AUTOMATIC RADAR TARGET RECOGNITION USING SUPERRESOLUTION MUSIC 2D IMAGES AND SELF-ORGANIZING NEURAL NETWORK

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ABSTRACT

The key problem in any decision-making system is to gather as much information as possible about the object or the phenomenon under study. In the case of the radar targets the frequency and angular information is integrated to form a radar image, which has high information content. A supper-resolution technique (MUSIC 2D) is used in the paper in order to reconstruct the target image. A supervised self-organizing neural network was developed to classify the images obtained in this way for ten different radar targets in an anechoic chamber.

1. INTRODUCTION

The basic approach for radar target recognition (see figure 1) is to extract some appropriate features, measure these features from the targets or target classes to be recognized at every (aspect and elevation) viewing angle anticipated, and finally use these features to train a classifier [1]. Recognition performance is determined by the quality of the target features used. The more precisely they represent the characteristics of the targets, the better the classification results are.
The spatial resolution has a great influence on this point [2]. This is the reason for we have chosen a superresolution technique to reconstruct the images of the radar targets.

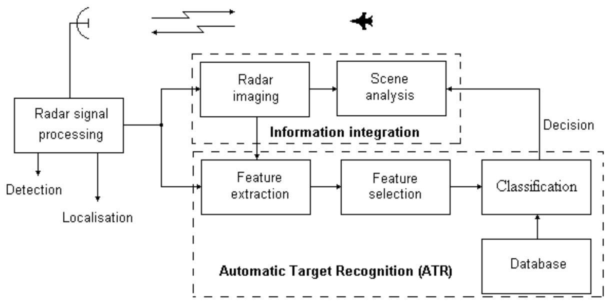

Figure 1: Integrated system for radar based situation assesment

The rest of the paper is organized as follows. Section II describes radar imaging algorithm using the MUSIC-2D (Multiple Signal Classification) method. Section III present the classifier developed to recognize this type of images. Some sample results are provided in Section IV and finally several conclusions are drawn in Section VI.

2. MUSIC-2D METHOD

Let us consider a target defined by N_{SC} scattering centers, illuminated under a given aspect set $\{\beta_n\}_{n=0..N_\beta-1}$, with a signal, whose band is sampled in N_F points $\{f_m\}_{m=0..N_F-1}$. The echo signal can be then expressed with the following relationship:

$$s(m,n)=\sum_{k=1}^{N_{SC}} q_k \exp\left[j\frac{4\pi}{c} f_m (x_k \cos\beta_n + y_k \sin\beta_n)\right] + u(m,n) \quad (1)$$

where $\{q_k\}_{k=1..N_{SC}}$ represent the reflection coefficients of the scattering centers and $u(m,n)$ stand for the zero mean, Gaussian white noise samples, with the variance σ^2.
A resampling procedure involving 2D interpolation is performed prior to the image reconstruction in order to realize a Cartesian grid with uniformly sampled data in Eq. (1). The new variables are defined as:

$$\begin{cases} f^x = f\cos\beta \\ f^y = f\sin\beta \end{cases} \quad (2)$$

and the corresponding resampling technique is shown on figure 2.

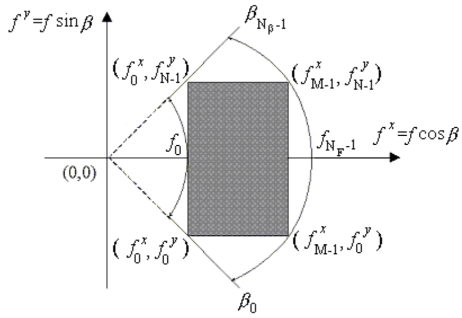

Figure 2: Resampling technique for reformatting radar data from polar into Cartesian coordinates

After resampling and interpolation Eq. (1) becomes:

$$s(m,n)=\sum_{k=1}^{N_{SC}} q_k \exp\left[j\frac{4\pi}{c} (f_m^x x_k + f_n^y y_k)\right] + u(m,n), \quad m=0..M-1,\ n=0..N-1 \quad (3)$$

