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Automatic Recognition of Digital Communication Signal

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Abstract

Automatic recognition of digital communication signals has seen increasing demands nowadays in various applications. This paper investigates the design of high efficient system for classification of the digital communication signals. The system includes two main modules: feature extraction and classification. In the feature extraction module we have used a novel balanced combination of the higher order moments (up to eighth), higher order cumulants (up to eighth) and spectral characteristics. In the classifier we have investigated the performances of the radial basis function (RBF) neural network, probability neural network (PNN) and multilayer perceptron (MLP) neural network. Then we have compared these systems. Experimental results show the proposed systems have high percentage of correct classification to discriminate the different types of digital signals even at very low SNRs.

Keywords: *Pattern Recognition; Higher-order moments and cumulants; Neural Networks; Spectral characteristics*

1. Introduction

Automatic signal classification is one of the most important parts in military and civil domains. Due to the increasing usage of digital signals in novel technology such as wireless communications, the recent researches have been focused on identifying these signal types. Generally, digital signal type identification methods fall into two main categories: decision theoretic (DT) methods and pattern recognition (PR) methods. DT methods use probabilistic and hypothesis testing arguments to formulate the recognition problem [1-3]. PR methods can be further divided in two main subsystems: the feature extraction subsystem and the classifier subsystem. In [4], the authors proposed a technique for identification ASK2, ASK4, PSK2, PSK4, FSK2 and FSK4 signals. The classifier is based on a decision flow. These digital signal types have been identified with a success rate around 90% at SNR=10 dB.

In [5], a method based on instantaneous information is presented for recognition of ASK2, ASK4, FSK2, FSK4, PSK2, PSK4 and QAM16 modulations. It is found that the success rate is over 99 % when SNR is 10 dB, while the success rate is over 95 % when SNR is 5 dB. As artificial neural network (ANN) is a good classifier, further work is focused on adoption of ANN approaches [6]. In [7-8] a method based on the combination of clustering and neural network is presented for recognition of BPSK, QPSK, 8PSK, 16QAM, 32QAM and 64QAM when SNR is higher than 4 dB, the classification rates of four modulation types: BPSK, QPSK, 8PSK and 16QAM all reach 100%. The classification rates of 32QAM and 64QAM are much higher too. For instance, the classification rate of 32QAM reaches 98% when SNR is 8 dB, and the classification rate of 64QAM is 86.4% even when SNR is 4 dB. In [9], author proposed a kernel method for recognition of AM, CW, 2FSK, 4FSK, 8FSK, BPSK, QPSK, 8PSK and SSB. The value of 95.44 and 97.67 accuracies are achieved at SNR=0 and 5 respectively. The recognition rate is increasing with SNR increasing. When SNR is more than 10dB, classification accuracy gets to 100%.

In [10] the authors used a MLP neural network as the classifier. This identifier showed a success rate about 93% at SNR=8dB for identification of ASK4, ASK8, PSK2, PSK4, PSK8, QAM8, QAM16, QAM32, QAM64 digital signals. In [11] the authors introduced a modulation classifier based on a combination set of the entropy and energy of the signal, variance of the coefficients wavelet packet transform, fourth order of moment and zero-crossing rate. The considered signal types were: 2ASK, 4ASK, 2PSK, 4PSK, 2FSK, 4FSK and 16QAM. In the classifier module, the two structures of the neural networks are used: multi-layer perceptron (MLP) neural network and radial basis neural networks. The accuracy rates of the MLP and RBF classification are 99.84% and 97.57 for SNR=5dB, respectively. The advantage with neural network is that it is capable of handling noisy measurements requiring no assumption about the statistical distribution of the monitored data. It learns to recognize patterns directly through typical example patterns during a training phase. In [12], Subtractive and c-means methods identified ASK4, ASK8, PSK2, PSK4, PSK8, QAM8, QAM32 and QAM64 modulations with a high rate of around 81.89 and 97.03% for SNR=0 respectively.

In this paper, we introduced two automatic techniques for recognition of digital signals by pattern recognition approaches. In them for the feature extraction part, we proposed a balanced combination of the higher order statistics. For identification we have used the neural networks as classifiers. The rest of paper is organized as follows: Section 2 presents the feature extraction. Section 3 presents the neural networks. Section 4 shows some of our simulation results. Finally, Section 5 concludes the paper.

