MILITARY TECHNICAL COLLEGE
CAIRO-EGYPT

ICEENG 98

FIRST INTERNATIONAL CONF. ON
ELECTRICAL ENGINEERING

AUTOMATIC MODULATION RECOGNITION:
A SURVEY AND OPEN ISSUES

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Abstract

This paper provides a tutorial review of modulation recognition techniques. The available modulation recognizers are classified into three main categories. The first category is concerned with the analog modulations only. The second category is concerned with the digital modulations only. The third category is concerned with both analog and digital modulation without any prior information about the nature of a signal. Comparisons between the available modulation recognizers in each category are developed. Some of these modulation recognizers utilize the decision-theoretic approach, some utilize the pattern recognition, some combine both approaches and the rest utilize the ANNs approach.

I. Introduction

Signals travelling in space with different modulation types and different frequencies fall in a very wide band. Usually, it is required to identify and monitor these signals either for military or for civilian purposes. Civilian purposes are such as signal confirmation, interference identification and spectrum management. Civilian authorities may wish to monitor their transmissions in order to maintain a control over these activities as well as detecting and monitoring the non-licensed transmitters. Military purposes are such as electronic warfare, surveillance and threat analysis. In electronic warfare applications, electronic support measures system plays an important role as a source of information required to conduct electronic counter measures, threat detection, warning, target acquisition and homing. Generally, any surveillance system in COMINT applications consists of three main blocks: receiver front-end (activity detection and frequency down conversion), modulation recognizer (key features extraction and classification) and output stage (normal demodulation and information extraction). At the output stage there are several functions performed and they are mainly related to information extraction, recording and exploitations. All these functions are preceded by signal demodulation. The prior information required for any modulation recognizer is the signal bandwidth, which can be determined in the receiver front-end

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stage. The information obtained from the receiver front-end, modulation recognizer and parameters estimator such as carrier frequency, signal bandwidth, modulation type, symbol rate, ... etc. are gathered to perform the signal demodulation and information extraction.

Generally, there are three philosophies for approaching the modulation recognition process in the available references namely 1) a decision-theoretic approach, 2) a statistical pattern recognition approach and 3) an artificial neural networks (ANNs) approach. In the decision-theoretic approach, probabilistic and hypotheses testing arguments are employed to formulate the modulation recognition problem. In the statistical pattern recognition approach, the classification system is divided into two subsystems. The first is a features extraction subsystem whose function is to extract the pre-defined features from the received data. The second is a pattern recognition subsystem, whose function is to indicate the modulation type of a signal. The work with pattern recognition comprises two phases - 1) a training phase to adjust the classifier structure and 2) a test phase that gives the classification decision. The work with ANNs approach comprises three main steps: 1) pre-processing and key features extraction, 2) a training phase to choose the best networks structure; e.g. determine the weights and biases of the chosen networks, and 3) a test phase, in which the performance evaluation of the chosen network is determined. The modulation recognizers, in the available references, were developed according to any of these approaches. There are also some recognizers combining these approaches. Also, there are five techniques for solving the modulation recognition problem. These are: 1) spectral processing, 2) instantaneous amplitude, phase, and frequency parameters, 3) instantaneous amplitude, phase, and frequency histograms, 4) combination of the previous three techniques and 5) universal demodulators.

Modulation recognition brings together many aspects of communication theory such as signal detection, parameter estimation, channel identification and tracking. Furthermore, modulation recognition environment may vary between two extremes - from no significant noise in the best situation to a very noisy one 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. These problems are such as: multi-path fading, weak signal reception, signal distortion, frequency instability, interference from adjacent channels and signal selection. These problems should be solved in pre-processing stage for perfect modulation recognition. The other problems are due to the nature of the received signal. These problems are such as: the weak segment of a signal (carrier absent or reduced and the pauses in transmission of analog modulation), lower SNR reception, and the transmission time and the speed of computation. The details for some of these problems are discussed in [24] and the suitable solutions are presented. Modulation recognition is extremely important for several reasons. First, application of a signal to an improper demodulator may partially or completely damage the signal information content. It is worth noting that any partial damage of the signal information content considerably confuses the following deciphering process which converts the demodulated message from its non-intelligible (ciphered) form to the intelligible (deciphered) one. Second, knowing the correct modulation type helps to recognize the threat and determine the suitable jamming waveform. Also, modulation recognition is important for national security.

From the modulation recognition point of view, there are many classifications for communication signals, as shown in Fig. 1. The first classification is according to the signal information content. In this classification any communication signal can be categorized as one of four categories: 1) amplitude signal, 2) angle modulated signal, 3) combined signal and 4) CW (unmodulated) signal. Amplitude signal is characterized by the useful information being in the signal envelope (or more precisely the instantaneous amplitude). Angle modulated signal is characterized by the useful

information being in the instantaneous phase or in the instantaneous frequency. Combined signal is characterized by the useful information is comprised in both the instantaneous amplitude and the instantaneous phase or frequency. CW signal is characterized by the fact that no useful information is transmitted. The second classification is according to the signal spectrum symmetry around the carrier frequency. Generally, the RF signal spectrum is composed of a carrier component plus two sidebands but in some types one or two of these components may be lost or reduced. Thus, due to the existence of the sidebands, any communication signal can be categorized as one of two categories: 1) symmetric signal and 2) asymmetric signal. Perfectly symmetric signal is characterized by the fact that the signal powers in the two sidebands are equal. Asymmetric signal is characterized by different powers in the two sidebands. The third classification is according to the nature of the modulating signal used. In this classification, any communication signal can be categorised as one of two categories: 1) analog modulated signal in which the modulating signal is analog such as speech signal and 2) digitally modulated signal, in which the modulating signal is digital such as data signal. In the first classification, it is required for any modulation recognizer to determine where the intercepted signal contains the useful information; that is to identify whether the information exists in the instantaneous amplitude, the instantaneous phase, the instantaneous frequency, or a combination of them. In the second classification, it is necessary to measure the signal spectrum symmetry around its carrier frequency. In the third classification, it is desired to know what is the source of the modulating signal.

This papers is concerned with reviewing the most recent papers (since 1984) in the area of modulation recognition. The available references [1]-[27] can be classified into three categories according to the modulation types considered in each of them. The first category is concerned with the recognition of analog modulations only (AMRAs) [4], [7], [15], [17], [20], [22], [25], [26] and [27]. The second category is concerned with the recognition of digital modulations only (DMRAs) [1], [6], [10], [11], [13], [14], [16], [18], [19], [21], [23], [25], [26] and [27]. The third category is concerned with the recognition of both analog and digital modulations without any prior information (ADMRAs) [2], [3], [5], [8], [9], [12], [26], and [27]. It is worth noting that in the first category, none of the available references considered the VSB, and the combined modulations except [22]and [25] - [27]. The oldest version of modulation recognizers [2] used a bank of demodulators, each used for only one type of modulation. An operator examining or listening to the demodulators outputs could decide about the modulation type of the received signal. This recognizer however requires long signal duration and highly skilled operator. The automation of this recognizer is achieved by introducing a set of intelligence decision algorithms at the demodulators output as shown in Fig. 2. However, the implementation of this recognizer is complex and requires excessive computer storage. Moreover, the number of modulation types that can be recognized is based on the number of the demodulators used.

II. Recognizers for Analog Modulated Signals Only (AMRAs)

Fabrizi et. al. [4] suggested a modulation recognizer which utilizes the decision-theoretic approach for analog modulations, 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 recognizer is used to discriminate between some types of analog modulation - CW, AM, DSB, SSB and FM. The performance evaluation of this recognizer is derived from 24 realizations each with 250 msec. length for each modulation type of interest. In [4], it is claimed that with these two

key features the discrimination between the AM and the FM signals could be achieved at SNR > 35 dB. However, SSB could be recognized from AM and FM signals at SNR > 5 dB.

Chan and Gadbois [7] developed a modulation recognizer which utilizes 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 shown in Fig. 3, as a decision criterion to decide about the correct modulation type. This recognizer is used for the recognition of some analog modulated signals - CW, AM, DSB, SSB and FM. The choice for the ratio R to discriminate between these modulation types is based on the following fact: in noise-free signals, the ratio R is ought to be zero for FM and CW signals and close to unity for AM signals. Also, the ratio R for DSB signal is ought to be 2 and it is equal to 1 for SSB signals. The simulation results for the developed recognizer were derived from 200 realizations for each modulation type of interest, each with length 2048 samples (equivalent to 20 msec.) [7, Table 3]. In [7] it is claimed that at SNR = 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. Furthermore, in [7] nothing is mentioned about the recognition of the VSB and the combined modulated signals. Moreover, since it depends on the envelope characteristics only, it cannot recognize the signals having both amplitude and phase information.

Nagy [15] proposed a modulation recognizer for analog modulations. In this recognizer, the **Chan and Gadbois** parameter [7], **R**, in addition to the variance of the instantaneous frequency normalized to the squared sample time are used as key features to discriminate between the different modulation type of interest. The modulation types that can be classified by this recognizer are AM, DSB, SSB, FM, and CW. In [15], it is mentioned that the performance evaluation of this recognizer was derived from 500 realizations, each with 250 msec. length for each modulation type. In [15], it is claimed that the different modulation types have been classified with success rate > 90.0% at SNR = 15 dB except the SSB (66.0% success rate). So, [15] 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 success rate 100%.

Jovanovic et. al. [17] introduced a modulation recognizer 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.

