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Araştırma Makalesi / Research Article

A Novel Analog Modulation Classification: Discrete Wavelet Transform-Extreme Learning Machine (DWT-ELM)

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Abstract
The aim of this study is to propose a method using discrete wavelet transform and extreme learning machine (DWT-ELM) in classification of communication signals. Six types of analog modulated signals as “AM”, “DSB”, “USB”, “LSB”, “FM” and “PM” are used for classification and analog modulated signal dataset consists of 1920 signals. These signals are also added white noise. Feature extraction is performed using different DWT filters. The feature vector obtained from DWT is used in classification. ELM is preferred due to its advantages over conventional back-propagation based classification. The feature vector is fed by the inputs of the ELM. The performance of the proposed method is evaluated for different types of DWT filters. In addition, compared results with similar study are presented to be able to determine the success of the proposed method.

Keywords: DWT-ELM, ELM classification, Wavelet Transform, Analog modulated signals.

Yeni Bir Analog Modülasyon Sınıflandırması: Ayrık Dalgacık Dönüşümü-Aşırı Öğrenme Makinesi (ADD-AÖM)

Öz
Bu çalışma, analog modüle edilmiş iletişim sinyallerinin sınıflandırılması için ayrık dalgacık dönüşümü - aşırı öğrenme makinesine (ADD-AÖM) dayalı yeni bir yöntem önermektedir. Sınıflandırma için AM, DSB, USB, LSB, FM ve PM olmak üzere altı tip analog modüle edilmiş sinyal kullanılır ve analog modüle edilmiş sinyal veri seti 1920 sinyalden oluşur. Bu sinyallere ayrıca beyaz gürültü eklenir. Özellik çıkarma işlemi, farklı ADD filtreleri kullanılarak gerçekleştirilir. ADD'den elde edilen öznitelik vektörü sınıflandırmada kullanılır. AÖM, geleneksel geri yayılmaya dayalı sınıflandırmaya göre avantajları nedeniyle tercih edilmektedir. Özellik vektörü, AÖM sınıflandırıcısının girişine beslenir. Önerilen yöntemin performansı, farklı ADD filtreleri için değerlendirilir. Ayrıca, önerilen yöntemin performansını değerlendirmek için benzer çalışma ile karşılaştırılan sonuçlar sunulmuştur.

Anahtar kelimeler: ADD-AÖM, AÖM sınıflandırma, Dalgacık Dönüşümü, Modüle edilmiş analog sinyaller.

1. Introduction

The analog modulated communication signal (AMCS) classification is stage between detection and demodulation of a signal. It is widely used in various fields, such as civil and military applications. In earlier studies on analog modulated communication signal classification, the measured parameters had been interpreted by an expert. The classification of AMCS has been made in three ways: classical methods, semi-automatic methods and automatic methods. In the classic method, spectrum feature, instantaneous amplitude and phase of the signal to be analysed are evaluated by human. The designed demodulator for one of each modulation type was utilized in the semi-automatic methods. Automatic methods for analog modulated communication signal classification automatically decide the modulation

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type. Automatic analog modulation classification methods can be divided: “decision-theoretic”, “statistical pattern recognition” approaches and intelligent system based approaches.

There have been existed some studies in literature on automatic classification of the AMCS. Ref. [1] proposes a modulation classifier using instantaneous frequency and amplitude. The proposed method can distinguish between “AM”, “FM” and “DSB” signals. Ref. [2] presented a modulation method based envelope characteristic of the signal for classification of “AM”, “FM”, “DSB” and “SSB” analog modulation types. Ref. [3] a method has been proposed to classify analog radio signals. A method for analog modulation classification is presented to distinguish AM and noisy environment in Ref. [4]. A modulation classifier is presented to distinguish “USB” and “LSB” in Ref. [5]. To recognize the modulation type, the presented method uses instantaneous frequencies of these signals. In Ref. [6], a modulation classifier is proposed for recognition of the modulation kinds such as “AM”, “DSB”, “VSB”, “LSB”, “USB”, “FM” and mixed modulation signals. Ref. [7] suggests a method based on decision theoretic approach. Ref. [8-10] present an automatic method based on ANN for modulation classifier. Ref. [11] proposes a new modulation classification method based on discrete wavelet neural network.

This study proposes a novel automatic analog modulation method based on DWT-ELM for recognition of the six modulation types. The modulation types are “AM”, “DSB”, “USB”, “LSB”, “FM” and “PM”. 1920 AMCS are generated by MATLAB Communication Toolbox and they are used for the training and testing of the proposed method. Performance of the proposed method is evaluated for different wavelet filter families such as “Symlets”, “Daubechies”, “Biorthogonals”, and “Coiflets”. Further, the results of the proposed method are compared with Ref. [11]. The obtained classification results show that the proposed method has better classification performance over previous studies.

This paper: Section 2 explains analog modulated signals, section 3 and section 4 presents DWT and ELM, respectively. The proposed method is given in Section 5. Application of the proposed method and obtained results is presented in Section 6. Finally, shows the results in Section 7.

