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# A new method for expert target recognition system: Genetic wavelet extreme learning machine (GAWELM)

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ABSTRACT

In last year's, the expert target recognition has been become very important topic in radar literature. In this study, a target recognition system is introduced for expert target recognition (ATR) using radar target echo signals of High Range Resolution (HRR) radars. This study includes a combination of an adaptive feature extraction and classification using optimum wavelet entropy parameter values. The features used in this study are extracted from radar target echo signals. Herein, a genetic wavelet extreme learning machine classifier model (GAWELM) is developed for expert target recognition. The GAWELM composes of three stages. These stages of GAWELM are genetic algorithm, wavelet analysis and extreme learning machine (ELM) classifier. In previous studies of radar target recognition have shown that the learning speed of feedforward networks is in general much slower than required and it has been a major disadvantage. There are two important causes. These are: (1) the slow gradient-based learning algorithms are commonly used to train neural networks, and (2) all the parameters of the networks are fixed iteratively by using such learning algorithms. In this paper, a new learning algorithm named extreme learning machine (ELM) for single-hidden layer feedforward networks (SLFNs) Ahern, Delisle, et al., 1989; Al-Otum & Al-Sowayan, 2011; Avci, Turkoglu, & Poyraz, 2005a, 2005b; Biswal, Dash, & Panigrahi, 2009; Frigui et al., in press; Cao, Lin, & Huang, 2010; Guo, Rivero, Dorado, Munteanu, & Pazos, 2011; Famili, Shen, Weber, & Simoudis, 1997; Han & Huang, 2006; Huang, Cai, Chen, & Liu, 2011; Huang, Chen, & Siew, 2006; Huang & Siew, 2005; Huang, Liu, Gao, & Guo, 2009; Jiang, Liu, Li, & Tang, 2011; Kubrusly & Levan, 2009; Le, Tamura, & Matsumoto, 2011; Lhermitte et al., 2011; Martínez-Martínez et al., 2011; Matlab, 2011; Nelson, Starzyk, & Ensley, 2002; Nejad & Zakeri, 2011; Tabib, Sathe, Deshpande, & Joshi, 2009; Tang, Sun, Tang, Zhou, & Wei, 2011, which randomly choose hidden nodes and analytically determines the output weights of SLFNs, to eliminate the these disadvantages of feedforward networks for expert target recognition area. Then, the genetic algorithm (GA) stage is used for obtaining the feature extraction method and finding the optimum wavelet entropy parameter values. Herein, the optimal one of four variant feature extraction methods is obtained by using a genetic algorithm (GA). The four feature extraction methods proposed GAWELM model are discrete wavelet transform (DWT), discrete wavelet transform–short-time Fourier transform (DWT–STFT), discrete wavelet transform–Born–Jordan time–frequency transform (DWT–BJTFT), and discrete wavelet transform–Choi–Williams time–frequency transform (DWT–CWTFT). The discrete wavelet transform stage is performed for optimum feature extraction in the time–frequency domain. The discrete wavelet transform stage includes discrete wavelet transform and calculating of discrete wavelet entropies. The extreme learning machine (ELM) classifier is performed for evaluating the fitness function of the genetic algorithm and classification of radar targets. The performance of the developed GAWELM expert radar target recognition system is examined by using noisy real radar target echo signals. The applications results of the developed GAWELM expert radar target recognition system show that this GAWELM system is effective in rating real radar target echo signals. The correct classification rate of this GAWELM system is about 90% for radar target types used in this study.



## 1. Introduction

In expert target recognition literature, radar target echo signals are used commonly as characteristic feature in the target recognition area. There are some disadvantages of using of 1-D radar target echo signal because of depending on the time and frequency

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shift. Many studies have been performed on 3-D time–frequency representations (TFR) of these 1-D echo signals for motion compensation for this aim (Ahern et al., 1989; Al-Otum & Al-Sowayan, 2011; Avci et al., 2005a, 2005b; Biswal et al., 2009; Cao et al., 2010; Famili et al., 1997; Frigui et al., in press; Guo et al., 2011; Han & Huang, 2006; Huang et al., 2006, 2011).

The discrete wavelet transform (DWT) is performed for image compression, edge detection, image classification, and more recently, target recognition as a new tool (Huang & Siew, 2005; Huang et al., 2009; Jiang et al., 2011; Kubrusly & Levan, 2009; Le et al., 2011; Nejad & Zakeri, 2011; Nelson et al., 2002; Tabib et al., 2009; Tang et al., 2011; Wang, Cao, & Yuan, 2011; Wink & Roerdink, 2010). The most significant aim in expert target recognition (ATR) is to separate the different target types (Kubrusly & Levan, 2009; Le et al., 2011; Nelson et al., 2002; Wink & Roerdink, 2010). Some researchers have explored the use of discrete wavelet transforms (DWT) for expert target recognition. It provides an extreme feature vectors (Famili et al., 1997; Kubrusly & Levan, 2009; Tabib et al., 2009; Tang et al., 2011; Wang et al., 2011; Wink & Roerdink, 2010; Worden, Staszewski, & Hensman, 2011; Yang, Xu, & Dai, 2010). Moreover, this is not common using (Nelson et al., 2002). It is explained in Famili et al. (1997) that preprocessing the data permits simple important feature extraction and increases resolution. The 1-D radar target echo signal is converted from the time domain to the frequency domain base by using the Fourier transform (Huang et al., 2011). Notwithstanding the Fourier transform is used for some expert radar target recognition applications. This Fourier transform is not very useful for these applications. Because the Fourier transform shows that a feature occurs somewhere in the signal, but not where. The using of DWT in expert radar target recognition is very useful because of the original feature space can be augmented by discrete wavelet transform coefficients. A smaller set of more robust features for the final classifier causes the effective results of using of DWT in expert radar target recognition (Huang & Siew, 2005; Huang et al., 2006, 2009, 2011; Jiang et al., 2011; Nelson et al., 2002; Tabib et al., 2009).

