Supervised classification by neural networks using polarimetric time-frequency signatures

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***Abstract*— This paper suggests a supervised classification process based on polarimetric time-frequency signatures by neural networks. The learning basis of the neural network is a set of canonical targets and the classification process is applied on anechoic chamber data. The results show different advantages but it is limited by the learning basis, the angular excursion and the frequency bandwith.**

I. Introduction

Conventional radar imaging techniques consider targets as a set of bright points. Indeed, it considers scatterers as isotropic for all the directions of presentation and white in the frequency band[1], [2]. Recent studies showed, using time-frequency analysis, the angular and frequency behavior of the spatial distribution of all image scatterers [3], [4], [5]. These representations, called hyperimages, showed that some scatterers were neither isotropic nor white. For example, this is the case with modern high-resolution SAR sensors using wide bandwidth and wide azimut beam width. This non-stationary behavior of scatterers can be explained by their material (dispersive), their geometry (anisotropic and dispersive) or their orientation (anisotropic). These studies show that some scatterers are non-stationnary in the energetic way.

Polarimetry is another information source about the geometry and the orientation of scatterers in radar imaging. Recent studies showed, using time-frequency analysis and polarimetric coherent decompositions, the polarimetric angular and frequency behavior of the spatial distribution of all image scatterers [6], [7]. These representations, called polarimetric hyperimages, showed that some scatterers were not polarimetric stationnary.

The aim of this paper is to classify scatterers according to their energetic or polarimetric behaviors. This paper presents the construction of polarimetric time-frequency signatures. Then, the signature of canononical targets is extracted and a process of classification is designed by neural networks to discriminate data from anechoic chamber.

II. Polarimetric HyperImages

A full polarimetric radar is generally designed to transmit and receive microwave radiations horizontally (h) or vertically (v) polarized. The polarimetric generalization of the scattering coefficient is called the scattering matrix $[\mathbf{S}]$ or Sinclair matrix:

$$[\mathbf{S}] = \begin{bmatrix} S_{hh} & S_{hv} \\ S_{vh} & S_{vv} \end{bmatrix}. \qquad (1)$$

The wavelet transform is applied on each of the four polarimetric channels. The resulting Sinclair scattering matrix now depends on the frequency and on the illumination angle and is called hyper-scattering matrix:

$$[\mathbf{S}](\mathbf{r},\mathbf{k}) = \begin{bmatrix} S_{hh}(\mathbf{r},\mathbf{k}) & S_{hv}(\mathbf{r},\mathbf{k}) \\ S_{vh}(\mathbf{r},\mathbf{k}) & S_{vv}(\mathbf{r},\mathbf{k}) \end{bmatrix}. \qquad (2)$$

By applying the polarimetric coherent decompositions to the hyper-scattering matrix, we obtain, on one hand, a polarimetric evolution of the scatterers versus emitted frequency and observation angle, on the over hand a polarimetric spatial response for each frequency and angle of illumination. This defines the polarimetric hyperimage concept [6], [7] see Fig. 1.

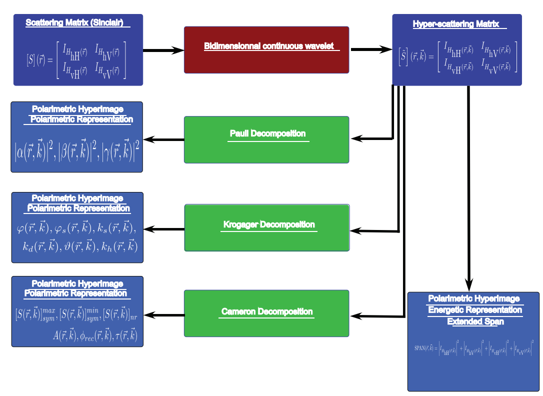

Fig. 1. Algorithm process to obtain polarimetric hyperimages

All in all, for each reflector located at $\mathbf{r}_0 = (x_0, y_0)^T$, we can extract its feature $\tilde{I}(x_0, y_0, f, \theta)$ for each frequency f and for each angle θ. This aspect is the one we have decided to point out in order to see if this quantity can be interpretable in terms of target characteristics. This signature is called polarimetric time-frequency signature.

