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A new automatic target recognition system based on wavelet extreme learning machine

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ABSTRACT

In this paper, an automatic system is presented for target recognition using target echo signals of High Resolution Range (HRR) radars. This paper especially deals with combination of the feature extraction and classification from measured real target echo signal waveforms by using X-band pulse radar. The past studies in the field of radar target recognition have shown that the learning speed of feedforward neural networks is in general much slower than required and it has been a major disadvantage. There are two key reasons forth is status of feedforward neural networks: (1) the slow gradient-based learning algorithms are extensively used to train neural networks, and (2) all the parameters of the networks are tuned iteratively by using such learning algorithms (Feng, Huang, Lin, & Gay, 2009; Huang & Siew, 2004, 2005; Huang & Chen, 2007, 2008; Huang, Chen, & Siew, 2006; Huang, Ding, & Zhou, 2010; Huang, Zhu, & Siew, 2004; Huang, Liang, Rong, Saratchandran, & Sundararajan, 2005; Huang, Zhou, Ding, & Zhang, in press; Huang, Li, Chen, & Siew, 2008; Huang, Wang, & Lan, 2011; Huang et al., 2006; Huang, Zhu, & Siew, 2006a, 2006b; Lan, Soh, & Huang, 2009; Li, Huang, Saratchandran, & Sundararajan, 2005; Liang, Huang, Saratchandran, & Sundararajan, 2006; Liang, Saratchandran, Huang, & Sundararajan, 2006; Rong, Huang, Saratchandran, & Sundararajan, 2009; Wang & Huang, 2005; Wang, Cao, & Yuan, 2011; Yeu, Lim, Huang, Agarwal, & Ong, 2006; Zhang, Huang, Sundararajan, & Saratchandran, 2007; Zhu, Qin, Suganthan, & Huang, 2005). To resolve these disadvantages of feedforward neural networks for automatic target recognition area in this paper suggested a new learning algorithm called extreme learning machine (ELM) for single-hidden layer feedforward neural networks (SLFNs) (Feng, Huang, Lin, & Gay, 2009; Huang & Siew, 2004, 2005; Huang & Chen, 2007, 2008; Huang, Chen, & Siew, 2006; Huang, Ding, & Zhou, 2010; Huang, Zhu, & Siew, 2004; Huang, Liang, Rong, Saratchandran, & Sundararajan, 2005; Huang, Zhou, Ding, & Zhang, in press; Huang, Li, Chen, & Siew, 2008; Huang, Wang, & Lan, 2011; Huang et al., 2006; Huang, Zhu, & Siew, 2006a, 2006b; Lan, Soh, & Huang, 2009; Li, Huang, Saratchandran, & Sundararajan, 2005; Liang, Huang, Saratchandran, & Sundararajan, 2006; Liang, Saratchandran, Huang, & Sundararajan, 2006; Rong, Huang, Saratchandran, & Sundararajan, 2009; Wang & Huang, 2005; Wang, Cao, & Yuan, 2011; Yeu, Lim, Huang, Agarwal, & Ong, 2006; Zhang, Huang, Sundararajan, & Saratchandran, 2007; Zhu, Qin, Suganthan, & Huang, 2005) which randomly choose hidden nodes and analytically determines the output weights of SLFNs. In theory, this algorithm tends to provide good generalization performance at extremely fast learning speed. Moreover, the Discrete Wavelet Transform (DWT) and wavelet entropy is used for adaptive feature extraction in the time-frequency domain in feature extraction stage to strengthen the premium features of the ELM in this study. The correct recognition performance of this new system is compared with feedforward neural networks. The experimental results show that the new algorithm can produce good generalization performance in most cases and can learn thousands of times faster than conventional popular learning algorithms for feedforward neural networks.

1. Introduction

So far, 1-D echo signals of High Resolution Range (HRR) have been directly used as features in the former automatic target recognition studies (Rong et al., 2009). This method has some disadvantages: They vary according to time and frequency shifts of 1-D radar target echo signal. Therefore, 3-D Time-Frequency Representations (TFR) of these 1-D echo signals are used because of the motion compensate and very suitable time-frequency localization features of TFR in later studies (Rong et al., 2009).

Military supports most of the work in High Range Resolution (HRR) target recognition (Huang, Zhu, & Siew, 2004). Target

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recognition area researchers appear to ignore the benefits that can be gained by proper transformations of the input signal (Huang et al., 2004, 2006).

The discrete wavelet transform (DWT) is used for image compression, edge detection, image classification, and more recently for target recognition as a new tool (Huang et al., 2004, 2006; Rong et al., 2009; Feng et al., 2009).