The feature extraction stage is most important stage of a pattern recognition (Ahalt, Jung, & Krishnamurthy, 1990; Du, Liu, & Bao, 2006; Du et al., 2011; Yang, Wang, Lu, Qi, & Jiao, 2009; Younus and Yang, 2011; Yun, Xuelian, Minglei, & Xuegang, 2011; Zhang, 2011; Zhang & Lei, 2011; Zhao & Ye, 2011; Zhengyou et al., 2011). In Cao, Lin, and Huang (2011), Cao et al. (2010), a new structure of wavelet neural networks (WNN) with extreme learning machine (ELM) is presented. In the suggested WNN, composite functions are used at the hidden nodes and the learning is performed using ELM. Herein, the input dataset is first processed by wavelet functions and then passed through a type of bounded nonconstant piecewise continuous activation functions. The domain of input space where the wavelets are not zero is performed to initialize the translation and dilation parameters by using this method. The created WNN is then trained with the computationally efficient ELM algorithm. Experimental results show that the suggested neural networks can achieve better performances in most cases than some relevant neural networks and learn much faster than neural networks training with the traditional back-propagation (BP) algorithm. In this paper, a novel genetic wavelet extreme learning machine classifier model (GAWELM) method is used as different from that described method in Cao et al. (2010, 2011). The advantages of this GAWELM methodology to the other method in Cao et al. (2010, 2011) can be summarized as follows.

In this paper, a novel *genetic wavelet extreme learning machine classifier model (GAWELM)* method for expert target recognition is presented. The *GAWELM* method uses a combination of genetic algorithm (GA), discrete wavelet transform (W) signal processing and extreme learning machine classifier (ELM) for efficient feature extraction from pre-processed real target echo signals. This new method for expert target recognition is named as GAWELM. In the radar automatic target recognition area, the novelties and superiorities other ELM methods of presented GAWELM in this paper can be summarized as follows:

- The first novelty in this study is the use of an effective adaptive feature extraction method for automatic target recognition.
- The second novelty in this study is the use of a genetic algorithm (GA) wavelet extreme learning machine (ELM) (GAWELM) model for selecting the feature extraction method and finding the optimum wavelet entropy parameter values.
- Moreover, in this study, an effective adaptive feature extraction method that increases percentage of the correct target recognition is developed.
- One of the most important novelties presented in this study is the development of the extreme learning machine (ELM) classifier for single-hidden layer feedforward 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 very slower than required and it has been a major disadvantage. There are two key reasons for this 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 (Han & Huang, 2006; Huang & Siew, 2005; Huang et al., 2006, 2009, 2011). To resolve these disadvantages of feedforward neural networks for automatic target recognition area in this paper, a new learning algorithm called extreme learning machine (ELM) for single-hidden layer feedforward neural networks (SLFNs), Han & Huang, 2006; Huang et al., 2006, 2009, 2011; Huang & Siew, 2005 which randomly chooses hidden nodes and analytically determines the output weights of SLFNs, is suggested. In theory, this algorithm tends to provide good generalization performance at highly fast learning speed.
- So far, this extreme learning machine (ELM) for single-hidden layer feedforward 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 networks (SLFNs) method firstly applied to automatic radar target recognition.

These novelties are presented for increasing the correct target recognition rates in this study.

The paper is organized as follows. In Section 2, discrete wavelet transform is introduced. In Section 3, time–frequency transforms are given. In Section 4, the entropy concept is introduced. In Section 5, genetic algorithms (GA) concept is presented. In Section 6, extreme learning machine (ELM) classifiers are reviewed. In Section 7, GAWELM for radar target recognition is presented. In Section 8, the experimental studies concluded by using GAWELM are explained and results of these experimental studies are given respectively. Finally, Section 9 presents discussion and conclusion.

## 2. Discrete wavelet transform

Discrete wavelet transforms (DWTs) are rapidly surfacing in fields as diverse as telecommunications and radar target recognition. Due to their suitability for analyzing non-stationary signals, DWTs have become a powerful alternative to Fourier methods in many target recognition applications (Guo et al., 2011; Younus and Yang, 2011).

The main advantage of DWT is a shifting window size. This shifting window size of DWT is large for slow frequencies. The shifting window size of DWT is small for the fast ones. So, an optimal time–frequency resolution is found in all frequency ranges. In DWT method, the window is adapted to the transients of each scale (Jiang et al., 2011).

DWT can be defined as a continuous time wavelet decomposition sampled at different frequencies and time instance (Al-Otum & Al-Sowayan, 2011; Zhang & Lei, 2011; Zhao & Ye, 2011). The discrete wavelet coefficients at level $m$ and time location $t_m$ can be expressed as Eq. (1):

$$d_m(h_m) = z(h)\psi_m(h - h_m) \tag{1}$$

Herein, $z(h)$ and the function $\psi_m$ are signal and the decomposition filter at frequency level $m$ respectively. The effect of the decomposition filter is scaled by the factor $2^m$ at stage $m$, but otherwise the shape is the same at all stages.

## 3. Time–frequency transforms

Herein, the short-time Fourier transform (STFT), the Born–Jordan time frequency transform (TFT), and the Choi–Williams time frequency transform (TFT) are used for adaptive feature extraction.

### 3.1. Short-time Fourier transform

Short-time Fourier transform (STFT) is also called as the time-dependent or the windowed Fourier transform, used to analyze non-stationary signals by dividing the whole signal into shorter data frames. The short-time Fourier transform (STFT) can be explained by Eq. (2):

$$Z(k) = \sum_{n=0}^{N-1} z(n)w(n - n_0)\exp\left(-\frac{j2\pi nk}{N}\right) \tag{2}$$

*Herein*, $Z$ is the short-time Fourier transform (STFT) of signal, $z$ is signal and $w$ is a window function to suppress side lobes respectively. The output of successive the short-time Fourier transforms (STFTs) can realize a very effective time–frequency representation of the signal. The radar echo signal is divided into short data frames by multiplying it by a moving window. The resulting divided radar target echo signals are zero outside their data frames. The frequency spectrum of each data frame is obtained using the STFT. One of the disadvantages of STFT is that the time frame for the analysis of the signal is fixed (Kubrusly & Levan, 2009; Le et al., 2011; Lhermitte et al., 2011; Martínez-Martínez et al., 2011; Matlab, 2011; Nejad & Zakeri, 2011; Nelson et al., 2002).

