Simple and Efficient Algorithm for Automatic Modulation Recognition for Analogue and Digital Signals

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Abstract In this paper we propose new analogue and digital recognition algorithm to discriminate between 15 signals (amplitude modulation (AM), frequency modulation (FM), double sideband modulation (DSB), lower sideband modulation (LSB), upper sideband modulation (USB), vestigial sideband (VSB), combined (AM FM), carrier wave (CW), Noise, binary amplitude shift keying (ASK2), ASK4, binary phase shift keying (PSK2), PSK4, binary frequency shift keying (FSK2) and FSK4). Six key features extracted from instantaneous information (amplitude and phase) and signal spectral, are used to fulfill the requirement of this algorithm. Computer simulations for the signals of interest corrupted by band limited Gaussian noise was performed, the simulation results show that the overall recognition rate can reach 99.6 % when the signal to noise ratio (SNR) = 3 dB. This algorithm uses a lesser number of features compared with most of the existing automatic analogue and digital modulation recognition algorithms, thus leading to lower computational load.

Keywords Features • Instantaneous information • Modulation recognition and algorithm

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1 Introduction

Generally, automatic modulation recognition algorithms can be classified into three groups depending on the signals used. The first group deals with analogue communication signals only. The second group deals with digital communication signals only. While the third group deals with both analogue and digital communication signals; this third group is preferred in the practical automatic modulation recognition algorithms.

Nandi and Azzouz in [1 3] developed three algorithms for analogue and digital modulation recognition to discriminate between thirteen signals (AM, FM, DSB, LSB, USB, VSB, combined (AM FM), ASK2, ASK4, PSK2, PSK4, FSK2 and FSK4). The overall recognition rate of these algorithms reached 94 % when SNR = 15 dB. The overall recognition rate was enhanced by using artificial neural networks (ANN), though, still less than 98 % when SNR = 15 dB.

Several other automatic modulation recognition algorithms have been established in the last few years to discriminate both analogue and digital communication signals. Cheol-Sun et al. [4] proposed algorithm to discriminate between nine signals using neural network and support vector machine the overall recognition rate reached 96 % when SNR = 5 dB. Jie Yang et al. [5] suggested algorithm to discriminate between nine signals the overall recognition rate reached 95 % when SNR = 7 dB. Xudong Liu et al. [6] proposed algorithm to discriminate between eleven signals the overall recognition rate reached 95 % when SNR $\geq$10 dB. Chisheng Li et al. [7] developed algorithm to discriminate between eleven signals the overall recognition rate reached 98 % when SNR $\geq$3 dB.

All the algorithms proposed in [4 7] have good performance at low SNR. But none of these algorithms contain VSB and Combined (AM FM) signals .Also some of these algorithms reduce the analogue or digital signals to get better recognition rate. While the algorithms proposed by Azzouz and Nandi do not have acceptable performance (effective at high SNR).

Our paper aims at the development of a new algorithm for the automatic modulation recognition of analogue and digital signals, using six features extracted from instantaneous information (amplitude and phase) and spectra of the intercepted signal, to discriminate between fifteen signals same as in [1 3], in addition to carrier wave (CW) and Noise signals at low SNR. This algorithm not only achieves a better recognition rate but also extends the number of analogue signals and reduces the computational loads.

This paper is organized as follows: Sect. 2 presents the key features used to fulfill the requirements of this algorithm. In Sect. 3, Computer simulations including the determination of thresholds, the flowchart and the simulation results are presented. Finally, the paper concludes in Sect. 4.

2 Feature Extraction

To discriminate the analogue and digitally modulated signals, six features extracted from instantaneous information (amplitude and phase) and spectra of the intercepted signals are used.

(1) The first feature (**P**); is used for the measuring the spectrum symmetry around the carrier frequency, and it is based on the spectral powers for the lower and upper sideband of the RF signal.
(2) The second feature ($\boldsymbol{\sigma_{dp}}$); is the standard deviation of the centered non-linear component of the direct instantaneous phase, evaluated over the non-weak interval of signal segment.
(3) The third feature ($\boldsymbol{\gamma_{max}}$); is the maximum value of the spectral power density of the normalized-centered instantaneous amplitude of the intercepted signal.
(4) The fourth feature ($\boldsymbol{\mu_a}$); mean of instantaneous amplitude squared.
(5) The fifth feature ($\boldsymbol{\mu_{aa}}$); the mean of normalized-centered instantaneous amplitude squared.
(6) The sixth feature ($\mathbf{V_{phs}}$); the variance of a non-linear component of the instantaneous phase squared.

