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Digital Modulation Classification Using Wavelet Transform and Artificial Neural Network

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Abstract
Received signals contain a vast amount of uncertainty due to the unknown modulating signals, communication channel, and noise. Therefore the modulation classification problem has to be approached based on artificial neural networks . In this work a digital modulation classification method is presented, based on discrete wavelet transform (DWT) and artificial neural networks (ANN) to distinguish digital modulation, like quadrature amplitude (QAM), phase shift keying (PSK), and frequency shift keying (FSK) signals. Feature extraction is performed via the DWT detail coefficients of the digital signals using (db4) mother wavelet, because of the usefulness of wavelet in signal de-noising .The extracted features are presented to an ANN for pattern recognition. In this work Levenberg-Marquardt error back propagation algorithm is used since it appears to be the fastest method for training moderate-sized feed forward neural networks (up to several hundred weights).The performance of the classification scheme is investigated through simulations using matlab-7, high recognition rates are obtained of about (97%).However, there are probabilities of misclassification of about (3%).

Keywords: Digital modulation classification, Discrete Wavelet Transform (DWT) and Artificial Neural Network (ANN) modulation recognition.

Introduction:

Modulation classification or recognition of digital communication signals is an important signal processing problem in communications, and its related fields. The interest in digital modulation classification has been growing since the last three decades up to date. It has several possible roles in both civilian and military applications such as signal confirmation, interference identification, spectrum management, and surveillance [1]. Modulation classification is an intermediate step between signal interception and demodulation [2]. Modulation classifiers, like general pattern recognition systems , consist of pre-processing, feature extraction, and decision parts. The feature extraction part reduces the dimensionality of the measurement by extracting the distinctive features which should be simple and fast to calculate. There are several ways to make the decision based on the obtained features such as decision functions, distance functions, and ANN. [3]

Recent developments in the field of ANN have made them a powerful tool for pattern recognition and classification. A variety of techniques have been proposed to distinguish digital modulation types. Many researchers proposed recognition schemes using ANN methods for example [2,4,5]. In these papers, features are extracted from the instantaneous amplitude, phase and frequency of the intercepted signal. These features are analyzed by a trained multi-layer preceptron (MLP).

In this work, the (DWT) is used for feature extraction, for pattern recognition and classification. Wavelet transform is used in communication signal processing, it has been used in digital modulation

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recognition (DMR)because of the capability of the extracted features from the DWT to capture all the major attributed of the intercepted signals in a relatively small number of components which is one of the primary requirements for a good ANN classifier , so, wavelets & neural networks can be successfully combined for pattern recognition and classification.[3,6]

There are two methods of using DWT & ANN for classification, the first method is the Classification Wavelet Network (CWN), in which the wavelet transform is applied in the first hidden layer of the network to extract compact features from input signals, and is followed by further layers to perform classification [7]. The second method which used in this work, is that the features were extracted from the coefficients of (DWT) of the communication signal after certain level of decomposition, and the extracted features are then fed to the neural network subsystem for classification.

Modulation Classification :

A modulation classifier can be described as a system comprising three parts as shown in fig.(1). The work of the pre-processor is increasing the performance of the classifier. The pre-processor removes disturbances from the signal such as interfering signals and increasing the (SNR) and also filtering the received signal, down conversing , equalizing, and sampling it and compensates for fading on the channel. This is only a preparation for the feature processor which extracts discrimination features of the signal before the classifier makes the decision about the modulation type of the given available data. The classification techniques are pattern recognition and decision .[3-5]

Let the received waveform $r(t)$, $0 \le t \le T$ be described as,

$r(t) = s(t) + n(t)$, ………………....(1)

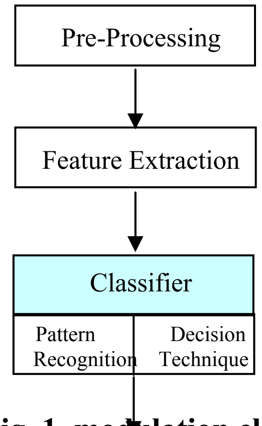


Fig. 1. modulation classifier parts.

where $s(t)$ is transmitted signal and $n(t)$ is an additive white Gaussian channel noise. The signal $s(t)$ can be represented in complex form as

$s(t) = s'(t)e^{j*f(\omega ct+\theta c)}$,…………….(2)

where ωc, is the carrier frequency and θc is the carrier phase. Generally, the complex envelope of $s(t)$ in (1) may be expressed

For QAM signal:-

$s'_{QAM}(t)=\sum_{i=1}^{N}(Ai+jBi)u_T(t-iT)$,……..(3)

$Ai,Bi\in\{2m-1-M,m=1,2,\dots,M\}$.

For PSK signal:-

$s'_{PSK}(t)= \sqrt{s}\sum_{i=1}^{N} e^{j\varphi i}u_T(t-iT)$,……..(4)

$\varphi i\in\{2\pi/M(m-1),m=1,2,..,M\}$.

