Feature Extraction for SAR Target Classification

M. Vespe†, C.J. Baker†, H.D. Griffiths†, P. Lombardo‡, D. Pastina‡

† University College London, ‡ University of Rome "La Sapienza"

Abstract: In this paper, radar target classification based on Synthetic Aperture Radar (SAR) images is investigated. Different criteria for extracting features from MSTAR data are presented, and classification rates shown, emphasizing where the useful information in terms of recognition resides. The combination of different features is also examined, linking the classification accuracy of the system to the information content of the features selected.

1 Introduction.

In radar target classification, a high degree of reliability is required. Automatic target Recognition (ATR) can be based either on 1-D signatures, i.e. features from the range profile collected by the system are the pattern used to train and test the classifier, or 2-D imageries. The former is often used for its simplicity in terms of implementation and signal processing but gives low classification rates if compared to the latter which, although the need of more accurate signal processing and particular movement requirements of the object, guarantees a more detailed representation of the target backscattering [1].

After introducing the data used, the procedure for extracting features from the 2-D signature is described. The focus is not to reach the highest classification rate but to understand if and where is possible to approach ATR with a more target geometry oriented method. The classification results obtained using the target information only (the feature vector *T*), the shadow information (*S*), and the classification rates based on the sole scattering centres information *P* are presented. Subsequently, the combinations of feature vectors are investigated. These features are target position invariant. They are also the result of hard thresholding the image, losing the single pixel's intensity for binary 2-D representations. This might overcome the high dependency of classification on the parameters of the radar collecting the data.

2. Data Description.

Moving and Stationary Acquisition and Recognition (MSTAR) public release data [2] are grouped in test (15° of depression) and training (17° of depression) sets. Each file is an X-Band SAR image produced by synthesizing approximately 2.95 degrees of aperture, i.e. one foot in cross range resolution is achieved. The bandwidth is 591 MHz i.e. the eventual image has the same cross and slant range resolutions. The images are taken over 360 degrees covering a large number of target orientation. Each image is already segmented and centred. In this paper the target set consists of three ground vehicles namely T72, BMP2 and BTR70. A variant of T72 (SN #812) is an independent target, in other words is included in the testing set but the classifier is trained on another variant of the same class. In Figure 1, the SAR intensity images of the three representative and independent targets are shown.

