Exploring New Features for a Wavelet Neural Digital Modulation Recognition System

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Abstract

Modulation recognition has been an important problem in both commercial and military wireless communication. Modulation recognition can be divided into two categories: identification between categories and identification in category. In this work a system is proposed for identification between categories of different digital modulated signals using a combination of discrete wavelet transform (DWT) and the linear predictive coding (LPC) with the probabilistic neural network (PNN) as a classification tool. It was found that the proposed system out performed any of the existing systems by using six DWT decomposition levels and 20 LPC coefficients. The symlet 20 wavelet filter proved to be the best candidate. The results showed that a 100% recognition can be achieved at a signal to noise ratio (SNR) of 2db for the digitally modulated signal.

Keywords: Modulation recognition, Wavelet, linear predictive coding, Probabilistic neural network.

استكشاف خصائص جديدة لنظام تمييز التضمين الرقمي مبني باستخدام التحويل المويجي والشبكات العصبية

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الملخص

يعتبر تمييز نوع التضمين مشكلة هامة في مجال الاتصالات اللاسلكية على حد سواء التجارية والعسكرية. ويمكن تقسيم تمييز التضمين إلى فئتين: تحديد نوع التضمين وتحديد درجة التضمين في فئة. في هذا العمل تم اقترح نظام لتحديد نوع التضمين بين فئات مختلفة من إشارات التضمين الرقمية باستخدام مزيج من تحويل المويجات المنفصل (DWT) و الترميز الخطي التنبؤي (LPC) مع أداة تصنيف هي الشبكة العصبية الاحتمالية (PNN). حيث تبين ان النظام المقترح فاق أي من النظم القائمة عن طريق استخدام ستة مستويات تحليل DWT و 20 معاملLPC. ثبت ان مرشح المويجات symlet 20 هو أفضل مرشح يمكن استخدامه للنظام المقترح. أظهرت النتائج التي التوصل الى تمييز 100٪ للإشارة المضمنة رقميا بوجود نسبة الضوضاء (SNR) 2db.

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1. 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. Modulation classification is an intermediate step between signal interception and demodulation [1].

Modulation classifiers are generally divided into two categories. The first category is based on decision-theoretic approach while the second on pattern recognition. The decision-theoretic approach is a probabilistic solution based on a priori knowledge of probability functions and certain hypotheses [2]. On the other hand, the pattern recognition approach is based on extracting some basic characteristics of the signal called features. This approach is generally divided into two subsystems: the features extraction subsystem and the classifier subsystem. However, the second approach is more robust and easier to implement if the proper features set is chosen [3]. In the past, much work has been conducted on modulation identification. The identification techniques, which had been employed to extract the signal features necessary for digital modulation recognition, include spectral-based feature set, higher order cumulates (HOC), constellation shape, and wavelets transforms. With their efficient performance in pattern recognition problems (e.g., modulation classification), many studies have proposed the application of artificial neural networks (ANNs) as classifiers [4].

Different modulation schemes have the characteristic of different transients in amplitude, frequency or phase. The wavelet transform (WT) is a powerful tool for analyzing non-stationary signals, which include digital communication signals, and the WT magnitude of communication signals vary with modulation types. The WT has capability to extract transient information which can be exploited for modulation classification [5].

The wavelet transform (digital and continuous) is used in communication signal processing, it has been used in digital modulation recognition (DMR) because of the capability of the extracted features from the WT 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.

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 [6]. The second method is that the features are 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. This method is used in this work.

2. Motivation and previous work

Wavelets and neural networks have been used in past and recent work. Azzouz E., Nandi A. [7,8] had the privilege of from the first that investigated the world of modulation recognition, they introduced neural networks as a new approach. In [9] Hong L. and Ho K. studied the use of continuous wavelet transform to distinguish QAM signal, PSK signal and

FSK signal. Ataollah E. et. al. used the radial basis function neural network as the classifier after extracting the features using a combination of higher orders of statistics (HOS)[10]. A combination of WT key features and Support Vector Machine (SVM) for classification is found in [5].

A comparison between the most used neural networks in modulation recognition (the multilayer perceptron and the probabilistic neural network) is found in [11]. Recently Hou Y., Feng H. [12] introduced the use of singular value decomposition to reduce the number of features extracted from the wavelet decomposition of the signal then the classification is achieved using the error back propagation network the approach used a two stage system first the classification is done on category bases then the exact type is found. In the above and others (not mentioned here) promising results are found. But more work is still needed to classify a digitally modulated signal specially at low levels of signal to noise (SNR) values.