2. Feature Extraction

In digital communications, according to the changes in the message parameters, we have three main digital signal types: ASK, PSK and QAM. Most of them are used in M-ary form [13]. These different types of radio signals have different characteristics. Therefore finding the proper features for recognition of them is a critical problem. In this paper the considered radio signals are included as: ASK4, ASK8, PSK2, PSK4, PSK8, QAM8, QAM16, QAM32 and QAM64. For simplifying the indication, these signals are substituted with P1, P2, P3, P4, P5, P6, P7, P8 and P9 respectively. Based on the extensive experiments and researches, a suitable combination of the higher order moments up to eighth and higher order cumulants up to eighth and spectral features are considered as the prominent features. Following phrases describe briefly these features.

2.1. Spectral Features

Spectral features were demonstrated to be suitable for signals which contain hidden information in a single domain, instantaneous amplitude, instantaneous phase or instantaneous frequency. In this paper, according to the considered digital signals, the following spectral features are selected:

2.1.1. σ_{aa} : Standard deviation of the absolute value of the normalized-centered instantaneous amplitude of a Signal, which is defined:

$$\sigma_{aa} = \sqrt{\frac{1}{Ns}\left(\sum_{A_n(i) \succ a_t} A_{cn}^{\,2}(i)\right) - \left(\frac{1}{Ns}\sum_{A_n(i) \succ a_t} |A_{cn}(i)|\right)^2} \tag{1}$$

Where $A_{cn}(i)$ is value of normalized-centered instantaneous at time, $t = i / f_s (i = 1,2,..., N_s)$, f_s is sampling rate and N_s is the number of samples per signal segment. a_t is the threshold value for $A_n(i)$ below which the estimation of the instantaneous phase is very noise sensitive.

$$A_{cn}(i) = A_n(i) - 1 \tag{2}$$

Where $A_n(i) = \frac{A(i)}{m_a}$, $m_a = \frac{1}{N_s}\sum_{i=1}^{N_s} A(i)$. It can be used to identify the ASK2 and ASK4. Because for ASK2, the absolute value of its instantaneous amplitude is a constant.

2.1.2. σ_{ap} : Standard deviation of the absolute value of the centered non-linear components of the instantaneous phase evaluated over non-weak segment of received signal.

$$\sigma_{ap} = \sqrt{\frac{1}{C}\left(\sum_{A_n(i) \succ a_t} \phi_{NL}{}^2(i)\right) - \left(\frac{1}{C}\sum_{A_n(i) \succ a_t} |\phi_{NL}(i)|\right)^2} \tag{3}$$

Where C is the number of samples in $\{\phi_{NL}(i)\}$ (at instant time $t = i/f_s$) for which $A_n(i) \succ a_t$ namely non-weak points. $\phi_{NL}(i) = \phi(i) - \phi_0$, where $\phi_0 = \frac{1}{N_s}\sum_{i=1}^{N_s}\phi(i)$ defined in literature and we improve it to $\phi_0 = \frac{1}{C_s}\sum_{a_n(i) \succ a_t}^{N_s}\phi(i)$.

2.1.3. σ_{af} : Standard deviation of the absolute value of the normalized-centered instantaneous frequency over non-weak segments of the intercepted signal:

$$\sigma_{af} = \sqrt{\frac{1}{C}\left(\sum_{A_n(i) \succ a_t} f_N^2(i)\right) - \left(\frac{1}{C}\sum_{A_n(i) \succ a_t} |f_N(i)|\right)^2} \tag{4}$$

$$f_N(i) = \frac{f_c(i)}{r_s},\ f_c(i) = f(i) - m_f,\ m_f = \frac{1}{N}\sum_{i=1}^{N} f(i)$$

Where r_s is symbol rate of digital sequence, C is the number of samples in $\{f_N(i)\}$ (at instant time $t = i/f_s$) for which $A_n(i) \succ a_t$ namely non-weak points.

2.1.4. $\gamma_{\max}$: is maximum value of the power spectral density of the normalized-centered instantaneous amplitude of the intercepted signal segment, and is defined by:

$$\gamma_{\max} = \max |FFT(A_{cn}(i))|^2 / N_s \tag{5}$$

This feature can express the character of signal's envelope and was added to differentiate between the modulation schemes that carry amplitude modulation and those that do not. For example, $\gamma_{\max}$ has a higher value for QAM8 than for ASK4 because the former has amplitude levels 1 and 3 whereas the latter has amplitude levels

1 and 1/3. For frequency modulated signal, there is no amplitude modulated information, so this parameter is very small.

