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A NEW METHOD FOR COMMUNICATION SYSTEM RECOGNITION*

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Abstract– Communication system recognition can be used in some civilian and military applications. The recognition of the system is done by inspecting the received signal properties like modulation type, carrier frequency, baud rate and so on. Therefore we need Automatic Modulation Recognition (AMR) in addition to carrier and baud rate estimation methods. In this paper we introduce a new AMR method based on time and spectral domain features of the received signal. A neural network is used as the classifier. A broad class of analog and digital modulations is considered. Baud rate and carrier frequency estimation is performed by existing methods referred to in this paper. Using this information the protocol used for signal transmission is detected.

Keywords– Modulation recognition, pattern recognition, communication system recognition, neural network

1. INTRODUCTION

Communication systems recognition can be used in some civilian and military applications. In order to accomplish the task, one should be able to extract some information from the detected signal. Recognizing the modulating scheme is an important step forward in this task.

Different methods of Automatic Modulation Recognition (AMR) can be categorized into two broad fields: Pattern Recognition and Decision Theoretic Approaches. In the past, decision making was the main method used by researchers like [1-6]; but in recent researches, pattern recognition methods are dominant, especially using neural networks. Some of the papers dealing with this subject include [7-11]. The aim of this paper is to introduce a proper method in order to automatically recognize the modulating scheme and data communication protocol.

Consider the case where decoding the data content of a previously unknown received signal is tried. In order to decode the data correctly we need some information from the received signal to be able to extract the data. In [12] a three step method for data decoding from an unknown received signal is introduced (Fig. 1). Actually the gap between the AMR step and the decoding step is too large, making the final step extremely difficult to achieve.

We propose an additional step named protocol recognition as in Fig. 2. In this paper we will introduce a new modulation classifier using features of the received signal in both time and spectral domain. Then using the modulation type in addition to the estimated baud rate and carrier frequency, the communication system type can be recognized using a database of system protocol features. There are a number of

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different methods for AMR introduced in the literature. Table 1 presents a brief review on the different approaches to the AMR problem.

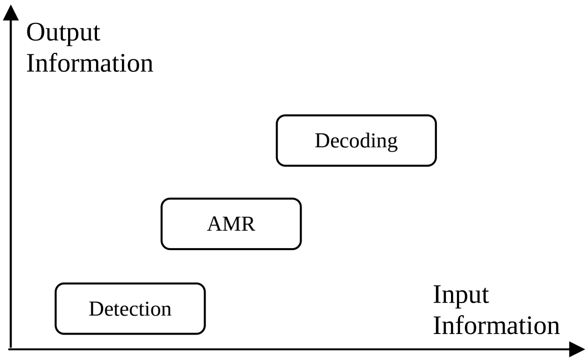


Fig. 1. The input/output information relationship

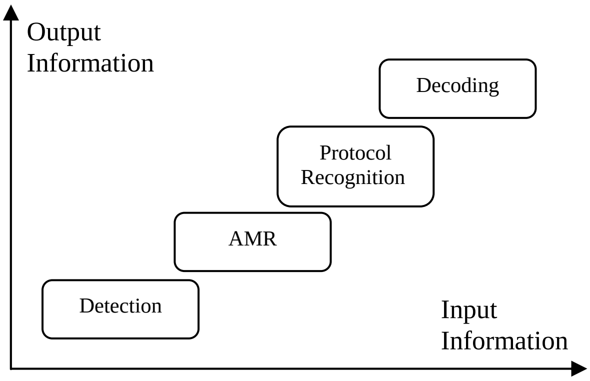


Fig. 2. The proposed input/output information relationship

Most of these methods have been proposed for a limited number of modulations. For example, extensive works are done to classify MPSK signals [1, 2, 5 and 16]. On the other hand each method uses its own assumptions about the known parameters of the received signal such as carrier frequency, SNR, baud rate and so on. So, combining different methods to recognize a broader class of modulation types is not a simple task. Consider, for example, a method designed to classify MPSK signals and another method for classification of MFSK signals. Besides any other different known and unknown parameter assumptions, the former method assumes that input signals are solely PSK modulated, but with different M. Therefore the response of the method to other signals, for example FSK signals, is not known. The problem is more severe if the methods assume different previously known parameters like SNR or carrier frequency.

The modulation set chosen in this paper includes AM, LSSB, USSB, FM, MASK, MPSK, MFSK all for M=2, 4, 8 and MSK (minimum shift keying). According to Table 1 there are a number of different methods to classify subsets of the above mentioned modulation schemes, but there is no method to recognize all of these 14 modulation schemes. We use some of the features introduced previously in the literature in our classification problem.

The above modulation schemes are selected from nine communication systems that we try to recognize. We have chosen the systems with different modulation schemes in order to increase the generality of our method. These systems are ACARS, ALE, ATIS, FMS-BOS, PACTOR-II, PSK31, DGPS, GOLAY and ERMES. Successful recognition of these sample systems makes it easier to expand our method to other communication systems. Table 2 gives a brief description of the chosen communication systems.