In this work a new type of features is examined, taking advantage of the progress made in the field of wavelet and neural network hopefully to achieve good results. This features are the linear predictive coding (LPC) features which are widely used in speech processing and were introduced by [13] to be used in modulation recognition. [13] used these features combined with continuous wavelet transform and his results stopped at a SNR of 7db. Later these features (LPC) were suggested by [14] with eight other features, but he did not recommend it in his optimal feature set. It was noticed in his work that he used ten coefficients, this is not a good choice, as the minimum number of coefficients that is to be used to best represent a spectrum must be at least 15 according to [15].

3. Modulation Classification

A modulation classifier can be described as a system comprising three parts as shown in Figure 1. The work of the pre-processor is increasing the performance of the classifier it is only a preparation for the feature extraction, which extracts discrimination features of the signal before the classifier makes the decision about the modulation type of the given available data.

In this work the pre-processor is a six stage digital wavelet decomposition. The feature extraction is an LPC coefficient extractor and finally a neural network known as the probabilistic neural network (PNN) achieves the classification.

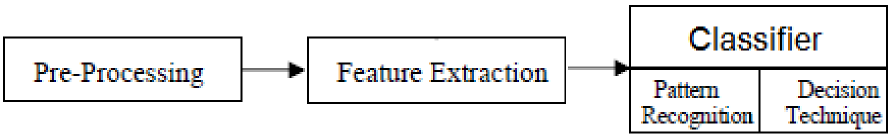


Figure 1: Typical modulation recognition system

4. Theoretical Background

4.1 Wavelet and Wavelet Packets

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.

According to the multi-resolution theory, any wavelet ψ that generates an orthogonal basis of $L^2(\mathrm{R})$ is characterized, by means of a filter bank construction, by a pair of discrete filters consisting of a high-pass (HPF) and a low-pass one (LPF) followed by sub-sampling by two to reduce redundancy. These filters belong to a particular class of filters, called *conjugate mirror filters*, and cascading these filters produces a fast discrete wavelet transform. Wavelet packet functions generalize the filter bank tree that relates wavelets and conjugate mirror filters. The lower, as well as the higher frequency bands are decomposed giving a balanced binary tree structure. See Figure 2. [16].

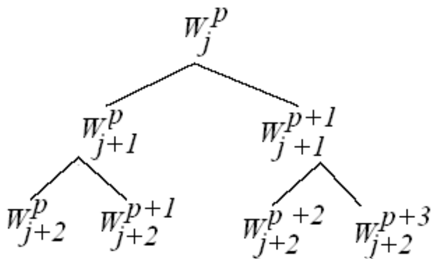


Figure 2: Binary tree of wavelet packet spaces

4.2. Linear Predictive Coding

The rationale in linear prediction (LP) analysis is that adjacent samples of the a waveform are highly correlated and thus, the signal behavior can be predicted to certain extent based on the past samples. The LP model assumes that each sample s[n] can be approximated by a linear combination of a few past samples [17]:

$$s[n] = \sum_{i=1}^{p} a[i]s[n-i] \qquad (1)$$

The order of the predictor is p. The goal of the LP analysis is to determine the predictor coefficients {a[i] / i = 1…, p} so that the average prediction error (or residual) is as small as possible. Any signal can be approximated with the LP model with an arbitrary small prediction error [17].

Use the LPC coefficients are not often as features themselves. It is observed in practice that adjacent predictor coefficients are highly correlated, and therefore, representations with less correlated features would be more efficient. A popular feature set is *linear predictive cepstral coefficients*. Given the LP coefficients ($a[k]$ k=1… p), the cepstral coefficients of $c[n]$ are computed using the following recursive formula [17]:

$$c[n] = \begin{cases} a[n] + \sum_{k=1}^{n-1} \frac{k}{n} c[k]a[n-k], & 1 \le n \le p \\ \sum_{k=n-p}^{n-1} \frac{k}{n} c[k]a[n-k], & n > p \end{cases} \qquad (2)$$

4.3 The Probabilistic Neural Network

Artificial neural networks (ANN) are adaptive models with a network-like structure consisting of a large number of processing units, called neurons.

In the present work a special type of neural network is used called Probabilistic Neural Network (PNN) (see [18] for details) .

The use of the probabilistic neural network (PNN) is motivated by its well known power full classification characteristics. So it is used in this work to classify the input (after extracting its features). Figure 3 shows the architecture of the probabilistic neural network used in this work.