The different target types are separated in target recognition (Feng et al., 2009; Huang et al., 2004). In literature, the discrete wavelet transform (DWT) provides a richer feature space (Feng et al., 2009; Huang & Chen, 2007, 2008; Lan, Soh, & Huang, 2009; Li, Huang, Saratchandran, & Sundararajan, 2005;). However, this DWT method does not have widespread use (Huang et al., 2004). In reference (Huang & Chen, 2008), it is claimed that preprocessing the data allows easier subsequent feature extraction and increased resolution. In former studies, the signal was converted from a time domain to a frequency domain using the Fourier transform by engineers (Huang et al., 2008). Notwithstanding, this Fourier transform is useful for some signal converting applications, this converting wasn't excessively useful for automatic target recognition applications. The wavelets give a new tool to the HRR signal classification. Nowadays, the wavelets are used for the HRR signal classification in automatic radar target recognition (Huang et al., 2005; Zhu et al., 2005). The wavelet decomposition methods are very new transforms. These transforms are local and connected to the time when it occurs. In wavelet decomposition applications, it has been found that the original feature space can be augmented by the wavelet coefficients and will yield a smaller set of more robust features in the final classifier (Huang et al., 2004, 2005, 2006; Li et al., 2005; Liang et al., 2006; Yeu et al., 2006; Zhu et al., 2005).

In this study a novel method for automatic system for target recognition is presented. A combination of wavelet signal processing and extreme learning machine (ELM) for single-hidden layer feedforward neural networks (SLFNs) are used to efficiently extract the features from the pre-processed real target echo signals and classification for the automatic target recognition among different targets.

In automatic target recognition and multiple-target tracking areas, the novelties presented in this paper can be summarized as follow:

1. In this study, an effective adaptive feature extraction method that increases percentage of the correct target recognition is developed.
2. The second novelty is the development of the extreme learning machine (ELM) for single-hidden layer feedforward neural networks (SLFNs) as an efficient classification method in radar automatic target recognition area. The past studies in the field of radar target recognition have shown that the learning speed of feedforward neural networks is in general much slower than required and it is a major disadvantage. There are two reasons for this situation: (1) the slow gradient-based learning algorithms are extensively used to train neural networks, and (2) all the parameters of the networks are tuned iteratively by using such learning algorithms (Huang et al., 2006, 2010, 2011, in press; Liang et al., 2006). To resolve these disadvantages of feedforward neural networks for automatic target recognition area in this paper suggested a new learning algorithm called extreme learning machine (ELM) for single-hidden layer feedforward neural networks (SLFNs) (Huang et al., 2006, 2010, 2011, in press; Liang et al., 2006) which randomly choose hidden nodes and analytically determine the output weights of SLFNs. In theory, this algorithm tends to provide good generalization performance at an extremely fast learning speed. So far, this extreme learning machine (ELM) for single-hidden layer feedforward neural networks (SLFNs) method has not been applied to automatic radar target recognition literature. In this study, this extreme learning machine (ELM) for single-hidden layer feedforward neural networks (SLFNs) method firstly applied to automatic radar target recognition.

In this study, an experimental setup is used for obtaining the real target echo signal data sets. The radar experiment set used in this study, is a multi-functional Lab-Volt radar set (Model No: 9620/21). Pulse target echo signals are transmitted to the computer by using an audio card which has 44 kHz sampling frequency.

The paper is organized as follows: In Section 2, radar target echo signals, in Section 3, the discrete wavelet transform (DWT), in Section 4, Single hidden layer feedforward networks (SLFNs) with random hidden nodes, in Section 5, extreme learning machine (ELM), in Section 6, the proposed structure of discrete wavelet transform – extreme learning machine (ELM) for single-hidden layer feedforward neural networks (SLFNs) are presented respectively. In Section 7, the application results of proposed automatic system for target recognition using target echo signals of High Resolution Range (HRR) radars based on discrete wavelet transform – extreme learning machine (ELM) for single-hidden layer feedforward neural networks (SLFNs) is presented. Finally, in Section 8, the discussion and conclusions are given.

2. The structure of radar target echo signals

The meaning of the word of echo is reflection. The radar echo signal is the reflection signal. It reflects from target to Radar. There are many studies, in which echo signal were used for automatic target recognition in the radar target recognition literature (Li et al., 2005; Huang & Chen, 2007, 2008; Huang et al., 2008; Zhu et al., 2005).

Pulsed radar target echo signals are used as real input space in this study. In this application study, an efficient feature extraction method is used for eight target objects, which are a small metal plaque, a large metal plaque, a large Plexiglas plaque, a corner reflector, a sphere, the side part of a cylinder, the lower part of a cylinder, and the crosswise part of a cylinder, are shown in Fig. 1.

In here, experimental studies are achieved by using multi-functional Lab-Volt radar experiment set. Pulse radar echo signals are obtained and taken into the computer by using an audio card which has 44 kHz sampling frequency. A sample obtained target echo signal can be given in Fig. 2.

3. The discrete wavelet transform (DWT)

Due to its suitability for analyzing non-stationary signals, discrete wavelet transform (DCT) has become a powerful alternative to the Fourier methods in many target recognition applications, where such signals abound (Zhang et al., 2007).

The features of discrete wavelet transform (DWT) are a flexible window size, being wide for slow frequencies and narrow for the fast frequencies. This DWT method provides to an optimal time-frequency resolution in all frequency ranges. Moreover, frequency windows are adapted to the transients of each scale (Huang & Siew, 2004).

