Algorithms for Automatic Modulation Recognition of Communication Signals

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***Abstract*—This paper introduces two algorithms for analog and digital modulations recognition. The first algorithm utilizes the decision-theoretic approach in which a set of decision criteria for identifying different types of modulations is developed. In the second algorithm the artificial neural network (ANN) is used as a new approach for the modulation recognition process. Computer simulations of different types of band-limited analog and digitally modulated signals corrupted by band-limited Gaussian noise sequences have been carried out to measure the performance of the developed algorithms. In the decision-theoretic algorithm it is found that the overall success rate is over 94% at the signal-to-noise ratio (SNR) of 15 dB, while in the ANN algorithm the overall success rate is over 96% at the SNR of 15 dB.**

***Index Terms*—Analog and digital modulations, artifical neural networks, automatic modulation recognition.**

I. Introduction

SOME MODULATION recognizers utilize the analog modulations only [1]–[6], some utilize the digital modulations only [7]–[11], and others utilize both the analog and the digital modulations [12]–[14]. The following is an overview for some of the recently published algorithms that utilize both analog and digitally modulated signals. Liedtke [12] used both the decision-theoretic approach and the pattern recognition approach to discriminate between some analog and digitally modulated signals. The modulation types classified by this recognizer are AM, ASK2 (amplitude shift keying), PSK2 (phase-shift keying), PSK4, FSK2 (frequency-shift keying). The hardware implementation of this recognizer is excessively complex. It is claimed that error-free modulation recognition was achievable at signal-to-noise ratio $(\mathrm{SNR}) \geq 18$ dB. In [13] Jondral proposed a modulation recognizer that utilizes the pattern recognition approach. The modulation types that can be classified by this recognizer are AM, single side-bound (SSB), ASK2, PSK2, FSK2, and FSK4. The frame length used in the performance evaluations is 4096 samples. It is claimed that all of the modulation types of interest have been classified with success rate ≥90% except SSB (=83%) and FSK4 (=88%). Nothing is mentioned in [13] about the SNR corresponding to the measured success rate. Dominugez *et al.* [14] follow the pattern recognition approach. The types classified by this recognizer are AM, double side-bound (DSB), SSB, FM, ASK2, ASK4, PSK2, PSK4, FSK2, and FSK4. They claimed that this recognizer performed well at $\mathrm{SNR} \geq 40$ dB. But at $\mathrm{SNR} = 10$ dB the probability of correct modulation recognition is 0% for all digital modulation types except for PSK4 (=7%) and at 15 dB the performance is still wanting especially for FSK4 (=56%), FSK2 (= 84%), and ASK4 (=87%). It is worth noting that the recognizers introduced in [12]–[14] utilize the pattern recognition approach which requires long signal duration and, hence, the processing time may be very long; this leads to the use of the pattern recognition algorithms in the offline analysis. Nonetheless, the work in [12]–[14] attempts to classify digital as well as analog modulations.

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II. Decision-Theoretic Approach

In this section a global procedure for analog and digitally modulated signals recognition, based on the decision-theoretic approach, is proposed. First, the intercepted signal frame with length K s is divided into M successive segments, each with length $N_s = 2048$ samples (equivalent to 1.76 ms), resulting in $M(= Kf_s/N_s)$ segments, where f_s is the sampling rate.

A. Classification of Each Segment

From every available segment, the suggested procedure to discriminate between the different types of modulation requires key features extraction and modulation classification.

1) Key Features Extraction: All of the key features used in the proposed modulation recognizer are derived from three important parameters—the instantaneous amplitude, phase, and frequency of the intercepted signal, except the signal spectrum symmetry which is derived from the RF signal spectrum. The four key features that were used in [6] for analog modulations recognition are also used here; they are the maximum value of the spectral power density of the normalized-centered instantaneous amplitude $\gamma_{\max}$, the standard deviation of the absolute value of the nonlinear component of the instantaneous phase in the nonweak segments of a signal σ_{ap}, the standard deviation of the direct value of the nonlinear component of the instantaneous phase in the nonweak segments of a signal σ_{dp}, and the ratio P which measures the spectrum symmetry of the RF signal. Two of the key features used in [10] for digital modulation recognition are also used here. These are the standard deviation of the absolute value of the normalized-centered instantaneous amplitude of a signal σ_{aa} and the standard deviation of the absolute value of the normalized instantaneous frequency of a signal σ_{af}, which is the same as σ_{fa} in [10]. For the completeness of the proposed global procedure for analog and digital modulations recognition, three new key features are introduced. These are:

