调制方式的识别

1. 研究意义

随着通信技术的发展，无线通信环境日益复杂。通信信号在很宽的频带上采用不同调制参数的各种调制方式。对未知信号调制方式的识别可提供信号的结构、信号源以及特性等有用信息，如何有效地识别和监视这些信号，在军事和民用领域都是重要的研究课题。

Automatic Modulation Classification (AMC)

- **Automatically identify the modulation types of the transmitted signals by observing the received data samples, which would be corrupted by the noise and fading channels.**

- **It is an intermediate operation between the signal detection and the data demodulation.**

AMC applications (cooperative and non-cooperative communication)

- **Software-defined radio**
- **Cognitive radio**
- **Intelligent modem**
- **Surveillance and electronic warfare**

AMC approaches

- **Decision-theoretic**
- **Pattern recognition**

Decision-theoretic approach

- **Decision-theoretic approach is based on the likelihood function, where the modulation classification can be deemed as a multiple-hypothesis test.**

- **The decision-theoretic classifiers with maximum likelihood (ML) are optimal, but the corresponding close-form solutions either are unavailable or involve the numerical search of high computation complexity.**

- **This approach is not robust with respect to the model mismatch in the presence of phase or frequency offsets, residual channel effects, and so on.**

Pattern recognition approach

- **The modulation classification module is composed of two subsystems;**
- **the first one is a feature extraction subsystem, which extracts the key features from the received signal;**
- **the second subsystem is a pattern recognizer, which processes those features and determines the modulation type of the transmitted signal according to a pre-designed decision rule.**

Decision-theoretic vs. Pattern recognition

- **The pattern recognition methods may be non-optimal but simple to implement and can often achieve the nearly optimal performance if carefully designed.**

- **The pattern recognition methods can be robust with respect to the aforementioned model mismatches.**

Pattern recognition approach: feature extraction

- **Geometry features**: **constellation diagram**
- **Statistics feature**: **PDF, moments, cumulants**
- **Time-domain features**: **instantaneous magnitude, instantaneous phase, instantaneous frequency**
- **Transformation-domain features**: **Fourier transformation, Wavelet transformation**

Pattern recognition approach: pattern recognizer

- **Decision tree**
- **Neural network**
- **Support vector machines**

2. 模拟调制方式的识别

模拟调制方式主要包括：**AM**、**FM**、**DSB**、**LSB**、**USB**等模拟调制类型。统一表示为

$$s(t) = a(t)\cos[\omega_c t + \phi(t)]$$

$\omega_c = 2\pi f_c$ 为载波频率

$\theta(t) = 2\pi f_c t + \phi(t)$ 为载波的瞬时相位

$\phi(t)$ 为相位调制信号

$a(t)$ 为幅度或幅度调制信号

(1) 调幅信号（AM）：

$$s(t) = a(t)\cos[\omega_c t + \phi(t)]$$

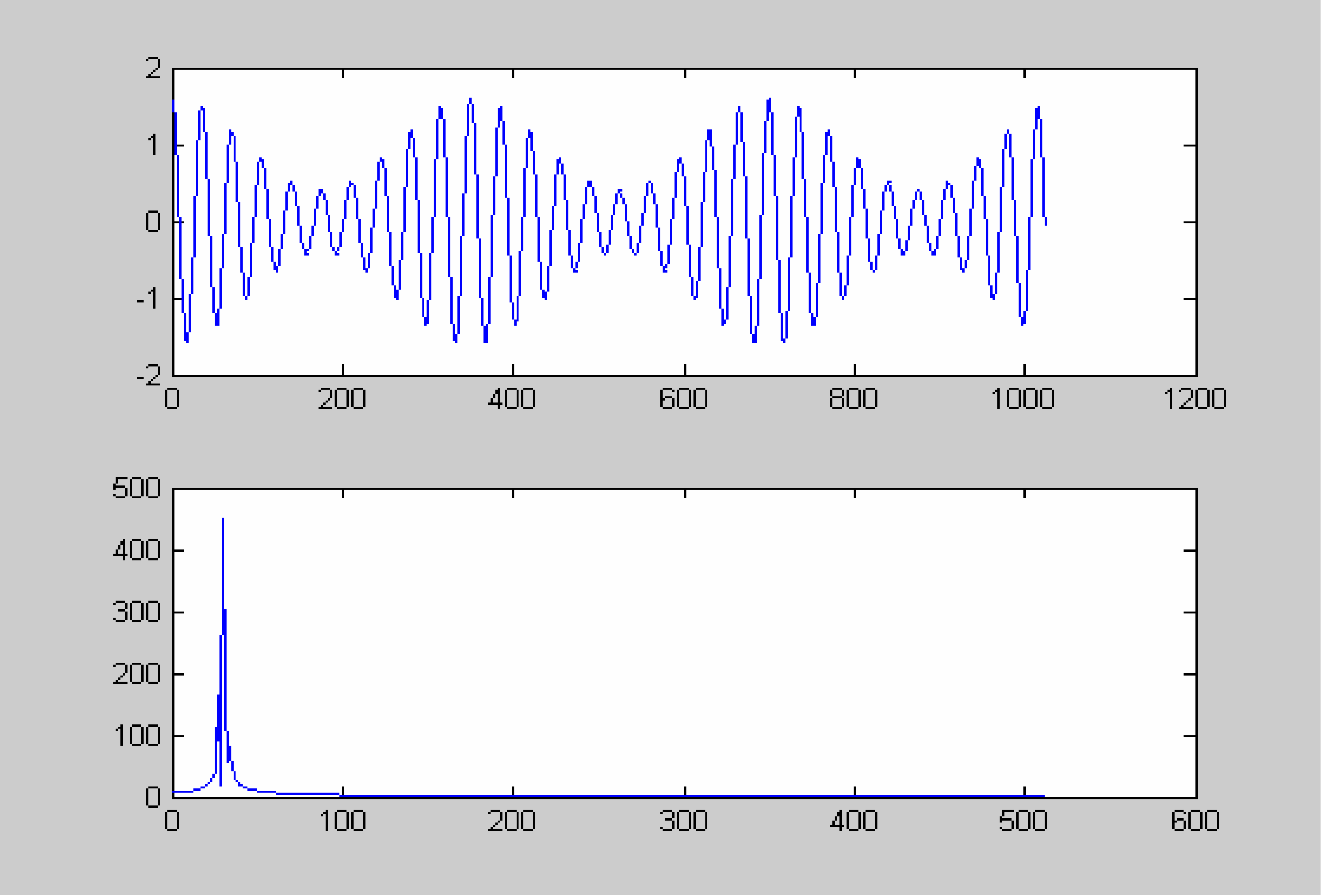
$$\phi(t) = 0 \qquad a(t) = [1 + r \cdot m(t)]$$