For FSK signal:-

$s'_{FSK}(t)=\sqrt{s}\sum_{i=1}^{N} e^{j(\omega_i t+\theta_i)} u_T(t-iT)$,...(5)

$\omega_i\in\{\omega_1,\omega_2,\dots,\omega_M\},\theta_i\in\{0,2\pi\}$

In (3), (4), and (5), S is the signal power, N is the number of observed symbols, T is the symbol duration and uT (t) is the standard unit pulse of duration T, it is assumed that the three signals have the same symbol duration. It can be seen from (3)-(5) that symbol changes will give rise to transients in the modulated signals. The transients are created independently in the changes of amplitude, phase and frequency respectively[8]. WT can characterize these transients effectively and allowing simple method for identification of the three signals since the analysis technique is required for non-stationary signal, which will analyze the signal frequency with time instants of occurring. The Fourier transform approach gives either the frequency components or time components. The wavelet transform has the special feature of multi-resolution analysis (MRA), which provides the necessary parameters to extract the feature of the modulated signals.[9]

The continuous WT of a signal s(t) is defined as [9]

$$CWT(a,\tau) = \int s(t)\psi^{*}{}_{a}(t)\, dt$$
$$= 1/\sqrt{a} \int s(t)\psi^{*}(t-\tau/a), \ldots\ldots\ldots\ldots\ldots\ldots(6)$$

where a is the scale, τ is the translation and the superscript * denotes complex conjugate. The function $\psi(t)$ is the mother wavelet and the baby wavelet ψ_a (t) comes from time-scaling and translation of the mother wavelet. The choice of a mother wavelet depends on its application. Some widely used wavelets are Morlet, Haar, Daubechies and Shannon [9].Due to its simple form and easy computation, Haar wavelet is widely used , in this study Daubechies 4 (db4) mother wavelet is used since better results are obtained with it.

Feature Extraction using WT:

Feature extraction is the key to pattern recognition. Two available sources of information involved with time and frequency domains are inherent in communication signals. When the signal includes important structures that belong to different scales, it is often helpful to decompose the signal into a set of 'detail components' of various sizes. DWT analyzes signals at different frequency bands with different resolutions by decomposing a signal into coarse approximation and detail information, so it is widely used in pattern recognition and classification. DWT employs two sets of function, known as the scaling functions and wavelet functions, which can be viewed as low-pass and high- pass filters[9,10], approximation coefficients (A), and detail coefficients,(D), as shown in Fig. (2).

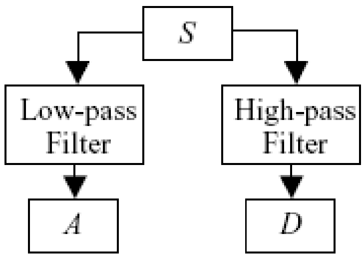


Fig. 2. DWT decomposition structure

The approximation coefficients are the high-scale, low-frequency components of the signal, while the detail coefficients are the low-scale, high frequency components. The DWT, or filtering, process can be repeated until only one approximation coefficient is found [9]. In this work , a randomly generated signal of 64 samples is processed ,so the feature extraction structure is performed using the wavelet detail coefficients using db4 coefficient filter of the wavelet decompositions at 6 levels , as shown in Fig.(3). It is clear from fig.(3) that d_1 represents the highest frequency region, d_2

the next lower frequency region, and so on.

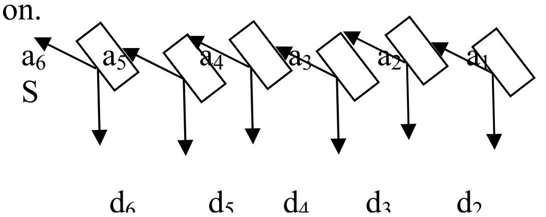


Fig. 3. Wavelet coefficients of the DWT at 6 levels

Sequences d_1, d_2, …, d_m are determined from a set of representative signals. The input feature vectors to a signal interpretation procedure can be computed from these sequences, which consists of simply determining every component *fm* of the feature vector (f_1,f_2, …, f_m) through the Euclidean norm of each sequence *dm*.

$$fm=||dm||^2 =[\sum_{i=1}^{N} dm^2\,(i)]^{1/2},\ldots\ldots\ldots\ldots(7)$$

This means that each feature f_m is determined as the square root of the energy of the wavelet coefficients in the corresponding cluster d_m. Consequently, the number of features for a signal *S* is equal to the number of sequences determined.

The physical meaning of each feature f_m , which is equal to that of a wavelet coefficient, namely represent time and frequency information of the regarded
signals *S*. A single feature especially describes a certain frequency rang (a scale *m*), which is equal to that described by the wavelet coefficients underlying this feature. And so constructed feature vectors are robust to noise in the corresponding signals *S*, which has been proofed in recent research work [10,11].

