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FAST ANALOG MODULATION RECOGNISER BASED ON THE COMPLEX ENVELOPE ONLY

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Abstract

In this paper, a fast and quick modulation recogniser for different types of analog modulations is developed. This recogniser utilises the decision-theoretic approach in which the extracted key features are compared with suitable thresholds to decide about the modulation type. In this recogniser, all the key features used are derived from the complex envelope of a signal. Thus, this recogniser is fast compared with those presented in the available references. Computer simulations for different types of band-limited analog modulated signals corrupted with band-limited Gaussian noise sequence have been carried out. It is found that this recogniser performs well and all the analog modulation types of interest - AM, DSB, LSB, USB, and FM - have been classified with success rate 100 % at the SNR of 10 dB.

Key Words

Modulation recognition, Analog modulations, Complex envelope

I. Introduction

There are three main philosophies for approaching the modulation recognition process in the available references namely, 1) a decision-theoretic approach, 2) a statistical pattern recognition, and 3) an artificial neural network (ANN) approach. Modulation recognition brings together many aspects of co-operative communication theory such as signal detection, parameter estimation, channel identification and tracking. Furthermore, modulation recognition environments may vary between two extremes - from no significant noise in the best situations to a very noisy with interference and fading. Moreover, there are many practical problems facing the modulation recognition process. Some of these problems are due to the radio communication channel and the intercept receiver such as multi-path fading effects, weak signals reception, signal distortion, frequency instability, interference from adjacent channels and signal selection. The other problems are due to the nature of the received signal such as the weak segments of a signal (carrier absent or reduced and the pauses in transmission of analog modulations), lower SNR reception, and the transmission time and the speed of computations. In most of the available reference [1]-[10], the key features used were derived from three parameters - the instantaneous

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amplitude, the instantaneous phase and the instantaneous frequency - of the intercepted signal. There are some numerical problems associated with the evaluation of these parameters such as: weak signal intervals, phase wrapping, linear phase component and the numerical derivative. The suitable solutions for these problems were introduced in [7]. Since the processing time has to be shorter than the transmission time for on-line analysis, this paper presents a faster algorithm compared with those introduced in the available references except [4].

The following is an overview for some of the recent published papers in the area of analog modulation recognition since 1984. **Fabrizi et. al.** [1] suggested a modulation recogniser which utilises the decision-theoretic approach, and it is based on the variations of both the instantaneous amplitude and the instantaneous frequency. The key features used are the ratio of the envelope peak to its mean, and the mean of the absolute value of the instantaneous frequency. This recogniser is used to discriminate between some types of analog modulation - CW, AM, FM and SSB. The performance evaluation of this recogniser was derived from 24 realizations each with 250 msec. length for each modulation type of interest. In [1], it is claimed that with these two key features the classification between the AM and the FM signals could be achieved at SNR > 35 dB. However, SSB could be recognised from AM and FM signals at SNR > 5 dB. **Chan and Gadbois** [2] developed a modulation recogniser which utilises the decision-theoretic approach, and it is based on the envelope characteristics of the intercepted signal. It uses the ratio **R** of the variance of the squared instantaneous amplitude to its mean square as a decision criterion to decide about the correct modulation type. This recogniser is used for the recognition of some analog modulated signals - AM, FM, DSB and SSB. The choice for the ratio R to discriminate among these modulation types is based on the following fact: in noise-free signals, the ratio R is ought to be zero for FM signals and close to unity for AM signals. Also, the ratio R for DSB signal is 2 and is 1 for SSB signals. The simulation results for this recogniser were derived from 200 realizations for each modulation type of interest, each with 20 msec. Length as is introduced in ([2], Table 3). In [2] it is claimed that at SNR of 7 dB, the probability of correct modulation recognition is 100% for FM signals, 90.5% for AM signals, 80.0% for SSB signals and 94.0% for DSB signals.

