AN EFFICIENT SAR ATR APPROACH

Ping Han [1,2] *Renbiao Wu* [2] *Yunhong Wang* [3] *Zhaohua Wang* [1*]

1. Institute of Electronic Information Engineering , Tianjin University, Tianjin, 300174, P.R.China

2. Institute of Communications and Information Processing, P.O.Box 9

Civil Aviation University of China, Tianjin, 300300, P.R.China

3. National Lab for Pattern Recognition, Institute of Automation Chinese Academy of Sciences, Beijing, 100080, P.R.China

ABSTRACT

Automatic Target Recognition (ATR) based on Synthetic Aperture Radar (SAR) imagery (denoted as SAR ATR for simplicity) is very important for battlefield awareness. Since SAR images are very sensitive to pose variation of targets, SAR ATR is a well-known very challenging problem. In this paper, an efficient SAR ATR algorithm is given, which uses KFD (Kernel Fisher Discriminant) as feature extractor and linear SVM (Support Vector Machine) as classifier. Experimental results evaluated with the MSTAR (Moving and Stationary Target Automatic Recognition) public data sets provided by DARPA(Defence Advanced Research Project Agency)/AFRL(Air Force Research Laboratory) show that the proposed scheme performs much better than the conventional template matching and SVM methods, especially when the target pose uncertainty is large, which is desirable for SAR ATR.

1. INTRODUCTION

SAR imaging is a well-established technology which has found a variety of applications, such as battlefield awareness. In 1995, DARPA and AFRL initiated a project named MSTAR in an effort to develop and evaluate an advanced ATR system. Unlike optical images which describe a good appearance of an object, SAR images are described by a set of scattering centers and are also highly variable with the pose of a target. How to extract robust features of targets when the pose uncertainty is large is crucial to SAR ATR.

In recent years, a kernel-based classification algorithm SVM[1] is very popular. One of the key ingredients responsible for the success of SVM is the use of Mercer kernels, allowing for nonlinear decision surface which even might incorporate some prior knowledge about the problem to solve. The use of kernel functions is not limited to SVM. KPCA[2] (Kernel Principal Component Analysis) and KFD[3] are also kernel-based algorithms which have been used in some other fields[4][5].

[*] This work was supported in part by the National Natural Science Foundation of China under Grant 69902009 and 60272049 ,the Excellent Young Teachers Program of MOE,P.R.China, and the Natural Science Foundation of Tianjin.

In this paper, an efficient SAR target nonlinear feature extraction based on KFD is studied. By defining a non-linear mapping from the input space to high dimensional space, we obtain a linearly separable distribution in the feature space where LDA(Linear Discriminant Analysis) is used to extract the most significant discriminanting features. Experimental results with MSTAR public data sets show the performance of classification and generalization based on KFD and linear SVM performs better than template-based approach[6] and other methods.

2. THE KFD METHOD [3]

The well known Fisher's linear discriminant analysis is a powerful linear classification technique. However, since LDA is a linear technique, it is too limited to capture interesting nonlinear structure in a data set. Non-linear generalizations can be used to make computation efficient in finding the feature in the feature space, which is non-linearly related to the input space.

Let Φ denote a non-linear mapping from the input data to some feature space F; $\chi_1 = \{\mathbf{x}_1^1, \ldots, \mathbf{x}_{l_1}^1\}$ and $\chi_2 = \{\mathbf{x}_1^2, \ldots, \mathbf{x}_{l_2}^2\}$ are samples from two different classes and let $\chi = \chi_1 \cup \chi_2 = \{\mathbf{x}_1, \ldots, \mathbf{x}_l\}$ be the mixed samples. Let

$$\mathbf{m}_i^\Phi = \frac{1}{l_i}\sum_{j=1}^{l_i}\Phi(\mathbf{x}_j^i) \qquad (1)$$

denote the mean vector of Class i (i=1,2) in F. Define the between and within class scatter matrices respectively as

$$\mathbf{S}_B^\Phi = (\mathbf{m}_1^\Phi - \mathbf{m}_2^\Phi)(\mathbf{m}_1^\Phi - \mathbf{m}_2^\Phi)^T \qquad (2)$$

$$\mathbf{S}_w^{\Phi} = \sum_{i=1,2}\sum_{x\in\chi_i}(\Phi(\mathbf{x})-\mathbf{m}_i^{\Phi})(\Phi(\mathbf{x})-\mathbf{m}_i^{\Phi})^T \quad (3)$$