Al-Jalili [20] proposed a modulation recognizer to discriminate between the USB and LSB signals. This recognizer 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 recognizer 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 [20] the performance measure is derived from 10 realizations, each with 128 msec. for each modulation type and it is claimed that this recognizer perform well for SNR $\geq$ 0 dB.

Nandi and Azzouz [22] introduced a global procedure for modulation recognition of the well known analog modulation types. This recognizer utilizes the decision-theoretic approach. It comprises two main steps. First, the decision about the modulation type is taken first from each

available segment. Second, a global decision is determined from all the available segments of the intercepted signal frame by comparing the global decision with each segment decision. The decision from each segment 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. The way for extracting these key features is as shown in Fig. 4. In this recognizer the decision about the modulation type is carried out according to the decision rules shown in Fig. 5. This recognizer is used to discriminate among the AM, DSB, VSB, LSB, USB, FM, and combined modulated signals. In [22], all the modulation types of interest have been classified with success rate > 90.0% at the SNR of 10 dB. Excluding the VSB, LSB, and USB, the success rate for all the other modulation types of interest is > 98.0%. Furthermore, **Azzouz and Nandi** [26] introduced a modification for the decision flow of the algorithm shown in Fig. 5. In [26], 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 for one the modified algorithms, the overall success rate is 99.4% at the SNR of 10 dB, and it is 99.9% at the SNR of 20 dB. In [22] and [26] due to the simplicity of both the key features extraction as shown in Fig. 4 and the decision rules as shown in [24; Figs. 2.3 and C.1-C.4] (simple logic functions), these algorithms can be used for on-line analysis. Moreover, **Nandi and Azzouz** proposed a modulation recognizer which utilizes the ANN approach [25] as shown in Fig. 6a. It is based on a single hidden layer ANN and the same data set used in [22]. 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 [27], **Azzouz and Nandi** introduced a double hidden layer ANN modulation recognition algorithm. Using the same data set in [22] and [25], it was found that all the modulation types of interest have been classified with success rate > 98.0%. The training and test procedure of the ANNs are shown in Figs. 6 and 7 respectively.

III. Recognizers for Digitally Modulated Signals Only (DMRAs)

Liedtke was the first to present the concept of modulation recognition applied to digital modulations. **Liedtke** [1] proposed a modulation recognizer for some types of digital modulations - ASK2, FSK2, PSK2, PSK4, PSK8 and CW. This recognizer utilizes the universal demodulator technique. The key features used to discriminate between these types are the amplitude histogram, the frequency histogram, the phase difference histogram, the amplitude variance, and the frequency variance. The classification procedure as shown in Fig. 8 comprises the following steps: 1) approximate signal bandwidth estimation, 2) signal demodulation and parameters extraction, 3) statistical computation, and 4) automation of modulation classification. In [1] it is clear that the hardware implementation of this recognizer is excessively complex. In [1], it is claimed that an error free signal, i.e. all the signal parameters such as the carrier frequency, symbol rate, ... etc. are exactly known, can be recognized at SNR >18 dB.

In [6] **DeSimio and Glenn** introduced an adaptive technique for classifying some types of digital modulations - ASK2, PSK2, PSK4 and FSK2. In this recognizer a set of key features derived from the signal envelope, the signal spectra, the signal squared and the fourth power of the signal are used to decide about the modulation type of the intercepted signal. These key features are the mean and variance of the envelope, the location of the peaks in the signal spectrum, the location of

the peaks around twice the carrier frequency of the spectrum of the signal square, and the location of the peaks around four time the carrier frequency of the spectrum of the signal raised to the fourth power. In [6], the classification procedure consists of the following steps: 1) feature vectors extraction, 2) weight vectors generation for each signal class and 3) modulation classification. In [6], the decision functions used are generated using an adaptive technique based on the LMS algorithm. Furthermore, the decision rule used is similar to that applied in the pattern recognition algorithms. So, any intercepting signal is divided into two sets: a learning set, which is used to perform the weight vectors and a test set that is used in the decision about the modulation type using the weight vectors generated from the learning set. This classifier is trained using the values of the extracted key features at 20 dB SNR. The only thing mentioned about the performance evaluation of this recognizer is its ability to discriminate between PSK2 and PSK4 at the SNR of 5 dB.

Polydoros and Kim [10] introduced a modulation recognizer, following the decision-theoretic approach, to discriminate between PSK2 and PSK4. In [10], all signal parameters such as the carrier frequency, the initial phase, the symbol rate and the signal-to-noise ratio are assumed to be available. This recognizer uses the log-likelihood ratio to estimate the number of levels, M, of the MPSK signals. Also, a comparison between three classifiers for MPSK signals had been introduced. These classifiers are: 1) phase-based classifier (PBC) that is based on the phase difference histogram, 2) square-law classifier (SLC) that is based on the fact that squaring of MPSK signal is MPSK with M/2 phase states, and 3) quasi-log-likelihood ratio (QLLR) classifier which uses the likelihood ratio estimation principles. In [10], it is proved analytically that the performance of the QLLR classifier is significantly better than the PBC or the conventional SLC. Also, it is claimed that the QLLR classifier can be extended to address MPSK signals classification with M > 4.

Hsue and Soliman [11] introduced a modulation recognizer based only on the zero-crossings characteristic of the intercepted signals. The modulation classification procedure comprises three steps: 1) extraction of the zero-crossing sequence, the zero-crossing interval sequence and the zero-crossing interval difference sequence, 2) inter-symbol transition (IST) detection as well as carrier frequency estimation and 3) decision about the modulation type. The phase and frequency information are derived from the zero-crossing sequence, the zero-crossing difference sequence and the zero-crossing interval difference sequence. The decision about the modulation type is based on the variance of the zero-crossing interval sequence, G, as well as the frequency and phase difference histograms. This recognizer can be implemented using a parallel processing technique to increase the speed of computations. Also, three processors are recommended, each processor associated to one of the above mentioned three sequences. However this recognizer is used to report the modulation type of constant amplitude signals such as CW, MPSK, MFSK. In this recognizer, the classification strategy as shown in Fig. 9 comprises two main steps; first discrimination of single-tone (CW and MPSK) from multi-tone (MFSK) signals, and secondly determination of the number of states (M). In [11], the discrimination between the single-tone and the multi-tone is based on comparing the variance of the zero-crossing difference sequence in the non-weak intervals of a signal with a suitable threshold. The determination of the number of states in single-tone signals is achieved by measuring the similarity of the normalized phase difference histogram. The determination of the number of states in multi-tone signals is based on the number of hills in the zero-crossing interval difference histogram. Finally, the performance of this recognizer were derived from 100 realizations for each modulation type of interest. From the simulation results it is claimed that a reasonable average probability of correct classification is achievable for SNR > 15 dB.

Also, **Soliman and Hsue** [13] introduced another modulation recognizer based on the statistical moments of the intercepted signal phase. In this recognizer, the even order moments of the signal phase are used to estimate the number of levels, M, in MPSK signals. The classification procedure comprises the following steps: 1) instantaneous phase extraction, 2) even order moments computation, 3) threshold comparison and 4) decision about the modulation type. It is claimed that the second order moment is sufficient to discriminate the CW from the MPSK signals and, the eighth order moment is adequate to classify BPSK signals with reasonable performance at low SNR. Also, it is claimed that the suggested classifier is better than the PBC and the SLC.

Assaleh et al. [14] proposed a modulation recognizer for some types of digital modulations. The types that can be classified by this recognizer are: CW, PSK2, PSK4, FSK2, and FSK4. The key features used were derived from the averaged spectrum of the instantaneous frequency. These key features are the mean and the standard deviation of the averaged instantaneous frequency, and the height of the spikes in the differential instantaneous frequency. It is claimed that the performance evaluation of this recognizer was derived from 1000 realizations for each modulation type of interest. Also, it was found that the success rate of the modulation type of interest is > 99.0 % at the SNR of 15 dB. As this recognizer uses the averaging over M successive segments, long signal duration is required and hence this recognizer is mainly suitable for the off-line analysis.

Nagy [16] introduced a suggested procedure for a modulation classifier of multichannel systems. This classifier was accomplished by dividing the analyzed signal into individual components and each signal component is classified using a single tone classifier. The types that have been classified by this recognizer are CW, ASK, PSK2, PSK4 and FSK2. The developed classifier comprises two steps. First, detect and filter each signal component in the estimated amplitude spectrum, e.g. the FSK2 is considered as two correlated ASK2 signals. Second, compute the differential phase to discriminate between the different types of single harmonic signal. In [16] the performance of the developed recognizer was derived from 100 realizations for each modulation type of interest. Finally, it is claimed that all the single-tone types (CW, ASK2, PSK2 and PSK4) have been classified with success rate > 90.0 % at 10 dB SNR except the ASK2 (=87.0 %).

Beidas and Weber [18] proposed a modulation recognizer for MFSK signals. This recognizer is based on the time-domain Higher-Order Correlations. This classifier is used to discriminate between the MFSK signals. This classifier comprises a bank of matched filter each of which is tuned to one of a prescribed frequency locations and a set of successive correlators. Also, it is based on comparing the log likelihood function with a suitable threshold to decide about the number of levels of MFSK signals. In [18], it is claimed that this recognizer immunes the imperfect knowledge of exact frequency locations.

