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Sensing of DVB-T Signals for White Space Cognitive Radio Systems

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***Abstract*—In cognitive radio networks, systems operating in digital television white spaces are particularly interesting for practical applications. In this paper, we consider single-antenna and multi-antenna spectrum sensing of real DVB-T signals under different channel conditions. Some of the most important algorithms are considered and compared, including energy detection, eigenvalue based techniques and methods exploiting OFDM signal knowledge. The obtained results show the algorithm performance and hierarchy in terms of ROC and detection probability under fixed false alarm rate, for different channel profiles in case of true DVB-T signals.**

***Keywords*-Cognitive radio; spectrum sensing; DVB-T; OFDM; white spaces.**

I. INTRODUCTION

The increasing demand for higher data rates in wireless communications is a strong driver for research and development of new communication technologies able to exploit transmission opportunities wherever licensed channels are not employed by primary users. One of most relevant developments in this context aims at exploiting the so called TV white spaces in order to provide internet access through broadband wireless communications.

Cognitive radio networks and systems [1] are based on an efficient *spectrum sensing* unit [2] in order to gain awareness of the available transmission opportunities through the observation of the surrounding electromagnetic environment. Such unit's ultimate goal consists in providing an indication on whether a primary transmission is taking place in the considered channel. Such indication is determined as the result of a binary hypothesis testing experiment wherein hypothesis $\mathcal{H}_0$ ($\mathcal{H}_1$) corresponds to the absence (presence) of the primary signal. Thus, the sensing unit collects samples of kind

$$y(n)|_{\mathcal{H}_0} = w(n) \tag{1}$$

$$y(n)|_{\mathcal{H}_1} = x(n) + w(n). \tag{2}$$

where $x(n)$ are samples of the primary transmitted signal and $w(n)$ are noise samples.

Given the vector y of all samples, the sensing algorithm builds a test statistics $T(y)$ and compare it against a predefined threshold θ. The performance of each detector is usually assessed in terms of *probability of detection* and *probability of false alarm*

$$P_d = \mathbb{P}(T(y) > \theta|\mathcal{H}_1) \tag{3}$$

$$P_{fa} = \mathbb{P}(T(y) > \theta|\mathcal{H}_0) \tag{4}$$

as a function of the signal-to-noise ratio (SNR) ρ, defined as

$$\rho = \frac{\mathbb{E}\|x(n)\|^2}{\mathbb{E}\|w(n)\|^2}. \tag{5}$$

Several methods have been proposed for the computation of the test statistics: a comprehensive description can be found in [3] and references therein. In this paper, we consider the most important of these algorithms, including energy detection, multi-antenna eigenvalue based techniques under both known and unknown noise variance, and techniques exploiting the signal characteristics.

The added value of this paper is that the algorithms are applied to real DVB-T signals generated by a transmitter implemented on a DSP board and applied to different realistic channel profiles. This way, the algorithms performance are evaluated and compared in realistic conditions, providing useful results for practical realizations.

This paper is organized as follows: Section II describes the main characteristics of the DVB-T standard OFDM signal and the considered channel models. Section III describes the sensing algorithms employed in this investigation. Finally, in Section IV the obtained results are shown and commented.

II. PRIMARY SIGNAL

The DVB-T standard [4] specifies a set of coded OFDM transmission schemes to be used for broadcasting of multiplexed digital television programs.

The transmitted signal consists of a sequence of fixed-duration OFDM symbols. A cyclic prefix (CP) is prepended to each symbol in order to avoid inter-symbol interference over frequency-selective fading channels. The most relevant parameters of DVB-T signals are shown in Table I.

The signal bandwidth is approximately 7.61 MHz, with an intercarrier frequency spacing of 8MHz. A subset of the available 2048 subcarriers (in 2k mode) or 8192 subcarriers (in 8k mode) are used to carry higher layer data and PHY-layer signalling information. The latter consists

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Table I
MAIN PARAMETERS OF DVB-T.