In order to take into account all the values of m and n it is more convenient to express this relationship in the following matrix form:

$$\boldsymbol{s} = A\boldsymbol{q} + \boldsymbol{u} \qquad (4)$$

where:

$$\boldsymbol{s} = \left[s(0,0) \;\; s(1,0) \;\; ... \;\; s(M-1,0) \;\; s(0,1) \;\; ... \;\; s(M-1,N-1) \right]^T$$

$$\boldsymbol{q} = \left[q_1 \;\; q_2 \;\; \cdots \;\; q_{N_{SC}} \right]^T$$

$$\boldsymbol{u} = \left[u(0,0) \;\; u(1,0) \;\; ... \;\; u(M-1,0) \;\; u(0,1) \;\; ... \;\; u(M-1,N-1) \right]^T$$

$$A = \left[\boldsymbol{a}(x_1, y_1) \;\; \boldsymbol{a}(x_2, y_2) \;\; ... \;\; \boldsymbol{a}(x_{N_{SC}}, y_{N_{SC}}) \right]$$

$$\boldsymbol{a}(x_k, y_k) =$$

$$\left[\exp\left(j\frac{4\pi}{c}(f_0^x x_k + f_0^y y_k \right) \;\; \exp\left(j\frac{4\pi}{c}(f_1^x x_k + f_0^y y_k \right) \;\; .... \right.$$

$$\exp\left(j\frac{4\pi}{c}(f_{M-1}^x x_k + f_0^y y_k \right) \;\; \exp\left(j\frac{4\pi}{c}(f_0^x x_k + f_1^y y_k \right) \;\; ....$$

$$\left. \exp\left(j\frac{4\pi}{c}(f_{M-1}^x x_k + f_{N-1}^y y_k \right) \right]^T$$

A is a $MN \times N_{SC}$ matrix related to the scattering center delays, while $\boldsymbol{a}(x, y)$ is the mode vector.

The MUSIC-2D involves, as a first step, the estimation of the autocorrelation matrix of the radar data, which is defined as:

$$R_{ss} = \mathcal{E}[\boldsymbol{s}\boldsymbol{s}^H] \qquad (5)$$

where $\boldsymbol{s}$ is the echo signal and $\mathcal{E}[\cdot]$ stands for the operator of statistical average.

The eigenanalysis of this matrix is then performed and the eigenvectors obtained are divided between the signal and the noise subspaces. The MUSIC-2D algorithm is based on the orthogonality relationship between the two subspaces. Let us define the $MN \times (MN - N_{SC})$ matrix E_n, whose columns are the $(MN - N_{SC})$ eigenvectors corresponding to the noise subspace. The location of each scattering center can be then estimated by searching the maxima of the function:

$$P_{MUSIC}(x, y) = \frac{1}{\boldsymbol{a}(x, y)^H E_n E_n^H \boldsymbol{a}(x, y)} \qquad (6)$$

where $\boldsymbol{a}(x, y)$ is the mode vector defined by Eq. (4).

The estimated autocorrelation matrix is calculated by averaging a set of observations. This averaging process would lead to an autocorrelation matrix of full rank only if the contributions of different scattering centers were decorrelated. However, in radar applications, usually only one data vector is available. Furthermore, the echo signals produced by scattering centers are coherent. Hence, increasing the number of observations does not have any effect on the autocorrelation matrix rank.

In order to restore the full rank of the autocorrelation matrix, even when only one data vector is available, we used a 2D generalization of the spatial smoothing method [3], well known for its effectiveness in the 1D case. The principle of this technique is shown on figure 3.

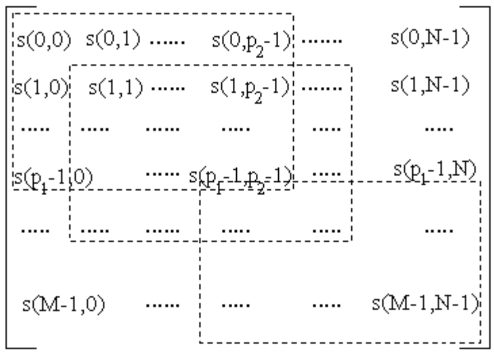

Figure 3: Principle of the 2D spatial smoothing technique

As it can be readily seen on figure 3, a number of $L = (M + 1 - p_1) \times (N + 1 - p_2)$ submatrices can be defined using the interpolated data. Each of them is a $p_1 \times p_2$ matrix. Let $\boldsymbol{s}_l$ the column vector obtained from the l[th] submatrix. The corresponding partial autocorrelation matrix can be then estimated as:

$$\hat{R}_l = \boldsymbol{s}_l \boldsymbol{s}_l^H \qquad (7)$$

The complete autocorrelation matrix is finally obtained using the following relationship:

$$R_{ss} = \frac{1}{2L} \sum_{l=1}^{L} \left(\hat{R}_l + J\hat{R}_l^* J \right) \qquad (8)$$

where J is the $p_1 p_2 \times p_1 p_2$ matrix:

$$J = \begin{bmatrix} 0 & \cdots & 0 & 1 \\ 0 & \cdots & 1 & 0 \\ \vdots & \ddots & \vdots & \vdots \\ 1 & 0 & \cdots & 0 \end{bmatrix}$$

The number of submatrices determines the decorrelation degree of the echo signals from the scattering centers. On the other hand p_1 and p_2 must be large enough to allow a very high resolution. A good trade off between the two constraints can be achieved if p_1 and p_2 are chosen about a half of M and N respectively.