Huang and Polydoros [19] introduced an algorithm for classifying the MPSK signals and it is based on the likelihood function of the instantaneous phase. This algorithm utilizes the decision-theoretic approach as the likelihood function of the instantaneous phase is compared with a suitable threshold. This recognizer can be considered as a generalization of the modulation recognizer introduced in [10] because it can be used for M > 4. In [20] it is claimed that the best performance for the known MPSK classifiers (PBC, SLC, and QLLR) can be obtained from the QLLR classifier.

Yang and Soliman [22] modify the modulation recognizer, introduced in [13] that uses the statistical moments as already mentioned to estimate M in the MPSK signals. This modification is in the way of approximating the probability distribution function of the instantaneous phase. In [22], the Fourier series expansion is used for the exact phase distribution approximation instead of the Tikhonov probability density function which is used in [13]. In [22] it is claimed that the proposed algorithm offers a 2 dB reduction of the SNR required for 99.0% success rate and it offers simpler moment computations than [13]. In both [13] and [21], nothing is mentioned about the performance evaluation of these two recognizers.

Azzouz and Nandi [23] proposed a modulation recognizer for the digital modulation types up to 4-levels (ASK2, ASK4, PSK2, PSK4, FSK2, and FSK4). The key features used are derived from three qualifying parameters - the instantaneous amplitude, the instantaneous phase, and the instantaneous frequency of the signal under consideration. These key features 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, 4) the standard deviation of the absolute value of the normalized-centered instantaneous amplitude, and 5) the standard deviation of the absolute value of the normalized instantaneous frequency. A detailed pictorial representation for key features extraction from a signal segment is shown in Fig. 10 in the form of a flowchart. In this recognizer, the discrimination between the different digitally modulated signals is as shown in Fig. 11. In [23], all the digital modulation types of interest have been classified with success rate > 90.0% at the SNR of 10 dB except PSK4 (89.25 % success rate). At the SNR of 20 dB all the modulation types of interest have been classified with success rate > 96.0%. Furthermore, Azzouz and Nandi [26] introduced a modification for decision flow of the algorithm shown in Fig. 11. In [26], 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 for one of the modified algorithms, the overall success rate is > 99.0% at the SNR of 10 dB, and it is 100% at the SNR of 20 dB. In [24] and [26] due to the simplicity of the both the key features extraction as shown in Fig. 4 and the decision rules as shown in [24; Figs. 3.4, C.5 and C.6] (simple logic functions), these algorithms can be used for on-line analysis. Moreover, Nandi and Azzouz proposed a modulation recognizer which utilizes the ANN approach [25]. It is based on a single hidden layer ANN and the same data set used in [24]. It was found that all the modulation types of interest have been classified with success rate > 93.0%. at 10 dB SNR and with success rate > 97.0% at 20 dB. In [27], Azzouz and Nandi introduced a double hidden layer ANN modulation recognition algorithm. Using the same data set in [23] and [25], it was found that all the modulation types of interest have been classified with success rate > 96.0%. except FSK2 (=92.5%) at the SNR of 10 dB but at SNR of 20 dB, the success rate is > 99.0%.

IV. Recognizers for Both Analog and Digital Modulations (ADMRAs)

In [2] Callaghan et al. proposed a modulation recognizer utilizing the envelope and the zero-crossings characteristics of the intercepted signal. This recognizer uses a phase-locked loop (PLL) for carrier recovery in the weak intervals of the intercepted signal segment. It is worth noting that in some modulation types such as DSB, MPSK and AM with high modulation depth, the carrier frequency may be severely suppressed or absent. Carrier recovery during the suppressed portions (weak intervals) is equivalent to receiving a signal with very low SNR. So, using the PLL as a carrier recovery (hardware solution) overcome the problem of needing high SNR for accurate

instantaneous frequency estimation from the zero-crossings. The accuracy of this recognizer deteriorates rapidly if the receiver is not perfectly tuned to the center frequency. The modulation types that can be recognized by this recognizer are CW, AM, FM, FSK2. In [2], it is claimed that this recognizer requires SNR > 20 dB for the correct recognition of the aforementioned modulation types.

Jondral [3] proposed a modulation recognizer utilizing the pattern recognition approach for the noise signal and two types of analog modulated signals - AM and SSB - as well as for four types of digitally modulated signals - ASK2, PSK2, FSK2 and FSK4. The key features used are derived from the instantaneous amplitude, phase and frequency. These key features are the instantaneous amplitude, phase difference and frequency histograms. In this classifier, the instantaneous amplitude histogram is computed for the normalized instantaneous amplitude. The normalization is done with respect to the maximum values of the intercepted signal. As this classifier uses the pattern recognition approach, the received signal is divided into two adjacent sets: learning set and test set. The segment length used in this recognizer is 4096 samples for each modulation type. In [3] real signals have been used and it is claimed that all the above mentioned modulation types have been classified with success rate > 90.0% except the SSB (=83.0%) and FSK4 (=88.0%).

Aisbett in [5] proposed a modulation recognizer, based on some key features derived from the instantaneous amplitude and the instantaneous frequency of a signal. In [5], it is mentioned that the developed key features are noise resistant, and they are A^2, AA' and A^2 where A is the signal envelope, A' is the signal envelope derivative and is the instantaneous frequency. The estimation of these key features is derived from 10 realizations, each with 90 msec. length, for each modulation type of interest. Also, another unbiased key feature is added in [5] which is the variance of the squared instantaneous amplitude minus its squared mean. The modulation types that can be classified by this recognizer are: AM, DSB, FM, ASK2, PSK2, FSK2, and CW signals. In [5], it is claimed that the success rate of the discrimination between the modulation types appears to be good at least for strong SNRs.

Petrovic et al. [8] suggested a modulation recognizer based on the variations and the zero-crossing rate of the AM detector output as well as the variations in the FM detector output. The modulation types that can be classified by this recognizer are AM, FM, SSB, CW, ASK2, FSK2. This modulation recognizer comprises three main steps as shown in Fig. 11. These are: 1) AM and FM demodulation, 2) Key features extraction, and 3) modulation classification. Three key features are derived from the AM detector output and they are: detect the presence of the signal, measure the amplitude variations and measure the instantaneous amplitude zero-crossing rate. Also for the FM detector output, a narrow band and a wide band FM detection are performed. The only thing that is mentioned about the performance evaluation is that the results of the preliminary test with real signals show the success of this recognizer.

Martin [9] proposed a modulation recognizer for some analog and digital modulation types. These types are: AM, FM, SSB, CW, ASK2, and FSK2. The key features used are derived from the instantaneous amplitude, the IF signal spectrum and its derivative. These key features are: the amplitude histogram, the signal bandwidth, and the relationship between the spectral components. In [9] real signals have been used and it is claimed that all the modulation types of interest have been classified with success rate > 90.0 % except the FM (=80.0%).

Dominguez et al. [12] introduced a modulation recognizer which is a general approach for both analog and digital modulations. This recognizer is concerned with some types of analog and

digitally modulated signals. These types are AM, DSB, SSB, FM, CW, noise and digitally modulated signals up to 4-levels. This recognizer comprises three subsystems: 1) pre-analysis subsystem, 2) features extraction subsystem and 3) classifier subsystem. The recognition algorithm is based on the histograms of the instantaneous amplitude, phase and frequency. In [12], it is claimed that this recognizer performed well and all types have been correctly classified at SNR > 40 dB. At the SNR of 10 dB the probability of correct modulation recognition is 0 % for all digital modulation types except for PSK4 (7.0%) and at 15 dB SNR the performance is still wanting especially for FSK4 (56.0%) , FSK2 (84.0%) and ASK4 (87.0%). In [12] the number of samples per segment used in the performance evaluations is 3000 samples. However, it should be noted that this work attempts to identify most of the well known analog and digital modulation types.

Nandi and Azzouz in [26] developed a modulation recognizer for the analog modulation types considered in [22] as well as the digital modulations types considered in [23]. The four key features used in [22] are also used for this recognizer. Two of the key features used in [23] - the standard deviation of the absolute value of the normalized instantaneous amplitude and frequency are also used in this algorithm. Three other key features are introduced. These features are: 1) the standard deviation of the normalized-centered instantaneous amplitude in the non-weak intervals of a signal segment, 2) the kurtosis of the normalized instantaneous amplitude, and 3) the kurtosis of the normalized instantaneous frequency. A detailed pictorial representation for the key features extraction from an RF signal is shown in Fig. 12 in the form of a flowchart. The discrimination between the different analog and digital modulation types are carried out according to the procedure introduced in Fig. 13. In this recognizer, it was found that all the modulation types of interest have been classified with success rate > 90.0% at the SNR of 15 dB, except AM (= 88.8%), ASK4 (= 77.3%), and FSK4 (= 88.0%). Also, in [26], an alternative view for the decision flow algorithm presented in Fig. 13 is introduced. Based on the aforementioned nine key features, many algorithms can be generated according to the sequence of applying these key features in the classification algorithm. The performance evaluations of the algorithms for the recognition of analog and digital modulations were derived from 400 realizations for twelve analog modulated signals (as in [22]) as well as the six digital modulated signals (as in [23]). In [26], it was found that the overall success rate is > 93.0% at the SNR of 15 dB. Finally, **Azzouz and Nandi** [27] introduced a modulation recognizer which utilizes the ANN approach. It was found that the overall success rate of this recognizer is > 96.0% at the SNR of 15 dB.

