SAR target recognition using multiple views decision fusion

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Abstract: In this paper, new synthetic aperture radar (SAR) image target recognition approach based on multiple views decision fusion is presented. Image chips are represented as feature vectors by 2-D wavelet transformation and principal component analysis algorithm. The feature vectors are classified by using algorithms of support vector machine (SVM). After multiple views of the same vehicle collected at different aspects classified by SVM, the outputs are then fused using Bayesian approach and the final classification decision is generated. Experiments are implemented with three class targets in Moving and Stationary Target Acquisition and Recognition (MSTAR) Program database. Experimental results indicate that there are significant target recognition performance benefits in the probability of correct classification when three or more views are used for decision fusion. Therefore, the approach proposed is an effective method for SAR image target recognition.

Key words: synthetic aperture radar (SAR), target recognition, multiple views, decision fusion, Bayesian

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1 INTRODUCTION

Synthetic aperture radar (SAR) image target recognition is essential in SAR image interpretation and analysis, which is a hot issue in SAR image processing and pattern recognition. Assuming that a target is detected and its position is known in the SAR image implies that a target chip can be extracted from the SAR image of a scene for recognition. Generally, target recognition consists of two processes: feature extraction and classification. Principal component analysis (PCA) is a very effective feature extraction algorithm. First, orthonormal vector basis is obtained through singular value decomposition and feature vector analysis. Feature vectors for representing chips are gained by mapping the chips to the orthonormal vector basis, which reduces the feature vectors in dimension significantly and reduces the processing time greatly (Safari *et al.*, 2004; Puyati *et al.*, 2006). In the classification step, multi-class support vector machine (SVM) is often used as classifier. SVM establishes the optimal classification surface in feature classes, therefore, has excellent classification performance (Zhao & Principe, 2001; Lee *et al.*, 2003; Safari *et al.*, 2004).

SAR images are highly sensitive to target aspect, due to shadowing effects, interaction of the signature with the environment, projection of a three dimensional scene onto a slant plane and other reasons due to the aspect dependence of radar cross-sections (O'Sullivan *et al.*, 2001; Brown, 2003). The ability to discriminate between targets in SAR imagery also varies greatly with target aspect. Therefore, we consider the exploitation of multiple views of a target may provide more robust classification performance than only using single view and the number of images needed to significantly improve performance. To solve these questions, Ettinger and Snyder (2002) have proposed a multi-look fusion method on hypothesis layer. Brown (2003) has proposed robust classifiers based on Bayesian approach.

This paper presented a new SAR image target recognition approach based on multiple views decision fusion. Image chips are represented as feature vectors by 2-D wavelet transformation and principal component analysis algorithm. The feature vectors are classified by using algorithms of support vector machine. After multiple views of the same vehicle collected at different aspects classified by SVM, the outputs are then fused using Bayesian approach and the final classification decision is generated. Experiments are implemented for verification and analysis with three class targets in MSTAR database.

2 SAR IMAGE TARGET RECOGNITION APPROACH

The SAR image target recognition approach proposed in this paper consists of four steps as shown in Fig. 1, which are preprocessing, feature extraction, SVM classification and Bayesian decision fusion.

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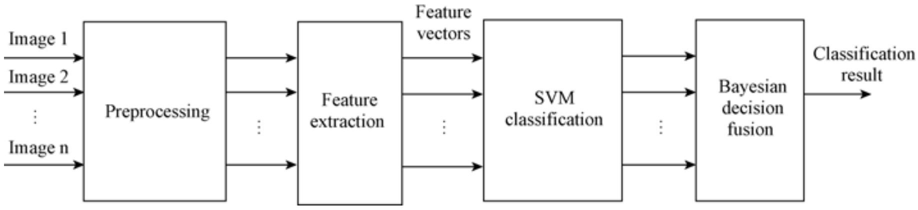

Fig. 1 Process diagram of SAR image target recognition

2.1 Data preparation

In this paper, SAR chips included in Moving and Stationary Target Acquisition and Recognition (MSTAR) Program database are used. The publicly released portion of the MSTAR database contains SAR images of 10 class vehicles. In this paper, we use three types of vehicles which are BMP2, BTR70, and T72. Each of the targets has views at 15° and 17° depression angles. The data in depression 17°are used for training and the other for testing. There are about 190—300 different aspect versions of each target at each depression angle. Table 1 lists type and sample number of training and testing set. Fig. 2 depicts original SAR target images at different aspects. Fig. 3 depicts multiple views of a target.