	2k mode	8k mode
Symbol duration (T_U)	$224\mu s$	$896\mu s$
Guard interval duration (Δ)	$7-56\mu s$	$28-224\mu s$
Number of active subcarriers	1705	6817
Subcarrier spacing (approx.)	4464Hz	1116Hz
CP duration ratio (Δ/T_U)	1/4, 1/8, 1/16, 1/32	
Constellations	QPSK, 16-QAM, 64-QAM	
Code rate	1/, 2/3, 3/4, 5/6, 7/8	

of pilot sequences, either allocated to fixed subcarriers (continual pilots) or scattered throughout OFDM symbols according to a periodic pattern, which are used for channel estimation at the receiver side, and Transmission Parameter Signaling (TPS) information, wherein encoded information about the current transmission parameters used on data subcarriers is delivered.

OFDM symbols with CP are grouped into frames and superframes: each frame consists of 68 symbols and each superframe consists of 4 frames.

In our study, we used a real encoded and modulated MPEG transport stream (TS) with code rate 5/6, 64-QAM constellation and CP ratio 1/4. The resulting bit rate is approx. 24.88 Mbits/s. At the sensing unit, the DVB-T signal was sampled at the nominal rate of 64/7 Msamples/s.

A. DVB-T signal characteristics

As a common assumption in the literature on spectrum sensing, the primary signal is modeled as a Gaussian process. Fig. 1 shows that, in the case of DVB-T signals, this assumption is well motivated. In fact, Fig. 1(a) shows the *pdf* of the real and imaginary parts of the DVB-T signal's complex envelope. Clearly, the Gaussian distribution is very well approximated. A more accurate evaluation is provided in Fig. 1(b), where the *quantile-quantile* plot of the DVB-T distribution vs. a zero-mean Gaussian distribution with same variance is shown.

Let us assume that the primary signal is detected through K sensors (receivers or antennas). Typically, a flat Rayleigh fading channel is considered in the literature. In such case, the received signal can be modeled as a linear mixture model of kind

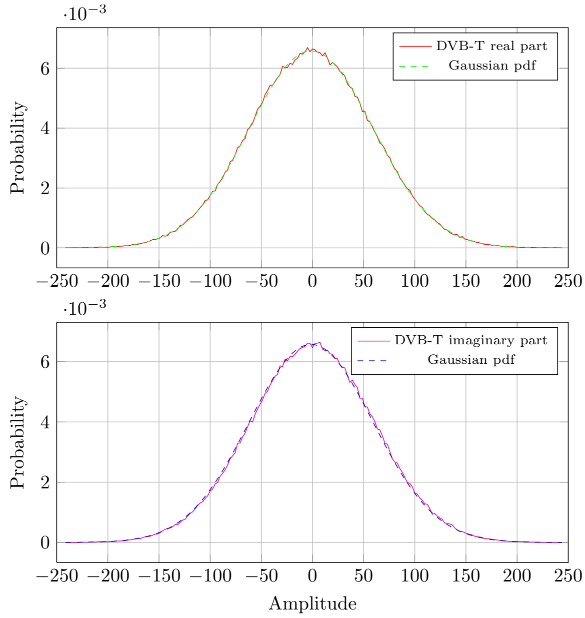
$$\boldsymbol{y}(n) = \boldsymbol{h}x(n) + \boldsymbol{v}(n) \tag{6}$$

where $\boldsymbol{h}$ is the K-element channel vector of size $K \times 1$ whose elements $h_i \sim N_{\mathbb{C}}(0, \sigma_h^2)$ are mutually independent. Moreover we apply the following normalization:

