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RADAR OBJECT RECOGNITION BY WAVELET TRANSFORM AND NEURAL NETWORK

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Abstract
This paper presents method of radar object recognition by wavelet transform and neural network. Analysing range profiles by wavelet transform can show information about tracking object more clearly. It also gives a method of constructing feature vector for automatic recognition, which can make the dimension of Feature vector be much smaller than dimension of primitive echo signal. A three-layer back propagation neural network is used as recognizer. This problem is aimed to radar systems with the duration of transmitted pulses longer than size of object.

Keywords - Radar, Wavelet transform, Neural network, Feature vector, Recognizer.

Introduction

Radar object recognition is of interest for civilian and military purposes. In a radar imaging system, the Information, which describes the object, is a function of time delay, envelope of backscattered signal and Doppler frequency. Most current approaches to the automatic radar object recognition are based mainly on utilization of high-resolution radars. These radars use search pulses, which are comparable with the observed target size. However, we will analysis and processing signals, which are of result simulating traditional radars.
Earlier methods of recognition by range profile are mainly matched filters [l] and neural networks [2], they use range profile directly. Selection of suitable of feature vector is crucial to success of object recognition. It can not only improve recognition correct rate, but also reduce the dimension of data fed to the recognizer [3]. Focus of this paper is small dimension feature vector construction

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Neural Network

In information technology, a neural network is a system of programs and data structures that approximates the operation of the human brain. A neural network usually involves a large number of processors operating in parallel, each with its own small sphere of knowledge and access to data in its local memory. Typically, a neural network is initially "trained" or fed large amounts of data and rules about data relationships (for example, "A grandfather is older than a person's father"). A program can then tell the network how to behave in response to an external stimulus (for example, to input from a computer user who is interacting with the network) or can initiate activity on its own (within the limits of its access to the external world).In making determinations, neural networks use several principles, including gradient-based training, fuzzy logic, genetic algorithms, and Bayesian methods. Neural networks are sometimes described in terms of knowledge layers, with, in general, more complex networks having deeper layers. In feed forward systems, learned relationships about data can "feed forward" to higher layers of knowledge. Neural networks can also learn temporal concepts and have been widely used in signal processing and time series analysis.
A biological neural network is composed of a group or groups of chemically connected or functionally associated neurons. A single neuron may be connected to many other neurons and the total number of neurons and connections in a network may be extensive. Connections, called synapses, are usually formed from axons to

dendrites, though dendrodendritic microcircuits and other connections are possible. Apart from the electrical signaling, there are other forms of signaling that arise from neurotransmitter diffusion.

Artificial intelligence and cognitive modeling try to simulate some properties of biological neural networks. While similar in their techniques, the former has the aim of solving particular tasks, while the latter aims to build mathematical models of biological neural systems.

In the artificial intelligence field, artificial neural networks have been applied successfully to speech recognition, image analysis and adaptive control, in order to construct software agents (in computer and video games) or autonomous robots. Most of the currently employed artificial neural networks for artificial intelligence are based on statistical estimations, classification optimization and control theory.
The cognitive modeling field involves the physical or mathematical modeling of the behavior of neural systems; ranging from the individual neural level (e.g. modeling the spike response curves of neurons to a stimulus), through the neural cluster level (e.g. modeling the release and effects of dopamine in the basal ganglia) to the complete organism (e.g. behavioral modeling of the organism's response to stimuli). Artificial intelligence, cognitive modeling, and neural networks are information processing paradigms inspired by the way biological neural systems process data

Wavelet Transformation

In The last few years there has been a great amount of interest in wavelet transforms, especially after the discovery of the discrete wavelet transform (DWT) by Mallat.The DWT can be viewed as a multiresolution decomposition of signal. This means that it decomposes a signal into its components in different frequency bands. The Inverse DWT (IDWT) dose exactly the opposite, i.e., it reconstruct a signal from its band component. The applications of this transform are numerous, ranging from image and speech compression to solving partial differential equations

