MODULATION DETECTION IN THE TIME-FREQUENCY DOMAIN FOR COGNITIVE RADIO SYSTEMS

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ABSTRACT

Modulation detection, which is one of the major tasks of an intelligent receiver in a cognitive radio communication systems, is an intermediate step between signal detection and demodulation. In this paper, we present a time-frequency based method for the detection of modulation type in the presence of noise. The Discrete Evolutionary Transform is used to distinguish PSK and FSK signals. The performance of the proposed method is compared with one of the Wavelet Transform based methods in the literature. Simulation results confirmed the virtue of the proposed method.

1. INTRODUCTION

Cognitive Radio (CR) communication systems can intelligently sense and interpret the communication environment and easily adapt the transmitting and receiving parameters in order to provide the most efficient bandwidth to the users and prevent inter-user aliasing [1]. CR's have three crucial tasks: To sense the frequency spectrum, to detect the modulation type of received signal and to analyze the communication protocol. The rapid development in communication protocols and interfaces leads the use of different type of signal and modulation. These advances come with the need of demodulation without any a priori information about on the modulated signal. Modulation detection algorithms can help to distinguish the modulation type of the signal at the receiver, with no or minimum a priori information such as carrier frequency or symbol rate. Software Defined Radios [2] allow the designer to use different radio functions as a software on the same hardware. While all the modulation, demodulation and encoding process are performed by software in Software Defined Radio, the modulation detection process in such multi-mode communication systems reduces the operation time as well as providing design ease.

The classification of analogue modulations types (Amplitude Modulations, Frequency Modulations, etc.) is relatively straightforward process. The variance of the modulated signal envelope can be used for the distinction [3]. Digital modulation classification techniques are widely separated into two main categories. The first one is likelihood based approaches [4, 5]. The likelihood based algorithms relies on the principle of comparing the predefined likelihood ratio with a specific threshold. Although these classifiers are optimal in the sense of statistics, they should know the likelihood function of the signal and require high computational load. In the second approach, the algorithms extract a distinctive feature of the received signal and employ this feature to identify the modulation type. Hence, they do not need any a priori information about the signal and they are called feature-based algorithms [6, 7]. The instantaneous amplitude, phase and frequency transitions of the different types of modulated signals will have different spectral characteristics in the time-frequency domain. In [7] the authors use Wavelet Transform (WT) to extract a distinctive feature to classify the digitally modulated signals. Constantbandwidth methods such as the Wavelet and Short-Time Fourier Transform provide estimates of signal spectrum with poor time-frequency (TF) resolution. The evolutionary spectral theory for the analysis of non-stationary random processes [8] has been extended to consider discrete-time, finite-support signals [9, 10, 11]. The Discrete Evolutionary Transform (DET) provides a tool for high-resolution representation of multi-component signals with linear instantaneous frequencies. In this paper, the DET is used to extract a distinctive feature and to distinguish the signals which are modulated by Phase Shift Keying (PSK) and Frequency Shift Keying (FSK) in the presence of channel noise.

The remainder of the paper is organized as follows. Section 2 defines the Discrete Evolutionary Transform by Gabor Expansion. Section 3 describes the process of feature extraction using the Discrete Evolutionary Transform and presents DET calculations of digitally modulated signals. The results and the comparison of classification performances with Wavelet Transform based detection algorithm are presented in Section 4. Conclusions are made in Section 5.

2. DISCRETE EVOLUTIONARY TRANSFORM BY GABOR EXPANSION

For a discrete-time signal $x(n), n = 0, 1, \cdots, N-1$, its Discrete Evolutionary Transform (DET) is defined in terms of sinusoids with time–varying amplitudes as:

$$x(n) = \sum_{k=0}^{K-1} X(n,k) e^{j\omega_k n} \tag{1}$$

where $\omega_k = 2k\pi/K$, K is the number of frequency samples and $X(n,k)$ the time-varying kernel of the DET. The above equation is analogous to the Wold–Cramer representation used to model the non–stationary processes as a combination of sinusoids with time–varying and random amplitudes [8]. The evolutionary spectrum of $x(n)$ is then given by,

$$S(n,k) = \frac{1}{K} |X(n,k)|^2 \tag{2}$$

[9]. It is shown in [12] that the kernel $X(n,k)$ may be calculated using conventional signal representations such as the

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Gabor expansion, that uses non-orthogonal basis, or the Malvar expansion that uses orthogonal basis.