- the standard deviation of the normalized-centered instantaneous amplitude in the nonweak segment of a signal and it is defined by

$$\sigma_a = \sqrt{\frac{1}{L}\left[\sum_{A_n(i)>a_t} A_{cn}^2(i)\right] - \left[\frac{1}{L}\sum_{A_n(i)>a_t} A_{cn}(i)\right]^2} \quad (1)$$

  where $A_{cn}(i)$ is the value of the normalized-centered instantaneous amplitude at time instants $t = i/f_s$, $(i = 1, 2, \cdots, N_s)$, f_s is the sampling rate (=1200 kHz), $A_n(i)$ is the normalized instantaneous amplitude at time instants $t = i/f_s$, L is the number of samples in $\{A_{cn}(i)\}$ for which $A_n(i) > a_t$, and a_t is a threshold for $A(t)$ below which the band-limitation is more affected on the instantaneous amplitude of the band-limited PSK2 and the band-limited PSK4 signals;
- the kurtosis of the normalized instantaneous amplitude μ_{42}^a defined by $\mu_{42}^a = E\{A_n^4(t)\}/\{E\{A_n^2(t)\}\}^2$;
- the kurtosis of the normalized instantaneous frequency μ_{42}^f defined by $\mu_{42}^f = E\{f_n^4(t)\}/\{E\{f_n^2(t)\}\}^2$, where $f_n(t)$ is the normalized instantaneous frequency, defined by $f_n(t) = f(t)/\max\{f(t)\}$, where $f(t)$ is the instantaneous frequency of the intercepted signal.

It is worth noting that there are slight modifications in the definitions of $\gamma_{\max}$ and the ratio P used in this paper compared to those in [6] and [10]. These modifications do not alter the results in [6] and [10]. The $\gamma_{\max}$ is modified to $\gamma_{\max} = \max DFT[A_{cn}(i)]^2/N_s$. The ratio P is modified to $P = (P_L - P_U)/(P_L + P_U)$, where $P_L = \sum_{i=1}^{f_{cn}} X_c(i)^2$, $P_U = \sum_{i=1}^{f_{cn}} X_c(i + f_{cn} + 1)^2$, and $(f_{cn} + 1)$ is the sample number corresponding to the carrier frequency (150 kHz). These modifications are made only to avoid the problem of long training time in the artificial neural network (ANN) algorithm.

2) Modulation Classification Procedure: A detailed pictorial representation of the proposed modulation classification procedure, based on the decision-theoretic approach, is shown in Fig. 1 in the form of a flowchart. In the decision-theoretic algorithm, every proposed key feature is used to divide any group of modulations into two possible sets by comparing it with a suitable threshold. Key features thresholds are chosen such that optimal correct decisions for all of the modulation types of interest is obtained and their determination is explained in Section IV-A.

B. Classification of a Signal Frame

As it is possible to obtain different classifications of these M-segments, the majority logic rule is applied, i.e., select the classification with largest number of repetitions. If two or more classifications have equal maximum numbers of repetitions, they are regarded as candidates for optimal decision. In this case, continue as follows: 1) group the segments corresponding to each of the candidate decision; 2) determine for every segment within a group the number of samples of the instantaneous amplitude falling below the threshold a_t. Evaluate the total numbers of these samples over the group; and 3) adopt the decision whose corresponding group has minimum number of samples falling below the threshold a_t. Due to the simplicity of both the key features extraction (using the conventional signal processing tools only) and the decision rules in Fig. 1, the proposed decision-theoretic algorithm can be used in the online analysis.

III. ANN Approach

The modulation recognizer based on the ANN approach is composed of the three main blocks [see Fig. 2(a)]: 1) the preprocessing in which the input key features are extracted from every signal frame as explained in Section II; 2) the training and learning phase to adjust the classifier structure; and 3) the test phase to decide about the modulation type of a signal. From Fig. 2(b) it is clear that the proposed ANN algorithm comprises three ANN's. The first one is used to discriminate between all of the modulation types of interest except the estimation of the number of levels in the M-ary amplitude shift-keying (MASK) and the M-ary frequency shift-keying (MFSK) decisions. The discrimination between ASK2 and ASK4 is achieved through the use of the second network, and the discrimination between FSK2 and FSK4 is achieved through the use of the third network.

