CLASSIFING ANALOGUE MODULATED COMMUNICATION SIGNALS USING BAYES DECISION CRITERION

Abdulkadir ŞENGÜR **İbrahim TÜRKOĞLU**

Özet **- Bu çalışma, analog modülasyonlu haberleşme işaretlerinin (AM, DSB, SSB (USB), LSB, FM) sınıflandırılması için bir algoritma sunmaktadır. Önerilen sınıflandırıcı, Bayes Karar kuralını ve birkaç anahtar özelliği belirlenen amaç çerçevesinde kullanmaktadır. Sınıflandırıcının performans değerlendirmesi, farklı modülasyon türleri için bilgisayar ortamında hazırlanan benzetimler ile gerçekleştirilmiştir. Benzetimlerden elde edilen sonuçlarda, başarımın %90 civarında olduğu görülmüştür.**

Anahtar Kelimeler **- Bayes Karar Kuralı, Analog Modülasyonlar, Sınıflandırma, Özellik Çıkarma.**

Abstract **- This paper presents an algorithm for classification of analogue modulated communication (AM, SSB (USB), LSB, DSB and FM) signals. The algorithm employs Bayes decision criterion where the identification of the different modulation type is performed by using a set of key feature extraction. The performance of the classifier has been evaluated by simulating different types of analogue modulated signals. It is shown that the success rate is about %90.**

Keywords **- Bayes decision rule, analog modulation, classification, feature extraction.**

I. INTRODUCTION

The interest in modulation recognition has been growing since 1980s up to now. It has some reasonable roles in both civilian and military applications such as signal confirmation, interference identification, monitoring spectrum management, surveillance and electronic warfare [1]. At the moment, the most attractive applications area is radio and other re-configurable communication systems. Modulation recognition is an intermediate step between signal detection and demodulation [2].

İ. TURKOĞLU, A. ŞENGÜR, Fırat Üniversitesi, Teknik Eğitim Fakültesi, Elektronik ve Bilgisayar Eğitimi Bölümü. ELAZIĞ

In addition to modulation type, some other parameters should be estimated before successful demodulation. There are two kinds of philosophies in approaching modulation classification problems; these are decision-theoretic approach and pattern recognition or feature extraction approach. In a decision theoretic approach, probabilistic arguments are employed to derive a proper classification rule. Typically this rule is hard to implement exactly. Modulation recognizers, like general pattern classification systems, consist of measurement; feature extraction and decision part. A simpler way to derive a classifier is to rely upon the pattern recognition concept of feature, which ingeniously assigns signatures to specific signal formats. The key advantage of a well-chosen feature set is of course simplicity. The received signal to be classified according to its modulation type contains much uncertainty, which should be encountered by statistical tools. Therefore the known methods are based on different statistics obtained from the received signal. Statistical pattern recognition is based upon a statistical analyisis of the data to be classified. The data are assigned to a particular class by compiling a probabilistic model (estimating probability density functions) of the data in N dimensional space and dividing the space into regions corresponding to each class, according to some criterion. The major accomplishments in statistical pattern recognition include Bayesian classifiers, distance classifiers and regression trees.

The following is an overview of some of the recently published modulation recognition methods. Fabrizi et al [3] suggested a modulation recognizer for analog modulations, based on the variations of both instantaneous amplitude and the instantaneous frequency. This recognizer is used to discriminate between some types of analog modulation AM, FM and SSB. Chan and Godbois [4] proposed a modulation recognizer based on the envelope characteristics of the received signal. Al-Jalili [5] proposed a modulation recognizer to discriminate between the USB and LSB signals. Azzouz and Nandi [6] proposed a modulation recognizer to classify the whole analog modulation types. Jovanovic et al [7] introduced a modulation recognizer to discriminate between a low modulation depth (AM) and pure carrier wave (CW) in a noisy environment. Azzouz and Nandi

[8] proposed an ANN classifier for modulation recognition.

In this study, Bayes decision criterion is used to solve the modulation recognition problem based on assumption that the decision problem is placed in probabilistic terms. The selected key-features are based on the work which previosly done by Azzouz and Nandi [1]. Although the correct classification rate of AM and FM is %100, the correct classification rate of DSB, USB (SSB) and LSB is about %85.