Wavelet transform is widely used in many field of signal processing, especially image compression, speech processing, computer vision. For radar signal processing, it has been used to detect moving targets [4]
The wavelet transform has become a useful computational tool for a variety of signal and image processing applications. For example, the wavelet transform is useful for the compression of digital image _les; smaller _les are important for storing images using less memory and for transmitting images faster and more reliably. The FBI uses wavelet transforms for compressing digitally scanned fingerprint images. NASA's Mars Rovers used wavelet transforms for compressing images acquired by their 18 cameras. The wavelet-based algorithm implemented in software onboard the Mars Rovers is designed to meet the special requirements of deep-space communication. In addition, JPEG2K (the newer JPEG image _le format) is based on wavelet transforms. Wavelet transforms are also useful for `cleaning' signals and images (reducing unwanted noise and blurring). Some algorithms for processing astronomical images are based on wavelet and wavelet-like transforms.

The important characteristics of wavelets are time-frequency location. We may have noticed that wavelet analysis does not use a time-frequency region, but rather a time-scale region. The continuous Wavelet transform is defined [6] as

$$W_x(a,b) = \frac{1}{\sqrt{a}} \int_{-\infty}^{\infty} x(t) g^*\left(\frac{t-b}{a}\right) dt,$$

Where x (t) is a signal**,** superscript “*” denotes complex conjugate, g (.) is a wavelet which changes according to the scale parameter a and translates by a factor b.
Discrete wavelet transform of ***x (t)*** is defined [6] as

$$DWT(m,n) = \frac{1}{\sqrt{a_0^m}} \sum_{k=-\infty}^{\infty} x(i) h\left(\frac{i - nb_0 a_0^m}{a_0^m}\right),$$

Where h (.) is discrete wavelet, a_0 and b_0 are the discrete scale **and** translation step sizes, respectively

Discrete wavelet transform can be calculated by Mallat’s pyramid algorithm as shown in fig. 1, where L, H represents a low-pass and a high-pass filter respectively decided by the wavelet basis separately, ↓2 means keeping one sample out of two. This very practical filtering algorithm yields a fast wavelet transform. The j-th high-pass filter's output produces detail wavelet coefficients $D_J(k)$, and the j-th low-pass filter's output produces approximation wavelet coefficients A_J.(k) Notices that the actual length of the detail and approximation coefficient vectors are more slightly than half the length of the original signal**.**