Table 1 Type and sample number of training and testing set

Training set	Sample number	Testing set	Sample number
BMP2_c21	233	BMP2_c21	196
BTR70_c71	233	BMP2_9563	195
T72_132	232	BMP2_9566	196
		BTR70_c71	196
		T72_132	196
		T72_812	195
		T72_s7	191

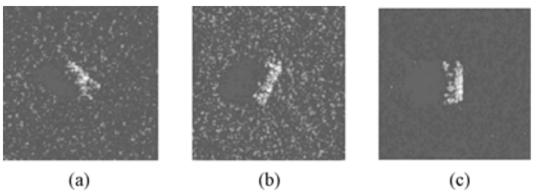

Fig. 2 Original SAR target images at different aspects
(a) BMP2, 320°; (b) BTR70, 62°; (c) T72, 90°

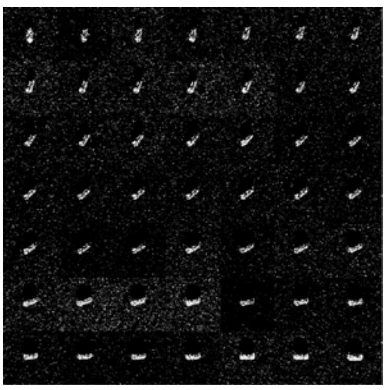

Fig. 3 Multiple views of a target

2.2 Preprocessing

Some feature extraction algorithms and classification algorithms are sensitive to location shift, rotation, and non-uniform illumination (Sandirasegaram & Englisth, 2005). So, preprocessing is necessary. In this paper, we first rotate each target to a vertical orientation using ground truth information to bring the targets into a standardized target orientation. Then, highest energy reflecting point of the target chip is found and located to the centre of a new chip, the size of which is 64 pixels by 64 pixels. The final preprocessing step is to normalize the target chips. Normalization alters the pixel values such that, the mean intensity is zero and the standard deviation value is one for each chip. Fig. 4 (a) and Fig.4 (b) respectively depict the chip of target T72 before and after preprocessing. Comparing Fig. 4 (a) and Fig. 4 (b), the chip after preprocessing is clearer than before and the details are enhanced.

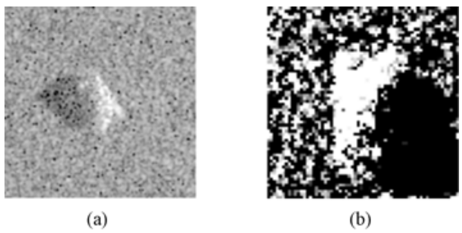

Fig. 4 (a) and (b) depict the chip of target T72 before and after preprocessing

2.3 Feature extraction

Feature extraction is an important step in the target recognition process. Feature extraction algorithms extract unique target information or signature from each chip. 2-D wavelet transformation is used here to perform 3 levels decomposition. LL3, which contains low frequency components, is picked for future extraction. PCA is then employed. LL3, of which the size is 8×8, is represented by a 64-dimension vector. Data matrix $\boldsymbol{X}_{m\times n}$ is composed of those vectors from all training set, where $m=64$ and n is the sample number in training set. We calculate the correlation matrix $\boldsymbol{C}=E[\boldsymbol{X}_{m\times n}\boldsymbol{X}_{m\times n}{}^{\mathrm{T}}]$. The eigenvectors $\boldsymbol{v}_i$ and eigenvalues λ_i, $i = 1,2,\cdots,m$, are computed from the correlation matrix. The eigenvectors with the largest p eigenvalues are selected for p vector as the orthonormal vector basis of the chip database. p is decided by $\bar{\lambda}_1+\bar{\lambda}_2+\cdots+\bar{\lambda}_p \geqslant 0.9$, where $\bar{\lambda}_1,\bar{\lambda}_2,\cdots,\bar{\lambda}_p$ are unitary largest p eigenvalues. The transformation matrix is formed from these eigenvectors in the column manner, which is $W=[v_1 v_2 \cdots v_p]^{\mathrm{T}}$. The extracted p dimension feature vectors y of the input data x, can be calculated by following equation: $y = W \cdot x$. Finally, we get a 24-dimension feature vector for each chip. Fig. 5 shows feature extraction process. Left is the preprocessed image, middle is LL3 after 3 levels 2-D wavelet decomposition and right is feature vector gained by PCA.

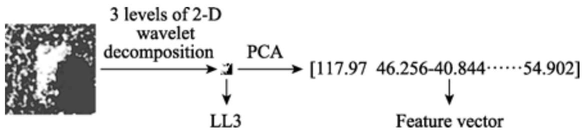

Fig. 5 Feature extraction process

2.4 Classification

Using the vector of extracted features, the classifier must be able to correctly decide which class the target belongs to. In this paper, we use support vector machine (SVM) as classifier. SVM, as a method of learning and separating binary classes, is superior in classification performance, and has been in the spotlight for pattern recognition. The basic principle of SVM can be generalized as follow (Vapnik, 1999): mapping the data to a high-dimension Euclidean space (feature space) using a nonlinear mapping $\phi : R^n \rightarrow E$, finding the decision surface in the new feature space, using kernel function for nonlinear mapping. Therefore, arbitrary test data x can be classified by

$$f(x) = \operatorname{sgn}\left\{ \sum_{i=1}^{l} \alpha_i^{*} y_i K(x_i, x) + b^{*} \right\} \tag{1}$$

where x_i is support vector, $y_i \in \{-1, 1\}$ is class label corresponded to x_i, $K(x_i, x)$ is kernel function, α_i^{*} is Lagrange multiplier corresponded to x_i, b^{*} is classification threshold value and sgn is symbol function.