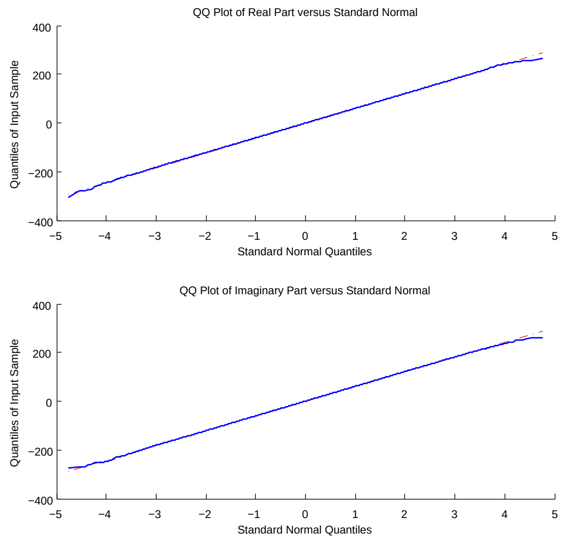
$$\sum_{n=1}^{K} h_n h_n^* = K. \tag{7}$$

Moreover, $\boldsymbol{v}(n)$ is the additive white Gaussian noise distributed as $N_{\mathbb{C}}(\mathbf{0}_{K\times 1}, \sigma_v^2 \mathbb{I}_{K\times K})$.

In order to assess the performance of the considered algorithms in a more realistic case, we used a frequency- and time-selective channel model, the 6-path Typical Urban (TU6) mobile radio propagation model developed by



(a) Estimated probability density function.



(b) Quantile-quantile plot.

Figure 1. Statistics of the DVB-T signal.

the COST 207 European project [5]. The Doppler spread has been set to 10Hz.

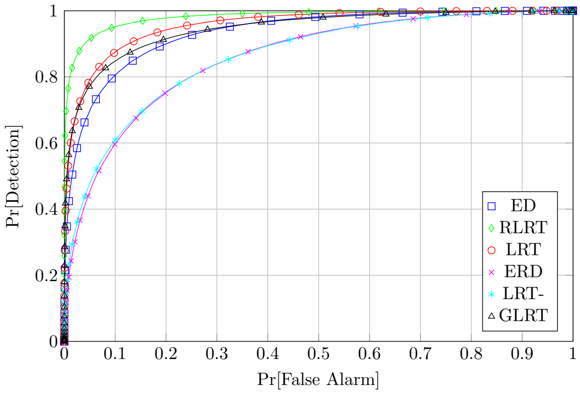
III. TEST STATISTICS

Let us suppose that the detector sensing algorithm builds its test statistic from K sensors (receivers or antennas) and N time samples. Let $\boldsymbol{y}(n) = [y_1(n) \dots y_k(n) \dots y_K(n)]^T$ be the $K \times 1$ received vector at time n, where the element $y_k(n)$ is the n-th discrete baseband complex sample at receiver k.

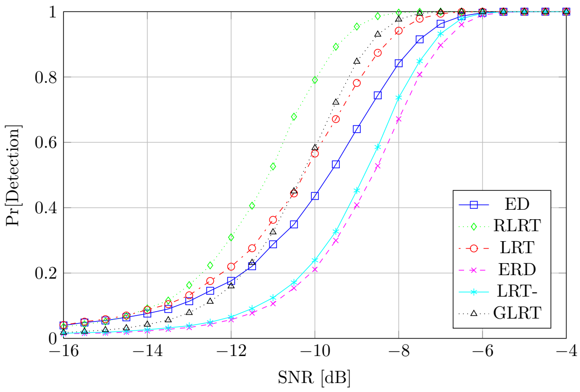
The noise is modeled as an additive white Gaussian noise process with zero mean and variance $\sigma_v^2 = N_0/2$, N_0 being the two-sided power spectral density of noise.