### 3.2. Born–Jordan time–frequency transform

Born–Jordan time–frequency transform has an inherent limitation concerning time–frequency methods, including the STFT, based on Heisenberg's uncertainty principle. Another significant limitation of Born–Jordan TFT is that it cannot be used if the data length is short. The disadvantage of the STFT can be overcome by using a generalized TFT with a specialized windowing function called the kernel (Cao et al., 2010; Famili et al., 1997; Guo et al., 2011; Han & Huang, 2006; Huang & Siew, 2005; Huang et al., 2006; Huang et al., 2009; Huang et al., 2011; Jiang et al., 2011; Kubrusly & Levan, 2009; Le et al., 2011; Lhermitte et al., 2011; Martínez-Martínez et al., 2011). Particularly, all TFT can be represented with Eq. (3):

$$C(t) = \frac{1}{4\pi^2} \times \int\int\int s\left(u - \frac{\tau}{2}\right)s^*\left(u + \frac{\tau}{2}\right)\phi(\theta,\tau)e^{-j\theta t - j\theta\tau + j\theta u}du\,d\tau\,d\theta \tag{3}$$

In Eq. (3), $\phi(\theta, \tau)$ is a two-dimensional function named the kernel, and $s(u - \tau/2)$ and $s^*(u + \tau/2)$ represent the signal and its complex conjugate respectively. In commonly, there are multiple frequencies in a signal. The time–frequency spectrum will also gives artificial frequencies in addition to the true ones present in the given signal. Many variant kernel functions have been performed to reduce the problem of artificial frequencies in the case of a multi-component signal. The Born–Jordan (BJ) TFT is one of these kernel functions types. The Born–Jordan TFT has a form of the kernel function in Eq. (4):

$$\phi(\theta,\tau) = \frac{\sin\left(\frac{\theta\tau}{2}\right)}{\frac{\theta\tau}{2}} \tag{4}$$

The Born–Jordan TFT eliminates the artificial frequencies, yet retains a higher time–frequency resolution than does the STFT (Cao et al., 2010; Famili et al., 1997; Guo et al., 2011). The one distinct advantage of the STFT over the Born–Jordan TFT is that no cross-term artifacts are presented in status of the signal contains multi-component frequencies (Cao et al., 2010).

### 3.3. Choi–Williams time–frequency transform

The Choi–Williams (CW) TFT represses the cross terms. The CW TFT kernel:

$$g(v,\tau) = e^{-v^2\tau^2/\sigma} \tag{5}$$

The Choi–Williams (CW) TFT is obtained by using Eq. (6).

$$p_{CW}(t,f) = \int\int \frac{\sqrt{\pi\sigma}}{\tau} e^{-\frac{\pi^2\sigma(u-t)^2}{\tau^2} - j2\pi f} s^*\left(u - \frac{\tau}{2}\right)s\left(u + \frac{\tau}{2}\right)du\,d\tau \tag{6}$$

Readers can find more information about Eqs. (2)–(6) in Nelson et al. (2002).

## 4. Entropy concept

Entropy is a general concept in many fields, signal processing, thermodynamic, etc., (Matlab, 2011). The measuring the entropy is a very effective tool for analysis of non-stationary signals (Nejad & Zakeri, 2011; Nelson et al., 2002; Tabib et al., 2009; Tang et al., 2011; Wang et al., 2011; Wink & Roerdink, 2010; Worden et al., 2011; Yang et al., 2010). The periodic signal has low entropy value. The non-periodic signal has high entropy value (Martínez-Martínez et al., 2011). There are many entropy calculating methods, which are threshold, norm, log energy, and sure (Zhengyou et al., 2011).

## 5. Genetic algorithm concept

In a genetic algorithm (GA) concept, an evolutionary process is performed for solving a problem (Guo et al., 2011). GA begins with a set of solutions that are represented by chromosomes. These solutions set are named a population. This genetic algorithm is iterated as long as during the new population is better than the old one. New solutions are determined according to their fitness values. The chromosome has the high fitness value can be reproduced for next generation (Guo et al., 2011).

The concept of a basic genetic algorithm can be shown as in below. It has nine phases, which are given as below. By using genetic algorithm, a new population is repeatedly created through phases 2–9 until an optimum population is found.

*Phase 1:* It is composed of a random population of $n$ chromosomes which is an appropriate solution for the problem. The large of $n$ is 30 in this study.
*Phase 2:* It is calculated the fitness $f(x)$ of each chromosome $x$, in the population (Guo et al., 2011). In these experimental studies, each of chromosomes in population is randomly composed.
*Phase 3:* It is chosen two parental chromosomes from among the chromosomes has higher the fitness value in population. The cross over operator is performed to these parental chromosomes. The purpose of cross over operator is obtaining the different chromosomes that have higher fitness values.
*Phase 4:* It is cross overed the parents with a crossover probability to create new chromosomes. If crossover is not performed, chromosome will be the exact copy of parents.
*Phase 5:* Each new chromosome is mutated with a mutation probability at each locus that is the position in the chromosome.
*Phase 6:* The new chromosomes are reconstructed from the new population.
*Phase 7:* The genetic algorithm is stopped, if the end condition is satisfied. The chromosomes have the best solution in current population are returned to next population.
*Phase 8:* It is branched to phase 2 and used the newly generated population for a further run of the algorithm.

## 6. Extreme learning machine classifier

The structure of a single layer feed forward neural network (SLFN) is shown in Fig. 1. The SLFNs can form boundaries with arbitrary shapes and approximate any function with arbitrarily small error in case of selecting suitable activation function (Han & Huang, 2006; Huang & Siew, 2005; Huang et al., 2006, 2009, 2011).

The $i$th output corresponding to the $j$th input pattern $x_j$ for a SLFN with $n$-inputs and $R$ outputs is shown as below:

$$s_{ji} = v_j l_i \tag{7}$$

Here, $l_i = [l_{i1}, l_{i2}, \ldots, l_{il}]^T$ is the weight vector connecting from the hidden layers to the $i$th output, $v_j$ is hidden layer output vector determined by Eq. (8).

$$v_j = [f(g_1 x_j + z_1), f(g_2 x_j + z_2), \ldots., f(g_k x_j + z_k)]^T \tag{8}$$

In Eq. (8), $g_k$ is the weight vector connecting from the inputs to the hidden layer and it is determined as Eq. (9). $z_m$ is also bias and $f(.)$ is the activation function.

$$g_k = [g_{k1}, g_{k2}, \ldots., g_{kn}]^T \tag{9}$$

The main aim of training process is to obtain network parameters that minimize error function defined by:

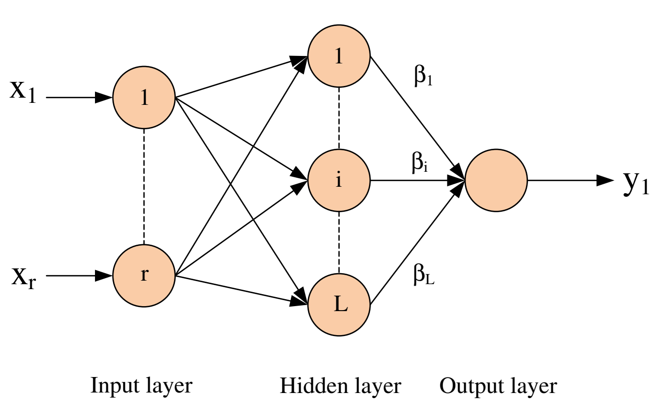


**Fig. 1.** Block diagram of SLFN.

$$E = \sum_{j=1}^{n} (s_j - h_j)^2 \tag{10}$$

This is equivalent to the solution of linear system as follows:

$$D = P \times U \tag{11}$$

Here, $P$ is the hidden layer output matrix. One of the solutions for this problem is ELM, the hidden layer output matrix $P$ is determined with random selecting of input weights $g$ and biases $z$ and then the output weights are computed by:

$$\hat{U} = P^* \times D \tag{12}$$

Here, $P^*$ is the pseudo inverse or Moore–Penrose generalized inverse of $P$.

The feed forward neural networks are the most significant limitation in their applications because of the learning speed of feed forward neural networks is more time-consuming than required (Han & Huang, 2006; Huang & Siew, 2005; Huang et al., 2006, 2009, 2011). There are two important causes for this state. One of these causes is slow gradient based learning algorithms used to train neural network and other cause is the iterative tuning of the parameters of the networks by these learning algorithms in Han and Huang (2006), Huang et al. (2006, 2009, 2011), Huang and Siew (2005). It is proposed a learning algorithm called ELM to deal with these limitations in Han and Huang (2006), Huang et al. (2006, 2009, 2011), Huang and Siew (2005). The input weights are randomly choosing whereas output weights of single layer feedforward neural networks (SLFN) are analytically calculated in this learning algorithm.

Some important features of extreme learning machine classifier can be sorted as below:

- The extreme learning machine classifier is highly fast.
- The extreme learning machine classifiers have better generalization performance.
- The extreme learning machine classifier tends to reach the solutions straightforward without trivial issues such as local minima, improper learning rate and over-fitting encountered in traditional gradient based learning algorithm.
- The extreme learning machine algorithm can be used to train SLFNs with many non-differentiable activation functions. The extreme learning machine classifier randomly selects and fixes the weights between input and hidden neurons based on continuous probability density function which is a uniform distribution function in the range $-1$ to +1. Then, it analytically computes the weights between hidden neurons and output neurons of the SLFN.

The extreme learning machine method for SLFNs named the extreme learning machine classifier can be briefly given as below:

Given a training set $Y = \{(x_i, t_i) | x_i \in R^n, t_i \in R^m, i = 1, 2, \ldots, N$, activation function $f(.)$ and the number of hidden nodes $L$:

- Randomly assign input weight $w_i$ and bias $b_i$, $(i = 1, 2, \ldots, N)$.
- Find the hidden layer output matrix $P$.
- Find the output weight $\gamma$ using $\gamma = P^* D$.

Where, $D$ is the target matrix, $P^*$ is the Moore–Penrose generalized inverse of the matrix $P$.

## 7. Target recognition system by using genetic algorithm wavelet extreme learning machine (GAWELM)

Expert target recognition system by using genetic algorithm wavelet extreme learning machine (GAWELM) proposed in this study consists of two parts: (a) data acquisition and (b) optimum feature extraction and classification using a genetic wavelet extreme learning machine (GAWELM) structure.

*7.1. Data acquisition from radar set to computer*

All of the original radar target echo (RTE) signals used in these experimental studies are obtained from multi function 9620/21 Model Lab-Volt radar experimental set (Ahern et al., 1989). The block diagram of this radar set is given in Fig. 2. Ahern et al. (1989) can be viewed for more information about this radar experimental set. The parameter values of this radar experimental set are given as below:

| | |
|---|---|
| Pulse width | 2 ns |
| RF oscillator | 9.4 GHz |
| Pulse repeat frequency (PRF) | 144 Hz |
| Distance between radar receiver antenna and targets table | 115 cm |

The radar echo signals of the pulse radar targets used in this study, which are the small metal plaque, the large metal plaque, the large plexiglas plaque, the corner reflector, sphere, the side part of a cylinder, the lower part of a cylinder, and the cross-section part of a cylinder, are transmitted from radar experimental set to the computer by using an audio card with 44 kHz sampling frequency. The echo signal of a small metal plaque target is given in Fig. 2.

The photo of the used multi-functional Lab-Volt radar experimental set is given in Fig. 3.

*7.2. Feature extraction and classification stages*

The most important section of pattern recognition is feature extraction stage (Yang et al., 2009; Zhang & Lei, 2011; Zhang & Zhou, 2011; Zhao & Ye, 2011; Zhengyou et al., 2011). Fig. 4 gives the GAWELM structure for the classification of radar echo signal of the radar experimental set mentioned above. In pattern recognition, the feature extraction is very significant topic because of since even the best classifier will perform poorly if the features are not chosen well. Therefore, feature extraction stage of pattern recognition is the most important component when designing the expert system.