SVM is a binary classifier in basic. Since our goal is to identify three types of targets in MSTAR dataset, we need to extend it to multi-class classifier. We first decompose the multi-class problem into several binary problems with one-against-one scheme, and use voting rule for decision making. Gaussian kernel function $K(x_i, x) = \exp\left\{ -\frac{|x - x_i|^2}{\sigma^2} \right\}$ is applied as the kernel function for SVM.

2.5 Bayesian decision fusion

At last step, SVM is used as a single view classifier to classify the target. Here, we apply Bayesian decision fusion method to extend single view classifier to multiple views classifier. Assuming that we have a set of K images of a target, each of which is classified into one of Q distinct classes. The output of our multi-class SVM classifier is in terms of score. In order to express the output of the classifier as the estimated posterior probability, $y_{k,q} = \frac{(S_{k,q})^n}{\sum_j (S_{k,j})^n}$, n=3 is performed for nonlinear transformation (Rizvi & Nasrabadi, 2003), where $S_{k,q}$, q = 1, 2,⋯, Q, $k = 1, 2, \cdots, K$ is the q th unconstrained output (score) of k th view from the output of the SVM classifier. $y_{k,q}$ represents the estimated posterior probability that k th image x_k belongs to the class q, estimated by SVM classifier.

$$y_k = \{ y_{k,q}; q = 1, 2, \cdots, Q \} \tag{2}$$

Using Bayesian rule, Eq. (2) can be expressed as:

$$P(q \mid x_k) = \frac{P(x_k \mid q) P(q)}{P(x_k)} \tag{3}$$

As the priori knowledge $P(q)$ is unknown, suppose the possibility of belonging to various classes is equal. So,

$$P(q) = \frac{1}{Q}, 1 \leqslant q \leqslant Q \tag{4}$$

For a certain target x_k, $P(x_k)$ is a fixed constant for all the classes. So, $y_{k,q}$ is equivalent to the likelihood probability $P(x_k|q)$. Using the log-likelihood function, yields

$$a_{k,q} = l(x_k \mid q) \tag{5}$$

The classification decision of k th view from SVM classifier is

$$\theta_k = \arg \max_{1 \leqslant q \leqslant Q} a_{k,q} \tag{6}$$

The joint probability of all views is defined as:

$$y_q = \prod_{k=1}^{K} P(x_k \mid q) \tag{7}$$

Substituting the log-likelihood of the probabilities, the Eq. (7) can be written as

$$a_q = \sum_{k=1}^{K} l(x_k \mid q) \tag{8}$$

The classification decision of K views is

$$\theta = \arg \max_{1 \leqslant q \leqslant Q} a_q \tag{9}$$

Bayesian decision fusion process is shown in Fig. 6. Left are three SAR images of target BMP2_9563, of which the aspects are 85°, 115° and 145° respectively. Middle is $y_{k,q}$ of three images after SVM classification and the class decisions for single view obtained from Eq. (6), which are class three, class one and class one respectively. We know form Fig. 6, the first view is misclassified as class three, if three views are recognized separately. Right in Fig. 6 gives a_q after three images Bayesian decision fusion and the final class decision obtained from Eq. (9), which is class one. We know from Fig. 6, the correct class of those three images can be obtained after Bayesian decision fusion. That is to say, Bayesian decision fusion can correct the error, which occurs when the first view is recognized alone.

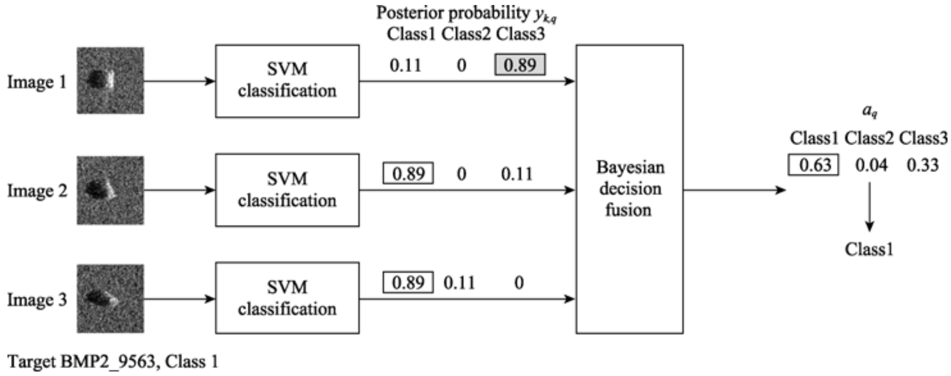

Fig. 6 Bayesian decision fusion process

3 EXPERIMENTAL RESULTS AND ANALYSIS

SAR signatures vary greatly with aspect, as shown previously in Fig. 3. Thus, recognition performance may also be expected to vary with target aspect. Given that this is the case, exploitation of multi-aspect images of a target should provide more robust recognition performance than only using single image. The number of multi-aspect images, the angular interval between them and the approaches used for exploitation, are all issues that affect the final recognition performance of a target.