DWT resolves to high frequency constituent within a small time window, and only low frequency constituent need large time windows. When, this state of DWT requires a cycle in a large time interval for a low frequency constituent, it requires a cycle in a much shorter interval for a high frequency constituent. Hence,

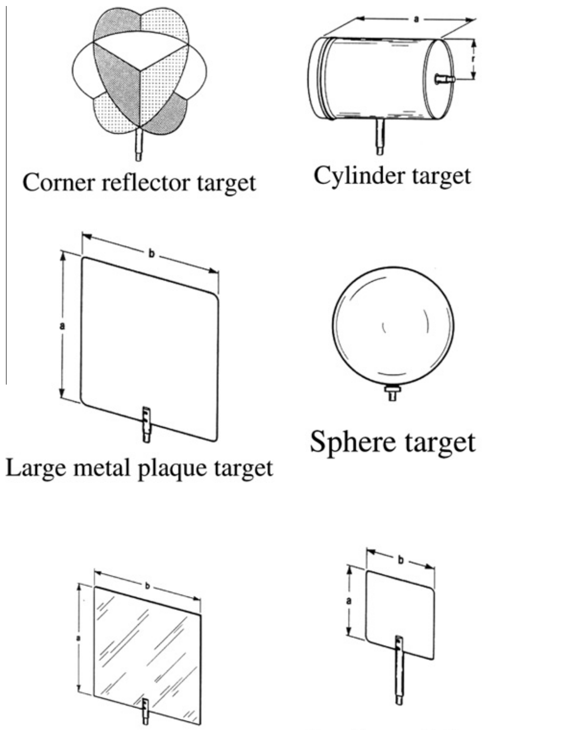

Fig. 1. Samples of used targets at radar experiment set for obtaining the target echo signal data sets.

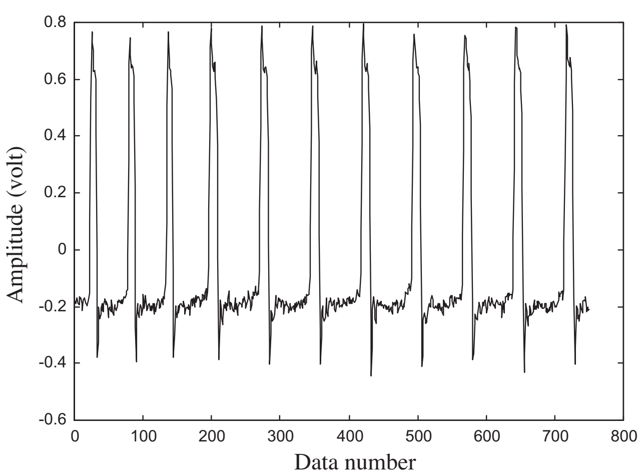

Fig. 2. A sample obtained target echo signal by using pulsed radar experimental set.

slow flexible constituents can only be defined over long time intervals but fast flexible constituents can be defined over short time intervals. DWT can be defined as sampled at variant frequencies at every level or stage of a continuous time wavelet decomposition (CWT). The DWT functions at level k and time location t_k can be explained as below:

$$j_k(t_j) = s(t)\psi_j\left(\frac{t-t_k}{2^k}\right) \tag{1}$$

Here, ψ_j is the decomposition filter at frequency level k. The effect of the decomposition filter is scaled by the factor 2^k at stage k, but otherwise the shape is the same at all stages. The synthesis of the signal from its time-frequency coefficients given in Eq. (2) can be regiven to explain the combination of the signal $s[i]$ from its DWT coefficients:

$$j[i] = s[i]f[i], \quad r[i] = s[i]l[i] \tag{2}$$

here, $f[i]$ is the impulse response of the high pass filter and $l[i]$ is the impulse response of the low pass filter (Huang & Siew, 2005). The readers can be found more information about the DWT in references (Zhang et al., 2007; Huang & Siew, 2004, 2005).

4. Single hidden layer feedforward networks (SLFNs)

In the Structure of Single Hidden Layer Feedforward Networks (SLFNs), f arbitrarily different samples can be given as (s_i, p_i) or G hidden nodes, where $s_{i1} = [s_{i1}, s_{i2}, \ldots, s_{il}]^T \in R^l$ and $p_{i1} = [p_{i1}, p_{i2}, \ldots, p_{il}]^T \in R^k$. Standard SLFNs with $\widetilde{G}$ hidden nodes and activation function $f(s)$ are mathematically modeled as on Eq. (3):

$$\sum_{i=1}^{\widetilde{G}} \gamma_i f_i(s_r) = \sum_{i=1}^{\widetilde{G}} \gamma_i f(j_i.s_r + c_i) = v_r, \quad r = 1, \ldots, G, \tag{3}$$

here $j_i = [j_{i1}, j_{i2}, j_{i3}, \ldots, j_{il}]^T$ is the weight vector connecting the ith hidden node and the input nodes, $\gamma_i = [\gamma_{i1}, \gamma_{i2}, \gamma_{i3}, \ldots, \gamma_{ik}]^T$ is the weight vector connecting the ith hidden node and the output nodes, and c_i is the threshold of the ith hidden node. $j_i.s_r$ denotes the inner product of j_i and s_r. The output nodes are chosen linear in this paper. The readers can find more information about the SLFNs in references Huang et al. (2010, 2011, in press).

