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NEURAL NETWORKS AND PRINCIPAL COMPONENT ANALYSIS APPLIED TO AUTOMATIC RADAR TARGET RECOGNITION BASED ON NATURAL RESONANCES[1]

JOSÉ A. GARZÓN-GUERRERO, DIEGO SALAS-GONZÁLEZ,

DIEGO P. RUIZ, AND MARIA C. CARRIÓN

Department of Applied Physics

University of Granada, Spain

jgarzon@ugr.es, dsalas@ugr.es, druiz@ugr.es, mcarrion@ugr.es

ABSTRACT

In this paper, a new classification scheme for radar target recognition is described. It uses a MLP neural network as classifier and complex natural resonances as inputs of the net. Benefit of using natural resonances is that they are aspect angle independent, i.e. scattering responses from different aspect angles of the same target can be represented by the same natural resonances. But the extraction process of natural resonances is an ill-conditioned problem and noise affects the parameter estimation. To improve the sensitivity to noise, it is proposed an algorithm that extracts the resonances from a reconstructed response generated by a PCA stage over a set of reference targets, prior to the MLP neural network classifier.

KEYWORDS
Radar target recognition, natural resonances, principal component analysis, neural network, matrix pencil.

1. Introduction

In present times, radar target recognition from the scattered electromagnetic fields of targets is still a challenging subject in signal processing and communications. This problem is not easy to solve, not only because scattering mechanisms are complicated (even for geometrically simple targets), but also due to these signals are strongly dependent on the frequency, polarization and the aspect angle of the transmitted and received signals. In particular, aspect dependency of the scattered signals makes the problem more complicated than the other parameters. For instance, the scattered responses at two different aspects of same target could be incorrectly identified as coming from two different targets, or in some cases two different targets at different aspects could be identified as the same target.

Many authors have proposed target classification techniques that use directly the time domain response and the frequency response to classify [1]-[2], increasing the

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computation time and keeping the dependence with the aspect angle. The extinction-pulse based techniques (E-pulse) use a specifically synthesized filter (one for each target class) to annihilate the scattered response of the detected target [3]-[4]. Complex natural resonances (or frequencies) are other features used as classification parameters [5]. The advantage of using them is that natural resonances are aspect independent.

Lately, artificial neural networks have been used to classify radar targets together with other techniques of feature extraction. Neural networks have provided effective classification in noisy environments. In [1], the time domain response is used as a neural network input. In [5], both a natural frequency-based method and an artificial neural network approach to tar-get recognition are described, improving the non-dependence on the aspect angle but this method suffer from sensibility to noise.

Therefore, to assure an adequate classification rate under different environments, it is necessary to develop methods of feature extraction that must have low aspect angle sensitivity, high sensitivity to geometrical and physical properties of the target (to discriminate a target from other similar targets), and must be robust to noise.

In this work, a new radar target recognition algorithm is presented. It is based on the aspect angle independence of the natural resonances and uses principal component analysis to make the parameter extraction of the natural resonances more stable to noise. These resonances are used as inputs of a neural network which assign a group class to each one.

2. Natural resonances

It is well known that when a radar target is excited by electromagnetic waves, its time domain response carries the signature of the target [3]-[4]. The complete response of such a target consists of two parts. The first part is known as the early-time scattering response, which appears when the excitation wavefront goes through the target. The second part, the late-time scattering response, appears when the excitation wave-front moves beyond the target. According to the singularity expansion method (SEM, [6]) the late-time electromagnetic field scattered in free space from a finite sized conducting body is represented as finite sum of M damped sinusoids:

$$y(t)=\sum_{i=1}^{M} R_i e^{s_i t} \qquad t>T_L \tag{1}$$

Where R_i and s_i (with i=1,...,M) are the complex residues and complex natural resonances (CNR), respectively. T_L is the beginning time of the late time response. CNRs appear in complex conjugate pairs , s_i=s$_i$+j?$_i$. The real part of each CNR is denoted by s$_i$ (damping factor) and the imaginary part by ?$_i$ (natural resonance frequency). CNRs of a radar target depend only on its geometry and its physical properties and are aspect independent features of its transient response.

In this work, the generalized pencil of functions method (GPOF) is used to extract the natural resonances [7]. It is computationally more efficient than other techniques. But the CNR extraction is an ill-conditioned problem, which implies that noise can be amplified through the extraction process. This means that a small quantity of noise in the time domain response could produce a huge change in the extracted CNRs. The extraction method makes the higher natural resonances pairs more vulnerable to noise than lower ones. Furthermore, dumping factors (s_i) are more sensitive to noise than resonance frequencies ($?_i$). Choosing only lowest CNRs helps to reduce this problem but it is convenient to improve their behaviour to noise. In this paper, CNRs are extracted from the step time domain response instead from the impulse response. Thus, the first CNRs are less dumped and more stable on time than the next ones.

