High Resolution Polarimetric SAR Target Classification with Vector Quantization

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ABSTRACT

An improved version of the SOFM/LVQ classifier currently used in an ATR system for SAR imagery is presented. This classifier was originally designed to construct a few number of templates to represent a set of targets with different orientations. The classifier accepts input target data, computes distances of this data with those representative templates, and then classifies this data to the target class with the shortest distance. With this distance discriminator, a good classification performance was obtained when only target data were tested. However, the simple distance measure produces poor classification results when unknown targets such as natural or manmade clutters are present and when each target is represented by a small number of templates. We correct this deficiency by incorporating an entropy measure into the original classifier. With this entropy discriminator, our system rejects a majority of the false alarms while maintaining a high correct classification rate with a relatively small number of templates for each target.

Keywords: neural networks, pattern recognition, template matching, SAR

1. INTRODUCTION

The synthetic aperture radar (SAR) is an airborne radar mapping technique for generating high resolution radar image. The moving radar synthesizes a long aperture as an aircraft flies along its path. During the flying, a sequence of reflectivity images of the scene is formed by the synthetic aperture and the radar line of sight. Each reflectivity image is projected into the range (oriented vertically) and cross-range (oriented horizontally) coordinates of the plane. The resulting projection of the scene can be either a single-channel HH (horizontal transmit, horizontal receive), HV (horizontal transmit, vertical receive), or VV (vertical transmit, vertical receive) polarization imagery. Some useful SAR references are listed in Wehner [1]. To build an automatic target recognition (ATR) system in the presence of a high resolution polarimetric SAR has three basic stages: the detection of the region of interest, the matching of the detection with the stored target templates, and the classification. One of the known techniques for the SAR target detection and estimation is the constant-false-alarm-rate (CFAR) detector. It identifies potential targets in the image on the basis of signal amplitude. Improved target detection performance is obtained by using fully polarimetric (HH, HV and VV) imagery processed by a polarization whitening filter (PWF) [2]. The detected objects are then matched against stored templates for classification. To construct target templates, one approach is to decompose each target class into a number of angle-indexed subclasses in order to handle the unknown orientation. With this approach, in order to achieve a reasonable performance, a large number of reference images is required for the classifier. Another approach is to use a neural network based technique to automatically "learn" the representative templates. The goal is to reduce the number of reference images while maintaining a reasonably high correct classification rate. We have developed a hybrid SOFM/LVQ (Self-Organizing Feature Map

/ Learning Vector Quantization) [6,7] neural network as a clustering technique to identify a small number of representative templates [3]. This hybrid SOFM/LVQ system, shown in Figure 1, performs three basic functions: the learning of the within-target homogeneity, the learning of the between-target heterogeneity and the identification of unknown targets. We have applied the SOFM/LVQ approach to the ATR problem with and without the PWF processed 1-D high resolution range data and obtained good classification results [3,4].

In this paper, we focus on the issue of how to identify and reject data from targets outside the given data set, such as man-made clutters or unknown targets. Instead of the 1-D high resolution range data (32 feature components), we use PWF processed 2-D ISAR images with the size of 32x20 pixels. The learning process therefore is very computationally intensive. To reduce the computation, we developed a window slicing approach to compress the data to a smaller dimension. To reject clutters, we use two discrimination measures, the distance and entropy measure. With the distance measure, we obtained a baseline of 95% mean probability of correct classification for known target data. However, it performs poorly in rejecting the clutters particularly in the case when a small number of templates is used for each target. We correct this deficiency by incorporating an entropy measure into the original classifier. With this entropy discriminator, our system rejects almost 90% of the false alarms while maintaining an 80% correct classification rate with only 4 templates for each target.