Fisher's linear discriminant in F is to maximize

$$J(\boldsymbol{\omega}) = \frac{\boldsymbol{\omega}^T\mathbf{S}_B^{\Phi}\boldsymbol{\omega}}{\boldsymbol{\omega}^T\mathbf{S}_w^{\Phi}\boldsymbol{\omega}} \quad (4)$$

where $\boldsymbol{\omega}\in F$ and has the form

$$\boldsymbol{\omega} = \sum_{i=1}^{l}\alpha_i\Phi(\mathbf{x}_i) \quad (5)$$

with $l = l_1 + l_2$.

By introducing kernel functions $k(\mathbf{x},\mathbf{y}) = (\Phi(\mathbf{x})\cdot\Phi(\mathbf{y}))$ instead of computing the dot-product in F, we can find Fisher's linear discriminant in F without explicitly mapping the input data to the feature space. The cost function for the Fisher's linear discriminant in F is to maximize

$$J(\boldsymbol{\alpha}) = \frac{\boldsymbol{\alpha}^T\mathbf{M}\boldsymbol{\alpha}}{\boldsymbol{\alpha}^T\mathbf{N}\boldsymbol{\alpha}} \quad (6)$$

where

$$\mathbf{M} = (\mathbf{M}_1-\mathbf{M}_2)(\mathbf{M}_1-\mathbf{M}_2)^T \quad (7)$$

$$(\mathbf{M}_i)_j = \frac{1}{l_i}\sum_{k=1}^{l_i}\mathrm{k}(\mathbf{x}_j,\mathbf{x}_k^i)$$

$$j = 1,2,\ldots,l \quad M_i \in R^{l\times 1} \quad (8)$$

with $(\mathbf{M}_i)_j$ being the j the element of $\mathbf{M}_i$.

$$\mathbf{N} = \sum_{j=1,2}\mathbf{K}_j(\mathbf{I}-\mathbf{1}_{l_j})\mathbf{K}_j^T \quad (9)$$

and

$$(\mathbf{K}_j)_{mn} = \mathrm{k}(\mathbf{x}_m,\mathbf{x}_n^j) \quad (10)$$

with $\mathbf{K}_j$ being the kernel matrix for Class j of dimension $l\times l_j$, $(\mathbf{K}_j)_{mn}$ the (m,n) th element of $\mathbf{K}_j$, $\mathbf{I}$ the identity matrix, and $\mathbf{1}_{l_j}$ the matrix with all entries $1/l_j$. The solution to the cost function can be obtained by finding the leading eigenvector α^* of $\mathbf{N}^{-1}\mathbf{M}$. To ensure $\mathbf{N}$ positive semidefinite and stable, we replace $\mathbf{N}$ by $\mathbf{N}_\mu$, where $\mathbf{N}_\mu = \mathbf{N}+\mu\mathbf{I}$. When μ is large enough, $\mathbf{N}_\mu$ will become positive semidefinite. The projection of a new pattern $\mathbf{x}$ onto $\boldsymbol{\omega}$ is given by

$$\mathrm{g}(\mathbf{x}) = (\boldsymbol{\omega}\cdot\Phi(\mathbf{x})) = \sum_{i=1}^{l}\alpha_i^*\,\mathrm{k}(\mathbf{x}_i,\mathbf{x}) \quad (11)$$

3. MSTAR PUBLIC DATASET

In the following sections, we will use the MSTAR public dataset[6] provided by DARPA/AFRL to evaluate the performance of the proposed method. For the sake of presentation, below we briefly introduce the dataset.