Pattern Recognition using ANN and the decision process:

Modulation classification is a problem well suited for pattern recognition. After extracting available information from the signal, a pattern recognition subsystem whose function is to indicate the modulation types is used to compare these features and make a decision. Neural networks have often be applied to classification problems as a technique to use a computed vector and arrive at a classification decision [3,4]

In recent years, the application of ANN to many pattern recognition problems is seen, including communication signal modulation recognition [5] Because the convergence characters depend on the complexity of the structure including the number of the layers and the output nodes, in this work a simple structure of ANN is chosen [with a 6-node input layer, a single hidden layer with 20 nodes and only a 3- node output layer instead of a 7-nodes output layer] for classifying seven signals: 8PSK (8-phase shift keying), 16PSK(16-phase shift keying), 2QAM (binary quadrature amplitude modulation), 8QAM (8- quadrature amplitude modulation),16QAM (16-quadrature amplitude modulation), 2PSK (binary phase shift keying) and 8FSK (8-frequency shift keying). Inputs to this network are the feature vectors extracted from the wavelet coefficients of the received signals as explained in the previous section . At the end of it's training, the net performs a binary classification on each given input pattern. The value of each neuron in the output layer are distinguished as "1" & "0", which forms the output vector from 001 to 111.

Among the many neural networks learning algorithms, the error back propagation (BP) algorithm is considered the most useful learning algorithm. However, in training and learning phase of the ANN, a network using standard BP learning algorithm may slow the process .

In order to improve the speeding characteristics, the algorithm of

Levenberg-Marquardt (LM) error back propagation is employed in this work.

At the end of its training, the net performs a binary classification on each given input pattern. The value of each neuron in the output layer are designated as '1' and '0', which forms the output vector from '001' to '111' to expressing different signals.

The idea of this work can be described through the flow chart shown in fig.(4) :

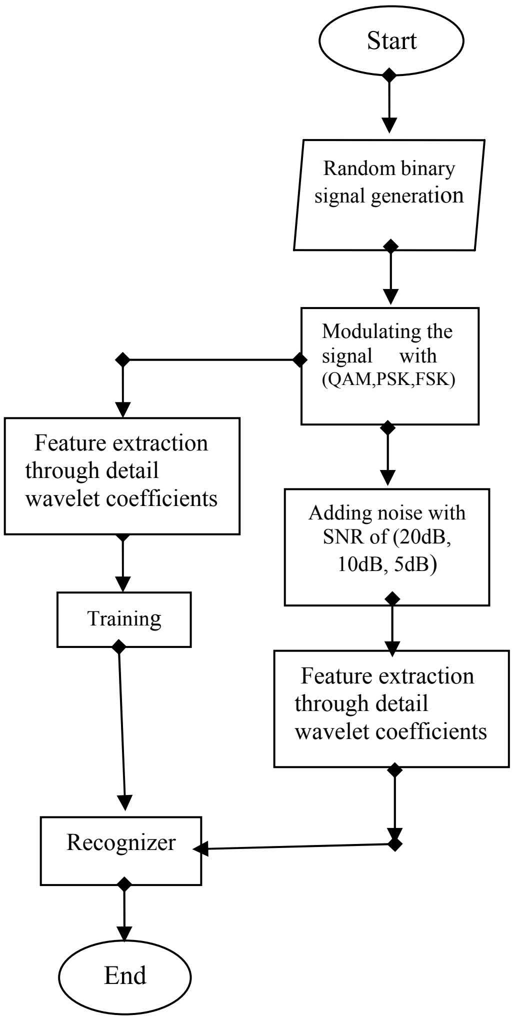


Fig. 4. The flow chart of the work.

Results and discussion:

The algorithm was applied for seven types of digital modulations (8PSK, 16PSK, 2QAM,8QAM,16QAM, 2PSK and 8FSK) and for different SNR ratios (20, 10, &5dB). The Haar (db1) mother wavelet is often used by researchers for the feature extraction part since it is the simplest mother wavelet , in this work db4 mother wavelet is used for the results were bertter than that of Haar wavelet, [7] it is inspected that better results can be obtained with mother wavelets with higher orders from this family, but higher orders means larger filter tap, so the processing complexity will increase.

The discrete signals for 2QAM are shown in fig. (5) [The random binary signal (64 bits), 2QAM signal, wavelet approximation and detail coefficients , first, second, third, forth, fifth, and sixth level detail coefficients] respectively. Fig.(6) shows the noisy 2QAM signal and all wavelet levels detail coefficients. The same signals of 2PSK signal are shown in fig.(7) and the noisy 2PSK signal is shown in fig.(8). The performance characteristics of the ANN system is shown in fig.(9), it is clear that the system has a good performance since it approaches to zero. The classification results of all modulation types are shown in tab.(1), higher classification rates were obtained with higher SNR except for the 8PSK modulation, other researchers like [2,4,10-13] obtained similar results for high order 8,16QAM, 8,16PSK & 8,16FSK modulation . The confusion matrix of the classifier at SNR=5dB is shown in tab.(2). It is clear that a high classification rate is obtained, however confusion occur between 8QAM &16QAM of about 1.3% and between 8PSK and 16PSK of about 1.1% when the signal to noise ratio is 5dB.