2.2. Higher Order Moments and Higher Order Cumulants

Probability distribution moments are a generalization of concept of the expected value. Recall that the general expression for the i^{th} moment of a random variable is given by [14]:

$$\mu_i = \int_{-\infty}^{\infty} (s-m)^i f(s) ds \tag{6}$$

Where m is the mean of the random variable. The definition for the i^{th} moment for a finite length discrete signal is given by:

$$\mu_i = \sum_{k=1}^{N} (s_k - m)^i f(s_k) \tag{7}$$

Where N is the length of data. In this study signals are assumed to be zero mean. Thus:

$$\mu_i = \sum_{k=1}^{N} {s_k}^i f(s_k) \tag{8}$$

Next, the auto-moment of the random variable may be defined as follows:

$$M_{pq} = E[s^{p-q}(s^*)^q] \tag{9}$$

Where p is called the moment order and s^* stands for complex conjugation of s. Assume a zero-mean discrete based-band signal sequence of the form $s_k = a_k + jb_k$. Using the definition of the auto-moments, the expressions for different orders may be easily derived. For example:

$$M_{83} = E[s^5(s^*)^3] = E[(a+jb)^5(a-jb)^3] \Rightarrow$$
$$\begin{aligned} M_{83} = E[(a^5 + j5a^4b + j^2 10a^3b^2 + j^3 10a^2b^3 + j^4 5ab^4 \\ + j^5b^5)(a^3 - j3a^2b + j^2 3ab^2 - j^3b^3)] \Rightarrow \end{aligned} \tag{10}$$
$$\begin{aligned} M_{83} = E[a^8 + j2a^7b - j^2 2a^6b^2 - j^3 6a^5b^3 + j^5 60a^3b^5 \\ + j^6 2a^2b^6 - j^7 2ab^7 - j^8b^8] \Rightarrow \end{aligned}$$
$$M_{83} = E[a^8 + 2a^6b^2 - 2a^2b^6 - b^8]$$

Consider a scalar zero mean random variable s with characteristic function:

$$\hat{f}(t) = E\{e^{jts}\} \tag{11}$$

Expanding the logarithm of the characteristic function as a Taylor series, one obtains:

$$\log \hat{f}(t) = k_1(jt) + \ldots + \frac{k_r(jt)^r}{r!} + \cdots \tag{12}$$

The constants k_r in (12) are called the cumulants (of the distribution) of s. The symbolism for p^{th} order of cumulant is similar to that of the p^{th} order moment. More specially:

$$C_{pq} = Cum[\underbrace{s,...,s}_{(p-q)terms}, \underbrace{s^*,...,s^*}_{(q)terms}] \tag{13}$$

For example:

$$C_{81} = Cum(s,s,s,s,s,s,s,s^*) \tag{14}$$

The n^{th} order cumulant is a function of the moments of orders up to (and including) n. Moments may be expressed in terms of cumulants as:

$$M\left[s_1,..,s_n\right] = \sum_{\forall v} Cum\left[\{s_j\}_{j\in v_1}\right]...Cum\left[\{s_j\}_{j\in v_q}\right] \tag{15}$$

Where the summation index is over all partitions $v=(v_1,...,v_q)$ for the set of indexes $(1,2,...,n)$, and q is the number of elements in a given partition. Cumulants may be also be derived in terms of moments:

$$Cum[s_1,..,s_n] = \sum_{\forall v}(-1)^{q-1}(q-1)!E[\prod_{j\in v_1} s_j]..E[\prod_{j\in v_q} s_j] \tag{16}$$

Where the summation is being performed on all partitions $v=(v_1,...,v_q)$ for the set of indictes $(1,2,...,n)$. We have computed all of the features for the digital signal types that are considered. Although all of these features may carry good classification information when treated separately, there is little gain if they are combined together (due to sharing the same information content). Then we have done extensive experiments and have selected the best features that make the highest performance for identification of the considered radio signals. Based on regarding to the structure of the classifier that will be explained in following sections, we have considered the second, fourth, sixth and eighth order of the moments and cumulant as the features. These features are: $\{C_{40}, C_{41}, C_{42}, C_{61}, C_{62}, C_{63}, C_{80}, C_{84}, M_{40}, M_{41}, M_{80}\}$

Therefore the total number of the statistical features is eleven. We have computed all of these features for the considered digital signals. Table1 shows the higher order moments and higher order cumulants for a number of the considered radio signal types. These values are computed under the constraint of unit variance in noise free.