A. Choice of ANN's Architectures

In the modulation recognition process the analog types of as the AM signals with different modulation depths are classified as AM signal, FM signals with different modulation indices are classified as FM signal, and combined (AM–FM) modulated signals with different modulation depth and different modulation index are classified as combined modulation. It was found that the best ANN structure contains three networks, as shown in Fig. 2(b). Only two of the output decisions of the first network require the additional two networks to complete the discrimination. These two decisions are the MASK decision and the MFSK decision. The second and third networks are used to estimate the number of levels M of the MASK and MFSK signals. For the first network, it was found that the best ANN possesses three neuron layers. The first hidden layer uses the log–sigmoid as the activation function, the second hidden layer uses the linear function as the activation function, and the third (output) layer uses the log–sigmoid function as the activation function. For the second and third networks, they are very simple as they use just one activation function, log–sigmoid, for the one-node input layer and two-node output layer network.

1) First Network Structure: In the developed ANN algorithm for both analog and digital modulations recognition, many structures have been tested for the first network. All of them contain a seven-node input layer, an 11-node output layer, and two hidden layers. The only difference between these structures is the number of nodes in the hidden layers. It is worth noting that throughout the rest of this paper, any

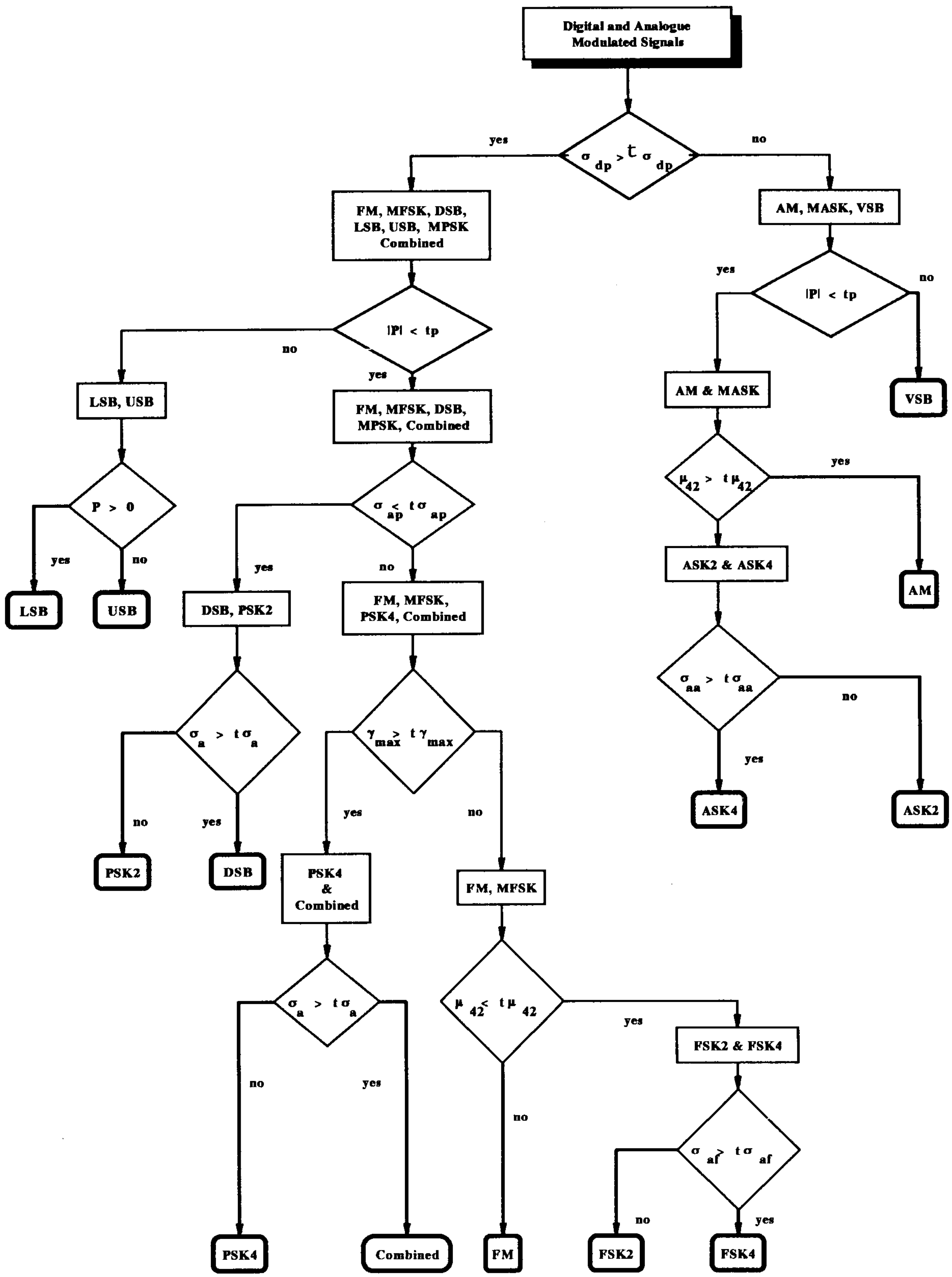


Fig. 1. Functional flowchart for the decision-theoretic algorithm.

network used is denoted by (S1-S2). This means that this network has a seven-node input layer, S1 nodes in the first hidden layer, S2 nodes in the second hidden layer, and an 11-node output layer. The selection of the network parameter is based on choosing the structure that gives the maximum probability of correct decisions and an optimum sum squared error (SSE). The dependence of the learning SSE on the number of epochs for these six networks structures is displayed in Fig. 3. Four of these six structures—(12-12), (12-15), (15-15), and (18-18)—give overall performance $>$ 95%. In this

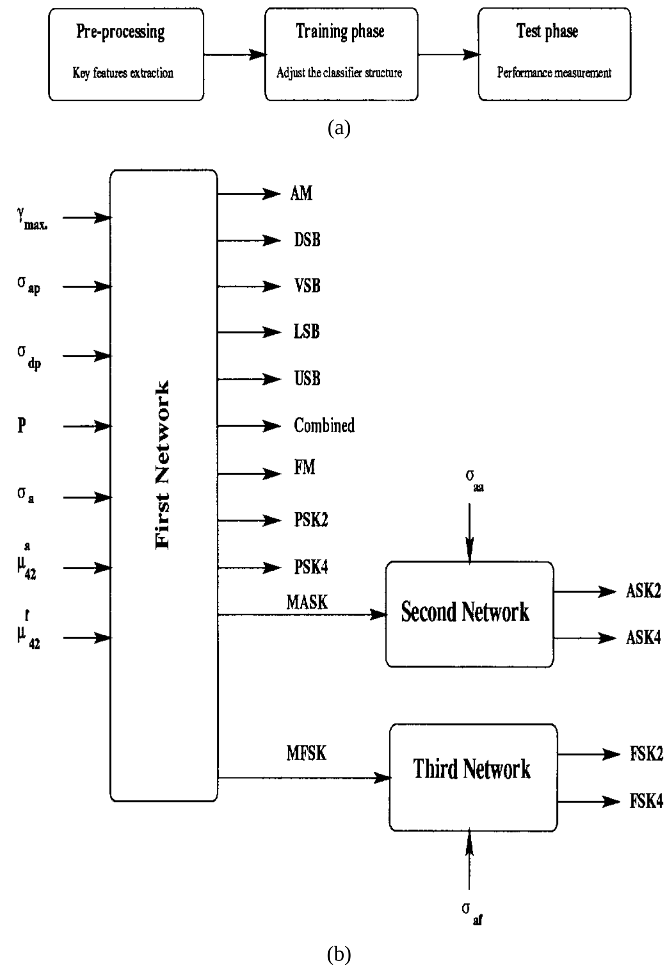


Fig. 2. Functional blocks of the ANN algorithm.

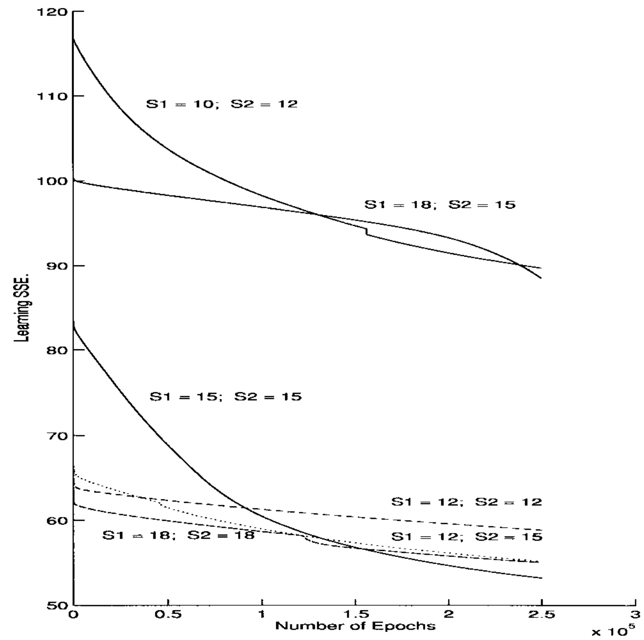


Fig. 3. Dependence of the learning SSE for six structures of the first network.