The features P, $\boldsymbol{\gamma_{max}}$ and $\boldsymbol{\sigma_{dp}}$ were proposed by Nandi and Azzouz in [1]. While the mean of instantaneous amplitude squared (μ_a) was proposed by Jaspal Bagga and Neeta Tripathi in [8]. μ_{aa} and V_{phs} are the two newly features.

The first new feature μ_{aa} is defined as

$$\boldsymbol{\mu_{aa}} = E\left(a_{cn}^2(i)\right) \tag{1}$$

$$a_{cn}(i) = \frac{(a(i) - E(a(i)))}{E(a(i))} \tag{2}$$

Where $a(i)$ the instantaneous amplitude and μ_{aa} the mean of normalized-centered instantaneous amplitude squared. This feature is used to discriminate between signals with constant amplitude (MPSK, MFSK and FM) and signals with no constant amplitude (DSB, MASK, COM and Noise). Also, it is used to discriminate the ASK2 from ASK4.

The second new feature, V_{phs}, is modified from V_{ph} proposed in [9] to discriminate between large types of the signals and defined as:

$$\mathrm{V_{phs}} = \frac{1}{\mathrm{c}} \sum_{\varnothing(\mathrm{i})<2_{\mathrm{t}}}^{\mathrm{c}} \varnothing^4(\mathrm{i}) - \left(\frac{1}{\mathrm{c}} \sum_{\varnothing(\mathrm{i})<2_{\mathrm{t}}}^{\mathrm{c}} \varnothing^2(\mathrm{i})\right)^2 \tag{3}$$

where c is the number of samples less than the threshold a_t, the value of a_t used equal $3\pi/2$. Ø is the non-linear component of the instantaneous phase at time instants $t = i/f_s$.

This feature leads to a complete classification of five modulated signal types, separating them into five regions simultaneously. Among the five sets, the first set consists of the FM signal and the second set consists of the PSK2 signal. The third set consists of the FSK2 signal and the fourth set consists of the FSK4 signal and the last set consists of PSK4 signal. This separation stage requires four proper threshold values of V_{phs} such as $t1_{(Vphs)}$, $t2_{(Vphs)}$, $t3_{(Vphs)}$ and $t4_{(Vphs)}$ and is performed by following procedure.

$V_{phs}<t1_{(Vphs)}$ first set: FM signal.
$t1_{(Vphs)} <V_{phs}<t2_{(Vphs)}$ second set: PSK2 signal.
$t2_{(Vphs)} <V_{phs}<t3_{(Vphs)}$ third set: FSK2 signal.
$t3_{(Vphs)} <V_{phs}< t4_{(Vphs)}$ fourth set: FSK4 signal.
$V_{ph}>t4_{(Vphs)}$ fifth set: PSK4 signal.

3 Computer Simulation

The software used is Matlab R2011b and the simulation parameters (carrier frequency (f_c), sampling frequency (f_s) and symbol rate (f_b)) are the same as mentioned in [1].

3.1 Thresholds Determinations

The thresholds for all features are shown in the Figs. 1 11, and the specific values are shown in Table 1.

Figure 1 shows that LSB, USB and VSB can be discriminated from others at SNR $\geq$3 dB by the threshold (t1).

Figure 2 shows that LSB can be discriminated from USB and VSB at SNR $\geq$ 0 dB by the threshold.

From Fig. 3, it can be observed that ASK2, ASK4, AM and CW can be discriminated from others at SNR $\geq$1 dB by the threshold (t2).

Similarly, from Fig. 4 it can be observed that USB can be discriminated from VSB at SNR $\geq$0 dB by the threshold (t3).

Figure 5 shows that DSB can be discriminated from COM and noise at SNR $\geq$0 dB by the threshold (t4).

Figure 6 shows that MPSK, MFSK and FM can be discriminated from DSB, COM and noise at SNR $\geq$2 dB by the threshold (t5).

Figure 7 shows that ASK2 can be discriminated from ASK4 at SNR $\geq$0 dB by the threshold (t6).

From Fig. 8 it can be observed that CW can be discriminated from ASK2, ASK4 and AM at SNR $\geq$0 dB by the threshold (t7).

Figure 9 shows that COM can be discriminated from Noise at SNR $\geq$0 dB by the threshold (t8).

From Fig. 10 it can be observed that AM can be discriminated from ASK2 and ASK4 signals at SNR $\geq$1 dB by the threshold (t9).

