Radar Target Identification Based on Feature Extraction Performed with RBF Artificial Neural Networks

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Abstract

An artificial neural network (ANN) approach for radar image processing is presented in this paper. A renewal concept of simple adaptive units as a foundation for network assembling allows one to design ANN-based feature extraction scheme for 2D-signal processing. It was shown that ANN implementing radial basis function (RBF) processing units can be applied for identification of radar targets described by the set of scatterers. The obtained results indicate a high accuracy estimation of separate scatters centers.

1. Introduction

This paper introduces an approach to increasing the performance of radar images processing through feature extraction scheme performed by artificial neural networks (ANN). First of all, a simple physical model of radar 2D image is presented. Target observation is carried out in the presence of additive Gaussian white noise. Antenna pattern and radar pulse form are assumed to be known. In order to increase radar image quality, which would be a step toward automatic target recognition, individual scatterers of complex target must be identified. These individual scatterers give the most intense response in received echo signals. In this paper we concentrate on the estimation of scatterer effective center positions as the most important part of identification and we will focus our attention on it.

The paper [1] proposes to use parametric methods for poles estimation in spectral domain, cause their complex-valued coordinates can be projected into the coordinates of the scatterers. This approach has a few advantages such as high accuracy and proved suboptimal nature, but it also has a few disadvantages such as high calculation cost, model inflexibility and the necessity to have radar image preliminary deconvolved that usually leads to solving a kind of ill-conditioned problems.

This paper proposes an alternative approach by using radial basis function (RBF) ANN assembled of simple adaptive units. In order to do that a source radar image is used in process of neural network training as desired output; hence, it's approximated by neural network. In case of successful approximation the parameters of scatterers can be estimated directly through the parameters of adaptive elements.

A model of time-space radar echo signal of complex target [1] is used as input data for identification task. This echo signal is generated in centimeter wavelength range by a system creating a coherent radio pulses. Antenna of such system performs azimuthal scanning and works both as sender and receiver of signal. We will also assume that the obtained image is high-definition on both distance (marked as ρ) and azimuth angle (marked as φ). The analytical expression (1) defines the time-space radar signal of complex target consisted of *P* scatterers. Typical structure of radar signal is shown on fig. 1, a.

$$\dot{x}(t,\theta) = \sum_{p=1}^{P} \dot{x}_p(t,\theta) + n(t) = \sum_{p=1}^{P} \dot{a}_p \dot{s}(t-\tau_p) f_A^2(\theta-\phi_P) + n(t) \tag{1}$$

where $\dot{x}(t,\theta)$ - time-space radar signal caused by a single (*p*-th) scatteter, $\dot{s}(t-\tau_p)$ – slice of complex radar image across the range axis (the form of this slice follows the form of probe pulse complex envelope), $f_A^2(\theta-\phi_P)$ – squared antenna pattern describing the form of scatterer in cross-range axis, ϕ_P - angle of direction of antenna's main, *n(t)* - additive Gaussian noise with uniform power distribution within radar band.

2. RBF-Neuron

The Gaussian function is typically used as a complex envelope for the probe pulse due to a pack of transformation any real pulse undergoes in transmitter and receiver. We will also assume that the squared antenna

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pattern is also matching Gaussian function form. The typical radar image created with such assumptions is shown on fig. 1, b. The test model consists of three scatterers with different relative intensity.

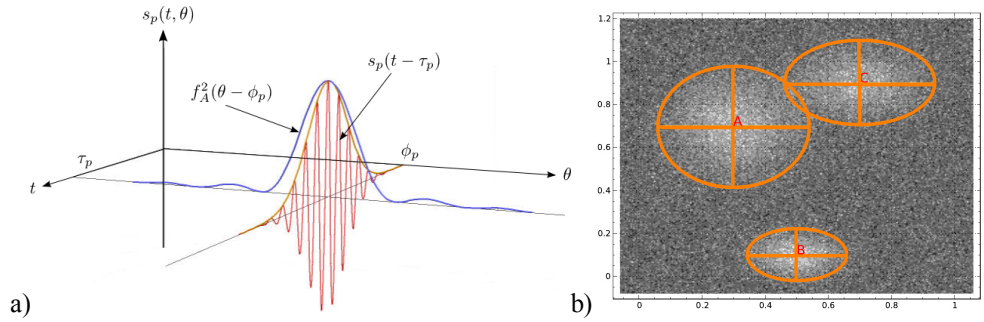

Fig. 1. a) Radar signal structure, b) Source radar image.

In order to solve identification problem for these three scatterers we propose to use neural network build with radial basis function neurons (*RBF-neurons*), which are described in [3].

The extraction feature ability of the RBF-neuron is determined by local interpolating properties of underlying radial basis function. Such a neuron will be bound to some local area of input image during the training process. One of the useful properties of such neural network is that this network will keep interpolation matrix nonsingular; this property is known as the Michelle theorem [2]. Figure 2 (a) shows functional scheme of a single RBF-neuron build as a composition of simple adaptive units such as summing junctions, constant adaptive amplifiers and branch points.