5. The structure of the extreme learning machine (ELM)

The difference of structure of the Extreme Learning Machine (ELM) from a standard SLFN is given below. According to this, given a standard SLFN with G hidden nodes and activation function $f: R \to R$ which is infinitely differentiable in any interval, for G arbitrary distinct samples (s_i, p_i), where $s_i \in R^l$ and $p_i \in R^k$ for any j_i and c_i randomly chosen from any intervals of R^l and R, respectively, according to any continuous probability distribution, then with probability one, the hidden layer output matrix N of the SLFN is invertible and $\|N\gamma - P\| = 0$ (Huang et al., 2010, 2011, in press).

Given any small positive value $\delta > 0$ and activation function $f: R \to R$ which is infinitely differentiable in any interval, there exists $G \leqslant \widetilde{G}$ such that for G arbitrary distinct samples (s_i, p_i), where $s_i \in R^l$ and $p_i \in R^k$, for any j_i and c_i randomly chosen from any intervals of R^l and R, respectively, according to any continuous probability distribution, then with probability one, $\|N_{Gx\widetilde{G}}\gamma_{\widetilde{G}} - P_{Gxk}\| < \delta$ (Huang et al., 2010, 2011, in press).

6. The proposed structure of discrete wavelet transform (DWT) – extreme learning machine (ELM)

In this study, a new Discrete Wavelet Transform (DWT) – Extreme Learning Machine (ELM) method is proposed for automatic radar target recognition. In Fig. 3, the structure of proposed method is given. According to this, the structure of proposed new DWT-ELM method for automatic radar target recognition system composes from (1) data acquisition and pre-processing and (2) feature extraction and classification stages.

6.1. Data acquisition and pre-processing stage of proposed DWT-ELM method

In these experimental studies, used original Radar Target Echo (RTE) signals are obtained using the multi-functional Lab-Volt radar experimental set. The picture of the used multi-functional Lab-Volt radar experimental set is shown in Fig. 4. The parameters

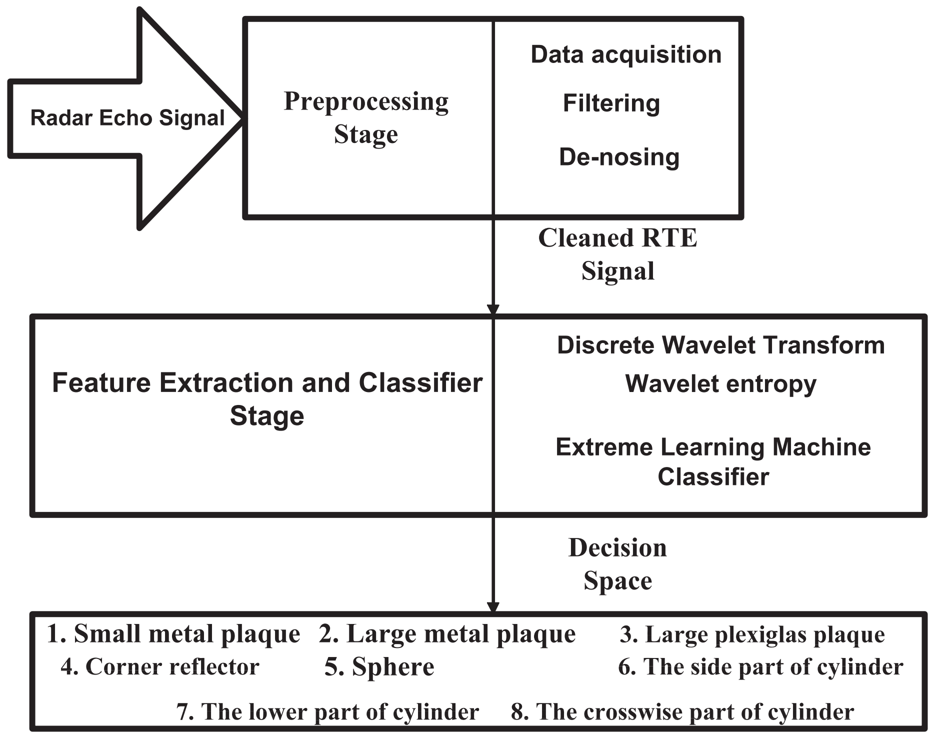

Fig. 3. The algorithm of the DWT-ELM for automatic radar target recognition system.

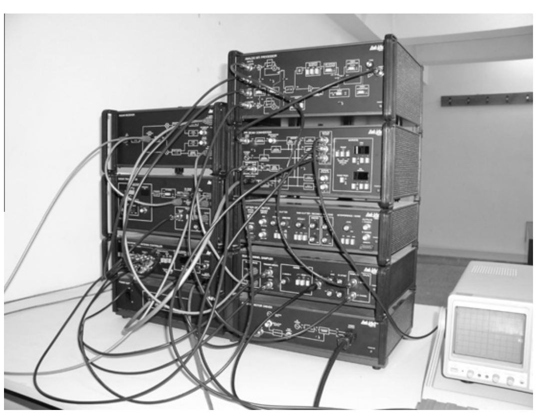

Fig. 4. The picture of the used multi-functional Lab-Volt radar experimental set (Model No: 9620/21).

of this radar experimental set for these experimental studies can be given as Pulse width: 2 ns, RF oscillator: 9.4 GHz, Pulse Repeat Frequency (PRF): 144 Hz, Radar receiver antenna – targets table between distances: 115 cm.