Table 1. Some of the Chosen Higher Orders Features for a Number of the Considered Radio Signal Types

	PSK2	PSK4	QAM32	QAM64	ASK4
M_{40}	1	-1	-0.19	-0.61	1.64
C_{61}	16	4	0	1.79	8.32
C_{80}	-244	-34	-1.99	-11.50	-30.08
C_{84}	-244	-18	16.61	24.11	-30.08

3. Neural Networks

3.1. Radial Basis Function Neural Network (RBFN)

Radial basis function neural networks (RBFNs) are efficient tools for multivariate approximation, time series forecasting, image processing, speech recognition, etc., because of their properties of localization, robustness and stability. The basic structure of an RBFN is a two-layer, feed-forward network in which the activation functions of the neurons of the hidden layer are radial basis functions (RBFs). Each hidden neuron computes the distance from its input to the neuron's central point, c, and applies the RBF to that distance. The neurons of the output layer perform a weighted sum between the outputs of the hidden layer and the weights of the links that connect both the output and the hidden layer; in other words, a linear function exists between the hidden layer and the output layer:

$$h_i(x) = \phi(\|x - c_i\|^2 / r_i^2) \tag{23}$$

$$f_j(x) = \sum w_{ij} h_i(x) + w_0 \tag{24}$$

Where x is the input, ϕ is the RBF, c_i is the center of the ith hidden neuron, r_i is its radius, w_{ij} is the weight links that connect hidden neuron number I and output neuron number j, and w_0 is a bias for the output neuron.

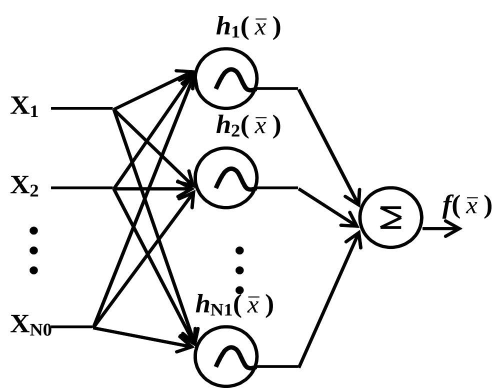

Figure 1. Radial Basis Function Neural Network Structure

In a general feed-forward network, the goal is to determine the suitable values for the weights w_{ij} in the network by minimization of an appropriate error function. In our study, the error function considered is the sum squared-error:

$$SSE = \sum (y_j - f_j(x))^2 \tag{25}$$

Where y_j is the target in the training set. The vector of weights, which minimizes the error function, is calculated using the normal equation, in matrix notation:

$$W = (H^T H)^{-1} H^T Y \tag{26}$$

Where $H_{ij} = h_j(x_i)$ is the design matrix and contains the response of the centers to the inputs of the training set. The problem of automatic RBFN design is an important subject. In this study, number of basis functions is equal to the number of training samples [15]. The basis functions are centered on the training samples and the only unknown parameters are the linear weights, which can be determined efficiently by solving the system of linear equations. For the RBF neural network, a Gaussian activation function and a single hidden layer with 150 neurons, mean squared error goal=0, spread of radial basis function=100, maximum number of neurons=150, number of neurons to add between displays=50. These values are gained based on the trial and error.

3.2. Multilayer Perceptron (MLP) Neural Network

We used MLP neural networks as a classifier. An MLP neural network consists of an input layer (of source nodes), one or more hidden layers (of computation nodes) and an output layer [16]. The number of nodes in the input and the output layers depend on the number of input and output variables, respectively. The recognition basically consists of two phases training and testing. In training stage, weights are calculated according to the chosen learning algorithm. The issue of learning algorithm and its speed is very important for MLP.

Among the learning algorithms of MLPs, back propagation (BP) algorithm is still one of the most popular algorithms. In BP a simple gradient descent algorithm updates the weight values:

$$w_{ij}(t+1) = w_{ij}(t) - \varepsilon \frac{\partial E}{\partial w_{ij}}(t) \tag{27}$$