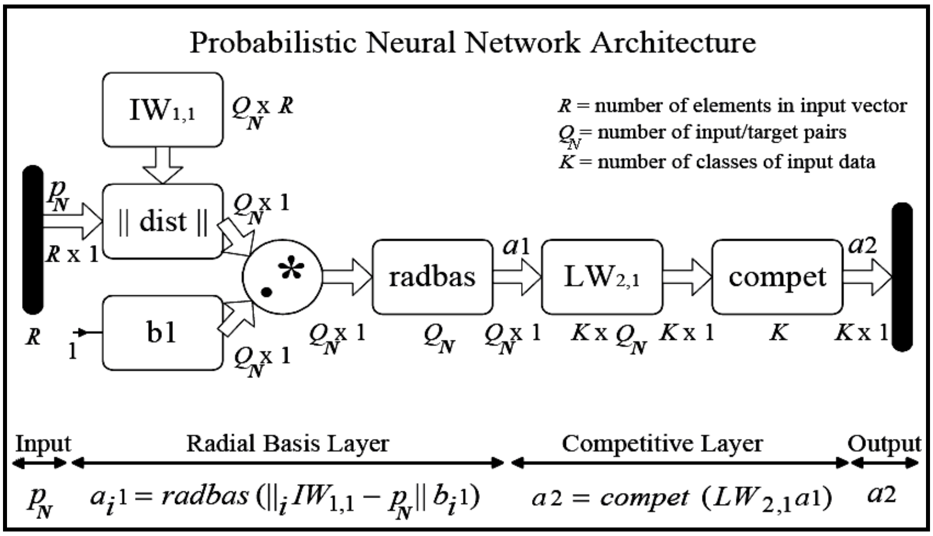


Figure 3: Architecture of the Probabilistic Neural Network

5. System Architecture for Modulation Recognition

Before describing the architecture of the proposed system it is needful to mention the types of digital modulation signal that the system distinguished. The four main modulation types (ASK, FSK, PSK, QAM) were categorized in three groups according to the main distinguishing varying characteristic (the amplitude for the 2, 4 8 ASK, the frequency for 2,4,8FSK and the phase for 2,4,8PSK &16,32,64QAM). The reason behind merging the two types (PSK & QAM) in one category is that the most variation in QAM is the phase, (for example 4QAM is a signal that varies between four values of phase with constant amplitude). On the other hand the most popular noise effect any digitally modulated signal (the white Gaussian noise) effects the amplitude more than the phase. Never the less, if a signal is found that it is a phase varying signal the decision that it is PSK or QAM can be then made in a next stage. Keeping in mind, that the aim of the proposed system is to distinguish the type of the input signal, not to demodulate it. The modulation parameters

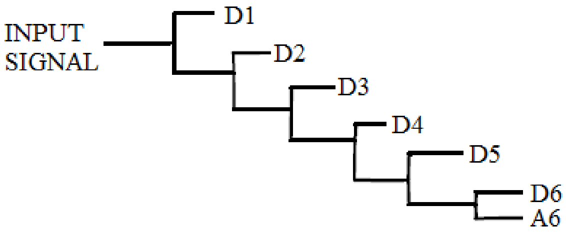
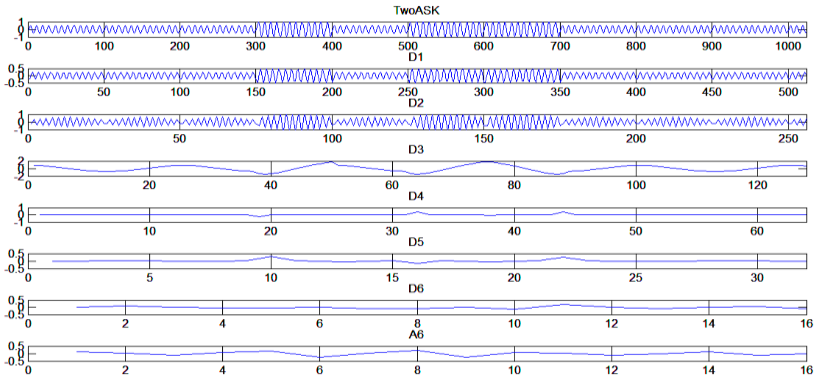


Figure 4:The proposed wavelet decomposition levels.

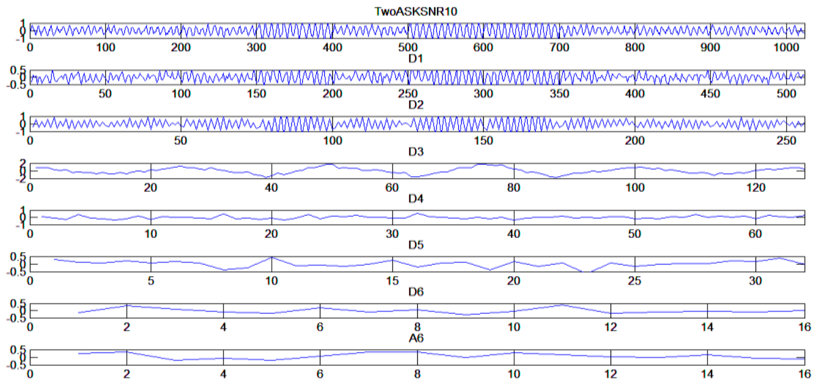
of the digital modulated signals that were used in this work are: Sampling frequency (Fs)=1.5MHZ
,Carrier frequency (Fc)=150 KHZ, Symbol rate (Rs)=12500 Symbol/s.

