COMPUTER VISION AIDED OFDM-BASED STANDARDS DETECTION AND CLASSIFICATION TECHNIQUE FOR COGNITIVE RADIO SYSTEMS

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ABSTRACT

This paper presents an innovative spectrum sensing scheme for Orthogonal Frequency Division Multiplexing (OFDM) signals based on enhancing the performance of the popular autocorrelation detectors (AD) using non-linear image processing methods. These methods improve the detection accuracy of the AD under particular false-alarm constraints. The proposed scheme is used in the detection of two OFDM systems, Long Term Evolution (LTE) and DVB terrestrial digital TV (DVB-T) under low signal to noise ratio (SNR) channel conditions. Results obtained show significant improvement in correct signals detection/classification up to 18% and 48% at a false-alarm of 5% and low SNR conditions equal to -18dB, using the combined AD and image processing scheme for the detection of LTE and DVB-T signals, respectively.

Index Terms— Spectrum Sensing, DVB-T, LTE, OFDM

1. INTRODUCTION

The surge in demand for bandwidth-intensive applications hosted on advanced mobile devices from video streaming to online gaming is pushing operators to redesign their networks for an overall shift towards cognitive heterogeneity in terms of coexistence of several wireless standards (Long Term Evolution (LTE), mobile WiMAX, WiFi), and to seek the enabling technology to access additional licensed or unlicensed (e.g., TV white-space (TVWS)) spectrum. This leads to the need for innovative techniques for spectrum sensing and signal classification methods to indicate occupied and available frequency bands and identify the type of signals occupying those bands.

Spectrum sensing techniques are in general divided into three categories [1] based on how much prior information on the signal is available at the detection stage [1]. Energy detectors (ED) [2], compares the received signal energy to a threshold value that depends on the signal to noise ratio (SNR) in the channel. ED are low complexity detectors and require no prior knowledge of the features of the sensed signals. ED requires an accurate knowledge of the noise statistics and its performance is highly sensitive to any inaccuracy in this knowledge. On the other hand, feature detection schemes such as autocorrelation detectors (AD) [4] and cyclostationarity detectors (CO) [6], [7] require information about the statistical properties of the detected signals. AD and CO algorithms achieve higher probability of correct detection (PD) than ED in practical communication systems [3]. Finally, matched filter detectors are suitable for the detection of a particular type of signals (e.g., DVB-T) of features explicitly known to the detector (e.g., preamble or pilot waveform) [1]. In the [9] authors introduced the use of a computer vision (CV) based method with general energy sensing detectors to improve the detection accuracy of a very general model of signals that are assumed to be compact in time and frequency, under medium to high signal to noise (SNR) AWGN channel conditions. To this end, in this paper we extend the use of CV towards the more realistic and comprehensive LTE and DVB-T OFDM signal models and with low SNR conditions. We investigate the improved detection accuracy of the well-known autocorrelation detectors using digital image processing methods such as Morphological Reconstruction (MR) to filter or smooth out undesired signals within the desired signal spectrum that usually increase the rate of false-detection. To the best of our knowledge, this is the first work that proposes the use of non-linear image processing tools to improve the detection performance of the autocorrelation detectors of OFDM-based standards. The remaining part of this paper is organised as follows. In section 2, we first present a background review of the spectrum sensing problem and the relevant formulation and key metrics. Then introduce the conventional autocorrelation detection algorithm and the used computer vision (CV) tools. In Section 3 we present in detail the proposed combined AD and CV scheme that is termed CV-AD scheme. Section 4 provides the numerical results obtained using three spectrum sensing schemes, the proposed CV-AD, conventional AD, and ED to detect two OFDM LTE and DVB-T signals. Finally Section 5 concludes the paper.

[1]For further information on state-of-the-art and recent advances in spectrum sensing algorithms refer to [3] (and references therein).

2. PROBLEM STATEMENT

2.1. System Model

In this section we investigate the system model considered in this paper. In this system, the received signal at time n, denoted by y_n, is given by:

$$y_n = A_n s_n + e_n \tag{1}$$

where A_n is the propagation channel gain, s_n is the primary user transmission signal and e_n is additive noise.