paper the (18-18) network is considered further to evaluate the performance of the ANN algorithm.

2) Second Network Structure: This network is used when the output decision of the first network is MASK. The second network is a very simple network with a one-node input layer and two-node output layer (no hidden layers). The input of this network is σ_{aa} and its output is the ASK2 or the ASK4 decisions.

3) Third Network Structure: This network is used when the output decision of the first network is MFSK. This network has the same structure as the second network, and its input is σ_{af} and its output is the FSK2 or the FSK4 decision.

IV. Performance Evaluation

The performance of the proposed algorithms are evaluated for 12 analog modulation types as well as six digital modulation types. The details of the computer simulations, corrupted with band-limited Gaussian noise, are discussed in [6] for the analog modulations and in [10] for the digital modulations.

A. Decision-Theoretic Algorithm

The optimum key features threshold values are chosen such that the optimum probability of correct decisions, based on each key feature, is obtained from the 400 realizations for each modulation type of interest at the SNR's of 15 and 20 dB. From Fig. 1, it is clear that each decision rule is applied to a set of modulation types G, separating it into two nonoverlapping subsets (A and B) according to

$$KF \underset{B}{\overset{A}{\gtrless}} x_{\rm opt} \tag{2}$$

where KF is the measured value of the chosen key feature and $x_{\rm opt}$ is the corresponding optimum threshold value. The optimum key feature threshold $x_{\rm opt}$ is determined from $x_{\rm opt} = \arg\min_x\{K(x)\}$ where

$$K(x) = \frac{P[A(x)/B]}{P[A(x)/A]} + \frac{P[B(x)/A]}{P[B(x)/B]} + |1 - P[A(x)/B] - P[A(x)/A]| \tag{3}$$

with the conditional probabilities $P[A(x)/A]$ (probability of correct decision for the subset A), $P[B(x)/B]$ (probability of correct decision for the subset B), $P[A(x)/B]$ (probability of incorrect decision for the subset A), and $P[B(x)/A]$ (probability of incorrect decision for the subset B). It was found that the optimum values for $t_{\gamma_{\max}}$, $t_{\sigma_{ap}}$, $t_{\sigma_{dp}}$, t_P, t_{σ_a}, $t_{\mu_{42}^a}$, $t_{\mu_{42}^f}$, $t_{\sigma_{aa}}$, and $t_{\sigma_{af}}$ are 2.5, $\pi/5.5$, $\pi/6$, 0.6, 0.13, 2.15, 2.03, 0.25, and 0.4, respectively. These thresholds values are used in measuring the performance of the proposed algorithm for analog and digital modulations recognition.

The results of the performance evaluation derived from 400 realizations for each type of modulations are summarized in Fig. 4 and Table I(a) for two values of SNR's (15 and 20 dB). The results in Table I(a) represent the performance evaluation for ASK2, ASK4, FSK2, and FSK4 signals at the SNR's of 15 and 20 dB. Thus, all types of analog and digital modulations have been correctly classified with more than 88% success rate except ASK4 (= 77.3%), and five of them have been classified with 100% success rate. Excluding the AM, FM, ASK4, and

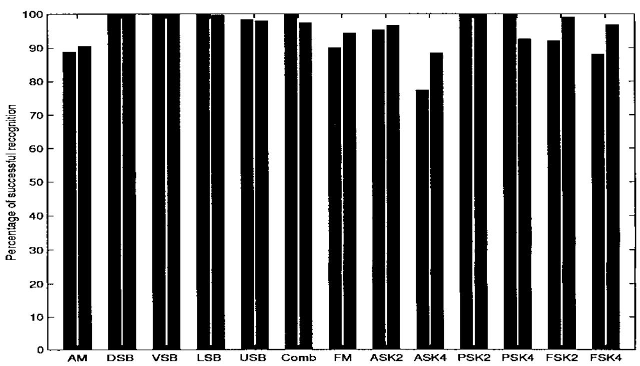
TABLE I
PERFORMANCE OF THE (a) DECISION-THEORETIC AND (b) ANN ALGORITHMS FOR DISCRIMINATING MASK AND MFSK