Applying BMP2, BTR70 and T72 three class images in MSTAR, our experiments are to examine the recognition performance sensitivity of the proposed approach to the number of views and the aspect intervals. Probability of correct classification (PCC) is calculated via correct classification sample number dividing by total sample number, which is the most important measurement for recognition performance. Fig. 7 shows PCC in our approach using 2—5 multi-aspect views with the aspect interval ranging from 1° to 60°. Fig. 7 shows the more the views are used, the higher the PCC is, and it arrives at 100% when five views are used in some aspect intervals. When three or more views are used, the PCC advances significantly compared with that when two views are used. That is because more information in multi-aspect views are exploited by algorithms when more views are used, which results in higher PCC. When only two views are used, aspect interval has few effects on the PCC. When three or more views are used, in a small aspect interval, which may be 20° approximately, the PCC increases with aspect interval increasing. Out of that aspect interval, the PCC has little relationship with aspect interval.

Table 2 lists the highest PCC obtained by our approach using 1—5 views respectively and compares them with PCC gotten by some typical recognition methods using single view. Applying our approach with single view means we make class decision just after image preprocessing, feature extraction and SVM classification. Ross *et al.* (1998) presented a template matching method, which formed templates by averaging training image samples in every 10° aspect unit and used minimum distance rule for matching. Nilubol and Pham (1998) took Radon transformation to images in a number of discrete angles, constructed feature vectors by statistical variables and used hidden Markov models for recognition. Zhao and Principe (2001) presented a method using support vector machine for recognition, which implemented without feature extraction, and used SVM to image samples for classification in every 30° aspect unit. From Table 2, we conclude the average PCC obtained from multiple views decision fusion is not only significantly higher than that obtained from several other methods using single view, but also higher than that obtained from our approach using single view.

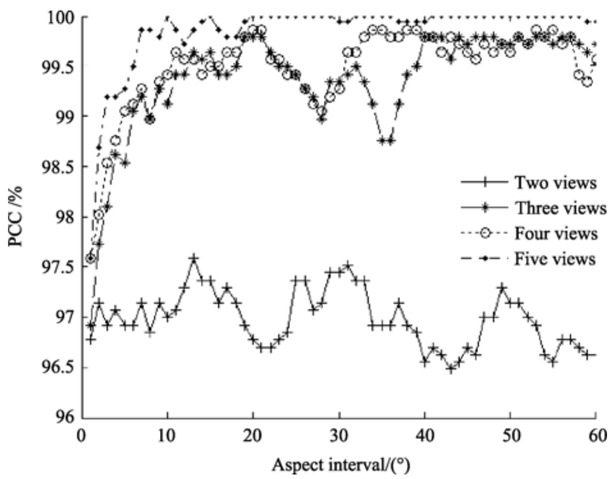

Fig. 7 Probability of correct classification for multiple views decision fusion

Table 2 Comparison for the probability of correct classification **/%**

	BMP2	BTR70	T72	Average
Single view	96.25	99.49	96.22	96.70
Two views	97.44	100.00	96.91	97.58
Three views	99.83	100.00	99.66	99.78
Four views	100.00	100.00	99.66	99.85
Five views	100.00	100.00	100.00	100.00
Template matching (Ross *et al.*)	82.79	93.37	94.50	89.30
HMM (Nilubol and Pham)	90.80	92.30	100.00	94.90
SVM (Zhao and Principe)	90.97	99.49	88.14	90.99

4 CONCLUSIONS

A SAR image target recognition approach based on multiple views Bayesian decision fusion was proposed in this paper. The recognition performance sensitivity of the proposed approach to the number of views and the aspect intervals was analyzed. Experimental results indicated that there were significant target recognition performance benefits in the probability of correct classification compared with some other methods using single view for recognition, when three or more views were used for decision fusion in some certain aspect intervals. Therefore, the approach proposed is an effective method for SAR image target recognition.

