Supervised Classification by Neural Networks Using Polarimetric Time-Frequency Signatures

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Abstract

This poster suggests a supervised classification of scatterers in radar imaging. Indeed, in usual radar imaging, it makes the assumption that scatterers are isotropic and white in the emitted frequency band. New radar imaging applications cannot make these hypotheses. Time-frequency analysis allows to release this main drawback. Radar polarimetry is another source of information about scatterers. This poster proposes to use jointly polarimetric time-frequency signatures to characterize scatterers by neural networks.

Context

See for example in Fig.1, a color coded RAMSES SAR image built using three subbands centered on the frequencies $f_c = 8.82$ GHz, $f_c = 9.37$ GHz and $f_c = 10$ GHz.

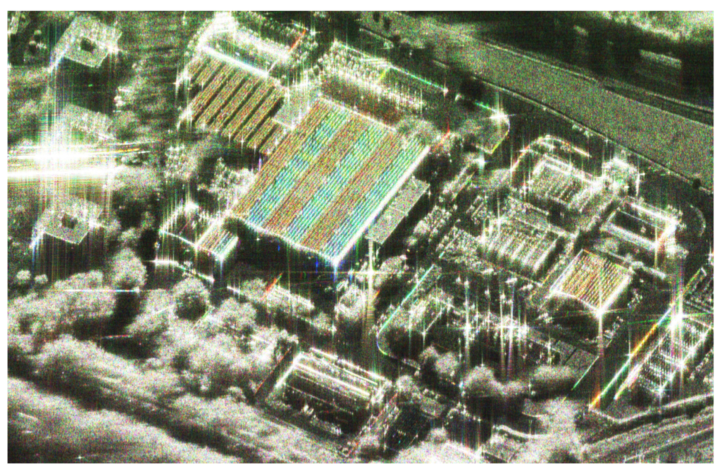

Fig.1: A SAR image which highlights dispersive scatterers.

Extended radar imaging

Let $\phi(\mathbf{k})$ be a mother wavelet supposed to represent the signal reflected by a reference target located around $\mathbf{r} = 0$ and backscattering the energy in the direction $\theta = 0$ and at the frequency f given by $k = \frac{2f}{c} = 1$.

A family of function is built $\Psi_{\mathbf{r}_0,\mathbf{k}_0}$ from $\phi(\mathbf{k})$ by the similarity group S:

$$\begin{aligned}\Psi_{\mathbf{r}_o,\mathbf{k}_o}(\mathbf{k}) &= \frac{1}{k_o}\, e^{-j2\pi\mathbf{k}.\mathbf{r}_o}\phi\left(\frac{1}{k_o}\mathcal{R}_{\theta_o}^{-1}\,\mathbf{k}\right)\\ &= \frac{1}{k_o}\, e^{-j2\pi\mathbf{k}.\mathbf{r}_o}\phi\left(\frac{k}{k_o}, \theta-\theta_o\right).\end{aligned}$$

The wavelet coefficient $C_H(\mathbf{r}_o, \mathbf{k}_o)$ is defined as the scalar product between the complex backscattering coefficient H and the wavelet $\Psi_{\mathbf{r}_o,\mathbf{k}_o}$:

$$C_H(\mathbf{r}_o, \mathbf{k}_o) = < H, \Psi_{\mathbf{r}_o,\mathbf{k}_o} > \quad (1)$$

The scalar product is defined as:

$$C_H(\mathbf{r}_o, \mathbf{k}_o) = \int_0^{2\pi} d\theta \int_0^{+\infty} \frac{k}{k_o}\, H(k,\theta)\, e^{+j2\pi\mathbf{k}.\mathbf{r}_o}\phi^*\left(\frac{k}{k_o}, \theta-\theta_o\right) dk$$

The hyperimage $S(\mathbf{r}, \mathbf{k})$ is then defined as the wavelet coefficients. The scalogram which is the square modulus of the wavelet coefficients defines the hyper-Image $\tilde{I}_H(\mathbf{r}, \mathbf{k})$.