The received samples are stored in a $K \times N$ matrix:

$$\boldsymbol{Y} \triangleq [\boldsymbol{y}(1) \dots \boldsymbol{y}(N)]. \tag{8}$$

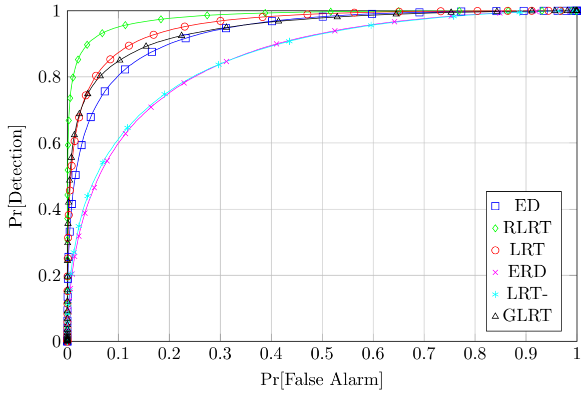


(a) Receiver operating curves (SNR = -10dB).

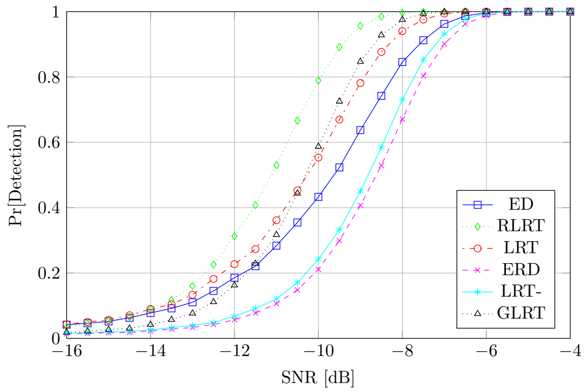


(b) Detection probability.

Figure 2. DVB-T signal through flat-fading channel.



(a) Receiver operating curves (SNR = -10dB).



(b) Detection probability.

Figure 3. Gaussian signal through flat-fading channel.

The sample covariance matrix $\boldsymbol{R}$ is:

$$\boldsymbol{R} \triangleq \frac{1}{N}\boldsymbol{Y}\boldsymbol{Y}^H \tag{9}$$

We will denote by $\lambda_1 \geq \ldots \geq \lambda_K$ the eigenvalues of $\boldsymbol{R}$, sorted in decreasing order.

Many spectrum sensing algorithms have been proposed in the literature. Reviews and comparisons can be found, for example, in [3], [6] and [7]. In this paper, we consider some of the most popular tests, with the aim of comparing them against true DVB-T signals. The considered tests are divided in three classes.

A. *Non-parametric tests, known noise variance*

These tests are non-parametric, i.e., do not exploit the knowledge of the signal characteristics. An excellent estimation of the noise variance σ_v^2 is supposed (obtained, for example, during a long training phase).

Energy Detection (ED): the test statistic is the average energy of the received samples, normalized by the noise variance:

$$T_{ED} = \frac{1}{KN\sigma_v^2}\sum_{k=1}^{K}\sum_{n=1}^{N}|y_k(n)|^2 \tag{10}$$

The energy detection method is probably the most popular technique for spectrum sensing, also thanks to its simplicity. Analytical performance expressions for this detector are well-known in the literature (e.g., [8]).

Roy's Largest Root Test (RLRT): this method tests the largest eigenvalue of the sample covariance matrix against the noise variance. The test statistic is

$$T_{RLRT} = \frac{\lambda_1}{\sigma_v^2} \tag{11}$$

The RLRT was originally developed in [9]. Performance analysis can be found, for example, in [10], [11], and [7]. For Gaussian signals and not too low signal-to-noise ratio, the RLRT is the best test statistics in this class.

Likelihood Ratio Tests (LRT): different LRT-based detectors were given in [6]. The complete, noise-dependent, log-likelihood ratio test statistic is given by

$$T_{LRT} = 2(N-1)\left[\log\left(\frac{\sigma_v^{2K}}{\det\boldsymbol{R}}\right) + \left(\frac{\mathrm{tr}\boldsymbol{R}}{\sigma_v^2} - K\right)\right] \tag{12}$$

Performance analysis for this test can be found, for example, in [6].

B. *Non-parametric tests, unknown noise variance*

These tests are again non-parametric, but the noise variance is supposed unknown.

