14th European Signal Processing Conference (EUSIPCO 2006), Florence, Italy, September 4-8, 2006, copyright by EURASIP

NEURAL NETWORK FOR POLARIMETRIC RADAR TARGET CLASSIFICATION

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ABSTRACT

In this paper, the Artificial Neural Network (ANN) paradigm is applied to radar target classification. Radar returns are simulated via an e.m code and time-domain polarimetric target features are extracted by means of Prony's algorithm.

Two different type of feedforward neural network has been adopted in order to classify the target echo, namely the Multi Layer Perceptron (MLP) and the Self Organizing Maps (SOM). The above-mentioned network have been tested on two type of simulated targets: a small tonnage ship with a low level of detail and medium tonnage ship with higher details. Each network has been trained on a wide range of signal-to-noise ratio, and with different data records number in order to assess the training invariant properties of each network. Finally, in the validation phase a fixed number of records has been considered to evaluate networks performances, which are given in terms of classification error.

1. INTRODUCTION

In maritime surveillance, ANN's are considered an attractive tool for targets classification. In this paper a fully polarimetric approach has been adopted in order to exploit the benefit of a neural network paradigm. The four co-registered complex range profiles (VV, HH, HV, VH) are simulated by means of an e.m. simulator, which makes use of both the Uniform Theory of Diffraction (UTD) and the Geometric Optics (GO). The received signal is corrupted by adding Gaussian white noise (AWGN) samples.

Such radar classifiers are assisted by a pre-processor and a post-processor, the former executes the features extraction from raw data, while the latter is specifically dedicated for visualization purpose [1]. The pre-processor implement a modified Prony algorithm [2] that extract a set of polarimetric parameters from the raw data. More precisely, it performs a range profile segmentation followed by scattering centre separation, thus a number of dominant scatterers are identified. For each scatterer is provided an elliptic geometric characterization, namely the major axis amplitude, the ellipse coefficient, the tilt angle and the ellipse position. This approach attempt to reduce the computational load, because it avoids an extensive processing of all the range bin of the four channels. It is worth noting that the number of the target scattering centres is much smaller than the number of the range bins. The post-processor in our case is a trivial assignment, it maps the output of the network in a label identifier (i.e. *target 1* or *target 2*). It is worth noting that in more complex classifier the post-processor gets even more sophisticated.

The neural classifier is composed by feedforward ANN's. More precisely we adopt a MLP and a SOM architectures, which represent respectively a multi-layer and a single-layer type of network topology. An outstanding summary of the state of this network and of its computational capabilities is given in [3]. In scientific literature ANN has been applied to radar target classification problem and several works are worth mentioning. In [4-5] ANN has been compared with conventional minimum distance classifier and decision-theoretic classification techniques. In both cases the authors show that the ANN based classification provides better performance. Furthermore, the clutter classification performance of ANN in an Air Traffic Control (ATC) environment has been evaluated, the authors demonstrate the generalization capabilities of a multilayered architecture.

This paper shows the performances achievable with polarimetric data in terms of correct classification for different SNR values. Furthermore, an example of the advantage achievable with respect to single polarisation data is given.

2. NEURAL NETWORK DESCRIPTION

A simple architecture, characterized by a limited number of neurons, has been adopted in this work. Since a mathematical solution for the selection of the topology of the network has not been developed yet, a pragmatic investigation is necessary. A preliminary study has suggested the selection of two feedforward neural network: MLP and SOM. As a matter of fact, these structure are widely used for classification purpose and ensure a straightforward hardware implementation. An exhaustive survey on neural networks hardware implementation is provided in [6].

2.1 A Brief description of the used MLP

A MLP structure is a multilayered network composed by two or more layers. The first layer is the input layers, while the last layer is the output layer, all the intermediate layer are defined as hidden layers. Neurons of the net are fully connected, this means that each neuron output of a given layer is fed to each neuron of the subsequent layer and so forth. The inputs of each neuron are weighted by a set of synaptic weight, which differ from one neuron to another.