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多方位角图像决策融合的 SAR 目标识别

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摘 要： 提出了一种基于多方位角图像决策融合的合成孔径雷达(SAR)图像目标识别方法。对目标切片图像用二维小波分解和主成分分析提取特征向量，利用支持向量机对特征向量进行分类，用贝叶斯方法对目标多幅不同方位角下图像的分类输出进行决策融合，得到最终类别决策。用 MSTAR 数据库中 3 个目标进行识别实验，实验结果表明，对 3 幅以上不同方位角的图像进行决策融合时，该方法可显著提高目标的正确识别率。该方法是一种有效的 SAR 图像目标识别方法。

关键词： 合成孔径雷达(SAR)，目标识别，多方位角图像，决策融合，贝叶斯

中图分类号： TP751.1/TP722.6 **文献标识码：** A

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Huan R H and Yang R L. 2010. SAR target recognition using multiple views decision fusion. *Journal of Remote Sensing*. **14**(2): 252—261

1 引 言

合成孔径雷达(Synthetic Aperture Radar, SAR)图像目标识别是SAR图像解译和分析的重要组成部分，是当前 SAR 图像处理和模式识别领域的研究热点。假设一幅 SAR 图像中的目标已被检测出且其位置得以确定，则可以从图像中提取包含目标的切片图像进行识别。目标识别主要包括特征提取和特征分类两个步骤。主成分分析(Principal Component Analysis, PCA)是一种十分有效的特征提取算法。通过奇异值分解和特征矢量分析得到切片数据的正交矢量基。将切片数据对该正交矢量基投影，可得到表征切片图像的特征，该特征在维数方面得到了显著的缩减，大大减少处理时间(Safari 等，2004; Puyati 等, 2006)。在特征分类步骤中，通常使用多类支持向量机(Support Vector Machine, SVM)作为分类器。支持向量机通过在特征类别中建立最优分类面，具有优越的分类性能(Zhao & Principe, 2001; Lee 等, 2003; Safari 等，2004)。由于阴影效应，信号与背景的交互，三维场景在斜平面的投影以及其他雷达横截面对方位角敏感的因素，SAR 图像对目标方位角的变化十分敏感(O'Sullivan 等, 2001; Brown, 2003)。对SAR图像中目标的辨识能力也会随着方位角的变化改变。考虑利用一个场景的多幅不同方位角下的 SAR 图像是否可以提高目标识别的性能，并且需要利用多少幅图像才可以显著提高性能。为了解决这个问题, Ettinger 和 Snyder (2002)提出了一种假设层多视融合方法, Brown (2003)提出了一种基于贝叶斯(Bayesian)方法的鲁棒分类器。

本文提出了一种利用目标多方位角图像进行贝叶斯决策融合的 SAR 图像目标识别方法。首先，对目标切片图像用二维小波分解和主成分分析提取特征向量，利用支持向量机对特征向量进行分类，用贝叶斯方法对目标多幅不同方位角下图像的分类输出进行决策融合，得到最终类别决策。用 MSTAR 数据库中 3 个目标对该方法进行验证和分析。

2 SAR 图像目标识别算法

本文的识别算法过程如图 1 所示由图像预处理、特征提取、SVM 分类和贝叶斯决策融合 4 个步骤组成。

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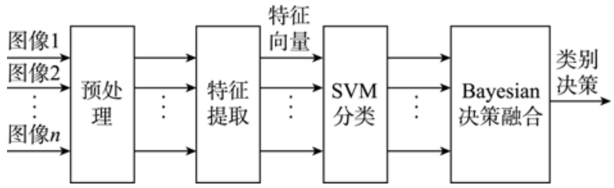


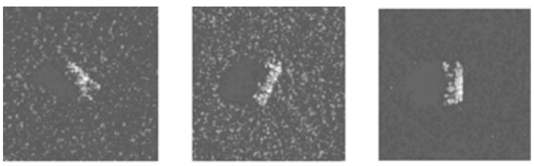
图 1 SAR 图像目标识别过程框图

2.1 实验数据

本文使用的数据是 MSTAR 项目组提供的 SAR 目标切片图像。MSTAR 数据公布了 10 类目标的 SAR 切片图像，本文使用其中的 BMP2, BTR70 和 T72 3 类目标数据。每一类目标包括俯视角分别为 15°和 17°的两组数据，其中，俯视角为 17°的数据作为训练样本，俯视角为 15°的数据作为测试样本。每类目标在每个俯视角下包含了大概 190—300 个不同方位角下的成像切片数据。表 1 是训练样本和测试样本的类别及其相对应的图像数目。图 2 是不同方位角下的 SAR 原始目标图像。图 3 是一目标在多个方位角下的图像。

表 1 训练样本、测试样本种类及样本数

训练样本	样本数	测试样本	样本数
BMP2_c21	233	BMP2_c21	196
BTR70_c71	233	BMP2_9563	195
T72_132	232	BMP2_9566	196
		BTR70_c71	196
		T72_132	196
		T72_812	195
		T72_s7	191



(a) (b) (c)