The problem definition and introducing the selected features used in the proposed AMR method is presented in Section 2. Section 3 is devoted to the proposed classifier which is a neural network. The carrier and baud rate estimation and the proposed system recognition method is introduced in Section 4. Results of simulation are presented in Section 5 and finally, conclusions are given in Section 6.

Table 1. Different approaches to the AMR problem

Approach	Features Type	Classification Method	Modulation Classes	Comments
Liedtke Approach [13]	Time domain features	Pattern recognition	ASK2,FSK2,PSK2,PSK4,PSK8,CW	SNR>18dB
Kim-Polydores Approach [14]	Likelihood ratio	Decision theory	BPSK,QPSK	known f_c synch. case
Whechel, et. al Approach [15]	Time domain features	Pattern recognition (Neural Network)	AM,DSB,SSB,FM,CW,QPSK,QASK	
Hsue-Soliman Approach [1]	Time domain features	Pattern recognition	MPSK,MFSK	SNR>15dB
Soliman-Hsue Approach [16]	Time domain features	Pattern recognition	MPSK	
Ghani-Lamontagne Approach [10]	Spectral features	Pattern recognition (Neural Network)	AM,LSSB,USSB,FM,ASK, BPSK,QPSK NCFSK,CPFSK,FSK,CW	
Louis-Sehier Approach [9]	Time domain features	Pattern recognition (Neural Network)	PSK2,PSK4,PSK8,OQPSK, MSK,QAM16 QAM64,FSK2,FSK4,FSK8	
Hung-Polydores Approach [2]	Likelihood ratio	Decision theory	MPSK	known f_c ,bit rate,SNR and signal power
Azzouz-Nandi Approach [17-20]	Time domain and spectral features	Pattern recognition	AM,LSSB,USSB,VSB,FM, ASK2,ASK4 PSK2,PSK4,FSK2,FSK4	
Al-Jalili Approach [21]	Time domain features	Pattern recognition	LSSB,USSB	
Hero-Hadinejad Mahram Approach [22]	Time domain features (constellation shape)	Pattern recognition	MPSK,QAM	
Sills Approach [23]	Likelihood ratio	Decision theory	BPSK,QPSK,8PSK,QAM16 ,QAM32 QAM64	known f_c ,bit rate,SNR and synch. and coherency
Lallo Approach [24]	Spectral features	Pattern recognition	MPSK,QAM,MFSK	
Mobasseri Approach [7]	Time domain features (constellation shape)	Pattern recognition	QAM	
Boudreau -et. al Approach [4]	Azzous and Nandi Features[24]	Pattern recognition	AM,FM,CW,DSB,FSK,PSK	
Lopatka-Pedzisz Approach [25]	Time domain features	Pattern recognition	ASK,4DPSK,16QAM,FSK	known f_c SNR>5dB
Nandi-Wong Approach [8]	Time domain and spectral features	Pattern recognition (Neural Network)	ASK2,ASK4,BPSK,QPSK,FSK2,FSK4 QAM16,QAM64	
Taira Approach [11]	Time domain features (constellation shape)	Pattern recognition (Neural Network)	High level QAM	
Kalinin-Kavalov Approach [26 and 27]	Time domain features	Pattern recognition (Neural Network)	BPSK,QPSK,QAM16	known f_c ,symbol duration, signal power and coherency
Delgosha-Menhaj Approach [29]	Time domain features	Pattern recognition (Neural Network)	QPSK,SQPSK,MSK	SNR>8dB
Ramakonar-et. al Approach [31]	Time domain features	Pattern recognition	FSK4,FSK8	
Spooner Approach [30]	Time domain features	Pattern recognition	QAM,PSK	
Nikoofar-*et al.* Approach [28]	Time domain features (constellation shape)	Pattern recognition	QAM,PSK	

Table 2. The selected communication systems description

System	Modulation	Comment	Baud rate	Frequency band	Application
ACARS	FSK-AM		2400 BPS	VHF	Aircraft Communication Addressing and Reporting System
ALE	FSK-SSB		125 BPS	HF	Automatic Link Establishment in HF radio systems
ATIS	FSK-FM	FSK F1=1300 HZ F2=2100 HZ	1200 BPS	VHF UHF	Automatic Transmitter Identification System in VHF-UHF radio systems
FMS-BOS	FSK-FM OR FSK	FSK F1=1200 HZ F2=1800 HZ	1200 BPS	VHF	radio signaling system for security authorities and organizations
GOLAY	FSK		300/600 BPS	VHF	a proprietary paging system
ERMES	4PAM-FM (4-FSK)		3125 BPS	VHF UHF	European Radio Message Standard
PACTOR-II	DBPSK DQPSK D8PSK		100 BPS	HF	data transmission system for radio amateur use
PSK31	DBPSK DQPSK		31.25 BPS	HF	text conversations between two or more parties for radio amateur use
DGPS	MSK		100/200 BPS	HF	Differential Global Positioning System

2. PROBLEM DEFINITION AND THE SELECTED FEATURES

Each type of modulation technique changes some parameters of the carrier signal according to the message to be sent. The main parameters of the carrier signal are frequency, phase and amplitude. So in order to recognize different modulation schemes, we should find some features that show the variation of these parameters.