The weights of the network, also called parameters, are evaluated during the training phase. The training algorithm can be selected among two different option: 1) Error Back Propagation – EBP and 2) Marquardt Back Propagation – MBP. We use the latter because in [7] has been proved that it is the faster method for feedforward network of moderate dimension. However, it is worth noting that both the training algorithm are gradient-based, and that they are different only for software implementation. Parameters update has been performed sequentially. For the hidden neurons a sigmoidal nonlinearity is selected, whereas the output layer is composed by one linear neuron. A rule of thumb, known as the Baum-Haussler rule [8], can be used to determine the number of hidden layer neurons. In this investigation the rule application suggest a maximum number of 29 hidden neurons. On the other hand the universal approximation theorem recommend a number of three layer for an MLP network to approximate an arbitrary continuous multidimensional function to any desired accuracy, which is basically our aim. The used MLP topology is showed in Fig. 1.

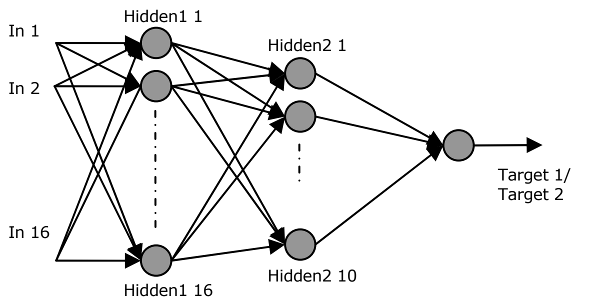

Figure 1 – MLP topology

2.2 A Brief description of the used SOM

The SOM structure is a single layer network. It is essentially a sheet of neurons connected by lateral inhibitory links. All the input are fed to each neuron, in this case called cell. At the end of the training stage each cell is tuned to a specific signal or classes of pattern. Therefore the necessary number of neurons is simply equal to the number of classes to be recognized. The training phase makes use of the Kohonen learning rule for updating sequentially the weights of the network. It is worth pointing out that in SOM there is no supervision during the training phase, on the contrary in MLP a supervised learning is necessary.

In Fig. 2 is showed the architectural graph of the SOM adopted in this work.

In Tab. 1 is provided a summary of the main characteristics of each network.

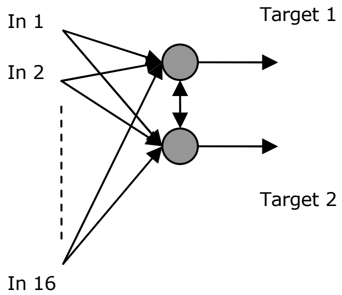

Figure 2 – SOM topology

Neural-based Classifier		
Parameter	*SOM*	*MLP*
Nr of Neurons	2	16+10+1
Nr of input	16	16
Nr of output	2	1
Nr of hidden neuron	-	16+10
Activation function	Linear	Sigmoidal/Linear
Learning rule	Kohonen	Levenberg-Marquardt
Training type	Sequential	Sequential

Table 1 – Network characteristics summary

3. FEATURE DESCRIPTION AND GENERATION

The use of full polarization improves the radar performance by adding information with respect to a single polarization radar. The received signal (scattering matrix) is generated by means of an e.m. simulator, namely *EMvironment* [9], provided with a computational engine based on high frequency raytracing techniques. The four channels are subsequently processed by a modified version of the Prony algorithm. A simulated scenario has been considered in order to give a effective evaluation of the neural-based classifier. In this section, we first give a summary description of the modified Prony algorithm, and secondly we provide an in-depth description of the simulation scenario.

3.1 Polarimetric feature extraction

The process involved in polarimetric feature extraction is described in [2]. In this paper a version of this algorithm has been implemented.