Conclusions and Future Works:-

A modulation classification algorithm is described based on DWT and ANN, which is suited for 7-band limited digital modulation schemes after adding white Gaussian noise with different SNRs. In this paper de-noised and compressed features for signal recognition are extracted from the detail coefficients of DWT, and for 6-decompositin levels using db4 mother wavelet.

The high recognition rate shown in tab.(1) indicates the robustness of the classifier. However, there are misclassifications and confusion in the classification process specially for SNR=5dB, which might be reduced By:-

1- Using different mother wavelets.

2-Using larger training sets for pattern recognition.

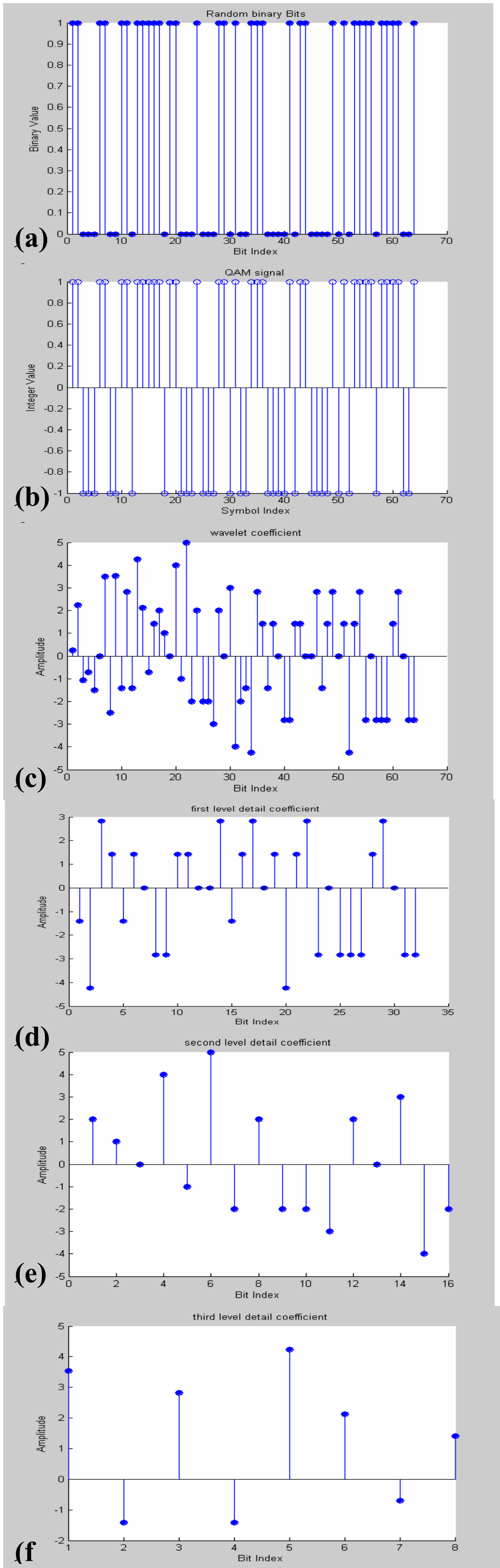
3-Using fuzzy logic for the decision part since fuzzy logic allows for values between 0&1, while in classic logic every thing can be expressed in binary terms (0,1) i.e. true or false. Fuzzy logic used to describe degrees of truth which is useful in the classification process.

Tab.(1)The accuracy rate of each signal at different SNR

signal	20dB	10dB	5dB
8PSK	99%	95%	97%
16PSK	98%	97%	96.2%
2PSK	100%	100%	100%
8FSK	97.5%	96%	94.5%
2QAM	100%	100%	100%
8QAM	98.5%	98%	93.5%
16QAM	99%	99.5%	94%

Tab.(2) Confusion matrix for SNR=5dB

Signal	8 PSK	16 PSK	2 PSK	8 FSK	2 QAM	8 QAM	16 QAM
8 PSK	97%	1.1 %					
16 PSK		96.2 %					
2 PSK			100 %				
8 FSK				94.5 %			
2 QAM					100 %		
8 QAM						93.5 %	1..3 %
16 QAM							94%