Pulsed Radar Echo signals obtained from the small metal plaque, the large metal plaque, the large plexiglas plaque, the corner reflector, the sphere and the cylinder targets are taken into the computer by using an audio card which has 44 kHz sampling frequency.

In the pre-processing, the obtained radar target echo signals are digitized to acquire the feature vector. The stages of the pre-processing can be shown as below:

(a) *Filtering process*: The acquired RTE signals are filtered by using high-pass filters to remove unwanted low-frequency components, because the RTE signals are generally in the range of 0.5–2 kHz. The filter used in these experimental studies is a digital FIR, which is a 50th-order filter with a cut-off frequency equal to 500 Hz and window type is the 51-point symmetric Hamming window.

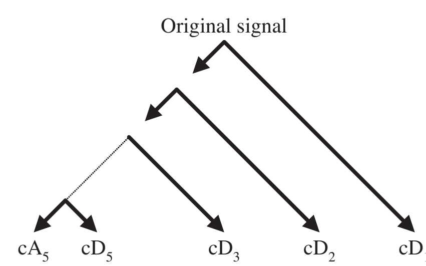

Fig. 5. The DWT decomposition structure by using Symlets wavelet filter of order 6.

(b) *De-noising process*: In this experimental study, used white noise is a random signal that includes equal amounts of every possible frequency, i.e., its FFT has a flat spectrum (Yeu et al., 2006). The radar target echo signals are filtered to reduce the effects of white noise by using DWT. The de-noising procedure includes three steps (Wang & Huang, 2005):

- *Decomposition process*: In this step, the DWT decomposition of the RTE signal is computed at level 5 and using the Symlets wavelet filter of order 6. This decomposition structure can be given as in Fig. 5.
- *The implementation of the thresholding process to detail coefficients*: In this step, the soft thresholding for each level from 1 to 5 is applied to the detail coefficients. This thresholding algorithm can be given as below:

1. Calculate wavelet transform and order the coefficients by increasing frequency. This will result in an array containing the time series average plus a set of coefficients of

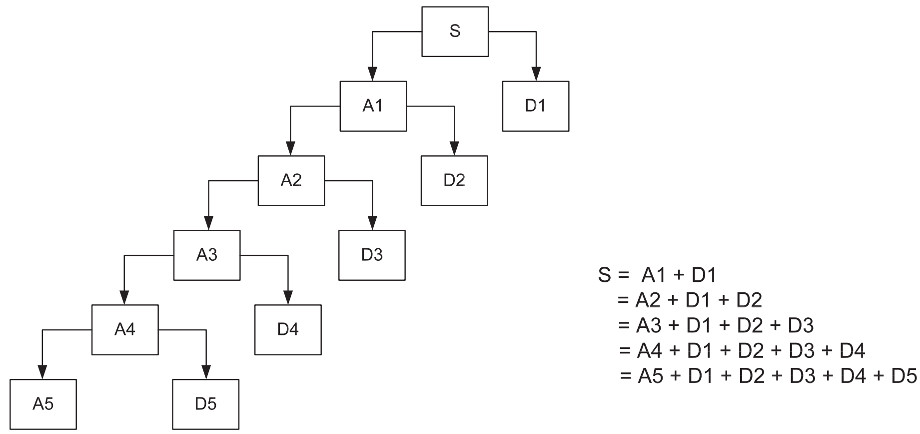

Fig. 6. The used reconstruction tree of RTE signals in this study.

length 1, 2, 4, 8, ... The noise threshold will be calculated on the highest frequency coefficient spectrum (this is the largest spectrum).

2. Calculate the median absolute deviation on the largest coefficient spectrum. The median is calculated from the absolute value of the coefficients. The equation for the median absolute deviation is shown below:

$$\delta(\mathrm{mad}) = \frac{\mathrm{median}\{|c_0|, |c_1|, \ldots, |c_{2^{n-1}-1}|\}}{0.6745} \quad (4)$$

Here c_0, c_1, etc. are the coefficients.
The factor 0.6745 in the denominator rescales the numerator so that δ(mad) is also a suitable estimator for the standard deviation for white noise (Wang & Huang, 2005; Wang et al., 2011).

3. For calculating the noise threshold I have used a modified version of the equation in below:

$$\tau = \delta_{\mathrm{mad}}\sqrt{\ln(N)} \quad (5)$$

In this equation N is the size of the time series.

4. Applying the soft thresholding to these coefficients. The threshold is subtracted from any coefficient that is greater than the threshold. This moves the time series toward zero.

```
a.  if (coef[i] <= thresh)
b.    coef[i] = 0.0;
c.  else
d.    coef[i] = coef[i] -
    thresh;
```

- *Reconstruction process*: In this step, DWT reconstruction is computed based on the original approximation coefficients of level 5 and the modified detail coefficients of levels from 1 to 5. For this aim, the wavelet reconstruction filters are used.