Gaussian function was chosen as an activation function in block *f* for RBF-neuron shown in fig. 3. This choice is based on the above-mention assumption made for model (1) in which both probe pulse and antenna pattern form are corresponding to normal curves. The response of the assembled RBF-neuron is a surface: its slices across azimuthal and distance axes will be Gaussian curves whereas the level slices will be elliptic curves. The center of such three-dimensional bell-like response will be located in the center of scatterer, that is a point with coordinates x_0 and y_0, while the width of the bell will be determined by neuron amplifiers coefficients k_x and k_y. Neural network will approximate source image using its RBF-neurons according to given accuracy, afterward the parameters of the scatterers will be estimated through the parameters of the neurons.

3. Network Structure And Learning Process

The papers [3] significantly develop the diagrammatic representation of ANN performing learning process. This approach provides one with powerful tools for network design and became a way to clarify the back-propagation essence in ANN courses. The authors shows [9] that this approach could be further developed into the concept of adaptive units.

In the most general way a single adaptive unit as well as the whole network performs a transform **T** of input vector **x** into output vector **y**:

$$\mathbf{y} = \mathbf{T}(\mathbf{x}, \mathbf{\Theta}) \tag{2}$$

Each *i*-th adaptive element has its own independent set of transform parameters $\mathbf{\Theta}_i$ which values are evaluated during the training process. All adaptive units are connected within a complex structure via two-directional links which allow signals to pass both in forward and backward directions. The simple units, such as adders, amplifiers, branching points and univariate transformers, can be properly combined into a complex unit and the whole networks can be considered as a top-level unit.

Neural network can be used in two main modes: operational mode and training mode. Within operational mode, neural network passes input signal $\mathbf{x}_F$ through itself in a forward direction and using the known transform **T** (naturally or as a composition of underlying units transforms) and parameters vector $\mathbf{\Theta}$ it can calculate output signal $\mathbf{y}_F$. Within training mode a set of transform parameters is adjusted using back-propagation signal $\mathbf{x}_B$. ANN presented in this paper were trained using supervised learning: during this process, a set of training examples was exposed to the network. A single training example is a tuple contained image point coordinates and the value of signal intensity in this point. A training process is an iterative process. On each step, forward and backward propagation signals are calculated and error signals obtained afterward are used to calculate local gradients of adaptive units. Local gradient vectors are used to adjust transform parameter vectors. A batch training mode is preferred [2] for the considered feature extraction problem the network is built for since it close to stochastic approximation problem. That means parameters are being adjusted once upon each full cycle is complete and the mean local gradient is obtained. A full training cycle is traditionally called epoch, it uses all training examples once. In order to assess neural network quality a loss function must be defined, in the case it will be root mean square (RMS) function:

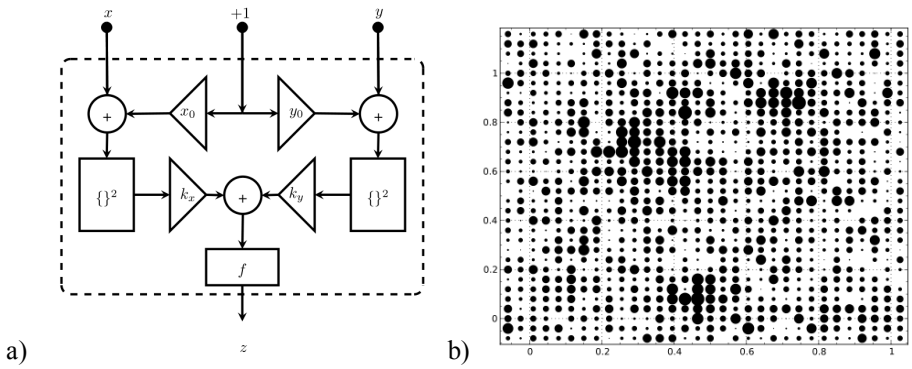

Fig. 2. a) Functional scheme of a single RBF-neuron, b) Input data sampled to learning

$$E = \frac{1}{2N}\sum_{n=1}^{N}(t_n - z_n)^2 \tag{3}$$

where N – number of point in source image; t_n – desired (or *target*) output value for n-th point; z_n – network output signal for n-th point coordinates as an input data.