Covariance property: covariance by a group of transformations, the similarity group $\mathcal{S}$ which acts on the physical variables $\mathbf{r}$ and $\mathbf{k}$ through rotations $[\mathrm{R}]_\alpha$, dilations a in length (or time) and translations $\delta\mathbf{r}$ as:

$$\begin{array}{lcl}\mathbf{r} & \longrightarrow & \mathbf{r}' = a\,[\mathbf{R}]_\alpha\,\mathbf{r} + \delta\mathbf{r}\\ \downarrow & & \downarrow\\ \mathbf{k} & \longrightarrow & \mathbf{k}' = a^{-1}\,[\mathbf{R}]_\alpha\,\mathbf{k}\,.\end{array}$$

The transformation law of the reflected signal $H(\mathbf{k})$ and its extended image $\tilde{I}(\mathbf{r}, \mathbf{k})$ is therefore given by:

$$\begin{array}{lcl}H(\mathbf{k}) & \longrightarrow & H'(\mathbf{k}) = a\,\exp(-2i\pi\mathbf{k}\cdot\delta\mathbf{r})\,H(a[\mathbf{R}]_\alpha^{-1}\,\mathbf{k})\\ \downarrow & & \downarrow\\ S(\mathbf{r},\mathbf{k}) & \longrightarrow & S'(\mathbf{r},\mathbf{k}) = S\left(a^{-1}\,[\mathbf{R}]_\alpha^{-1}\,(\mathbf{r}-\delta\mathbf{r}), a\,[\mathbf{R}]_\alpha^{-1}\,\mathbf{k}\right)\,.\end{array}$$

Polarimetric hyperImages

The wavelet transform is applied on each of the four polarimetric channels.

The resulting Sinclair scattering matrix, called hyper-scattering matrix, now depends on the frequency and on the illumination angle:

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

Polarimetric Hyperimage concept: Polarimetric evolution of the scatterers versus emitted frequency and observation angle

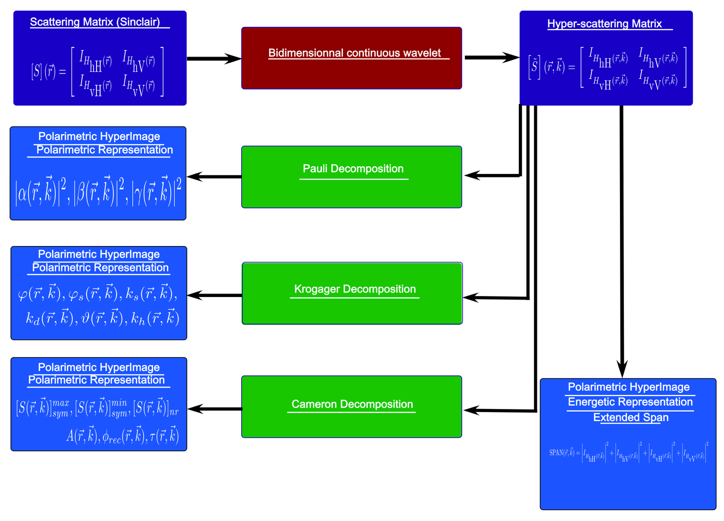

Fig. 2: Algorithm to build polarimetric hyperimages.

Multi-layers perceptron

A multi-layer perceptron is a feedforward artificial neural network model that maps sets of input data onto a set of appropriate output.

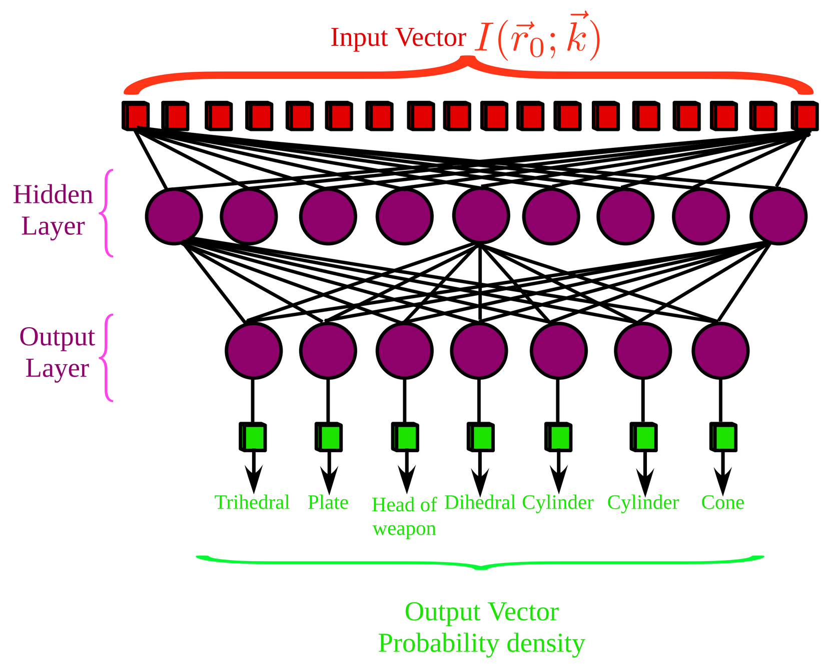

Fig. 3: Architecture of a multi-layer perceptron.