II. CLASSIFICATION ALGORITHM

Figure 1 shows the developed modulation classification algorithm by us. Feature extraction is the first step of the proposed modulation classification process. Firstly, we should find some useful parameters for characterizing the modulation types in order to reach the aim of the study. The second step is the classification stage. We can use any classifier at this point. In this study a Bayesian classifier is preferred, and the last step is the determining of the modulation type.

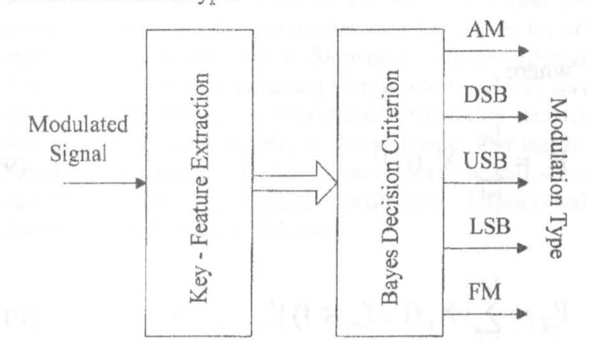

Figure 1. The structure of modulation recognizer

II.1 Bayes Decision Theory

Bayes decision theory is a fundamental statistical approach to the problem of pattern recognition. This approach is based on the assumption that the decision problem is posed in probabilistic terms, and all of the relevant probability values are known [9]. The central problem in statistical pattern recognition is the development of decision functions from sets of finite patterns of different classes so that the functions will partition the input space into regions, each of which contains the sample patterns belonging to each class. The input space is $x \in X \subseteq R^N$ and the response space is $y \in Y = \{y_1 \ldots\ldots y_k\}$, where x and y are the input pattern and the class label, respectively. The measurement x and y may be considered in a probabilistic framework, and viewed as a single observation of the random variables X and Y. In general, the most information that can be known about the input space is the a posteriori probabilities.

$$P(y_k \mid x) \quad \text{for } k = 1,\ldots\ldots K. \tag{1}$$

This is the probability that pattern x comes from class y_k. In this framework pattern classification is posed as a statistical decision problem; one evaluate the K a posteriori probabilities and selects the largest. The a posteriori probabilities $P(y_k \mid x)$ are not known, but may be calculated from the a priori probabilities $P(y_k)$ and the conditional density function $p(x \mid y_k)$ using Bayes theorem;

$$P(y_k \mid x) = \frac{P(y_k).p(x \mid y_k)}{p(x)} \tag{2}$$

where

$$p(x) = \sum_{j=1}^{K} P(y_j).p(x \mid y_j) \tag{3}$$

Note that p (x) is the probability density function of the input space. When the true class distributions are not known, the a priori probabilities are often made equal:

$$P(y_k) = 1/k \quad \text{for } k=1,\ldots,K. \tag{4}$$

To summarize, Bayes decision rule is really nothing more than the implementation of the decision function,

$$d_k(x) = p(x \mid y_k).P(y_k), \qquad k = 1,\ldots\ldots K \tag{5}$$

Where pattern x is assigned to class y_i if for that pattern $d_i(x) > d_j(x)$ for all $j \neq i$. This Bayes decision rule has the property that the probability of classification error is minimized making Bayes classifier statistically superior to any other.

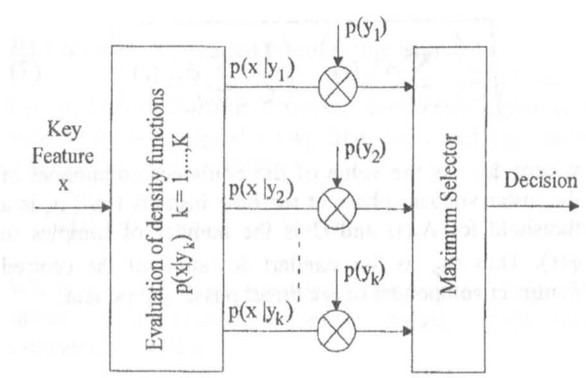

Figure 2. A classifier based on Bayes decision criterion

The challenge here lies in estimating the densities $p(x \mid y_k)$ from the training data [10].