Where w_{ij} represents the weight value from neuron j to neuron i, ε is the learning rate parameter, E represent the error function. Resilient back propagation (RPROP) algorithm considers the sign of derivatives as the indication for the direction of the weight update. In doing so, the size of the partial derivative does not influence the weight step. The following equation shows the adaptation of the update values of Δ_{ij} (weight changes) for the RPROP algorithm. For initialization, all Δ_{ij} are set to small positive values:

$$\Delta_{ij} = \begin{cases} \eta^{+} \times \Delta_{ij}(t-1) & if \ \frac{\delta E}{\delta w_{ij}}(t-1)\frac{\delta E}{\delta w_{ij}}(t) \succ 0 \\ \eta^{-} \times \Delta_{ij}(t-1) & if \ \frac{\delta E}{\delta w_{ij}}(t-1)\frac{\delta E}{\delta w_{ij}}(t) \prec 0 \\ \eta^{0} \times \Delta_{ij}(t-1) & Otherwise \end{cases} \tag{28}$$

Where $\eta^0 = 1,\ 0 \prec \eta^- \prec 1 \prec \eta^+, \eta^{-,0,+}$ are known as the update factors, w_{ij} represents the weight value from neuron j to neuron I and E represents the error function. Whenever the derivative of the corresponding weight changes its sign, it implies that the previous update value is too large and it has skipped a minimum. Therefore, the update value is then reduced (η^-) as shown above. However, if the derivative retains its sign, the update value is (η^+) increased. This will help to accelerate convergence in shallow areas. To avoid over acceleration, in the epoch following the application of (η^+), the new update value is neither increased nor decreased (η^0) from the previous one. Note that values of Δ_{ij} remain non-negative in every epoch. This update value adaptation process is then followed by the actual weight update process, which is governed by the following equations:

$$\Delta_{ij} = \begin{cases} -\Delta_{ij}(t-1) & if \ \frac{\delta E}{\delta w_{ij}}(t) \succ 0 \\ +\Delta_{ij}(t) & if \ \frac{\delta E}{\delta w_{ij}}(t) \prec 0 \\ 0 & Otherwise \end{cases} \tag{29}$$

$$w_{ij}(t+1) = w_{ij}(t) - \Delta w_{ij}(t) \tag{30}$$

In this study we utilize a single layer feed-forward back propagation network that its parameters selected for the algorithm empirically. They were as follows: transfer function for the hidden layer: Tan-Sigmoid, transfer function for the output layer: Linear, back propagation network training function: trainrp (Resilient back propagation). The MLP classifier was tested with 20 neurons for two hidden layers.

3.3. Probabilistic Neural Network (PNN)

The probabilistic Neural Network (PNN) algorithm represents the likelihood function of a given class as the sum of identical isotropic Gaussians [17]. The PNN is a direct continuation of the work on classifiers. The probabilistic neural network (PNN) learns to approximate the pdf of the training examples. More precisely, the PNN is interpreted as a function which approximates the probability density of the underlying examples' distribution (rather than the examples directly by fitting).The PNN consists of nodes allocated in three layers after the inputs:

- Pattern layer: there is one pattern node for each training example. Each pattern node forms a product of the weight vector and the given example for classification, where the weights entering a node are from a particular example. After that, the product is passed through the activation function:

$$\exp[(\mathrm{x}^{\mathrm{T}} \mathrm{w}_{\mathrm{ki}} - 1)/\sigma^2 \tag{31}$$

- Summation layer: each summation node receives the outputs from pattern nodes associated with a given class:

$$\textstyle\sum_{\mathrm{i}=1}^{\mathrm{Nk}} \exp[(\mathrm{x}^{\mathrm{T}} \mathrm{w}_{\mathrm{ki}} - 1)/\sigma^2 \tag{32}$$

- Output layer: the output nodes are binary neurons that produce the classification decision:

$$\textstyle\sum_{\mathrm{i}=1}^{\mathrm{Nk}} \exp[(\mathrm{x}^{\mathrm{T}} \mathrm{w}_{\mathrm{ki}} - 1)/\sigma^2 > \sum_{\mathrm{j}=1}^{\mathrm{Nj}} \exp[(\mathrm{x}^{\mathrm{T}} \mathrm{w}_{\mathrm{kj}} - 1)/\sigma^2 \tag{33}$$

The only control factor that needs to be selected for probabilistic neural network training is the smoothing parameter (i.e., the radial deviation of the Gaussian functions). As with RBF [18] networks, this parameter needs to be selected to cause a reasonable amount of overlap - too small deviations cause a very spiky approximation which cannot generalize, too large deviations smooth out detail. In this study the smoothing parameter considered 100 by error and trial method.