3. Using principal component analysis

Suppose that **X** (a $m \times n$ matrix) is a target late-time response library, where n is the number of different target models that the system can classify and m is the number of samples of each late-time scattering response. All signals in the library are taken in controlled conditions. The principal component analysis (PCA) transforms the original set of m variables by way of an orthogonal transformation to a new set of uncorrelated variables or principal components. The technique carries out a straightforward rotation from the axes of the original space to the new one and the principal components are extracted in decreasing order of importance. A successful extraction means that the first few 'p' components ($p<<m$) accumulate the most of the variation in the original data [8].

Variables or samples must be standardized before applying the PCA. Such standardization means that the principal components are found from the correlation matrix instead of the covariance matrix.

PCA solution gives a matrix of eigenvectors **E** ($m \times m$) and associated eigenvalues $?_i$ (i=1,..., m). The sum of the eigenvalues is equal to m, the same that sum of the variances of the standardized variables. The proportion of the total variation accumulated in the i_{th} component is $?_i/m$. Assuming that the first p principal components are sufficient to retain the behaviour of the original m variables, a new matrix of eigenvectors $\mathbf{E}_p$ ($p \times m$) can be selected in order to reduce the dimensionality of data.

Let **x** ($m \times 1$) be a noisy measure of a scattering response of a target belonging to one of the models contained in the original data matrix **X**. This response can be projected in the PCA space generated by $\mathbf{E}_p$. Let a ($p \times 1$) be the projection vector of original data onto the p principal components:

$$\mathbf{a} = \mathbf{E}_p \mathbf{x} \tag{2}$$

Projections onto the principal components with index higher than p have been removed. The lost information corresponds mainly to noise data [8]. Original response **x** can be reconstructed using the transformation matrix $\mathbf{E}_p$ again:

$$\mathbf{x}_r = \mathbf{E}_p^T \mathbf{a} = \mathbf{E}_p^T \mathbf{E}_p \mathbf{x} \tag{3}$$

Where the superscript T denotes the transpose matrix and x_p is the reconstructed response after removing noisy components in the PCA projection stage. Therefore, PCA is used to minimize the error of the estimation of complex natural resonances.

4. Target recognition algorithm

In this paper, a complex natural resonance method is described. This algorithm will be denoted by NR-PCA (from Natural Resonance-Principal Component Analysis method).

The algorithm consists of two stages.

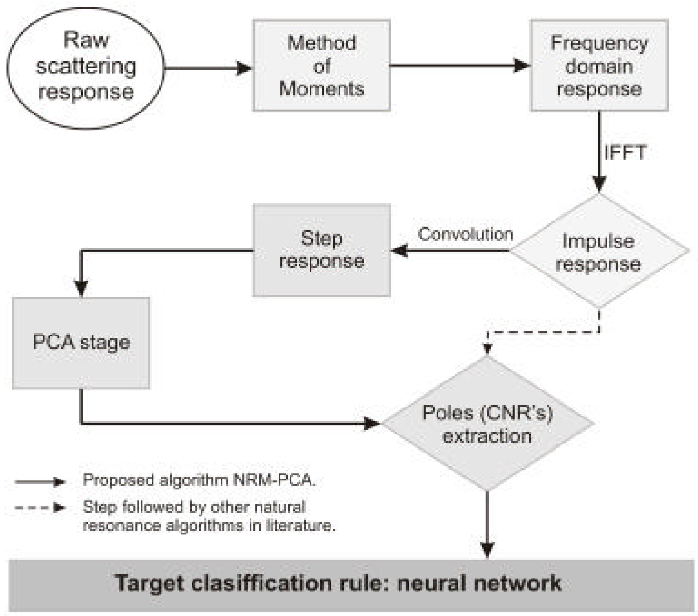

Figure 1. Step diagram of the proposed algorithm: NR-PCA.

4.1 Stage 1: training and reference data

In the first stage, which only must be done one time, a set of raw scattering responses of several targets must be chosen as a set of reference signals (**X**), at least one for each different target model (with different geometrical and physical properties). However, the more different aspect angles per target exist, the more effective this PCA stage is. The raw data set is converted to the frequency domain using the method of moments algorithm [3]. Following that, the impulse response of the target can be obtained by inverse Fast Fourier transforming (IFFT) the calculated frequency-domain data. Time domain step response is used instead of impulse response as seen in section 2. The step response can be obtained by either integrating the impulse response or convoluting the impulse response with a unit step function. Late-time interval must be chosen from the step response. Next, the PCA method (section 3) is applied to this data, obtaining the transformation matrix $\mathbf{E}_p$.