Figure 11 shows that FM, PSK2, PSK4, FSK2 and FSK4 signals can be discriminated from one another at SNR $\geq$3 dB by the four different thresholds (t10, t11, t12 and t13).

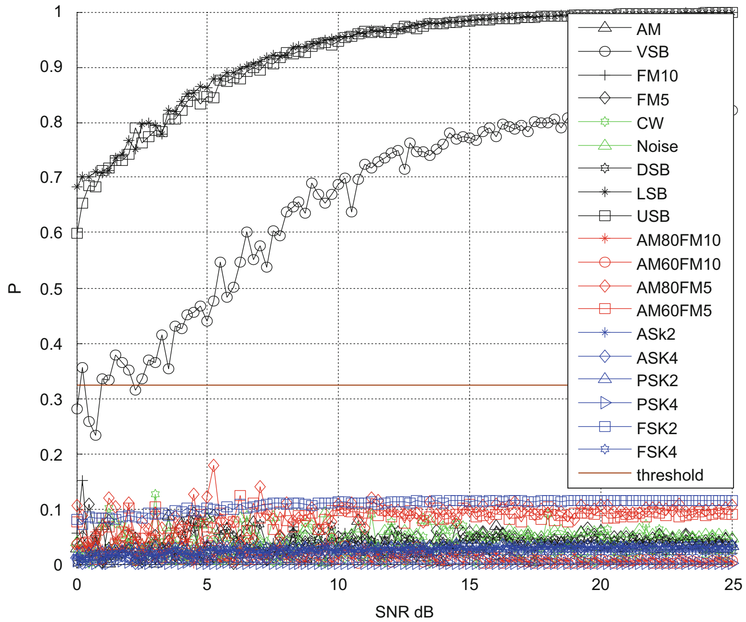

Fig. 1 Using feature |p| to discriminate SSB and VSB from other signals

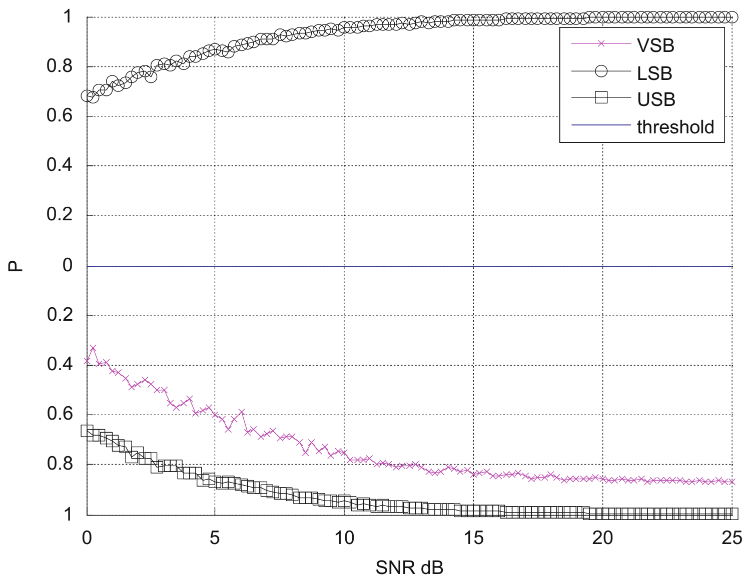

Fig. 2 Using feature P to discriminate LSB from USB and VSB