V. Comparisons of the reviewed modulation recognizers

From the presentation of the aforementioned modulation recognizers (section II, III, and IV), we fined that some of these recognizers utilize the decision theoretic approach, some utilize the pattern recognition approach, some utilize the ANNs approach and others utilize combination of these approaches. Table I gives a comparison between the modulation recognizers used for analog modulated signals only. The table indicates the approach used in each recognizer. It also provides the weak and strong points of each recognizer. Table II and III do the same thing for DMRAs and ADMRAs respectively.

Table 1 Comparisons between the available AMRAs

Modulation Recognizer	Approach	Frame Length	Considered Modulation Types	General Comments
Fabrizi [4]	DT	250 msec.	CW, AM, SSB, FM	It is required SNR >35 dB for AM, and FM
Chan & Gadbois [7]	DT	20 msec.	AM, FM, DSB, SSB	The threshold SNR for correct recognition is >7dB
Nagy [15]	DT	250 msec.	AM, SSB, DSB, FM, CW	The success rate is 100% at SNR >15 dB except SSB (=94.0%)
Jovanovic [17]	DT	-	AM, CW	The Perform well at poor SNR
Al-Jalili [20]	DT	128 msec.	LSB, USB	The success rate is 100% at SNR of 0 dB. It require long signal duration.
Nandi & Azzouz [22]	DT	1.7 msec.	AM, DSB, VSB, LSB, USB, FM, Combined	The success rate is > 90.0% at 10 dB SNR.
Nandi & Azzouz [25]	ANNs (Single)	1.7 msec	AM, DSB, VSB, LSB, USB, FM, Combined	All the types have been classified with 98.0% at 10 dB SNR except USB (95.0%)
Nandi & Azzouz [26]	DT	1.7 msec	AM, DSB, VSB, LSB, USB, FM, Combined	The over all success rate is > 99.0% at 10 dB SNR.
Nandi & Azzouz [27]	ANNs (Double)	1.7 msec	AM, DSB, VSB, LSB, USB, FM, Combined	All the types have been classified with success rate > 98.0% at SNR of 10 dB.

* DT   Decision-Theoretic

Table 2 Comparisons between the available DMRAs

Modulation Recognizer	Approach	Frame Length	General Comments	General Comments
Liedtke [1]	DT & PR	-	ASK2, FSK2, PSK2, PSK4, PSK8, and CW	All the signal parameters need to be exactly known. These types can be recognized at SNR > 18 dB
DeSimio & Glenn [6]	PR	-	ASK2, FSK2, PSK4 and FSK2	The discrimination between PSK2 and PSK4 is achieved at SNR > 5 dB.
Polydoros & Kim [10]	DT	-	PSK2 and PSK4	The QLLRC is better than PBC and SLC.
Hsue & Soliman [11]	DT & PR	1024 samples	CW, MPSK, MFSK	Reasonable average prob. of correct recognition at SNR >15 dB.
Soliman & Hsue [13]	DT	-	MPSK	The PSK2 can be classified at low SNR
Assaleh et. al. [14]	DT	-	CW,PSK2, PSK4, FSK2, FSK4	The success rate is > 99.0% at SNR of 15 dB.
Nagy [16]	DT	-	CW, ASK, PSK2, PSK4, FSK2	The success rate is > 90.0% at SNR of 10 dB except ASK2 (=87%).
Beidas & Weber [18]	DT	-	MFSK	Using the likelihood ratio to decide about M in MFSK.
Azzouz & Nandi [23]	DT	1.7 msec	ASK2, ASK4, PSK2, PSK4, FSK2, and FSK4	The success rate is > 90.0% at SNR > 10 dB except PSK4 (=89.2%).
Nandi & Azzouz [25]	ANNs (Single)	1.7 msec	ASK2, ASK4, PSK2, PSK4, FSK2, and FSK4	All the types have been classified with success rate > 93. 0% at SNR > 10 dB.
Azzouz & Nandi [26]	DT	1.7 msec	ASK2, ASK4, PSK2, PSK4, FSK2, and FSK4	All the types have been classified with success rate > 99.0% at SNR > 10 dB.
Azzouz & Nandi [27]	ANNs (Double)	1.7 msec.	ASK2, ASK4, PSK2, PSK4, FSK2, and FSK4	All the types have been classified with success rate > 96% at SNR > 10 dB except FSK2 (=92.5%).

** PR   Pattern recognition   & *** ANNs   Artificial Neural Networks

Table 3 Comparisons between the available ADMRAs

Modulation Recognizer	Approach	Frame Length	Considered Modulation Types	General Comments
Callaghan et. al. [2]	DT	-	CW, AM, FM, FSK2	It is required SNR > 20 dB for correct recognition. This recognizer cannot recognize DSB and MPSK signals.
Jondral [3]	PR	4096 samples	AM, SSB, ASK2, PSK2, FSK2, FSK4	The success rate > 90.0% except SSB (=83.0%) and FSK4 (=88.0%)
Aisbett [5]	DT	90 msec.	AM, CW, DSB, FM, ASK2, PSK2, FSK2	Perform well on strong SNR
Petrovic et. al. [8]	DT	-	AM, SSB, FM, CW, ASK2, FSK2	This recognizer is tested with real signals.
Martin [9]	DT & PR	-	AM, FM, SSB, CW, ASK2, FSK2	The success rate is > 90.0% except FM (=80.0%) It is tested by real signals.
Dominguez [12]	PR	3000 samples	AM, DSB, SSB, FM, CW and Digitally modulated signals up to 4-levels	Correct recognition for these types at SNR > 40 dB.
Azzouz & Nandi [26]	DT	1.7 msec	AM, DSB, VSB, LSB, USB, FM, Combined, and 4-levels digital modulations	The overall success rate is > 93.0% at SNR > 15 dB
Azzouz & Nandi [27]	ANNs	1.7 msec	AM, DSB, VSB, LSB, USB, FM, Combined, and 4-levels digital modulations	The overall success rate is > 96.0%at SNR > 15 dB

IV. Open Issues and Proposals for Solutions

While the work of **Azzouz and Nandi** [22-27] have treated many of the shortcomings found in the previous papers in the domain, they still have some shortcomings that need further investigations. In this section, we discuss these shortcomings and provide outlines of possible solutions. The first shortcoming is that assume exact knowledge of the carrier frequency. In practice, this assumption is not valid. Indeed, the carrier frequency of the intercepted signal is unknown and has some instability. This instability will create a noisy component in the instantaneous phase of the intercepted signal. Consequently, signals having amplitude modulation only may be erroneously classified as signals having both amplitude and phase information. To overcome this problem, we propose the use of one or more of the three following solutions: (1) on-line estimation of the carrier frequency, (2) increasing the phase threshold used in isolating phase signals, and (3) using the higher order statistics to reduce the effect of the noisy phase component. The carrier frequency instability will create also the following problem. In [22] and [24-27], the spectrum symmetry about the assumed carrier frequency is used to discriminate between symmetric signals (such as AM, DSB and FM signals) and spectrum asymmetric signals (such as SSB and VSB signals). The carrier frequency instability will disturbs the spectrum symmetry about the assumed carrier frequency as depicted in Fig. 14 in which the spectrum of an AM signal is considered. According to this figure, the power of the spectrum portion to the right side of the assumed carrier is much higher than its left side since the carrier usually contains a large part of the total power. In such a case, the signal will be erroneously classified as an upper sideband signal. This problem will take place even when on-line estimation of the carrier frequency is used since there will be always some frequency estimation error. The great part of the power included in the carrier component will cause a significant spectrum asymmetry about the estimated carrier frequency even when the estimation error is small. This problem may be overcome by excluding a zone with an "appropriate" width centered at the assumed carrier, when examining the spectrum symmetry.

The second shortcoming is the use of high sampling frequency that is equal to eight times the carrier frequency. This results in big storage and computational requirements. This shortcoming may be overcomed by the use of band-pass sampling instead of the low-pass sampling used the previous algorithms. It may also be overcome by the use of key features that may require less storage and computation requirements such as those derived from the complex envelope of a signal.

The third shortcoming is that the simulations therein use sampling frequency that is synchronized with the carrier frequency. In practice, however, the carrier frequency is generated by the hostile transmitter whereas the sampling frequency is generated at the interception receiver. Consequently, the two frequencies are not synchronized. Therefore the simulations should be redone with the two frequencies being asynchronous with each other.

VII. Conclusions

A survey for the most of the recent papers published in the area of modulation recognition is introduced. Three group of algorithms - one for analog modulations only, the second for digital modulations only and the third for both analog and digital modulations, without any prior information about the nature of a signal, are presented. Most of these recognizers deal with a subset of the well known modulation types and a few of them considered the most common modulation types. In [22] and [23], twelve analog modulated signals and six digitally modulated ones have been carried out to measure the performance of the presented algorithms. Comparisons between the presented recognizers in each group are presented. Also, some general comments about each recognizer are summarized in Tables I-III. Finally, proposals solutions for most of the short comings in the available references are presented.