For training neural network, same reference signals, **X**, can be used, but only one response for each reference target is necessary (they can be of any aspect angle). Complex natural resonances are extracted from the reconstructed late-time response $\mathbf{x}_r$ as seen in expression 3. These resonances will be the inputs of the network. A multilayer perceptron (MLP) with back-propagation algorithm is used as classifier. The number of nodes (or neurons) in the input layer, output layer and hidden layers depends on the specifical characteristics of the problem. The weight vector is updated according to the back-propagation algorithm until the output layer produces the desired value for a given input. Error is minimized with the gradient descent method with momentum. The final weight vector is obtaining as a result of training [9].

4.2 Stage 2: classification scheme

The second stage is testing and classification. The proposed classification scheme is shown in figure 1. It consists of the following steps:

– Target frequency domain response is calculated from its raw scattering response (method of moments).
– IFFT is applied to obtain the impulse response. The result is convoluted to found the step response.
– This step response of the late-time scattering is reconstructed by way of PCA projection matrix $\mathbf{E}_p$ (calculated in section 4.1) such as seen in expression 3.
– Natural resonances are extracted from the reconstructed signal, $\mathbf{x}_r$. GPOF method is used here (see section 2).
– CNRs (or their individual components, s_i and $?_i$) are used as inputs of the trained MLP. The neural network classifies the target into all possible original reference classes.

5. Simulations and results

Suppose that four classes or reference targets must be classified: four thin conducting wires of relative lengths L_R=0.7, 0.8, 0.9 and 1, with $L_{Ri}=L_i/L$, being L_i the length of the *i*-target of the library and L the length of a reference wire. To simplify, the range for aspect angle will be 30º-60º. Scattering responses have been synthesized according with the description followed by [10].

For the PCA training stage, two scattering responses for each target class at two aspect angles (30º, 60º) are taken. Matrix $\mathbf{E}_p$ is calculated with *p*=15 (in this case, the first fifteen principal components accumulate 99.8% of the original data variation).

For neural network training, only a scattering response for each target is used. Due to the few different targets to classify, the classifier MLP will have only a hidden layer. The first natural resonance (s_1 and $?_1$) and the natural frequency $?_2$ belonging to the second natural resonance pair will be the inputs of the net.

5.1 Results

A large set of noisy test signals is generated for each reference target. The noisy time domain signal of each class is obtained by adding white noise to the time domain signal of the corresponding reference target. The signal-to-noise ratio is:

$$SNR(dB) = 10\log\frac{1}{\sigma}\sum_{k=1}^{N}\frac{|y_k|^2}{N}$$

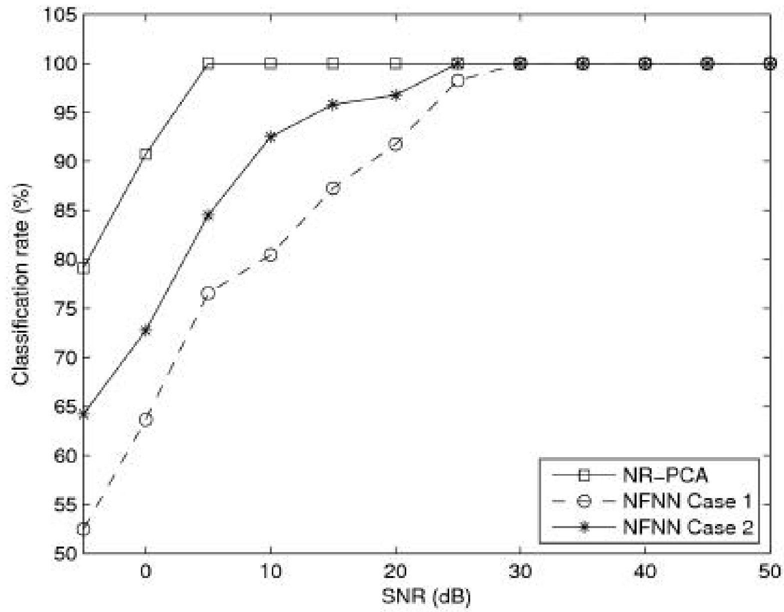

Figure 2. Mean values of classification rates obtained with the algorithm proposed in this paper, NR-PCA, in comparison with two schemes described in [5], NFNN Case 1 and Case 2. SNR range is -5dB:50dB.