瞬时幅度： $A(t) = \left|1 + r \cdot m(t)\right|$

瞬时相位： $\theta(t) = 2\pi f_c$

非线性分量： $\varphi(t) = 0$

$r = 0.5$ $\qquad$ $m(t) = \cos(2\pi f_m t)$



（2）调频信号有：

$$s(t) = a(t)\cos[\omega_c t + \phi(t)]$$

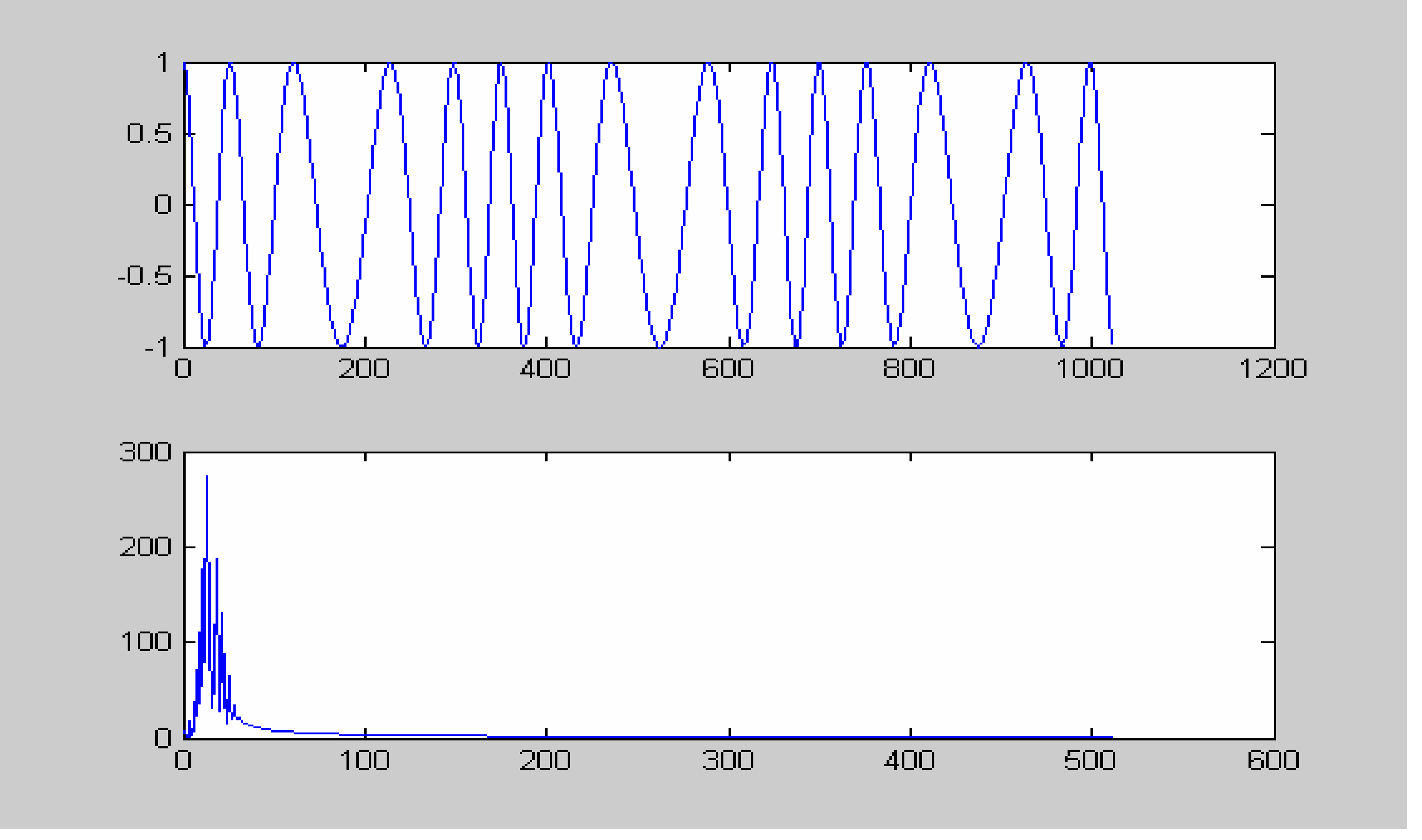
$$a(t) = A_c \qquad\qquad \phi(t) = k_f \int_{-\infty}^{t} m(\tau)d\tau$$

瞬时幅度： $A(t) = A_c$

瞬时相位： $\theta(t) = 2\pi f_c + k_f \int_{-\infty}^{t} m(\tau)d\tau$

非线性分量： $\varphi(t) = k_f \int_{-\infty}^{t} m(\tau)d\tau$

$$m(t) = \cos(2\pi f_m t)$$



（3）DSB信号：

$$s(t) = a(t)\cos[\omega_c t + \phi(t)]$$

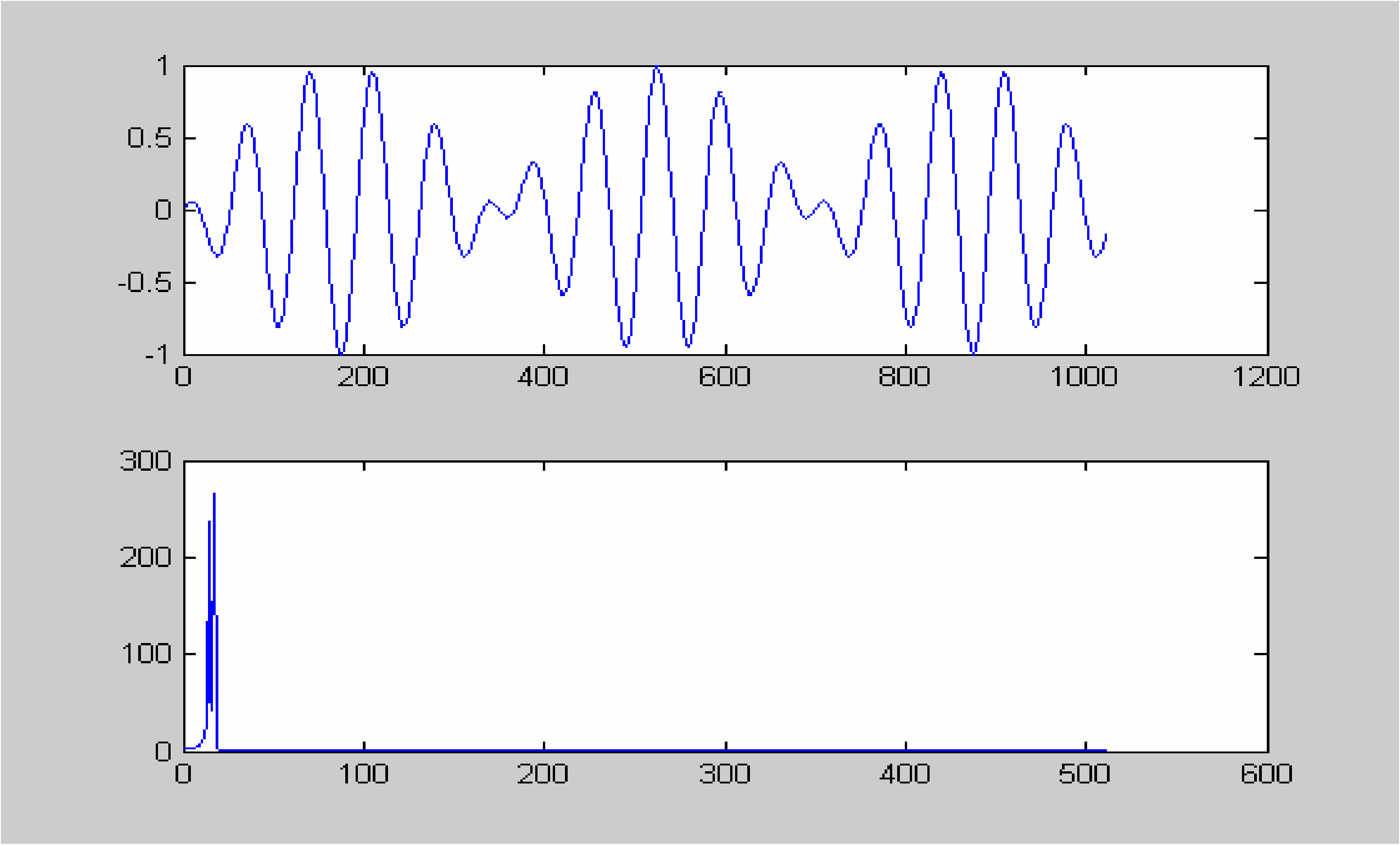
$$a(t) = m(t) \qquad\qquad \phi(t) = 0$$