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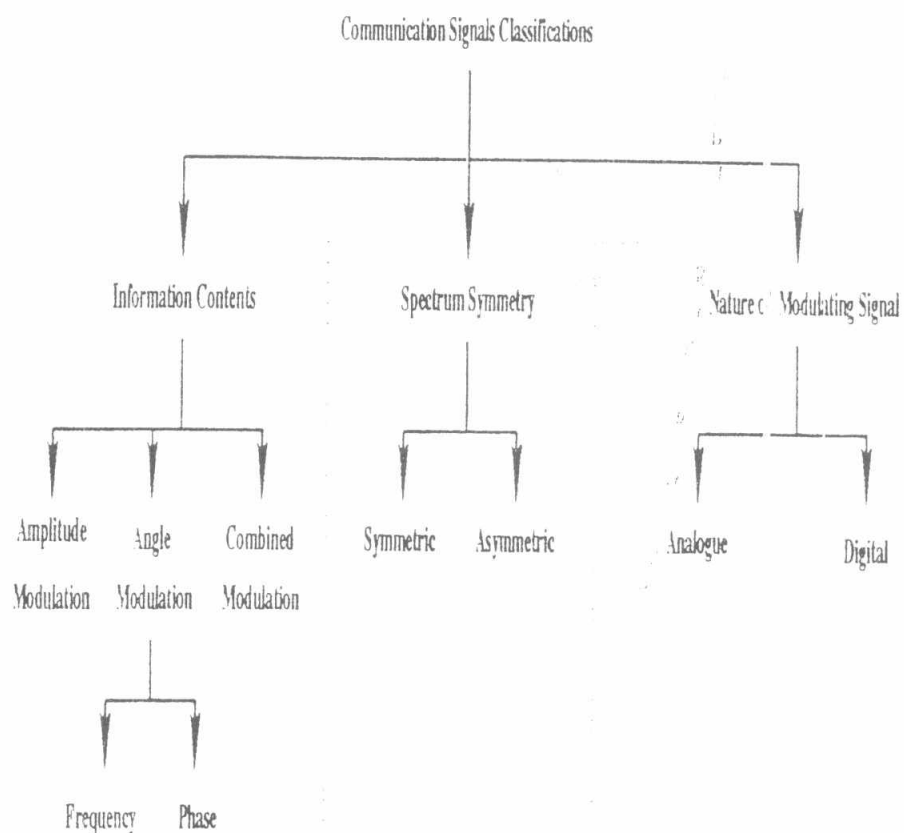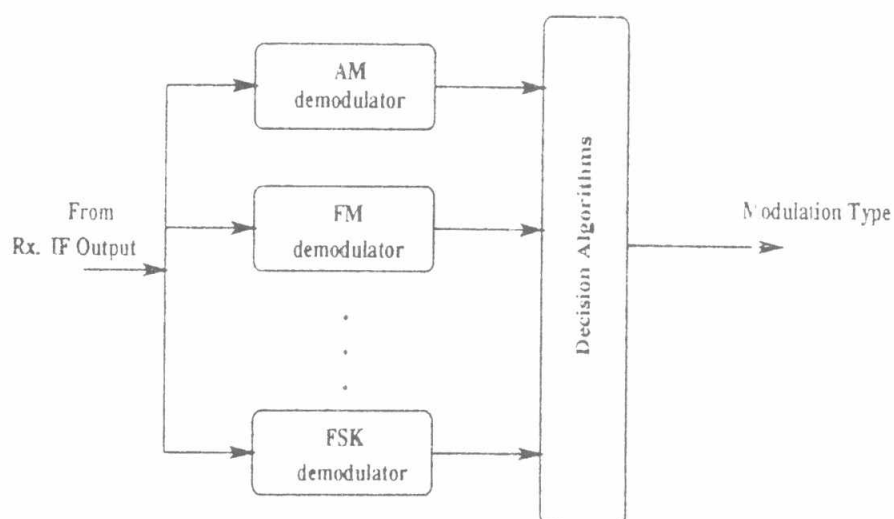
Fig. 1 Communication signals classifications

Fig. 2 A modulation recogniser using a bank of demodulators
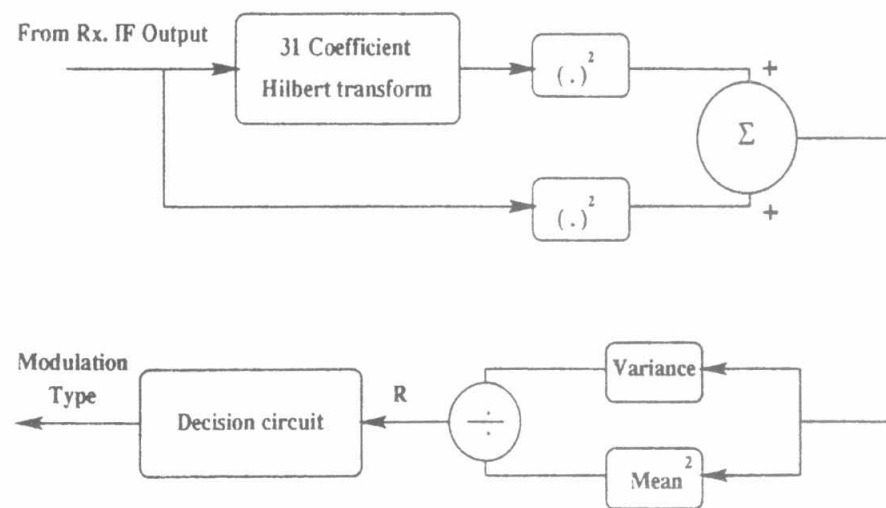and a sety of decision algorithms.

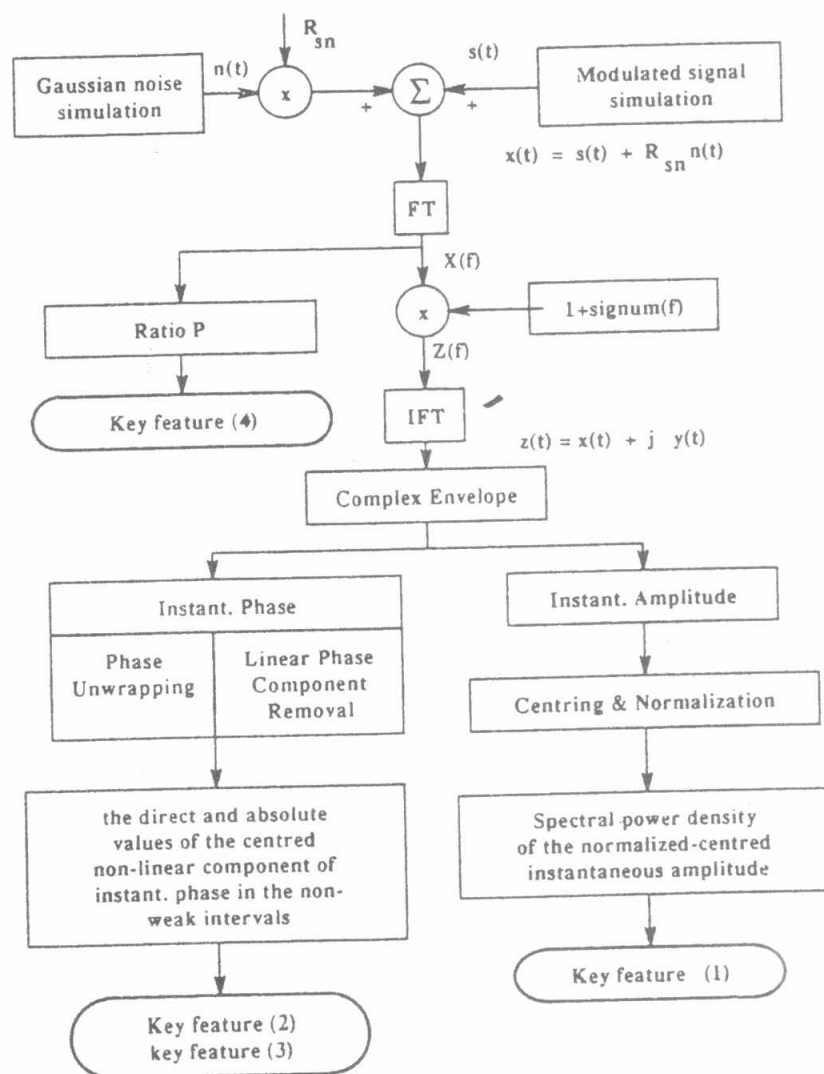Fig. 3 Block scheme of the recogniser using the envelope characteristics only

$$x(t) = s(t) + R_{sn} n(t)$$

$$z(t) = x(t) + j\ y(t)$$

Fig. 4 Functional flowchart for key features extraction in the AMRAs [22]