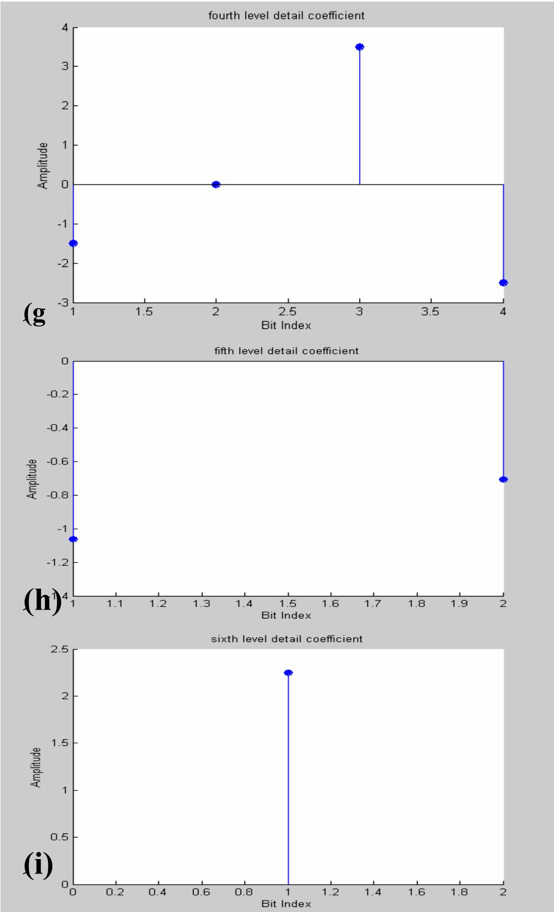
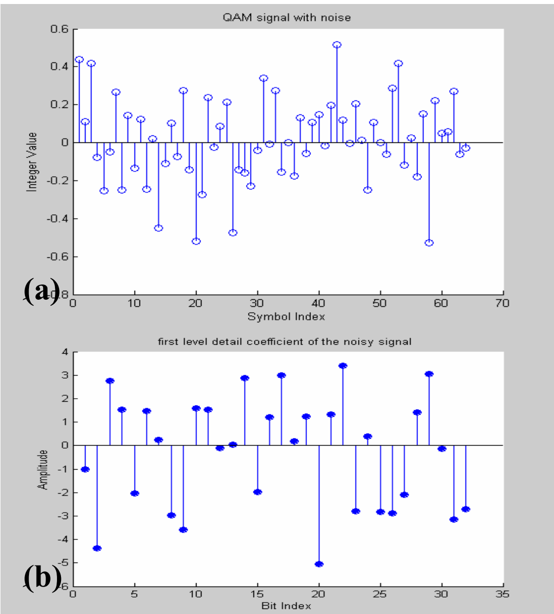


Fig.(5) (a)The random binary signal, (b)2QAM signal, (c)wavelet approximation and detail coefficients , (d)first, (e)second, (f)third, (g) forth,(h) fifth, and(i) sixth level detail coefficients



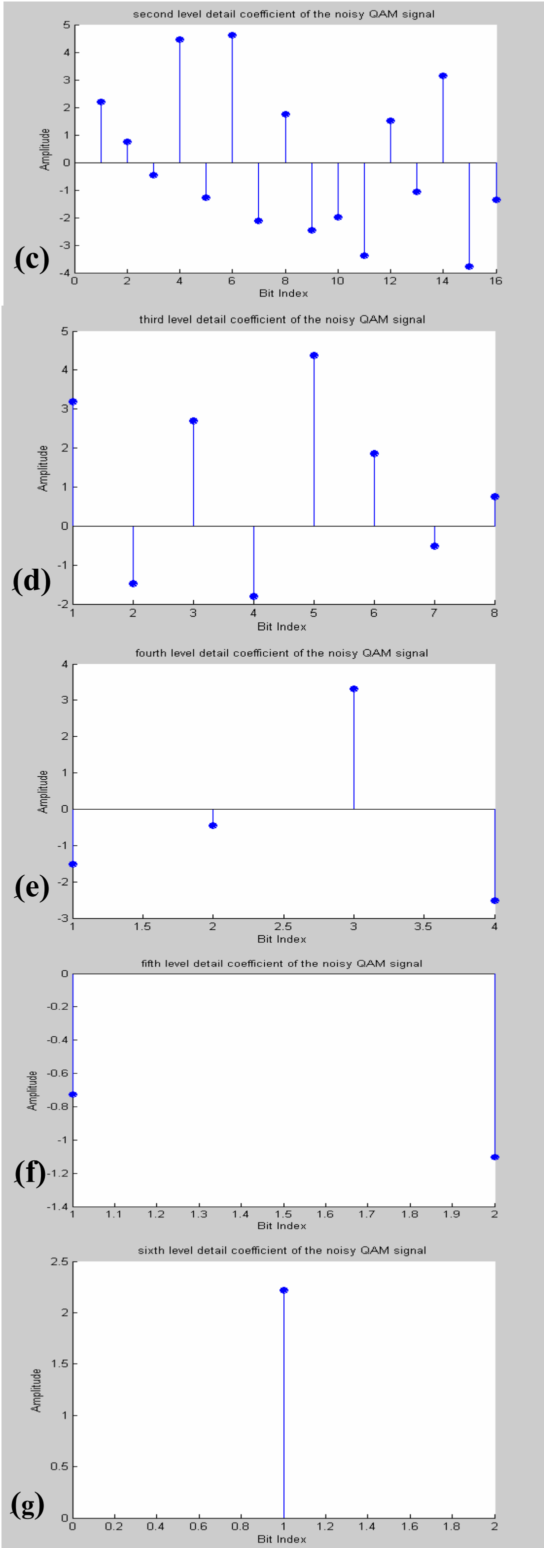
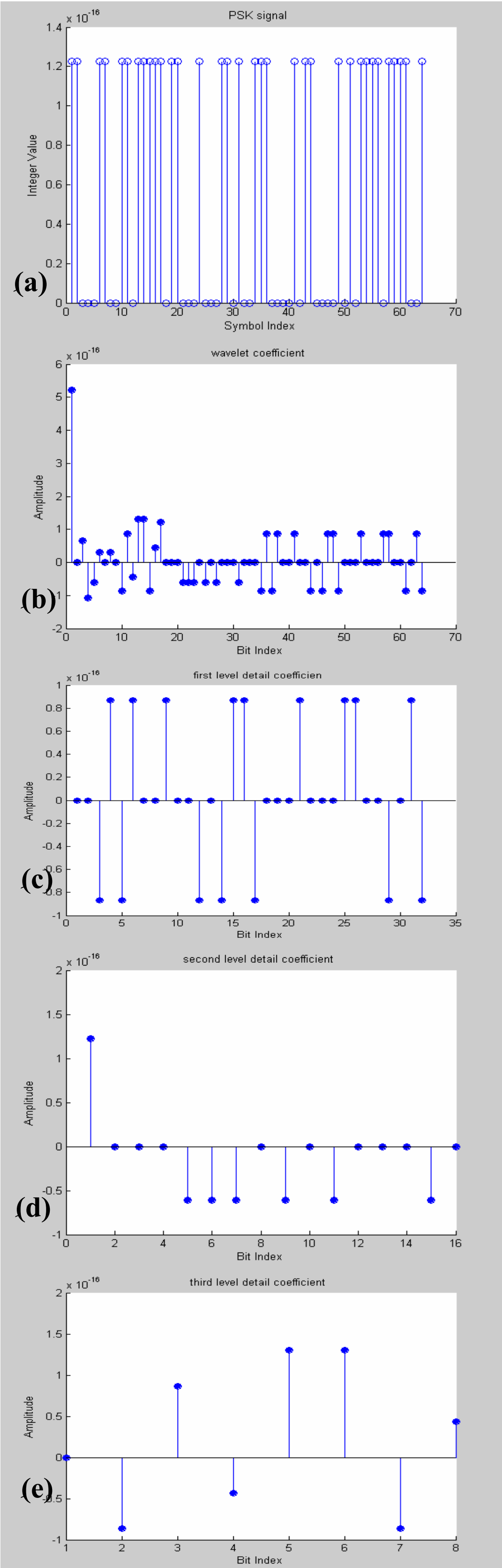


