREE-CLASS PROBLEM ON THE MSTAR DATABASE

Class	1			2	3		
Target	*BMP2*			*BTR70*	*T72*		
	SN-9563	*SN-9566*	*SN-C21*	*SN-C71*	*SN-132*	*SN-812*	*SN-S7*
Train Data	233	0	0	233	232	0	0
Test Data	195	196	196	196	196	195	191

B. *Analysis of Kernel Functions*

In order to validate and analyze the performance of the dynamic kernel dictionary learning algorithm under different kernel functions, 5000 samples from the data are selected as the experimental data. The initial dictionary is set as a 50 × 100 random Gaussian matrix $\boldsymbol{D}$, and the initial sparsity is set as 3. The selected kernel functions are polynomial kernel function, Gaussian kernel function, logarithmic kernel function and Cauchy kernel function respectively.

Fig. 1 is the reconstruction error of the dynamic kernel dictionary algorithm vs. signal-to-noise ratio (SNR) with different kernel functions for 50 iterations.

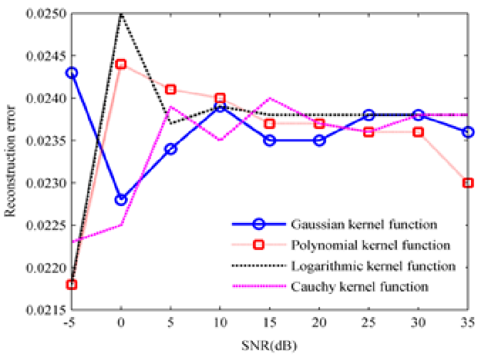

Fig.1. Comparison of reconstruction error in different SNR

From the Fig.1, we can see that the reconstruction errors of dictionary learning methods under different kernel functions are lower than 0.025 with the change of SNR. The reconstruction error of the kernel dictionary learning algorithm using polynomial kernel functions decreases with the increase of SNR. In summary, the DKDL algorithm's reconstruction error is smaller than others and has better stability through using logarithmic kernel function.

C. *Experimental Results*

During the recognition experiment of SAR target, no noise was added, the initial sparsity was set to 3, and the experiment was repeated 20 times under each SNR. The polynomial kernel function's parameters are $\alpha=1, c=1, d=0.5$.

Table 2 shows the SAR target recognition results of the four different methods. From the experiment results, it is obvious that DKDL method proposed by this paper has better recognition performance in terms of recognition accuracy than the three other methods. The method proposed in this article gets the recognition rate 0.9773.

TABLE II. RECOGNITION RATE OF FOUR METHODS ON MSTAR DATABASE

Methods	Recognition Rates
[23]	0.915
[24]	0.9385
[25]	0.9648
DKDL	**0.9773**

In order to compare the recognition performance of SAR images with different SNR, Gaussian white noise of -5dB ~ 35dB was added to the test samples of SAR image datasets, and the recognition rate of different algorithms with SNR were obtained.

Fig. 2 shows that the average recognition rate of SAR images with DKDL under the low signal-to-noise ratio is above 0.8, much higher than the other three methods. With the increase of SNR, the average recognition rate of SAR images also increases with the four methods and finally stabilizes. The recognition rate of dynamic kernel dictionary learning algorithm is above 0.97. The recognition rate of dynamic kernel dictionary learning algorithm under the same SNR is higher than the other three methods. In summary, dynamic dictionary learning algorithm recognition performance is superior to other algorithms; moreover, DKDL is more robustness.

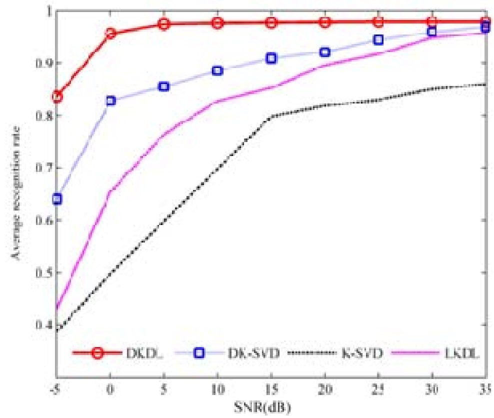

Fig.2. Comparison of four methods on MSTAR database

V. CONCLUSION

A novel SAR target recognition method based on dynamic kernel dictionary learning (DKDL) is proposed. In this method, linearly inseparable feature data in SAR images are mapped into in a high dimensional feature space using kernel trick, and the nonlinear data can be classified better. And then the sparse the sparse coefficients are dynamically calculated in kernel space so that different target data correspond to different sparsity. Experimental results on MSTAR datasets confirmed that DKDL has the best recognition accuracy, especially, it has better robustness to noise. In the future, we will focus on how to address the problem of SAR recognition under a complex background and expression more effectively and efficiently.

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