

AN ALGORITHM OF DIGITAL MODULATION IDENTIFICATION BASED ON INSTANTANEOUS FEATURES

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ABSTRACT

Automatic modulation identification plays an important role in non-cooperative communication systems. An improved approach, based on instantaneous features and binary tree classifier has been proposed for the classification of Medium Frequency (IF) digital signals at low signal-to-noise ratio (SNR) situation. Mean filter was applied to suppress the noise and five new characteristic parameters such as m_{aa} , m_{af} , m_{ap} , r_{af} and m_{aa1} , were extracted for the classifying. It is shown that the proposed algorithm has better performance than the traditional approaches. Theoretical arguments are verified via extensive simulations. Simulation results indicate that the correct classification probability (P_{cc}) with proposed algorithm has been improved compared with the traditional method.

Keywords: *Modulation Identification, Instantaneous Features, Parameter Optimization, Decision Classification*

1. INTRODUCTION

Automatic digital communication signal recognition is a technique that recognizes the type of the received signals with some assumptions. It is widely used in military and civil domains, such as interference recognition, spectrum sensing, electronic confrontation, etc.

Generally, the methods for modulation type classification can be divided into two types: the statistical pattern recognition and the decision theory [1-2]. The statistical pattern recognition method suffers from less computational complexity compared with the decision theory, though it is sensitive to impairments like phase frequency offset. It can be divided into three main subsystems: the signal pre-processing subsystem, the feature extraction subsystem and the classifier subsystem. The former pre-processes the signal (e.g. noise reduction, carrier frequency estimation, symbol rate estimation, etc.), the second subsystem extracts the features (e.g. spectral characteristics, instantaneous characteristics, higher-order cumulants, etc.), and the last determines the membership of signal (e.g. neural networks, support vector machine (SVM), etc.) [3-10]. The method based on instantaneous features can be extracted easily and has strong practicality.

Many modulation classification techniques based upon instantaneous characteristics have been published in the literature. E.E. Azzoz and A.K. Nandi [11-13] solve the problem by using the instantaneous characteristics of IF modulation signals, but only works well at high signal-to-noise ratio (SNR). In order to improve the ability of noise reduction, wavelet de-noising was applied before extracting features, which needs decomposition signals firstly, then reconstructed signals with the proceed coefficients[14], but the processing is very complex and it is impossible for realizing in engineering.

It is known that instantaneous features have poor anti-noise ability, when the SNR is too low, the signal will be drowned in the noise which causes the difficulty in feature extraction. In order to solve the above problems, the de-noising method based on mean filter was applied. Five new features were extracted via the instantaneous characteristics. Lastly, different modulation schemes were discriminated using the binary tree classifiers. This paper is organized as follows: firstly the model of modulating signals is described in section 2. In section 3, we present the modulation recognition method, and simulation results are described. Finally, conclude the paper.

2.SIGNAL MODEL

The channel noise is assumed to be additive white Gaussian noise (AWGN). The received IF signals (ASK\FSK\PSK) can be defined as follows.

For MASK signals

$$x_{MASK}(t) = [\sum_n a_n g(t - nT_s)] \cos w_c t + n(t) \tag{1}$$

Where $g(t)$ is a pulse shaping function, T_s is a symbol duration, w_c is carrier frequency, a_n is the baseband signal ($a_n=0,1,\dots,M-1$), and $n(t)$ corresponds to a complex additive white Gaussian noise with zero mean and variance $N_0/2$.

For MFSK signals

$$x_{MFSK}(t) = A \exp(jw_n t) g(t - nT_s) \cos w_c t + n(t) \tag{2}$$

Where A is the unknown amplitude factor and w_n can be defined as follows

$$w_n \in \{(2m - 1 - M)\Delta w, m = 1, 2, \dots, M\} \tag{3}$$

Where Δw is the frequency offset of FSK signals?