Firstly, the electric field is evaluated on a grid of receiver suitably chosen in order to satisfy the *equivalence theorem*. Such theorem provides the basis for the numerical evaluation of the total e.m. field at the radar antenna for any given configuration and polarization by means of irradiation integral method. The Scattering matrix is evaluated as the ratio between the e.m. field previously evaluated and the transmitted e.m. field for any polarizations:

$$S_{scat}(f_n) = \begin{bmatrix} S_{hh}(f_n) & S_{hv}(f_n) \\ S_{vh}(f_n) & S_{vv}(f_n) \end{bmatrix}$$

Where f_n is evaluated as follows:

$$\begin{cases} f_n = f_{\min} + n \cdot \Delta f \\ \Delta f = \dfrac{f_{\max} - f_{\min}}{N-1} \end{cases} \quad with\ n = 0,...,N-1$$

where $f_{\min}$ and $f_{\max}$ are respectively the minimum and maximum transmitted frequency.

Secondly, in order to apply the parametric Prony model, S_{scat} has been transformed to a transmitted left circular wave response as follows:

$$\begin{bmatrix} S_{hl}(f_n) \\ S_{vl}(f_n) \end{bmatrix} = \begin{bmatrix} S_{hh}(f_n) & S_{hv}(f_n) \\ S_{vh}(f_n) & S_{vv}(f_n) \end{bmatrix} \cdot \begin{bmatrix} 1 \\ j \end{bmatrix} \cdot \frac{1}{\sqrt{2}} \tag{1}$$

Thirdly, a decomposition in complex exponential sequences is performed:

$$\begin{bmatrix} S_{hl}(f_n) \\ S_{vl}(f_n) \end{bmatrix} = \sum_{k=1}^{M} \begin{bmatrix} a_{hk} \\ a_{vk} \end{bmatrix} \cdot p_k^n,\ n = 0,...,N-1 \tag{2}$$

where M is the model order which is equal to the number of dominant scattering centres, p_k are the relative pole and a_{hk} e a_{vk} are complex amplitude coefficient. The method of extraction is based on: 1) poles estimation by using linear prediction filter 2) amplitude terms estimation by least mean square technique. It is worth noting that the model order should be evaluated by means of model selection criteria (such as MDL, AIC and so on). In this work a fixed value equal to $M = 4$ has been adopted. This order is sufficient to represent effectively the scattered field of both the targets.

Finally, a feature extraction method is applied to eq. (2) in order to assess the used features.

More precisely, we estimate the four parameter, namely the major axis A_k, the tilt angle ϕ_k, the ellipticity τ_k and the scattering centre position r_k.

In formulae:

$$\begin{cases} r_k \approx \left(1 - \dfrac{\arg(p_k)}{2\pi}\right) R \\ \phi_k = \dfrac{1}{2}\arctan\left[\tan(2\alpha_k)\cos(\delta_k)\right] \\ \tau_k = \dfrac{1}{2}\arcsin\left[\sin(2\alpha_k)\sin(\delta_k)\right] \\ A_k = \left\| a_{hk} \right| \cos(\phi_k) + \left| a_{vk} \right| e^{i\delta_k} \sin(\phi_k) \right| \end{cases} \tag{3}$$

Where $\alpha_k = \arctan\left(\dfrac{|a_{vk}|}{|a_{hk}|}\right)$ and $\delta_k = \angle a_{vk} - \angle a_{hk}$ and $(\cdot)R$ is the R-modulo operator, where R is the unambiguous distance $c/2\Delta f$. Attention has to be taken in evaluating ϕ_k, more precisely:

$$\phi_k = \begin{cases} \phi_k - \dfrac{\pi}{2} & if \quad 0 \le \phi_k \le \dfrac{\pi}{4},\ \alpha_k > \dfrac{\pi}{4} \\ \phi_k + \dfrac{\pi}{2} & if \quad -\dfrac{\pi}{4} \le \phi_k \le 0,\ \alpha_k > \dfrac{\pi}{4} \end{cases} \tag{4}$$

3.2 Simulation scenario

Two type of ships have been considered: a small tonnage ship with a low level of detail and medium tonnage ship with higher details. The former is 42 meter long and 12 meter high above sea surface, the latter is 100 meter long and 21 meter high.

