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Low-complexity cyclostationary-based modulation classifying algorithm

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ABSTRACT

In this paper a low-complexity cyclostationary-based modulation classifier is presented, which is capable of distinguishing between OFDM, GFSK and QPSK modulations. The classifier computes and analyses the cyclic autocorrelation of the received signals in an implementation-efficient manner. Instead of computing a high number of values of the cyclic autocorrelation like other implementations, which leads to a non-implementable solution, it computes 3 values, allowing a real-time hardware implementation of the algorithms at a limited cost. The performance is evaluated through simulations in MATLAB, under white Gaussian noise and receiver impairments such as frequency offset, I/Q imbalance and DC offset. In order to assess the actual performance and complexity of the classifying algorithm, an FPGA-based implementation is presented in this document. Performance results with real signals are provided, which validate the ones obtained through simulations.

1. Introduction

Modulation classifiers have become a challenging and important task in cognitive radio and software defined radio systems. They aim to detect the modulation format of the received signal, thus providing more information than a traditional spectrum sensing algorithm. Usually, spectrum sensing algorithms, based on energy detection, matched filtering or cyclostationary characteristics, only determine whether a channel is available or not. These free channels can be used by cognitive radio users, which are allowed to opportunistically share the media with licensed users without interfering them. In addition to finding free channels as in traditional spectrum sensing algorithms, a modulation classifier can distinguish between several modulations formats. This information can be used by the cognitive node, for example, to obtain more suitable statistics, to make decisions in function of the detected signal or to distinguish its network from other transmissions.

The two main solutions to carry out this task are: likelihood based classification and feature based classification [1]. With likelihood based classification, the decision is taken through a function which is calculated under the entire possible hypothesis, choosing the one which maximizes the function. The major disadvantage of this approach is that information about the channel must be known. With the feature based classification, the receiver extracts several characteristics of the signal, which are then analyzed by a classifier in order to establish the modulation format. The most common features in the literature are: signal statistics [2], signal wavelet transform [3], cummulants [4] or cyclostationary characteristics [5]; while classifiers can be implemented using neural networks, support vector machines, k-nearest neighbor, naïve Bayes, linear discriminant analysis or neuro-fuzzy algorithms [5].

The main feature classifiers across the literature are based on cyclostationary characteristics, which are obtained from spectral correlations and are robust against model mismatches. A cyclostationarity-based neural network classifier is proposed in [5] to distinguish between FSK, PSK, PAM and QAM. Several classifiers have been studied based on cyclostationary characteristics in [6] to distinguish between BPSK, QPSK, FSK and MSK; concluding that naïve Bayes and linear discriminant analysis provide best trade-off between classification accuracy and complexity. However, cyclostationary-based classifiers are a complex solution due to the requirement of a high sampling frequency and the computational complexity of involved operations. Compressed sensing has been proposed in [7] in order to solve the first problem. Nevertheless, computational complexity is not addressed, making its real application to cognitive radio uncertain. Therefore, a simpler solution is required in order to be implemented on real hardware and at limited cost.

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In this paper we propose a low-complexity cyclostationary-based modulation classifier capable of distinguishing between OFDM, QPSK and GFSK. These three modulations have been chosen because they are the main solutions in the ISM bands. In the proposed classifier, an energy detector is used prior to classification to distinguish between noise and signal, after which cyclostationary features are extracted for classifying the modulation. In order to reduce the involved computational complexity, the amount of computed cyclostationary features has been limited, 3 values of the cyclic autocorrelation are computed. As a result, the FPGA implementation of the modulation classifier has been possible. Therefore, this is, at the best of the authors knowledge, the first implementation of a cyclostationary classifier which is capable of distinguishing between 3 modulations. Furthermore, the proposed implementation determines the modulation in a reasonable period of time (200 samples of the signal). Its performance has been evaluated through simulations in MATLAB and with real signals using the FPGA-based implementation, under white Gaussian noise and receiver impairments such as frequency offset and I/Q imbalance. Its effectivity has also been compared in simulation with an optimal cyclostationary-based classifier.

The remainder of the paper is organized as follows: Section 2 provides a detailed description of the modulation classifier. The performance of the system through simulations is shown in Section 3. Section 4 describes the FPGA implementation, the real-time performance of the algorithm with real signals and the computation complexity. Finally, the conclusions of the paper are presented in Section 5.

2. Cyclostationary-based modulation classifier

The modulation classifier is composed of two parts; the cyclostationary characteristics are first extracted, after which a naïve Bayes-based classifier establishes the modulation format. Both cyclostationary extractor and classifier are explained in this section. Since a reduced-complexity FPGA implementation is targeted, a low-complexity approach of the algorithms has been designed.