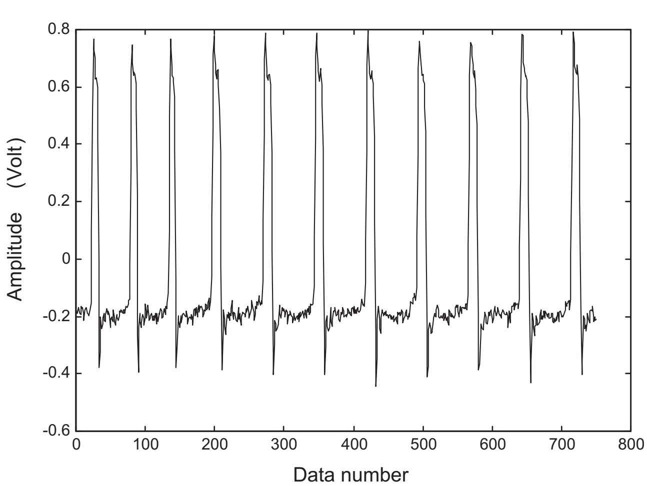


**Fig. 2.** The echo signal of a small metal plaque target.

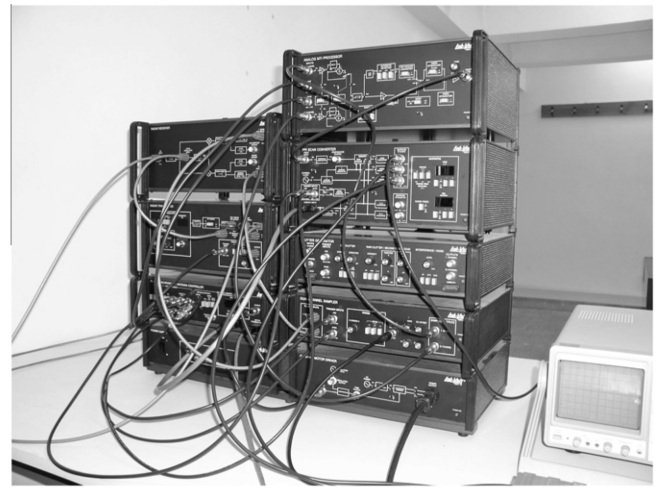

**Fig. 3.** The photo of the used multi-functional Lab-Volt radar experimental set (Model No: 9620/21).

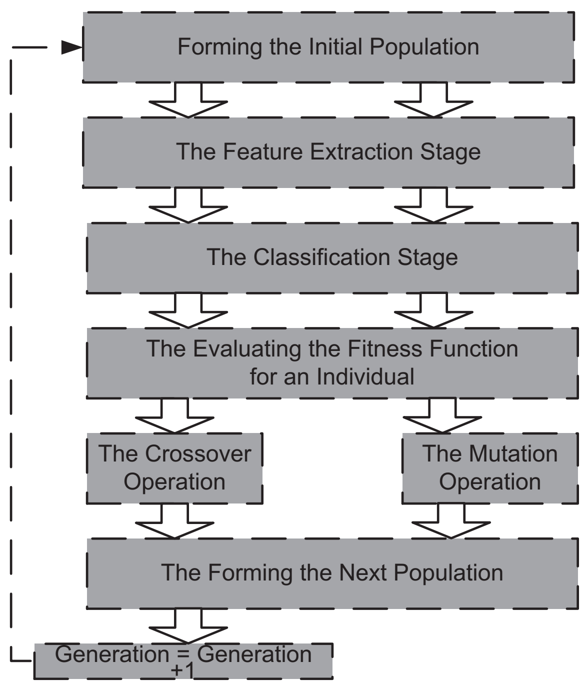


**Fig. 4.** Block diagram of the GAWELM.

The RTE signals are rich in detail and highly random. In this study, the GAWELM structure is realized for obtaining the optimum feature extraction and classification.

*7.2.1. The types of entropy used in this experimental study*

The types of entropy used in these experimental studies can be given in Table 1.

Readers can find more information about types of entropies in Zhengyou et al. (2011).

*7.2.2. Optimum feature extraction and classification by using GAWELM*

The feature extraction methods, which are used by a genetic algorithm in this study, are outlined below:

- *Feature extraction method based on DWT:* The DWT structure and reconstruction tree at level 5 of the radar target echo signals are given as Fig. 4. Herein, DWT is used for the radar

**Table 1**
The types of entropy used in these experimental studies.

| Type of entropy | Equation of Entropy |
|---|---|
| The norm entropy $E(s)$ | $E(s) = \sum_{i=1} \lvert s_i \rvert^p$ for $1 \le p < 2$ |
| The sure entropy $E(s)$ | $\lvert s_i \rvert \leqslant \varepsilon \Rightarrow E(s) = \sum_{i=1} \min(s_i^2, \varepsilon^2)$ here, $\varepsilon$ is a positive threshold value |
| The log energy entropy $E(s)$ | $E(s) = \sum_i \log_2 s_i^2$ with the convention $\log_2 0 = 0$ |

target echo signal by using the Daubechies-4 DWT decomposition filter. Hereby, one vector approximation coefficients cA and five vectors of detail coefficients cDs are obtained.

- *Feature extraction method based on DWT–STFT:* Herein, the same DWT process in feature extraction method 1 is performed for the radar echo signals. Then, the STFT is realized for each vector of the obtained DWT coefficients.
- *Feature extraction method based on DWT–BJTFT:* This method includes the application of BJ TFT to each vector of the obtained DWT coefficients.
- *Feature extraction method based on DWT–CWTFT:* This method includes the application of CW TFT to each vector of the obtained DWT coefficients.

The DWT at five levels of a radar echo signal can be given as in Fig. 5.

*7.2.3. The genetic algorithm used in these experimental studies*

The structure of GA is composed for determining the most efficient of the four feature extraction methods, optimum $p$ parameter value of the norm entropy and optimum $\varepsilon$ parameter value of the sure entropy for automatic target recognition. The performed operations of the GA used in this application can be given as below.

*7.2.3.1. The obtaining of initial population.* The each of 30 random chromosomes includes 10 bits. 1st and 2nd bites of each of chromosomes represent one of the four feature extraction methods, which are based on DWT, DWT–STFT, DWT–BJ TFT and DWT–CW TFT. 3rd, 4th, 5th and 6th bits of chromosome represent the $p$ parameter value of the norm entropy. 7th, 8th, 9th and 10th bits of each chromosome represent the $\varepsilon$ parameter value of the sure entropy. $\varepsilon$ is the threshold for the sure entropy and must be such that $1 \leqslant \varepsilon \leqslant 8$ (Worden et al., 2011; Yang et al., 2009, 2010; Younus and Yang, 2011; Zhang & Lei, 2011; Zhang & Zhou, 2011; Zhao & Ye, 2011; Zhengyou et al., 2011). The sensitive value for the $p$ parameter is 1/15 since; the $p$ parameter is represented by using three bits for each chromosome of the population. The values of the $p$ parameter are 1, 1.066, 1.133, 1.199, 1.265, 1.331, 1.397, 1.463, 1.529, 1.595, 1.661, 1.727, 1.793, 1.859, 1.925 and 1.991. The values which the $\varepsilon$ parameter can get are 1, 1.466, 1.933, 2.399, 2.865, 3.331, 3.797, 4.263, 4.729, 5.195, 5.661, 6.127, 6.593, 7.059, 7.525 and 7.991. The example chromosome coded binary can be given as below:

| The feature extraction method | | The values of the $p$ parameter | | | | The values of the $\varepsilon$ parameter | | | |
|---|---|---|---|---|---|---|---|---|---|
| 1 | 0 | 1 | 1 | 0 | 1 | 0 | 0 | 1 | 1 |

*7.2.3.2. Feature extraction.* The feature extraction is the most important phase of this method. The performed operations in this stage are given below:

Each of the chromosomes of the population includes one of the four feature extraction methods, a $p$ parameter value of the norm entropy and a $\varepsilon$ parameter value of the sure entropy. One of the feature extraction methods, a value of the parameter $p$, and a value of the parameter $\varepsilon$ are defined by this chromosome. Then, this chromosome is given to a feature extraction mechanism.