3. SART CLASSIFIER

The SART (Supervised ART) [4] uses the principle of prototype generation like the ART neural network, but unlike this one, the prototypes are generated in a supervised manner. It has the capability to learn fast using local approximations of the class pdf and its operation does not depend on any chosen parameter.

Each class $C_j = \left\{ \boldsymbol{x}_k^{(j)} \right\}_{k=1..N_j}$ is represented by one or several prototypes $\left\{ \boldsymbol{p}_k^{(j)} \right\}_{k=1..P_j}$ which approximate the modes of the underlying probability density function (pdf), with N_j and P_j the number of vectors and of the prototypes corresponding to the class j. The prototypes are equivalent to the codebook vectors used by the vector quantization techniques or to the centers used by the radial basis function based training algorithms.

The training algorithm starts by randomly setting one prototype for each class. The basic idea is to create a new prototype for a class whenever the actual set of prototypes is not able anymore to classify the training data set satisfactorily using the nearest prototype rule:

$$\left\|\boldsymbol{x}-\boldsymbol{p}_l^{(i)}\right\| = \min_{j=1..M,k=1..N_j} \left\|\boldsymbol{x}-\boldsymbol{p}_k^{(j)}\right\| \Rightarrow \boldsymbol{x} \in C_i \quad (9)$$

If, for example, the vector $\boldsymbol{x}$ previously classified do not actually belongs to the class C_i, but to another class, say C_r, then a new prototype $\boldsymbol{p}_{N_r+1}^{(r)} = \boldsymbol{x}$ will be added to the list of prototypes of the class C_r. The prototypes are updated during each epoch using the mean of the samples which are correctly classified by each of them:

$$\boldsymbol{p}_l^{(i)} = \frac{1}{\mathrm{card}\left\{A_l^{(i)}\right\}} \sum_{\boldsymbol{x}_m \in A_l^{(i)}} \boldsymbol{x}_m \quad (10)$$

with:

$$A_l^{(i)} = \left\{\boldsymbol{x}_m^{(i)} \middle| \left\|\boldsymbol{x}_m^{(i)}-\boldsymbol{p}_l^{(i)}\right\| = \min_{j=1..M,k=1..N_j} \left\|\boldsymbol{x}_m^{(i)}-\boldsymbol{p}_k^{(j)}\right\|\right\} \quad (11)$$

If a prototype does not account for a minimum number of training vectors (typically 1) it is canceled because it is supposed to represent outliers:

$$\mathrm{card}\left\{A_l^{(i)}\right\} \le N_t \Rightarrow \boldsymbol{p}_l^{(i)} \text{ is canceled} \quad (12)$$

The updating process is repeated as long as there are classification errors on the training samples and as long as it dynamically changes the location of the prototypes.

The classifier can be easily fitted with a neural network structure in a very similar manner to the LVQ (Learning Vector Quantization) or RBF (Radial Basis Function) neural networks (see figure 4).

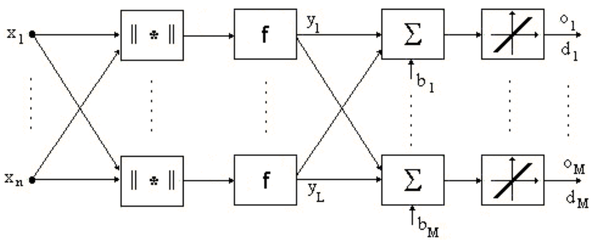

Figure 4: SART classifier structure

Just like for this two neural networks, the output level is constituted by a MADALINE (Multiple Adaptive Linear Network) [5]. It is aimed to combine the hidden layer outputs, such as only one output neuron represent each class. The Widrow-Hoff rule is used to train this layer:

$$\begin{cases}\Delta w_{ij} = \eta(d_i - o_i)y_j \\ \Delta b_i = \eta(d_i - o_i)\end{cases} \quad (13)$$

where w_{ij} and b_i are the neuron weights and bias, y_j stand for the outputs of the hidden layer, d_i and o_i denote the desired and real neuron outputs and η is the learning rate.