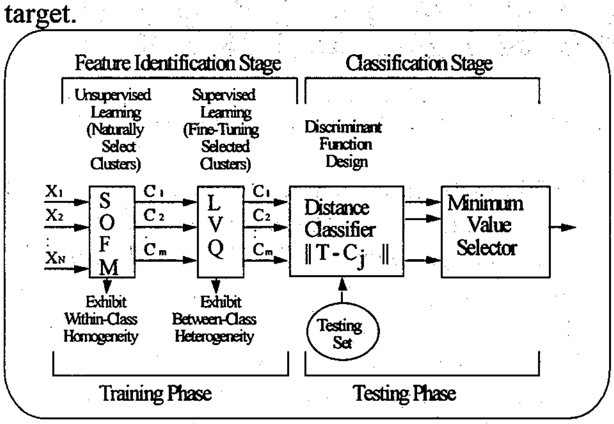


Figure 1. A hybrid SOFM/LVQ target classifier for ATR. It consists of several SOFM models reside in the SOFM block to learn the angle-invariant features detected in each class of target training samples. This is to learn the class-conditional probability distributions of each target. After learning is completed, cluster vectors in each SOFM model represent templates of a given class training samples. We then assign a known target label to each template. The function of LVQ block is to group those labeled templates as an initial cluster vectors to learn classification boundaries. After LVQ training is done, the distance discriminant function is used to classify input data to the target class with the shortest distance.

2. TARGET CLASSIFICATION WITH CLUTTERS

The matching templates used for this study of ATR consisted of four representative targets, a Dodge van, a Chevrolet Camaro, a Dodge pickup truck, and an International bulldozer. The data was obtained using a rotary platform millimeter-wave radar which was obtained from MIT Lincoln Laboratory. It was the Inverse Synthetic Aperture Radar (ISAR) turntable target data with 35 GHz normal frequency, 5.5° degree depression angle, 1 ft range resolution, and calibrated I & Q channels with HH (horizontal transmit, horizontal receive), HV (horizontal transmit, vertical receive), VV (vertical transmit, vertical receive). Figure 2 shows an example of four single-channel (HH) targets at a 0.4° azimuth. The PWF imagery obtained by combining the HH, HV and VV polarizations of the International bulldozer at different orientations is shown in Figure 3. The entire database consists of about 5600 PWF templates for each target. Of which, 5280 templates are used as the training data, the remaining templates are used for testing the classifier. Since the absolute amplitude is an unknown parameter for radar data, we normalize the training samples and normalize the clusters obtained at each adaptation step of the SOFM and LVQ algorithms. The distance measure in the SOFM and LVQ thus is implemented as a linear correlator for the unit energy radar samples.

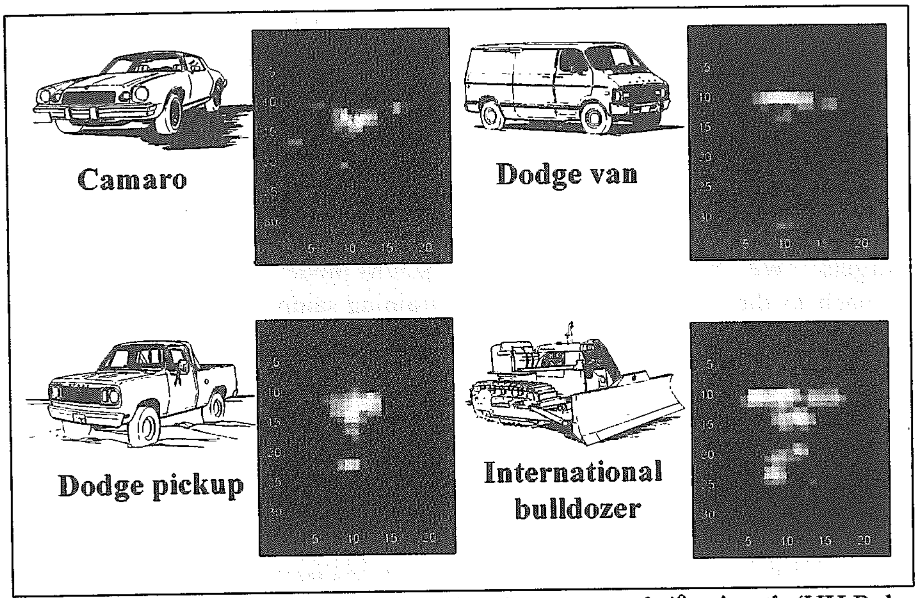


Figure 2. An example of 1 ft x 1 ft ISAR template images at a 0.4° azimuth (HH Polarization).