Fig.(6) (a)The noisy 2QAM signal (SNR=10dB), (b) first, (c)second, (d)third, (e) forth, (f) fifth, (g)sixth level detail coefficients.



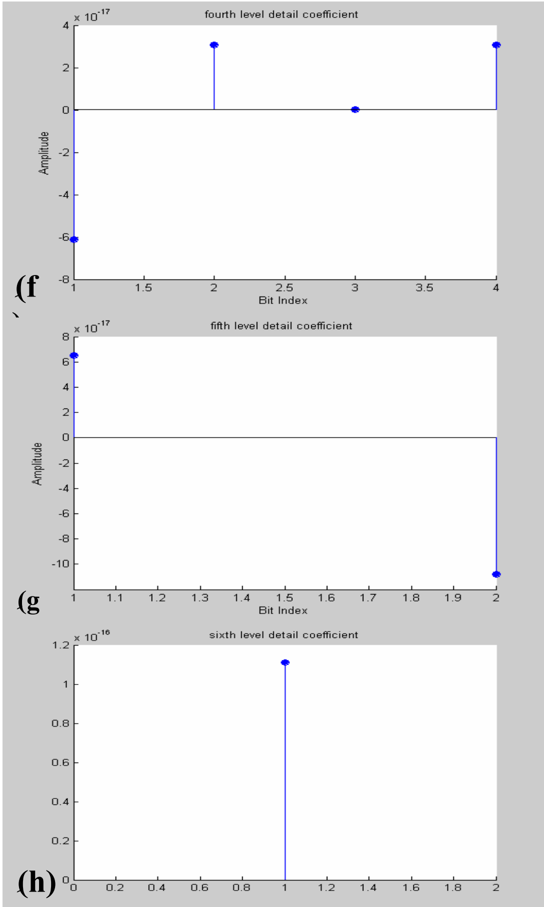
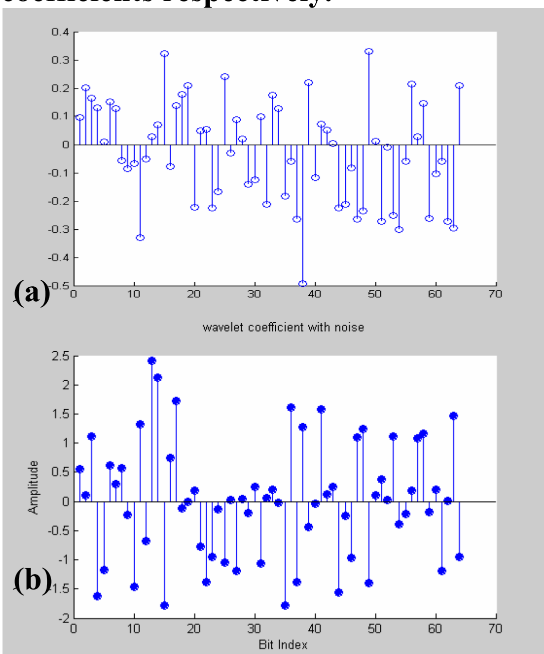
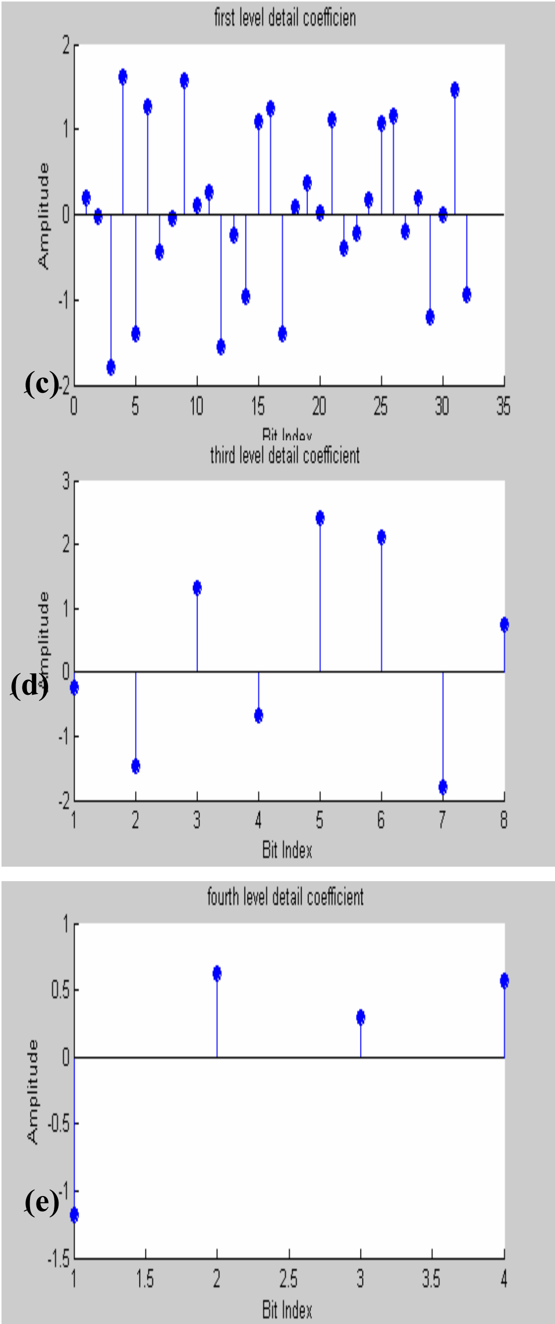


Fig.(7),(a) The 2PSK signal ,(b) wavelet approximation and detail coefficients , (c) first, (d) second, (e) third, (f) forth, (g) fifth, and(h) sixth level detail coefficients respectively.





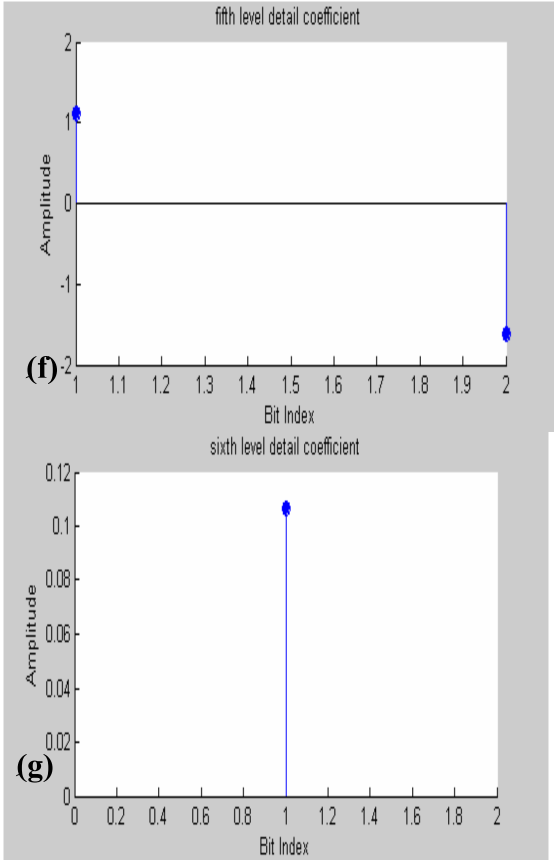


Fig.(8) (a)The noisy 2PSK signal (SNR=10dB), (b) first, (c)second, (d)third, (e) forth, (f) fifth, (g)sixth level detail coefficients.