For MPSK signals

$$x_{MPSK}(t) = A \exp(j\varphi_n) g(t - nT_s) \exp(j\theta_n) \cos w_c t + n(t) \tag{4}$$

Where θ_n is phase shift, and phase sequences defined as follows:

$$\varphi_n = \{\pi(2m + 1) / M, m = 0, 1, \dots, M - 1\} \tag{5}$$

3.MODULATION RECOGNITION METHOD

A. Instantaneous features and noise Restriction

The analytical form $z(t)$ of received signal $x(t)$ through Hilbert transform is

$$z(t) = x(t) + jH[x(t)] \tag{6}$$

And $H[x(t)]$ is

$$H[x(t)] = x \frac{1}{\pi} \int_{-\infty}^{+\infty} \frac{x(\tau)}{t - \tau} d\tau \tag{7}$$

$z(t)$ can be expressed in polar coordinates

$$z(t) = a(t) \cdot e^{j\varphi(t)} \tag{8}$$

The instantaneous amplitude $a(t)$ is

$$a(t) = \sqrt{\text{Re}^2[z(t)] + \text{Im}^2[z(t)]} = \sqrt{x^2(t) + H^2[x(t)]} \tag{9}$$

The instantaneous phase $\varphi(t)$ is

$$\varphi(t) = \arctan \left\{ \frac{\text{Im}[z(t)]}{\text{Re}[z(t)]} \right\} = \arctan \left\{ \frac{H[x(t)]}{x(t)} \right\} \tag{10}$$

The phase sequence contains the linear part, which is contributed by the carrier, and the nonlinear part, which is contributed by the baseband signal. The algorithms of phase unwrapping and linear programming are needed in estimating unwrapped instantaneous nonlinear phase [11].

The instantaneous frequency can be defined as follows

$$w(t) = \frac{d\varphi(t)}{dt} = \frac{d}{dt} \left\{ \arctan \left\{ \frac{H[x(t)]}{x(t)} \right\} \right\} = \frac{H'[x(t)]x(t) - x'(t)H[x(t)]}{[a(t)]^2} \tag{11}$$

Where

$$H'[x(t)] = \frac{d}{dt} \{H[x(t)]\} \tag{12}$$

$$x'(t) = \frac{d}{dt} \{x(t)\}$$

Due to using of the instantaneous features, the traditional modulation classification algorithms have poor anti-noise ability. De-noising can be done to improve the classification algorithms performance.

Mean filter is linear filter, which is widely used for the restorations of signals and images corrupted by noise. The author found that ripple is presented due to the use of Hilbert transform when extracting analytical form of original real signal. Using the mean filter can smooth the amplitude and inhibit the effecting of noise.

Figure 1 and Figure 2 are the results of the instantaneous phase of BPSK signal and instantaneous frequency of 2FSK signal and post filter under the conditions of White Gaussian Noise interference. Results present that the instantaneous parameter become flatter and smoother after filtering, which is important in improving the recognition performance at low SNR.

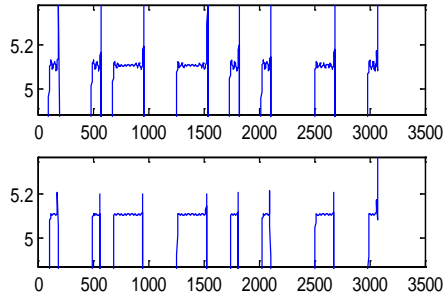


Figure 1. Instantaneous phase of BPSK signal pre- and post filter(AWGN, ∞ dB)

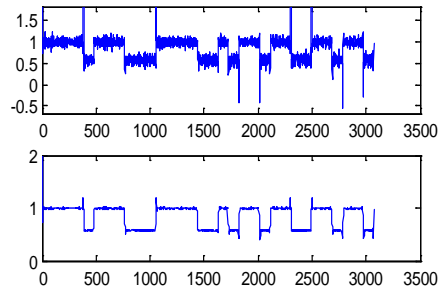


Figure 2. Instantaneous phase of 2FSK signal pre- and post filter(AWGN, 20dB)