The structure of our multi-layer perceptron is composed of nodes whose the processing is :

$$a_j^{(1)} = \sum_{i=1}^{d} w_{ij}^{(1)} x_i + b_j^{(1)}$$

where $a_j^{(1)}$ associated input with each hidden unit. Here $w_{ij}^{(1)}$ represents the elements of the first-layer weight matrix and b_j are the bias parameters associated with the hidden unit. The variables $a_j^{(1)}$ are then transformed by the non-linear activation function of the hidden layer. The activation function is $\tanh(.)$. The outputs of the hidden units are given by:

$$z_j = \tanh a_j^{(1)}$$

with the following property $\dfrac{dz_j}{da_j^{(1)}} = 1 - z_j^2$.

The z_j are then transformed by the second layer of wheights and biases to give second-layer activation values $a_k^{(2)}$:

$$a_k^{(2)} = \sum_{j=1}^{M} w_{ij}^{(2)} z_j + b_k^{(2)}$$

Finally, these values are passed through the output-unit activation function to give output values y_k. For the more usual kind of classification problem in which we have c mutually exclusive classes, we use the softmax activation function of the form:

$$y_k = \frac{\exp a_k^{(2)}}{\sum_{k'} a_{k'}^{(2)}}$$

Results

The target under study is a "Cyrano" weapon model.

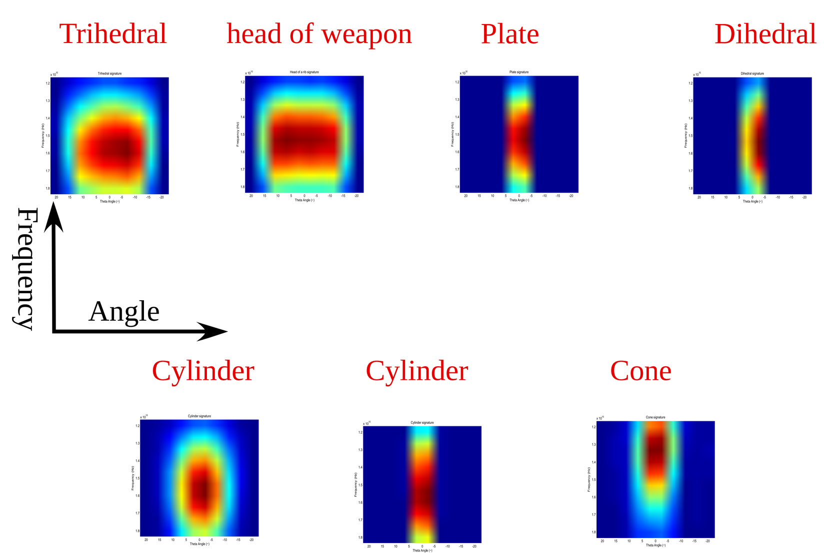

Fig. 4: Learning basis extracted from the extended Span.

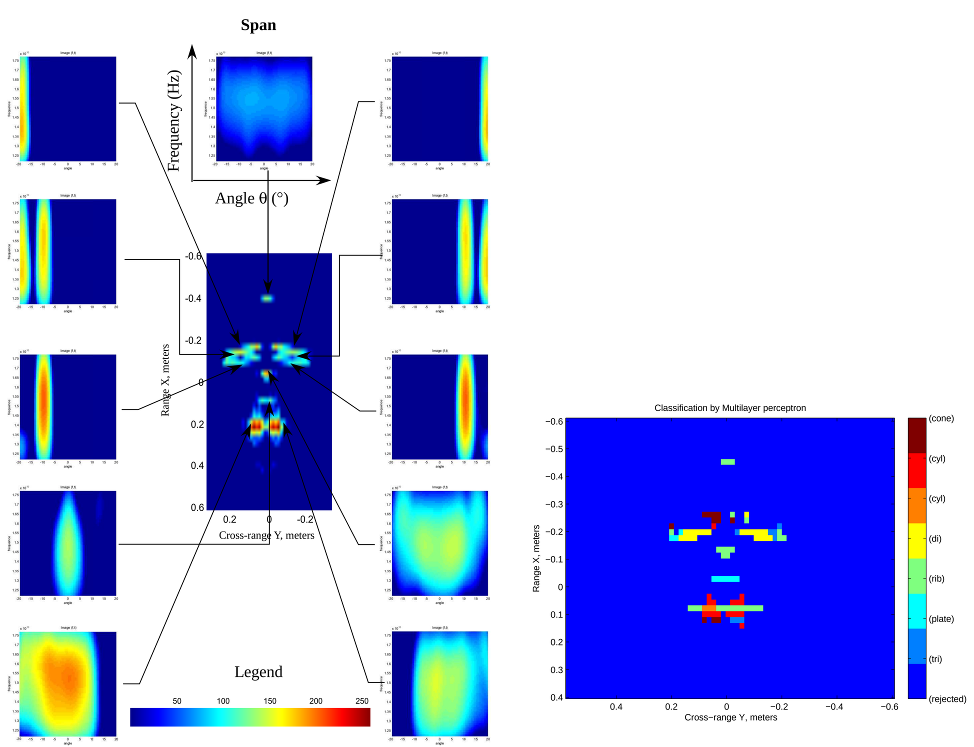

Fig. 5: Signatures extracted from the extended Span and classification results.