The radar antenna is located *h* meter above the sea surface and at a distance of R_0 meters from the bow of the ship in order to illuminate the target with low grazing angle β (about 1.5°) and in non ambiguous range condition.

The transmitted signal is formed by 64 frequencies stepped by 1 MHz starting from 1 GHz. The propagation vector is coplanar with the longitudinal axis of the ship.

The receivers grid is composed by 200x150 elements stepped by $\lambda_{\min}/3$ (in agreement with the equivalence theorem assumption) for the small tonnage ship and by 300x200 for the medium ship.

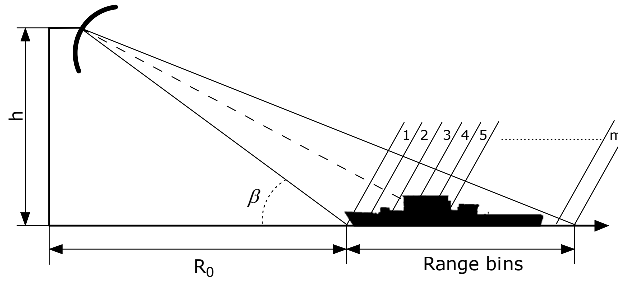

Figure 3– Scenario geometry

4. NUMERICAL RESULTS

The polarimetric features of each target, extracted with the modified Prony method, are fed to the neural networks summarized in Tab. 1.

Both networks has been trained with different set of signal-to-noise ratio and with different number of training records. The noise is addictive and uncorrelated and the SNR is defined for each of the two polarimetric channel as $SNR = P_S/\sigma^2$, where $P_S = \sum_{n=0}^{N-1} \dfrac{|S_{hl}(f_n)|^2 + |S_{hl}(f_n)|^2}{N}$,

$$\begin{bmatrix} S_{hl}^N(f_n) \\ S_{vl}^N(f_n) \end{bmatrix} = \begin{bmatrix} S_{hl}(f_n) + N_{hl}(f_n) \\ S_{vl}(f_n) + N_{vl}(f_n) \end{bmatrix} \quad \text{and}$$

$N_{hl,vl}(f_n) \in wgn(0, \sigma^2/2)$, with $n = 0,\ldots,N-1$.

For training purpose we decided to cover a wide range of training opportunity:

$$\begin{cases} SNR_{train} \in [-15, -5, +5, +15, +20]\,dB \\ Records_{train} \in \{100, 200, 300\} \end{cases}$$

Therefore, the number of tested network configurations is equal to 30 (i.e 5x3x2).

The performance of the networks are provided in terms of classification error, i.e:

$$\xi\ (\%) = \frac{nr\ failure}{nr\ validation\ trial} \cdot 100 \tag{5}$$

This measure of performance is evaluated during the validation phase. The validation set, composed by 1500 records, is calculated at different signal-to-noise ratio, i.e:

$$SNR = \left(-20 + 4 \cdot n\right)\ dB \qquad n = 0,1,2,\ldots,10$$

A number of 1500 records is found to be sufficient to attain a steady value of classification error. The results of the validation phase are showed in Fig. 4-8, each figure represents a given SNR_{train}. Figures led us to the following remarks:

- MLP architecture generally provides better results than SOM.
- MPL architecture trained with low SNR_{train} , namely *-10 dB, -5 dB* achieves better performance as the number of training records increases.
- The best performances are obtained with a MLP architecture trained with 300 records per target and with a SNR_{train} equal to *5 dB.*
- SOM trained with SNR_{train} less than *-5 dB* are unable to classify.
- SOM trained with SNR_{train} equal to *5 dB* classifies with poor performances and only around the signal-to-noise ratio used during the training.
- SOM architecture provides classification performances relatively insensitive to changes in training records number.
- SOM architectures provide best results if trained with SNR_{train} greater than *15 dB.*

We found that MLP architecture achieves better performances in a noisy environment if the network is trained with low signal-to-noise ratio values, similar conclusion have been reported in [4].