B. Feature Extraction

The identification performance is poor at low SNR with the traditional method based on instantaneous features, and the expression of the characteristic parameters is extremely complex. For example, Fourier transform is applied when extracting the features, which has large calculation and will consume lots of logic resource in FPGA. In order to reduce the computational complexity, five characteristic parameters (m_{aa} , m_{af} , m_{ap} , r_{af} , m_{aa1}) are used.

m_{aa} is the mean value of the absolute value of the normalized-centered instantaneous amplitude of the signal

$$m_{aa} = \frac{1}{N_s} \sum |a_{cn}(i)| \quad (13)$$

N_s is the number of statistical samples, $a_{cn}(i)$ is the value of the normalized-centered instantaneous amplitude, it can be defined as follows

$$a_{cn}(i) = \frac{a(i)}{\sum_{i=1}^N a(i) / N_s} - 1 \quad (14)$$

m_{aa} is used to discriminate between 2ASK and 4ASK as one group and BPSK, QPSK, 2FSK and 4FSK as the second group. The range of envelope fluctuation for ASK signals is large, while it's small

for PSK signals, and FSK signals are constant envelope which has no amplitude information.

m_{af} is the mean value of the absolute value of the normalized-centered instantaneous frequency, evaluated over the non-weak segments of the signal

$$m_{af} = \frac{1}{c} \sum_{a_n(i) > a_t} |f_N(i)| \quad (15)$$

Where $\phi_{NL}(i)$ is the value of the non-linear component of the instantaneous phase, c is the number of samples, and a_t is a threshold for $a_n(i)$ below which the estimation of the instantaneous phase is very sensitive to the noise.

$$\phi_{NL}(i) = \psi(i) - \frac{1}{N_s} \sum_{i=1}^N \psi(i) \quad (16)$$

Where $\psi(i)$ is the instantaneous phase of the signal, N_s is the number of samples, m_{af} is used to discriminate between 2FSK and 4FSK.

m_{ap} is the mean value of the absolute value of the normalized-centered instantaneous phase, evaluated over the non-weak segments of the signal

$$m_{ap} = \frac{1}{c} \sum_{a_n(i) > a_t} |\phi_{NL}(i)| \quad (17)$$

m_{ap} is used to discriminate between BPSK and QPSK.

m_{aa1} is the mean value of the absolute value of the secondary normalized-centered instantaneous amplitude of the signal

$$m_{aa1} = \frac{1}{N_s} \sum |a'_{cn}(i)| \quad (18)$$

$a'_{cn}(i)$ is the value of the secondary normalized-centered instantaneous amplitude, and it is used to discriminate between 2ASK and 4ASK.

r_{af} is the ratio of the square of the mean value to the standard deviation of the normalized-centered instantaneous frequency of the signal

$$r_{af} = \frac{m_{af}^2}{\sigma_{af}} \quad (19)$$

It is used to discriminate between 2FSK and 4FSK as one group and BPSK, QPSK as the second group.

C. Classifier

The proposed approach is used to identify 2ASK, 4ASK, 2FSK, 4FSK, BPSK and QPSK signals by applying the decision tree classifier. Threshold values are assumed to be thr_{maa} , thr_{map} , thr_{maf} , thr_{maa1} , thr_{raf} . The identifying process can be

divided into six stages as following. Figure 3 shows the flow chart of the recognition algorithm.

Step1 Do Hilbert transform of the received signal $x(t)$, obtain the orthogonal I/Q signals r , and then reduce noise by mean filter, go to step 2.

Step2 Extract m_{aa} , if $m_{aa} > thr_{maa}$, the modulation type is 2ASK or 4ASK, and go to step 3. Otherwise the modulation type is BPSK, QPSK, 2FSK or 4FSK, and go to step 4.

