Automatic Target Recognition of SAR Images Using Radial Features and SVM

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Abstract:
The armed forces use a variety of sensor information to locate and target enemy forces. Because of the large area and sparse population, the surveillance becomes a difficult problem. With technological advances, the armed forces can rely upon different types of image data like, infrared data, and radar data. Due to the enormous amount of data, it becomes very difficult to analyse the data without pre-processing and later to detect or classify target data. To full fill this gap this paper reports an algorithm for automatic target recognition in the battle field. This work focuses on synthetic aperture radar (SAR) images for recognizing enemy targets with more accuracy. The available images (MSTAR public open database which is freely available in open literature) is used for experimentation and training the SVM (Support vector Machine). The data will be pre-process first. The pre-processing is required to distinguish the target from clutters like building, trees etc., and non-target objects such as confuse vehicles etc., which is very much required for identifying the targets like Battle tank or armoured personnel carrier effectively. The clutters create noise which is to be removed in pre-processing. The algorithm will help to recognize specific class of the targets e.g., T-72 tank on the basis of target signature. The automatic target recognition is based on the location and orientation. The SVM is used for the classification. SVM are trained and validated with a test set to determine the best performance. The resulting SVM has a recognition rate of 98%.
Keyword
Support Vector Machines, Moving and Stationary Target Acquisition and Recognition (MSTAR), statistical learning theory, pattern recognition.

1. Introduction:

The SVM was used for linear two-class classification with margin, where margin means the minimal distance from the separating hyper plane to the closest data points. SVM learning machine seeks for an optimal separating hyper plane, where the margin is maximal. An important and unique feature of this approach is that the solution is based only on those data points, which are at the margin. These points are called support vectors. The linear SVM can be extended to nonlinear one when first the problem is transformed into a feature space using a set of nonlinear basis functions. In the feature space - which can be very high dimensional - the data points can be separated linearly. An important advantage of the SVM is that it is not necessary to implement this transformation and to determine the separating hyper plane in the possibly very-high dimensional feature space, instead a kernel representation can be used, where the solution is written as a weighted sum of the values of certain kernel function evaluated at the support vectors.

Support Vector machines (SVM) are a new statistical learning technique that can be seen as a new method for training classifiers based onpolynomial functions, radial basis functions, neural networks, splines or other functions. Support Vector machines use a hyper-linear separating plane to create a classifier. For problems that cannot be linearly separated in the input space, this machine offers a possibility to find a solution by making a non-linear transformation of the original input space into a high dimensional feature space, where an optimal separating hyper plane can be found. Those separating planes are optimal, which means that a maximal margin classifier with respect to the training data set can be obtained.

The SAR images considered in this paper have a resolution of one sample per foot. The one-foot resolution of the radar images allows the radar to easily discriminate small to large vehicles from the surrounding terrain. This makes it particularly useful for military applications. With the high resolution a vehicle produces a magnitude image consisting of a large number of pixels rather than a single magnitude return that is characteristic of other types of radar.

So, a SAR image conveys more information than just target location. Being able to discriminate targets into separate classes of vehicles provides a greater level of battlefield awareness to the radar operator. The benefit of being able to accurately discriminate between enemy, friendly, and non-military targets is obvious.

The Moving and Stationary Target Acquisition and Recognition (MSTAR) data set is a collection of SAR images taken of soviet made military vehicles. The United States Air Force released the collection to the public for research purposes. Each target image in the dataset is of a single target vehicle. The images consist of complex

Manuscript received February 5, 2012
Manuscript revised February 20, 2012

valued pixels representing the magnitude and phase of the radar return within one foot by one foot range bins. Each image is contained in a separate file. The files contain a header that lists information about the target parameters including: target model number; type of vehicle (tank, transport, truck, etc.); serial Number of the Target; pose (Azimuth Heading); pitch; roll; yaw; Radar Depression Angle; Radar
Ground Squint Angle; range; and several other parameters. The remainder of this paper is organized as follows: section 2 present the related work. Architecture and modelling are described in section 3. Section 4 is dedicated to algorithms. Finally, in section 5, we conclude and give avenues for future work.