2. Material and Methods

2.1. Analog Modulated Signals (AMS)

An AMS *f(t)* can be formulated as follows [11]:

$$f(t) = e_c s(t) \cos(2\pi f_c t + \varphi(t) + \theta_0) \tag{1}$$

Here; f_c is carrier frequency, $\varphi(t)$ is phase of signal, $\mathrm{s}(t)$ is signal envelope and θ_0 is initial phase of signal. It is shown that e_c controls power of the carrier signal. Six AMS types used in this study is presented as follows [11]:

(Transmission carrier amplitude modulation “AM”); The equation for this signal is shown below:

$$f(t) = 1 + m.f(t).\cos(2\pi f_c t) \tag{2}$$

(Double sideband with supress carrier AM “DSB”); The equation for this signal is shown below:

$$f(t) = f(t).\cos(2\pi f_c t) \tag{3}$$

(Upper side band modulation “USB”); The equation for this signal is shown below:

$$f(t) = f(t).\cos(2\pi f_c t) - h(t).\sin(2\pi f_c t) \tag{4}$$

(Lower side band modulation “LSB”); The equation for this signal is shown below:

$$f(t) = f(t).\cos(2\pi f_c t) + h(t).\sin(2\pi f_c t) \tag{5}$$

(Frequency modulation “FM”); The equation for this signal is shown below:

$$f(t) = \cos(2\pi f_c t + K_f \int_{-\infty}^{t} x(\tau)d\tau) \quad (6)$$

(Phase modulation "PM"); The equation for this signal is shown below:

$$f(t) = \cos(2\pi f_c t + 2\pi\varphi(t) + \theta_0) \quad (7)$$

2.2. Discrete Wavelet Transform (DWT)

Basic feature extraction constitutes an important step in pattern classification. Time and frequency information of AMS is important. Since the modulated signal may contain different components, it is correct to separate the signal into "detail components" [12]. The DWT analyzes the signal with various resolutions by decomposing the approximate and detailed coefficient signals in various frequency bands, so it is often used in the model classification [12].

The DWT consists of two parts as shown in Figure 1. These are low and high pass filters. After the modulated signal is applied to these filters, approximate and detail coefficients are obtained.

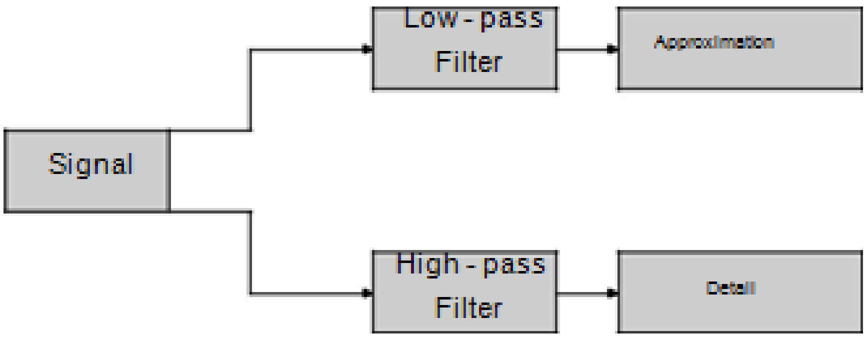

Figure 1. DWT decomposition structure

In the DWT method, when resolving high frequency components in a minor window, they need large time windows to solve low frequency components. Because the signal has low and high frequency components. At the same time, components with high frequency are represented in smaller time intervals, while components with low frequency are represented in larger time intervals. The equality of DWT function is shown below [13]:

$$d_m(t_m) = x(t)\psi_m(\frac{t-t_m}{2^m}) \quad (8)$$

In this equation, "ψ_m " is the m level decomposition filter. In DWT transformation, it is divided into its components as 2^m according to the value of m. Time-frequency coefficients obtained from the signal [14]:

$$d[n] = x[n]h[n], \qquad c[n] = x[n]g[n] \quad (9)$$

In Equation 9, " $h[n]$"is the "impulse respons"e of the "high-pass filter", "$g[n]$ "is the "impulse response" of the "low-pass filter" [12, 15, 16].

2.3. Extreme Learning Machine

ELM can be called a single hidden layer feed forward network without a neuron in its hidden layer [17], [18]. For the ELM method; Output function for "Single Hidden Layer Feed Forward Neural Networks" (SLFN) is given below.

$$f_L(x) = \sum_{i=1}^{L} \beta_i h_i\,(x) = h(x)\beta \tag{10}$$

In the equation; $\beta = [\beta_1, \ldots, \beta_L]^T$ is the output weight vector. $h\,(x) = (h1\,(x). \ldots, hL\,(x)]$ is the feature mapping of the equation ELM. The hidden neurons used in ELM may have different output functions and they may not be unique.

ELM uses two steps when training the SLFN. These are linear parameter decoding and random feature mapping. The ELM uses some nonlinear mapping functions to initialize the hidden layer, thus extracting the feature space for input data. The random feature differs from current learning algorithms, such as deep neural networks [19], that use the mapping phase, SVM, Auto (Encoders/Decoders). The mapping functions used in the ELM method can be nonlinear piecewise continuous functions.

ELM is more efficient than conventional Back-Propagation (BP) neural networks. The reason for this is that hidden node parameters used in ELM are randomly generated. Randomly generated nodes were created according to the probability distribution.