At this point only autonomous learning algorithms are used to train neural network, such algorithms require only signals existing within a single unit to adjust its own transform parameters. Only local gradient value $\delta\theta_m$ and its history are used to calculate adjustment value $\Delta\theta_m$ for transform parameters vector θ_m of m-th neuron. The basic method for such autonomous approach to training process is well-known gradient descent method. Gradient or steepest descent method uses the following expression to calculate adjustment value $\Delta\theta$ from local gradient value $\delta\theta$ and training speed coefficient ε:

$$\Delta\theta = -\varepsilon \cdot \delta\theta \tag{4}$$

This method stands as a basement for all first-order learning methods and some of so-called quasi-second order methods. Network hierarchal structure allows calculating local gradient values sequentially from the input node to the output node. The work [4] proposes to describe such process of error signal backpropagation by means of adjoint network constructed by the set of rules. This representation is a useful tool allowing describing backpropagation process visually. The authors find this technique to be powerful tool to help with derivation some analytical expression. It was also used by some other authors [2] in the similar way to describe visually backpropagation process in static and dynamic neural network signal processing.

4. Application

An object-oriented approach in software developing matches the proposed adaptive unit concept. Architecture of the developed software as well as class hierarchy was defined using universal model language (*UML*) notation. Object-oriented language Python was used as primary programming language with mathematics software system Sage. On the one hand this conjunction allows simple writing of mathematical expression and on the other hand it has a convenient set of object-orientated tools. Python and Sage is available under terms of GPL and Creative Commons License respectively and they both have many third-party packages supported by world-wide research communities.

Developed software prototype [6] is split into two libraries: basic and additional ones. Both parts are implemented as Python modules; the basic library contains all necessary classes to perform neural network modeling while the additional library contains classes and methods to visualize results using Sage package as its backend to interact with user. Additional library uses Sage standard classes in order to make fancy data outputs such as graphs drawing, tables and plots.

A numerical modeling is performed in order to estimate the efficiency of the proposed method. A test radar signal is generated according to expression (1) with three scatterers, the corresponding input image is shown on fig. 1,b. This image is sampled and used for the training process: x and y coordinates on the image as input data and the z value (intensity of the radar signal at the given point as the output) data. At the end of the training process using gradient descent method an approximated image (fig. 3,b) is generated by neural network processing. Because of the known structure of the used neural networks it's now possible to extract the approximated parameters of the scatterers: each RBF-neuron represents one scatter on the input image.

It is important to note the generalizing abilities of neural network: the approximated image does not contain the noise. Network output signal is defined by the expression 5. Figure 3,b also schematically shows both real scatterers locations and estimated locations, it's clear that the centers of each scatterer are estimated quite accurate, but effective

widths are not so accurate. Such behavior of neural network can be easily explained: the almost exact estimation of scatterer centers is much more important to minimize RMS value than the effective widths; hence, they will the first item to estimate more precisely.

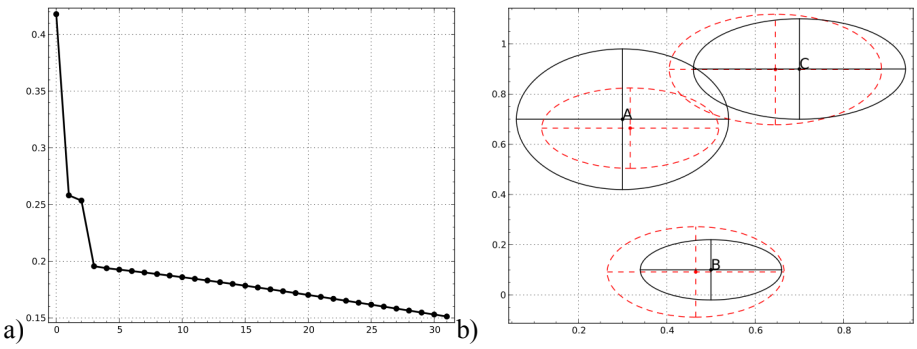

Fig. 3. a) RMS values changes over training epochs, b) Test model consisting of three scatterers (solid line) and it's estimation (dashed line).

Figure 3,a shows changing of RMS during training process. At the final stage of training RMS is still going to decrease, that is because of slow changing of effective widths. A higher value of parameter ε (see expression 4) may be selected in order to achieve accurate approximation quicker, but in case of too high value of ε a risk of training process becoming unstable appears.

$$x_a(r,\theta) = \sum_{p=1}^{P} g_p(t,\theta) \tag{5}$$

where $x_a(r,\theta)$ - approximated radar image, $g_p(t, \theta)$ - output signal of p-th RBF-neuron bringing out the position of single scatterer.

Note the difference between expression 5 and 1: there is no noise part $n(t)$ in 5 because its dispersion included in approximation error (RMS value). A more thorough analysis and comparison of the proposed approach with the other methods are the tasks for the future research as well as applying other training methods.

As the conclusion we should note that the paper proposed an approach to solve scatterer identification task via radial basis artificial neural networks. The concept of adaptive units is used as the foundation for building the network because of preserving physical matter of adaptive element parameters. In order to demonstrate proposed approach, the problem of identifying three simple scatterers in a radar image was solved. The results indicate a high accuracy identification of scatterers centers and lower performance in estimation their width.

5. References

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