瞬时幅度： $A(t) = |m(t)|$

瞬时相位： $\theta(t) = \begin{cases} 2\pi f_c & m(t) \geq 0 \\ 2\pi f_c + \pi & m(t) < 0 \end{cases}$

非线性分量： $\varphi(t) = \begin{cases} 0 & m(t) \geq 0 \\ \pi & m(t) < 0 \end{cases}$

$$m(t) = \sin(2\pi f_m t)$$



（4）SSB信号：

$$s(t)=m(t)\cos(2\pi f_c t)+\widehat{m}(t)\sin(2\pi f_c t) \qquad (\text{LSB})$$

$$s(t)=m(t)\cos(2\pi f_c t)-\widehat{m}(t)\sin(2\pi f_c t) \qquad (\text{USB})$$

瞬时幅度： $A(t)=\sqrt{m^2(t)+\widehat{m}^2(t)}$

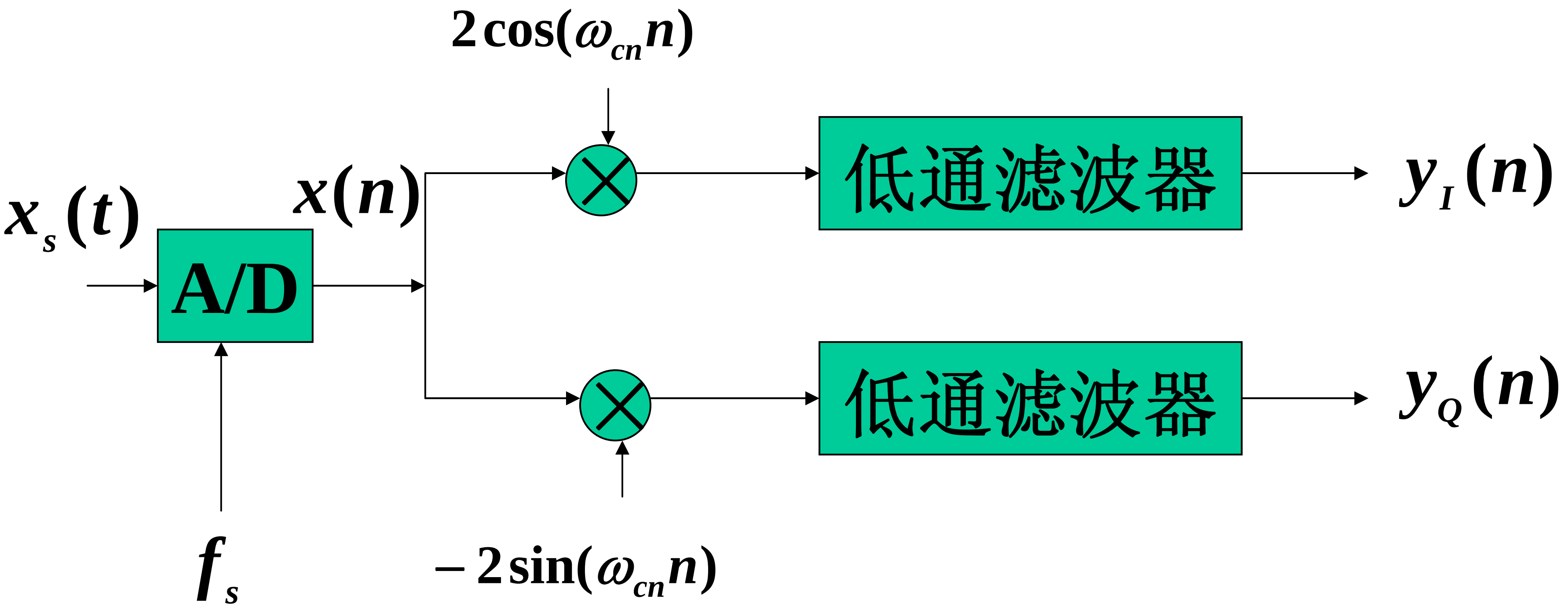
瞬时相位： $\theta(t)=2\pi f_c t+\arctan\left(\dfrac{\hat{m}(t)}{m(t)}\right) \qquad (\text{LSB})$

$$\theta(t)=2\pi f_c t-\arctan\left(\frac{\hat{m}(t)}{m(t)}\right) \qquad (\text{USB})$$

非线性分量： $\varphi(t)=\arctan\left(\dfrac{\hat{m}(t)}{m(t)}\right) \qquad (\text{LSB})$

$$\varphi(t)=-\arctan\left(\frac{\hat{m}(t)}{m(t)}\right) \qquad (\text{USB})$$

信号的正交变换



$\omega_{cn} = 2\pi f_c / f_s$ 已知

瞬时幅度：$A(n)=\sqrt{y_I^2(n)+y_Q^2(n)}$

瞬时相位：$\theta(n)=\arctan\left(\dfrac{y_Q(n)}{y_I(n)}\right)$

当载频完全已知时，瞬时相位的非线性分量 $\varphi(n)$ 等于瞬时相位 $\theta(n)$

瞬时频率：$f(n)=\dfrac{\theta(n)-\theta(n-1)}{2\pi T_s}$ （需要解混叠）

对于模拟调制方式识别，需要以下四个特征参数

（1）零中心归一化瞬时幅度谱密度的最大值

$$\gamma_{\max} = \max|DFT(A_{cn}(i))|^2 / N$$

其中： N 为采样点数

$$A_{cn}(i) = A_n(i) - 1$$

$$A_n(i) = \frac{A(i)}{m_a} \qquad m_a = \frac{1}{N}\sum_{i=1}^{N} A(i)$$

$\gamma_{\max}$ 用于判断信号的幅度调制信息。

区分：FM || AM、DSB、LSB、USB

（2）零中心瞬时相位非线性分量绝对值的标准差

$$\sigma_{ap}=\sqrt{\frac{1}{C}[\sum_{A_n(i)>a_t}\varphi_{NL}^2(i)]-[\frac{1}{C}\sum_{A_n(i)>a_t}\left|\varphi_{NL}(i)\right|]^2}$$

其中 a_t 是归一化瞬时幅度的门限，当 $A_n(i)$ 大于门限时，可以认为该时刻的数据属于强信号段，否则属于弱信号段。在弱信号段，瞬时相位对噪声很敏感。C 为强信号段中数据个数。

$$\varphi_{NL}(i)=\varphi(i)-\frac{1}{N}\sum_{i=1}^{N}\varphi(i)$$

区分： AM、DSB || LSB、USB

（3）零中心瞬时相位非线性分量的标准差

$$\sigma_{dp}=\sqrt{\frac{1}{C}\left[\sum_{A_n(i)>a_t}\varphi_{NL}^2(i)\right]-\left[\frac{1}{C}\sum_{A_n(i)>a_t}\varphi_{NL}(i)\right]^2}$$