Other than the filter functions listed in Table 2, there are also functions such as fuzzy ELM [20-22] and wavelet ELM [23-26]. In the next step, the weights denoted by and combining the hidden layer and the output layer are solved by reducing the approximate error to the square error.

$$\min_{\beta \epsilon \mathbf{R}^{L\times m}} ||\mathbf{H}\beta - \mathbf{T}||^2 \tag{11}$$

Here **"H"** is the "hidden layer" output matrix given in the Eq. (12):

$$\mathbf{H} = \begin{bmatrix} h(x_1) \\ \vdots \\ h(x_N) \end{bmatrix} = \begin{bmatrix} h_1(x_1) & \ldots & h_L(x_1) \\ \vdots & \vdots & \vdots \\ h_1(x_N) & \vdots & h_L(x_N) \end{bmatrix} \tag{12}$$

This symbol ($\|.\|$) is used to show the Frobenius norm. The most appropriate solution for Eq. (11) is given below:

$$\beta^* = \mathrm{H}^{\dagger}\mathrm{T} \tag{13}$$

The "H" given here indicates the generalized inverse of the "H" matrix with Moore-Penrose. There are many effective methods to solve the problem given in the above equation, such as "orthogonal projection method", Gaussian elimination, "iterative method" and "single value decomposition (SVD)" etc. [27].

The difference of "ELM" from traditional learning algorithms is to simultaneously satisfy a few salient targets [28-30]. Generalization performance is not considered in most algorithms when the feedforward neural networks are proposed for the first time.

2.4. Proposed Method

In this paper, AMS dataset is created by MATLAB Communication Toolbox. In these signals, "a message signal", which is a real "voice signal" with band-limited to 4 kHz, is used. Extensive simulation studies are performed to produce analog-modulated signals using different values of signal parameters such as phase, modulation index, "Signal-to-Noise Ratio" (SNR), and frequency deviation in FM, phase deviation in PM. The 320 signals are obtained for each of analog-modulation signals by means of simulation studies. The details of analog modulated signal generation are given in Table 1.

The steps of the proposed method is given in Figure 2. The proposed method can be divided into four steps: signal generation, feature extraction, training and testing.

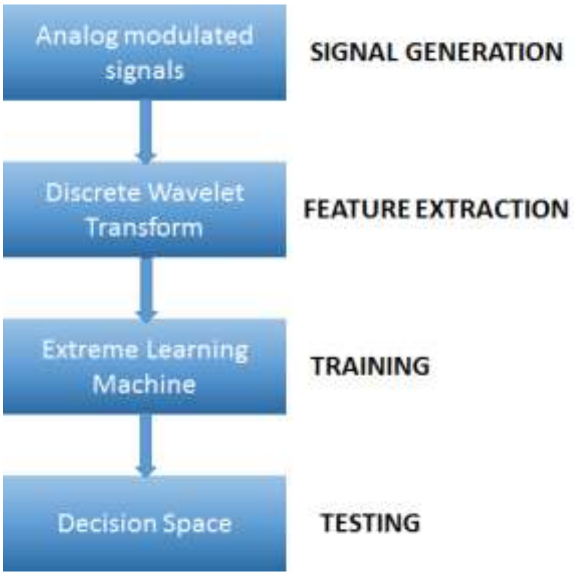

Figure 2. Steps of the proposed method

1920 AMS are created by using functions in "MATLAB Communication Toolbox" for "AM", "DSB", "USB", "LSB", "FM", and "PM". In the feature extraction step, the DWT is applied to the AMS. Tree structure with 7-level was used in DWT decomposition. Daubechies wavelets ("db2", "db3", "db5", "db8", "db10"), "Symlets wavelets" ("sym2", "sym3", "sym5", "sym7", "sym8"), "Biorthogonal wavelets" ("bior1.3", "bior2.2", "bior2.8", "bior3.5", "bior6.8") and "Coiflets wavelets" ("coif1", "coif2", "coif3", "coif4", and "coif5") are used in DWT decomposition. Thus, a comparison study is performed by using different wavelet filter type. After the AMS are separated into their components by filters, seven detail coefficients and one approximation coefficient are obtained. Then, the adaptive wavelet norm entropy *E(s)* given in Eq.14 is computed for each of "DWT coefficients".

$$E(s) = \frac{\sum_i |s_i|^p}{N} \tag{14}$$

Here, *s* is terminal node signal, and *p* is power. In this study, *p* parameter value is selected between (12) and its value is update by step increments of 0.1. Further, *p* parameter is normalized by using its maximum value. The real voice signal used in this study are depicted in Figure 3. "DWT" of an "AM" modulated signal are given in Figure 3 for "db2", "sym5", "bior6.8", and "coif3" wavelet filters.