2. Related Work:

The SAR image is usually affected by a multiplicative noise known as speckle [1] mainly due to the interference constructively or destructively of radar waves. These interferences produce light and dark pixels in SAR image. This noise provides a poor quality of SAR image and consequently, the interpretation of image and shape detection becomes difficult [1]. Increasing the image quality and reducing speckle effect becomes a crucial process in the recognition system.
According to literature, there exist different filters able to reduce speckle, so, speckle noise is not strong in the reconstructed images [2]. Hence, use a linear filter followed by median filter.
The SAR images are very noisy due to the image formation and lack resolution due to the radar wavelength, which makes the classification of SAR vehicles a non-trivial problem [3]. Unlike optical images, the SAR images of the same target taken at different aspect angles show great differences, which precludes the existence of a rotation invariant transform. This results from the fact that a SAR image reflects the fine target structure (point scatter distribution on the target surface) at a certain pose. Parts of the target structure will be occluded when illuminated by the radar from another pose, which results in dramatic differences from image to image taken with angular increments of only a few degrees.

2.1 Literature Survey:

It is possible to create intelligent systems capable of mimicking traits found in humans is a challenge that researches have been working on for decades [4, 5]. There has been some limited success in applying artificially intelligent systems to specific domains, and to recognition problems in particular. For example, optical character recognition [6, 7], Speech recognition [8, 9] and, more recently, in face recognition [10, 11] The field of automatic target recognition (ATR) has many new challenges, but it is hoped that some of the knowledge gained from these related domains can be successfully applied to ATR.
A few scientists approach to automatic target recognition applied to SAR images .The main approaches are based on a likelihood test under a conditionally Gaussian model, log-magnitude least squared error, and quarter power least squared error. All approaches evaluated for a wide range of parameters. For all of these approaches , the database used for training is same set of images and their performance is evaluated under identical testing conditions in terms of confusion matrices, orientation estimation error etc.,. Using MSTAR data, the resulting performance for a number of four class automatic target recognition (ATR) problems representing both standard and extended operating conditions is studied and compared the performance corresponding conditionally Gaussian models. Performance is measured quantitatively using the Hilbert- Schmidt squared error for orientation estimation and the probability of error for recognition.
For the MSTAR dataset used, the results indicate that algorithms based on conditionally Rician and conditionally Gaussian yield similar results when a rich set of training data is available, but the performance under the Rician model suffers with smaller training sets. Due to the smaller number of distribution parameters, the conditionally Gaussian approach is able to yield better performance for any fixed complexity. Automatic classification of targets in SAR imagery is performed in using topographic features. Three strategies of learning and representation to build the features are compared: support vector machine, quadratic mutual information cost function for neural networks, and a principal component analysis extended with multi-resolution. Experimental results using MSTAR dataset show better results.
SAR system employs a linear antenna that is mounted in the direction of the heading of the aircraft. The aircraft heading is called the cross range direction. The antenna has a main lobe which points towards a direction perpendicular to the azimuth direction. This direction is called the range direction. A SAR system can be viewed as a linear array of antennas. The received signal of an array of antennas can be phase combined to produce a finer beam width than that of the individual antennas in the array.

3. Methodology

3.1 Data Acquisition:

Synthetic-aperture radar (SAR) is a form of radar in which multiple radar images are processed to yield higher resolution images than would be possible by conventional means. Either a single antenna mounted on a moving

platform (such as an airplane or spacecraft) is used to illuminate a target scene or many low-directivity small stationary antennas are scattered over an area near the target area. The many echo waveforms received at the different antenna positions are post-processed to resolve the target. SAR can only be implemented by moving one or more antennas over relatively immobile targets, by placing multiple stationary antennas over a relatively large area, or combinations thereof. SAR has seen wide applications in remote sensing and mapping.
The SAR Automatic Target Recognition experiment is performed using the MSTAR database to classify the targets. The image data are composed of 80 by 80 SAR images chips roughly centred on three types of military vehicles: the T72, BTR70, and BMP2 (the T- 72 is a tank and the other two vehicles are armoured personnel carriers). Examples of the SAR images are shown in the following Figure.1and 2 these images are a subset of the 9/95 MSTAR (Moving and Stationary Target Acquisition and Recognition) Public Release Data, where the pose (aspect angles) of the vehicles lies between 0 to 360). The system focuses on target images because it is available in the open literature as a pilot study that can be used as a base for further comparisons.