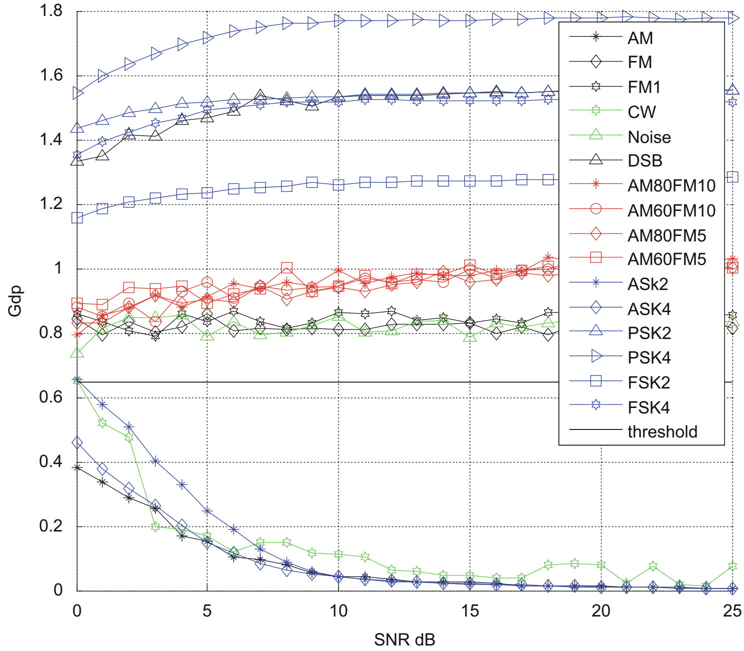

Fig. 3 Using feature $\boldsymbol{\sigma_{dp}}$ to discriminate MASK, AM and CW from other signals

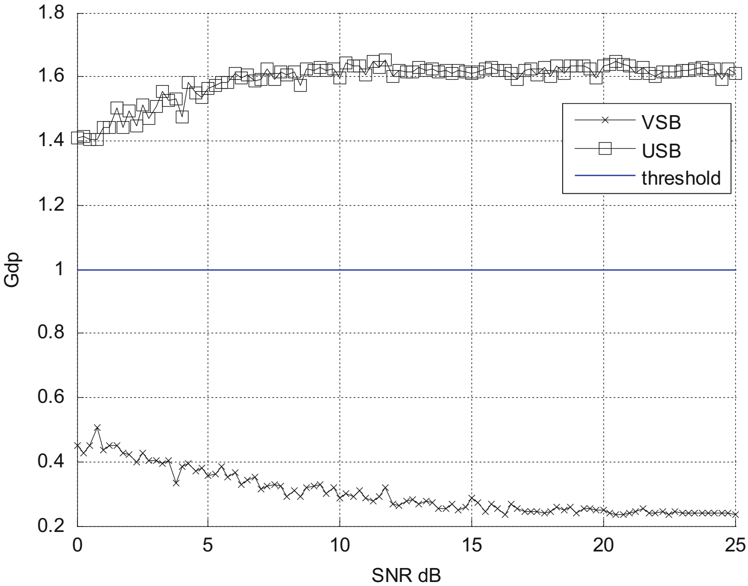

Fig. 4 Using feature $\boldsymbol{\sigma_{dp}}$ to discriminate USB from VSB signals

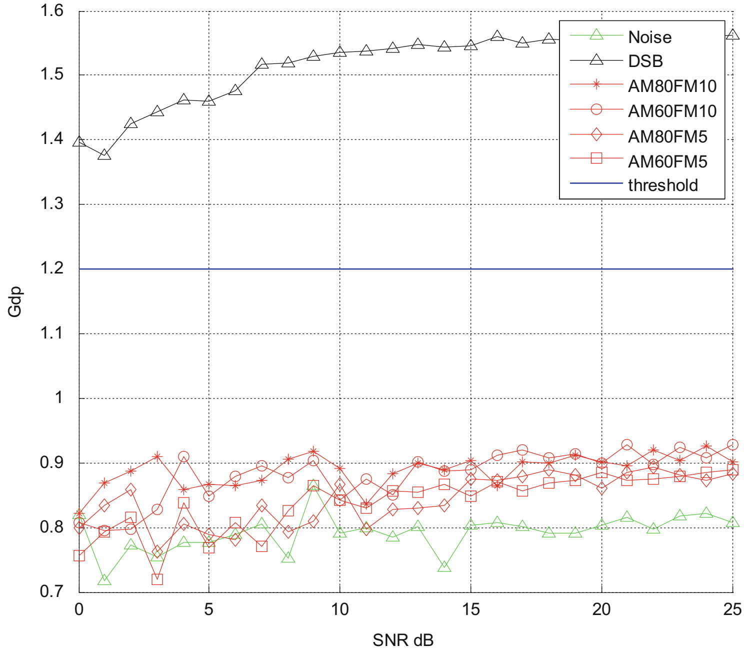

Fig. 5 Using feature $\boldsymbol{\sigma}_{\mathbf{dp}}$ to discriminate USB COM and noise from DSB signals