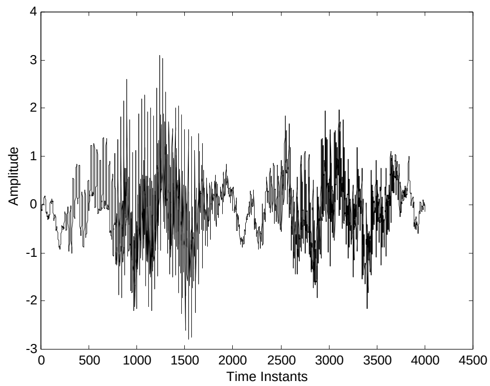

Figure 3. Real voice signal

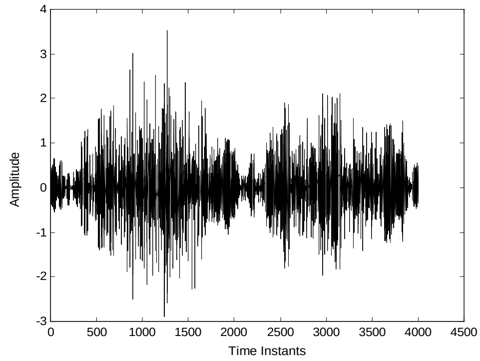

Figure 4. AM modulated signal with "m = 0.5", and "$\theta_0 = 0$"

The feature extraction method (FEM) for different wavelet filter types used in this study is given in Table 2.

In this study, ELM is preferred as classifier due to its superiority over traditional backpropagation algorithms. Tangent sigmoid is used in the "activation function" preference.

3. Results

The experiments are performed for classification of the six analog modulated signals. For this aim, 320 signals are generated for each analog modulated signals. 50% of analog modulated signals (960 signals) is used for training of the ELM classifier and remaining signals (960 signals) for testing of the ELM. These training and testing of the classifier are repeated for each of FEMs. In Table 3, the obtained results are given in terms of "training time" and "classification accuracy" for each FEM. This table shows that FEM-18 reaches to "desired error value" in the "shortest time" whereas FEM-17 reaches longest time. FEM-2 has the best training performance among other FEMs and FEM-18 has the worst training performance. p parameter value is 1 at the end of update for FEM-2. Updated p parameter value is 1.1 for FEM-18. In Table 3, HNN is hidden neuron number of ELM, TEN is training epoch number, the LVP is last value of p parameter, MSE is mean square error and TA is percent testing accuracy.

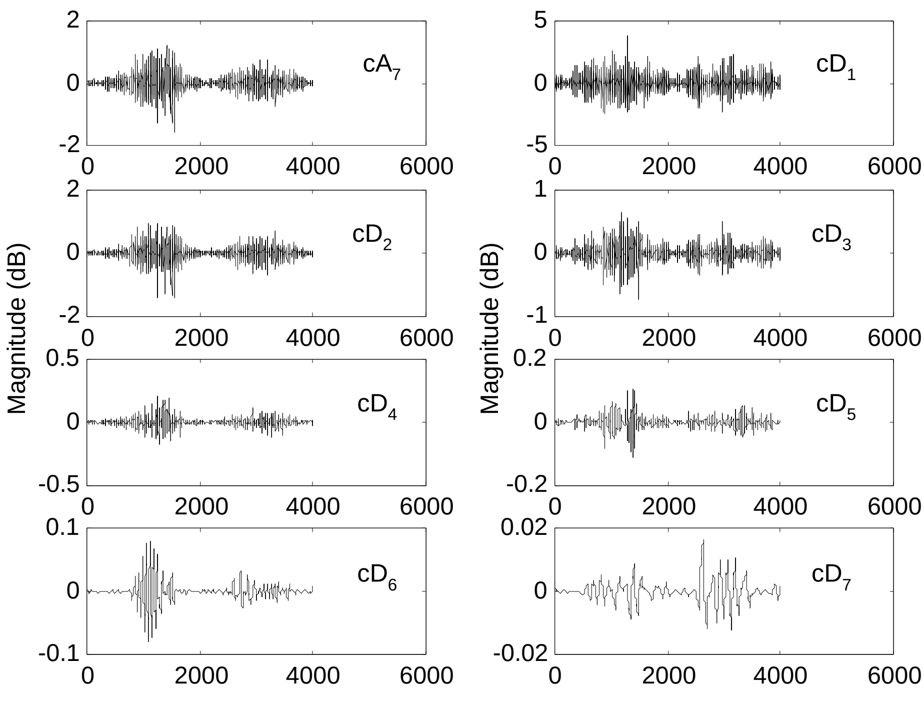

Figure 5. Waveforms showing the detail and approximate coefficients of the AM signal up to the 7th level of decomposition ("db2" wavelet filters)