Analogue
Modulated Signal

$\sigma_{dp} < t(\sigma_{dp})$

yes   no

$|P| < t(P)$

$|P| < t(P)$

yes

yes   no

no

$\gamma_{max} < t(\gamma_{max})$

$P > 0$

no   yes

yes   no

$\sigma_{ap} < t(\sigma_{ap})$

yes

no

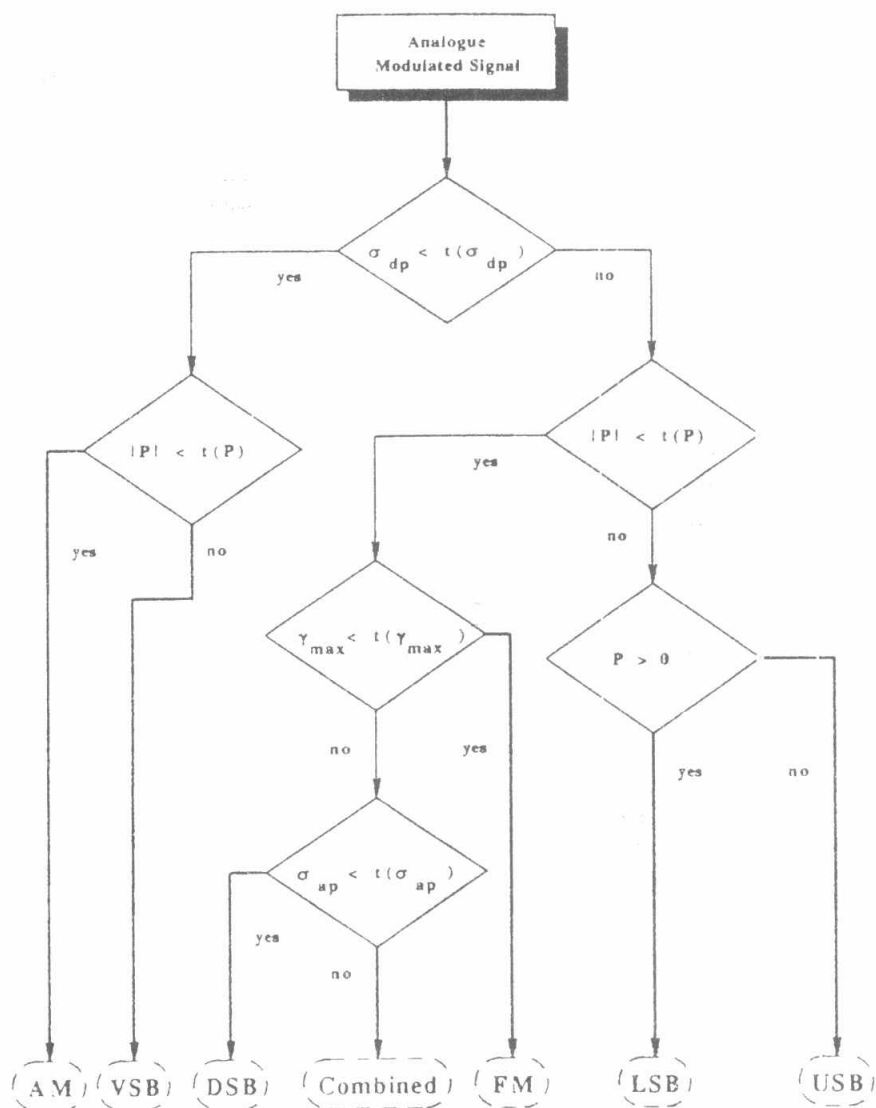(A M) (VSB) (DSB) (Combined) (FM)   (LSB)   (USB)

Fig. 5. Functional flowchart for AMRA [22]

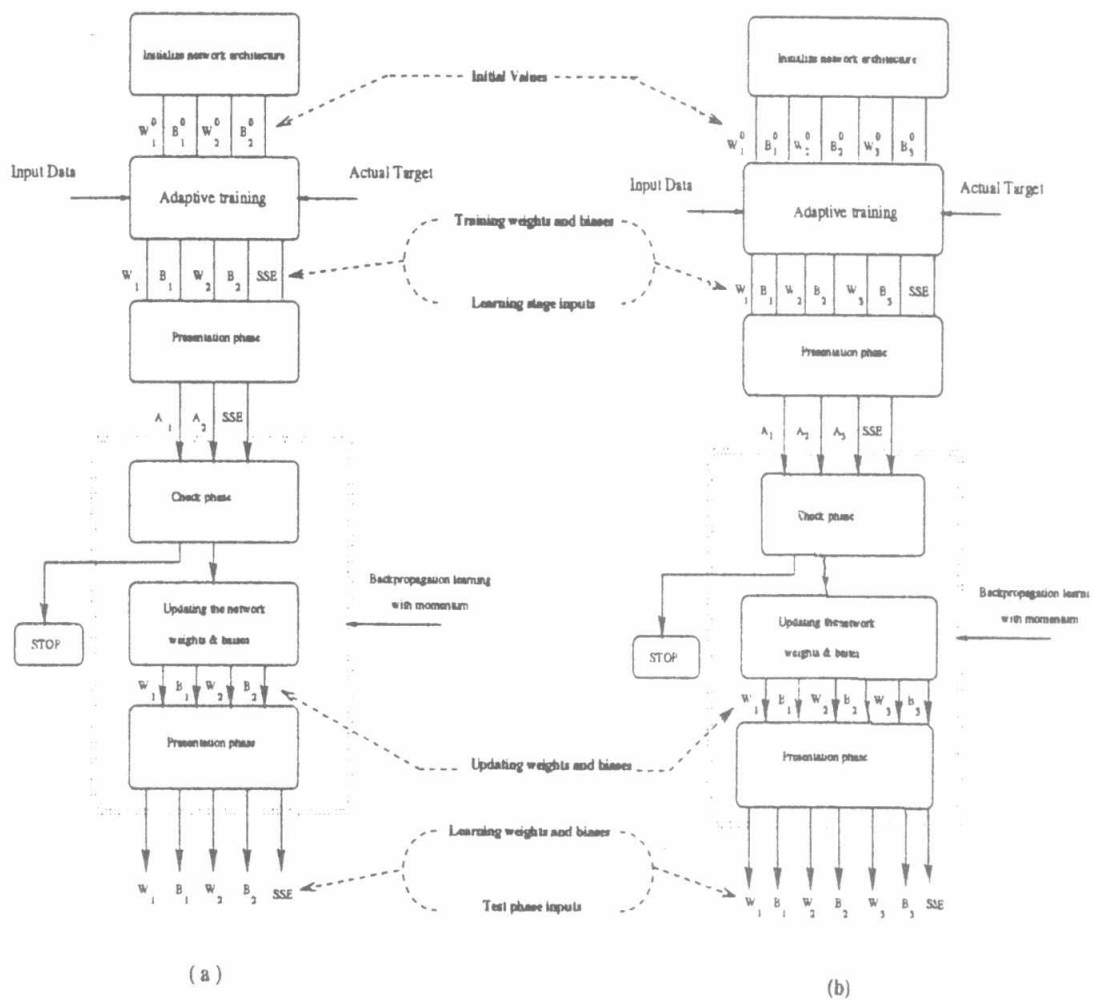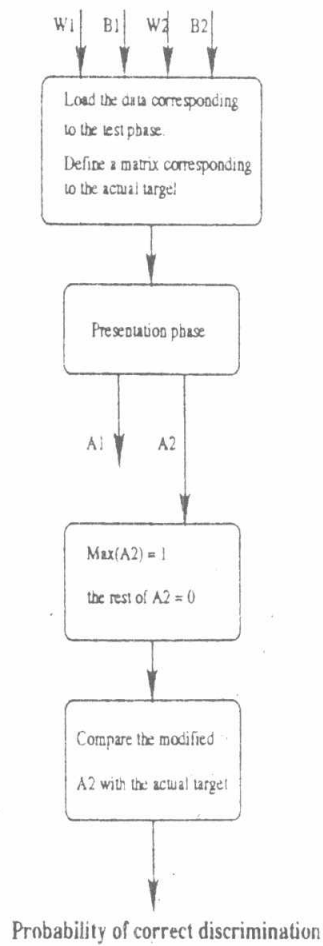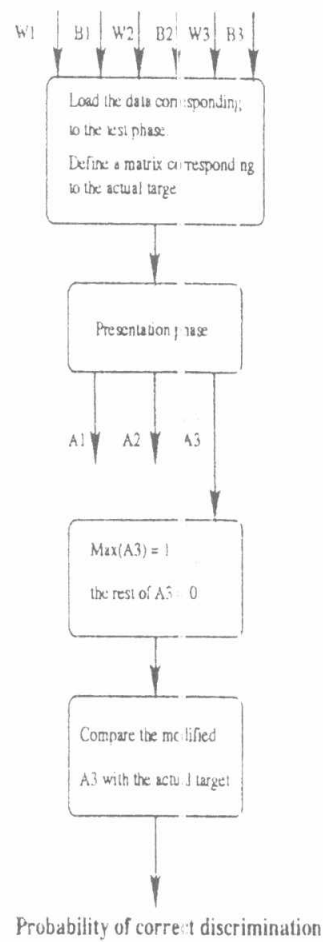Fig. 6 Training procedure of the ANN algorithm:
(a) single hidden layer, and (b) two hidden layer

Weights and biases of the trained network

```
W1   B1   W2   B2
 │    │    │    │
 ▼    ▼    ▼    ▼
┌─────────────────────────┐
│ Load the data corresponding
│ to the test phase.
│
│ Define a matrix corresponding
│ to the actual target
└─────────────────────────┘
            │
            ▼
┌─────────────────────────┐
│    Presentation phase    │
└─────────────────────────┘
      │          │
   A1 ▼       A2 ▼
            │
            ▼
┌─────────────────────────┐
│    Max(A2) = 1           │
│    the rest of A2 = 0    │
└─────────────────────────┘
            │
            ▼
┌─────────────────────────┐
│ Compare the modified     │
│ A2 with the actual target│
└─────────────────────────┘
            │
            ▼
```

Probability of correct discrimination

(a)

Weights and biases of the trained network

```
W1   B1   W2   B2   W3   B3
 │    │    │    │    │    │
 ▼    ▼    ▼    ▼    ▼    ▼
┌─────────────────────────┐
│ Load the data corresponding
│ to the test phase
│
│ Define a matrix corresponding
│ to the actual target
└─────────────────────────┘
            │
            ▼
┌─────────────────────────┐
│    Presentation phase    │
└─────────────────────────┘
    │       │       │
 A1 ▼    A2 ▼    A3 ▼
            │
            ▼
┌─────────────────────────┐
│    Max(A3) = 1           │
│    the rest of A3 = 0    │
└─────────────────────────┘
            │
            ▼
┌─────────────────────────┐
│ Compare the modified     │
│ A3 with the actual target│
└─────────────────────────┘
            │
            ▼
```