The greatest advantages of PNNs are the fact that the output is probabilistic (which makes interpretation of output easy), and the training speed. Training a PNN actually consists mostly of copying training cases into the network, and so is as close to instantaneous as can be expected. The greatest disadvantage is network size: a PNN network actually contains the entire set of training cases, and is therefore space-consuming and slow to execute. PNNs are particularly useful for prototyping experiments (for example, when deciding which input parameters to use), as the short training time allows a great number of tests to be conducted in a short period of time.

4. Simulation Results

In this study, we examined the three most popular and efficient neural networks and performed a comparative study on the digital modulated communication signals. We used 100 modulated signals of each modulation type and 9 different modulations. The length of each digital signal type has 100 samples that are used for simulations. All of the considered digital signal types are simulated in MATLAB (2009a) environment. The simulated signals were also band limited and Gaussian noise was added according to SNR values -2, -1, 0, 1, 2, 4, 6 dB. In this study, the considered modulated signals are included as: ASK4, ASK8, PSK2, PSK4, PSK8, QAM8, QAM16, QAM32 and QAM64. For simplifying the indication, these signals are substituted with the eleven statistical features below: $\{C_{40}, C_{41}, C_{42}, C_{61}, C_{62}, C_{63}, C_{80}, C_{84}, M_{40}, M_{41}, M_{80}\}$

Table 2 shows the recognition performances of the classifiers (Pc) with the three neural networks in both testing and training stages at different SNR values for all of the proposed modulations. According to the recognition performances in the table, all the neural networks have a high performance even in extremely low SNR conditions. In comparison with the neural networks together, the multilayer perceptron (MLP) neural network shows a very excellent recognition performance that is a few better than RBF and PNN neural networks even in extremely low SNR conditions. But, the radial basis function (RBF) neural network is able to recognize the considered modulations with value of 100% accuracy earlier than MLP and PNN neural networks at SNR=1. And also, the probabilistic neural network (PNN) has a very low timing that it is extremely better than MLP and RBF neural networks. The low timing is a very important factor for some applications. PNN, MLP and RBF neural networks have lower to higher timing respectively from left to right.

Table3 shows the recognition performances of the classifiers (Pc) for all of the proposed modulations except ASK8. From the results of the Table, it can be concluded that more confusion of the classifier performance is related to the similarity of the ASK4 and ASK8 features and by omitting ASK8, the performances of the classifiers are generally very high even at extremely low SNRs for 8 modulations with around 100% performance accuracy.

Table 2. Performances of the Neural Networks in Different SNRs for 9 Modulated Signals

SNR (db)	MLP P_c (%)		PNN P_c (%)		RBF P_c (%)	
	Train	**Test**	**Train**	**Test**	**Train**	**Test**
-2	96.3334	95.7778	94.7408	93.1333	99.1482	93.1333
-1	97.7407	97.9556	96.0371	96.4445	100.000	96.8222
0	99.6296	99.5111	98.6667	98.8889	100.000	99.5111
1	99.9630	99.9333	99.85189	99.9778	100.000	100.000
2	100.000	100.000	100.000	100.000	100.000	100.000
4	100.000	100.000	100.000	100.000	100.000	100.000
6	100.000	100.000	100.000	100.000	100.000	100.000

Table 3. Performances of the Neural Networks in Different SNRs for the 8 Modulated Signals

(omitted ASK8 modulation)

SNR (db)	MLP P_c (%)		PNN P_c (%)		RBF P_c (%)	
	Train	**Test**	**Train**	**Test**	**Train**	**Test**
-2	99.8438	99.8750	99.6250	99.7150	100.000	99.1500
-1	100.000	100.000	100.000	100.000	100.000	99.9750
0	100.000	100.000	100.000	100.000	100.000	100.000
1	100.000	100.000	100.000	100.000	100.000	100.000
2	100.000	100.000	100.000	100.000	100.000	100.000
4	100.000	100.000	100.000	100.000	100.000	100.000
6	100.000	100.000	100.000	100.000	100.000	100.000

4.1. Discussion and Comparison

Direct comparison with other works is difficult in radio signal recognition. As for neural network-based signal recognizers, Nandi and Wong [4] proposed a technique to discriminate among digital signals using wavelet transform and neural network and 99.39% accuracy is achieved at SNR=4 for ten modulations. In [19], a fuzzy classifier was used in this technique. For SNR>5 dB, the classifier worked properly. When SNR was less than 5 dB, the performance was worse. In [20], the performance of classification of the considered modulations is 92% that this amount of accuracy cannot be acceptable at SNR=20. In [21], the authors proposed an efficient classifier based on multi-layer perceptron (MLP) neural network and radial basis neural networks for recognition of the seven considered modulations (ASK2, ASK4, PSK2, PSK4, FSK2, FSK4, QAM16).