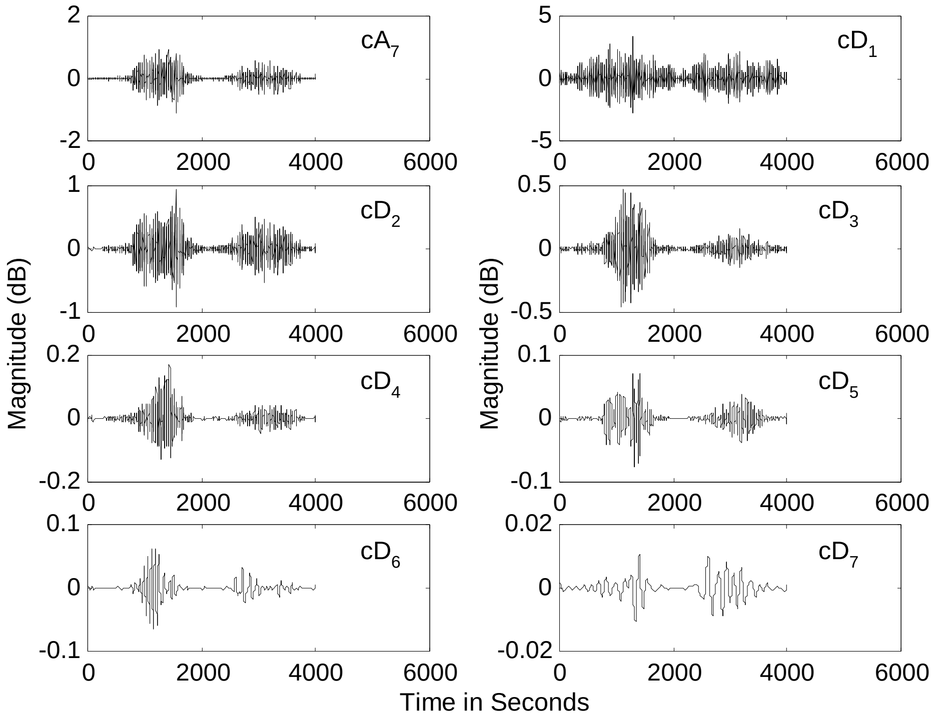

Figure 6. Waveforms showing the detail and approximate coefficients of the AM signal up to the 7th level of decomposition ("sym5" wavelet filters)

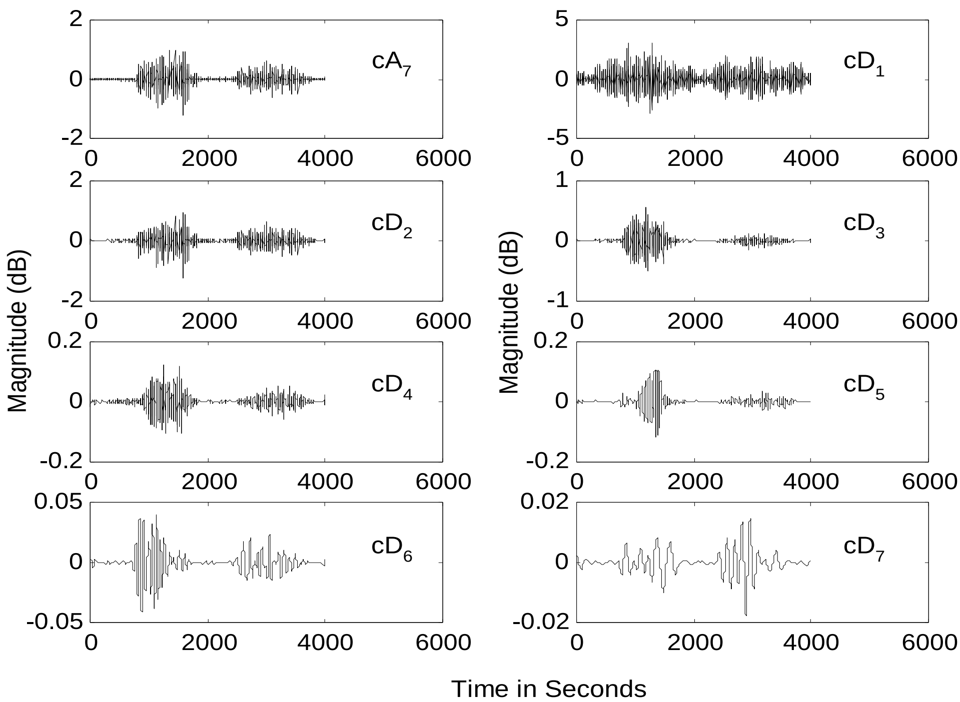

Figure 7. Waveforms showing the detail and approximate coefficients of the AM signal up to the 7th level of decomposition ("bior6.8" wavelet filters)

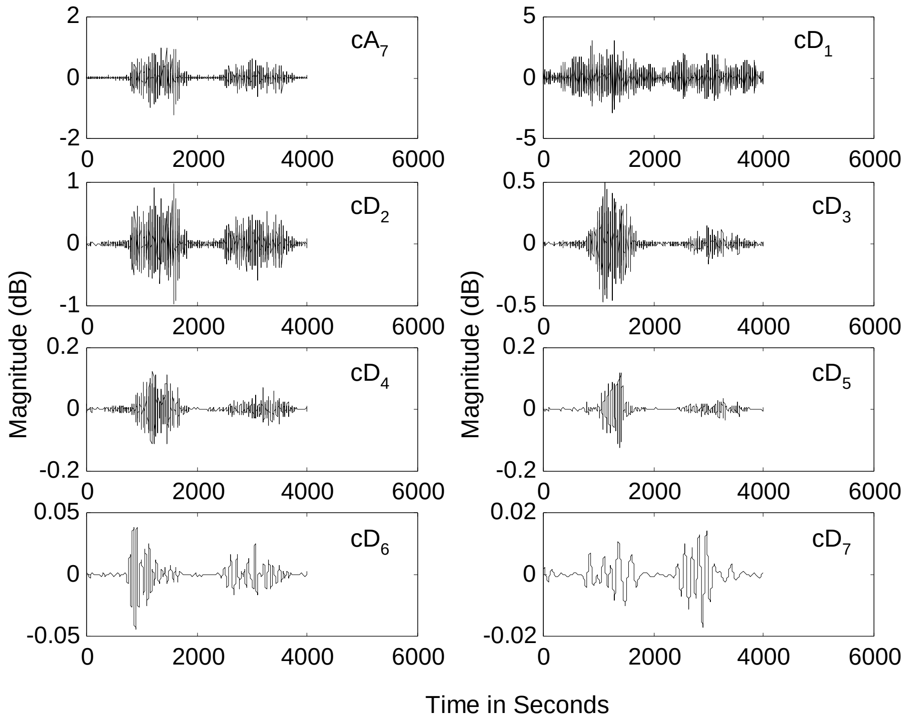

Figure 8. Waveforms showing the detail and approximate coefficients of the AM signal up to the 7th level of decomposition ("coif3" wavelet filters)