Nagy [3] proposed a modulation recogniser for analog modulations. In this recogniser, the **Chan and Gadbois** [2] parameter, **R**, in addition to the variance of the instantaneous frequency normalized to the squared sample time are used as key features to discriminate among the modulation types - AM, DSB, SSB, FM, and CW. In [3], it is mentioned that the performance evaluation of this recogniser was derived from 500 realizations, each with 250 msec. length for each modulation type. In [3], it is claimed that the different modulation types have been classified with success rate > 90.0% at the SNR of 15 dB except the SSB had been classified with success rate 66.0%. So, **Nagy** developed another key feature, which is the mean value of the instantaneous frequency. In this case the SSB has been classified with success rate > 94.0% at SNR = 15 dB, and the other types have been classified with 100% success rate. **Jovanovic et. al.** [4] introduced a modulation recogniser to distinguish between a pure carrier wave (CW) and a low modulation depth AM in a noisy environment. The key feature used is the ratio of the variance of the in-phase component to that of the quadrature component of the complex envelope of a signal. The only thing that mentioned about the performance evaluation is that the proposed key feature is a highly reliable tool for separating the AM signals with low modulation depth from the unmodulated carrier even if the SNR is poor. All-Jalili [5] proposed a modulation recogniser to discriminate between the USB and LSB signals. This recogniser is based on the fact that the instantaneous frequency of the USB signal has more -ve frequency spikes than the +ve ones, and the opposite for the LSB signal. The key feature used in this recogniser is defined as the ratio, **G**, of the number of -ve spikes to the number of the +ve ones of the instantaneous frequency. So, **G** > 1 for USB and **G** < 1 for LSB. In [5] the performance measure was derived from 10 realizations, each with 128 msec. for each modulation type and it is claimed that this recogniser performs well for the SNR of 0 dB.

Nandi and Azzouz [6] introduced a global procedure for modulation recognition of the well known analog modulation types. This recogniser utilises the decision-theoretic approach. The decision about the modulation types is based on four key features. These are: 1) the maximum value of the spectral power density of the normalized-centered instantaneous amplitude, 2) the standard deviation of the absolute value of the centered non linear component of the instantaneous phase in the non-weak intervals of a signal segment, 3) the standard deviation of the direct (not absolute) value of the centered non-linear component of the instantaneous phase, and 4) the RF spectrum symmetry measure around the carrier frequency of the intercepted signal. This recogniser is used to discriminate among the AM, DSB, VSB, LSB, USB, FM, and combined modulated signals. In [6], all the modulation types of interest have been classified with success rate > 90.0% at the SNR of 10 dB. Furthermore, **Azzouz and Nandi** [9] introduced a modification for the decision flow of the algorithm presented in [6]. In [9], it is mentioned that, based on the aforementioned four key features, many algorithms can be developed according to the chosen decision flow. It was found that, the overall success rate is 99.4% at the SNR of 10 dB, and it is 99.9% at the SNR of 20 dB. Moreover, **Nandi and Azzouz** proposed a modulation recogniser which utilises the ANN approach [8]. It is based on a single hidden layer ANN and the same data set used in [6]. It was found that all the modulation types of interest have been classified with success rate > 95.0%. Excluding the USB, the success rate is > 98.0% at 10 dB SNR. In [10], **Azzouz and Nandi** introduced the double hidden layer ANN modulation recognition algorithm. Using the same data set in [6], it was found that all the modulation types of interest have been classified with success rate > 98.0%.

In the next section, the proposed algorithm, using new and fast key features derived from the complex envelope of a signal is introduced. The details of computer simulations are presented in section 3. The performance evaluations of the proposed algorithm are presented in section 4. Finally, the paper is concluded in section 5.

2. Proposed Modulation Recognition Algorithm

This paper introduces an algorithm for modulation recognition, in which the problems associated with the evaluation of the instantaneous amplitude, phase and frequency are elevated. In this algorithm, all the key features used are derived from the complex envelope of the received signal using the conventional signal processing tools. Similar to the decision-theoretic algorithms, introduced by the author and others in [6-10] the intercepted signal frame is divided into a set of adjacent segments each of length N = 2048 samples (equivalent to 1.7?7 msec.) and this results in $M_s = (L \, f_s) / N$ segments, where f_s is the sampling rate and L is the intercepted signal frame length. From every available segment, three key features are extracted from the real and imaginary parts of the complex envelope. However the mathematical expressions for the real and imaginary parts of the complex envelope of a signal are shown in Table 1. All the key features used in the developed algorithm are derived from the complex envelope of a signal using the conventional signal processing tools. The first key feature is the mean value of the real part, R (t), of the complex envelope of a signal and it is defined by

$$m = \frac{\sum_{i=1}^{N} R(i)}{N} \qquad (1)$$

where N is the number of samples per segment. The second key feature is the power contained in the imaginary part, I (t), of the complex envelope (P_i). It is given by

$$P_i = \frac{\sum_{i=1}^{N} I^2(i)}{N} \qquad (2)$$

The third key feature is derived from two new signal parameters. These are:

$$C_1(t) = R(t) + I_H(t) \qquad (3)$$

where $I_H(t)$ is the Hilbert transform of I (t), and

$$C_2(t) = R(t) - I_H(t) \qquad (4)$$

Thus, the third key feature is the relation between the power contained in the parameter $C_1(t)$ and that in $C_2(t)$. Let them respectively denoted by P_{c1} and P_{c2} and they are defined as

$$P_{c1} = \frac{\sum_{i=1}^{N} C_1^2(i)}{N} \qquad (5)$$

and

$$P_{c2} = \frac{\sum_{i=1}^{N} C_2^2(i)}{N} \qquad (6)$$

Thus, the third key feature, P_c, is defined as

$$P_c = \frac{P_{c1} - P_{c2}}{P_{c1} + P_{c2}} \qquad (7)$$

Due to the simplicity of the key features extraction, the developed algorithm can be used in real field applications. Anyway, a detail pictorial representation of the proposed analog modulation recognition algorithm is shown in Fig. 1 in the form of a flowchart. It is worth noting that each decision rule is applied to a set of modulation types separating them into two non-overlapping subsets.