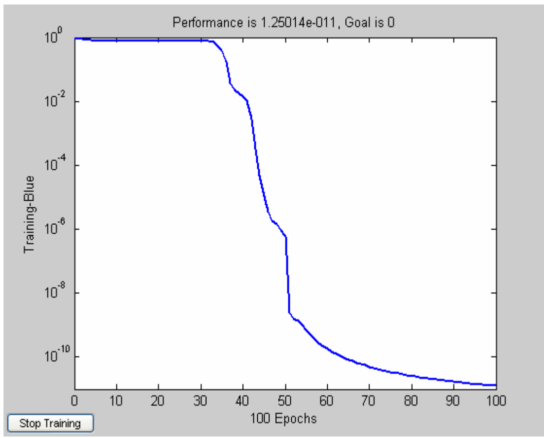


Fig.(9): The performance characteristics curve of the ANN system.

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ناسینەوەی جۆری تێهەڵچونی دیجیتال بە بەكاهێنانی گۆرانی شەپۆلكە و تۆری خانە مێشكییە دەستكردەكان

فاتیمە كامیل فایەق

بەشی كارەبا-كۆلیجی ئەندازیاری-زانكۆی سەلاحەدین هەولیز-هەریمی كوردستان-عیراق

پوختە

سیگناڵی گەیشتوو برێكی زۆر لە نادروستی تێدا بە دی دەكرێت بە بۆنەی نەزانینی جۆری سیگناڵ كە تێهەڵچونی بۆ كراوە و جۆری كەناڵی گەیاندن لە گەڵ وژە وژ كە وایكرد كێشە دروست بێت لە پرۆسەی تێهەڵچون، بۆیە بە پشت بەستن بە خانەمێشكییە دەستكردەكان هەوڵی ناسینەوەی جۆری تێهەڵچەن بزانرێت.

لەم كارەدا رێگەیەك خرایە بەر دەست بۆ ناسینەوەی جۆری تێهەڵچوون، كە لە سەر بناغەی گۆرانی شەپۆلكە و تۆری خانە مێشكییە دەستكردەكان دروست كراوە بۆ ئەوەی جۆری تێهەڵچونی وەكو QAM, PSK, FSK بناسێتەوە. تاییە تمەندیەكانی سیگناڵ بە دەست دەهێنرێت لە رێگەی گۆرانی شە پۆلكە و بەكارهێنانی (db4) بە بۆنەی ئەو سوودەی كە گۆرانی شە پۆلكە ئەییەخشێت بۆ لابردنی وژەوژ. تاییە تمەندە بەدەستهێنراوەكان دەدرێنە تۆری خانە مێشكییە دەستكردەكان بە مەبەستی ناسینەوەی. لەم كارە ریگەی error back propagation لە جۆری LM بە كار هێنرا، چونكە خیرا ترین رێگەیە بۆ قەبارەی ئەو بەشە كە تاییەتە بە فێركردن لە تۆری خانە مێشكییە دروستكراوەكان و زیاتر لە سەدەها ئەوەندەی كێشەكان. تاییە تمەندییەكانی ئەم رێگەیە تاوتویٚ كرا بە بەكاهێنانی matlab7. رێژەیەكی بەرز لە ناسینەوە بەدەستهێنرا (٩٧٪) بەلاٚم لە گەڵ ئەوەشدا رێژەیەك هەبوو كە تیایدا هەڵە لە ناسینەوە روویدا (٣٪)..

تصنيف التضمين الرقمي باستخدام تحويل المويجة و الشبكات العصبية الصناعية

فاطمة كامل فائق

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الخلاصــة

الإشارة المستقبلة تحتوي على مقدار من عدم الدقة نتيجة عدم معرفة نوع الإشارة التي قد تم تضمينها وطبيعة الوسط الناقل والضوضاء، مما أدى إلى مشاكل في التضمين ومن ثم الإعتماد على طريقة الشبكات العصبية الصناعية، ANN لغرض التصنيف.

في هذا العمل تم عرض طريقة لتصنيف التضمين الرقمي والتي تعتمد على تحويل المويجة وشبكات العصبية الصناعية لأجل التعرف على نوع التضمين لإشارات الQAM، PSK، و FSK. تم استخراج خصائص الإشارة من خلال أخذ تحويل المويجة (DWT) لها وباستخدام المويجة الأم (db4) بسبب الإستفادة التي يتم الحصول عليها من تحويل المويجة في عملية إزالة الضوضاء. الخصائص المستخرجة يتم عرضها على شبكة عصبية صناعية لأجل التعرف إليها ففي هذا العمل تم استخدام خوارزمية التغذية الخلفية للخطأ من نوع الLM لأنها الطريقة الأسرع لحجم الجزء الخاص بعملية التعلم للشبكة العصبية لأكثر من عدة مئات من الأوزان. خصائص منظومة التصنيف قد تم دراستها باستخدام matlab7 ، ولقد تم الحصول على نسبة عالية للتعرف في حدود (٩٧٪) على الرغم من وجود احتماليات للخطأ في التصنيف بنسبة (٣٪).

وەرگیراوە لە ٢٠٠٨/١٠/٢٦ دا , و پەسەند كرا لە ٢٠٠٩/٣/٤ دا

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