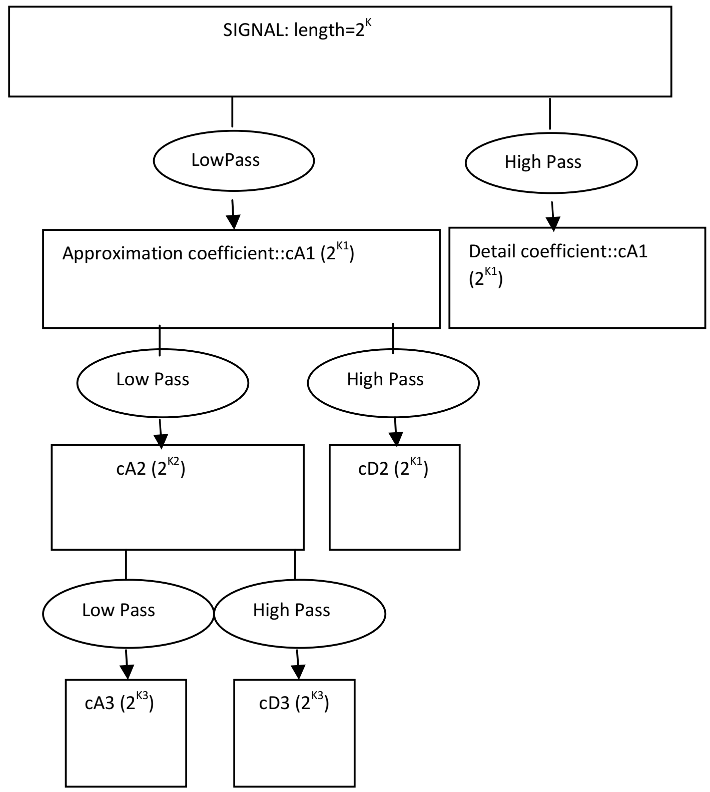

Fig.1 Mallat's pyramid algorithm

Constructing Feature Vector Using Wavelet Coefficients

In general system recognition has two stages, feature extraction and recognition. The purpose of the feature extraction stage is to reduce the complexity of the input space by mapping raw inputs into feature vectors in a feature space. Feature extraction, which generally may either be a linear or non-linear transformation, is designed to preserve dominant information about recognition of object while ignoring information that is orthogonal to discrimination task. This is done by either reducing the dimensionality of input vectors or by mapping a large number of inputs into a relatively small number of feature vectors

The Wavelet transform has advantage of a physical meaningful interpretation that *canno*t be claimed by classical detection method such as matched filtering. However we *canno*t feed the entire wavelet transformation to recognizer, for it will result in too large recognizer and long calculation time. Then feature vector of small dimension is expected, and at the same time the feature vector must represent main properties of wavelet coefficients

Extraction of feature vector involved three phases:

1. Pre-processing,
2. Feature extracting by wavelet transform,
3. Construction feature vector.

When we define feature vector as [y (l), y (2)... y (N)], range profile vector is [x (l), x (2)... x (L)] that ha**s** been pre-processed aim**s** at removing effect of profile shift and its absolute amplitude. When the range profile vector pre-processing a**s**

$$x_p(i) = \frac{x(i)}{\sum_{i=1}^{N} x(i)^2},$$

Then absolute amplitude's effect is removed

The algorithm of constructing feature vector consist of next steps

- Threshold wavelet coefficients

$$\text{if} \quad |D_j(k)| < |max_j - min_j| \cdot 0,1 \quad \text{then } D_j(k) = 0$$

$$\text{else} \quad D_j(k) = \frac{D_j(k)}{|D_j(k)|}$$

For a given *j*, max $_j$, is the maximum of D_J (k), *and* max $_j$, is the minimum of D_J (k),

- Weight of detail coefficient

$$D_j(k) = \frac{D_j(k)}{2^{J-j}},$$

Where j is level decomposition and J number of decompositions.

- Constructing feature vector

$$y(i) = a_J(i) + \sum_{j=1}^{J} D_j\left(i2^{J-j}\right),$$

Where $i = 1, 2 \ldots N$.

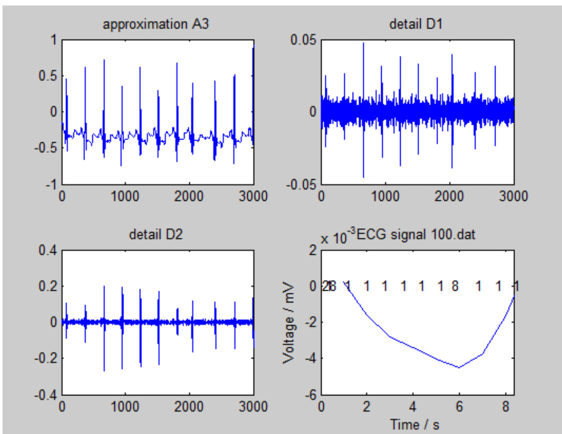

Fig2. Wavelet decomposition of radar signal

Radar Object Recognition System And Recognition Result

The objective of radar object recognition system is to assign observed input vector to one of several types. In general an object recognition system has two stages, extraction stage and recognition. The purpose of the feature extraction stage is to reduce the complexity of the input space by mapping raw inputs into feature vector in a feature space. Feature extraction, which generally may either, be a linear or non-linear transformation. This is designed to preserve type discriminate information while ignoring information that is orthogonal to the discrimination task. This is done by either reducing the dimensionality of input vectors or by mapping a large number of inputs into a relatively small number of feature vectors

Radar object recognition system based on wavelet transform and neural network shown in fig.3 was simulated in Matlab 5.3. A three-layer feed forward neural network was used as the recognizer, which has 5 neurons in input layer with the tansig transfer function, 25 neurons in hidden layer with the tansig transfer function and 1 neuron on output layer with