Table 1. The details of AMS generation

Signal type	Modulation index	White Gaussian noise with SNR	initial phase	Phase deviation	Total
"AM"	0.2, 0.5 and 1	Between 0 - 60 dB	$0, \pi/6, \pi/2$	-	320
"DSB"	-	Between 0 - 60 dB	$0, \pi/6, \pi/2$	-	320
"USB"	-	Between 0 - 60 dB	$0, \pi/6, \pi/2$	-	320
"LSB"	-	Between 0 - 60 dB	$0, \pi/6, \pi/2$	-	320
"FM"	1.5 and 10	Between 0 - 60 dB	$0, \pi/6, \pi/2$	-	320
"PM"	-	Between 0 - 60 dB	$0, \pi/6, \pi/2$	$\pi/9, \pi/12, \pi/18$	320

Table 2. FEM for different wavelet filter types used in this study

	Wavelet filter type	FEM	Wavelet filter type
"FEM-1"	"db2"	"FEM-11"	"bior1.3"
"FEM-2"	"db3"	"FEM-12"	"bior2.2"
"FEM-3"	"db5"	"FEM-13"	"bior2.8"
"FEM-4"	"db8"	"FEM-14"	"bior3.5"
"FEM-5"	"db10"	"FEM-15"	"bior6.8"
"FEM-6"	"sym2"	"FEM-16"	"coif1"
"FEM-7"	"sym3"	"FEM-17"	"coif2"
"FEM-8"	"sym5"	"FEM-18"	"coif3"
"FEM-9"	"sym7"	"FEM-19"	"coif4"
"FEM-10"	"sym8"	"FEM-20"	"coif5"

Table 4 depict the "classification performance" of the FEM-2. As seen clearly from Table 4, two "AM signals" are classified as "LSB" and one "AM" signals as "DSB". 157 "AM" signals have been correctly classified. The classification performance of other FEMs are illustrated in Tables 5-23.

Table 3. Training time and classification accuracy for different FEMs

FEM	HNN	TEN	LVP	MSE	TA
FEM-1	60	781	1.2	0.00000190	96.45
FEM-2	80	142	1	0.00000050	99.27
FEM-3	80	672	1.1	0.00000450	96.66
FEM-4	120	354	1.3	0.00000053	96.14
FEM-5	40	1132	1.5	0.00000153	95.52
FEM-6	60	784	1	0.00000451	95.52
FEM-7	40	537	1	0.00000130	95.93
FEM-8	30	2044	1.3	0.00000530	96.66
FEM-9	60	632	1.2	0.00000826	97.29
FEM-10	80	636	1.1	0.00000637	97.08
FEM-11	50	872	1.3	0.00000536	95.93
FEM-12	60	845	1.3	0.00001638	96.56
FEM-13	80	726	1.2	0.00000647	95.41
FEM-14	60	937	1.1	0.00003256	95.93
FEM-15	30	546	1.1	0.00001738	95.52
FEM-16	40	382	1.2	0.00000345	96.14
FEM-17	100	3163	1.1	0.00000748	95.62
FEM-18	80	76	1.1	0.00001839	95.20
FEM-19	80	373	1.3	0.00002673	96.04
FEM-20	60	537	1	0.00000378	96.56

Table 4. Performance of the proposed method for FEM-2

Actual	**Estimated**					
	"AM"	"DSB"	"USB"	"LSB"	"FM"	"PM"
"AM"	159	1	-	-	-	-
"DSB"	1	158	-	1	-	-
"USB"	-	-	160	-	-	-
"LSB"	-	-	-	159	1	-
"FM"	-	-	-	-	160	-
"PM"	-	1	1	1	-	157
Total	160	160	161	161	161	157

Table 5. Performance of the proposed method for FEM-1

Actual	**Estimated**					
	"AM"	"DSB"	"USB"	"LSB"	"FM"	"PM"
"AM"	155	2	1	-	2	-
"DSB"	2	150	2	4	1	1
"USB"	-	3	154	1	2	-
"LSB"	1	2	-	155	1	1
"FM"	-	-	3	2	155	-
"PM"	-	2	-	1	-	157
Total	158	159	160	163	161	159

Table 6. Performance of the proposed method for FEM-3

Actual	**Estimated**					
	"AM"	"DSB"	"USB"	"LSB"	"FM"	"PM"
"AM"	152	3	2	2	-	1
"DSB"	-	153	2	2	1	2
"USB"	2	-	157	-	-	1
"LSB"	1	2	-	155	1	1
"FM"	2	2	1	1	153	1
"PM"	1	-	-	-	1	158
Total	158	160	161	160	156	164