III. Classification process

A. The multi-layer Perceptron

A multi-layer perceptron is a feedforward artificial neural network model that maps sets of input data onto a set of appropriate output. It is a modification of the standard linear perceptron in that it uses three or more layers of neurons (nodes) with non linear activation functions, and is more powerful than the perceptron in that it can distinguish data that is not linearly separable or separable by a hyperplane [8].

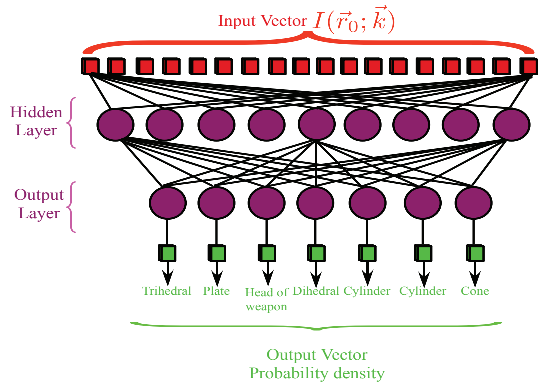

Fig. 2. Architecture of the multi-layer perceptron

The structure of a node is defined by $y_k = \phi\left(\sum_{j=0}^{m} w_{kj}x_j\right)$ where ϕ is the transfer or activation function, w_{kj} is the weight of the j-th input of the k-th node, x_j is the input, y_k is the output of the k-th node. We choose the softmax activation function because we are in a classification problem with p-class [9]. Our multi-layer perceptron is a three layers whose the number N_{in} of nodes of the input layer is equal to the number of input and the number N_{out} of nodes in the output layer is equal to the number of class to obtain a probability density whose the maximum defines the scatterer class. The number N_{hl} of nodes of the hidden-layer is $N_{hl} = \sqrt{N_{in}N_{out}}$. The structure of our multi-layer perceptron is described by Fig. 2.

B. The learning Basis

The learning basis is composed of seven canonical targets: trihedral, dihedral, head of weapon, plate, two cylinders, and cone. The backscattering coefficient is measured for a frequency bandwith between 12 GHz and 18 GHz with a sampling step of 7.50 MHz and for an angular excursion between -20 and 20 with a sampling step of 0.5. From the image the polarimetric time-frequency signatures are extracted and selected manually. Then, the signature is translated in the angle domain to release the orientation phenomena. Indeed, two scatterers of same nature with different orientation must have the same classification.This learning basis is sent to the neural network for a supervised learning based on the scaled conjugate gradiant algorithm.

IV. Results

The target under study is a ”Cyrano” weapon model in steel. The backscattering coefficient is measured for a frequency bandwith between 12 GHz and 18 GHz with a sampling step of 7.50 MHz and for an angular excursion between -20 and 20 with a sampling step of 0.5. From the image the polarimetric time-frequency signatures are extracted and sent to the neural network. The results of the extended span are represented on Fig. 3. The head of ”Cyrano” is classified as a head of weapon. The trailing edges of wing are identified as dihedral. It can be explained by the fact the responses of the edges and of diplane are directive responses. The closed air exit is classified as a specular plate because the response is directive. The open air intake is identified as a head of weapon because the polarimetric time-frequency signature is isotropic and non-dispersive. For the stabilizers the classification is a melting pot of cylinder, head of weapon and cone contribution.

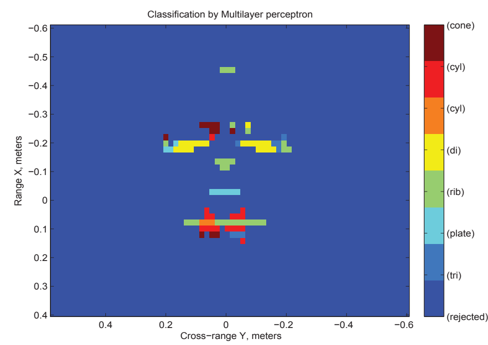

Fig. 3. Classifications results obtained by the multi-layer perceptron in using the extended Span

V. Conclusion

The polarimetric hyperimages allow to extract polarimetric time-frequency signatures. These signatures charcterize scatterers and a supervised classification highlight this point of view. Future work will consist to improve the learning basis and will use it to classify scatterers on SAR images.

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