FM and AM analog modulations are described according to the following formula [32]

$$y(t)=A[1+mx(t)]\cos(2\pi f_c t+k_d \int x(t)dt) \qquad (1)$$

where m is the AM modulation depth, K_d is FM modulation index, $x(t)$ is the modulating signal and f_c is the carrier frequency.

The digital modulations are represented as [33]

$$\text{MASK:}\quad S_m(t)=\mathrm{Re}[A_m U(t)e^{j2\pi f_c t}] \qquad \text{m=1,2,..,M}$$

$$\text{MPSK:}\quad S_m(t)=\mathrm{Re}[AU(t)e^{[2\pi f_c t+\frac{2\pi}{M}(m-1)]}] \qquad \text{m=1,2, ..., M} \qquad (2)$$

$$\text{MFSK:}\quad S_m(t)=\mathrm{Re}[AU(t)e^{j2\pi(f_c+f_m)t}] \qquad \text{m=1,2,..,M}$$

Minimum shift keying can be described as continuous phase modulation according to

$$\text{MSK:}\quad S(t)=A\cos[2\pi(f_c+\frac{1}{4T}I_n)t-\frac{n\pi}{2}I_n+\theta_n] \qquad nt\le t\le(n+1)T \qquad (3)$$

Where $\theta_n = \pi h \sum_{k=-\infty}^{n-1} I_k$, I_n are data amplitudes and *h* is called modulation index.

Now we need some features to show the variation in amplitude, phase and frequency of the received signal.

According to Table 1, many different features have been introduced previously to classify subsets of the modulation schemes considered in this paper, but there is no method to recognize all of them simultaneously. So both time domain features introduced by Azzouz and Nandi [17] and spectral features proposed by Ghani and Lamontagne[10] are used for our classification problem. But there are some difficulties in combining the selected set of features in a way to make the proposed system efficient and reliable. Since we have used the neural networks as our classifier it is possible to use the hierarchical method for classification [9]. Therefore we consider AM, LSSB, USSB, FM, ASK2, ASK4, PSK2, PSK4, FSK2 and FSK4 as *metagroup1* and the remaining ones (ASK8, PSK8, FSK8 and MSK) as *metagroup2*. We use two different neural networks with two different features for the two mentioned *metagroups*. The first neural network classifies the received signal in AM, LSSB, USSB, FM, ASK2, ASK4, PSK2, PSK4, FSK2, FSK4 and *metagroup2*. If the signal is classified as *metagroup2* by the first neural network (Fig. 3), then the second neural network classifies it in ASK8, PSK8, FSK8 and MSK.

For *metagroup1* we use the nine time domain features proposed by Azzouz and Nandi [17] which are described in Table 3 and are evaluated as follows:

$$1\text{-}\ \gamma_{\max} = \max\left|DFT(a_{cn}(i))\right|^2 / Ns \tag{4}$$

Ns : Number of samples per block

a_{cn} : Normalized-centered instantaneous amplitude

$$2\text{-}\ \sigma_{ap} = \sqrt{1/c(\sum_{a_n(i)>a_t} \phi_{NL}^2(i)) - (1/c \sum_{a_n(i)>a_t} \left|\phi_{NL}(i)\right|)^2} \tag{5}$$

ϕ_{NL} : Centered-nonlinear component of instantaneous phase, C: Number of samples in ϕ_{NL} for which a_n (i) > a_t , the threshold value of $a_n(i) = \dfrac{a(i)}{mean(a(i))}$ and a(i) is the instantaneous amplitude.

$$3\text{-}\ \sigma_{dp} = \sqrt{1/c(\sum_{a_n(i)>a_t} \phi_{NL}^2(i)) - (1/c \sum_{a_n(i)>a_t} \phi_{NL}(i))^2} \tag{6}$$

$$4\text{-}\ P = \frac{P_L - P_U}{P_L + P_U} \tag{7}$$

where

$$P_L = \sum_{i=1}^{fcn} \left|X_c(i)\right|^2 \ , \quad P_U = \sum_{i=1}^{fcn} \left|X_c(i + f_{cn} + 1)\right|^2 \quad , \qquad f_{cn} = \frac{f_c N_S}{f_S} - 1$$

$X_c(i)$: Fourier transform of RF signal

$$5\text{-}\ \sigma_{aa} = \sqrt{1/Ns(\sum_{i=1}^{Ns} a_{cn}^2(i)) - (1/Ns \sum_{i=1}^{Ns} \left|a_{cn}(i)\right|)^2} \tag{8}$$

$$6\text{-}\ \sigma_{af} = \sqrt{1/c(\sum_{a_n(i)>a_t} f_N^2(i)) - (1/c \sum_{a_n(i)>a_t} \left|f_N(i)\right|)^2} \tag{9}$$