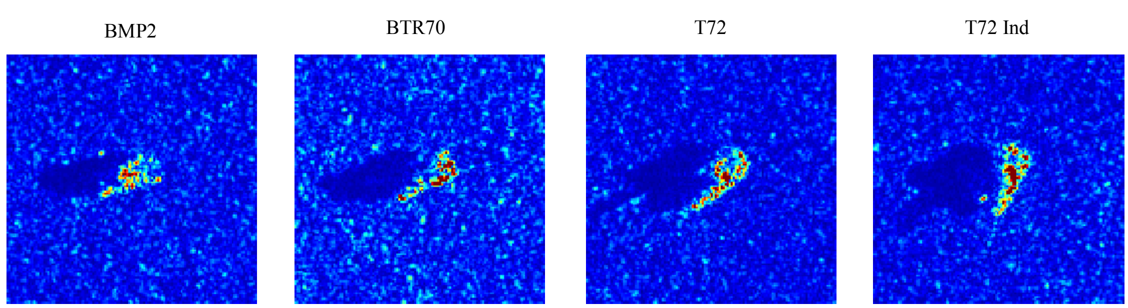

Figure 1: *MSTAR images of the sub-population problem*

3. Feature Extraction.

Feature extraction is a procedure that reduces the dimension of the pattern and finds a more appropriate sub-space in the feature space that represents the input patterns for the classifier. In this paper, different features are selected and extracted from SAR images and, subsequently, Principal Component Analysis (PCA) is applied on the feature vector to further reduce the pattern dimensionality. Extracting features as radar scattering properties has the consequence of not only reducing the recognition computational burden but also selecting the useful information and discharging redundancy and confusing patterns in terms of classification. Even if the training and testing data were collected at different depression angles, the clutter structure between images belonging to the same target doesn't effectively vary. Conversely, the clutter backscattering near different targets is remarkably different. This implies that keeping the clutter in the images represents a considerable help for the classifier but it is confusing if the input target presents a different clutter environment. For this reason, in this paper the first step deals with the clutter removal from the images. The image processing consists of the application of a hard thresholding algorithm based on a non-linear filter. In order to detect shadow and target areas, since the target is roughly in the centre of the image, a clutter area is selected. Then the standard deviation and the mean value of the clutter are estimated and the thresholds for highlighting the shadow and the target area are set as a combination of these two parameters and applied to each pixel neighbourhood. The shadow region is characterized by a lower standard deviation and mean value whilst the target area has a higher mean value as well as variance since the edges and the scattering centres increase the pixels intensity variability. Two images are then obtained: the shadow and the target shapes (Figure 2). To avoid peaks and shadows belonging to the clutter to be selected, after applying the two thresholds, all the regions in each image are labelled and only the most extended selected.

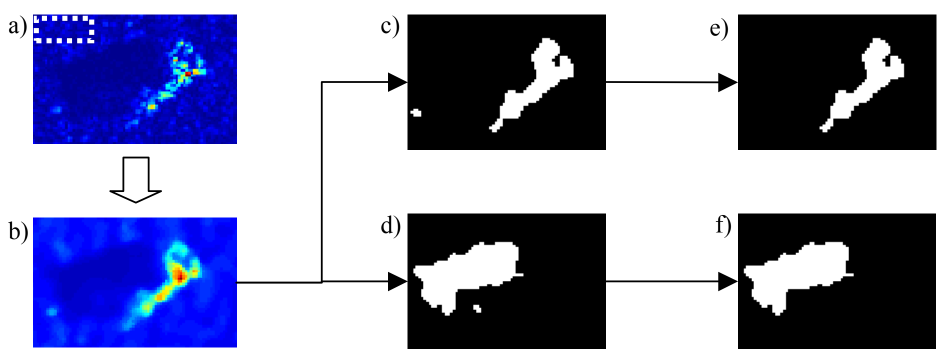

Figure 2: *Image processing: the mean value and standard deviation are calculated for a clutter region from the original image (a). Two different thresholds are applied to the smoothed version (b): the target (c) and shadow (d) areas detected. After labelling, the most extended areas are selected to avoid peaks and shadows belonging to the clutter to be present in the final mask images (e), (f).*

These masks are the features for classification and they represent a hard threshold of the images, that is that the information content of the pattern is translated into a binary image after applying soft thresholds. Considering the only target mask, the first attempt to classify the objects has been made on the contour information only, forming the feature T vector as follows:

- $T(1)$ = number of pixels contained in the area;
- $T(2)$ = number of pixels contained in the convex area;
- $T(3)$ = major axis length;
- $T(4)$ = minor axis length;
- $T(5)$ = eccentricity;
- $T(6)$ = orientation.

The same parameters can be extracted for the shadow mask in order to form the feature vector *S*. By concatenating the target and shadow features, the vector $A=[T\ S]$ represents the information from both the outlines. Further information about the principal scattering centres has been eventually measured by forming the vector *P* representing their pixel coordinates, related to the target area centroid, in descending order of intensity.

In a typical pattern recognition problem, it is often necessary to reduce the dimension of the input of the classifier. This is mainly due to an intrinsic degree of redundancy of the data. Considering the feature vector, the number of its elements can be reduced with an information loss that is negligible until a certain threshold is reached. Furthermore, dimensional reduction algorithms emphasize the differences between patterns. Principal Components Analysis (PCA [3]) is a statistical method to represent the data in a different vector basis so that similarities in the data can be removed. After subtracting the mean $\bar{f}$ from each of the vectors of the training set *F* and producing a zero-mean set of data, the covariance matrix *C* is obtained:

$$Cov(F) = \frac{1}{N}\sum_n (f_n - \bar{f}) \cdot (f_n - \bar{f})^T \tag{1}$$

Subsequently, after calculating the eigenvectors of $Cov(F)$, a selection of the *P* more significant eigenvectors with the larger eigenvalues form the new basis vector $V = (v_1, v_2, ..., v_P)$. The test and training feature vectors can now be transformed as follows:

$$f' = V^T (f_n - \bar{f}) \tag{2}$$

The number of principal components is PCs= *M-P,* where *M* is the original dimension of f, is chosen on the basis of the classification rate achieved, which usually becomes stable after the necessary PCs to fully describe the data.