In this phase, feature extraction process is performed by using feature extraction method, value of the parameter $p$, and value of the parameter $\varepsilon$ represented with this chromosome. Twenty radar echo signals that have variant distances to radar transmitter antenna are used for each of targets. These target used in these experimental studies 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 targets. Therefore, the total number of the obtained radar echo signals from the radar experimental set is $8 \times 20 = 160$. Then, the noises, which have different white-noise amplitudes (Signal/Noise Rate (SNR) = −2, −3, −4 and −5 dB), are added to each of these original 160 radar echo signals. Therefore, 160 numbers of original signals and 640 number noisy radar echo signals are obtained (total 800 radar echo signals).

Thus, total of 800 numbers radar echo signals are processed in this feature extraction mechanism. The values of the norm entropy, sure entropy, and log energy entropy for each of the wavelet decomposition coefficients cA, $cD_1$, $cD_2$, $cD_3$, $cD_4$, and $cD_5$ are acquired by using the feature extraction method, value of the parameter $p$, and value of the parameter $\varepsilon$ represented by a relevant chromosome for each of these 800 radar echo signals. Thus, total 18 entropy values are calculated for each of these 800 signals.

160 numbers original radar echo signals of these total 800 numbers original and noisy radar echo signals are used for training of ELM classifier in GAWELM system. The rest of the radar echo signals are used in the testing of the proposed GAWELM method for automatic radar target recognition. 100% correct recognition rate is obtained for the eight variant radar target echo signals in training experimental studies. This status clearly shows the effectiveness and the reliability of the proposed approach for extracting features from radar echo signals.

*7.2.3.3. Classification.* In this phase, the GAWELM system performs the classification task by using features obtained from previous feature extraction phase. The extreme learning machine (ELM) architecture and training parameters used in this study are given in Table 2. These training parameters of ELM classifier used in this study such as type of activation function and the number of hidden nodes are determined for the best performance of this ELM after several variant experiments (Han & Huang, 2006; Huang & Siew, 2005; Huang et al., 2006, 2009, 2011).

The realized stages in this phase can be summarized as below:

- The feature vectors formed in the feature extraction phase are used as input of the extreme learning machine (ELM) classification.
- The Training Accuracy Rate (TAR) of the ELM is calculated at the final of the training of the ELM classifier.

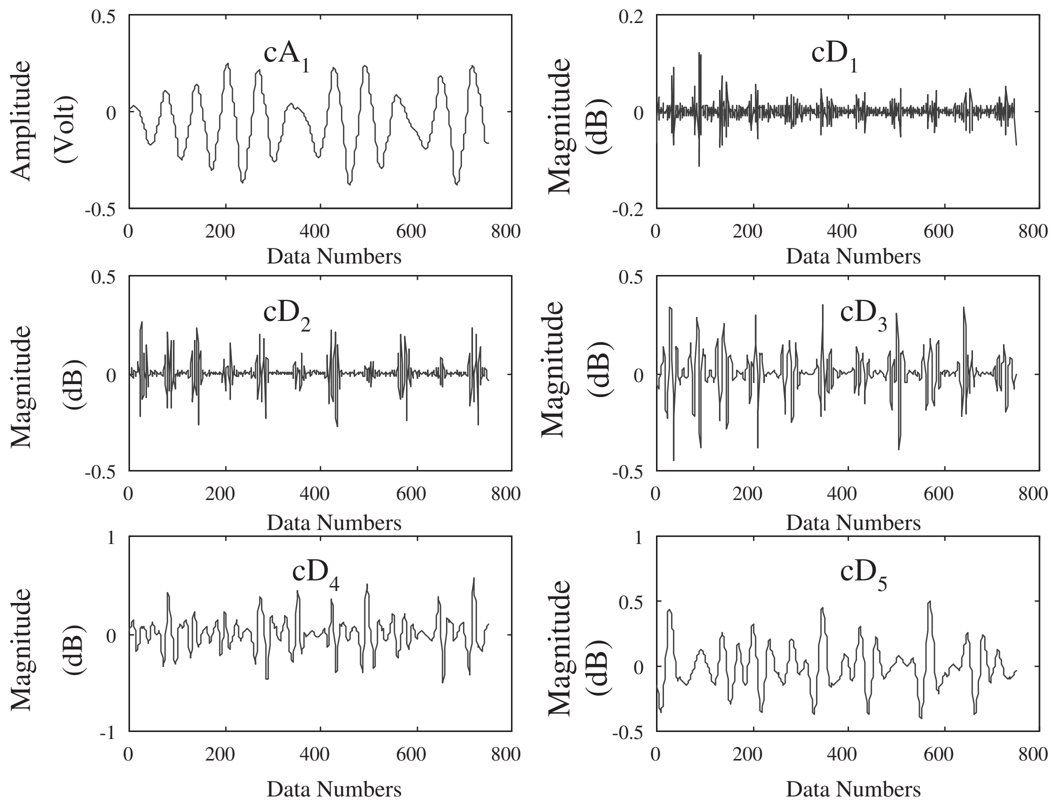


**Fig. 5.** The DWT at five levels of a radar echo signal.

*7.2.3.4. Obtaining of the fitness function for a chromosome.* The TAR of the ELM is compared with Threshold Rate (TR) of GAWELM for calculating the fitness function of each of chromosomes. The TR value was selected about 95% for these experimental studies. If the calculated TAR at result of ELM training for each of chromosomes is equal to TR or less than TR, this chromosome has suitable parameter values, which are the feature extraction method, value of the parameter *p*, and value of the parameter $\varepsilon$. The fitness function value of this chromosome is appropriate for using of this chromosome in next generation.

The fitness functions are calculated for all 30 numbers chromosomes in population. 10 numbers chromosomes have highest fitness function value are selected and saved. Other 20 numbers chromosomes in population are eradicated.

The chromosomes have same fitness value are selected for next generation. Thus, the 10 numbers chromosomes have highest fitness functions in current population are saved for the next population.

*7.2.3.5. Crossover.* In this stage, 40% portion of the chromosomes, which have highest fitness functions, is randomly selected and performed the crossover operator to them. Two bits of each of 12 random chromosomes are randomly selected and swapped in the crossover operation. 12 new chromosomes are formed from these crossover operations.