$f_N(i)$: Normalized-centered instantaneous frequency

$$7\text{-}\ \sigma_a = \sqrt{1/c\Big(\sum_{a_n(i)>a_t} a_{cn}^2(i)\Big) - \Big(1/c \sum_{a_n(i)>a_t} a_{cn}(i)\Big)^2} \quad (10)$$

$$8\text{-}\ \mu_{42}^{a} = \frac{E\{a_{cn}^4(i)\}}{\{E\{a_{cn}^2(i)\}\}^2} \quad (11)$$

where E{} means Expected value.

$$9\text{-}\ \mu_{42}^{f} = \frac{E\{f_N^4(i)\}}{\{E\{f_N^2(i)\}\}^2} \quad (12)$$

f_N : Normalized-centered instantaneous frequency

Table 3. Time domain features [17]

Feature	Description
$\gamma_{\max}$	Maximum value of the spectral power density of the normalized-centered instantaneous amplitude of the signal
σ_{ap}	Standard deviation of the absolute value of the centered non-linear component of the instantaneous phase, evaluated over the non-weak intervals of the signal
σ_{dp}	Standard deviation of the centered non-linear component of the instantaneous phase, evaluated over the non-weak intervals of the signal
P	Is used for measuring the spectrum symmetry around the carrier frequency
σ_{aa}	Standard deviation of the absolute value of the normalized- centered instantaneous amplitude of the signal
σ_{af}	Standard deviation of the absolute value of the normalized-centered instantaneous frequency, evaluated over the non-weak intervals of the signal
σ_a	Standard deviation of the normalized-centered instantaneous amplitude, evaluated over the non-weak intervals of the signal
μ_{42}^{a}	Kurtosis of the normalized-centered instantaneous amplitude of the signal
μ_{42}^{f}	Kurtosis of the normalized-centered instantaneous frequency of the signal

For the *second metagroup* we use the spectrum of the signal as the feature as proposed in [10]. In this neural network, the Welsh periodogram of the signal is used as a feature for classification. To reduce the dimension of the input data, the main lobe of the periodogram containing most of the information is used and the remaining parts are discarded. The proper interval of periodogram is chosen after checking all the modulation set spectrums. It is trivial that signals with a higher bit rate will take more bandwidth than lower bit rates. Therefore, in order to choose the proper interval of the spectrum, the highest bit rate in our data base, which belongs to ERMES protocol (3125 bps), is considered. We have used 256 point FFT and it seems that a 6 point interval around a carrier frequency which has a 28.125 KHz bandwidth contains the proper portion of the main lobe. Hence we are sure that the selected interval will contain the main lobe of the spectrum of other systems with lower bit rates.

The classification procedure is performed frame by frame. For the first neural network each frame contains 2048 samples of the received signal. The modulating scheme is deduced after the integration of the result of all available signal frames. The modulating scheme with the greatest number of recurrences is considered as the modulating scheme. For the second neural network, the features are extracted from the signal frames of 8192 sample lengths for better spectrum estimation. Again each frame is considered separately and the final decision is made after integrating the result of each frame classification.

3. NEURAL NETWORK STRUCTURE

We have used the concept of hierarchical neural networks described in [9]. In this method classification can be done in successive steps. The outputs can be classified in groups called *metagroup*s and the neural network classifies these *metagroups* first. Then classification can be done within each *metagroup* in the same manner. Our neural network classifies two *metagroups* mentioned in part 2. The input data is classified as one of the first *metagroup* members or just as metagroup 2. So we do not need an additional neural network for classification of the first *metagroup* subsets, however signals belonging to the second *metagroup* are classified to the final output result using another neural network structure. This method is shown in Fig. 3.

In Fig. 3, Net1 is a feed forward neural network with two hidden layers. The structure is chosen after extensive simulation tests. The number of nodes is 9 in the input layer, 75 in the first hidden layer, 75 in the second hidden layer and 11 in the output layer. The number of nodes is chosen to get the best performance results. The activation function used is log-sigmoid in the input and two hidden layers and a pure linear function in the output layer. The network is trained using a variable rate back propagation learning algorithm [36]. This training scheme converges faster and avoids falling in a shallow minimum, leading to better results.

With standard steepest descent, the learning rate is held constant throughout training. The performance of the algorithm is very sensitive to the proper setting of the learning rate. If the learning rate is set too high, the algorithm can oscillate and become unstable. If the learning rate is too small, the algorithm takes too long to converge. It is not practical to determine the optimal setting for the learning rate before training, and, in fact, the optimal learning rate changes during the training process as the algorithm moves across the performance surface.