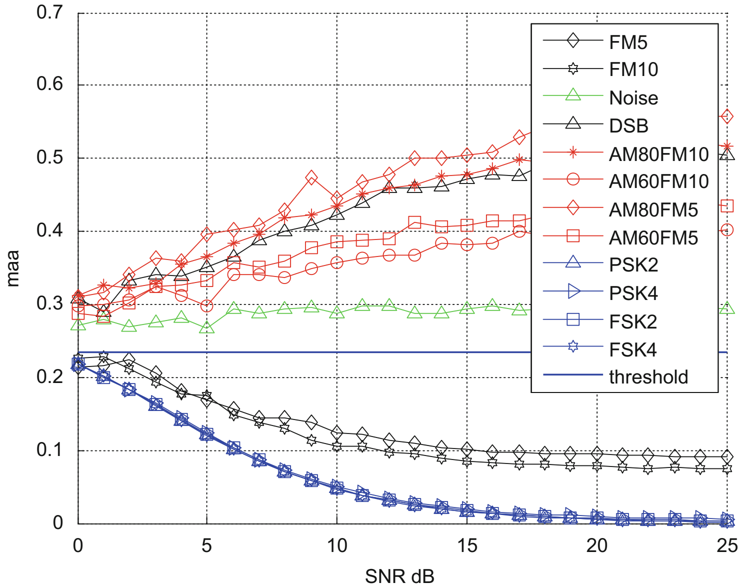

Fig. 6 Using feature $\boldsymbol{\mu}_{\mathbf{aa}}$ to discriminate MPSK, MFSK and FM from other signals

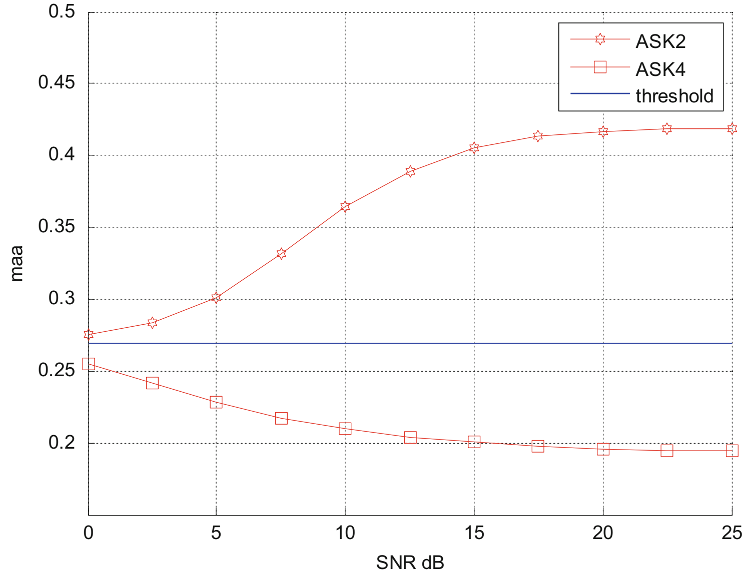

Fig. 7 Using feature μ_{aa} to discriminate ASK2 from ASK4 signals

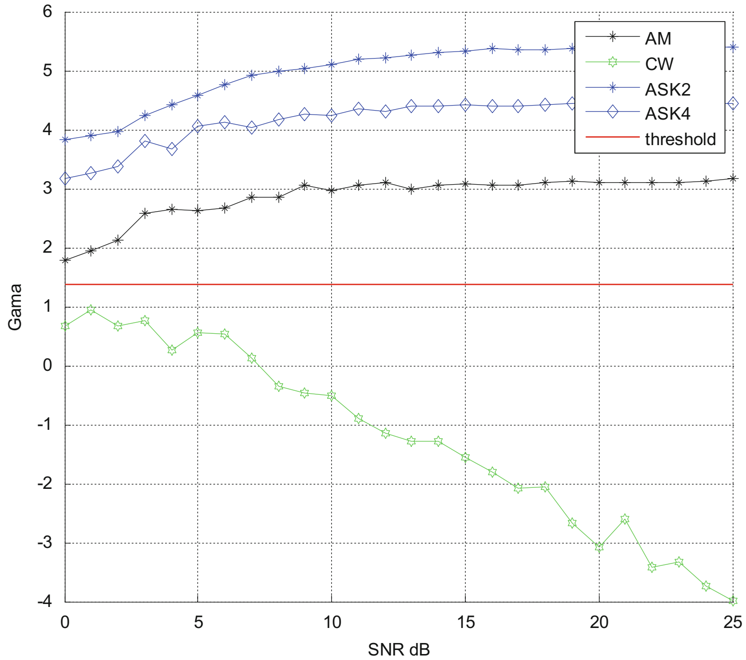

Fig. 8 Using feature γ_{max} to discriminate CW from MASK and AM signals. (The logarithm is used to make the different between two groups clear)