2.1. Cyclostationary characteristics extraction

The first step is to extract the cyclostationary features of the received signal, which will allow for modulation classification. Generally, modulated signals are cyclostationary, which means that their autocorrelation is periodic. This periodicity is normally due to cyclic prefix, synchronization frames, preambles and/or modulation itself, among other reasons. [8]. Therefore, the autocorrelation of a cyclostationary signal (x) can be expressed by Fourier Series:

$$R_x(t,t+\tau) = \sum_{\alpha=0}^{\infty} R_x^{\alpha}(\tau)e^{j2\pi\alpha t}, \tag{1}$$

where τ is the lag, α is the cyclic frequency and R_s^{α} is the cyclic autocorrelation, which corresponds to the coefficients of the Fourier Series, defined as:

$$R_x^{\alpha}(\tau) = \lim_{T\to\infty} \int_{-T/2}^{T/2} x(t)x^*(t-\tau)e^{-j2\pi\alpha t}dt, \tag{2}$$

which for discrete-time signals could be approximated by:

$$R_x^{\hat{\alpha}}[d] = \frac{1}{N}\sum_{n=0}^{N-1} x[n]x^*[n-d]e^{-j\frac{2\pi\hat{\alpha}n}{N}}, \tag{3}$$

where $\hat{\alpha}$ is α in the discrete domain and N is the number of samples of the discrete signal. In cyclostationary signals, there are some values of α and τ ($\hat{\alpha}$ and d for discrete-time signals) which make the cyclic autocorrelation different from zero. These values depend on the periodicity of the autocorrelation. Moreover, different modulations have different cyclostationary characteristics, which allow the distinction between them.

Table 1
Parameters of the signals detected by the classifier.

	Bandwidth	FFT Size	Cyclic Prefix	Modulation
QPSK	6,4 MHz	–	–	–
GFSK	6,4 MHz	–	–	–
OFDM	20 MHz	64	16	16-QAM

The classifier extracts some cyclostationary characteristics of the received signals according to Eq. (3). Then, these characteristics are normalized by the energy of the received signal. In particular, 3 characteristics are computed, for 3 pairs of $\hat{\alpha}$ and d ($R_x^{\hat{\alpha}}[d] = R_x^0[2], R_x^0[4], R_x^{32}[0]$). These 3 characteristics allow distinguishing OFDM, QPSK and GFSK signals for a received signal length of $N = 200$ samples and a sampling frequency of 40 MHz. Table 1 summarizes the main parameters of the considered OFDM, QPSK and GFSK modulations.

The higher bandwidth in the OFDM signals leads to a narrower autocorrelation, as shown in Fig. 1. Therefore, $R_x^0[2]$ allows distinguishing between OFDM and QPSK or GFSK signals. Likewise, the GFSK signal can be distinguished from QPSK because of its narrower autocorrelation, being $R_x^0[4]$ used to compute this distinction. However, $R_x^0[4]$ is not sufficient and another characteristic, $R_x^{32}[0]$, is used because it becomes zero for GFSK signals, as shown in Fig. 2.

To show how distinctive these characteristics are for different modulations, their values are represented for several OFDM, QPSK and GFSK signals in Fig. 3a and b (SNR = 15 dB) and 3c and 3d (SNR = 30 dB). These results also show, as stated before, that OFDM signals can be identified using $R_x^0[2]$, while QPSK and GFSK signals can be distinguished using $R_x^0[4]$ and $R_x^{32}[0]$.

2.2. Modulation classifier

A naïve Bayes classifier has been used in order to determine the modulation of the received signal using the extracted characteristics. This classifier applies the Bayes theorem to take decisions, which means that it decides the more probable hypothesis.

The detector obtains $R_x^0[2], R_x^0[4]$ and $R_x^{32}[0]$, and compares these values with two thresholds. The thresholds have been fixed in function of the Probability Density Function (PDF) of every modu-

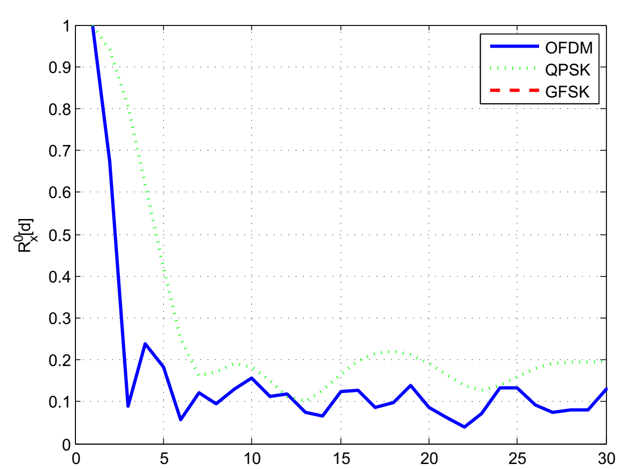

Fig. 1. Autocorrelacion ($R_x^0[d]$) of OFDM, QPSK and GFSK signals.