图 2 在不同方位角下的 SAR 原始目标图像
(a) BMP2, 320°; (b) BTR70, 62°; (c) T72, 90°

2.2 预处理

目标位置的平移、旋转以及不均匀的散射会对特征提取和分类算法的性能产生影响(Sandirasegaram & Englisth, 2005)。本文对 SAR 幅度图像进行预处理。首先根据每幅目标图像数据中的方位角信息，将每个目标调整到标准方位角，这里取 90°作为标准方位角；然后寻找每个目标的最高能量散射点作为中心点形成新目标图像，新目标图像尺寸为 64×64 像元；最后，对新目标图像的幅度值作归一化，使归一化后图像中各像元的幅度值的均值为 0，标准差为 1。图 4(a)和(b)分别是目标 T72 预处理前后的 SAR 图像。

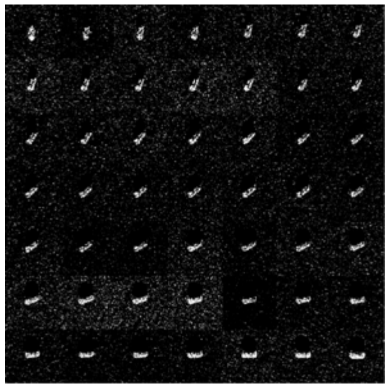
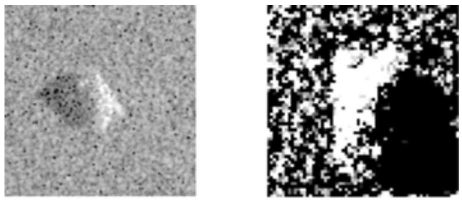


图 3 一目标在多个方位角下的图像



(a) (b)

图 4 (a)和(b)分别是目标 T72 预处理前后的 SAR 图像

2.3 特征提取

特征提取是目标识别过程中的重要步骤。本文对预处理后的 SAR 目标图像作 3 层二维小波分解，提取 3 层分解后的低频子带图像 LL3，用主成分分析进行下一步特征提取。先将大小为 8×8 像元的 LL3 表示成一个 64 维的矢量，用训练样本生成的矢量组成数据矩阵 $\boldsymbol{X}_{m\times n}$，其中 m=64, n 是训练样本的数目。计算自相关矩阵 $\boldsymbol{C}=E[\boldsymbol{X}_{m\times n}\boldsymbol{X}_{m\times n}^{\mathrm{T}}]$，将 $\boldsymbol{C}$ 作特征值分解，得到特征矢量 $\boldsymbol{v}_i$ 和特征值λ_i, i = 1,2,⋯,m。选择λ_i 中最大 p 个值对应的特征矢量为切片数据的基向量，其中 p 取使 $\bar{\lambda}_1+\bar{\lambda}_2+\cdots+\bar{\lambda}_p \geqslant 0.9$ 的最小整数，$\bar{\lambda}_1,\bar{\lambda}_2,\cdots,\bar{\lambda}_p$ 是归一化后 p 个最大的特征值。 将这些特征矢量作为列向量可构造变换矩阵 $\boldsymbol{W}=[\boldsymbol{v}_1\boldsymbol{v}_2\cdots\boldsymbol{v}_p]^{\mathrm{T}}$，则输入数据 $\boldsymbol{x}$ 的 p 维特征向量 $\boldsymbol{y}$ 可由 $\boldsymbol{y}=\boldsymbol{W}\cdot\boldsymbol{x}$ 提取。最后，每幅切片图像可得到一个 24 维的特征向量。图 5 是特征向量提取示意图，其中最左边是预处理后图像，中间是经过 3 层二维小波分解后得到的低频子带图像 LL3，右边是经主成分分析提取的特征向量。

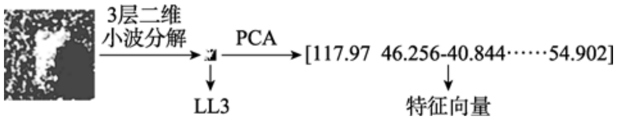


图 5　特征提取过程示意图

2.4　分　类

通过对上述提取出的特征向量进行分类，分类器必须正确地判断出目标所属的类别。本文使用支持向量机作为分类器。支持向量机作为一种二值学习和分类算法，在分类性能上具有优越性，广泛应用于模式识别领域。支持向量机概括为(Vapnik, 1999)：首先通过非线性变换 $\phi: R^n \to E$ 将输入数据变换到一个高维欧几里德空间(特征空间)，然后在这个特征空间中求取最优决策面，其中非线性变换是通过内积函数实现的。所以，任意一个测试数据 $\boldsymbol{x}$ 可由下式进行分类：

$$f(\boldsymbol{x}) = \operatorname{sgn}\left\{\sum_{i=1}^{l} \alpha_i^* y_i K(\boldsymbol{x}_i, \boldsymbol{x}) + b^*\right\} \tag{1}$$

其中 $\boldsymbol{x}_i$ 是支持向量，$y_i \in \{-1, 1\}$ 是对应于 $\boldsymbol{x}_i$ 的类别标记，$K(\boldsymbol{x}_i, \boldsymbol{x})$ 是核函数，α_i^* 是对应于 $\boldsymbol{x}_i$ 的 Lagrange 乘子，b^*是分类阈值，sgn 是符号函数。