3.2 Data pre-processing:

Because we want to classify the target (and not the clutter) it is not much meaningful to take the complete original images as input for the classifier. The main work before doing classification is the pre-processing and feature extraction of the data. In order to standardize the information of each image to be classified some degree of pre-processing is required, so that the images are adjusted for the used classifier.

3.3 Binarization

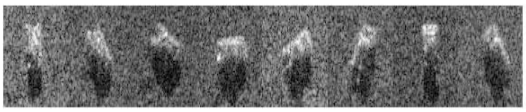

Figure 1: A sample SAR image (courtesy: MSTAR Public Open Database)

Otsu proposed an algorithm for automatic threshold selection from a histogram of image. Let the pixels of a given image.

Let the pixels of a given image be represented in L gray levels [1, 2,.L]. The number of pixels at level is denoted by in, and the total number of pixels by N=n1 + n2 + …. + ni …. Then suppose that the pixels were dichotomized into two classes C0 and C1, which denote pixels with levels [1… k] and [k+1… L], respectively. This method is based on a discriminant criterion, which is the ratio of between-class variance and total variance of gray levels.

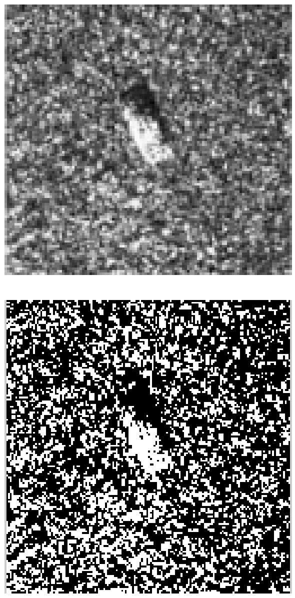

Figure 2: Binarization of an image

The Otsu algorithm determines the threshold by determining the grey level k that maximizes the "between-class variance". L.:^...C of the grey level histogram, where:

$$\sigma_B^2(k) = \frac{[\mu_T\omega(k) - \mu(k)]^2}{\omega(k)[1-\omega(k)]}$$

3.4 Filtering:

Median filtering is to replace each pixel value in an image by the median of its neighbourhood

Procedure of Median filtering (filter size nxm):

☐ Sort the pixel values in the nxm sub-image, centered at (x,y), to find the median;

☐ Replace the pixel value f(x,y) by the median.

The median filter is normally used to reduce noise in an image, somewhat like the mean filter. However, it often does a better job than the mean filter of preserving useful detail in the image.
The median filter considers each pixel in the image in turn and looks at its nearby neighbors to decide whether or not it is representative of its surroundings. Instead of simply replacing the pixel value with the mean of neighboring

pixel values, it replaces it with the median of those values. The median is calculated by first sorting all the pixel values from the surrounding neighborhood into numerical order and then replacing the pixel being considered with the middle pixel value. (If the neighborhood under consideration contains an even number of pixels, the average of the two middle pixel values is used.) Figure 3 illustrates an example calculation.

