Paper

Fuzzy logic classifier for radio signals recognition

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Abstract — This paper presents a new digital modulation recognition algorithm for classifying baseband signals in the presence of additive white Gaussian noise. Elaborated classification technique uses various statistical moments of the signal amplitude, phase and frequency applied to the fuzzy classifier. Classification results are given and it is found that the technique performs well at low SNR. The benefits of this technique are that it is simple to implement, has generalization property and requires no apriori knowledge of the SNR, carrier phase or baud rate of the signal for classification.

Keywords — modulation recognition, fuzzy logic.

1. Introduction

The problem of automatic classification of the applied modulation type of a digital transmission has received international scientific attention for over a decade now.

An automatic modulation classifier is a system that automatically identifies the modulation type of the received signal. It is an intermediate step between signal interception and information recovery. When the modulation scheme of a received signal is identified, an appropriate demodulator can be selected to demodulate the signal and then recover the information.

Modulation type classifiers play an important role in some communication applications such as signal confirmation, interference identification, surveillance, monitoring, spectrum management, electronic warfare, military threat analysis, or electronic counter-counter measure [6].

In this paper, we propose a new pattern recognition approach based on various statistical characteristics of the signal amplitude, phase, and frequency. Theoretically, feature patterns should produce independent and isolated classes. In practice, the classes are overlapped and it is hard to classify observed pattern to only one class. In such a case, there is a need to specify the grade of membership to each class. This method is naturally implemented as a fuzzy classifier.

Extracted features are applied to the Mamdani fuzzy classifier [4]. Chosen features create a low order modulation type model. This increases the generalization capability of the model, reduce computational complexity, simplify fuzzy rules and improve decision process.

In Section 2, we give signal model and problem formulation. In Section 3, the feature extraction process is shown and in Section 4 the classification algorithm is discussed. Section 5 illustrates the experimental results and conclusions are presented in Section 6.

2. Signal models

Let us assume knowledge of the carrier frequency. Received baseband signal can be expressed as

$$s(t) = x(t)e^{j\Theta_c} + n(t)\ , \tag{1}$$

where Θ_c is the carrier phase and $n(t)$ is a complex white Gaussian noise.

For quadrature amplitude modulation (QAM) signals,

$$x_{QAM}(t) = \sum_{i=1}^{N}(A_i + jB_i)u(t - iT), \tag{2}$$

where $A_i, B_i \in \{2m-1-M,\, m = 1,2,\ldots,M\}$. When B_i in Eq. (2) is zero, then QAM signal becomes amplitude shift keying (ASK) signal.

For phase shift keying (PSK) signals,

$$x_{PSK}(t) = \sqrt{S}\sum_{i=1}^{N} e^{j\varphi_i}u(t - iT), \tag{3}$$

where $\varphi_i \in \{\frac{2\pi}{M}(m-1),\, m = 1,2,\ldots,M\}$.

For frequency shift keying (FSK) signals,

$$x_{FSK}(t) = \sqrt{S}\sum_{i=1}^{N} e^{j(\omega_i t + \Theta_i)}u(t - iT), \tag{4}$$

where $\omega_i \in \{\omega_1, \omega_2, \ldots, \omega_M\}, \Theta_i \in (0, 2\pi)$.

In Eqs. (2), (3) and (4), S is the signal power, N is the number of observed symbols, T is the symbol duration and $u(t)$ is the pulse shape of duration T.

3. Feature extraction

On the basis of Eqs. $(2 \div 4)$, one can see that for specific modulation type, one or more parameters are being changed. In ASK case – amplitude is being modulated, for FSK signals – frequency, QAM is the case where both amplitude and phase are being changed. Number of parameters and the way in which they are changed are specific to each modulation type. They may be described by a set of statistical parameters related to its moments and distributions. After initial selections we have chosen three of them as most comprehensive way of signal description.

The first feature we propose to use is a kurtosis of a signal envelope. Kurtosis is a measure of how outlier-prone the distribution is. The kurtosis of the normal distribution is 3. Distributions that are more outlier-prone than the normal distribution have kurtosis greater than 3, distributions that are less outlier-prone have kurtosis less than 3. Theoretically, the envelope distribution of PSK and FSK signals is a Rician distribution. In practice, this distribution may be approximated by Gaussian distribution for SNR > 10 dB. In that case, kurtosis for these signals will be approximately equal 3. If we receive ASK signal, envelope distribution will be a mixture of Rayleigh and Rician distribution, and kurtosis will be approximately 1. In M-ary ASK and QAM cases, distributions will be a combination of distributions given above.