The proposed system has three main stages (as mentioned previously). In the first stage (the pre processing) the digital modulated signal is introduced to a depth six wavelet decomposition levels, see Figure 4.

After entering the various type of noise, the contaminated digitally modulated signals, to the wavelet decomposition levels above, it was noticed that the noise was concentrated in the two detail levels D1 and D2, so they were discarded, and only D3 to A6 were entered to the next stage (the feature extraction), Figure 5 shows an example of a 2ASK signal and its decomposed versions, ((a) without noise and (b) with noise added).



(a)



(b)

Figure 5:An example of a 2ASK signal and its decomposed versions without noise (a) and with noise added (b)

The next stage is the feature extraction, in this stage the LPCC (linear predictive cepstral coefficients) are found for each decomposition level. since the signal changes continuously (effected be the modulating information), the signal must be processed in short segments (windows), within which the parameters remain quasi-stationary.

On the other hand, due to the down sampling in every wavelet level the window must be taken large enough so the window in the last level will have enough samples to extract features from them. For example a window of 1024 samples at level six will have only sixteen samples, this number is very small to extract the feature coefficients from them. The effect of the size of the window on the performance of the system will be discussed later.

At this point the digital modulated signal is converted from time varying signal to a set of feature vectors. These feature vectors are combined to form a feature matrix. This feature matrix has all the characteristic of the signal. The above steps are repeated for all type of modulation signals under test to get its feature matrix. These matrices are then combined to form what is known as the training matrix that is used to train the neural network.