The filtering part of the reconstruction process also bears some discussion, because it is the choice of filters that is crucial in achieving perfect reconstruction of the original signal. The type of this filter was selected at results of some testing for optimum reconstruction result. The downsampling of the signal components performed during the decomposition phase introduces a distortion called aliasing. It turns out that by carefully choosing filters for the decomposition and reconstruction phases that are closely related (but not identical), it can eliminate the effects of aliasing. A technical discussion of how to design these filters is available in Wang and Huang (2005). The low- and high-pass decomposition filters (L and H), together with their associated reconstruction filters (L′ and H′), form a system of what is called *quadrature mirror filters*.

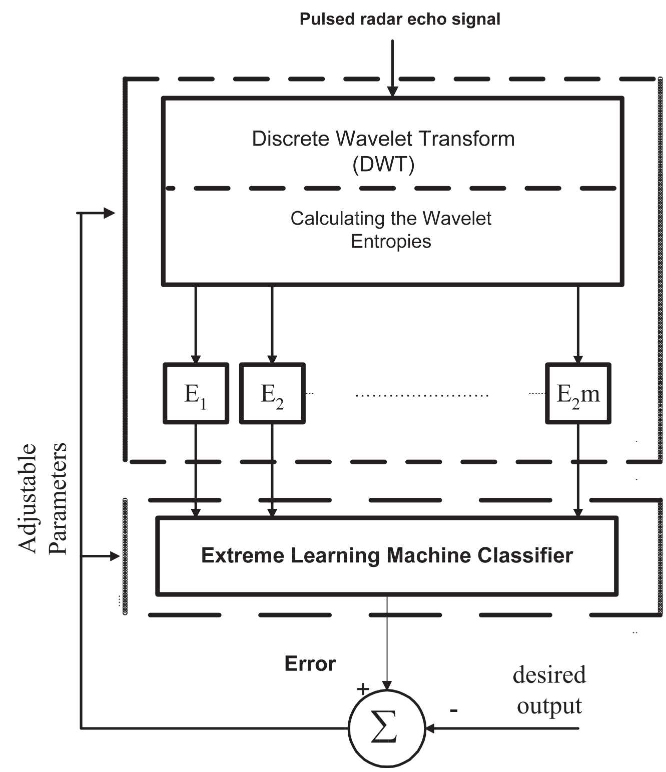

Fig. 7. The structure of a new proposed DWT-ELM for automatic radar target recognition.

In this study, Symlets wavelet filter of order 6 is used for reconstruction of the original signal. In reconstruction process, the Matlab functions are used (Liang, 2008; Pei, Bao, & Xing, 2002; Wang & Huang, 2005; Wang et al., 2011). The reconstruction tree used in this study can be given as below in Fig. 6:

In here, S is original RTE signal, A_i is ith level approximation of the original RTE signal, D_i is ith level detail of the original RTE signal.

These values of the used parameter, which are DWT decomposition level, wavelet filter type, soft thresholding value, etc. in these experimental studies are selected by testing to find the their optimal values.

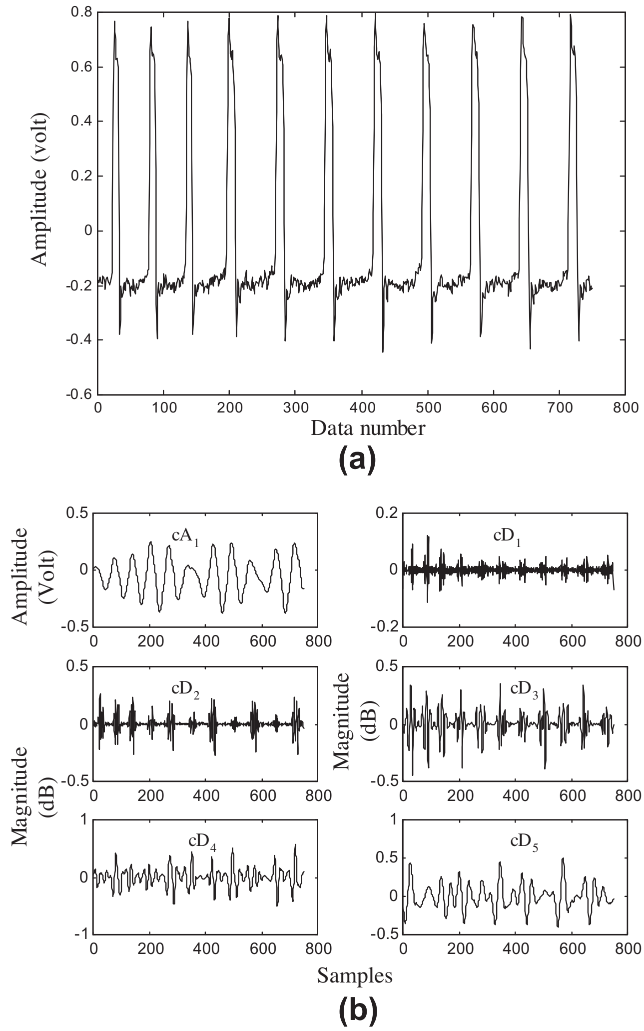

Fig. 8. (a) Original RTE signal and (b) wavelet decomposition at five levels of this RTE signal.