其中 a_t 是归一化瞬时幅度的门限，当 $A_n(i)$ 大于门限时，可以认为该时刻的数据属于强信号段，否则属于弱信号段。在弱信号段，瞬时相位对噪声很敏感。C 为强信号段中数据个数。

$$\varphi_{NL}(i)=\varphi(i)-\frac{1}{N}\sum_{i=1}^{N}\varphi(i)$$

区分：**AM || DSB**

（4）信号频谱关于载波频率对称性的度量

$$P = \frac{P_L - P_U}{P_L + P_U}$$

P_L 是信号功率谱的下边带

$$P_L = \sum_{i=1}^{N_c - 1} |S(i)|^2$$

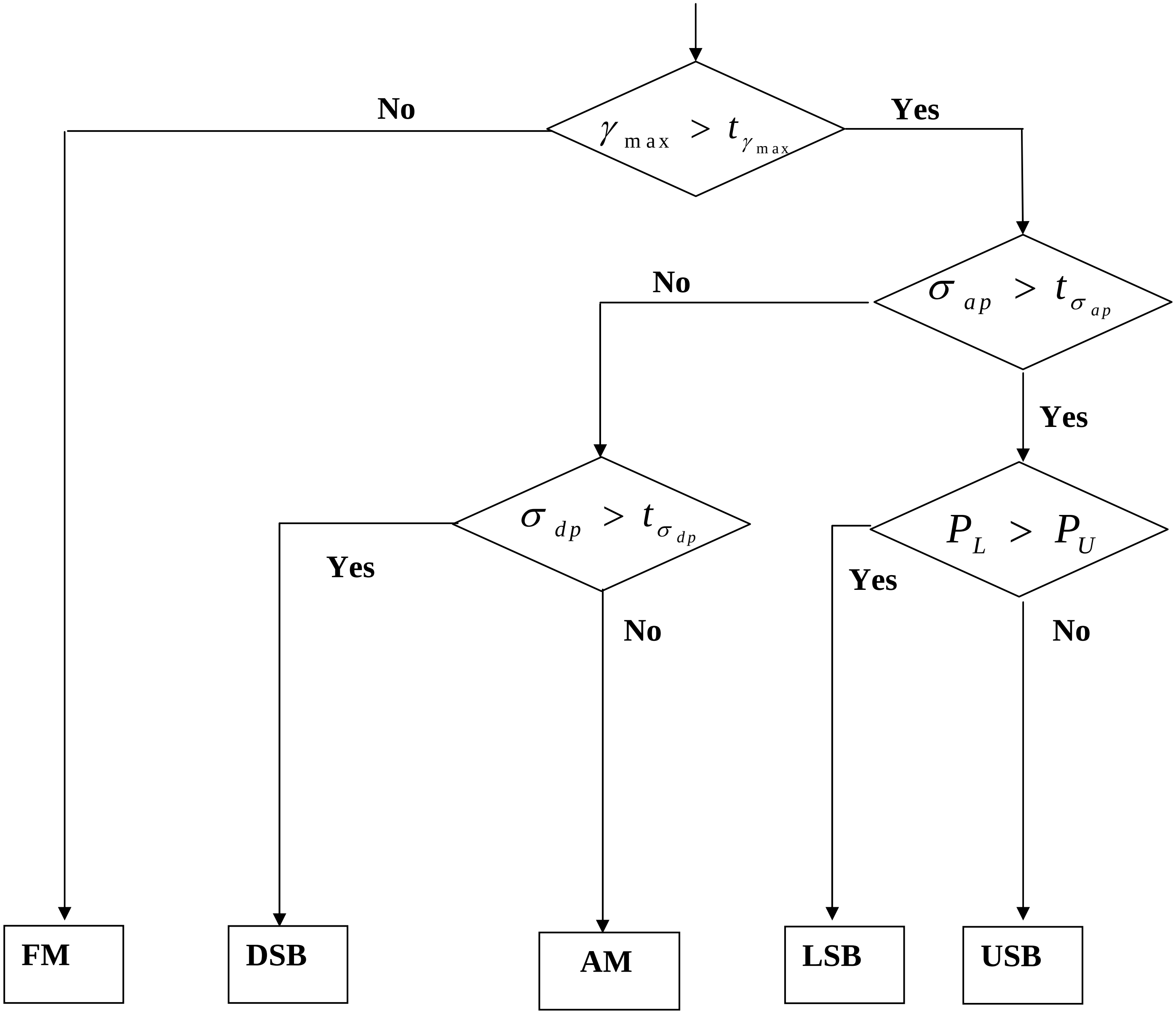
P_H 是信号功率谱的上边带

$$P_H = \sum_{i=1}^{N_c - 1} |S(i + N_c)|^2$$

$$N_c = f_c N / f_s$$

$S(i)$ 是中频信号 $s(n)$ 的 DFT。

利用 P_L 和 P_H 区分：USB || LSB



$\gamma_{max} > t_{\gamma_{max}}$
No
Yes
$\sigma_{ap} > t_{\sigma_{ap}}$
No
Yes
$\sigma_{dp} > t_{\sigma_{dp}}$
Yes
No
$P_L > P_U$
Yes
No
FM
DSB
AM
LSB
USB

模拟调制方式识别

3. 数字调制方式的识别

数字调制信号主要包括有：2ASK、4ASK、2FSK、4FSK、BPSK和QPSK。

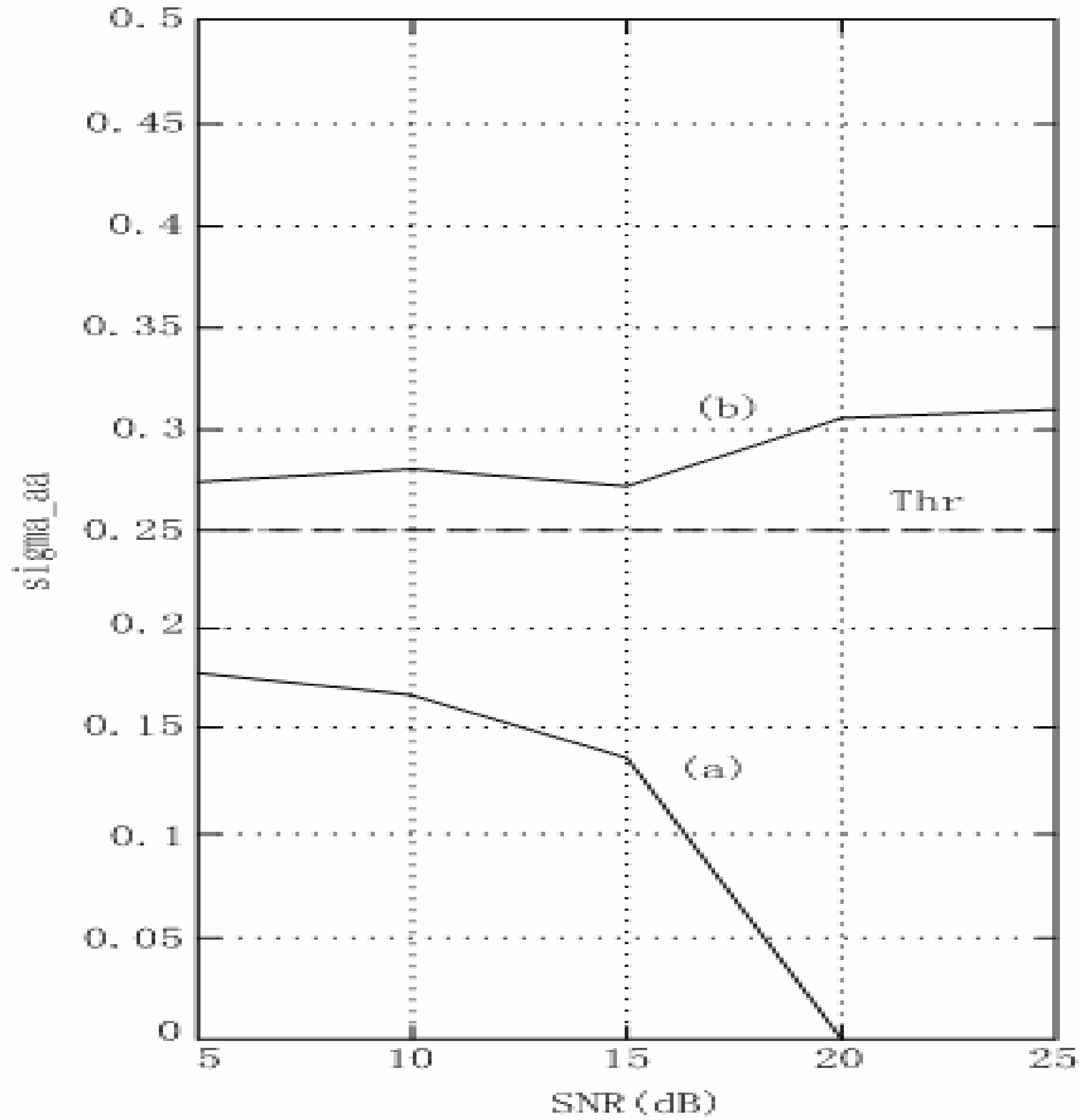
用于数字调制信号自动识别的特征参数除了前面用于模拟调制信号识别的前3个参数外，还需要再加上以下2个特征参数：