The performance of the steepest descent algorithm can be improved if we allow the learning rate to change during the training process. An adaptive learning rate attempts to keep the learning step size as large as possible while keeping learning stable. The learning rate is made responsive to the complexity of the local error surface.

In adaptive learning rate, the training procedure is as follows. First, the initial network output and error are calculated. At each epoch new weights and biases are calculated using the current learning rate. New outputs and errors are then calculated. If the new error exceeds the old error by more than a predefined ratio, (1.04 in our simulations), the new weights and biases are discarded. In addition, the learning rate is decreased (by multiplying by 0.7 in our simulations). Otherwise, the new weights, etc., are kept. If the new error is less than the old error, the learning rate is increased (by multiplying by 1.05 in our simulations). This procedure increases the learning rate, but only to the extent that the network can learn without large error increases.

The second neural network named Net2 in Fig. 3 is a one hidden layer feed forward neural network that is trained using the same method as Net1. It has only one input node. There are 80 nodes in its hidden layer and log-sigmoid function is used in its input and the hidden layer and a pure linear function in the output layer.

For each modulation type we have used 240 blocks of data each containing 2048 samples of the signal with SNRs varying from 0 to 55 dB for training the networks and another set of the same size but different from those used for training as the test set. The SNR levels are increased in 5dB steps. Therefore 12 levels of SNR is used and each 20 frames of data is in one SNR level. The stop margin of training was 300 epochs or an RMS rate of less than 0.01. The maximum value of output nodes is considered for a classification result.

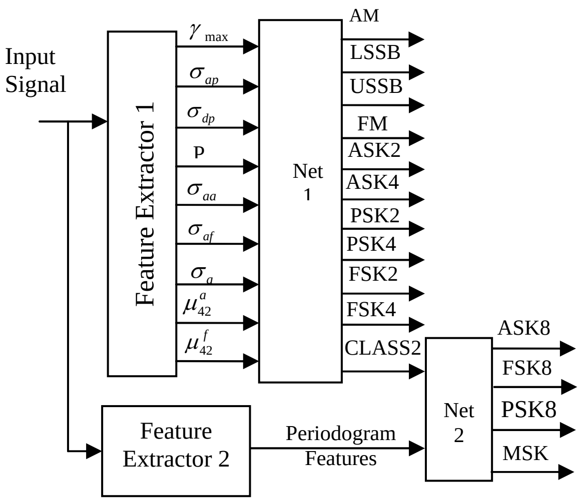


Fig. 3. The neural network structure used in our method

4. SYSTEM RECOGNITION

Figure 4a depicts the general block diagram of the proposed signal intercept system. As this figure shows, the whole expected radio frequency (RF) spectrum is searched for signal presence using a scanning energy detector receiver. As soon as the presence of a signal is detected ($S_1(t)$), its frequency band is down converted to intermediate frequency (IF). In this step we have only a rough estimate of the carrier frequency(f_{RF}). The IF signal ($S_2(t)$) is processed by an AMR block using the presented algorithms of Sections 2 and 3. The precise carrier frequency is also estimated (f_c). For carrier frequency estimation we have used the zero crossing method of [1] with some modifications. Using the recognized modulation type (*Mod. Typ.*) and the estimated carrier frequency (f_c) the demodulated signal can be derived ($x[n]$).

The system recognition block in Fig. 4a, uses f_c , f_{RF} , *Mod. Typ.* and $x[n]$ and recognizes the communication system type.

The main features of the 9 systems used in the system recognition process (modulation scheme, bit rate and carrier frequency) are presented in Table 2. Further details can be found in [35]. Fig. 4.b shows the proposed system recognition decision tree. In the proposed scheme we need two main blocks, baud rate estimator and carrier frequency estimator.

For carrier frequency estimation we have used the zero crossing method of [1] with some modifications and the baud rate is estimated using the method proposed in [34].

Using the recognized modulation type, estimated carrier frequency and baud rate, the system can be recognized using the decision tree given in Fig. 4.b. It should be noted that according to Table 2, some of the systems use two-step modulations. For example ACARS (Aircraft Communication Addressing and Reporting System) uses FSK modulation for base band modulation of data and then AM modulates the resultant signal in VHF band. FMS-BOS also uses a two-step modulation FSK-FM. In these cases the final modulation type is recognized and the system can be recognized by processing the demodulated signal.

It can be seen that our proposed AMR algorithm can recognize more modulation classes than are used in the 9 communication systems of Table 2. So, although we considered nine classes of communication systems in this research, expanding the number of classes is straightforward using the principles given here. According to Fig. 4, it can be seen that the main source of error in system classification is the AMR error. Due to a large difference in baud rate or carrier frequency, the classification based on these two parameters has a negligible error relative to the AMR error(The simulations show that for SNR>15dB the classification error between ATIS and FMS-BOS due to the carrier frequency estimation error is less than 0.5 percent and the baud rate classification error is almost zero). So in the next section we solely present the performance of the AMR algorithm.