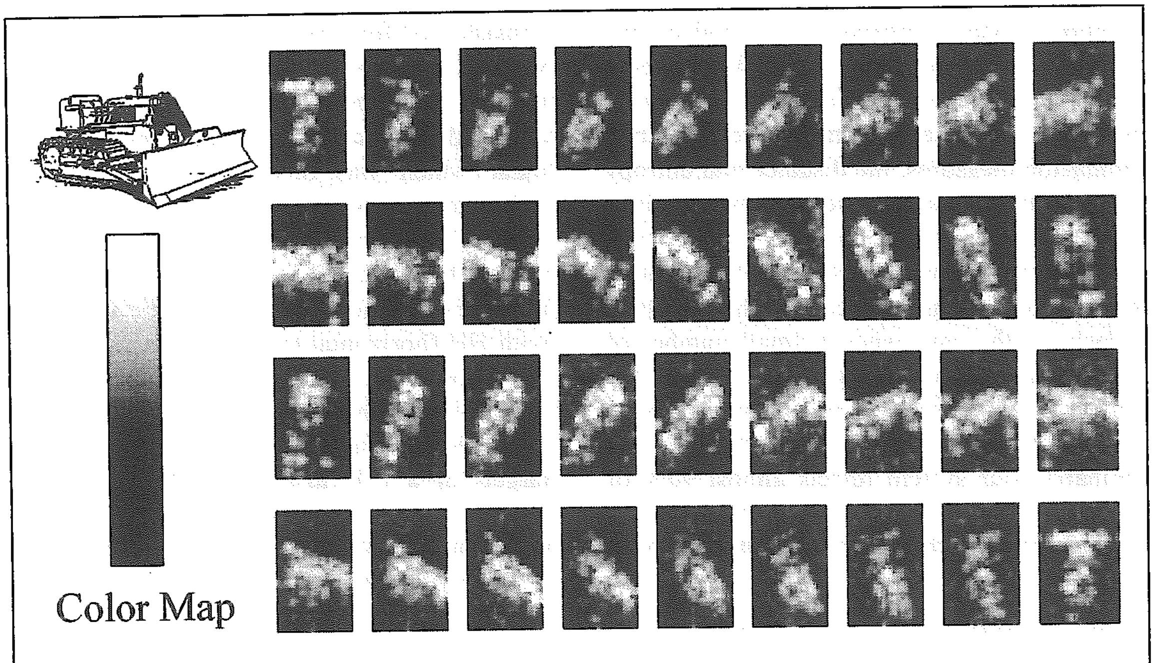


Figure 3. The International bulldozer of 1' by 1' resolution PWF image at a 10 degree increment.

2.1 Window Slicing Technique for Compressing 2-D ISAR images

The above SOFM/LVQ training procedure has been applied to the 1-D high resolution range data with a good performance [2,3]. When applied to the PWF 2-D ISAR image case, the training task becomes too computationally intensive. This is because each 2-D ISAR image has the size of 32x20 pixels which is much larger than the size of a 1-D signature (i.e. 32 dimensions). Furthermore, even with approximately 21,000 sample data, the ratio of sample size to feature size is rather small. This small ratio could lead to a bias in estimating the true performance of the classifier [11]. To reduce the computational burden and enlarge the ration of sample size to feature size, we have developed a window slicing approach to scale down the image size. Figure 4 provides a pictorial description of the window slicing technique used for the geometric transformation. Each new pixel value is the average of pixel values located in an NxN subimage. By using a 4x4 size window with 50% overlap, a 32x20 PWF 2D ISAR image is reduced to a 15x9 image. This also increases the ratio of sample size to feature size by a factor of 4.74. Figure 5 shows the original 32x20 and the 15x9 extracted feature image of the bulldozer. With the compressed data, the algorithm performs reasonably well on both training and testing data sets as shown in Table 1 and Table 2, respectively. Note that, the system is able to achieve an 86% correct classification rate even with only 4 clusters for each target.

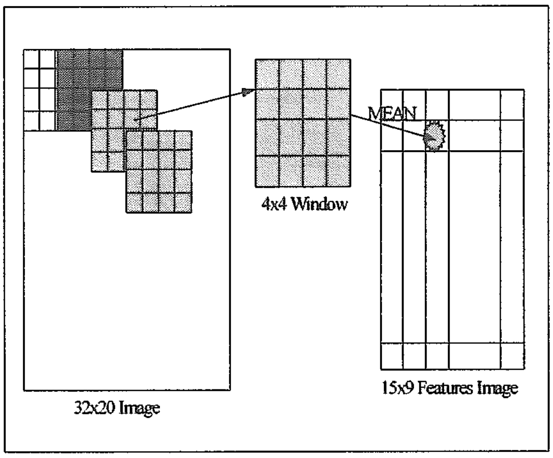


Figure 4. Window slicing technique for compressing an image.