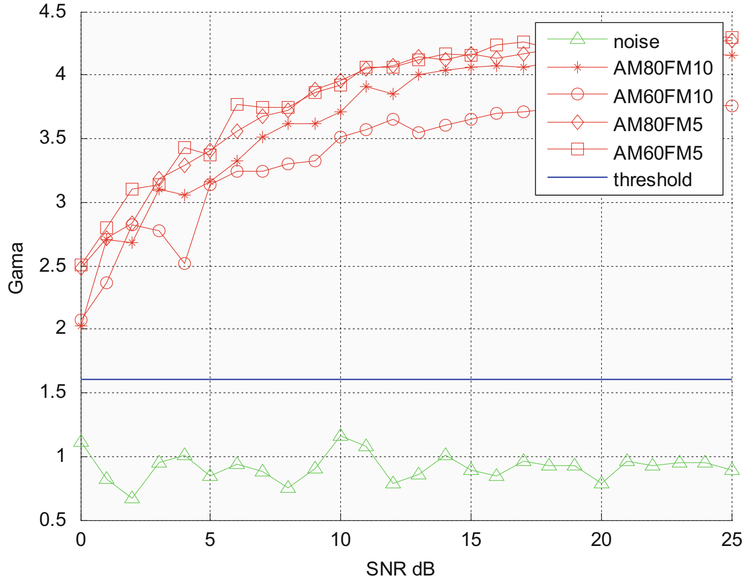

Fig. 9 Using feature $\boldsymbol{\gamma_{max}}$ to discriminate COM from Noise signal. (The logarithm is used to make the different between two groups clear)

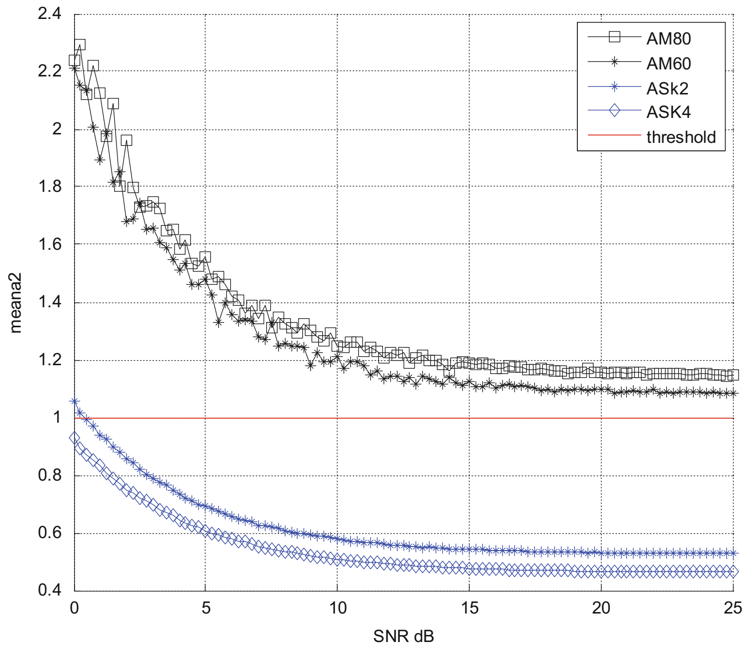

Fig. 10 Using feature $\boldsymbol{\mu_a}$ to discriminate AM from ASK2 and ASK4 signals

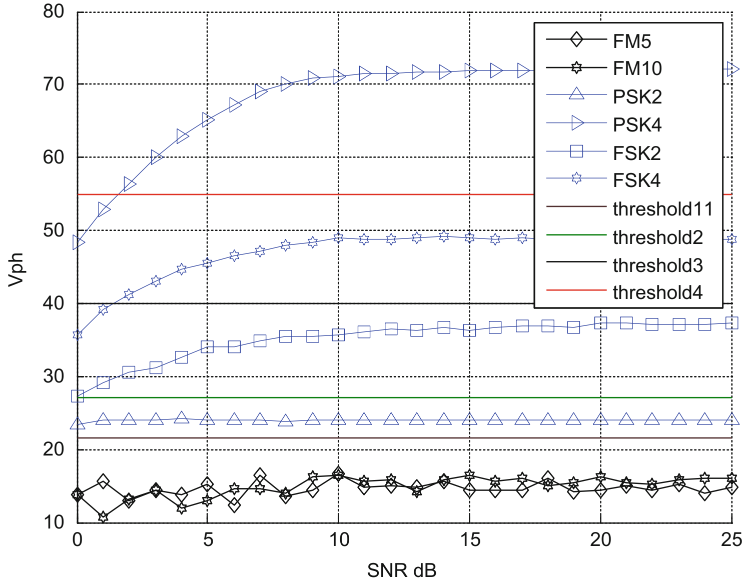

Fig. 11 Using feature $\mathbf{V_{phs}}$ to discriminate MPSK, FM and MFSK from one another