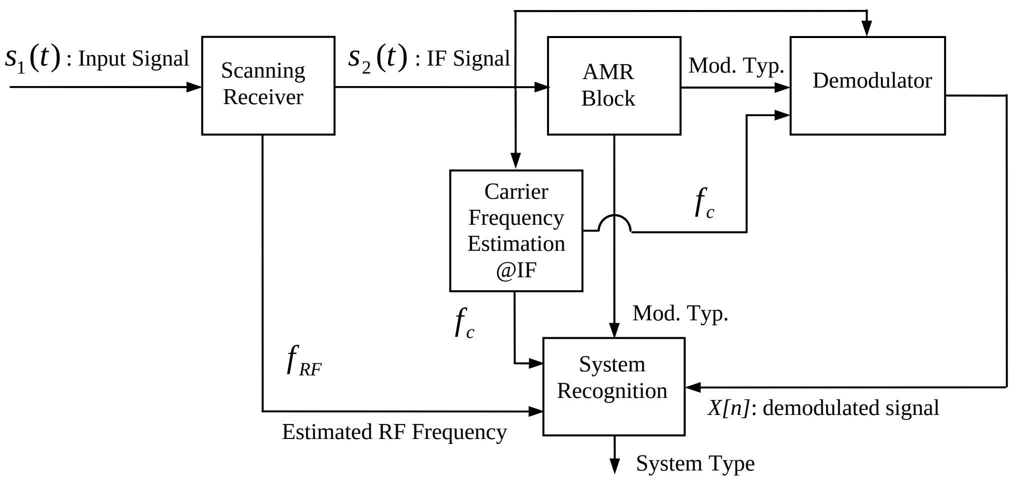


Fig. 4. a) Block diagram of the signal intercept system

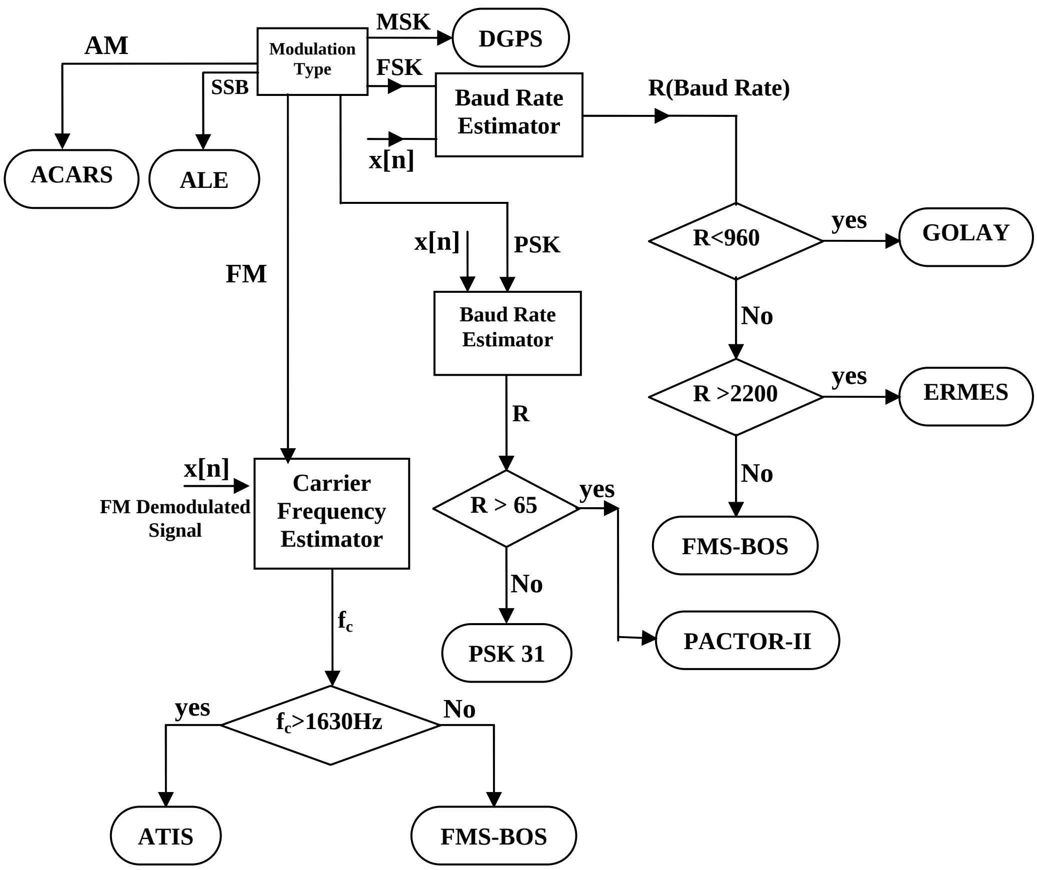


Fig. 4. b) System recognition decision tree

5. SIMULATION RESULTS

For simulation we choose an IF frequency equal to 150 KHz for our simulations. Two parameters which affect the selection of IF frequency are baud rate and the modulation type. The highest baud rate has the widest spectrum and the modulation type also affects the spectrum width. In our case 150 KHz value for IF frequency is chosen according to these parameters. The IF signals are sampled with a 1200 KHz sampling frequency which is high enough to avoid aliasing. In order to make our decision more reliable, at least a few bits of information should be received.