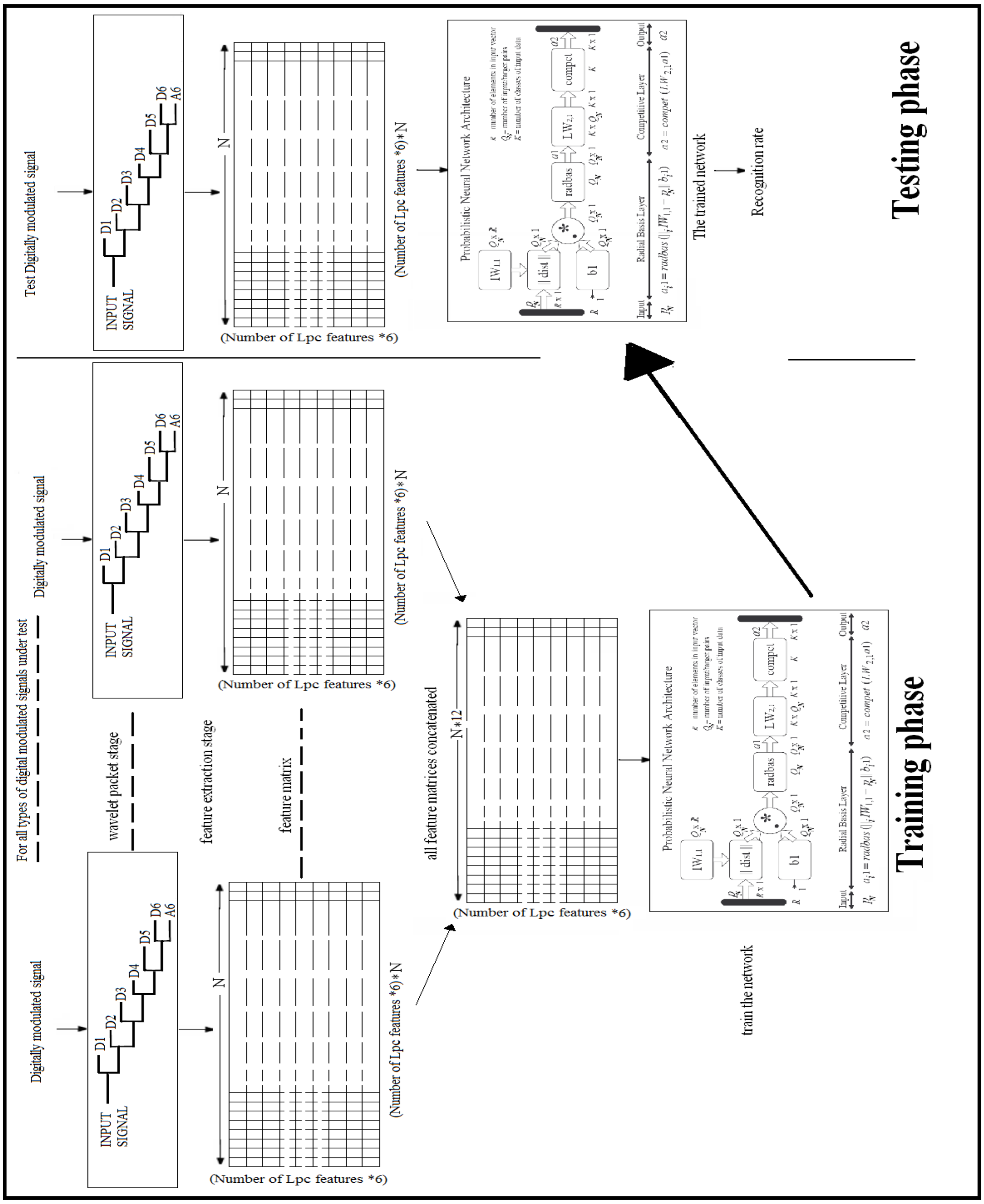


Figure 6: Architecture of the system used (training phase and testing phase)

The neural network used is the probabilistic neural network (as mention previously). It has a number of input nodes equal to the number of coefficients used to represent each level (this number is varied to find the best value as it will be seen later) multiplied by six (the number of decomposition levels). The output nodes are only three and the network has an output for every input vector, then the recognition rate is calculated (for example 20 ones, 10 twos and 70 threes for an input of 100 feature vector means that we have an input of type QAM or PSK with a certainty of 70%).

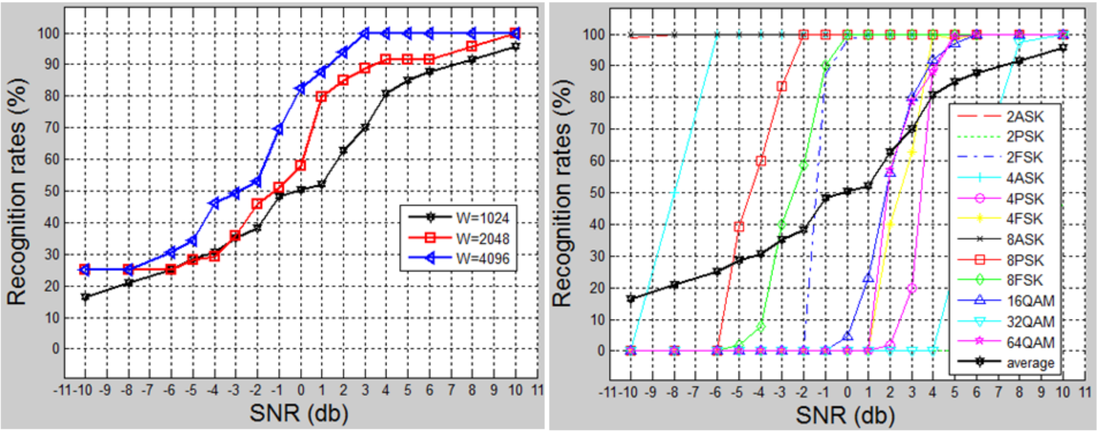
Figure 6 shows a block diagram of the proposed system to illustrate the overall procedure. In the Figure N equal the number of feature vectors which equal the number of samples in the input signal divided by the length of the window.

6. Experiments and Results

A set of experiment were performed to find the best window size, number of LPC coefficients and the type wavelet filter to optimize the proposed system to give a maximum average recognition rate with respect to a lowest SNR for the input. For all the experiments the modulation parameters were taken as mentioned in section 7 and the number of symbols was equal to 5000.

6.1 Finding the Best Window Size

The aim of the first test was to find the best window size taking a constant arbitral value for the number of LPC coefficients equal to 15 (as suggested for speech processing [16] and taking the most popular type of wavelet filter this is the "haar" wavelet filter or Daubechies one (db1). The result of this experiment is shown in Figure 7. The values for the window size was taken equaling 1024, 2048 and 4096 sample. The reason behind taking the window size a power of two is the down sampling in each stage of wavelet and starting from 1024 because after six levels of decomposition all what will have is 16 samples which is hardly sufficient to extract the LPC coefficients.



(a) (b)

Figure 7: (a)The average recognition rates for different window size (b)Detailed results for the window size of 1024 sample.

It is clear from Figure 7. that increasing the size of the window leads to a better performance. But it is also noticed that at low values of SNR the results are convergent. On the other hand a large window size will lead to a degradation in the system performance because of the time needed to find the LPC coefficients from a large amount of date making the system not practical.