Traditional discrete Gabor expansion [13] represents a signal as a combination of basis functions that are obtained by translating a single window uniformly in time and frequency. Hence Gabor basis functions allow a sinusoidal and constant-bandwidth analysis. However, if the signal to be analyzed does not satisfy the constant-bandwidth condition, i.e., if the frequency components change with time, its TF representation will not be parsimonious [9]. A multi–window Gabor expansion is presented in [10], using basis functions $\tilde{h}_{i,m,k}(n)$, that are obtained by scaling and translating in time and frequency a mother window:

$$\tilde{h}_{i,m,k}(n) = \tilde{h}_i(n-mL)e^{j\omega_k n}. \tag{3}$$

Then the multi-window Gabor representation of $x(n)$,

$$x(n) = \frac{1}{I}\sum_{i=0}^{I-1}\sum_{m=0}^{M-1}\sum_{k=0}^{K-1} a_{i,m,k}\tilde{h}_i(n-mL)e^{j\omega_k n}. \tag{4}$$

Synthesis windows $\tilde{h}_i(n)$ are obtained from a unit-energy mother window $g(n)$ by scaling in time $h_i(n) = 2^{i/2}g(2^i n)$, $i = 0,1,\cdots,I-1$, and periodically extending by N. Here I denotes the number of scales used and L,M,L',K positive integers satisfy the condition $LM = L'K = N$. L and L' are the sampling steps in time and frequency, M and K are the number of samples in time and frequency respectively. The Gabor coefficients $a_{i,m,k}$, may be calculated by the analysis windows $\tilde{\gamma}_i(n)$ that are bi-orthogonal to $\tilde{h}_i(n)$ [13]:

$$a_{i,m,k} = \sum_{n=0}^{N-1} x(n)\tilde{\gamma}_i^*(n-mL)e^{-j\omega_k n}. \tag{5}$$

Now, by considering the representations of $x(n)$ in equations (1) and (4), the DET kernel $X(n,k)$ is

$$\begin{aligned} X(n,k) &= \frac{1}{I}\sum_{i=0}^{I-1}\sum_{m=0}^{M-1} a_{i,m,k}\,\tilde{h}_i(n-mL) \\ &= \frac{1}{I}\sum_{i=0}^{I-1} X_i(n,k) \end{aligned} \tag{6}$$

where $X_i(n,k)$ show the kernels calculated for different scales. They may be combined using arithmetic average or other averaging techniques [10]. Substituting $a_{i,m,k}$ in (5) into (6), we get

$$X(n,k) = \sum_{\ell=0}^{N-1} x(\ell)\,\mathrm{w}(n,\ell)\,e^{-j\omega_k \ell} \tag{7}$$

where $\mathrm{w}(n,\ell)$ is a time-dependent window function given by

$$\mathrm{w}(n,\ell) = \frac{1}{I}\sum_{i=0}^{I-1}\sum_{m=0}^{M-1}\tilde{\gamma}_i^*\,(\ell-mL)\,\tilde{h}_i(n-mL). \tag{8}$$

By considering all possible scales, a high-resolution representation for the signal may be obtained by combining the kernel set $\{X_i(n,k)\}$ [10]. However, this is not sufficient in general; because signals with wide-band components may require non-sinusoidal basis functions for a compact representation. In such cases, a fractional time–frequency representation will be more appropriate for the spectral signals [14].

3. MODULATION DETECTION BY DISCRETE EVOLUTIONARY TRANSFORM

3.1 Signal Models

The digitally modulated signal, which is corrupted by additive channel noise, at the input of the modulation detector can be defined as

$$y(n) = x(n) + v(n), 0 \le n \le N_0 - 1 \tag{9}$$

where $x(n)$ is the transmitted modulated signal. The channel noise is modeled by a zero mean complex Gaussian noise with the variance of σ_v^2. As we will concentrate on the detection of phase shift keyed and frequency shift keyed signals, the time-varying mathematical expressions of PSK and FSK modulated signals are given below,