Two separate sets of signals have been used for training and testing the neural network. The results are presented in Tables 4 and 5. It should be mentioned that the results have been evaluated considering 20 frames of signal in each SNR. In Tables 4 and 5 the performance of the neural network for *Class1 and 2* signals is presented separately. The whole performance has been shown in Table 6.

Table 4. The percent of correct decision probability of the first class

SNR(dB)	0	5	15	25	35	45	55
AM	87.51	90	90	100	100	100	100
LSSB	15	55.5	90	100	100	100	100
USSB	17	85.7	95	100	100	100	100
FM	90	85	90	100	100	100	100
ASK2	90	100	100	100	100	100	100
ASK4	80	100	100	100	100	100	100
PSK2	10	35	80	100	100	100	100
PSK4	15	65	95	100	100	100	100
FSK2	85	75	100	100	100	100	100
FSK4	75	100	100	100	100	100	100

Table 5. The correct decision probability of the second class

SNR	0 dB	5 dB	15 dB	25 dB	35 dB	45 dB	55 dB
ASK8	15	60	80	100	100	100	100
PSK8	45	70	90	95	100	100	100
FSK8	30	75	87.5	97	100	100	100
MSK	20	60	95	100	100	100	100

Table 6. Simulation results: Input modulations *vs*. deduced modulations at 15dB SNR

Input Modulation	Recognized Modulation scheme							
	AM	LSSB	USSB	FM	MASK	MPSK	MFSK	MSK
AM	90%	-	-	-	10%	-	-	-
LSSB	-	90%	-	-	-	5.5%	3.5%	1%
USSB	-	-	95%	-	-	4%	1%	-
FM	-	-	-	90%	-	-	10%	-
ASK2	-	-	-	-	100%	-	-	-
ASK4	-	-	-	-	100%	-	-	-
ASK8	20%	-	-	-	80%	-	-	-
PSK2	-	-	-	-	-	80%-20%(error)	-	-
PSK4	-	-	-	-	-	95%-5%(error)	-	-
PSK8	-	-	-	-	-	90%-10%(error)	-	-
FSK2	-	-	-	-	-	-	100%	-
FSK4	-	-	-	-	-	-	100%	-
FSK8	-	-	-	13.5%	-	-	87.5%	-
MSK	-	-	-	0.5%	-	-	4.5%	95%

Although the modulation subset considered in this paper is different from that of [17] and [10], we compare the performance of our method with the methods of Azzouz[17] and Ghani[10] in Table 7 at SNR equal to 15 dB. As it is clear from Table 7, the proposed method presented in this paper has almost the same performance compared to [17] and [10], but in a broader class of modulations.

Table 7. Comparison of our method with Azouz[17] and Ghani[10] at 15 dB SNR

	AM	LSSB	USSB	FM	ASK2	ASK4	PSK2	PSK4	FSK2	FSK4
Azzouz [17]	88.5	99.8	98.5	90.1	96.8	86.5	99.5	96.8	99	99.5
Ghani [10]	97.1	99.2	99	89.9	96.1	------	96.8	99.1	100	------
Our Method	90	90	95	90	100	100	85	95	100	100

We have also investigated the result of the reduction of the frame length. As one might expect, reducing the frame length decreases the number of bits of information in the frame and can reduce our decision reliability drastically. The results shown in Fig. 5 indicate that, the number of bits less than 5 makes the correct decision impossible. Although this figure has been obtained for PSK31 protocol with 31.25 baud, it can be used as a figure of merit for all other protocols too. In the simulations corresponding to Fig. 5, for testing the effect of the number of received bits on the decision, we assumed a noise-less channel, so the result does not contain the effect of SNR levels.

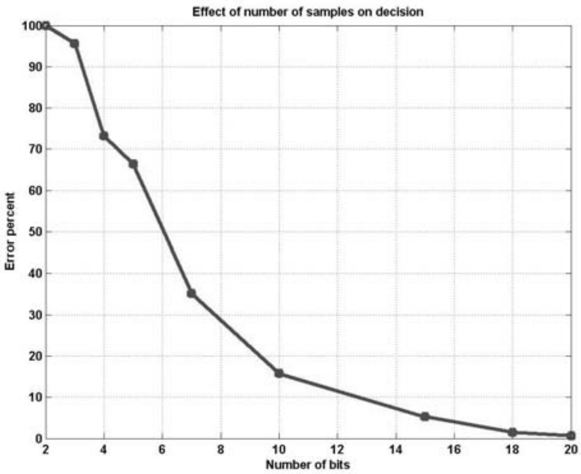


Fig. 5. Effect of number of bits on decision error

Figure 6 shows the effect of the number of frames on decision errors. Because the decision is made on a frame basis, it is expected that integrating the decision results on more frames will increase the accuracy. In this situation, although each frame is classified independently by the neural network as a modulation type, a group of frames are considered together for integration before final decision making. As the number of frames in the integration process increases, the error reduces.