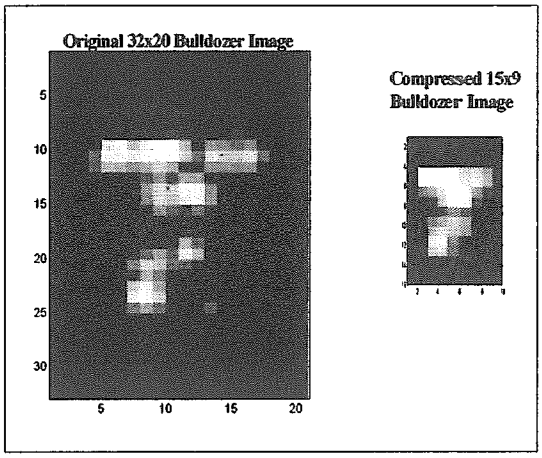


Figure 5. Original and compressed image of the International bulldozer at a 0° angle.

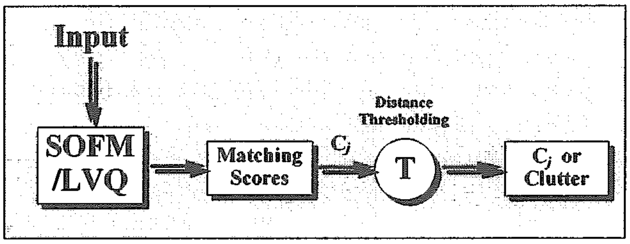


Figure 6. Block diagram of using distance thresholding technique for identifying false alarms.

Table 1. Probability of correct classification table for 21158 entries of PWF training data.

	Number of clusters for each target					
Target	4	8	18	36	72	144
Camaro (5282)	98.35 %	98.47 %	98.03 %	99.11 %	99.92 %	100.00 %
Dodge Van (5282)	89.87 %	91.54 %	97.65 %	99.07 %	99.20 %	99.64 %
Dodge Pickup (5312)	80.23 %	84.21 %	93.30 %	96.89 %	97.99 %	98.70 %
Bulldozer (5282)	78.97 %	88.24 %	98.92 %	99.49 %	100.00 %	100.00 %
Average	86.85 %	90.60 %	96.97 %	98.64 %	99.28 %	99.58 %

Table 2. Probability of correct classification table for 1405 entries of PWF testing data.

	Number of clusters for each target					
Target	4	8	18	36	72	144
Camaro (351)	98.01 %	98.29 %	97.44 %	98.86 %	99.72 %	100.00 %
Dodge Van (351)	88.03 %	89.74 %	95.73 %	98.29 %	97.72 %	98.86 %
Dodge Pickup (352)	79.83 %	83.81 %	92.90 %	96.88 %	97.16 %	98.58 %
Bulldozer (351)	78.92 %	87.18 %	98.58 %	99.43 %	100.00 %	100.00 %
Average	86.19 %	89.75 %	96.16 %	98.36 %	98.65 %	99.36 %

2.2 Classification with Unknown Targets

To explore the third function of our SOFM/LVQ approach addressed in the above, we test our system with clutters. To discriminate clutters from targets, in the simplest case, a Euclidean distance measure is used. In other words, the rejection mechanism is simply implemented as a static threshold applied to the winning cluster. As shown in Figure 6, the detected objects that pass the SOFM/LVQ classifier are matched against the representative templates. The matching score of the winner is recorded. If the match score exceeds a specified threshold, the detected object is assigned to the winning class; otherwise, the detected object is considered as a clutter. To study the effectiveness of this discriminator, the distance histograms with 4 and 144 templates are shown in Figure 7 and Figure 8, respectively. As can be seen from the figures, the distance distributions between targets and clusters are well-separated when a larger number of clusters are used, while they are heavily-overlapped when only 4 clusters are used for each target. This indicates that the simple distance discriminator will work well only when enough number of clusters is assigned to each target, which is obviously not computationally attractive. The performance curves shown in Figure 9 compare the correct classification (recall) rate versus the clutter rate. In Figure 9, each curve corresponds to a classifier with a certain number of templates and a point on the curve corresponds to a particular distance threshold. For example, when 4 clusters are used for each target, in order to reject 90% of clutters, the threshold needs to be increased to the point that the average recall rate will be reduced to under 40%; and in order to have an 80%