The block diagram of the GAWELM is given in Fig. 6.

*7.2.3.6. Mutation.* In this mutation operation, the bit inversion method is performed as mutation operator (Guo et al., 2011). The mutation operation is appropriated by using the 0.3% portion of the total bit number of three other chromosomes. In bit inversion method, value of a bit is converted from 1 to 0 and vice versa. At result of this stage, three new chromosomes are obtained. Then, these 15 numbers chromosomes obtained at results cross-over and mutation operations are added to original 15 numbers chromosomes. Thus total 30 numbers chromosomes for the population of the next generation are obtained.

**Table 2**
ELM architecture and training parameters.

| | |
|---|---|
| *Architecture* | |
| The number of layers | Input number: 18 |
| | 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 networks (SLFNs) |

The goal of GAWELM performed herein is to determine the most appropriate feature extraction method from among four variant feature extraction methods, the optimum value of the *p* parameter value in the norm entropy, and the optimum value of the $\varepsilon$ parameter value in the sure entropy.

## 8. The obtained results of experimental studies by using GAWELM

The architecture and the training parameters of the ELM are given in Table 2. In this study, experiments are performed by using total 800 radar echo signals of small metal plaque, large metal plaque, large Plexiglas plaque, corner reflector, sphere, the side part of a cylinder, the lower part of a cylinder, and a cross-section part of cylinder targets. In classification stage of GAWELM, 160 radar target echo signals for these targets are used. The rest of these 800 signals are used for testing the performance of the GAWELM. In these experiments, correct classification ratio is calculated about 100%. The obtained optimum feature extraction methods, values of the parameter $p$, and values of the parameter $\varepsilon$ by using the GAWELM algorithm are given in Table 3.

The iterations of GAWELM are terminated at end of 40th generation. In testing stage, 95.50% and 93.80% correct testing rates are calculated by using DWT–STFT and DWT–CW TFT on GAWELM method respectively. The same targets and radar experimental set are performed with this study in previous automatic target recognition (ATR) studies Avci et al., 2005a, 2005b. In Avci et al. (2005a), wavelet neural network (WNN) and in Avci et al. (2005b), Wavelet Adaptive Network Based Fuzzy Inference System (WANFIS) is used for automatic target recognition (ATR) studies. The average target classification success rates are about 90% for both WNN and WANFIS methods. GAWELM method has 95.50% target accuracy rate for the same dataset. The most significant reasons of GAWELM's superiority are the optimum feature extraction method selection and obtaining the values of optimum entropy parameters. The GAWELM method has a longer training time-composed of genetic algorithm (GA) training and extreme learning machine classifier (ELM) than WNN and WANFIS methods. This status is the most significant disadvantage of GAWELM compared to WNN and WANFIS methods. The training time of the GAWELM is about fifteen times of the each training times of WNN and WANFIS methods for one generation. In addition to, the very small time spent can be disregarded in obtaining the correct recognition performance.

The comparison results with previous studies have same conditions, dataset and experimental set (Avci et al., 2005a, 2005b) are also given in Table 4 to show validity of suggested GAWELM