支持向量机的基本理论只考虑了二值分类这一最简单的情况，我们需要识别 MSTAR 数据中的 3 类目标，因而需要用“一对一”组合方式构造多个 2 类支持向量机，然后用投票法进行判决来将 2 类分类器扩展成多类分类器。SVM 的核函数选用高斯径向基(RBF) $K(\boldsymbol{x}, \boldsymbol{x}_i) = \exp\left\{-\dfrac{|\boldsymbol{x} - \boldsymbol{x}_i|^2}{\sigma^2}\right\}$核函数。

2.5　贝叶斯决策融合

上一个步骤中，SVM 作为一个单图像分类器对目标进行分类。这里，用贝叶斯决策融合方法将单图像分类器扩展成多方位角图像分类器。假设我们有一目标的 K 幅方位角图像，每幅图像分别被标记为 Q 个类别中的一类。由于多类 SVM 分类器的输出是分数形式的，为了将分类器的输出表示成后验概率形式，用 $y_{k,q} = \dfrac{\left(S_{k,q}\right)^n}{\sum_j \left(S_{k,j}\right)^n}$，$n$=3 进行非线性变换(Rizvi & Nasrabadi, 2003)，其中 $S_{k,q}$是 SVM 的第 k 个方位角图像的第 q 个非限制输出(分数)，$q = 1,2,\cdots,Q$; $k = 1,2,\cdots,K$。$y_{k,q}$表示由 SVM 分类器估计得到的第 k 个方位角图像 x_k属于类别 q 的后验概率：

$$y_k = \left\{y_{k,q}; q = 1, 2, \cdots, Q\right\} \tag{2}$$

根据贝叶斯准则，可将式(2)表示为：

$$P(q \mid x_k) = \frac{P(x_k \mid q) P(q)}{P(x_k)} \tag{3}$$

因为 $P(q)$的先验知识未知，假定属于各个类别的可能性相等，也就是说

$$P(q) = \frac{1}{Q},\ 1 \leqslant q \leqslant Q \tag{4}$$

对于一个确定的目标 x_k，$P(x_k)$是一个确定的常数值，对所有类别都相等，因此求取后验概率的最大值可以简化为求取似然概率 $P(x_k|q)$的最大值。

用对数形式表达 $P(x_k|q)$，得到：

$$a_{k,q} = l(x_k \mid q) \tag{5}$$

从 SVM 分类器得到的第 k 个方位角图像的类别决策为：

$$\theta_k = \arg\max_{1 \leqslant q \leqslant Q} a_{k,q} \tag{6}$$

多个方位角图像的联合似然概率为：

$$y_q = \prod_{k=1}^{K} P(x_k \mid q) \tag{7}$$

用对数形式表示式(7)为：

$$a_q = \sum_{k=1}^{K} l(x_k \mid q) \tag{8}$$

则 K 个方位角图像分类器的类别决策为：

$$\theta = \arg\max_{1 \leqslant q \leqslant Q} a_q \tag{9}$$

贝叶斯决策融合过程如图 6。图 6 中，左边为目标 BMP2_9563 的 3 幅方位角约为 85°，115°和 145°的 SAR 图像。中间给出了这 3 幅图像分别经过 SVM 分类后得到的 $y_{k,q}$ 值，并由(6)式得到单图像的类别决策：分别为类别 3，类别 1 和类别 1。可见，如果对单图像进行识别，则图像 1 就会被误判为类别 3。右边给出了对这 3 幅图像进行贝叶斯决策融合后的 a_q 值，并由式(9)得到最后的类别决策为类别 1。可见，经过贝叶斯决策融合后，可得到这3幅图像的正确类别(即纠正了单独识别图像 1 时产生的错误)。

3　实验结果与分析

同一场景不同方位角下的SAR图像存在着很大的差异，如图 3。目标的分类效果也随着方位角的改变而改变。所以，用目标多幅不同方位角的图像进行分类将比单幅图像得到更优的分类效果。不同方位角下图像的数目，它们之间的方位角间隔，决策