Table 1
DWT-ELM architecture and training parameters.

Architecture	
The number of layers	
	Input Number: 8
	Hidden Layer Number: 1
	Neuron Number of Hidden Layer: 20
	Output: 1
Activation functions	Tangent Sigmoid
Learning rule	The Extreme Learning Machine (ELM) for Single-hidden Layer Feedforward Neural Networks (SLFNs)
Sum-squared error	0.0000001

6.2. Feature extraction and classification stage of proposed DWT-ELM method

In these experimental studies, the structure of a new proposed DWT-ELM is used. This proposed DWT-ELM can be given as in Fig. 7. In this feature extraction and classification stage of a new proposed DWT-ELM for automatic radar target recognition, there are two stages: (1) Feature Extraction Stage and (2) Classification Stage. The Feature extraction stage is the key for pattern recognition so that it is the most significant constituent of designing the automatic system based on pattern recognition since the best classifier will perform poorly if the features are not chosen well. An effective feature extractor should reduce the pattern vector (i.e., the original waveform) to a lower dimension that includes most of the useful information from the original vector.

The RTE signals are affluent in detail and highly non-stationary. The steps of the feature extraction and classification stage of proposed DWT-ELM can be given as below:

- ***Discrete wavelet transform (DWT)***: This DWT layer is used for feature extraction from RTE signals. The DWT decomposition tree structure has 5 levels in these experimental studies. In these experimental studies, 8 targets are used to obtain the RTE signals. 15 RTE signals that have variant distances to radar transmitter antenna are used for each of these targets. So, the total number of the acquired RTE signals from the radar experimental set is 120. The decomposition tree can be given as in Fig. 8. The DWT decomposition is applied to the RTE signal by using the Symlets 6 wavelet decomposition filters. Thus, an approximation coefficient cA and five of detail coefficients cDs of each of used RTE signals are obtained. In Fig. 8, the obtained RTE signal and wavelet decomposition at 5 levels of this RTE signal are given respectively.
- ***The calculating of wavelet entropy***: The entropy contains information-related properties for a true representation of a given signal. The concept of entropy is commonly used in many fields, which are signal processing, image processing, etc., (Wang & Huang, 2005; Wang et al., 2011). The using of entropy is an appropriate method to show the disorder of non-stationary signals. In these experimental studies, defined the sure entropy can be given in Equal (6). Here, the sure entropy is calculated by using the dataset at the terminal node signals obtained from wavelet decomposition:

$$E(s) = \sum_{i=0} \min(s_i^2, \varepsilon^2)/N \quad \text{if } |s_i| \leqslant \varepsilon. \tag{6}$$

  Here, the wavelet entropy E is a real number, s is the terminal node signal and s_i is the ith waveform of terminal node signals. In these experimental studies, the threshold ε is used as $1 \leqslant \varepsilon \leqslant 8$. During the DWT-ELM learning process, the ε parameter is updated by using 0.1 increasing steps together with the weights to minimize the error. The resultant entropy data are normalized with $N = 100$. So, the feature vector is extracted by computing the six wavelet entropy values per RTE signal.
- ***DWT-ELM classifier***: This *DWT-ELM Classifier* layer the automatic classification using features from DWT. The training parameters and the structure of the *DWT-ELM Classifier* used in these experimental studies are shown in Table 1. The values of these parameters, which are type and number of activation function, learning rate are evaluated for the best performance after several different experiments.

7. The application results of proposed DWT-ELM method for automatic radar target recognition

In these experimental studies, 15 RTE signals that have variant distances to radar transmitter antenna are used for each of used targets, which are small metal plaque, large metal plaque, large plexiglas plaque, corner reflector, sphere, the side part of cylinder, the lower part of cylinder and the crosswise part of cylinder

Table 2
The results of testing experimental studies of proposed DWT-ELM method for automatic radar target recognition.

	Small metal plaque	Large metal plaque	Plexiglas plaque	Corner reflector	Sphere	The side part of cylinder	The lower part of cylinder	The crosswise part of cylinder
Total number of samples	45	45	45	45	45	45	45	45
Correct classification #	43	41	43	40	42	42	39	41
Incorrect classification #	2	4	2	5	3	3	6	4
The average recognition (%)	95.55	91.11	95.55	88.88	93.33	93.33	86.66	91.11

Table 3
The performance comparing results of proposed DWT-ELM method with BP and SVM methods.

Algorithms	Spent time (s)		Correct recognition rate (%)	
	Training	Testing	Training	Testing
ELM	0.189	0.0076	100	91.94
SVM	0.486	0.0109	97.36	89.55
BP	7.892	0.0984	96.54	87.23

targets. So, the total number of the acquired RTE signals from the radar experimental set is $8 \times 15 = 120$. At a later stage, the noises, which have different white-noise amplitudes (Signal/Noise Rate (SNR) = −2 dB, −3 dB, and −5 dB), are added to each of these original 120 RTE signals. Therefore, 120 numbers of original signals and 360 number noisy RTE signal are obtained (total 480 RTE signals).