II.2 Feature Extraction

Feature extraction is the key to pattern recognition. The key features used in this study are obtained from the instantaneous parameters of the received signal[1]. The first feature is the maximum value of the normalized centred instantaneous amplitude of the intercepted signal and it is calculated as follow;

$$\gamma_{max} = \max(| fft(a) |^2 / N) \qquad (6)$$

Where; "a" is the normalized centered instantaneous amplitude of the intercepted signal and N is the number of the sample in the range. Figure 3 shows the parameters, which are extracted from the each modulated signal according to the first key feature.

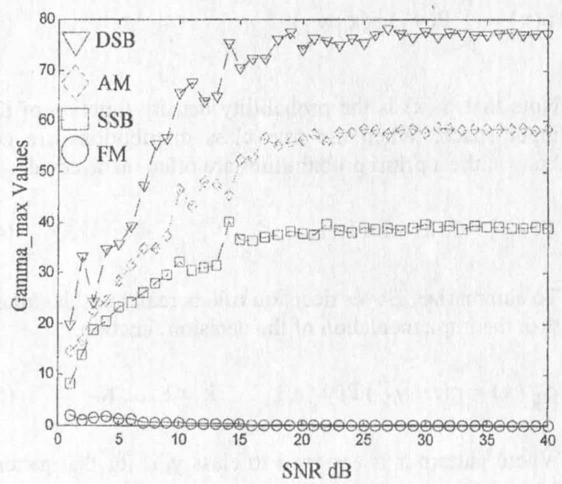

Figure 3. Dependence γ_{max} on the SNR

The second key feature σ_{dp} is defined as follow;

$$\sigma_{dp} = \sqrt{\frac{1}{C}\left(\sum_{A_n(i)>t_a} \phi_{NL}^2(i)\right) - \left(\frac{1}{C}\sum_{A_n(i)>t_a} \phi_{NL}(i)\right)^2} \qquad (7)$$

where ϕ_{NL} is the value of the nonlineer component of the instantaneous phase at the time instants $t=i/f_s$, t_a is a threshold for $A_n(i)$ and C is the number of samples in $\phi(t)$. Thus σ_{dp} is the standart deviation of the centred nonlineer component of the direct phase component.

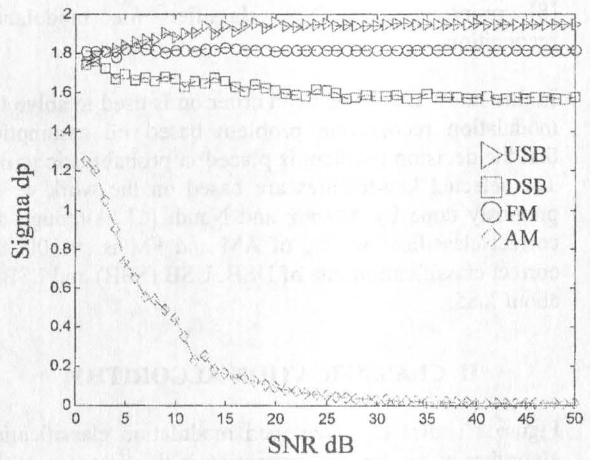

Figure 4. Dependence of σ_{dp} on the SNR

The third key feature is used for distinguishing SSB signals as a subset.

$$P = \frac{P_L - P_U}{P_U + P_L} \qquad (8)$$

where

$$P_L = \sum_{i=1}^{f_{cn}} | X_c(i) |^2 \qquad (9)$$

$$P_U = \sum_{i=1}^{f_{cn}} | X_c(i + f_{cn} + 1) |^2 \qquad (10)$$

where, $X_c(i)$ is the fourier transform of the intercepted signal $X_c(i)$, (f_c+1) is the sample number corresponding to the carrier frequency, f_c and f_{cn} is defined as;