（1）零中心归一化瞬时幅度绝对值的标准偏差

$$\sigma_{aa}=\sqrt{\frac{1}{N}\left(\sum_{i=1}^{N}A_{cn}^{2}(i)\right)-\left(\frac{1}{N}\sum_{i=1}^{N}|A_{cn}(i)|\right)^{2}}$$

因为2**ASK**信号零中心归一化的瞬时幅度在+0. 5, −0. 5两个电平间变动，于是它的绝对值是恒定的，不具有绝对的幅度信息。而另一方面，4**ASK**调制信号同时具有绝对和直接的幅度调制信息。因此可以作为两种调制类型的判决特征。

区分：**2ASK || 4ASK**


0.5
0.45
0.4
0.35
0.3
0.25
0.2
0.15
0.1
0.05
0
sigma_aa
(b)
Thr
(a)
5
10
15
20
25
SNR (dB)

(a) 2ASK (b) 4ASK

（2）零中心归一化非弱信号瞬时频率绝对值的标准偏差

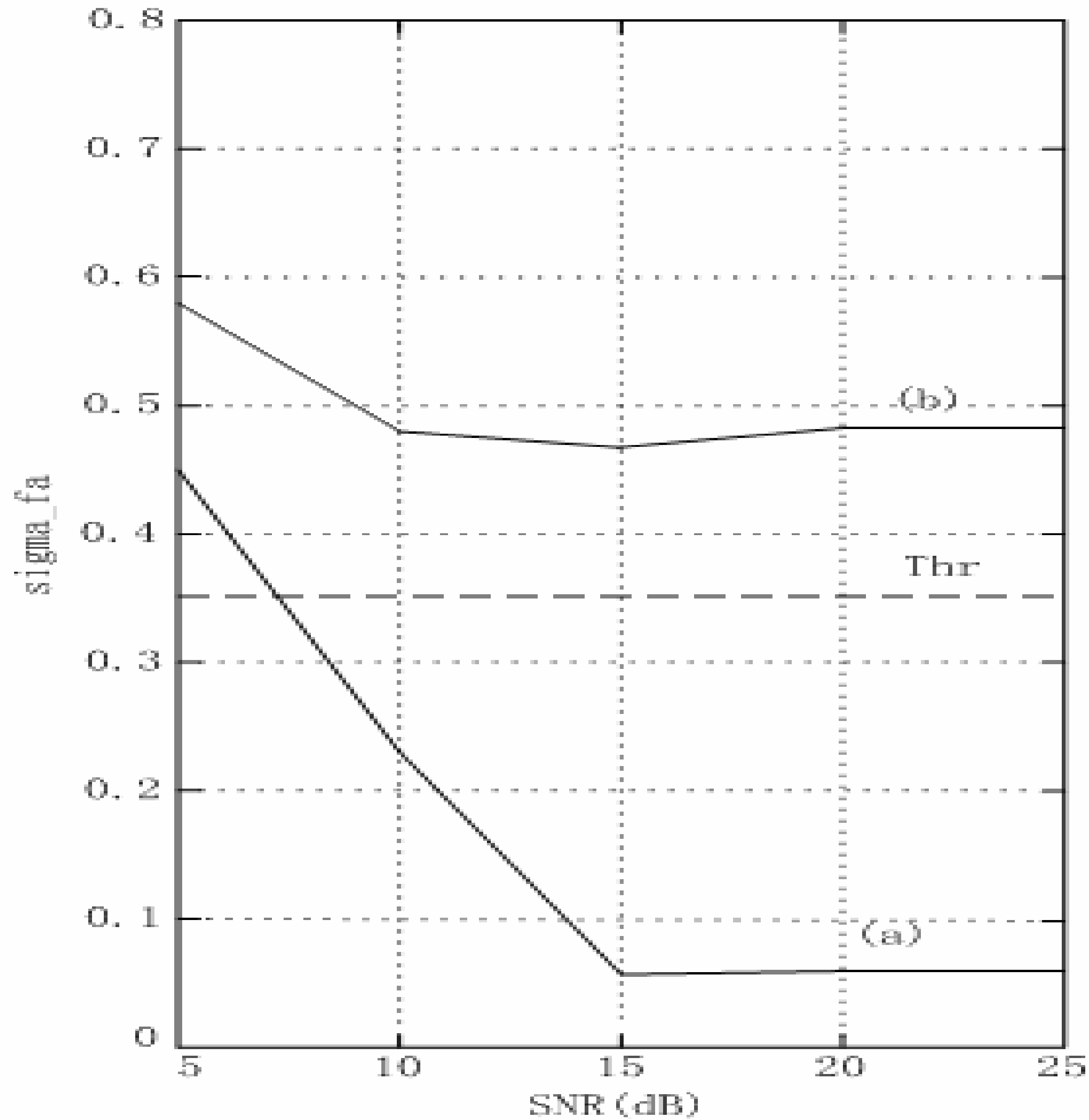
$$\sigma_{fa}=\sqrt{\frac{1}{C}\left(\sum_{A_n(i)>a_t} f_N^{\ 2}(i)\right)-\left(\frac{1}{C}\sum_{A_n(i)>a_t}|f_N(i)|\right)^2}$$