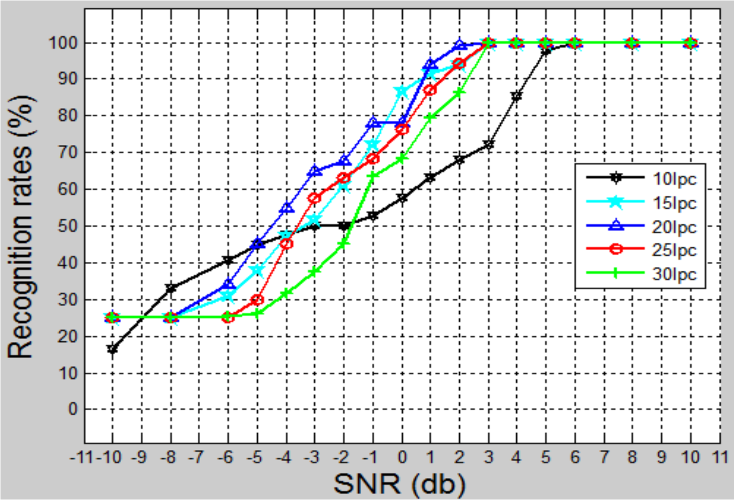


Figure 8: The average recognition rates for different number of LPC coefficients using haar wavelet filter.

6.2 Finding the Best Number of LPC Coefficients

After finding a suitable window size the next step is to find the best number of LPC coefficients that gives a sufficient performance without enlarging the computations. Figure 8 shows the results of these experiments were the window size is fixed to 4096 sample and the wavelet filter was "haar".

It can be seen from the previous Figure that a sufficient performance can be achieved by a number of LPC coefficients equal to or greater than 15 as proposed by [15] for speech processing. But it is noticed that increasing the number of LPC coefficients does not enhance the performance in fact the best performance for the proposed system is found at a number of LPC coefficients equal to 20

6.3 Finding the Best Wavelet Filter

The final set of experiments that were performed was to find the best type of wavelet filter. Although the "haar" wavelet filter is the most popular one, in this work other types are investigated, for the window size of 4096 and 20 LPC coefficients, and these filter types are: Daubechies 1-5,7,9,12,15,20 and 25 (Figure 9). Coiflet 1-5 (Figure 10), Symlet 2-5,7,9,12,15,20 and 25, Discrete Meyer (Figure 11), Biorthogonal 1.1, 1.3, 1.5, 2.2, 2.4, 2.6, 2.8, 3.1, 3.3, 3.5, 3.7, 3.9, 4.4, 5.5 and 6.8, (Figure 12) Reverse

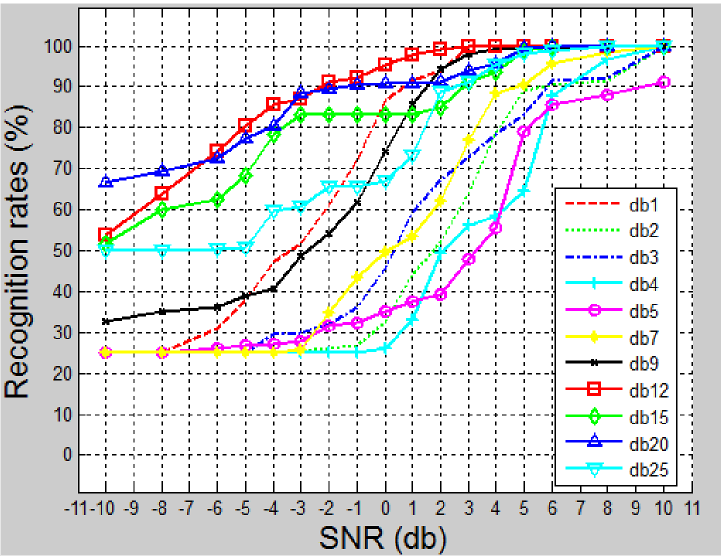


Figure 9: The average recognition rates for the Daubechies wavelet family

Biothogonal 1.1, 1.3, 1.5, 2.2, 2.4, 2.6, 2.8, 3.1, 3.3, 3.5, 3.7, 3.9, 4.4, 5.5 and 6.8 (Figure 13).