Furthermore, we experience that a training performed with a number of records equal to 300 provides robust MLP classifier (with SNR_{train} greater than *-5 dB*).

SOM architecture shows a progressive improvement in performance as the SNR_{train} increases. It is worth pointing out that acceptable results are produced only if the SNR_{train} is greater than *5 dB.*

Both the considered architectures fail when trained with very low signal-to-noise ratio, i.e. SNR_{train} less than *-15 dB*. It is interesting to note that the higher the SNR_{train} , the lower the performance gap between the two architectures.

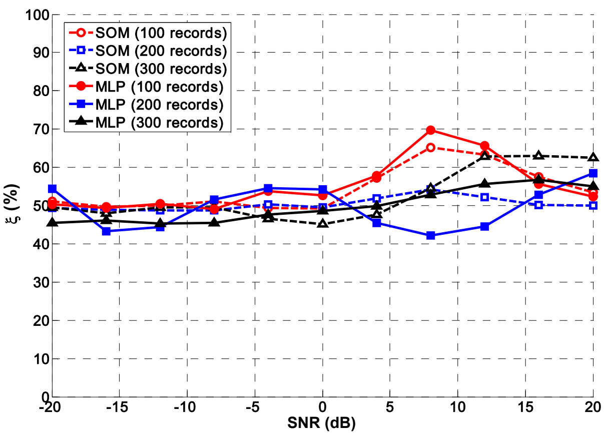

Figure 4 – ANN performances, SNR_{train} = *-15 dB.*

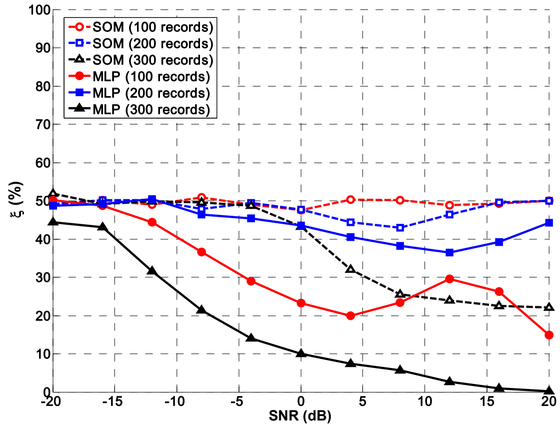

Figure 5 – ANN performances, SNRtrain = -5 dB.