The proposed algorithm in this paper is able to recognize different kinds of the digital radio signal even at very low SNRs; For instance it has a success rate of98.33% at SNR= -2dB and 100% accuracy is achieved at SNRs>0 for the nine considered modulations. Also, for classification of the eight modulations, the performances of the recognizer achieved100% at SNR>-2dB. Results show that the proposed hybrid intelligent technique has very high classification accuracy even at very low levels of SNR with a little number of the features.

Figure 2 shows a comparison of the performance classifiers with different SNRs using the column chart. The figure shows the average accuracies of recognition versus SNR ratio for different modulation types of ASK, PSK and QAM families. This figure illustrates the effects of the different SNR conditions on the performances of the classifiers in testing stages. According to this comparison, As SNR condition increases, the correct recognition of modulation can be better and in low SNRs, the performance of modulations recognition decreases. It can be found MLP neural network as a classifier has high recognition accuracy better than others at low SNR conditions. And also at SNR=1, the performance accuracy of the PNN classifier is very close to value of 100%. The RBF neural network achieved 100% accuracy at SNR=1 earlier than MLP and PNN neural networks. As seen from the figure, the accuracy of the PNN classifier for SNR<1 is worse than the two other neural networks. For SNR conditions higher than one (SNR>1), all the three proposed neural networks are able to recognize correctly all the 9 modulations with 100% accuracy.

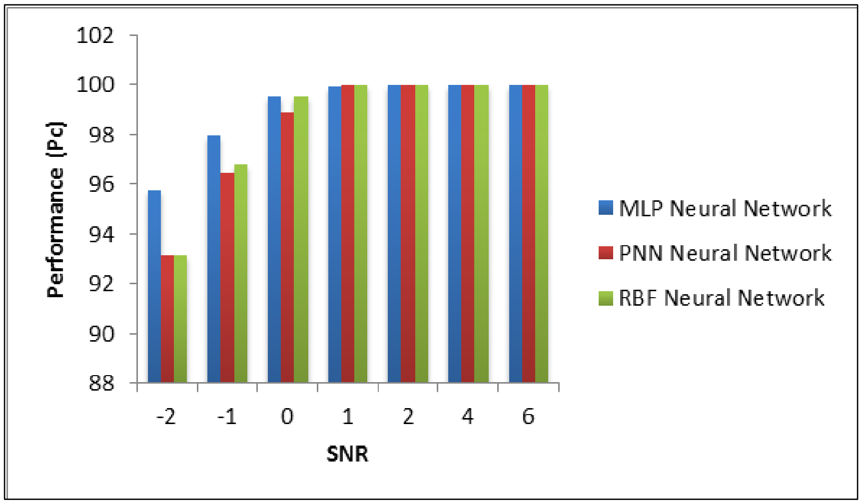

Figure 2. A Comparison of the performances of the classifiers at different SNRs

5. Conclusion

Automatic recognition of digital signal formats is an important subject for novel communication systems. In this study, digital signals recognition based on the efficient features using the neural networks is presented. A comparative study is given which uses three important neural networks. A basic introduction of modulation recognition was given followed by a brief description of the most representative techniques used in this paper. By using the considered features and classifiers, we have presented extremely efficient recognizers which are able to recognize digital signals with an acceptable performance even at low SNRs. This recognizer identifies a lot of digital signal types with high accuracy even at very low SNRs.

The performance of the neural networks as a recognizer is extremely high even at very low SNRs. The MLP classifier for recognition of the nine proposed modulations has a very success rate of around 99.51% at SNR=0 dB, 99.93% at SNR=1 dB and the performances of the recognizer is 100% for SNR>1dB. The RBF identifier has a very high accuracy of around 99.51% at SNR=0 dB and 100% for SNR>1dB. And also the PNN identifier has a very high accuracy of around 98.89% at SNR=0 dB, 99.98 at SNR=1and 100% for SNR>1dB. For the classification of the eight proposed modulations (except ASK8 modulation), almost all the neural networks have an extremely acceptable rate of around more than 99% at SNR=-2 dB and the value of 100% accuracy for SNR>-2. Among the neural networks, the performances of MLP and RBF classifiers using the proposed features are higher than PNN even at very low SNR conditions.