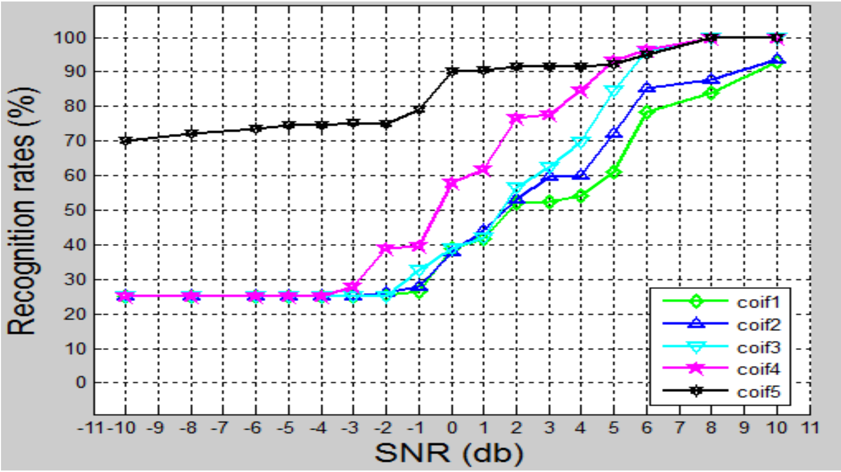


Figure 10: The average recognition rates for the Coiflet wavelet family.

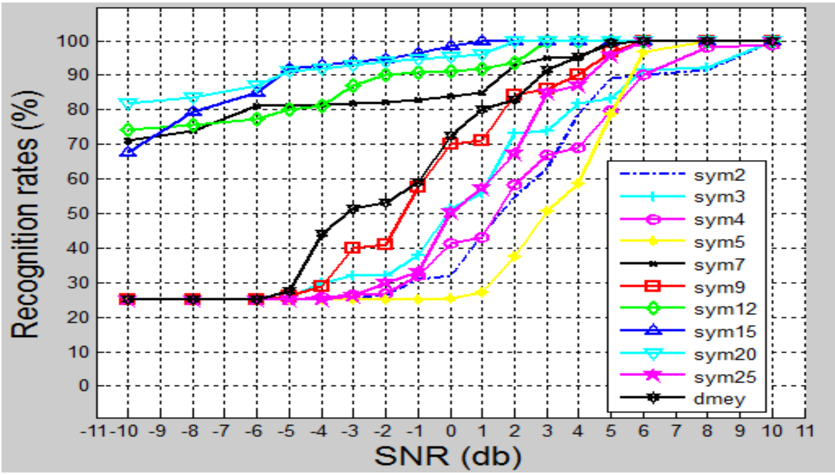


Figure 11: The average recognition rates for the Symlet and Discrete Meyer wavelet family.

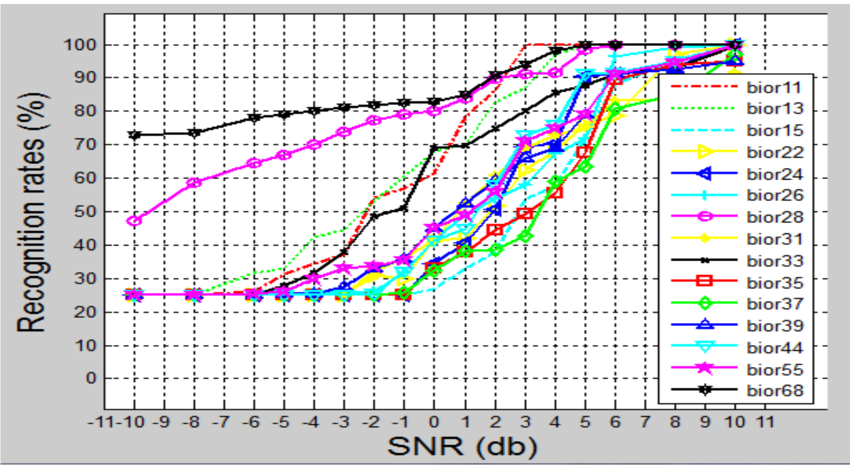


Figure 12: The average recognition rates for the Biorthogonal wavelet family.

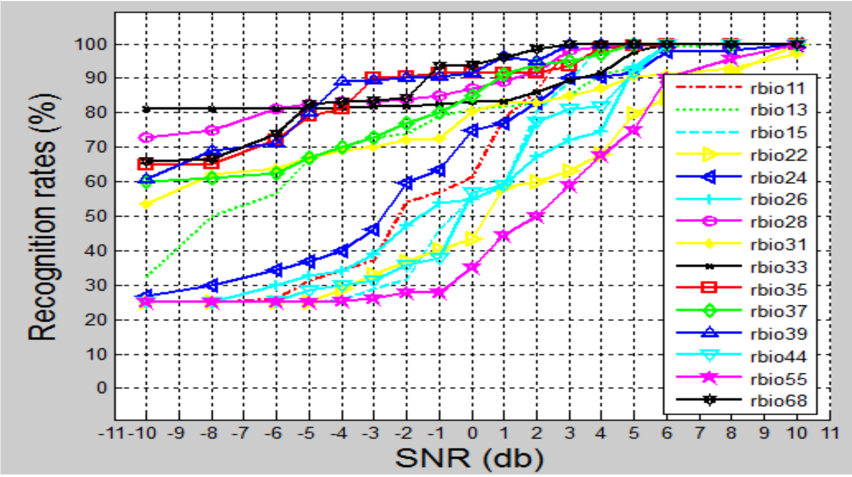


Figure 13: The average recognition rates for the Reverse Biothogonal wavelet family.