Second feature we extract from the phase histogram of the analyzed signal. One well-known asymptotic expression of a phase probability density function (PDF) under assumption that $\sigma_w \to 0$ is a Tikhonov probability density function:

$$f_\phi(\phi_0) \cong \frac{exp\left[2\gamma\cos(\phi_0)\right]}{2\pi I_0(2\gamma)}; \ -\pi < \phi_0 \le \pi; \ \gamma = \frac{A^2}{2\sigma_w^2}\,, \quad (5)$$

where σ_w is the noise standard deviation, $I_0[\cdot]$ is the zero-order modified Bessel function of the first kind. The approximation in (5) is considered good for values of $\gamma > 6$ dB and is considered fair for γ around 0 dB. For M-ary PSK signals, $M = 2^\alpha, \alpha = 0,1,2...$, the PDF of ϕ_α is a sum of the noncentral Tikhonov functions [6]:

$$f_\phi(y;\alpha) = \frac{1}{2^\alpha}\sum_{k=1}^{2^\alpha}\frac{exp\{[2\gamma\cos[y-\eta_k(\alpha)]\}}{2\pi I_0(2\gamma)}\,, \qquad (6)$$

where $\eta_k(\alpha)$ is the phase of k-th phase state and can be expressed as

$$\begin{aligned} \eta_k(\alpha) &= \frac{(2k - 2^\alpha - 1)}{2^\alpha}\,, \\ k &= 1,2,\ldots,2^\alpha\,, \\ \alpha &= 0,\ldots,\log_2 M\,. \end{aligned}$$

The number of peaks in the phase PDF, indicates the number of signal phase states. Generally, $f_\phi(y;\alpha)$ approaches $1/2\pi$ for SNR $\to -\infty$ dB or $\alpha \to \infty$. When we compute FFT magnitude of the phase histogram, it is easily seen that for M-ary PSK and QAM signals there are spectral lines that indicates M-ary number. For ASK and FSK signals, there are no spectral lines and the power spectral density (PSD) is much smoother. If we compute derivative of that PSD, this effect will be more visible. Figure 1 shows both: PSD and its derivative for ASK and 4DPSK signals. If in the received signal, phase is a parameter being modulated (PSK, QAM), the variance of the PSD derivative should be large. In the other case (ASK, FSK), variance should be smaller.

Third feature we propose is a mean signal frequency. Suppose that the receiver is tuned to signal center frequency. Digitally modulated signals we can model as a set of complex exponentials. In this case, one can estimate signal PSD by Burg's method [3]. This method fits an autoregressive (AR) model to the signal by minimizing the forward and backward prediction errors while constraining the AR parameters to satisfy the Levinson-Durbin recursion. The PSD estimated in this way is much smoother than estimated by nonparametric methods (Welch, FFT), and the spectrum consists only the meaningful part of the signal. This meaningful part means surroundings of the carier frequencies

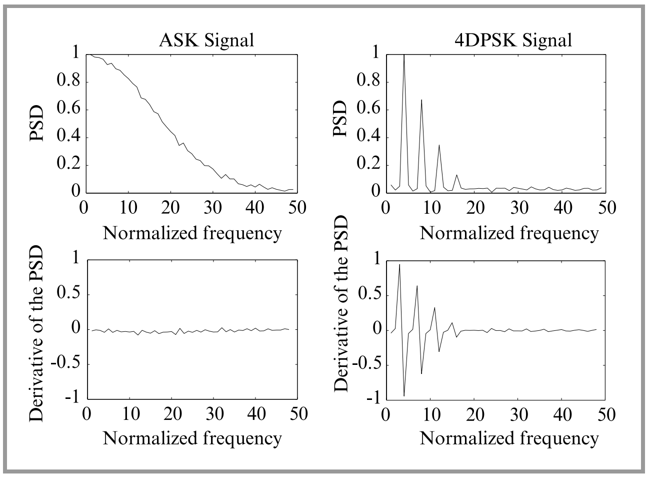

Fig. 1. PSD and its derivative (ν = 200 Bd; SNR = 15 dB).

in ASK, PSK and QAM signals. If the assumption concerning proper tuning of the receiver is reached, then the mean of the absolute value of instantaneous frequency is approximately zero for ASK, PSK, and QAM signals, and is larger for FSK and MSK signals. Its value depends on the symbol rate and the frequency deviation.

These features create overlapped classes, and it is hard to say what means for example "large variance". To solve this problem, we conducted experiments to define the membership functions for each feature. There are three membership functions for the amplitude, two for the phase, and two for the frequency feature. We also defined membership functions for the classifier output. This output produces fuzzy decisions.

Applied modulation type may be in some degree ASK, PSK or FSK. Membership functions used for the inputs are sigmoidal:

$$f(x,a,c) = \frac{1}{1+e^{-a(x-c)}}\,, \qquad (7)$$

where a is the stretch parameter, and c is the mean parameter.