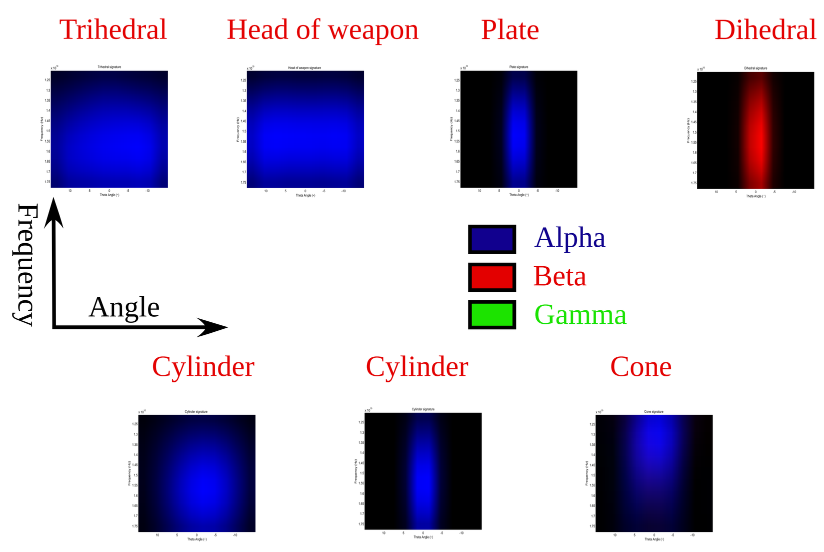

Fig. 6: Learning basis extracted from the Pauli time-frequency signatures.

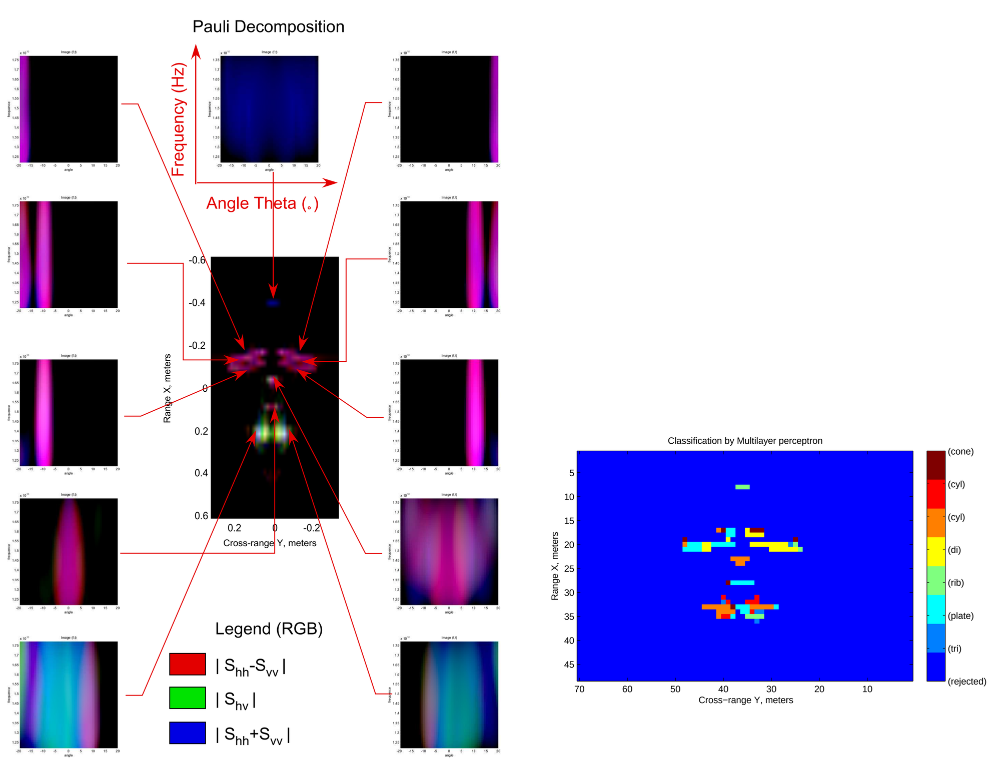

Fig. 7: Signatures extracted from the Pauli time-frequency representation and classification results.

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