$$f_{cn} = \frac{f_c N_s}{f_s} - 1 \qquad (11)$$

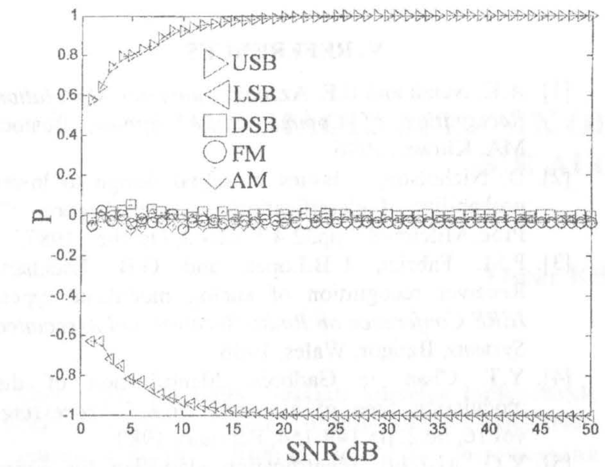

Figure 5. Dependence of the ratio P (USB, LSB) on the SNR

II.3 Classification of the Patterns

The proposed classification procedure for discriminating the analog modulated communication signals is based on a Bayes Decision rule. First of all, we should find the proper probability distribution function for inputs for all type of modulations. Arena Statistical software (Arena Version 3.01, System modeling Corporation) [11,12] was used for determining the conditional probability density functions $p(x \mid y_k)$ at the Bayes decision rule. Our inputs, which were extracted from intercepted signal, are matched to the exponential distribution. Exponential distribution is defined as follow;

$$f(x) = \frac{1}{\beta} e^{\frac{-x}{\beta}} \quad \text{if } x > 0 \qquad (12)$$

where β is the mean of the input vector. After this process, we used Bayes decision criterion defined as Equation 2. The a priori probability is 1/5 because there are five different modulation classes. Figure 6 shows the Arena's input analyzer software result.

II.4 Arena Software Input Analyzer Results

Distribution Summary

Distribution :	Exponential
Expression :	11 + EXPO(28.9)
Square Error :	0.079467

Chi Square Test

Number of intervals	= 5
Degrees of freedom	= 3
Test Statistic	= 20.8
Corresponding p-value	< 0.005

Kolmogorov-Smirnov Test

Test Statistic	= 0.243
Corresponding p-value	< 0.01

Data Summary

Number of Data Points	= 49
Min Data Value	= 12
Max Data Value	= 82.6
Sample Mean	= 39.9
Sample Std Dev	= 15.5

Histogram Summary

Histogram Range	= 11 to 83
Number of Intervals	= 7

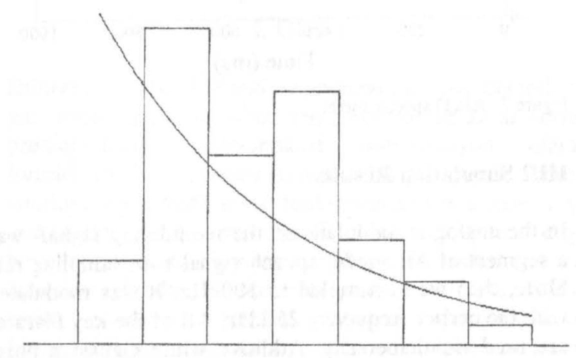

Figure. 6. Exponential Distribution.

III. SIMULATIONS

To test the algorithm of Fig.1, 50 simulated signals of each of the modulation type have been generated and processed in the MATLAB (version 5.3) and Toolboxes (The MathWorks Inc.). Each of these 50 signals was extracted by using three key-features for realizing the proposed modulation classification algorithm. Figure 3, 4, 5 shows the parameter distribution for the proposed modulation type. On the other hand, we used Arena Statistical software for matching the proper probability distribution for our parameters that were extracted from the modulated communication signals.

III.1 Specific Simulated Modulating Signal

For analog modulation schemes, the source signal is a simulated voice signal using first order autoregressive AR(1) process of the form;

$$x(i) = 0.914.x(k-1) + n(t) \qquad (13)$$

Where n(k) is a white Gaussian noise process. Figure 7 shows an autoregressive speech signal, which was simulated at Matlab.