3. Computer Simulations

In this paper, the carrier frequency, f_c, and the sampling rate, f_s, were respectively chosen to be 150 kHz and 1200 kHz. The procedure used for the generation of a non-intelligible speech signal of length 1.707 msec (equivalent to 2048 samples), is presented in [7]. AM, DSB, FM signals have been derived from a general expression [11]

$$s(t)=(A + m\, x_1(t)) \cos [\, 2\pi f_c t + K_f \int_{t}^{\infty} x_2(\;)\, d \;\,], \tag{8}$$

where $x_1(t)$ and $x_2(t)$ are two modulating signals (simulated speech signals), m is a coefficient determined by the desired amplitude modulation depth (Q) [11], and K_f is a frequency deviation coefficient and it is determined by the frequency modulation index (D) [11]. It is worth noting that Q in the simulations here takes the values 60% and 80%, and D takes the values 5 and 10. Also, the SSB (i.e. LSB or USB) signals were generated according to the expression in [11].

$$s(t)= x(t) \cos(2\pi f_c t) \pm y(t) \sin(2\pi f_c t) \tag{9}$$

where $x(t)$ is a simulated speech signal and $y(t)$ is its Hilbert transform. The -ve sign in (9) is used for USB signal whereas the +ve sign is used for LSB one. Anyway, a complete illustration for the computer simulations for different types of analog modulations as well as a band-limited Gaussian noise - defined in (10) - and they are used in the performance evaluations were introduced in [7].

$$n(t)= n_c(t) \cos(2\pi f_c t) + n_s(t) \sin(2\pi f_c t) \tag{10}$$

4. Performance Evaluation

In this paper, the analog modulation types that can be classified are: AM (with different modulation depth), DSB, LSB, USB, and FM (with different modulation index). Simulations of different modulation types corrupted with a band-limited Gaussian noise have been carried out at different SNR to evaluate the performance of the developed algorithm. The performance evaluation of the proposed algorithm for analog modulation recognition is derived from 400 realizations at different values of SNRs (5 dB and 10 dB) for each modulation type of interest. From Table 2 (SNR = 5 dB), it is clear that all types of analog modulations of interest have been correctly classified with 100 % success rate except the DSB (=93.25%). In Table 3 (SNR = 10 dB) all the modulation types have been classified with success rate 100%.

5. Conclusions

The aim of this paper is to recognise automatically som types of analog modulations in communication signals. The current approach has bee to carry out this task using key features derived from the complex envelope of a signal. Furthermore, two new signal parameters are proposed to fulfil the requirements of the proposed algorithm. It is worth noting that all the suggested key features can be extracted using the conventional signal processing tools. So, the proposed algorithm can be implemented at extremely low cost and it seem to be suitable for the on-line analysis. Extensive simulations of seven analog modulation types have been carried out at different SNR. Sample results have been presented at the SNR of 5 dB and 10 dB only. It is found that the threshold SNR for correct signal classification is about 5 dB, which is an improvement both in the reduced SNR threshold. Furthermore, the speed of computation of the developed algorithm should be faster than the others [1-10] since the key features used here were derived from the complex envelope only of a signal and not from the instantaneous phase and frequency. Currently the work is under way to implement and test the suggested ideas in this paper for digital modulations

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Table 1 Real and imaginary parts of the complex envelope for different analog modulation types

Modulation Types	*Real Part R (t)*	*Imaginary part I (t)*
AM	$A[1+Q\,x(t)] + n_c(t)$	$n_s(t)$
DSB	$A\,x(t) + n_c(t)$	$n_s(t)$
LSB	$A\,x(t) + n_c(t)$	$-A\,y(t) + n_s(t)$
USB	$A\,x(t) + n_c(t)$	$A\,y(t) - n_s(t)$
FM	$A[n_c(t) + \cos\varphi(t)]$	$A[n_s(t) + \sin\varphi(t)]$

Table 2 Confusion matrix for the developed algorithm [based on 400 realization] at SNR = 5 dB.