The number of the neurons on the hidden layer is equal to the number of prototypes. Each neuron computes firstly the distance between the test vector $\boldsymbol{x}$ and the associate prototype. This distance is then normalized in order to take into account the different spreads of the clusters represented by the prototypes:

$$\tilde{d}_k = d_k / d_{k\max} = \left\|\boldsymbol{x}-\boldsymbol{p}_k\right\| / d_{k\max} \quad (14)$$

where:

$$d_{k\max} = \max_{\boldsymbol{x}_i \in A_k} \left\|\boldsymbol{x}_i - \boldsymbol{p}_k\right\| \quad (15)$$

The neuron outputs are finally calculated using the following relationship:

$$y_k = f(\tilde{d}_k) = \left(1+\tilde{d}_k^2\right)^{-1} \quad (16)$$

The choice of the function f has been motivated by the fact that its value at the cluster boundaries equals 0.5. Indeed, it can be readily seen that:

$$f(\tilde{d}_k)\Big|_{d_k = d_{k\max}} = f(1) = 0.5 \quad (17)$$

An important property of the described algorithm is that it needs no initial system parameter specifications and no prespecified number of codebook or center vectors. Indeed, unlike for the RBF or LVQ neural network, the number and the final values of the prototypes are automatically found during the training process for the SART classifier.

4. SIMULATION RESULTS

The classification technique previously described have been used to classify the MUSIC-2D images of 10 scale reduced (1:48) targets (Mirage, F14, Rafale, Tornado, Harrier, Apache, DC3, F16, Jaguar and F117). The real data were obtained in the anechoic chamber of ENSIETA (Brest, France).

Each target is illuminated in the acquisition phase with a frequency stepped signal. The data snapshot contains 32 frequency steps, uniformly distributed over the band B=[11650,17850] MHz, which results in a frequency increment Δf=200 MHz. Consequently, the slant range resolution and ambiguity window are given by:

$$\Delta R_s = c/(2B) \cong 2.4 \text{ m}, W_s = c/(2\Delta f) = 0.75 \text{ m} \quad [18]$$

For each of the 10 targets 100 images are generated corresponding to 100 angular positions, from -5^0 to 44.5^0, with an angular increment of 0.5^0. An example is provided on the figure 5 for the Mirage aircraft scale reduced model. Note that the scattering centers of the target are clearly identified and their relative positions are specific for each target.

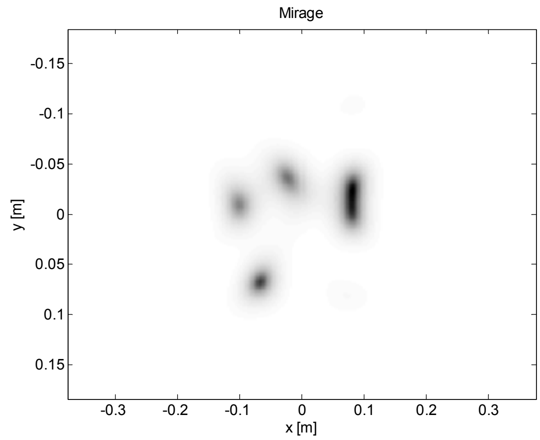

Figure 5: Image of a Mirage aircraft obtained with MUSIC-2D method

When all the images are available, the training set is formed by randomly selecting 1/2 of them, the others being considered as the test set. A Monte-Carlo analysis has been performed in order to estimate the classifier performances. The mean classification rates for each classifier and each target are also shown on figure 6.

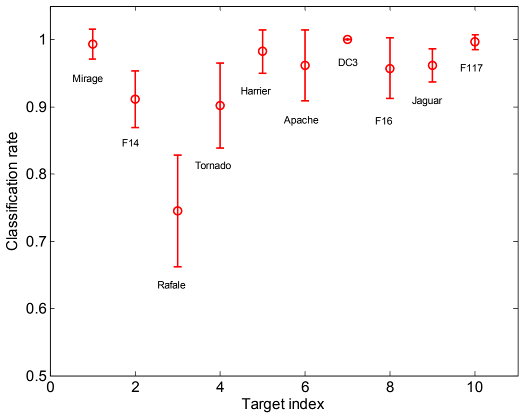

Figure 6: Mean classification rates for each target

5. CONCLUSION

The proposed approach has been validated as an appropriate concept for the classification of the radar targets based on their 2D superresolution images. It is mainly characterized by:

a) precision, given by the use of a superresolution algorithm (MUSIC-2D);
b) effectiveness, provided by a the self-organizing classifier (SART);

As a future work we are going to made the classification system invariant when the pitch and the roll motion components of a radar target are also considered. The basic idea is to train the classifier with a vector set issued from a discretization of the whole angular domain $\{\beta_n, \varepsilon_k, \alpha_l\}_{n=1..N_\beta, k=1..N_\varepsilon, l=1..N_l}$ rather than for azimuth aspects only. In this way the recognition system will be able to classify the targets irrespective of their position in the 3D space.

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