120 numbers original RTE signals of these total 480 original and noisy RTE signals are used for training of ELM classifier. The rest of the RTE signals are used in the testing of the proposed DWT-ELM method for automatic radar target recognition. In training experimental studies, 100% correct recognition rate is obtained for the 8 variant radar target echo signals. This status clearly shows the effectiveness and the reliability of the proposed approach for extracting features from RTE signals. The results of testing experimental studies of proposed DWT-ELM method for automatic radar target recognition can be shown in Table 2. According to these results, the average recognition rate of proposed DWT-ELM method for automatic radar target recognition is about 91.94%.

In this section, the performance of the proposed ELM learning algorithm for automatic radar target recognition is compared with the popular algorithms of feedforward neural networks like the conventional BP algorithm and support vector machines (SVMs) by using same feature vector (Avcı, Türkoğlu, & Poyraz, 2005a, 2005b; Kubrusly & Levan, 2009; Le, Tamura, & Matsumoto, 2011; Pei et al., 2002; Wink & Roerdink, 2010). All the experimental studies for the BP and ELM algorithms are carried out in MATLAB 7.7.0 (Liang, 2008; Tabib, Sathe, Deshpande, & Joshi, 2009). environment running in a PC has quad core and 4×2.83 GHz CPU. Although there are many variants of BP algorithm, a faster BP algorithm called Levenberg–Marquardt algorithm is used in our simulations.

The Levenberg–Marquardt algorithm is faster than all traditional BP learning algorithms in feedforward neural networks (Huang et al., 2010, 2011, in press). The experimental studies for SVM are carried out by using compiled C-coded SVM packages: LIBSVM (Huang, Chen, & Siew, 2006) running in the same PC. In these experimantal studies, the radial basis function is used as kernel function in SVM, whereas the activation function used in proposed ELM learning algorithms is a simple tangent-sigmoidal function: $f(x) = ((1 - \exp(-x))/(1 + \exp(-x)))$.

In these experimental studies, all the inputs (attributes) have been normalized into the range [0, 1] while the outputs (targets) have been normalized into [−1, 1]. In end of training stage of ELM learning algorithm, the training time of ELM is mainly spent on calculating the Moore–Penrose generalized inverse H^{-1} of the hidden layer output matrix H.

In Table 3, The performance comparing results of proposed DWT-ELM method with BP and SVM methods are given as below:

8. Discussions and conclusion

In this study, an automatic system for the interpretation of the RTE signals by using pattern recognition is developed and the target recognition performance of this method is demonstrated on 8 variant targets, which are the small metal plaque, large metal plaque, large plexiglas plaque, corner reflector, sphere, the side part of cylinder, the lower part of cylinder, and the crosswise part of cylinder.

In here, an automatic system is presented for target recognition using target echo signals of High Resolution Range (HRR) radars. This paper especially deals with combination of the feature extraction and classification from measured real target echo signal waveforms using X-band pulse radar. The past studies in the field of radar target recognition have shown that the learning speed of feedforward neural networks is in general very slower than required and it has been a major disadvantage. There are two key reasons fort his status of feedforward neural networks: (1) the slow gradient-based learning algorithms are extensively used to train neural networks, and (2) all the parameters of the networks are tuned iteratively by using such learning algorithms (Huang et al., 2006, 2010, 2011, in press; Liang et al., 2006). To resolve these disadvantages of feedforward neural networks for automatic target recognition area in this paper suggested a new learning algorithm called extreme learning machine (ELM) for single-hidden layer feedforward neural networks (SLFNs) Huang et al., 2006, 2010, 2011, in press; Liang et al., 2006 which randomly chooses hidden nodes and analytically determines the output weights of SLFNs. In theory, this algorithm tends to provide good generalization performance at extremely fast learning speed. Moreover, the Discrete Wavelet Transform (DWT) and wavelet entropy is used for adaptive feature extraction in the time-frequency domain in feature extraction stage to strengthen the premium features of the ELM in this study. The correct recognition performance of this new system is compared with feedforward neural networks. The experimental results show that the new algorithm can produce good generalization performance in most cases and can learn thousands of times faster than conventional popular learning algorithms for feedforward neural networks.

The experimental results show that the proposed new learning algorithm called extreme learning machine (ELM) for single-hidden layer feedforward neural networks (SLFNs) can perform an effective interpretation. The performance of the new Discrete Wavelet Transform (DWT)-Extreme Learning Machine (ELM) method for automatic radar target recognition is given in Tables 2 and 3.

The experimental results have demonstrated that the discrete wavelet transform (DWT) decomposition and calculating of wavelet entropy are effective tools for extracting information from the RTE signal dataset. The suggested feature extraction method is robust against to noise in the RTE signal dataset.

In this paper, the application of the wavelet entropy in the wavelet layer of DWT-ELM to the adaptive feature extraction from

RTE signals are introduced. The wavelet entropy used in these experimental studies is very effective feature for characterizing the RTE signal.

The most important aspect of the new Discrete Wavelet Transform (DWT)-Extreme Learning Machine (ELM) method for automatic radar target recognition is the ability of self-organization of the DWT-ELM without requirements of programming and the immediate response of a trained net during real-time applications.

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