Dimension of feature vector is

$$N = \frac{L}{2^J}.$$

First step of the algorithm aims to remove little components under 10 % of processing signal. In step 2 we distinguish wavelet coefficients of different scale in feature vector and step 3 remain the dimension of feature vector be equal to (7), that is $1\backslash 2^J$ of the input signal

the purelin transfer function. The learning process containing 107

Epochs. The tansig and purelin transfer functions used in Matlab are tan-sigmoid and linear transfer function respectively. The Levenberg-Marquardt method of the learning is used. It is the fastest training algorithm for networks of moderate size. It has memory reduction feature for use when the training set is large.

Output of the neural network is number, which is associated with one of recognized radar object. The neural network was trained on PC Pentium II 400 *MHz* with RAM 64 MB. Elapsed time was 159 s. Process training of neural network shows in fig.4. For recognition were simulated five kinds of objects called object 1 through 5. These simulated backscattered signals from objects, which are represented by signal x_P (i) after preprocessing, are shown in fig.5.

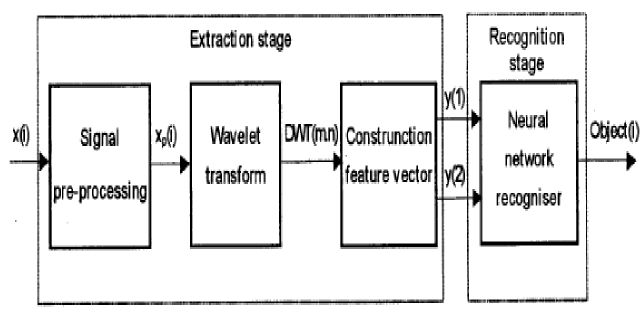

Fig.3 Radar Object Recognition System

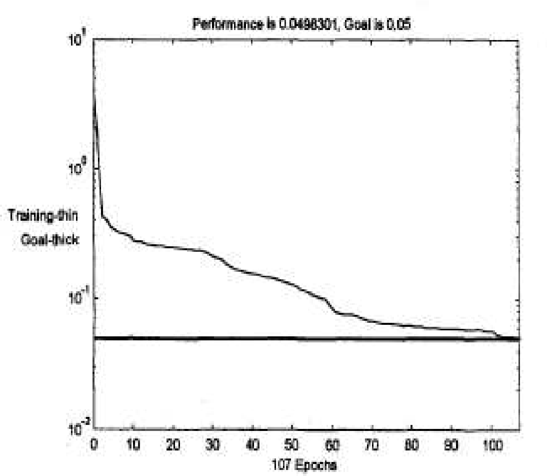

Fig.4 .Radar object recognition system

The simulated primitive echo has 32 samples in range and 50 periods in cross range. Four-step multiresolution decomposition is done using Mallat's pyramid algorithm. The dimension of output feature vector is 2. The simulated signals were divided into two sets, training set and test set. Training set was used to train a neural network and test set was used to examine recognition result. Reception results for signal-to-noise (SNR**)** 20 dB are shown in tab. 1. We aimed decrease of *SNR* opposite results in [7] by increasing training set and structure of neural network.