Step3 Extract m_{aa1} , if $m_{aa1} > thr_{maa1}$, the modulation type is 4ASK. Otherwise the modulation type is 2ASK, and end the process.

Step4 Extract r_{af} , if $r_{af} > thr_{raf}$, the modulation type is 2FSK or 4FSK, go to step 5. Otherwise the modulation type is BPSK or QPSK, and go to step 6.

Step5 Extract m_{af} , if $m_{af} > thr_{maf}$, the modulation type is 4FSK. Otherwise the modulation type is 2FSK, and end the process.

Step6 Extract m_{ap} , if $m_{ap} > thr_{map}$, the modulation type is QPSK. Otherwise the modulation type is BPSK, and end the process.

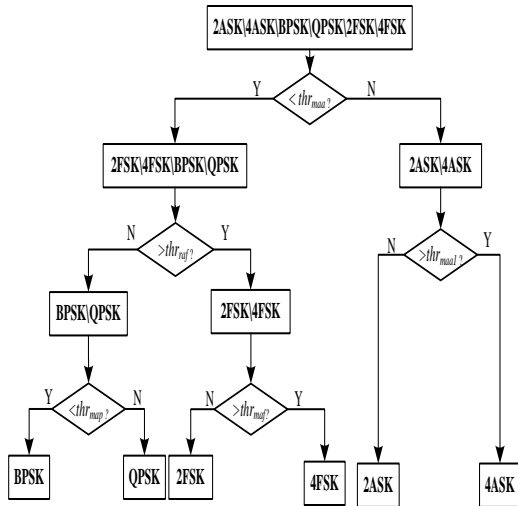
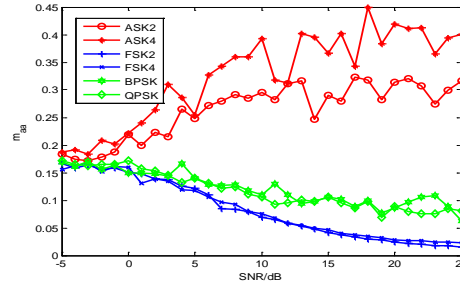


Figure 3. Flow chart of the recognition algorithm

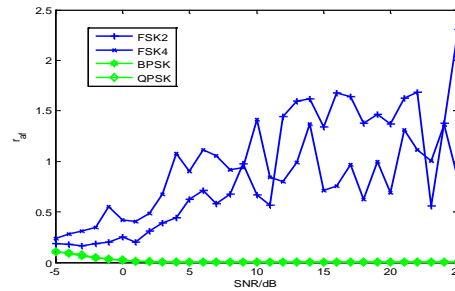
4.RESULTS AND DISCUSSION

In this section, a variety of simulation tests are carried to illustrate the performance of the proposed classification algorithms in Matlab. The pool of modulation consists of 2ASK, 4ASK, 2FSK, 4FSK, BPSK and QPSK signals. The symbol rate $r_b=12.5\text{KB/s}$, the carrier frequency $f_c=150\text{ KHz}$, and the sampling frequency $f_s=1200\text{ KHz}$, AWGN is added. The number of the symbols in the test is set to 32. We evaluate the proposed algorithm via Monte Carlo experiments at different SNR from -4 dB to 24 dB.

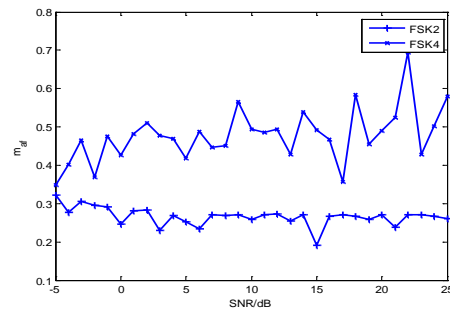
Figure 4 shows the values of the characteristic parameter at different SNR, we can distinguish different signals clearly when the SNR is 0dB except m_{aa1} . This is due to that bandwidth limitations of the ASK signals bring about great influence to the instantaneous envelope, and the secondary normalized-centered instantaneous amplitude further weakens the distinction between 2ASK and 4ASK.