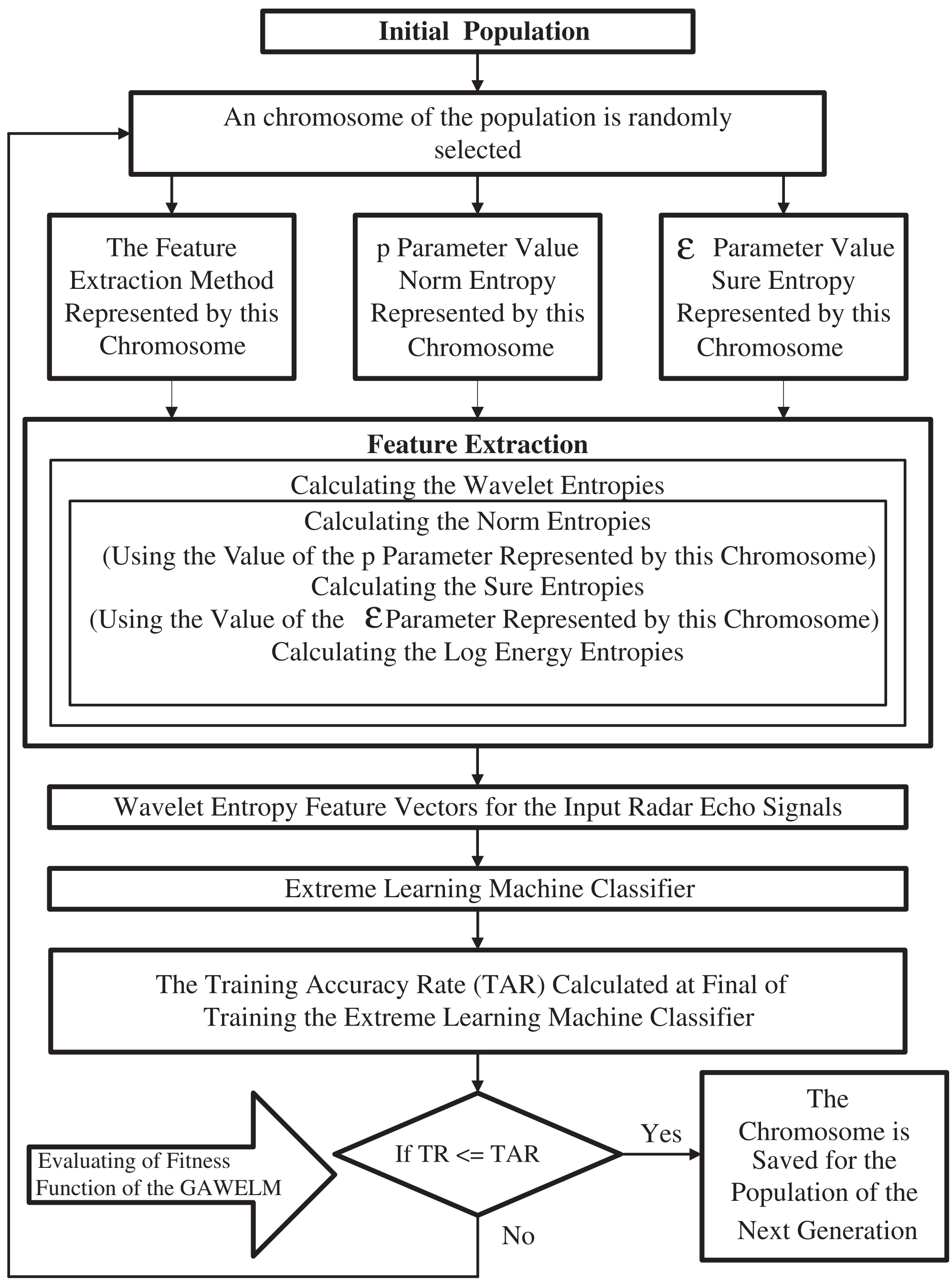


**Fig. 6.** The block diagram of the GAWELM.

**Table 3**
The obtained classification performance by using the GAWELM algorithm.

| Generation number | The selected feature extraction method | The obtained optimum $p$ parameter value | The obtained optimum $\varepsilon$ parameter value | The obtained TAR value of the ELM (%) | The classification performance of the GAWELM (%) |
|---|---|---|---|---|---|
| 2 | DWT–STFT | **1.793** | **2.399** | **99.30** | **95.50** |
| 7 | DWT | 1.199 | 1.933 | 97.45 | 88.75 |
| 12 | DWT–CW TFT | 1.925 | 3.797 | 99.08 | 93.80 |
| 28 | DWT–BJTFT | 1.463 | 4.729 | 96.70 | 87.50 |
| 14 | DWT–STFT | 1.066 | 7.525 | 95.10 | 83.75 |

**Table 4**
The comparison results of suggested GAWELM method and previous methods, which used same dataset and features.

| Ref. | Methods | Training | | Testing |
|---|---|---|---|---|
| | | Time (seconds) | Accuracy (%) | Accuracy (%) |
| (Avci et al., 2005a) | WNN | 14.63 | 96.043 | 91.625 |
| (Avci et al., 2005b) | WANFIS | 22.28 | 95.127 | 90.225 |
| In this study | GAWELM | **68.08** | **100** | **95.50** |

**Table 5**
The comparison results of suggested GAWELM method with other some automatic target recognition methods used the radar echo signals in literature.

| Ref. | Methods | Training | | Testing |
|---|---|---|---|---|
| | | Time (seconds) | Accuracy (%) | Accuracy (%) |
| (Avci et al., 2005a) | WNN | 14.63 | 96.043 | 91.625 |
| (Avci et al., 2005b) | WANFIS | 22.28 | 95.127 | 90.225 |
| (Ahalt et al., 1990) | PCA | NA | 93.000 | 81.637 |
| (Du et al., 2006) | Nearest neighbor classifier | 17.67 | 91.46 | 88.21 |
| (Yun et al., 2011) | Multitask learning | NA | 97.000 | 89.46 |
| (Du et al., 2011) | k-NN | NA | 93.67 | 87.37 |
| In this study | GAWELM | **68.08** | **100** | **95.50** |

method. As shown from this table, the highest training and testing accuracies are calculated by using GAWELM method. The suggested GAWELM method in this study shows a good classification performance even though the feature vector is directly used without reduction.

As shown from Table 5, GAWELM method has high performance than other automatic target recognition methods in literature (Ahalt et al., 1990; Avci et al., 2005a, 2005b; Du et al., 2006; Du et al., 2011; Yun et al., 2011). Most important cause of this is the optimum feature extraction method and values of optimum entropy parameters selection talent of the GAWELM.

## 9. The Discussion and conclusion

In last year's, various radar target recognition studies were performed (Cooke, Martorella, Haywood, & Gibbins, 2006; Cooke, Redding, Schroeder, & Zhang, 2000; Liu, McLernon, Ghogho, Hu, & Huang 2012). In this paper, a target recognition system is introduced for automatic target recognition (ATR) using real radar target echo signals. This study concludes a combination of an adaptive feature extraction and classification by using optimum wavelet entropy parameter values. The optimum features used in this study are obtained from radar target echo signals. Herein, a genetic wavelet extreme learning machine classifier model (GAWELM) is developed for automatic target recognition. The GAWELM composes of three stages. These stages of GAWELM are genetic algorithm, wavelet analysis and extreme learning machine (ELM) classifier. The genetic algorithm (GA) stage is used for obtaining the feature extraction method and the optimum wavelet entropy parameter values. Herein, the optimal one of four variant feature extraction methods is obtained by using a genetic algorithm (GA). The four feature extraction methods proposed GAWELM model are discrete wavelet transform (DWT), discrete wavelet transform–short-time Fourier transform (DWT–STFT), discrete wavelet transform–Born–Jordan time–frequency transform (DWT–BJTFT), and discrete wavelet transform–Choi–Williams time–frequency transform (DWT–CWTFT). The discrete wavelet transform stage is performed for optimum feature extraction in the time–frequency domain. The discrete wavelet transform stage includes discrete wavelet transform and calculating of discrete wavelet entropies. The extreme learning machine (ELM) classifier is performed for evaluating the fitness function of the genetic algorithm and for classification of radar targets. The performance of the developed GAWELM automatic radar target recognition system is examined by using noisy real radar target echo signals. The applications results of the developed GAWELM expert radar target recognition system show that this GAWELM system is effective in rating real radar target echo signals. The correct classification rate of this GAWELM system is about 95.50% for radar target types used in this study.

The results of the experimental studies in Section 9 show that the proposed GAWELM expert radar target recognition system method can yield an effective interpretation of the radar targets used. The correct recognition performance of the proposed GAWELM system is given in Tables 3–5.

The feature extraction stage is a very significant issue in pattern recognition. The proposed feature extraction methods which are mentioned in Section 7.2.2 are robust to noise in the radar target echo signals.

As shown in Table 3, the optimum feature extraction and classification results are obtained by using wavelet entropy in the feature extraction mechanism of the GAWELM. The information obtained from the wavelet entropy is related to the energy and amplitude of the underlying signal. Namely, the useful information for optimum feature extraction from RTE signals can be obtained by using wavelet entropy features in GAWELM method.

The most important aspect of the GAWELM system is the ability of self-organization of the GAWELM without requirements such as programming. The GAWELM is very effective for real time radar target recognition applications due to its rapid response. These features of GAWELM system compose more suitable system for automatic RTE signal classification. The results in Tables 3–5 show the superior automatic target recognition ability of this new GAWELM assistance system.

The automatic recognition performances of this GAWELM system in this study show that this GAWELM system is rapid, easy to operate, and inexpensive. This GAWELM system presents some advantages in military applications. In future studies, GAWELM system will be applied to radar target Doppler signals.

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