Where s^2 is the variance of Gaussian noise, $\mathbf{y}_k$ is the time domain response, and N is the number of samples in the signal.

In order to analyze the performance of the proposed algorithm (NR-PCA), it will be compared with two schemes described in [5]: NFNN Case 1 and NFNN Case 2 (Natural Frequency Neural Network). These algorithms extract natural resonances from the noisy signal directly (using GPOF). The first CNR (Case 1) or the two first CNRs (Case 2) are used as inputs of the neural network. Figure 2 shows the comparison between the three methods. Signal-to-noise ratio values of the test vary between -5dB and 50dB. The mean value of classification rate is 100% for SNR of 30dB and higher in the three methods. NFNN Case 2 produces bad classification results at lower SNRs because the extraction of natural resonances directly from noisy signals makes the second CNR wrong estimated. The first CNR accumulates less error than the second (see section 2). Therefore, NFNN Case 1 has a better behaviour at lower SNR than Case 2. At SNR=-5dB, the classification rate of Case 1 is reduced up to only 64.4%.

On the other hand, the proposed algorithm, NR-PCA, has a good noise performance and maintains a 100% classification rate with SNR=5dB and higher. Even in the worst case with SNR=-5dB, classification rate is 79.1%. Assignment errors are produced by the creation of spurious poles in GPOF due to a bad signal reconstruction in PCA stage.

5.2 Discussion

The classification scheme presented in this paper have advantages and disadvantages compared with other methods. The first advantage of using the proposed NR-PCA algorithm comes from the aspect independence of the natural resonances of a target. In practice, since the aspect angle is not known a priori, using natural resonances is preferable, instead of using time or frequency domain responses.

Other benefit is the small size of the input vectors for the neural network. Techniques based on using time or frequency responses directly as input can contain several hundreds of data. The input vectors of the NR-PCA algorithm are comprised by one or two complex natural resonance pairs at most, which means two or four real numbers. The smaller the input vector, the less convergence time the network uses in training and classifying targets.

Noise behaviour is also improved in the NR-PCA algorithm. Estimation of complex natural resonances directly from the scattering responses can be ineffective when signals are very noisy. The proposed scheme can extract CNRs correctly even in very low SNRs due to the previous PCA stage. Hence, up to four useful CNRs can be extracted from a target response with low SNR, with a estimation error lower than 2% relative to the theoretical value from the target [10].

But there are also handicaps of the proposed algorithm. The first liability is that two additional stages are added to the classification process: a stage of signal reconstruction through PCA and a step of CNRs extraction. Recognition time can be increased in these stages, but the saved time due to the input vector size can compensate this losing.

Another disadvantage is that spurious CNRs can sometimes appear when the GPOF method is applied to a very noisy response. This may be due to non-linearity in the data as the PCA has the inherent weakness of assuming linearity of data. It could also be as a result of the effect of the noise on the estimation of principal components. Last inconvenient is that the neural network is trained through a fixed data set of reference targets. If a new target is added to the set, the network must be trained again.

6. Conclusion

Principal problems in radar target classification methods come from the fact that scattering responses are strongly dependent on the aspect angle of emitted and received signals. Thus, a same object can generate different responses and could be wrong classified. Using complex natural resonances can be a solution as CNRs have the inherent property of aspect angle independence. Generalized pencil of functions method (GPOF) is used to extract CNRs from the time domain step response. The first CNRs extracted from the step response are less dumped than next ones.

But extraction process is an ill-conditioned problem (it is highly sensitive to noise) which implies that CNRs extracted from signals with lower SNR can be wrong estimated. To avoid this effect, a previous stage is added before applying GPOF: original data are PCA transformation, which eliminates some noisy components. CNRs are extracted from the reconstructed signal, and their estimation errors are minimized.

A MLP neural network is used as classifier. The input vectors are the first CNR pairs (or any of their individual components). Convergence time is lower than in other techniques due to the small size of the inputs. At lower SNR, the classification rate is higher in the proposed algorithm, NR-PCA, than in other schemes in the described in literature [5].

A negative point of the NR-PCA algorithm is that spurious CNRs can sometimes appear in the extraction process from very low SNR signals. Another disadvantage is that the neural network must be trained again if a new object is included in the reference data set.

In summary, a new classification scheme for radar target recognition is described, which is aspect independent and robust to noise, improving the existing similar methods in literature.

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