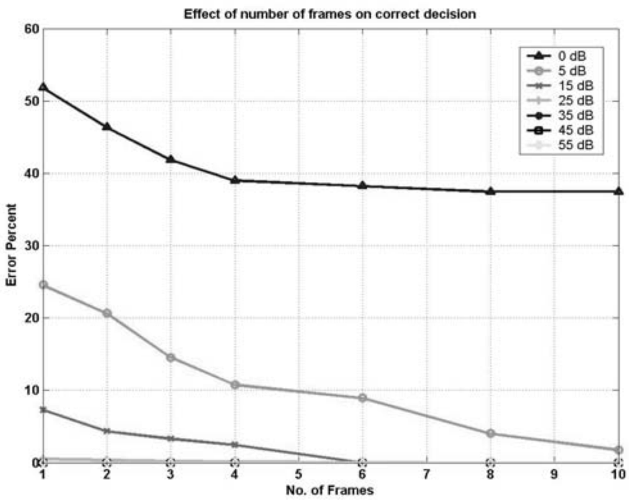
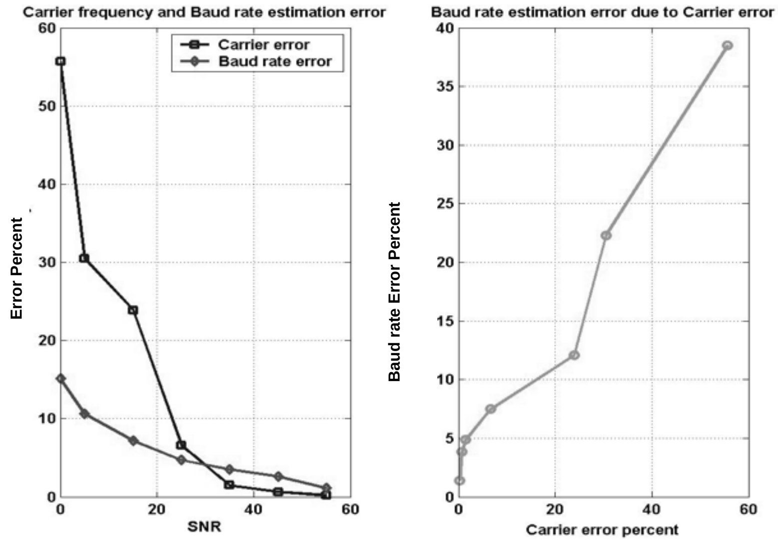


Fig. 6. Effect of frame number on average decision error

The next step is to estimate carrier frequency and baud rate. Using the methods mentioned in Section 4, the carrier frequency and baud rate can be estimated effectively in SNRs above 15 dB. Fig. 7 shows both carrier frequency and baud rate RMS(root mean square) estimation error in percentage. In Fig. 7a the performance of the baud rate estimator is considered against noise where carrier frequency is assumed to be known exactly. But in Fig. 7b the effect of carrier frequency estimation error on the performance of the baud rate estimator is evaluated. In this figure the noise is not considered. The results are obtained for a carrier frequency equal to 150 KHz, and obviously depend on the carrier frequency. But it can be seen that the performance of the baud rate estimator decreases as the carrier frequency estimation error increases.



(a) (b)

Fig. 7. Carrier frequency and baud rate estimation error

In our application the baud rate estimation error is not as important as the carrier frequency estimation error. A rough estimation of the baud rate can be used in the system database table to match the nearest value. However the effect of the estimation error of the carrier frequency is more severe. This is why the simple but fast baud rate estimator of [34] can be effectively used in our method.

Using the recognized modulation scheme and estimated baud rate and carrier frequency and comparing this information with the known expected values for the nine systems mentioned earlier, the protocol can be recognized.

6. CONCLUSION

We have developed a method for recognition of communication systems based on modulation recognition and baud rate and carrier frequency estimation. For automatic modulation recognition we have developed a new method based on two different sets of features which have been proposed in the literature for different applications, to recognize a wide set of 14 modulation schemes. These modulation schemes have not been considered together in a classification problem previously. The proposed AMR method does not need a prior knowledge of SNR, carrier phase and symbol rate. The classification procedure is performed by the hierarchical neural network. The back propagation training method with a variable learning rate is used. Simulation results show that the overall performance of the AMR method used in this paper is above 75%, even in SNR as low as 5 dB. For SNR above 35 dB, the performance reaches 100%. Although we considered nine classes of communication systems in this research, expanding the number of classes is straightforward using the principles given here.

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