The MSTAR data used in our experiment consisted of 1 foot resolution, X-band, three types of ground military vehicles, the T72, BMP2, BTR70. Each target has SAR images (called SAR chips) separated by 1^0 azimuth increments within an angular coverage between 0^0 to 360^0. Each image has a size of 128 by 128 pixels. Training dataset are taken at a depression angle of 17^0, and the testing set at 15^0. They are slightly different so as to test the generalization ability. Variants (different serial number) of the three targets were also used in the testing dataset. The training and testing datasets contain 698 and 1365 SAR chips, respectively. Their optical and SAR image samples are shown in Fig.1.

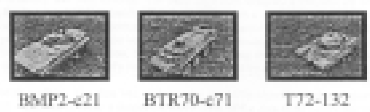

Fig.1(a) Optical images of training samples

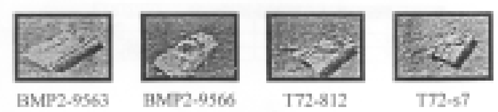

Fig.1(b) Optical images of additional testing samples

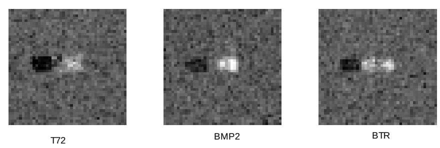

Fig.1(c) SAR images of training samples

Fig.1 Optical and SAR image samples of targets

4. PREPROCESSING

Some preprocessing of SAR images needs to be done before feature extraction and classification. In the log-domain, the strong corner reflectors in the SAR imagery are de-emphasized and hence more emphasis was on the shape and shadow regions of the target. We first calculate the log-magnitude of SAR images to reduce the dynamic range

$$\mathbf{g}(m,n) = \log_{10}[\mathbf{S}(m,n)+1] \quad (12)$$

where $\mathbf{S}(m,n)$ denotes the magnitude matrix of SAR target image whose dynamic range is from 0 to 255. Since the logarithm is not defined for 0, we add the value 1 to the image before taking the logarithm.

Second, Fourier Transform (FT) of the log-magnitude images is performed for the purpose of image shift alignment. Only half of the normalized amplitude of the FT is used as input data due to the shift- invariance and symmetric property of FT

$$\left|F[\mathbf{g}(m,n)]\right| = \left|F[\mathbf{g}(m-m_0, n-n_0]\right| \qquad (13)$$

$$|\mathbf{G}(u_m, v_n)| = |\mathbf{G}(-u_m, -v_n)| \qquad (14)$$

where F denote the two dimension FT and $\mathbf{G}(u_m, v_n)$ is the FT of the image.

5. TARGET FEATURE EXTRACTION

After the preprocessing, the image vectors are obtained by lexicographically rearranging the columns (or rows). As Fig.2 shows, SAR images of the same target taken at different aspect angles show great differences.

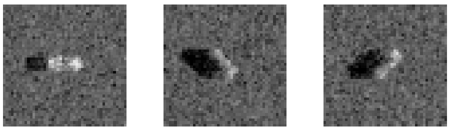

Fig.2 BTR SAR images taken at different aspect angle

To obtain the efficient target feature, the target feature extraction is performed in every P degree in azimuth by binning the training data, respectively. In the experiment, we set $P = 10^0, 30^0, 90^0, 360^0$ respectively. Then the whole aspect range are divided into 360/P bins. In order to use KFD to extract the target feature, the classification problems which are not binary are partitioned into two-class problems. In each aspect bin, three groups of optimal vectors α^* are calculated between every two classes. They are $\alpha^*_{T72-BMP}$, $\alpha^*_{T72-BTR}$ and $\alpha^*_{BMP-BTR}$. Then the projection of each training target on the corresponding α^* is used as target feature. They are