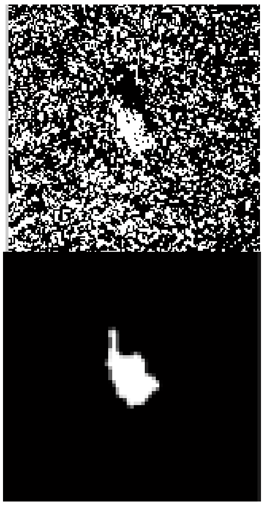

Figure 3: Binary image and filtered image

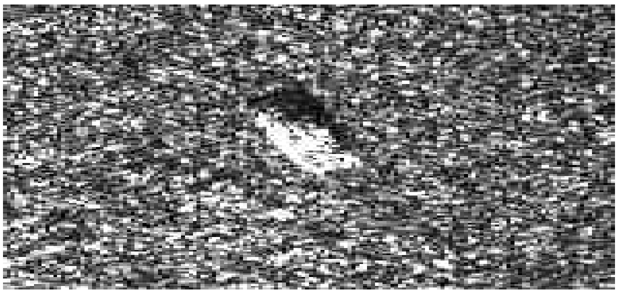

Figure 3: a) 2S1 image before Filtering

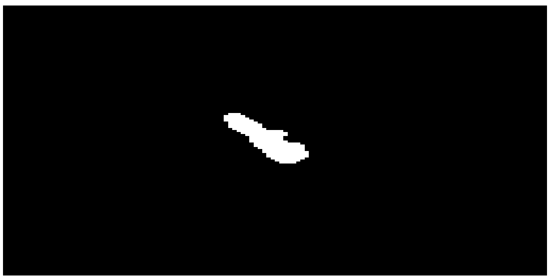

Figure 3:b) 2S1 image after Filtering

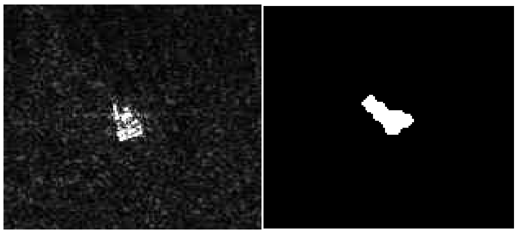

Figure 4: a) 2S1 image before Filtering b) 2S1 image after Filtering

In general, the median filter allows a great deal of high spatial frequency detail to pass while remaining very effective at removing noise on images where less than half of the pixels in a smoothing neighborhood have been effected. (As a consequence of this, median filtering shown in Figure 4(a,b): can be less effective at removing noise from images corrupted with Gaussian noise.)

4. Feature Extraction:

Feature extraction is a method to find an appropriate subspace in the original feature space as shown below in Figure 5. The subspace is based on transformation of the original feature set and it should be big enough to maintain minimal loss of information and small enough to minimize the complexity of classifier. Usually the transformed feature set will provide better discriminative ability than the original feature set but it may not have a clear physical meaning.
The image sizes are 128px x 128px for the MSTAR.Once the pre-processing of the image is over, extract features from the bitmaps of the images.

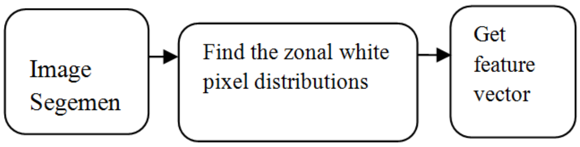

Figure 5: Feature Extraction using Zernike

4.1 Feature Extraction using Radial Method:

The pixel distributions in the different zones of the character in the image segment are calculated. The pixel distributions are stored as feature vector.

Find the centre of the image segment.

- In each of the four quadrants, divide the image into 4 sectors and 3 tracks.
- To divide each of the 4 quadrants of the image into 4 sectors use the formula sin θ=(opposite side/hypotenuse)

- Find the total number of white pixels in each of the sectors.
- Dividing the each sector of the image into 3 circular tracks is implemented by :
- Find the distance of each white pixel from the centre using the co-ordinate method i.e. using the formula ((x-i)2+(y-j)2)½

- Find the number of white pixels having the distance from the centre in the range r to r±r/3; r±r/3 to r±2r/3 and r±2r/3 to 2r where r is the distance of the centre from the left end of the image in each sector.
- Thus we obtain 48 zonal pixel distributions as shown below in Figure 6.