Table 7. Performance of the proposed method for FEM-4

Actual	Estimated					
	"AM"	"DSB"	"USB"	"LSB"	"FM"	"PM"
"AM"	155	2	1	-	-	1
"DSB"	-	157	1	2	-	-
"USB"	3	1	149	1	3	3
"LSB"	1	2	-	152	3	2
"FM"	-	-	3	1	154	2
"PM"	-	1	-	-	3	156
Total	159	163	154	156	163	164

Table 8. Performance of the proposed method for FEM-5

Actual	Estimated					
	"AM"	"DSB"	"USB"	"LSB"	"FM"	"PM"
"AM"	154	1	-	2	1	2
"DSB"	-	155	-	1	2	2
"USB"	2	2	152	3	1	-
"LSB"	-	3	2	152	1	2
"FM"	1	1	-	2	156	-
"PM"	5	3	-	2	2	148
Total	162	165	154	162	163	154

Table 9. Performance of the proposed method for FEM-6

Actual	Estimated					
	"AM"	"DSB"	"USB"	"LSB"	"FM"	"PM"
"AM"	152	3	-	1	2	2
"DSB"	1	154	-	1	1	3
"USB"	1	3	150	2	2	2
"LSB"	-	2	2	153	1	2
"FM"	2	1	1	2	154	-
"PM"	2	2	1	1	-	154
Total	158	165	154	160	160	163

Table 10. Performance of the proposed method for FEM-7

Actual	Estimated					
	"AM"	"DSB"	"USB"	"LSB"	"FM"	"PM"
"AM"	153	3	2	-	-	2
"DSB"	1	155	1	2	-	1
"USB"	2	1	152	1	2	2
"LSB"	1	2	-	154	2	1
"FM"	4	-	2	1	151	2
"PM"	1	1	-	-	2	156
Total	162	162	157	158	157	164

Table 11. Performance of the proposed method for FEM-8

Actual	Estimated					
	"AM"	"DSB"	"USB"	"LSB"	"FM"	"PM"
"AM"	152	3	2	-	1	2
"DSB"	1	153	2	2	1	1
"USB"	1	1	155	1	1	1
"LSB"	1	1	-	156	1	1
"FM"	-	-	-	1	157	2
"PM"	1	1	1	1	1	155
Total	156	159	160	161	162	162

Table 12. Performance of the proposed method for FEM-9

Actual	Estimated					
	"AM"	"DSB"	"USB"	"LSB"	"FM"	"PM"
"AM"	155	1	1	1	1	1
"DSB"	1	154	-	2	2	1
"USB"	-	-	157	1	-	2
"LSB"	1	1	-	156	1	1
"FM"	-	-	-	1	157	2
"PM"	1	1	1	1	1	155
Total	158	157	159	162	162	162

Table 13. Performance of the proposed method for FEM-10

Actual	Estimated					
	"AM"	"DSB"	"USB"	"LSB"	"FM"	"PM"
"AM"	152	3	-	1	2	2
"DSB"	-	157	1	2	-	-
"USB"	-	3	154	1	2	-
"LSB"	-	-	-	159	1	-
"FM"	-	-	3	2	155	-
"PM"	1	1	1	1	1	155
Total	153	163	159	166	161	157

Table 14. Performance of the proposed method for FEM-11

Actual	Estimated					
	"AM"	"DSB"	"USB"	"LSB"	"FM"	"PM"
"AM"	152	3	2	-	1	2
"DSB"	1	154	-	2	2	1
"USB"	2	1	152	1	2	2
"LSB"	-	3	2	152	1	2
"FM"	-	-	3	2	155	-
"PM"	1	1	-	-	2	156
Total	155	162	159	157	163	163

Table 15. Performance of the proposed method for FEM-12

Actual	Estimated					
	"AM"	"DSB"	"USB"	"LSB"	"FM"	"PM"
"AM"	155	1	1	1	1	1
"DSB"	1	155	1	2	-	1
"USB"	2	1	152	1	2	2
"LSB"	-	2	2	153	1	2
"FM"	1	1	-	2	156	-
"PM"	-	1	-	-	3	156
Total	159	161	156	159	163	162

Table 16. Performance of the proposed method for FEM-13

Actual	Estimated					
	"AM"	"DSB"	"USB"	"LSB"	"FM"	"PM"
"AM"	152	3	-	1	2	2
"DSB"	1	153	2	2	1	1
"USB"	2	2	152	3	1	-
"LSB"	-	2	2	153	1	2
"FM"	1	1	-	-	154	4
"PM"	1	3	1	2	1	152
Total	157	164	157	161	160	161

Table 17. Performance of the proposed method for FEM-14

Actual	Estimated					
	"AM"	"DSB"	"USB"	"LSB"	"FM"	"PM"
"AM"	152	3	-	1	2	2
"DSB"	1	155	1	2	-	1
"USB"	2	1	152	1	2	2
"LSB"	-	2	2	153	1	2
"FM"	4	-	2	1	151	2
"PM"	1	-	-	-	1	158
Total	161	161	157	158	157	167