In a cognitive radio (CR) system interference between the primary (licensed) user (PU) and any secondary (unlicensed) users (SU), who are trying to opportunistically access the spectrum, is avoided using the ability of the CR to accurately sense its radio environment in order to dynamically allocate those secondary users to available spectrum resources. In general, spectrum sensing is performed based on a binary hypothesis test on the presence or absence (null hypothesis) of the primary signal in a given spectrum:

$$y_n = \begin{cases} e_n & \mathrm{H}_0 \\ A_n s_n + e_n & \mathrm{H}_1 \end{cases} \tag{2}$$

The sensed sub-band is assumed to be a white area if it contains only a noise component, as defined in H_0; while, the existence of primary user signals in noise in a specific band is given by H_1 that means the band is occupied. The key parameters of all spectrum sensing algorithms are the false alarm probability P_F and the detection probability P_D. P_F is the probability that the sensed sub-band is classified as a PU data while actually it contains noise, thus P_F should be kept as small as possible. P_D is the probability of classifying the sensed sub-band as a PU data when it is truly present, thus the sensing algorithms should try to maximize P_D. To design the optimal detector based on Neyman-Pearson criteria, we aim to maximize the overall P_D under a given overall P_F. According to those definitions, P_F is given by:

$$P_F = P(\mathrm{H}_1 \mid \mathrm{H}_0) = P(\text{ PU is detected} \mid \mathrm{H}_0). \tag{3}$$

On the other hand, P_D is given by:

$$\begin{aligned} P_D &= 1 - P_M = 1 - P(\mathrm{H}_0 \mid \mathrm{H}_1) \\ &= 1 - P(\text{ PU is not detected} \mid \mathrm{H}_1) \end{aligned} \tag{4}$$

where P_M indicates the probability of missed detection. In order to infer the nature of the received signal, we use a decision threshold which is determined using the required P_F given by (3). The threshold Th for a given false alarm probability is determined by solving the following equation:

$$P_F = P(y_n \text{ is present} \mid \mathrm{H}_0) = 1 - F_{\mathrm{H}_0}(Th). \tag{5}$$

One well known algorithm that can jointly perform PU spectrum sensing and classification is autocorrelation based detection. In the following subsection, we propose enhancing its performance by using computer vision tools.

2.2. Autocorrelation based-spectrum sensing

Many communication signals contain redundancy, introduced for example to facilitate synchronization by channel coding or to circumvent inter-symbol interference. This redundancy occurs as non-zero average autocorrelation at a certain time lag l. The autocorrelation function at l can be estimated from:

$$\hat{r}_l(\mathbf{y}) = \frac{1}{N-l} \sum_{n=0}^{p-l-1} y_{n+l}\, y_n^* \qquad l \geq 0 \tag{6}$$

Any signal except for the white noise signal will have non-zero autocorrelation function values at specific time lags larger than zero. This simplistic view will be obscured, in practice, by the fact that we have to estimate the autocorrelation function locally on stochastic signals and noise. This will inevitably generate spurious values not accounted for above. The autocorrelation function is proportional to the received signal variance, and its use in spectral sensing is therefore also dependent on knowledge of the noise variance or a reliable estimates of the of the signal variance based on long signal observations. If we assume that the noise level is constant, then the observed variance of the received signal is lower bounded by the noise itself.

To detect the existence/non-existence of OFDM signals we can use functions of the autocorrelation lags, where the autocorrelation is based on (6). Therefore, the autocorrelation-based decision statistic is given by [5]

$$\Upsilon_{AD}(\mathbf{y}) = \sum_{l=1}^{L} w_l \frac{\mathrm{Re}\{\hat{r}_l\}}{\hat{r}_0} \tag{7}$$

where the number of lags, L, is selected to be an odd number. The weighting coefficients w_l could be computed to achieve the optimal performance, and is given by:

$$w_l = \frac{L + 1 + |l|}{L+1} \tag{8}$$

With decision threshold γ_{AD}, the probability of false alarm of this detector is

$$P_{FA,AD} = Q\left(\gamma_{AD}\left[\frac{\gamma_{AD}^2}{p} + \frac{1}{2p}\sum_{l=1}^{L} w_l^2\right]^{-\frac{1}{2}}\right) \tag{9}$$

where Q is the generalized Marcum Q-function.

2.3. Computer Vision Tools

The proposed approach uses two non-linear image processing tools to enhance the accuracy of PU signals detection at the SU side. Those tools are:

- **Morphological Reconstruction (MR)**. MR involves the use of non-linear image processing tools (e.g., erosion and dilation) to reconstruct an original image "marker" of unknown information about its features into a new image "mask" of parts that can be easily extracted and represented by meaningful information [12]. Moreover, the use of MR will smooth out spurious points that may cause false detections [9].