The advantage of the neural networks technique as recognizers is that these methods do not require to be specified the number of the clusters in data sets before the process. The presented classification is not limited to any special class of modulations. On the other hand, this approach could be extended and modified to recognize other types of modulated communication signals. The validity analysis is performed and simulation results are given.

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References

[1] W. Sue, L. X. Jeffersonand Z. Mengchou, "Real-time modulation classification based on maximum likelihood", IEEE Comm Letters, vol. 12, no. 11, **(2008)**.
[2] K. E. Nolan, L. Doyle, P. Mackenzie and D. O. Mahony, "Modulation scheme Ccassification for 4G software radio wireless network", Proc. IASTED, **(2002)**.
[3] W. Wei and J. M. Mendel, "Maximum-likelihood classification for digital amplitude-phase modulations", IEEE Transactions on Communications, vol. 48, no. 2, **(2000)**, pp. 189-193.
[4] B. G. Mobasseri, "Digital modulation classification using constellation shape", Signal Processing, vol. 80, no. 2, **(2000)**, pp. 251–277.
[5] Y. -Q. Hu, J. Liu and X. -H. Tan, "Digital modulation recognition based on instantaneous information", The Journal of China Universities of Posts and Telecommunications, vol. 17, no. 3, **(2010)** June, pp. 52–59.
[6] M. L. D. Wong and A. K. Nandi, "Automatic digital modulation recognition using artificial neural network and genetic algorithm", Signal Process, vol. 84, **(2004)**, pp. 351–365.
[7] E. Avci, D. Hanbay and A. Varol, "An expert discrete wavelet adaptive network based fuzzy inference system for digital modulation recognition", Expert Syst. Appl., vol. 33, **(2007)**, pp. 582–589.
[8] A. -S. Liu and Q. Zhu, "Automatic modulation classification based on the combination of clustering and neural network", The Journal of China Universities of Posts and Telecommunications, vol. 18, no. 4, **(2011)** August, pp. 13–19.
[9] X. Zhou, Y. Wu and D.-L. Wang, "Application of kernel methods in signals modulation classification", The Journal of China Universities of Posts and Telecommunications, vol. 18, no. 1, **(2011)** February, pp. 84–90.
[10] Y. Zhao, G. Ren, X. Wang, Z. Wu and Gu, "Automatic digital modulation recognition using artificial neural networks", Proc. ICNNSP, **(2003)**, pp. 257-260.
[11] A. Ebrahimzadeh, H. Azimi and S. A. Mirbozorgi, "Digital communication signals identification using an efficient recognizer", Measurement, vol. 44, **(2011)**, pp. 1475–1481.
[12] M. Azarbad, A. Ebrahimzade and M. Yousefi, "A Comparison of Clustering Algorithms for Recognition of Radio Communicattion Signals Based on the HOS", Proceedings of the IASTED International Conference, Signal Processing, Pattern Recognition, and Applications (SPPRA 2011), 10.2316/P.2011.721-009, **(2011)**.
[13] J. G. Proakis, "Digital Communications", New York: McGraw-Hill, **(2001)**.
[14] P. McCullagh, "Tensor Methods in statistics", Chapman & Hall, **(1987)**.
[15] S. A. Kassam and I. Cha, "Radial basis function networks in nonlinear signal processing applications", In: Proc. ACSSC., **(1993)**, pp. 923-7. S.
[16] Haykin, "Neural Networks: A Comprehensive Foundation", 2nd ed., Prentice-Hall, NJ, USA, **(1999)**.
[17] H. G. C. Traven, "A Neural Network Approach to Statistical Pattern Classification by "Semi-Parametric" Estimation of Probability Density Functions", IEEE Transactions on Neural Networks, vol. 2, **(1991)**, pp. 366-377.
[18] S. Chen, "Orthogonal Least Squares Learning Algorithm for Radial Basis Function Networks", IEEE Transactions on Neural Networks, vol. 2, no. 2, **(1991)**.
[19] K. Hassan, I. Dayoub, W. Hammouda and M. Berbineau, "Automatic modulation recognition using wavelet transform and neural network", in: Proceedings of IEEE Conference on Intelligent Transport Systems Telecommunications, **(2009)**, pp. 234–238.
[20] L. De Vito, S. Rapuano, "Validating a method for classifying digitally modulated signals", Measurement, vol. 42, **(2009)**, pp. 427–435.
[21] S. A. Ebrahimzade, "A novel method for automatic modulation recognition", Applied Soft Computing, vol. 12, **(2012)**, pp. 453–461.

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