3. ENTROPY MEASURE AS A DISCRIMINATOR FOR CLASSIFICATION WITH CLUTTERS

To correct the deficiency with the simple distance discriminant described above, we propose another discriminator based on the entropy measure. To define entropy, first, for a given observation S, let

(1) $P(O_{ji}|C_j,S)$ be the conditional probability that the template (orientation) selection is O_{ji}, given that it selects target class C_j,

(2) $P(C_j|S)$ be the probability that a selection is C_j,

(3) $P(O_{ji},C_j|S)$ be the joint probability of O_{ji} and C_j,

where C_j is the *j-th* target class and O_{ji} is the *i-th* template of the class C_j.

(1) and (2) are evaluated from the SOFM and LVQ respectively, i.e.,

$$P(O_{ji}|C_j,S) \approx \frac{\exp(-\frac{1}{2}(S-\hat{O}_{ji})^2)}{\sum_j \exp(-\frac{1}{2}(S-\hat{O}_{ji})^2)} \quad (5)$$

or

$$P(O_{ji}|C_j,S) \approx \frac{\exp(-\frac{1}{2}(1-(S\cdot\hat{O}_{ji})))}{\sum_j \exp(-\frac{1}{2}(1-(S\cdot\hat{O}_{ji})))} \quad (5')$$

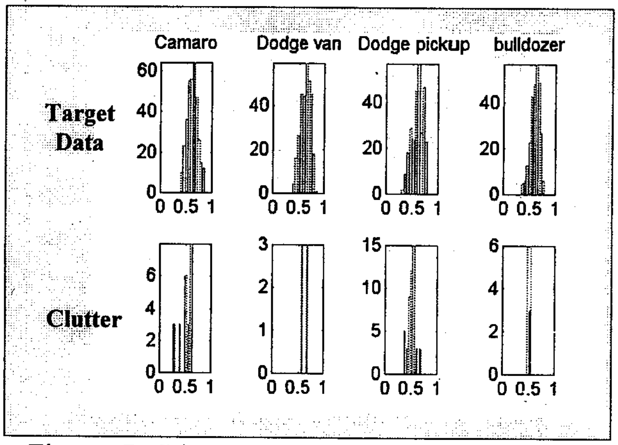


Figure 7. Distance histogram using SOFM / LVQ classifier with 4 clusters of each target.

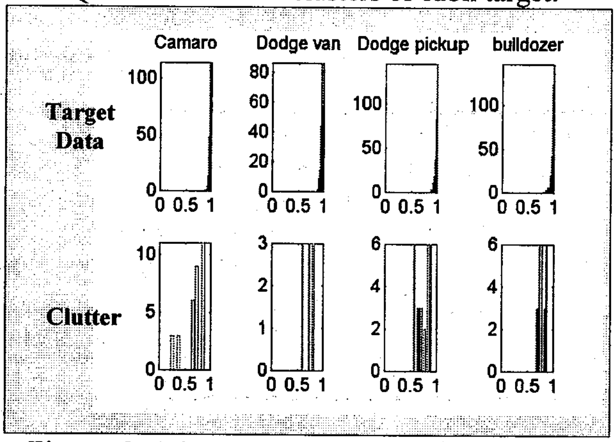


Figure 8. Distance histogram using SOFM / LVQ classifier with 144 clusters of each target.