Simulated Modulation Types	AM	DSB	LSB	USB	FM
AM - Q=60 %	100%	-	-	-	-
AM - Q=80 %	100%	-	-	-	-
DSB	-	93.25%	-	-	6.75%
LSB	-	-	100%	-	-
USB	-	-	-	100%	-
FM - D=5	-	-	-	-	100%
FM - D=10	-	-	-	-	100%

Table 3 Confusion matrix for the developed algorithm [based on 400 realization] at SNR=10 dB.

Simulated Modulation Types	AM	DSB	LSB	USB	FM
AM - 60 %	100%	-	-	-	-
AM - 80 %	100%	-	-	-	-
DSB	-	100%	-	-	-
LSB	-	-	100%	-	-
USB	-	-	-	100%	-
FM - 5	-	-	-	-	100%
FM - 10	-	-	-	-	100%

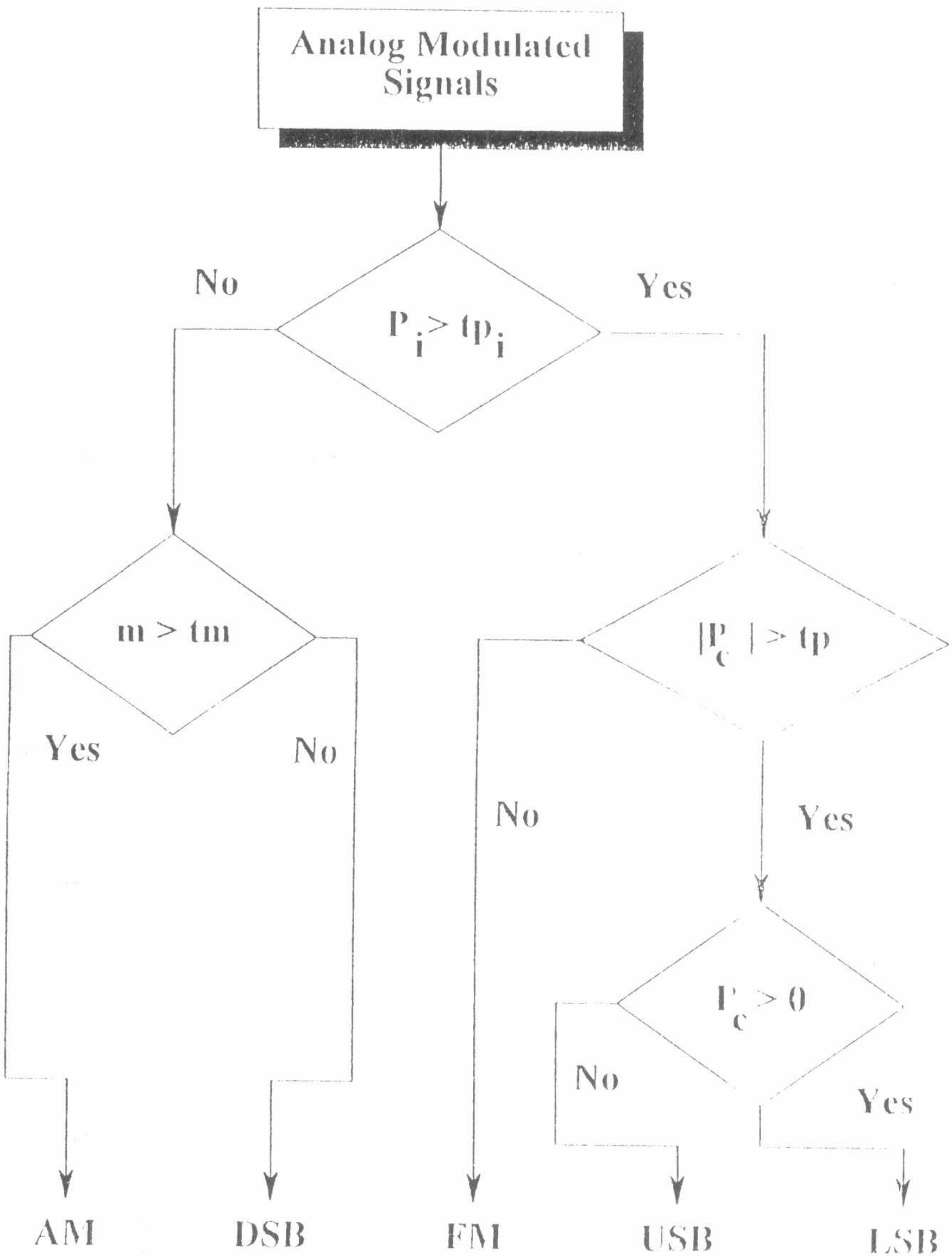

Fig. 1. Functional flowchart for the proposed algorithm