Simulation Result

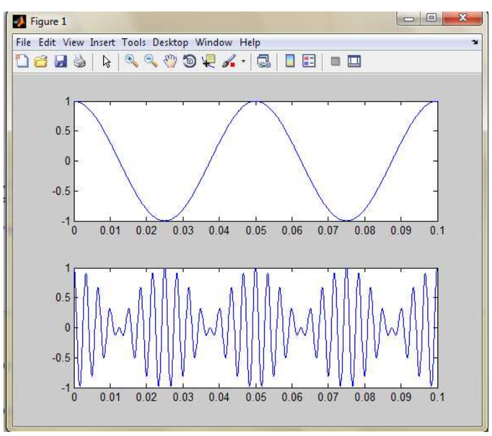

Fig.4 Input and modulated signal

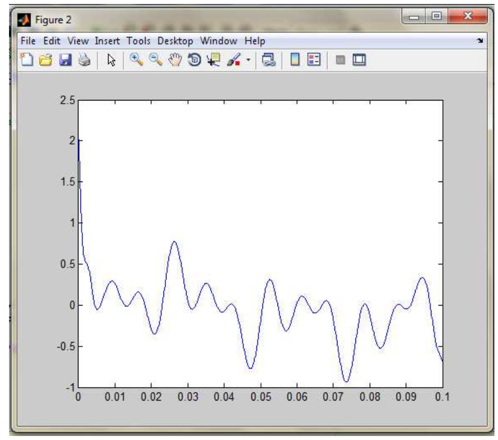

Fig.5 Scattered signal for a First Object

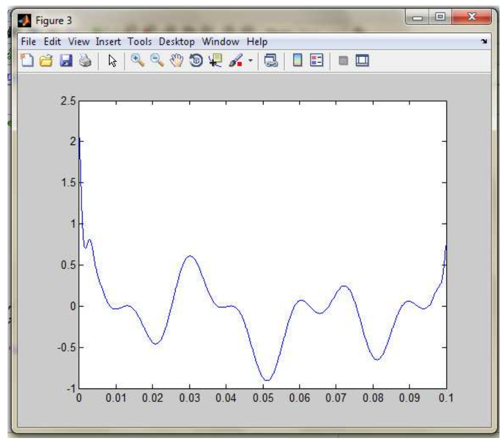

Fig.6 Scattered signal for second object

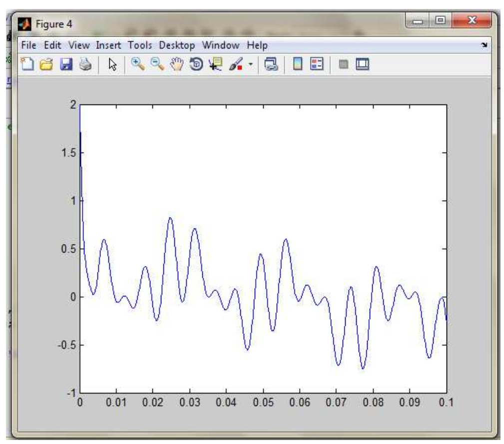

Fig.7 Scattered signal for third object

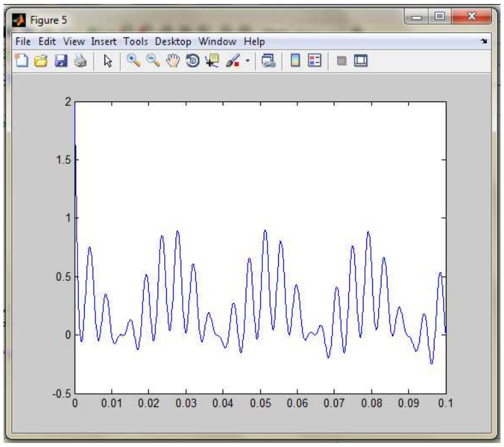

Fig.8 Scattered signal for fourth object Recognizer:-

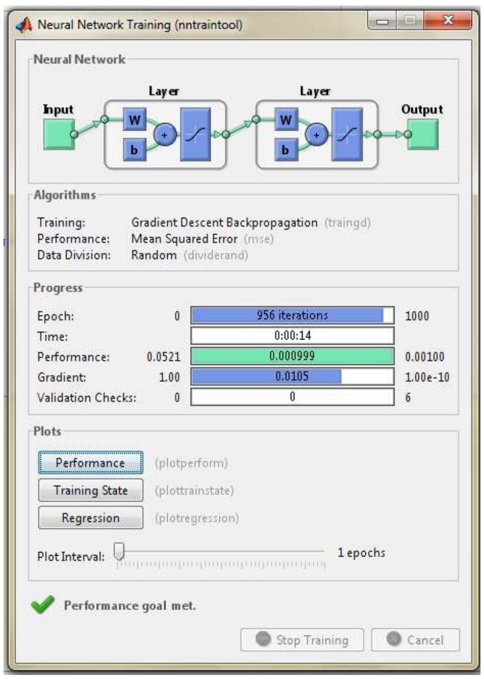

Fig.9 Neural network recognizer

Recognized Output

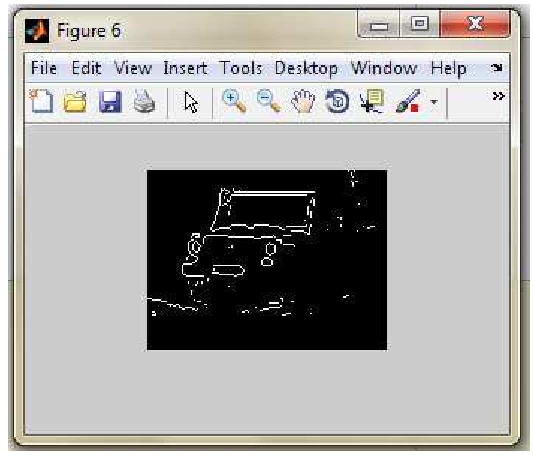

Fig.10 First Object

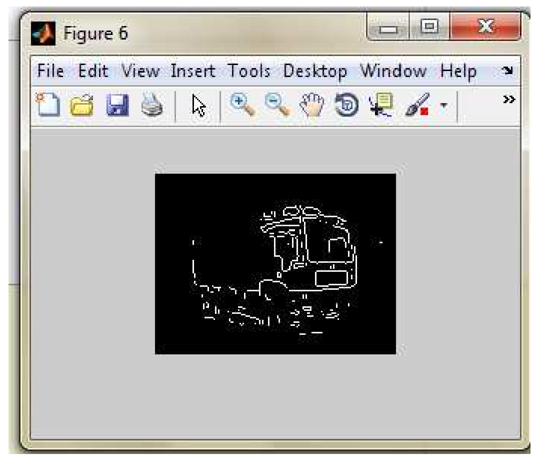

Fig.11 Second Object

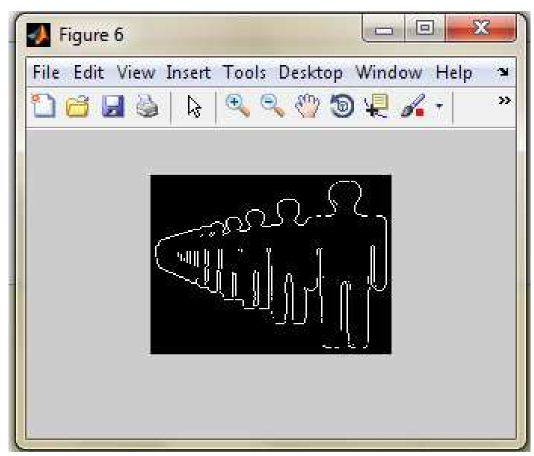

Fig.12 Third Object

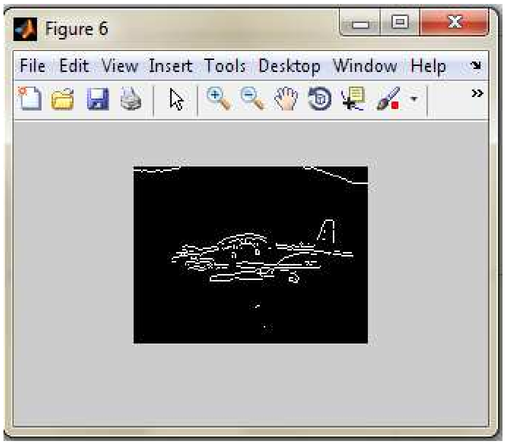

Fig.13 Fourth Object

Conclusion

A wavelet based recognizer is not computationally intensive and produces reliable recognition results that are, under certain measurement scenarios, superior to those of other recognizer. This paper presented radar Object recognition method based on wavelet transform and back propagation neural network. Wavelet transform and pre-processing of input vector by the algorithm presented above, we can decrease dimension of feature vector, which feed the neural network recognizer. The simulation results suggest that, with a further sophisticated a truly practical system will be developed. Some issues are addressed in the future in particular, strategies for recognition of low SNR

Acknowledgment

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