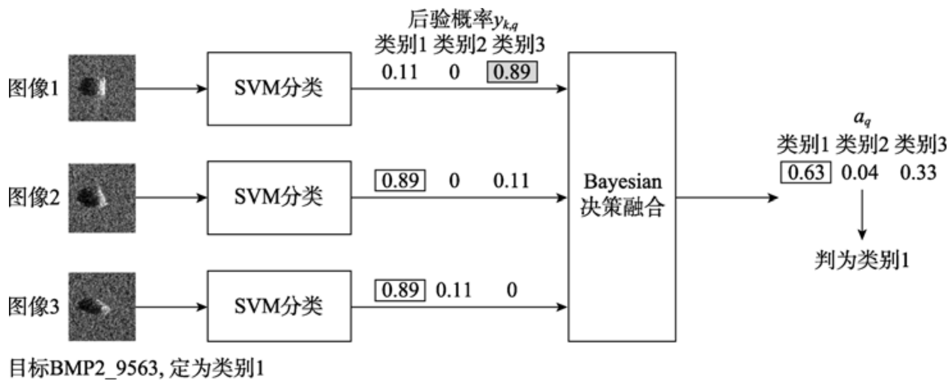


图 6 贝叶斯决策融合过程示意图

融合的方法会影响到目标的最终识别结果。

应用 MSTAR 中的 BMP2、BTR70 和 T72 3 类目标图像数据，实验分析了多方位角图像决策融合后识别性能与图像数和方位角间隔的关系。识别率是正确识别样本数与总样本数的比值，是衡量识别性能的最重要指标。图 7 给出了使用该方法时，图像数分别为 2—5 幅，方位角间隔由 1°变化到 60°的识别率变化曲线。由图 7 可见，图像数目越多，该方法得到的识别率越高，当用 5 幅图像决策融合时得到的识别率在某些方位角间隔下为 100.00%；当 3 幅及以上图像决策融合时，识别率较 2 幅图像决策融合有了显著提高，这是由于图像数目越多，算法利用的不同方位角图像的信息越多，则识别率也越高。方位角间隔大小对 2 幅图像决策融合的识别率没有明显影响，当 3 幅及以上图像决策融合时，在一定的方位角间隔内(20°左右)，识别率随方位角间隔的增大而增加，在此间隔之外，识别率趋于稳定，与方位角间隔的关系不明显。

表 2 列出了用本文方法在图像数分别为 1—5 幅时得到的最高识别率与几种典型的利用单幅图像进行识别的方法得到的识别率比较。将本文方法用于单幅图像就是对图像进行预处理、特征提取和 SVM 分类后不进行决策融合而直接得到类别决策。Ross 等(1998)给出了一种模板匹配法，该方法以 10°为方位单元，对每个方位单元内的训练图像样本取平均作为模板，用最小距离准则作匹配完成分类。Nilubol 和 Pham (1998)对目标图像求多个离散角度上的 Radon 变换，用变换后生成的一系列统计量组成特征向量，用隐马尔可夫模型(Hidden Markov Model, HMM)完成识别。Zhao 和 Principe (2001)给出了一种支持向量机分类方法，该方法没有进行任何特征提取，以 30°为方位单元，在每个方位单元内对图像样本用支持向量机完成分类。由表 2 可见，多方位角图像决策融合得到的平均识别率不但明显高于其他几种利用单幅图像进行识别的方法得到的平均识别率，且高于本文方法在单幅图像情况下得到的平均识别率。

表 2 识别率比较

/%

	BMP2	BTR70	T72	平均
单幅图像	96.25	99.49	96.22	96.70
2 幅图像	97.44	100.00	96.91	97.58
3 幅图像	99.83	100.00	99.66	99.78
4 幅图像	100.00	100.00	99.66	99.85
5 幅图像	100.00	100.00	100.00	100.00
Ross 等的模板匹配法	82.79	93.37	94.50	89.30
Nilubol 和 Pham 的 HMM 法	90.80	92.30	100.00	94.90
Zhao 和 Principe 的 SVM 法	90.97	99.49	88.14	90.99

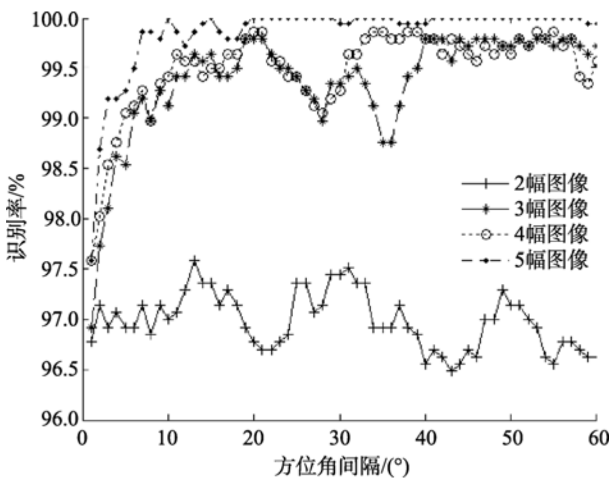


图 7 多方位角图像决策融合的识别率

4 结 论

本文提出了一种利用目标多方位角图像进行贝

叶斯决策融合的 SAR 图像目标识别方法，分析了多方位角图像决策融合后识别性能及图像数和方位角间隔的关系。实验证实，用该方法以一定方位角间隔对 3 幅及以上不同方位角的图像进行决策融合后得到的正确识别率较其他一些利用单幅图像识别的方法得到的识别率有了显著的提高。因此，该方法可有效应用于 SAR 图像目标识别，提高目标的正确识别率。

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