Table 18. Performance of the proposed method for FEM-15

Actual	Estimated					
	"AM"	"DSB"	"USB"	"LSB"	"FM"	"PM"
"AM"	151	2	2	3	1	1
"DSB"	1	155	1	2	-	1
"USB"	-	-	157	1	-	2
"LSB"	2	2	1	149	3	3
"FM"	3	1	1	2	152	1
"PM"	2	3	1	-	1	153
Total	159	163	163	157	157	161

Table 19. Performance of the proposed method for FEM-16

Actual	Estimated					
	"AM"	"DSB"	"USB"	"LSB"	"FM"	"PM"
"AM"	154	2	-	1	1	2
"DSB"	1	153	2	2	1	1
"USB"	2	1	152	1	2	2
"LSB"	1	1	-	156	1	1
"FM"	2	2	1	1	153	1
"PM"	1	1	1	1	1	155
Total	161	160	156	162	159	162

Table 20. Performance of the proposed method for FEM-17

Actual	Estimated					
	"AM"	"DSB"	"USB"	"LSB"	"FM"	"PM"
"AM"	151	3	4	2	-	-
"DSB"	2	154	3	-	-	1
"USB"	2	1	149	3	2	3
"LSB"	1	2	1	155	1	-
"FM"	3	1	-	1	154	1
"PM"	-	3	1	-	1	155
Total	159	164	158	161	158	160

Table 21. Performance of the proposed method for FEM-18

Actual	Estimated					
	"AM"	"DSB"	"USB"	"LSB"	"FM"	"PM"
"AM"	155	1	1	2	-	1
"DSB"	1	156	1	1	1	-
"USB"	2	1	151	1	3	2
"LSB"	1	-	3	153	1	2
"FM"	3	1	-	-	149	7
"PM"	5	1	1	2	1	150
Total	167	160	157	159	155	162

Table 22. Performance of the proposed method for FEM-19

Actual	Estimated					
	"AM"	"DSB"	"USB"	"LSB"	"FM"	"PM"
"AM"	153	3	2	2	-	-
"DSB"	1	153	3	2	-	1
"USB"	-	1	155	-	2	2
"LSB"	1	2	2	152	2	1
"FM"	-	2	3	1	154	-
"PM"	2	2	1	-	-	155
Total	157	162	167	158	156	158

Table 23. Performance of the proposed method for FEM-20

Actual	Estimated					
	"AM"	"DSB"	"USB"	"LSB"	"FM"	"PM"
"AM"	155	3	1	1	-	-
"DSB"	1	153	3	2	-	1
"USB"	-	1	157	-	1	1
"LSB"	1	2	2	154	1	-
"FM"	-	2	3	1	153	1
"PM"	2	1	1	-	1	155
Total	159	162	167	158	156	158

From above tables, it is shown that FEM-2 has the best classification accuracy for analog modulation types. Table 24 shows the classification accuracy for each FEM.

Table 24. Performance comparison between the proposed method and Ref. [11] for analog modulated signal classification

FEMs	Classification accuracy (%)	
	This study	**Ref. [11]**
FEM-1	96.45	99.27
FEM-2	99.27	98.22
FEM-3	96.66	97.60
FEM-4	96.14	95.52
FEM-5	95.52	95.31
FEM-6	95.52	95.31
FEM-7	95.93	97.91
FEM-8	96.66	95.52
FEM-9	97.29	93.33
FEM-10	97.08	96.35
FEM-11	95.93	96.04
FEM-12	96.56	93.33
FEM-13	95.41	93.95
FEM-14	95.93	97.91
FEM-15	95.52	94.06
FEM-16	96.14	97.50
FEM-17	95.62	95.72
FEM-18	95.20	96.66
FEM-19	96.04	92.08
FEM-20	96.56	94.68
Mean accuracy (%)	96.2715	95.81

The results obtained from this table show that the performance of the proposed method is 96.2715. Traditional approaches such as "Decision Theory", "Statistical Pattern Recognition"; It is disadvantageous due to large-size feature vectors, complex algorithms and the need for large storage space [31]. The proposed method eliminates drawbacks mentioned above. Therefore, the proposed method is an alternative approach to conventional approaches such as "Decision Theory", "Statistical Pattern Recognition", presented for classification of AMS. However, a poor classification performance can be obtained for signals with higher SNR when ELM classifier is trained by using signals with lower

SNR [32]. Both smaller size and more efficiently feature vector and a compact set of features are obtained by using DWT. Thus, the classification performance is improved by using DWT. Performance of the proposed method for analog modulated signal classification is also presented in Table 24 as compared with Ref [11]. This table reveals that the proposed method shows a more effective classification performance than results of Ref [11].

4. Conclusion

This study proposes a method based on DWT-ELM for analog modulation classification. For this aim, a modulated "real voice signal" using the 6 different "AMS" schemes as "AM", "DSB", "USB", "LSB", "FM", and "PM" is used for experimental study. The classification performance of the proposed method is evaluated for 20 different feature extraction algorithms. Further, "White Gaussian Noise" is added to analog signals. Same experiments are conducted for analog signals added white Gaussian noise. Results from this study were compared with the previous study. However, from the experimental results, it can be said that the proposed method has a better performance against noise.

Author's Contributions

All contributions belong to the author in this paper.

Statement of Conflicts of Interest

No potential conflict of interest was reported by the authors.

Statement of Research and Publication Ethics

The authors declare that this study complies with Research and Publication Ethics.

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