Probability of correct discrimination

(b)

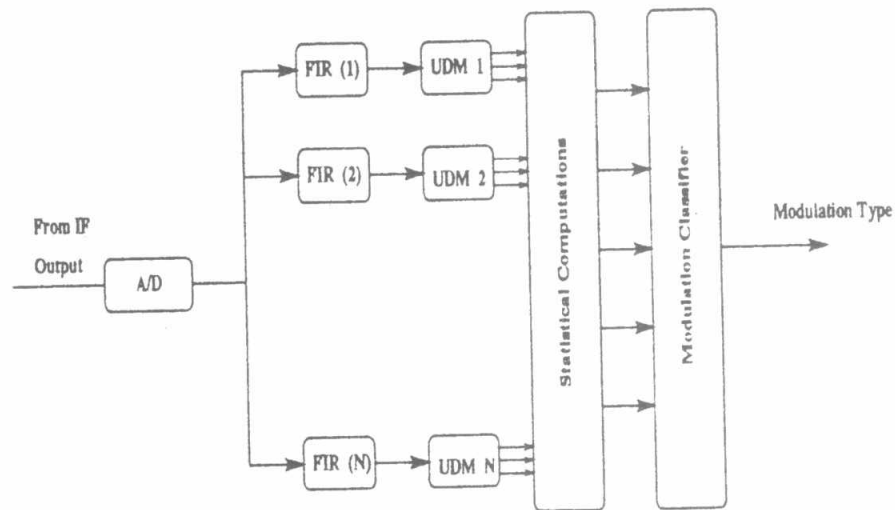*Fig. 7 Test procedure of the ANN algorithm:*
(a) single hidden layer, and (b) two hidden layer
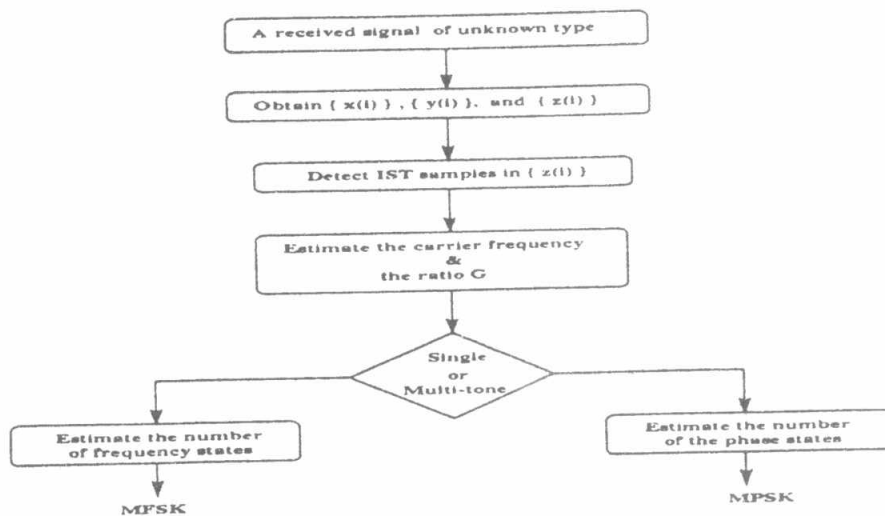
Fig. 8 Liedtke modulation recognizer [1]

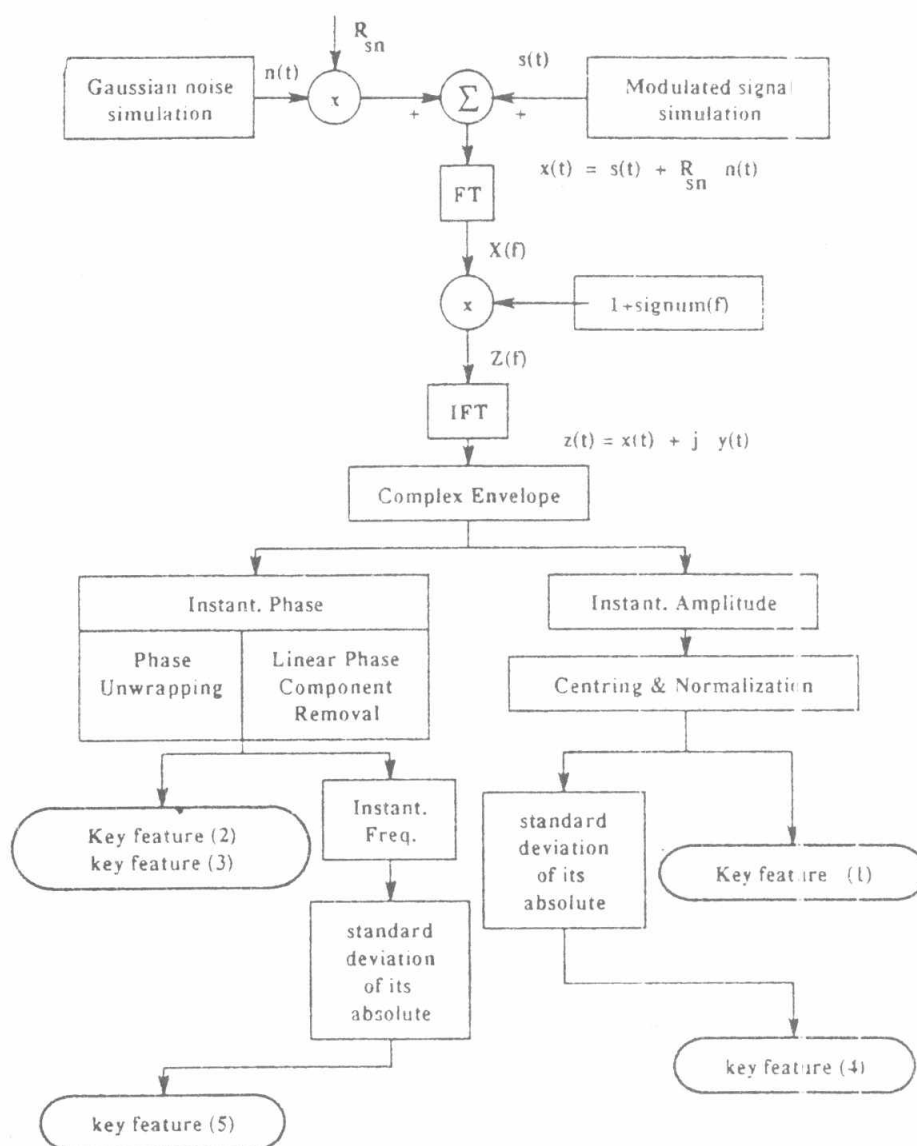*Fig. 9 Block scheme of a recognizer based on zero-crossings of a signal[23]*

$$x(t) = s(t) + R_{sn}\, n(t)$$

$$z(t) = x(t) + j\, y(t)$$

Fig. 10 Functional flowchart for key features
extraction in the DMRAs [23].

Digitally modulated signal

$\gamma_{max} < t(\gamma_{max})$

no   yes

$\sigma_{ap} < t(\sigma_{ap})$

yes

$\sigma_{af} < t(\sigma_{af})$

no

$\sigma_{dp} < t(\sigma_{dp})$

no   yes

no   yes

$\sigma_{aa} < t(\sigma_{aa})$

no   yes

PSK4   PSK2   ASK4   ASK2   FSK4   FSK2
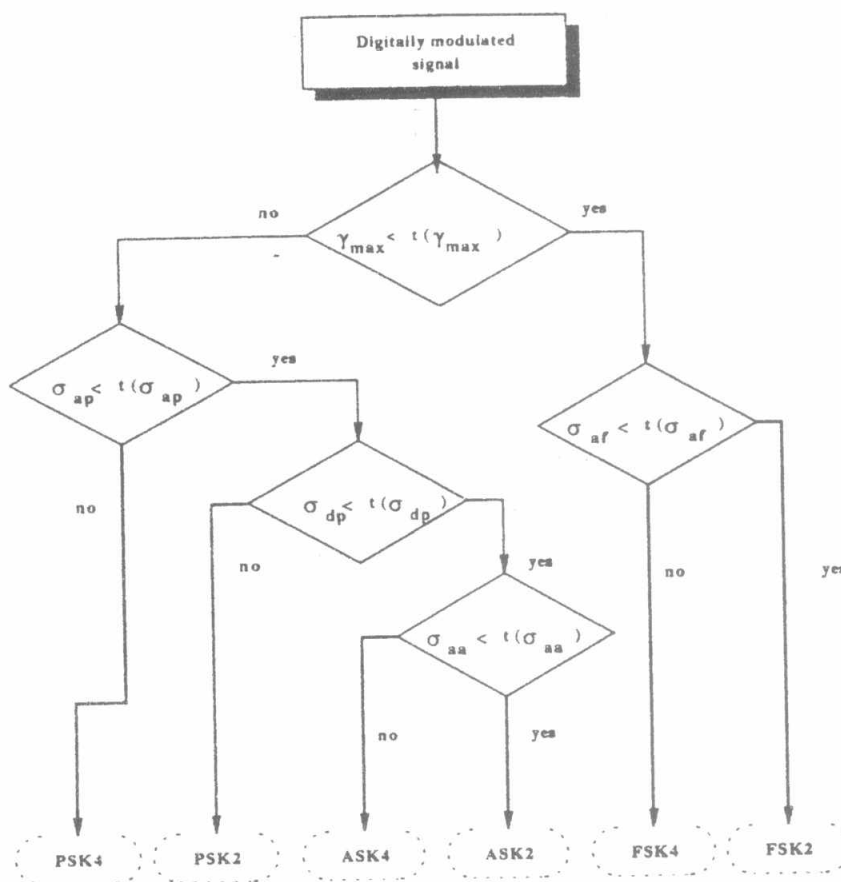
Fig. 11 Functional flowchart for DMRA [23]