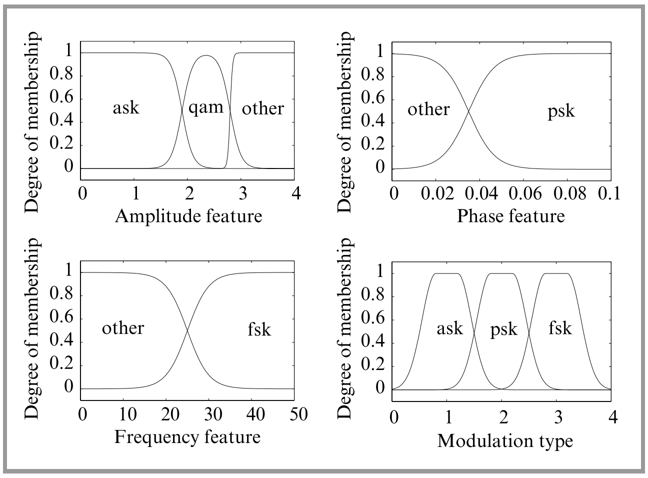

Fig. 2. Membership functions for the inputs and the output.

Membership function for the output is a generalized bell-shaped one:

$$f(x,a,b,c) = \frac{1}{1+|\frac{x-c}{a}|^{2b}}\ , \tag{8}$$

where c locates the center of the curve, a is the stretch parameter, and b is related to its width. Figure 2 shows all these membership functions for the inputs and the output.

4. Classification

After the features are extracted, the classification process can be applied. Because membership functions overlap each other, the fuzzy rules of classification and inference were used.

We constructed five rules to specify which modulation type has been applied in the received signal. We also used symbolic descriptions for the features and for the fuzzy sets. *A, ϕ, ω* are the features extracted from signal envelope, phase and frequency, whereas *ask, psk, qam, fsk, mfsk* and *other* are fuzzy sets associated with appropriate membership functions. The proposed rules are as follows:

If (A is ask) and ϕ is other) and (ω is other) then (type is ask)
If (A is qam) and (ϕ is psk) and (ω is other) then (type is ask)
If (A is qam) and (ϕ is psk) and (ω is other) then (type is psk)
If (A is other) and (ϕ is psk) and (ω is other) then (type is psk)
If (A is other) and (ϕ is other) and (ω is fsk) then (type is mfsk)

Weighting coefficients for these rules are assumed: 1, 0.5, 0.5, 1 and 1 respectively. The classifier is based on Mamdani fuzzy classifier [4] with following parameters:

- AND method: PROD;
- IMPLICATION method: MIN;
- AGGREGATION method: PROBOR;
- DEFUZZYFICATION method: CENTROID.

The answer of the classifier can be given either as the single output or as three-output. Single output gives the number, which indicate what type of modulation has been applied. This value ranging from 0 to 4, where 1 corresponds to ASK signal, 2 to PSK signal, 3 to FSK signal and combined modulation types are indicated as an intermediate numbers (i.e. QAM may be represented as 1.5). The three-output answer gives three numbers, which specify the degree of membership of the three basic modulation types (i.e. QAM may be represented as: 0.5, 0.5, 0).

5. Experimental results

In this section, we demonstrate the performance of the suggested algorithm. Our goal is to discriminate between ASK, 4DPSK, 16QAM and FSK signals. We assume that we have 8000 samples of the complex signal, sampling frequency is 8 kHz, baud rate is 200 Bd and in FSK case – frequency shift is orthogonal. We use three-output classifier answer, and four signals for tests (ASK, 4DPSK, 16QAM and FSK).

As we increase SNR, the performance of the classifier improves. For SNR $>$ 5 dB, the classifier output is very good. When SNR is less than 5 dB then classifier performance is getting worse. The worst results we get for the 16QAM case: when SNR = 0 dB, then analysed signal is classified as a PSK signal. We have to notice that classifier was trained only for SNR $>$ 5 dB (for distinguishing membership functions), and its behavior for SNR $<$ 5 dB results from its generalization property. Table 1 shows simulation results of estimated correct classification probabilities versus SNR for four tests signals and 100 repetitions.

Table 1
Probability of correct recognition versus SNR

SNR [dB]	0	2	4	6	8	10
ASK	0.91	0.99	1.00	1.00	1.00	1.00
4DPSK	0.85	0.90	0.95	0.98	1.00	1.00
16QAM	0.00	0.31	0.73	0.95	0.99	1.00
FSK	0.99	1.00	1.00	1.00	1.00	1.00

6. Conclusions

In this paper a new method for the automatic modulation classification of ASK, PSK, QAM and FSK signals has been presented. This method requires no apriori knowledge of the SNR, carrier phase, or baud rate of the signal. Simulation results proved that the elaborated algorithm, using proposed set of the features is very robust with respect to SNR. The robustness of the classifier follows from its fuzzy structure. The cost of this achievement lies in the additional complexity of the inference process. Simulations showed that for SNR larger than 5 dB, classifier works properly. Soft decisions generated by the classifier carry two types of information: the applied modulation type and the degree of membership of this type. It can be used as a parameter in the next stage of the classification process, identification of the constellation shape and M-ary number in PSK and QAM signals or determining number of frequencies and shifts in FSK signals. It allows to create intelligent radio links, efficient monitoring and control systems.

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