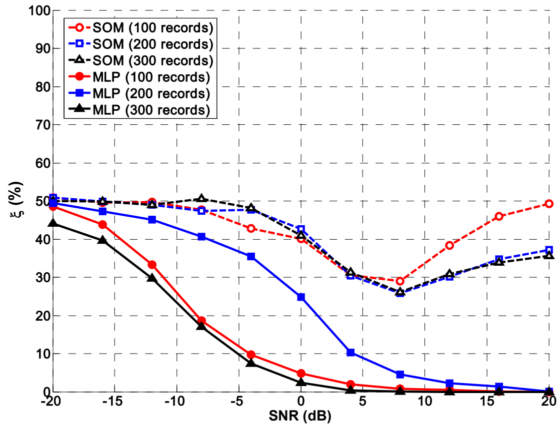

Figure 6 – ANN performances, SNR_{train} = *5 dB.*

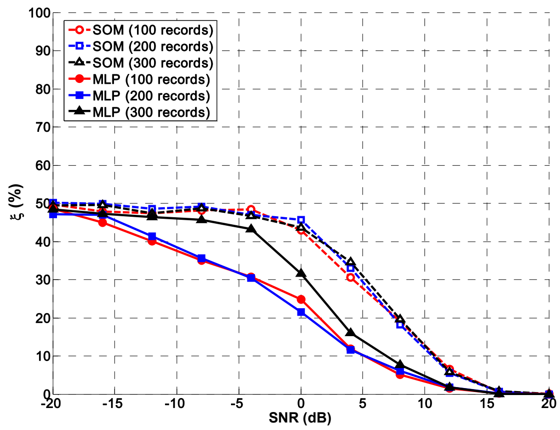

Figure 7– ANN performances, SNR_{train} = *15 dB.*

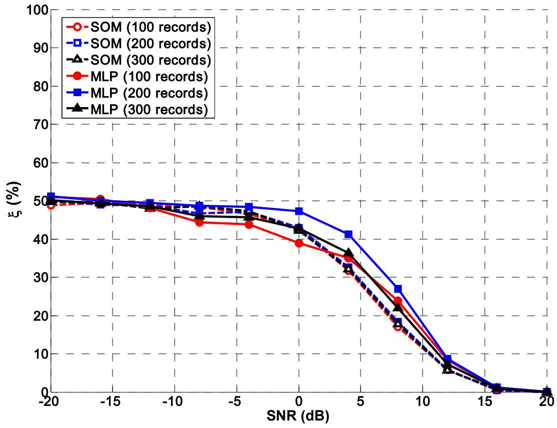

Figure 8– ANN performances, $SNR_{train} = 20$ dB.

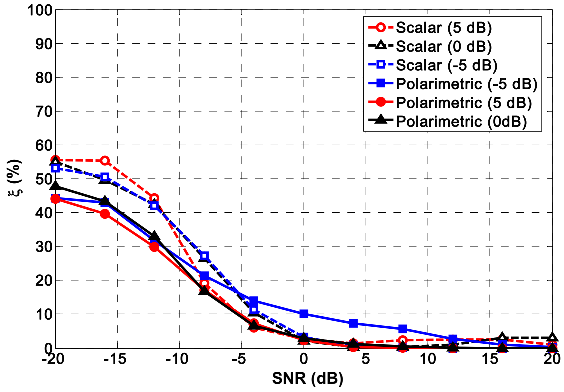

Figure 9– Scalar vs Polarimetric performances (300 records–MLP)

Finally, in Fig. 9 is reported the classification improvement obtained by using fully polarimetric data (*hl* and *vl* channels) rather than single polarization data (*vl* channel). The architecture evaluated is the MLP with 300 training records, which has provided the better results.

The performance improvement is notable for low *SNR* values, whereas for high *SNR* classification performances are comparable. This is mainly a consequence of the robustness of the modified Prony algorithm procedure that highly reduce the effect of noise.

5. CONCLUSION

In this paper, we have presented the results of a study which attempt to evaluate the performance of ANN as fully polarimetric radar classifier. In order to demonstrate the effectiveness of a neural-based approach, we reproduce a simulated scenario with an e.m simulator (i.e *EMvironment*). The received signal is processed by means of a modified Prony algorithm which provides a set of polarimetric features.

The aforementioned features are forwarded to the neural classifier, the output of the classifier is a simple label that identify the nature of the target. MLP provides better performance rather than SOM in most cases, on the contrary SOM has showed a stronger records training invariance for SNR_{train} greater than 5 dB.

MLP networks have shown an evidence of success in classifying synthetic radar targets, even in adverse environment (i.e low SNR). Moreover, polarimetric neural-based classifier provide better results rather than scalar neural-based classifier, especially when background noise is particularly severe, underlining the effectiveness of polarimetric approach in target classification problem.

Future researches will be focalized on methods able to join the advantage of both the net. Specifically, it would be desirable to reach the MLP performances jointly with the training parameters invariance typical of the SOM. Another problem we have to deal with is the polarimetric features dependency with the target motion (mainly aspect angle and relative velocity). This more general invariance is necessary in order to enhance the neural classifier skill in real scenario.

ACKNOWLEDGMENT

The authors would like to thank Prof. Agostino Monorchio for the use of the software *EMvironment*. Special thanks also go to Alessandro Corucci and Filippo Menegato for their useful help with the simulations.
The work is supported by Galileo Avionica S.p.A..

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