其中 $f_N(i)=f_c(i)/r_b$ $\quad f_c(i)=f(i)-m_f$

$$m_f=\frac{1}{N}\sum_{i=1}^{N} f(i)$$

r_b 为符号速率

区分：2FSK || 4FSK

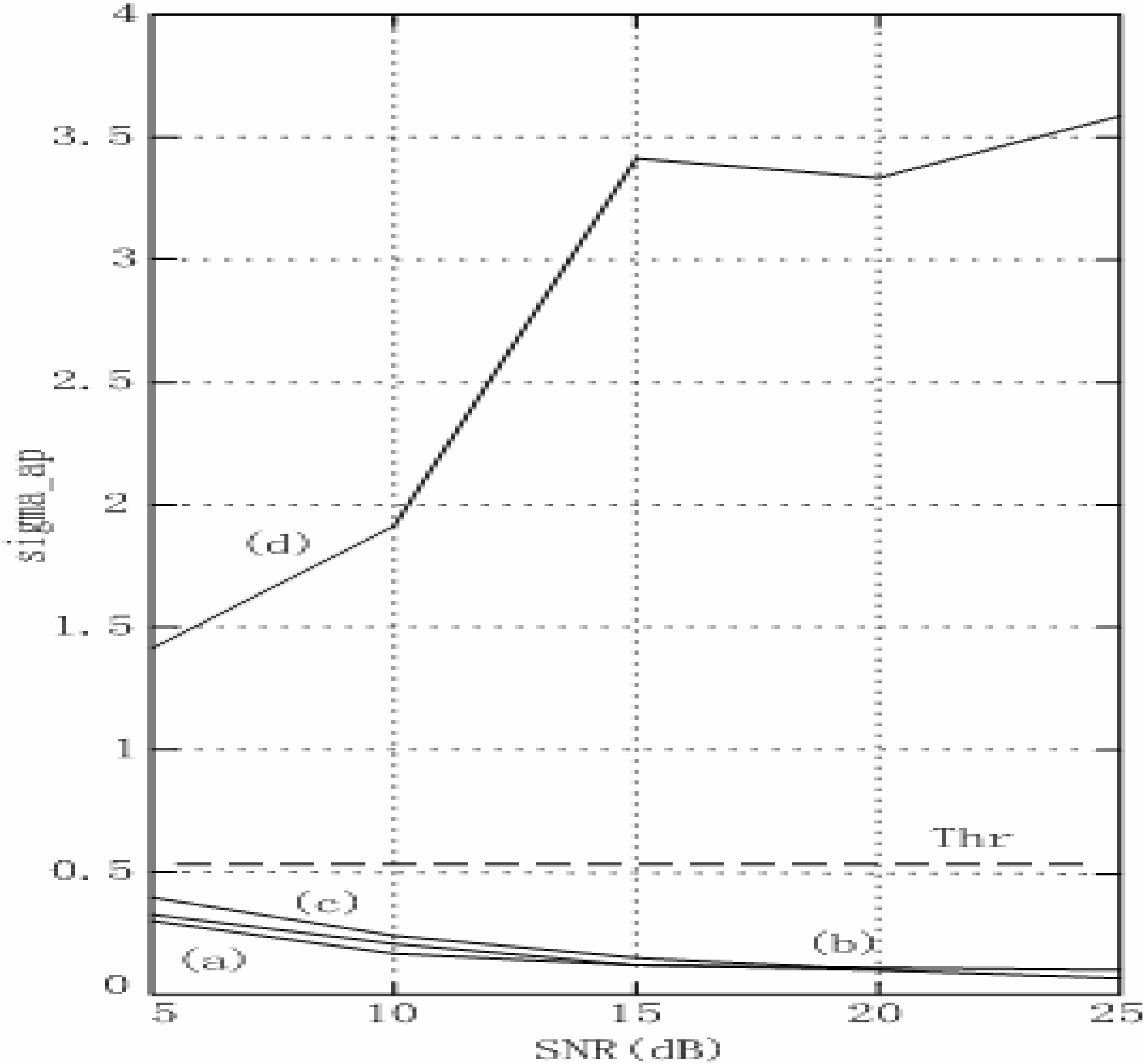


（a）2FSK （b）4FSK

σ_{ap} 可以把(2**ASK**、4**ASK**、2**PSK)**和4**PSK**信号区分开。

对于2**ASK**、4**ASK**调制信号来说，并不含有绝对相位信息。对于2**PSK**信号，其相位为**0**或者π，因此其绝对值取平均得到 π**/2**，4**PSK**调制信号既有绝对的相位信息，也有直接的相位信息。因此该特征量可以将该集合分为**{2ASK**、4**ASK**、2**PSK}{4PSK}**两个集合。

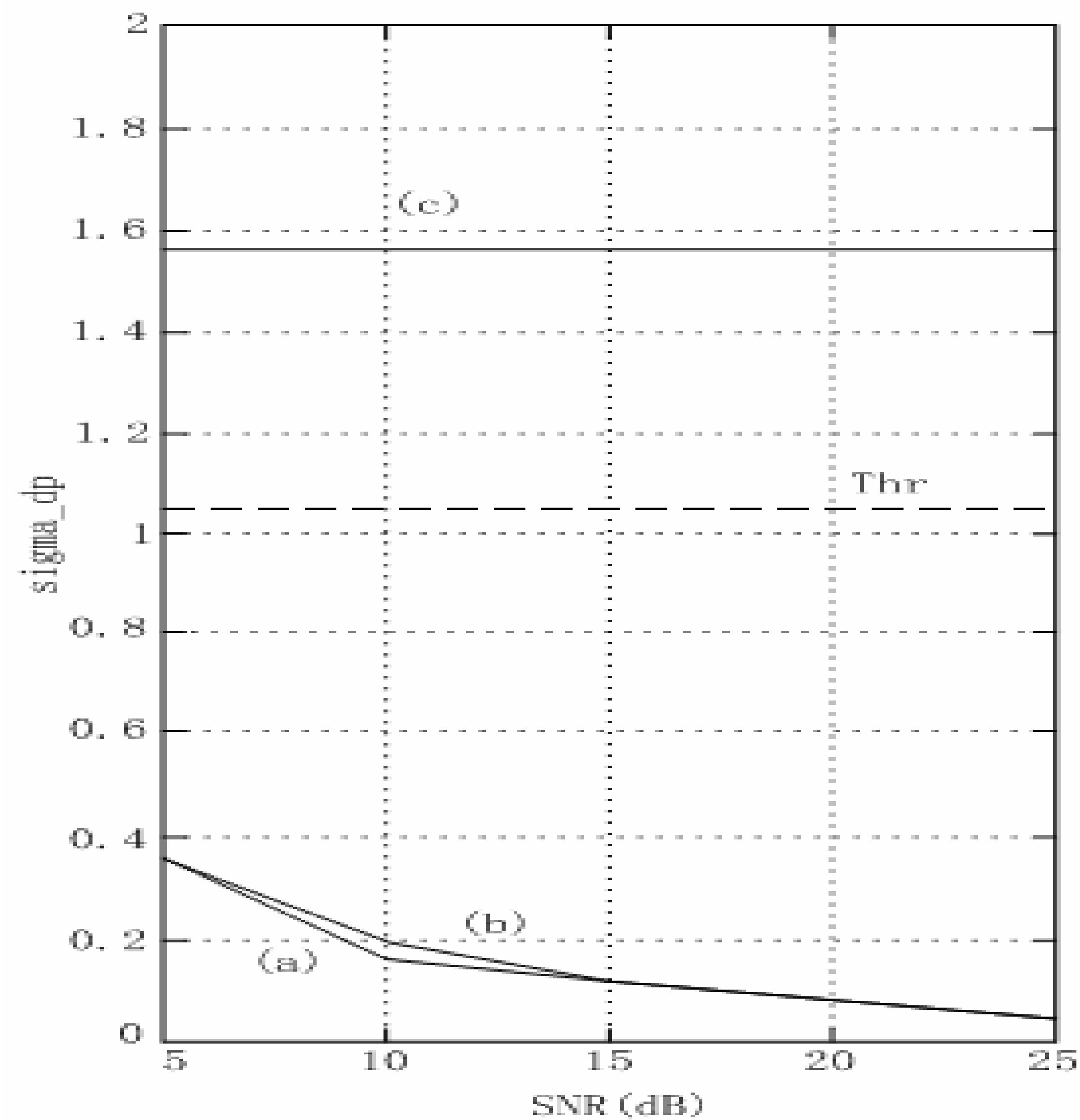
区分：4PSK || 2ASK、4ASK、2PSK



（a）2ASK （b）4ASK （c）2PSK （d）4PSK

σ_{dp} 可以把（**2ASK**、**4ASK**）与**2PSK**信号区分开。**2ASK**、**4ASK**本身并没有直接相位信息，**2PSK**信号则有直接相位信息。