$$\begin{cases} g(\mathbf{x}_{T72})_{T72-BMP} = \sum_{i=1}^{N} \alpha^*_{iT72\_BMP}\, \mathrm{k}(\mathbf{x}_i, \mathbf{x}_{T72}) \\ g(\mathbf{x}_{BMP})_{T72-BMP} = \sum_{i=1}^{N} \alpha^*_{iT72\_BMP}\, \mathrm{k}(\mathbf{x}_i, \mathbf{x}_{BMP}) \end{cases} \qquad (15)$$

$$\begin{cases} g(\mathbf{x}_{T72})_{T72-BTR} = \sum_{i=1}^{N} \alpha^*_{iT72\_BTR}\, \mathrm{k}(\mathbf{x}_i, \mathbf{x}_{T72}) \\ g(\mathbf{x}_{BTR})_{T72-BTR} = \sum_{i=1}^{N} \alpha^*_{iT72\_BTR}\, \mathrm{k}(\mathbf{x}_i, \mathbf{x}_{BTR}) \end{cases} \qquad (16)$$

$$\begin{cases} g(\mathbf{x}_{BMP})_{BMP-BTR} = \sum_{i=1}^{N} \alpha^*_{iBMP-BTR}\, \mathrm{k}(\mathbf{x}_i, \mathbf{x}_{BMP}) \\ g(\mathbf{x}_{BTR})_{BMP-BTR} = \sum_{i=1}^{N} \alpha^*_{iBMP-BTR}\, \mathrm{k}(\mathbf{x}_i, \mathbf{x}_{BTR}) \end{cases} \qquad (17)$$

where N is the number of training samples of two targets in each aspect bin.

Fig.3 shows the feature histogram of T72-BMP2 where $P = 90^0$, and the kernel function we selected is $k(\mathbf{x}_i, \mathbf{x}) = \exp(-\gamma \|\mathbf{x} - \mathbf{x}_i\|^2)$ with $\gamma = 0.25$.