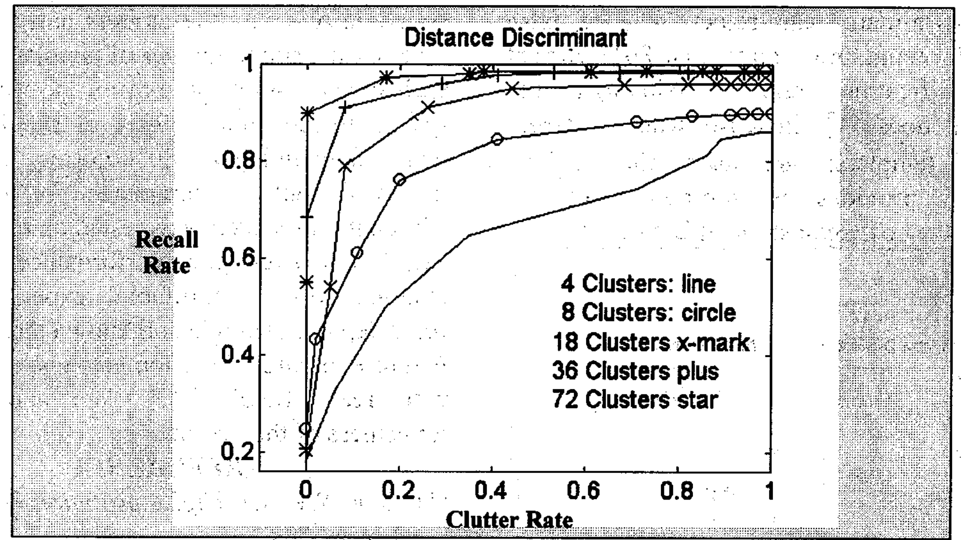


Figure 9. System performance curves using distance discriminant.

where $\hat{O}_{ji}$ is the intermediate template obtained from the SOFM learning stage only, and

$$P(C_j|S) \approx \frac{\underset{i}{Max}\{\exp(-\frac{1}{2}(S-O_{ji})^2)\}}{\sum_j \underset{i}{Max}\{\exp(-\frac{1}{2}(S-O_{ji})^2\}} \quad (6)$$

or

$$P(C_j|S) \approx \frac{\underset{i}{Max}\{\exp(-\frac{1}{2}(1-2(S\cdot O_{ji})))\}}{\sum_j \underset{i}{Max}\{\exp(-\frac{1}{2}(1-2(S\cdot O_{ji})))\}} \quad (6')$$

where O_{ji} is the final template obtained at the end of the LVQ stage.

With (5') and (6') the entropy can then be obtained as

$$H = -\sum_{j,i} P(O_{ji}, C_j|S)\cdot\log(P(O_{ji}, C_j|S)) \quad (7)$$

where with the Bayes' Rule,

$$P(O_{ji}, C_j|S) = P(O_{ji}|C_j, S)\cdot P(C_j|S) \quad (8)$$

This entropy provides an uncertainty measure of the association between data and target. The rationale is that the target data should have a smaller entropy than that of the clutter when matching against the templates. Therefore, given an input data, S, the discrimination function is (see Figure 10):

decide S is class $C = C_j$, if $H < H_\theta$; otherwise, decide S is an unknown class (clutter) and is rejected; where H_θ is the entropy threshold.

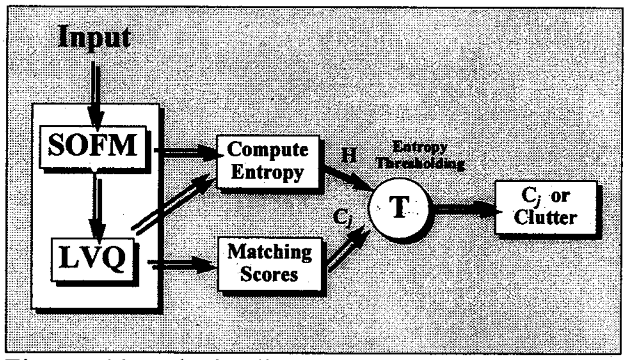
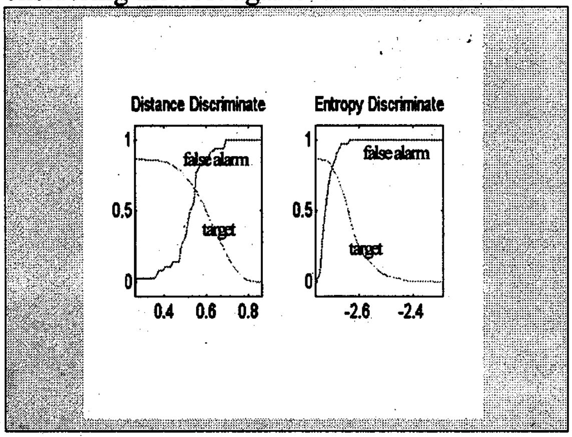
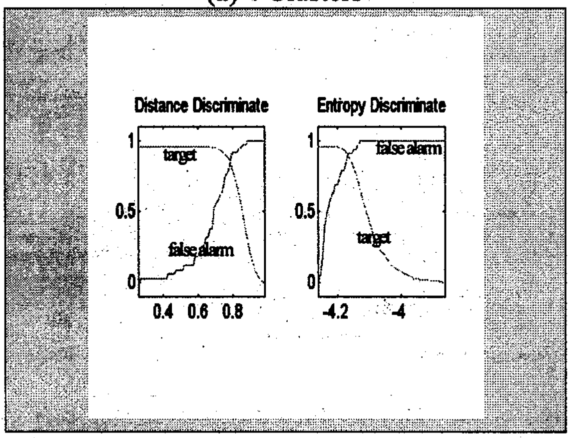


Figure 10. Block diagram using the entropy thresholding technique for identifying false alarms.