- **Extraction of connected components**. The detection of OFDM signals that belong to different standards involve searching the generated "mask" for objects/regions that share specific features of the different OFDM standards. For example Figs. 3 and 4 demonstrate the "marker" image and the morphologically reconstructed "mask" image using and an 8 point-connectivity region search [12].

3. COMPUTER VISION AIDED AUTOCORRELATION DETECTOR

Fig. 1 shows a block diagram of the proposed CV-AD detection scheme. First, the autocorrelation function of the sensed input signal $y(t)$ is computed then processed using two non-linear image processing tools. A suitable threshold value is calculated based on the output image energy and that is how the final signal detection decision is made. For example, Fig.

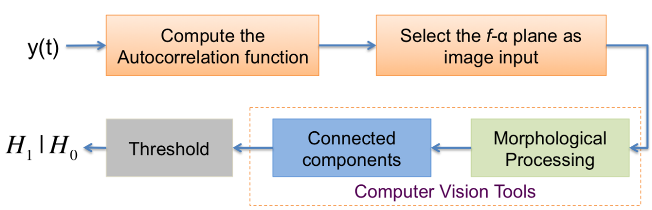

Fig. 1. Signal detection flow.

2 shows the autocorrelation function of a noise free DVB-T signals. The locations of the autocorrelation peaks are specific to the DVB-T standards. This feature can be used to improve the detection of those signals in presence of other OFDM-based signals such as LTE or WiMAX that have their autocorrelation peaks at different locations [4]. Extracting the (f, α) plane from Fig. 2, we obtain for the "marker" DVB-T signal at SNR = -5dB in Fig. 3. The peaks location correspond to the highly contrasted regions in that plane, we can observe four regions in the (f, α) plane that the CV techniques help to emphasize compared to the remaining parts of the image. Fig. 3 is considered as the input of the computer vision algorithms. The output is shown in Fig. 4. Finally, the threshold value is calculated from the energy present in the new image, Fig. 4, looking at the expected peak positions for specific wireless standards in the image provided by the CV tools. The x- and y-axis in Figs. 3 and 4 represent the frequency f and the cyclic frequency α, respectively.

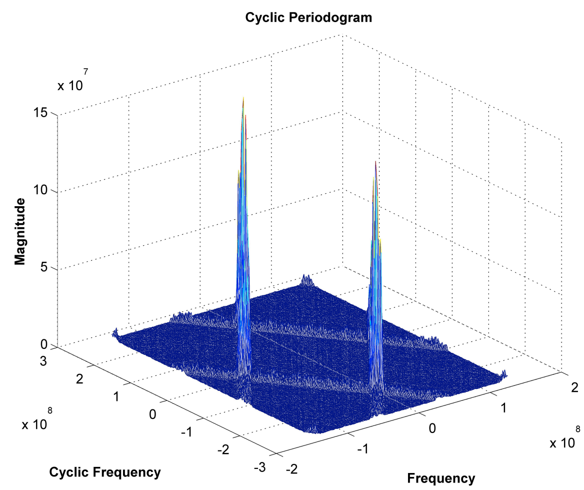

Fig. 2. Cyclic Autocorrelation Function for DVB-T signal example computed according to Eq. (6)

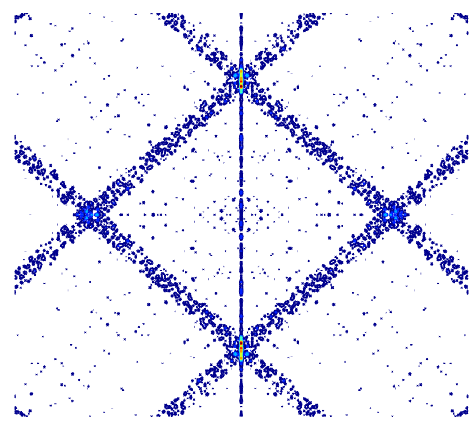

Fig. 3. Original "marker" image of the DVB-T signal for the (f, α) plane at SNR = -5dB

4. SIMULATIONS AND RESULTS

In this paper we simulate the detection of two OFDM-based DVB-T and LTE systems using three spectrum sensing detectors. The combined CV-AD, conventional AD, and ED. The simulation parameters used in this paper for the DVB-T signals are are given in Table 1, while LTE signals are of bandwidth 10 MHz and using normal cyclic prefix (CP). For more details on LTE parameters used in this paper see ref [15], [16] and [17] for LTE specifications and simulations.