区分：**2PSK || 2ASK、4ASK**

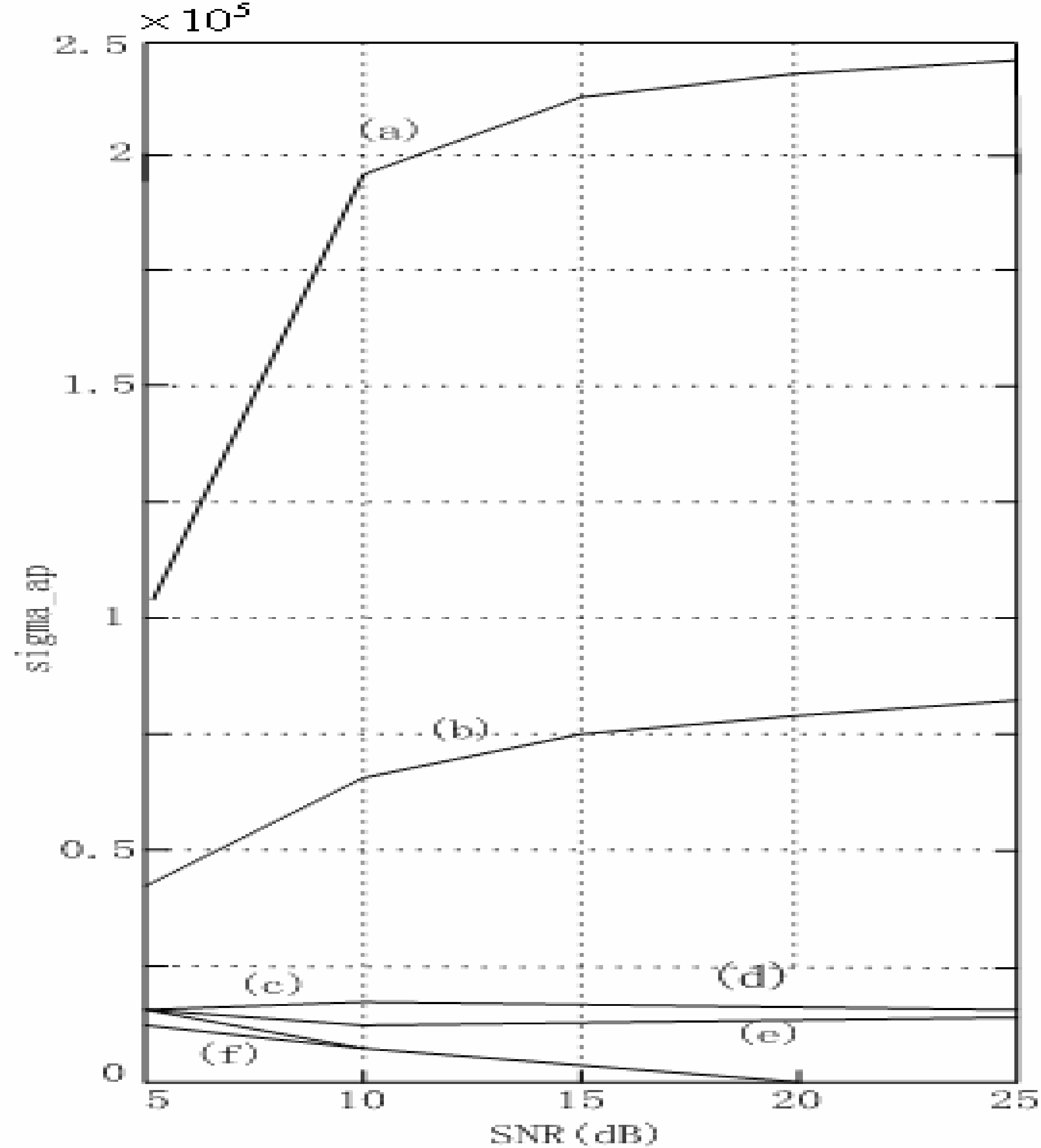


（a）2ASK （b）4ASK （c）2PSK

γ_{max} 可以把（2**FSK, 4FSK**）与（2**ASK, 4ASK, 2PSK, 4PSK**）区分开。

因为2**FSK**与4**FSK**具有恒定的瞬时幅度，它们的归一划瞬时中心幅度为零，因此其功率谱为零，即他们本身不含有幅度信息。而另一方面，2**ASK**，4**ASK**含有幅度信息， **PSK**信号的限带效应也具有幅度调制信息。

区分：**2FSK、4FSK || 2ASK、4ASK、2PSK、4PSK**



（a）2ASK

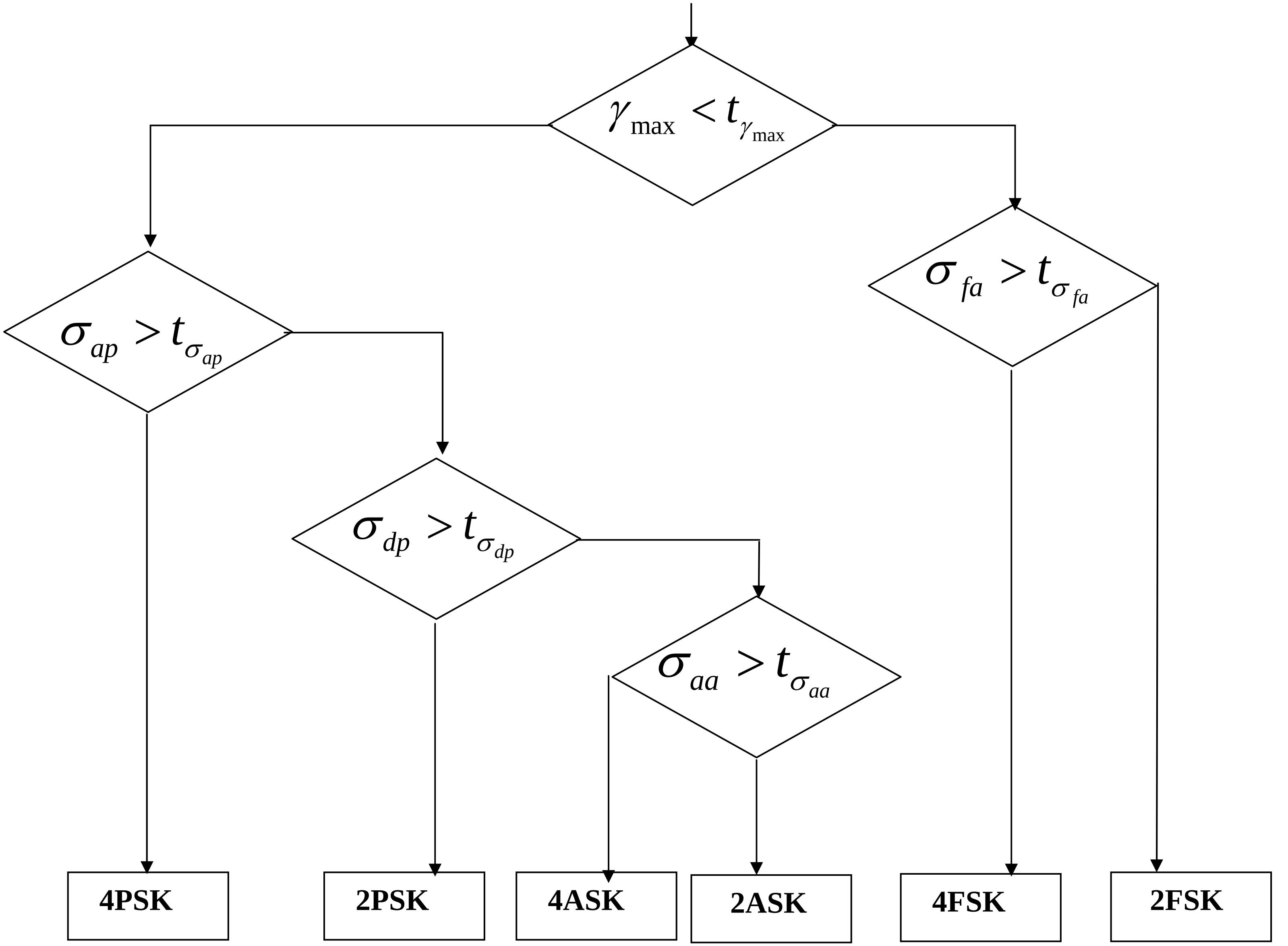
（b）4ASK

（c）2PSK

（d）4PSK

（e）2FSK

（f）4FSK


$\gamma_{\max} < t_{\gamma_{\max}}$
$\sigma_{ap} > t_{\sigma_{ap}}$
$\sigma_{fa} > t_{\sigma_{fa}}$
$\sigma_{dp} > t_{\sigma_{dp}}$
$\sigma_{aa} > t_{\sigma_{aa}}$
4PSK
2PSK
4ASK
2ASK
4FSK
2FSK