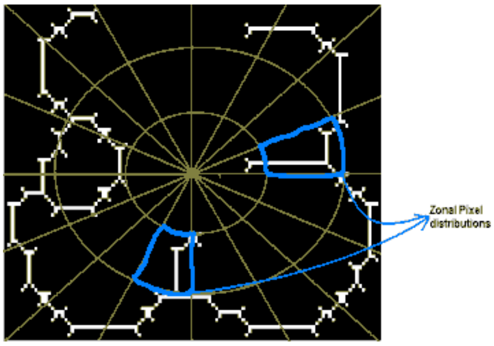

Figure 6.Zonal Pixel Distributions

5.0 Classification with Support Vector Machines:

One major advantage of SVM's over other traditional classifiers is that pre-processing of the data is not essential before training or classifying. The image data are composed of 80 by 80 SAR images chips roughly cantered on three types of military vehicles: the T72, BTR70, and BMP2 (the T- 72 is a tank and the other two vehicles are armoured personnel carriers). Examples of the SAR images are shown in Figure 2 and 3. These images are a subset of the 9/95 MSTAR (Moving and Stationary Target Acquisition and Recognition) Public Release Data, where the pose (aspect angles) of the vehicles lies between 0 to 360 degrees. This image set was chosen because this is available in the open literature a pilot study that can be used as a base for further comparisons and system architecture is shown in figure 7.

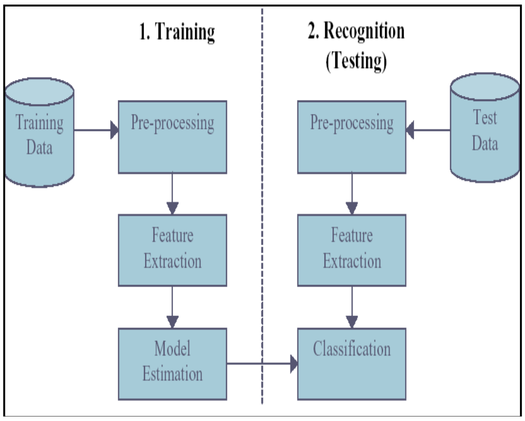

Figure 7: System Architecture

Experimental results

The SVM is trained on imagery with 17-degree depression angle experimental data shown below in table 1. For testing, data with a 15-degree depression angle is used.

Class Type	Vehicle type	Total no. of images	Trained images	Testing set
1	2S1	45	30	15
2	A04	109	80	29
3	A05	110	80	30
4	A07	76	60	16
5	A10	111	80	31
6	A32	74	60	16
7	A62	110	80	30
8	A63	113	80	333
9	A64	114	80	34
10	BRDM2	58	45	13
11	ZSU	107	80	27
12	SLICY	103	80	23

Table-1 Experimental data

Conclusion:

Even with the high levels of distortion and variation in the MSTAR images, many ATR systems have been demonstrated to produce classification rates from 80% to close to 100%. The application of automatic target recognition (ATR) technology is a critical element of electronic warfare (EW), advanced avionics, smart weapons, and intelligence, surveillance, reconnaissance (ISR).Recapitulating we can conclude with the following results:

Because of reasons of simplicity and the variety of parameters in other classifiers we used in our investigations SVM. Because our "features" are the image pixels target centring is essential. Here we get target classification rates of 96% for the M5 case. Allowing additional shifts for a fine adjustment the classification rate can be increased to 98%.

We considered recognition of several versions (variants) of three objects: 2S1, BRDM_2 and ZSU_23_4, and rejection of two objects: A05and A04 For each target, images were captured at two different depression angles (15° and 17°) over a full 0°-360° range of aspect view About 200-300 different aspect view images of each object are available. The 2S1 and ZSU_23_4 have variants present in the database. These are vehicles with different serial numbers. A benchmark experiment was proposed to evaluate MSTAR classification algorithms in which the 2S1, BRDM_2 and ZSU_23_4 are used as object classes. All aspect views of the three targets at a 17° depression angle are used for training. The test set consists of all aspect views of the three targets (and their variants) to be recognized at a different 15° depression angle.

Investigations show that the pre-processing of the data has extreme significance in the identification process. The applied classifier is then the last step with less importance. The requirements on the datasets are the strict independence of the measured test and training data. Once again, the advantage of using a SVM classifier is that it consumes less memory than many other methods and makes decisions very quickly. We are calculating the Radial Features, which are used as feature vector. This approach takes very less time as compared to fixed window-size approach to process any image. It gives good recognition result for the images of different resolution and as the resolution of image increases, rate of recognition also increases.

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