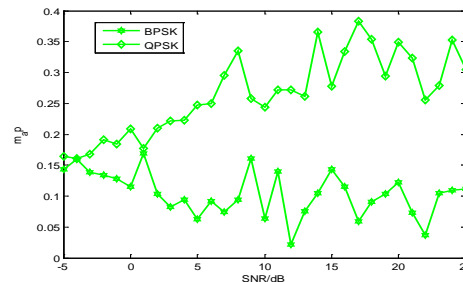
(a) characteristic parameter m_{aa}



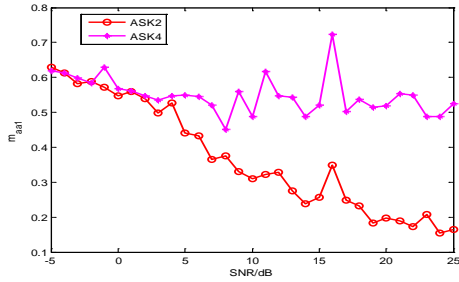
(b) characteristic parameter r_{af}



(c) characteristic parameter m_{af}



(d) characteristic parameter m_{ap}



(e) characteristic parameter m_{aa1}

Figure 4. The curve of characteristic parameter with improved method

Figure 5 shows the correct classification probability P_{cc} from 100 Monte Carlo trials for each modulation type with the proposed algorithm. The result presents that the correct classification probability P_{cc} is above 85% for SNR=0 dB except 2ASK signal. And when SNR=10dB, P_{cc} is above 90% for all signals.

Figure 6 shows the correct classification probability P_{cc} of the proposed algorithm and the traditional algorithm. We note that the P_{cc} reaches to 96% for SNR=8 dB with the new algorithm, while the P_{cc} is only 75% with the traditional approaches. The P_{cc} with the proposed method improves about 4 dB compared with the traditional algorithms.

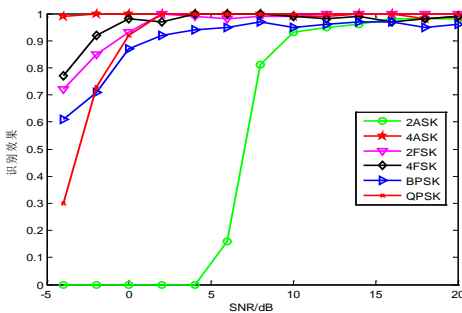


Figure 5. Recognition performance with new method under different SNR for each signal

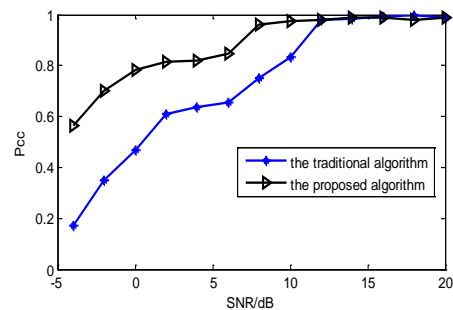


Figure 6. Recognition performance with different methods under different SNR

5.CONCLUSIONS

A new approach has been proposed for the automatic modulation classification of IF ASK\FSK\PSK signals at low SNR. It is based on mean-filter de-noising, instantaneous features and binary tree classifier. Firstly, mean filter has been applied to restrain noise. Then, five characteristic parameters (m_{aa} , m_{af} , m_{ap} , r_{af} , m_{aal}) are extracted. Lastly, signals are distinguished by binary tree classifier. Simulation results show that the correct classification probability can reach to 96% at SNR of 8dB, and the correct classification probability P_{cc} with the proposed algorithm has been greatly improved at low SNR situation compared with the traditional methods.

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