$$\begin{aligned} x_{PSK}(n) &= \mathrm{Re}\left\{g(n)\sqrt{\frac{2E}{N_0}}e^{j2\pi(m-1)/R}e^{j2\pi f_c n}\right\} \\ &= \sqrt{\frac{2E}{N_0}}g(n)\cos\left[2\pi f_c n + \frac{2\pi}{R}(m-1)\right] \\ &\qquad 1 \le m \le R, 0 \le n \le N_0 - 1, \end{aligned} \tag{10}$$

$$\begin{aligned} x_{FSK}(n) &= \mathrm{Re}\left\{g(n)\sqrt{\frac{2E}{N_0}}e^{j2\pi m\Delta f n}e^{j2\pi f_c n}\right\} \\ &= \sqrt{\frac{2E}{N_0}}g(n)\cos\left[2\pi f_c n + 2\pi m\Delta f n\right] \\ &\qquad 1 \le m \le R, 0 \le n \le N_0 - 1. \end{aligned} \tag{11}$$

Here, E is signal energy per symbol, f_c is the carrier frequency , R is the number of phase or frequency which carries the transmitting information, Δf is frequency spacing and the N_0 the period of the input symbol sequence. $g(n)$ function determines the pulse shape of the signal and usually chosen as an unit hight square wave which has the same period with the message signal.

3.2 Feature Extraction By DET

In [7] the authors proved that the application of Wavelet Transform (WT) on a digitally modulated signal will result in distinctive patterns for different types of signals. The magnitude of the WT gives an important clue about the type of the modulation. The authors also proved that the histogram of the magnitude of the WT will distinguish the modulation levels of FSK and PSK signals. The PSK modulated signal has (R-1) peak, whereas the FSK modulated signal has (R/2+1) peaks depending on the modulation level.

Digitally modulated signals are time-varying signals, so time-frequency tools can be used to analyze the instantaneous changes in phase and frequency. Recent researches [15, 16] focus on time-frequency analysis methods are for modulation detection. When the signal is a non-stationary random process these algorithms can be inadequate. We employ DET to provide high-resolution representation of time-varying signals. In Fig. 1 and Fig. 2 the evolutionary spectrums calculated by the sinusoidal DET are given for 2PSK and 2FSK modulated signals.

These figures refer to the input signal which is [1,0,1,1,1,0,1,0]. We can easily see that spectrum has distinct peaks when the phase of the input signal changes in

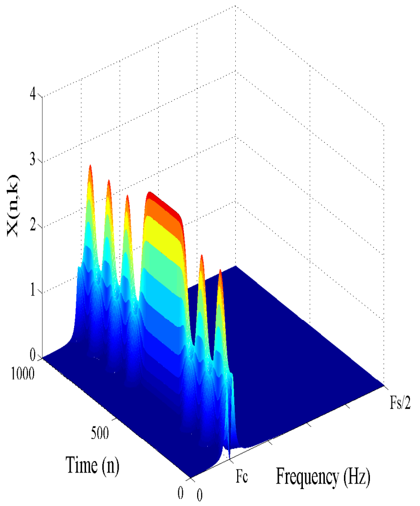

Figure 1: DET based evolutionary spectrum of the 2PSK Signal.

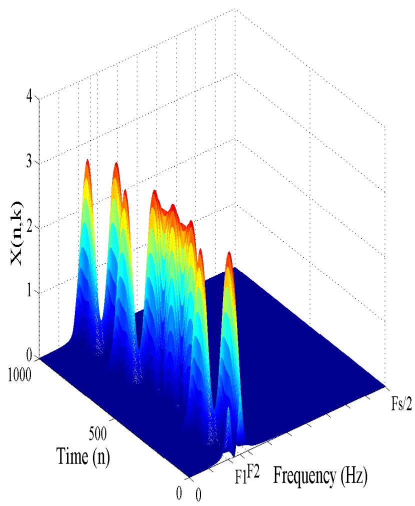

Figure 2: DET based evolutionary spectrum of the 2FSK Signal.

PSK modulation. The amplitude of the spectrum remains steady when the input signal does not change. Peaks occur in two different frequencies in FSK modulation, when the input signals changes. An important fact which can be interpreted from the figure is that, the energy of the signal fluctuates rapidly when the phase or the frequency of the input signal changes. In PSK spectrum, fluctuation levels are higher than the FSK spectrum. This property can be used as a feature to classify two different modulation types.