Table 1 The threshold values

Feature	Threshold		Function	Figures
$\mathbf{\|P\|}$	t1	0.325	Discriminate LSB, VSB, USB from AM, DSB, VSB, FM, FSK2, FSK4, ASK2, ASK4, PSK2, PSK4, COM, CW, Noise	Fig. 1
P	0		Discriminate LSB from USB and VSB	Fig. 2
$\boldsymbol{\sigma_{dp}}$	t2	0.7	Discriminate AM, ASK2, ASK4, CW from DSB, FM, FSK2, FSK4, PSK2, PSK4, COM and Noise	Fig. 3
	t3	1	Discriminate VSB from USB	Fig. 4
	t4	1.2	Discriminate DSB from COM and Noise	Fig.5
$\boldsymbol{\mu_{aa}}$	t5	0.235	Discriminate DSB, Noise and COM from PSK2, PSK4, FM, FSK2 and FSK4	Fig. 6
	t6	0.265	Discriminate ASK2 from ASK4	Fig. 7
$\boldsymbol{\gamma_{max}}$	t7	5	Discriminate COM from Noise	Fig. 8
	t8	4	Discriminate CW from AM, ASK2 and ASK4	Fig. 9
$\boldsymbol{\mu_{a}}$	t9	0.97	Discriminate AM from ASK2 and ASK4	Fig. 10
$\mathbf{V_{phs}}$	t10	22.5	Discriminate FM from PSK2, PSK4, FSK2and FSK4	Fig. 11
	t11	25	Discriminate PSK2 from PSK4, FSK2 and FSK4	
	t12	40	Discriminate FSK2 from PSK4and FSK4	
	t13	55	Discriminate FSK4 from PSK4	

3.2 Flowchart of Automatic Recognition of Analogue and Digital Signals

Figure 12 shows that the sequence order of selecting the features to discriminate between signals of interest.