We apply this entropy rejection mechanism to the same clutter data used in the previous section. The resulting performance curves with 4 and 18 clusters using distance and entropy discriminants is shown in Figure 11. In these curves, the correct classification rates and false alarm rates are plotted against distance and entropy thresholds. Figure 12 is the system performance curves similar to Figure 9. As shown in the figures, the overall performance with the entropy discriminator has improved significantly compared to that of the distance discriminator, particularly when a fewer number of templates are used for each target. For example, with only 4 templates for each target, the entropy discriminator can reject 90% of false alarms while maintaining almost an 80% correct target classification rate. Although the performance doesn□ increase when a larger number of templates are used, the entropy discriminator provides an alternative way in considering the cost against the effectiveness.



(a) 4 Clusters



(b) 18 Clusters

Figure 11. Performances of distance and entropy discriminant using 4 and 18 clusters.

5. CONCLUDING REMARK

We proposed a neural network based classification technique for high resolution SAR target data. This system uses the SOFM/LVQ to construct a set of templates for each target and uses two discrimination measures, distance and entropy, to eliminate falsely detected clutters. With the distance measure, we have obtained a baseline of 95% mean probability of correct classification with known target data. However, it performs poorly in rejecting the clutters particularly in the case when a small number of templates is used for each target. With the entropy discriminator, the system rejects almost 90% of the false alarms while maintaining an 80% correct classification rate with only 4 templates for each target. Although this system was tested on real ISAR data and showed a very good performance, the data was obtained from a "turntable" experiment with a fixed depression angle and known target locations. A future research direction is to test this algorithm with real "field" SAR data and study the robustness of the system.

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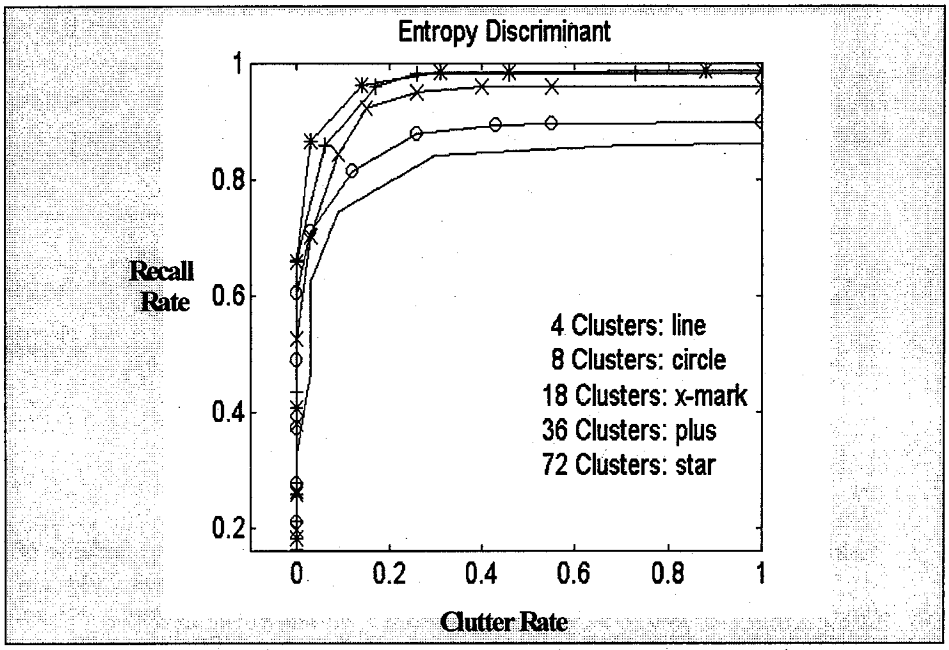

Figure 12. System performance curves using entropy discriminant.