The detection process is shown in Fig. 3. The DET of received signal is calculated by Gabor coefficients. Then, we calculate the energy of the signal spectrum at the phase or frequency change moments. After comparing the results with a threshold value, we can easily decide the type of the modulation. The threshold for a specific modulation level can be analyze by calculation of the minimum value of Evolutionary Spectrum. At the last step, the modulation level of the signal can be find by analyzing the histogram of the signal's DET as in [7].

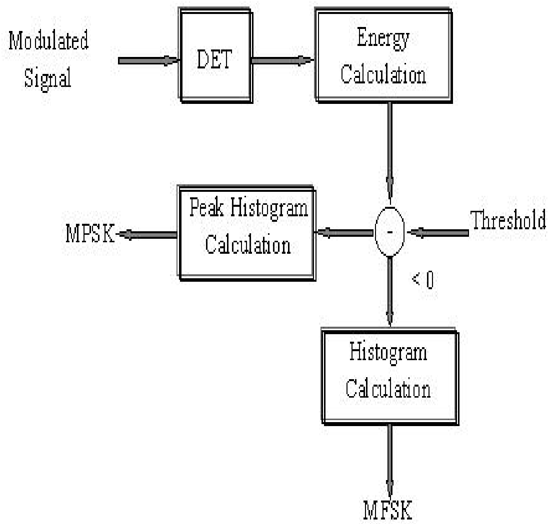

Figure 3: DET based Modulation Detection Algorithm.

4. SIMULATION RESULTS

The performance of the system system is computed for three different levels ($R \in 2,4,8$) of PSK and FSK modulated signal. The carrier frequency and the sampling frequency is chosen as 15 kHz and 150 kHz respectively. The symbol rate is 1200 symbols per second. The rate of classification results are obtained via taking the average of Monte Carlo trials. The number of symbols in each signal sequence is 50 and 100. Rates of correct classification results are given in Table 1, Table 3 and Table 5. The percentages of correct classification with Wavelet Transform based detector [7] are also given in Table 2, Table 4 and Table 6 under the same simulation conditions.

5. CONCLUSIONS

In this paper, we present a time-frequency based method for the detection of modulation type in the presence of noise, in cognitive radio communication systems. When the frequency components of the modulated signal change with time, our algorithm offers a high-resolution analysis. The performance of the proposed method is compared with one of the existing Wavelet Transform based method in the literature. Simulation results confirmed the virtue of the proposed method under the same noise conditions.

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Table 1: DET Based Classification Results Between PSK and FSK (SNR=13dB)

Modulation Type	PSK	FSK
2PSK	99 %	1 %
4PSK	97 %	3 %
8PSK	98 %	2 %
2FSK	0 %	100 %
4FSK	0 %	100 %
8FSK	0 %	100 %

Table 2: WT Based Classification Results Between PSK and FSK (SNR=13dB)

Modulation Type	PSK	FSK
2PSK	98 %	2 %
4PSK	95 %	5 %
8PSK	96 %	4 %
2FSK	0 %	100 %
4FSK	0 %	100 %
8FSK	0 %	100 %

Table 3: DET Based Classification Results For MPSK (SNR=13dB)

Modulation Type	2PSK	4PSK	8PSK
2PSK	99 %	1 %	0 %
4PSK	0 %	98 %	2 %
8PSK	0 %	0 %	100 %

Table 4: WT Based Classification Results For MPSK (SNR=13dB)

Modulation Type	2PSK	4PSK	8PSK
2PSK	94 %	6 %	0 %
4PSK	0 %	83 %	17 %
8PSK	0 %	0 %	100 %

Table 5: DET Based Classification Results For MFSK (SNR=15dB)

Modulation Type	2FSK	4FSK	8FSK
2FSK	97 %	2 %	1 %
4FSK	0 %	100 %	0 %
8FSK	0 %	0 %	100 %

Table 6: WT Based Classification Results For MFSK (SNR=15dB)

Modulation Type	2FSK	4FSK	8FSK
2FSK	93 %	7 %	0 %
4FSK	0 %	100 %	0 %
8FSK	0 %	0 %	100 %