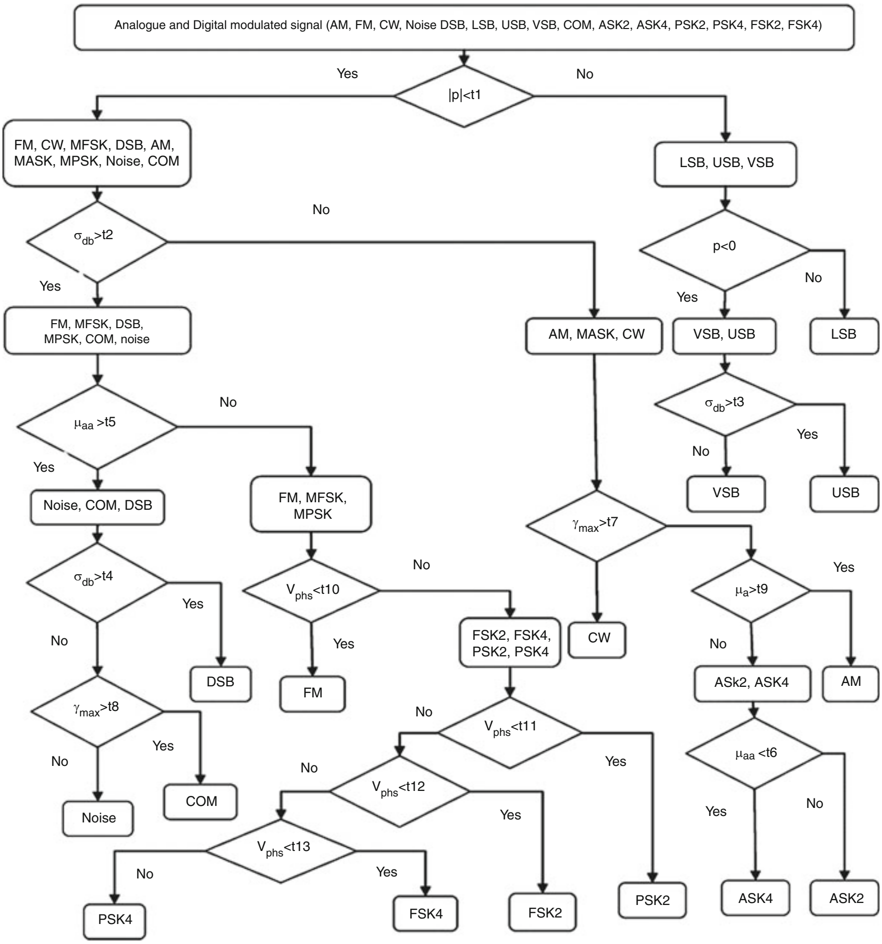

Fig. 12 Functional flowchart of automatic recognition algorithm

3.3 Simulation Results and Analysis

500 iterations are used to get the recognition rates in Tables 2 and 3.

Table 2 shows that, by using $\boldsymbol{\mu}_{\mathbf{aa}}$ to discriminate ASK2 from ASK4 the average recognition rate can reach 98 % when SNR $= -2$ dB. Also to discriminate constant amplitude signals from non-constant amplitude signals the average recognition rate can reach 99.9%, when SNR $=$ 2 dB.

Table 3 shows that, by using V_{phs} to discriminate PSK2, PSK4, FM, FSK2 and FSK4 signals from one another, the average recognition rate can reach 98.3 % when SNR $=$ 2dB.

By using these six features, an average recognition rate not less than 99.6 % can be achieved when SNR $=$ 3 dB, as shown in Fig. 13 which is much better than those in [1 7] and [9].

Table 2 The results of feature $\boldsymbol{\mu}_{\mathbf{aa}}$

SNR/dB	4 (%)	3 (%)	2 (%)	≥0 (%)	SNR/dB	0 (%)	2 (%)	≥3 (%)
ASK2	100	100	100	100	DSB, COM and Noise	100	100	100
ASK4	6.2	50.4	96	100	Constant amplitude signals	41.2	99.8	100
Average recognition	53.1	75.2	98	100	Average recognition rate	70.6	99.9	100

Table 3 The results of feature V_{phs}

SNR/dB	0(%)	2(%)	≥3(%)
PSK2	100	100	100
PSK4	0	93.6	100
FSK2	100	100	100
FSK4	0	97.8	100
FM	100	100	100
Average recognition rate	60	98.3	100

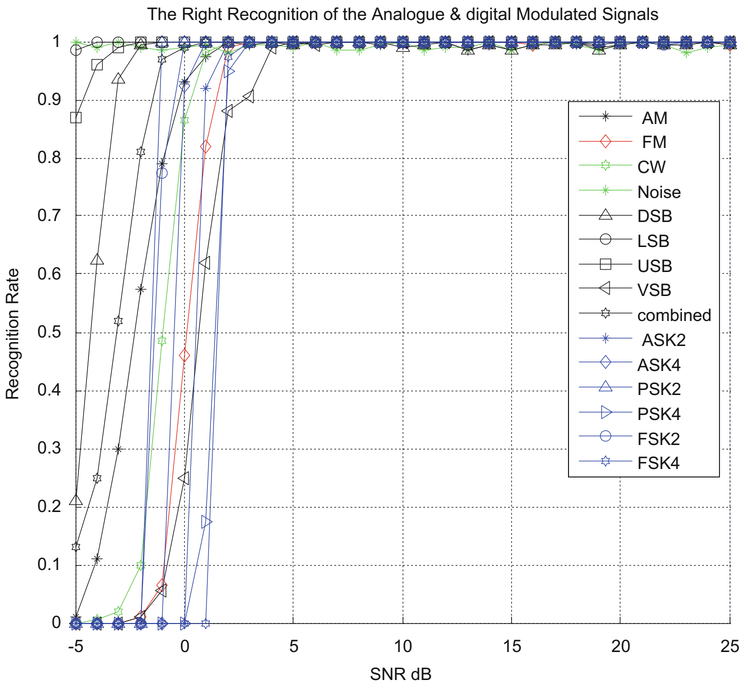

Fig. 13 The overall performance of the algorithm

4 Conclusion

In this paper we propose two new features based on the instantaneous amplitude and phase. By using these two new features, along with four other previously proposed features, an average recognition rate not less than 99.6 % can be achieved when SNR = 3 dB. This algorithm not only gives a better recognition rate, compared to existing algorithms, but it is also easier to compute. The simulation results also show that only one feature can be used to discriminate the FM, MPSK and MFSK signals from one another. This is more feasible in practical scenarios.

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