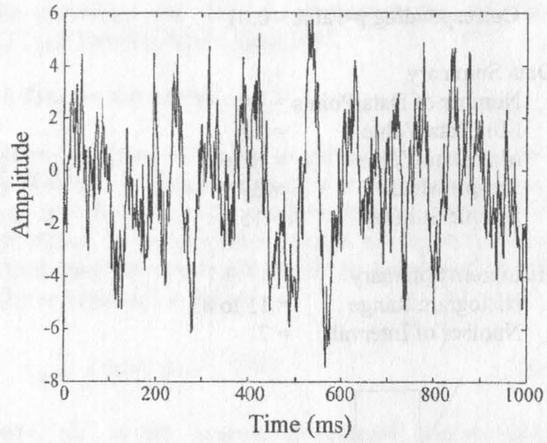

Figure 7. AR(1) speech signal

III.2 Simulation Results

In the analogue modulations, the modulating signal was a segment of AR model speech signal with sampling rate 8kHz, then we re-sampled to 100kHz. It was modulated with the carrier frequency 25 kHz. All of the key features are used simultaneously. Additive white Gaussian noise was added to the modulated signals before convertion to the complex envelope representation. Table 1 shows the classification results of computer simulation.

Table 1. The classification results

	Estimated Modulation Type				
Actual Modulation Type	AM#	DSB#	SSB#	FM#	PM#
AM#	50				
DSB#		42			8
LSB(SSB)#		7	43		
LSB#		8			42
FM#				50	

IV. CONCLUSION

The aim of this paper has been to classify the types of analogue (AM, DSB, USB, LSB and FM) modulations in communication signals using Bayes Decision criterion. Several key-features have been used for this recognizer. Computer simulations show that the performance of the classifier is satisfactory. Amplitude modulated (AM) and Frequency modulated (FM) signals can be classified as 100% success rate. SSB, signals can be classified as %86, LSB and DSB can be classified as %84 success rate. We believe that using efficient and extensive statistical key features will increase the success rate in the future studies.

V. REFERENCES

[1]. A.K. Nandi and E.E. Azzouz, *Automatic Modulation Recognition of Communication signals*, Boston, MA: Kluwer, 1996.

[2]. D. Nicholson, " Issues in signal design to lower probability of classification and identification ", Proc. Milcom 87, pp32.4.1-32.4.3, October, 1987.

[3]. P.M. Fabrizi, L.B.Lopez and G.B. Lockhart, Receiver recognition of analog modulated types, *IERE Conference on Radio Receiver and Associated Systems*, Bangor, Wales, 1986.

[4]. Y.T. Chan ve Gadbois, Identification of the modulation type of a signal, *Signal Processing*, vol.16, no.2, pp.149-154, February 1989.

[5]. Y.O. Al-Jalili, Identification algorithm for upper sideband and lower sideband SSB signals, *Signal Processing*, vol.42, no.2, pp.207-213, March 1995.

[6]. A.K. Nandi and E.E. Azzouz, Algorithms For Automatic Modulation Recognition Of Communication Signals, *IEEE Transactions on Communications*, vol. 46, April 1998.

[7]. S.D. Jovanovic, M.I. Doroslovacki and M.V. Dragosevic, Recognition of low modulation index AM signals in additive Gaussian noise, *Europen Association for Signal Processing*, V. conference, pp.1923-1926, 1990.

[8]. A.K. Nandi and E.E. Azzouz, Algorithms for Automatic Modulation Recognition of Communication signals, *IEEE Trans. on Comm.*, vol. 46, no.4, pp.431-436, April 1998.

[9]. R. O. Duda, and P.E. Hart, *Pattern Classification and Scene Analysis*, Stanford Research Institute, New York, 1989.

[10]. Englehart, K., "Signal Representation for Classification of the Transient Myoelectric Signal", Phd Thesis, New Brunswick University, Canada, 1998

[11]. Kelton W.D., Sadowski R.P. and Sadowski D.A., Simulation with Arena, McGraw-Hill Inc. New York, 1998

[12]. Tanyıldızı E., Development of new software for computer aided software, Master Thesis, Firat University, Turkey 2002.