$$x(t) = s(t) + R_{sn} \, n(t)$$

$$z(t) = x(t) + j \, y(t)$$
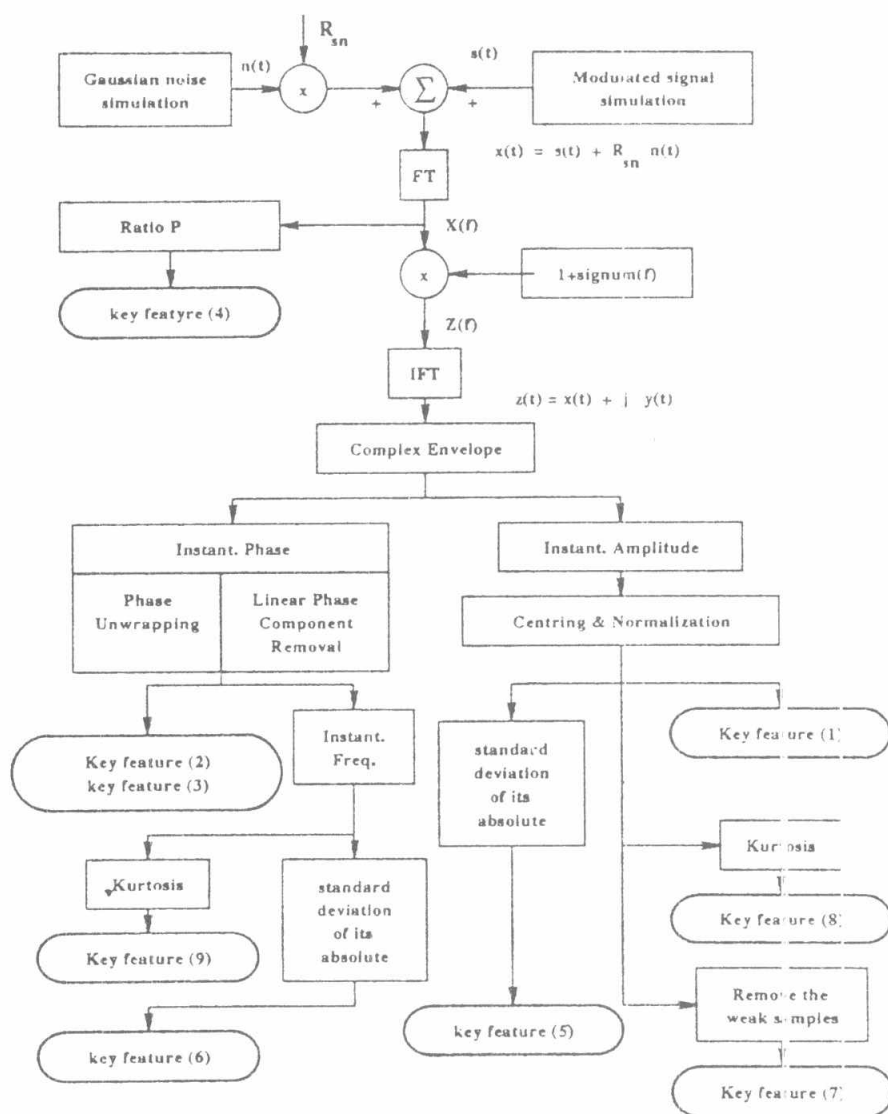
*Fig. 12 Functional flowchart for key features
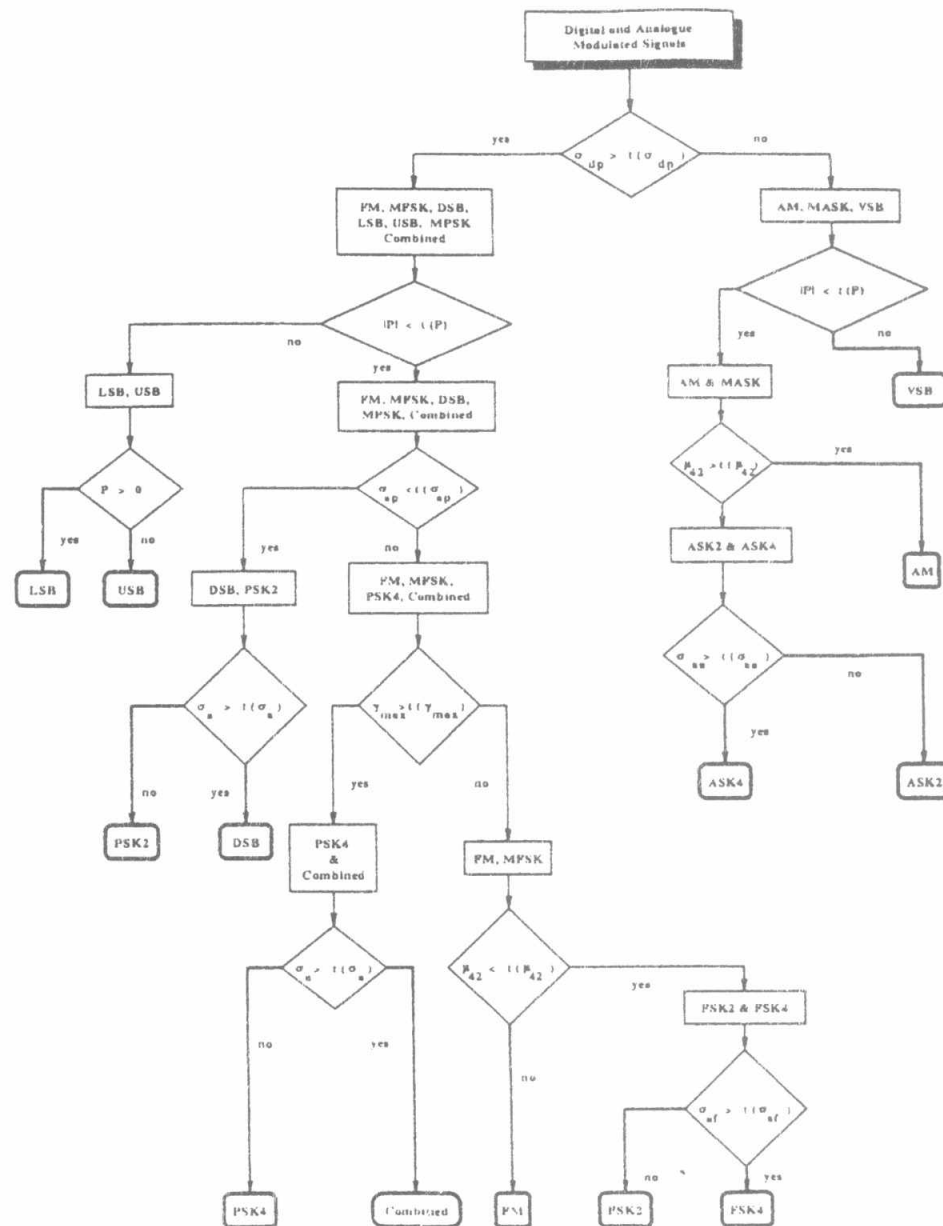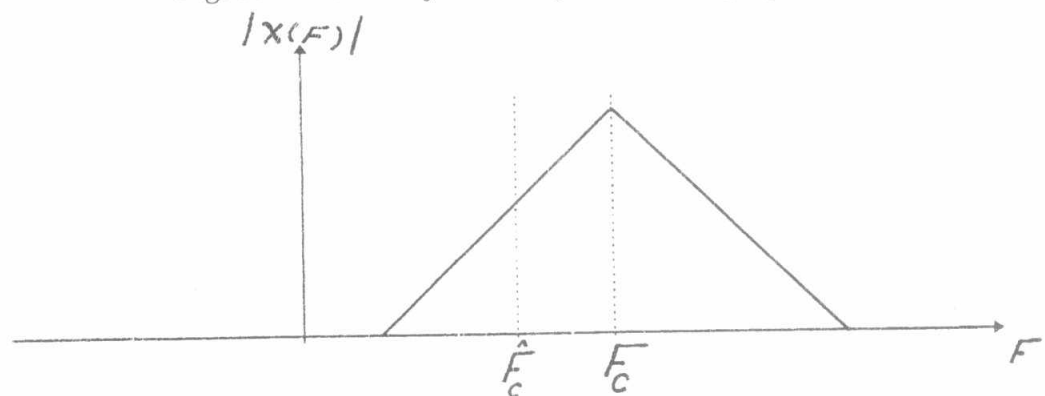extraction in the ADMRAs [26].*

Fig. 13 Functional flowchart for ADMRA [26]

Fig. 14 Spectrum shape of AM signal