数字调制方式识别

4. 模拟、数字调制信号的联合自动识别

假设所需识别的信号调制就是前面介绍的模拟调制和数字调制类型的总和，共**11**种即：**AM**、**FM**、**DSB**、**LSB**、**USB**、**2ASK**、**4ASK**、**2FSK**、**4FSK**、**2PSK**、**4PSK**。用于模拟数字调制信号联合自动识别的特征参数除前面已介绍的**6**种特征参数，还需要增加以下3种新的特征参数。

σ_a --零中心归一化非弱信号段瞬时幅度的标准偏差

$$\sigma_a = \sqrt{\frac{1}{C}[\sum_{a_n(i)>a_t} A^2{}_{cn}(i)] - [\frac{1}{C}\sum_{a_n(i)>a_t} A_{cn}(i)]^2}$$

σ_a 主要用来区分是**DSB**信号还是**2PSK**信号。因为对于**2PSK**信号，无幅度调制信息（除了在相邻符号变化时刻），所以 $\sigma_a \approx 0$;而对**DSB**信号, 含有幅度调制信息，故 $\sigma_a \neq 0$ 。这样可以通过设置合理的判决门限

$t(\sigma_a)$ 来判别**DSB**信号还是**2PSK**信号。

μ_{42}^{a} --零中心归一化瞬时幅度的紧致性（四阶矩）

$$\mu_{42}^{a}=\frac{E\left\{A_{cn}^{4}(i)\right\}}{\left\{E\left[A_{cn}^{2}(i)\right]\right\}^{2}}$$

μ_{42}^{a} 主要用来区分是**AM**信号还是**ASK**信号。因为对**AM**信号，其瞬时幅度具有较高的紧致性， 即 μ_{42}^{a}值较大，而对**ASK**信号由于只有**2**个或者**4**个电平值，其紧致性较差，即 μ_{42}^{a} 值较小。所以可以通过设置一个适当门限 $t(\mu_{42}^{a})$ 来判别是**AM**信号还是**ASK**信号。

μ_{42}^{f} --零中心归一化瞬时频率的紧致性（四阶矩）

$$\mu_{42}^{f} = \frac{E\left\{f_N^{4}(i)\right\}}{\left\{E\left[f_N^{2}(i)\right]\right\}^{2}}$$

μ_{42}^{f}主要用来区分**FM**信号还是**FSK**信号。 因为对**FM**信号，其瞬时频率具有较高的紧致性，即值 μ_{42}^{f} 较大，而对**FSK**信号其瞬时频率只有**2**个或者**4**个值，其紧致性较差，即 μ_{42}^{f} 较小。

5. Maximum Likelihood Classification

5.1 Signal Model

Complex envelope of the observed waveform:

$$r(t) = s(t) + w(t), \qquad 0 \le t \le NT_s$$

where

T **is the symbol duration**

N **is the number of observed symbols.**

***w*(*t*) is assumed to be white and Gaussian with two-sided power spectral density $N_0/2$**

$$s(t) = \sqrt{2S}\sum_{n=0}^{N-1} a_n^{(k)} p(t - nT) e^{j\theta_0}$$

Assuming perfect knowledge of symbol duration, timing epoch and carrier frequency, the matched filter output has the form

$$r_n = \sqrt{E}a_n^{(k)}e^{j\theta_0} + w_n, \qquad n = 0,\dots, N-1$$

5.2 Maximum Likelihood Classification with carrier phase known

Multiple hypothesis testing problem:

$$\mathrm{H}_k: \qquad \mathbf{r} = \sqrt{E}\, e^{j\theta_0} \mathbf{a}^{(k)} + \mathbf{w}, \qquad k = 1, \ldots, K$$

where

$$\mathbf{r} = [r_0 \cdots r_{N-1}]^{\mathrm{T}}$$

$$\mathbf{a} = [a_0^{(k)} \cdots a_{N-1}^{(k)}]^{\mathrm{T}}$$

$$\mathbf{w} = [w_0 \cdots w_{N-1}]^{\mathrm{T}}$$

When unknown parameters are modeled as random variables and their joint pdf is known, the pdf of r_n**, conditioned on** H_k**, is**

$$f\left(r_n / \mathrm{H}_k\right) = \sum_{a_n^{(k)}} f\left(r_n / a_n^{(k)}, \mathrm{H}_k\right) P\left(a_n^{(k)} / \mathrm{H}_k\right)$$

$$f\left(r_n / \mathrm{H}_k\right) = \sum_{a_n^{(k)}} f\left(r_n / a_n^{(k)}, \mathrm{H}_k\right) P\left(a_n^{(k)} / \mathrm{H}_k\right)$$

where

$$f\left(r_n / a_n^{(k)}, \mathrm{H}_k\right) = \frac{1}{\pi N_0} \exp\left(-\frac{\left| r_n - \sqrt{E} a_n^{(k)} e^{j\theta_0} \right|^2}{N_0} \right)$$

$$P\left(a_n^{(k)} / \mathrm{H}_k\right) = \begin{cases} \dfrac{1}{M_k}, & a_n \in A^{(k)} = \left\{ b_1^{(k)}, \ldots, b_{M_k}^{(k)} \right\} \\ 0, & otherwise \end{cases}$$

$$f\left(r_n / \mathrm{H}_k\right) = \sum_{m=1}^{M_k} \frac{1}{M_k \pi N_0} \exp\left(-\frac{\left| r_n - \sqrt{E} b_m^{(k)} e^{j\theta_0} \right|^2}{N_0} \right)$$

Assuming that the data from different symbols are independent, the log-likelihood function is

$$\ln\left[f\left(\mathbf{r} / \mathrm{H}_k\right)\right] = \ln\left[\prod_{n=0}^{N-1} f\left(r_n / \mathrm{H}_k\right)\right]$$

$$= \sum_{n=0}^{N-1} \ln \sum_{m=1}^{M_k} \frac{1}{M_k \pi N_0} \exp\left(-\frac{\left| r_n - \sqrt{E} b_m^{(k)} e^{j\theta_0} \right|^2}{N_0} \right)$$

after a constant factor is omitted,

$$\ln\left[f\left(\mathbf{r} / \mathrm{H}_k\right)\right] = \sum_{n=0}^{N-1} \ln \sum_{m=1}^{M_k} \frac{1}{M_k} \exp\left(-\frac{\left| \sqrt{E} b_m^{(k)} \right|^2 - 2\,\mathrm{Re}\left(\sqrt{E} r_n b_m^{*(k)} e^{-j\theta_0} \right)}{N_0} \right)$$

ML classification method chooses the hypothesis whose log-likelihood is maximized, i.e.

$$\hat{\mathrm{H}}_k = \arg\max_{\mathrm{H}_k} \ln\left[f\left(\mathbf{r} / \mathrm{H}_k\right)\right]$$