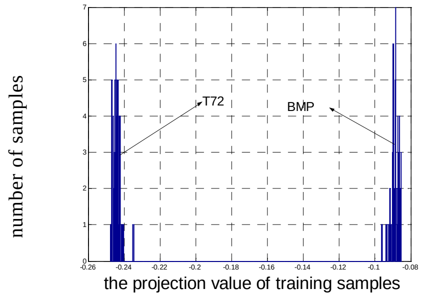

Fig. 3(a) 0^0-90^0

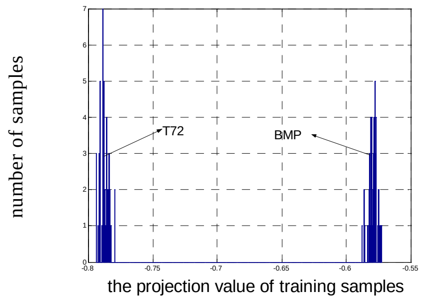

Fig. 3 (b) 90^0-180^0

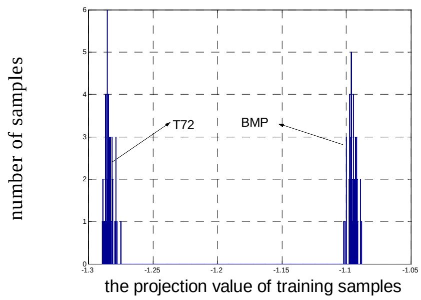

Fig. 3 (c)180^0-270^0

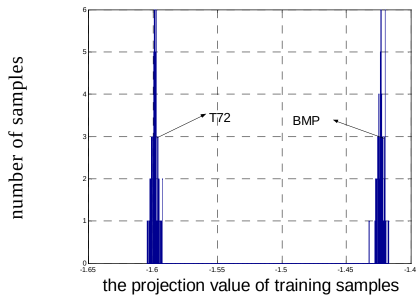

Fig. 3 (d) 270^0-360^0

Fig.3 Target feature histogram of T72_BMP, P=90^0

6. CLASSIFICATION

We can see from Fig.3 that T72 and BMP2 are well separated after feature extraction. Linear classification technique may be used to estimate the optimal threshold on the extracted feature. To use the feature in classification, we need to find a suitable threshold which can either be chosen as the mean of the average projection of the two classes or by training a linear SVM on the projections. But to obtain a minimum error rate or a high classification accuracy in the test set, the classifier should have large margins around its decision boundary and a good generalization ability, especially when the number of training examples is much smaller than the dimensionality of the input space in our experiments. We prefer to select a linear SVM to estimate the threshold. The classification problems are still partitioned into two-class problems. In each pose bin, three SVM classifiers are trained, they are T72-BMP2,T72-BTR70, and BMP2-BTR70. Target pose information (approximate) is used to select the corresponding classifier when a test image is to be classified.

7. EXPERIMENTAL RESULTS

Table1 shows the probability of correct classification of KFD plus linear SVM classification algorithm for different aspect increments. We also present other results derived by using other state-of-art methods of target feature extraction or classifiers to evaluate the performance of the proposed approach, such as the target classified directly using nonlinear SVM without feature extraction, LDA plus linear SVM and the conventional template matching which is the baseline for comparison. All results are listed in Table1.

Note that template matching based approach is very sensitive to the pose uncertainty. Its performance will degrade rapidly if the aspect binning size is increased. But for our method, when the sector size is 90^0 (which means the pose uncertainty could be as large as 90^0), best performance is achieved (correct classification rate is 97.14%). Even if without binning the data, we still get good results (95.6%). This is mainly because we make a more efficient target feature extraction using KFD by introducing the right kernel function and parameter. In addition, the classification speed of our approach is much faster than template matching based approach.

It can be noted also that all kernel-based methods tested in our experiments are less sensitive to pose uncertainty than the conventional template matching based method, and the proposed approach performs better than other methods.

8. CONCLUSIONS

The performance of KFD based SAR ATR is investigated in this paper. Experimental results show that KFD plus linear SVM outperforms the conventional template matching and other kernel-based ATR methods. Especially, it is very robust to the pose uncertainty. Good ATR performance can be achieved even if we have no knowledge about the target pose information.

REFERENCES

[1]. V.Vapnik, The nature of statistical learning theory, NewYork,Springer,Verlag,1995.

[2]. B.Schölkopf,A.Smola and K.-R.Müller. “Nonlinear component analysis as a kernel eigenvalue Problem”. Neural Computation, Vol.10, pp1299-1319,1998.

[3]. S. Mika, G. Rätsch, J. Weston, B. Schölkopf, and K.-R. Müller. “Fisher discriminate analysis with kernels”. in Neural Networks for Signal Processing IX, Y.-H. Hu, J. Larsen, E. Wilson, and S. Douglas, Eds. Piscataway, NJ: IEEE, pp41-48,1999.

[4]. Bernhard Schölkopf, SebastianMika, Chris J.C.Burges, Philipp Knirsch, Klaus-Robert Müller, Gunnar Rätsch, AlexJ.Smola, “Input Space vs. Feature Space in Kernel-Based Methods”, IEEE Trans.on Neural Networks, 10(5), pp1000-1017, 1999.

[5]. V.Roth and V.Steinhage, “Nonlinear discriminant analysis using kernel functions,”in Advances in Neural Information Processing Systems12, MA: MIT. Press, pp568-574, 2000.

[6]. Timothy Ross, Stephen Worrell, Vincent Velten, John Mossing, and Michael Bryant. “Standard SAR ATR evaluation experiment using the MSTAR public release data set”. SPIE,Vol.3370, pp566-573, April 1998.

Table1. Comparison of different ATR methods under different sector size

	10^0	30^0	90^0	360^0
Template matching	95.09%	83.08%	56.92%	47.76%
Nonlinear SVM	94.65%	95.45%	95.24%	86.08%
LDA+ linear SVM	92.16%	96.7%	96.7%	89.01%
KFD + linear SVM	**93.85%**	**95.75%**	**97.14%**	**95.6%**