	SNR = 15 dB		SNR = 20 dB	
	ASK2	ASK4	ASK2	ASK4
ASK2	98.3%	1.7%	100%	
ASK4	0.2%	99.8%		100%
	SNR = 15 dB		SNR = 20 dB	
	FSK2	FSK4	FSK2	FSK4
FSK2	100%		100%	
FSK4	0.7%	99.3%		100%

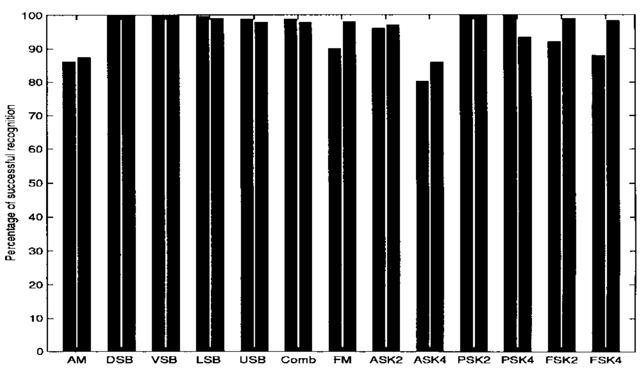
(a)

	SNR = 15 dB		SNR = 20 dB	
	ASK2	ASK4	ASK2	ASK4
ASK2	97.0%	3.0%	100%	
ASK4		100%		100%
	SNR = 15 dB		SNR = 20 dB	
	FSK2	FSK4	FSK2	FSK4
FSK2	97.5%	2.5%	100%	
FSK4		100%		100%

(b)



(a)



(b)

Fig. 4. Percentage of successful recognition from decision-theoretic and ANN algorithms. In each pair of vertical bars the first one corresponds to decision-theoretic and the second one corresponds to ANN. (a) 15 dB SNR. (b) 20 dB SNR.

FSK4, the success rate for all analog and digital modulations is $>$ 92% at both 15 and 20 dB.

B. The ANN Algorithm

In the proposed ANN algorithm most of the modulation types are completely classified through the use of the first network. Only four types—ASK2, ASK4, FSK2, and FSK4—require additional networks. The training has been done using only 50 frames at each SNR (15 and 20 dB) for each analog and digital modulation types, while the performance is measured for the 400 frames of each modulation type of interest and at two SNR values (15 and 20 dB). Results are presented in Fig. 4 and Table I(b). The results in Table I(b) represent the performance evaluation for the ASK2 and ASK4 signals using the second ANN, and for the FSK2 and FSK4 signals using the third ANN. It is clear that all types of analog and digital modulations have been correctly classified with more than 88% success rate. Excluding the AM, ASK4, and PSK4, the success rate is $>$ 94% at the SNR of 15 dB for all analog and digital modulations. Excluding the AM, ASK4, and PSK4, the success rate is $>$ 97% at 20 dB for all analog and digital modulations. Generally, the results obtained from the ANN approach are better than those obtained by the decision-theoretic approach. The datasets used in the two algorithms are exactly the same. Therefore, direct comparisons of these two approaches can be made. In the decision-theoretic algorithm the overall success rate is $>$ 94% at the SNR of 15 dB, while the overall success rate is $>$ 96% at the SNR of 15 dB for the ANN algorithm.

V. CONCLUDING REMARKS

The aim of this paper has been to recognize automatically the types of modulations in communication signals using the decision-theoretic approach and the ANN approach. A number of key features has been proposed for these recognizers. Extensive simulations of twelve analog and six digital modulation signal types have been carried out at different SNR's. Sample results have been presented at the SNR's of 15 and 20 dB only. In the decision-theoretic algorithm it is found that the overall success rate is over 94% at the SNR of 15 dB while the overall success rate in the ANN algorithm is over 96% at the SNR of 15 dB. Given that the results using the decision-theoretic algorithm are comparatively good and that the largest number of modulation types have been considered here, results from the ANN algorithm are very encouraging and point toward the adoption of ANN approaches [15].

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