Fig. 5 and Fig. 6 show the signal detection performance and the ROC curves, respectively, for the optimal energy de-

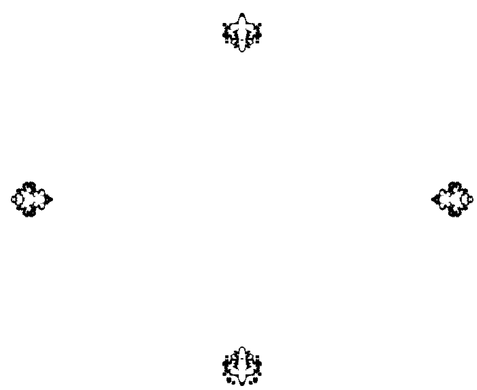

Fig. 4. The "mask" image of Fig. 3 for the (f, α) plane at SNR = -5dB.

Bandwidth	8MHz
Mode	2K
Guard interval	1/4
Channel	AWGN
Sensing time	1.25ms

Table 1. The chosen DVB-T primary user signal parameters

tector with known noise variance (ED), conventional AD and the computer vision aided autocorrelation detector (CV-AD) for LTE and DVB-T. The first remark is that ED performance is independent of the simulated standard, which is consistent with the fact that the ED depends only on the SNR value and sensing time, which is fixed at 1.25 ms assumed for both standards. Also, both figures clearly show the significant CV-AD performance compared with that of the conventional AD. For example, in Fig. 5, a performance gain of 5 dB is achieved at P_{FA} = 0.05, for both LTE and DVB-T. While in Fig. 6 correct detection/classification improvements of up to 18% and 48% at P_{FA} = 0.05 and SNR = -18dB is observed. Beside the ED which is not suitable to classify OFDM standards, the proposed CV-AD offers the best performance at low SNR conditions.

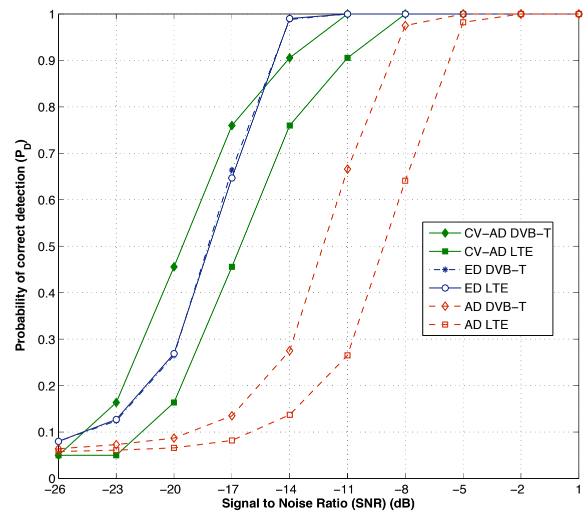

Fig. 5. Probability of correct detection (P_D) versus signal to noise ratio (SNR) in dB at P_{FA} = 0.05.

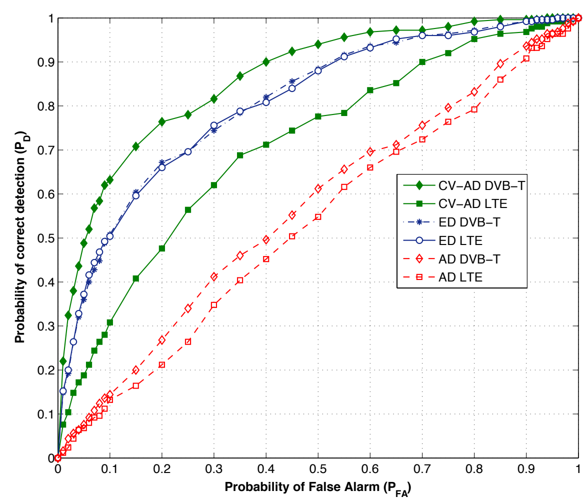

Fig. 6. Probability of correct detection (P_D) versus Probability of False Alarm (P_{FA}), or ROC, at SNR = -18 dB.

5. CONCLUSIONS

In this paper we propose an enhanced autocorrelation detection approach based on advanced image processing tools that improve the OFDM-based standards detection/classification in low SNR channel conditions. The proposed CV-AD scheme significantly outperforms conventional AD schemes with increased OFDM signals detection/classification up to 18% and 48% at low SNR value. This makes the CV-AD an interesting candidate for sense/classify *apriori* unknown OFDM-signals in future cognitive multi-standard/multi-band systems. Finally, future work will investigate the CV-AD performance in fading channel conditions.

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