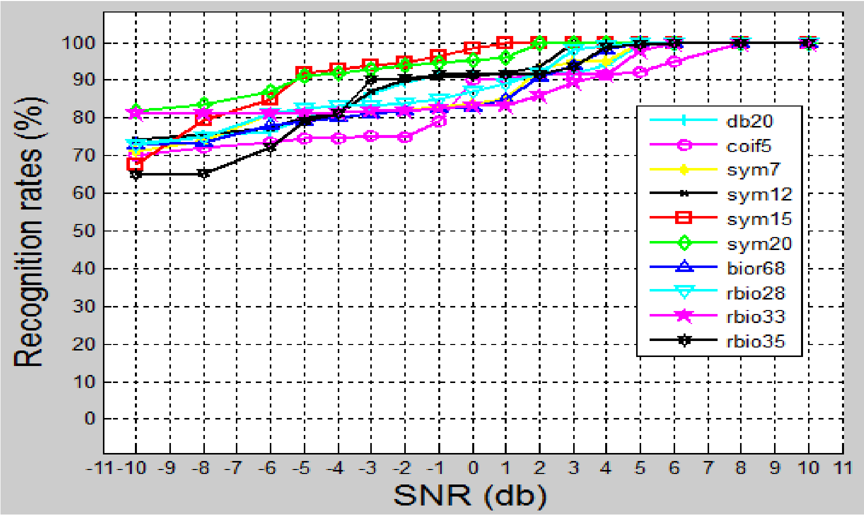


Figure 14: The average recognition rates for the best ten results for the proposed system.

As a result of all the previous experiments the proposed system has a best performance for a window size of 4096 samples, 20 LPC coefficients and a sym20 wavelet filter. Figure 14 show the best ten results for the proposed system. The selection of the best performance is chosen according to the overall performance, so by using sym15 wavelet filter a better performance is obtained at a SNR of 1db but it is noticed that the performance degrade very fast after a value of -5db so the decision was to use sym20 wavelet filter

Table 1: Comparison of proposed system with existing methods (1-8 from[19]).

No.	Feature	Model	Modulation schemes	Lower SNR (db)	% of recognition
1.	Variance of HWT magnitude and normalized HWT magnitude	Hong and Ho	QPSK, 4FSK, 16QAM	5	97%
2.	Mean and Variance of complex Shannon	Pavl´ık	BPSK, CPFSK, MS	8	93.1%

	WT magnitude				
3.	Mean, variance, and correlation coefficient of the received signal	Le Guen and Mansour	ASK2, ASK4, PSK2, PSK4, FSK2, FSK4	12	Not mentioned
4.	DFT of phase PDF	Sapiano et al.	BPSK, QPSK, 8PSK	10	92%
5.	Variance ofWT magnitude	Ho et al.	BPSK, QPSK, 8PSK, 2FSK, 4FSK, 8FSK, MSK	6	96%
6.	Fourth- and second-order moments of the received signal	Martret and Boiteau	QPSK, 16QAM	5	95%
7.	Eighth-order cyclic cumulants of the received signal	Dobre et al.	BPSK, QPSK, 8PSK, 4ASK, 8ASK, 16QAM, 64QAM, 256QAM	9	95%
8.	Histogram peaks in WT magnitude and mean & variance of normalized histogram	P. Prakasam and M. Madheswaran	BPSK, QPSK, 8PSK, 16PSK, 2QAM, 4QAM, 8QAM, 16QAM, GMSK, MFSK	5	96.8%
9.	**LPC coefficients, DWT and PNN**	**Proposed with wavelet filter sym20**	**2-8ASK, 2-8FSK, 2-8PSK, 16-64QAM**	**2**	**100%**

7. Conclusions

A new approach by using a well known set of features for speech recognition (LPC coefficients) were combined with wavelet and neural network to result in a new powerful digital modulation recognition system. Three most important variables were examined these are the number of samples to be processed each time to get the feature vector (window size), the number of LPC feature coefficient, and the type of wavelet filter. The results showed that excellent results were obtained as compared with the state of the art work using the proposed system with a 4096 window size,20 LPC coefficients and the sym20 wavelet filter (Table1).

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