4. *K*-NN Classification Results.

K-Nearest Neighbours (*K*-NN) is a rule-based method to classify patterns. The rule consists in measuring and minimising the number of *K* distances from the object to the elements of the training set. Generally, for a given classification problem, a small *K* leads to a large misclassification rate. On the other hand, setting *K* to large values implies high computational efforts and not necessarily a better classification performance. A solution is the *cross-validation*, that is classifying known patterns (validation set) with different *K* to establish the minimum error. After this procedure, a *K=5* has been selected for this particular application.

	Target (*T*)			Shadow (*S*)			Scattering Centres (*P*)		
Predicted / Actual	T72	BTR70	BMP2	T72	BTR70	BMP2	T72	BTR70	BMP2
T72	189	3	4	80	76	40	112	22	62
BTR70	3	173	18	13	146	35	40	115	39
BMP2	20	26	149	46	72	77	63	30	102
T72Ind	185	6	4	58	89	48	102	22	71
Accuracy	87.34 %			51.85 %			56.24 %		

Table 1: *Confusion matrices and classification accuracies related to different feature vectors.*

In Table 1, the classification rates on feature vector containing the information about the sole target shape, the shadow outline and the scattering centres locations are shown. The confusion matrix is a well-known method to evaluate the classification performances of ATR. The input is the actual target class and is the first column of the matrix. Hence, each row represents the output of the classifier when a single class target is the input. The diagonal of the matrix is a measure of the correct classification rate, that is the classifier accuracy. The independent target classification outcome is also a measure of the classification performances: in this case the correct classification is T72, any other class label is a measure of the misclassification rate.

The information contents of the scattering centres locations and of the shadow characteristics are not a reliable source for classifying objects if compared to the target contour only. This is mainly due to the different depression and aspect angles between training and test sets. This slightly changes the shadow shape and the location of scattering centres, but sufficiently to make classification a difficult task. What is expected is the increase in correct classification rates by concatenating and combining the feature vectors (*T*, *S* and *P*). This is not always true and the consequences of adding extra-information could be confusing rather than a benefit. For instance, if the classifier using *T* only decides for class *A*, the information contained in the vector *S* could be not clear and the target misclassified.

	T+S			*T+P*			*S+P*			*T+S+P*		
Predicted / Actual	T72	BTR70	BMP2	T72	BTR70	BMP2	T72	BTR70	BMP2	T72	BTR70	BMP2
T72	188	3	5	190	2	4	97	43	56	191	2	3
BTR70	3	174	17	3	168	23	18	139	37	3	170	21
BMP2	19	24	152	15	27	153	36	35	124	16	170	154
T72Ind	186	5	4	186	6	3	96	35	64	186	6	3
Accuracy	87.75 %			87.33 %			61.58 %			88.02 %		

Table 2: *Confusion matrices and classification accuracies based on feature combination. T=target, S=shadow, P=scattering centres.*

In Table 2, the classification rates of all the possible combinations of feature vectors are described. The incidence of the target's shape (*T*) on the correct classification rates is larger than the features from shadow and peaks location. Same results can be observed for the independent target.

5. Conclusions.

In this paper, features from 2-D signatures are selected and used for identifying radar targets. The result of hard thresholding the image is the extraction of target outline, shadow contour and few main peaks locations. The peculiarities of these features are their invariance to the location of the target in the image, i.e. no need of centring algorithms, and their independence of the intensities of the singular pixel. The feature vector is derived from a binary version of the image which is the outcome of a processing involving a neighbourhood of pixels' mean value and variance rather than each pixel's intensity. This approach is useful when training and test sets are the result of different radar measurements because of its adaptivity to the clutter level of the image.

References.

[1] Novak L.M., "A Comparison of 1-D and 2-D Algorithms for Radar Target Classification", *IEEE International Conference on Systems Engineering*, (August) 1991 pp 6 – 12.

[2] https://www.sdms.afrl.af.mil/datasets/mstar/

[3] Theodoridis S., and Outroumbas K.: 'Pattern recognition'(Academic Press, 1999).