Generalized Likelihood Ratio Test (GLRT): this method uses as test statistic the ratio

$$T_{GLRT} = \frac{\lambda_1}{\frac{1}{K}\mathrm{tr}(\boldsymbol{R})} \tag{13}$$

Performance analysis can be found for example in [12].

It is interesting to note that the GLRT is equivalent (up to a nonlinear monotonic transformation) to [7]:

$$T_{GLRT'} = \frac{\lambda_1}{\frac{1}{K-1}\sum_{i=2}^{K}\lambda_i}. \tag{14}$$

The denominator of $T_{GLRT'}$ is the maximum-likelihood (ML) estimate of the noise variance assuming the presence of a signal, hence the GLRT can be interpreted as a largest root test with an estimated $\hat{\sigma}_v^2$ instead of the true σ_v^2.

Eigenvalue Ratio Detector (ERD): the test statistic (also called maximum-minimum eigenvalue, or condition number test) is the ratio between the largest and the smallest eigenvalue of $\boldsymbol{R}$

$$T_{ERD} = \frac{\lambda_1}{\lambda_K} \tag{15}$$

Performance analysis can be found, for example, in [13], [14].

Noise-independent LRT (LRT-): an alternative log-likelihood ratio was derived in [6], under the assumption of unknown noise variance:

$$T_{LRT-} = 2(N-1)\left[\frac{\frac{1}{K}\sum_{i=1}^{K}\lambda_i}{\left(\prod_{i=1}^{K}\lambda_i\right)^{1/K}}\right]^K \tag{16}$$

In statistics, this method has been known for many years as the *sphericity test* [15], [16]. Performance analysis for cognitive radio applications can be found, for example, in [6].

C. Parametric tests

Primary OFDM signal detection is considered. Primary signal detectors that exploit the presence of the CP in OFDM transmissions have been proposed. In [17] the detectors based on CP correlation described in [18] have been improved, applied to a real scenario and implemented using a software-defined radio platform.

As previously stated, DVB-T signal consists of OFDM modulated symbols of which a-priori parameter knowledge is assumed, such as: the number of subcarriers, cyclic prefix length, constellation type or the code rate. The aim of parametric test statistics is to exploit signal parameter knowledge (i.e., signal features) in order to enable primary signals detection with high sensitivity.

The algorithm implemented in [19] using SDR is the well known CP-based spectrum sensing. Assuming N_s=N_c+N_d as the samples in a captured OFDM symbol (cyclic prefix plus data samples respectively), the correlation function (3) in [17], reproduced in (17) for clarity, provides the analysis of $2N_d$+N_c samples coherently averaged over K symbols.

$$R_{xx}^{(CP)}[n,\tau] = \frac{1}{KN_s}\left|\sum_{k=0}^{K-1}\sum_{n=\tau+kN_s}^{\tau+(k+1)N_s-1} x^*[n]x[n+N_d]\right| \tag{17}$$

where τ represents the synchronization mismatch between our capture and the symbol start. It can be modelled as uniformly distributed over the interval [0,N_c+N_d-1], that defines the minimum period in which one correlation maximum occurs.

The coherent averaging before taking the absolute value allow us to improve sensitivity, in presence of AWGN noise, at the cost of a larger capturing interval. Moreover, to enable the implementation of these algorithms, it is necessary to define a noise estimation algorithm to set a threshold that guarantees certain detection performance in terms of probability of false alarm (P_{FA}) and probability of detection (P_D).

In this paper, a slight improvement in terms of noise estimation accuracy (i.e., correlation noise) with respect to [17] is presented. In fact, without any a-priori assumption, the correlation noise estimation should be performed by analyzing the received samples when the H_0 hypothesis is true. Hence training periods with only noise samples must be performed periodically (e.g., to track system temperature changes). To avoid dedicated training, we observed that noise samples can be gathered in between two consecutive correlation maxima. The correlation function $\tilde{R}$ used to estimate the average correlation noise level, correspond to the function R excluding $2N_c$ samples around the detected maxima. Our optimized CP-based algorithm can thus be resumed as following:

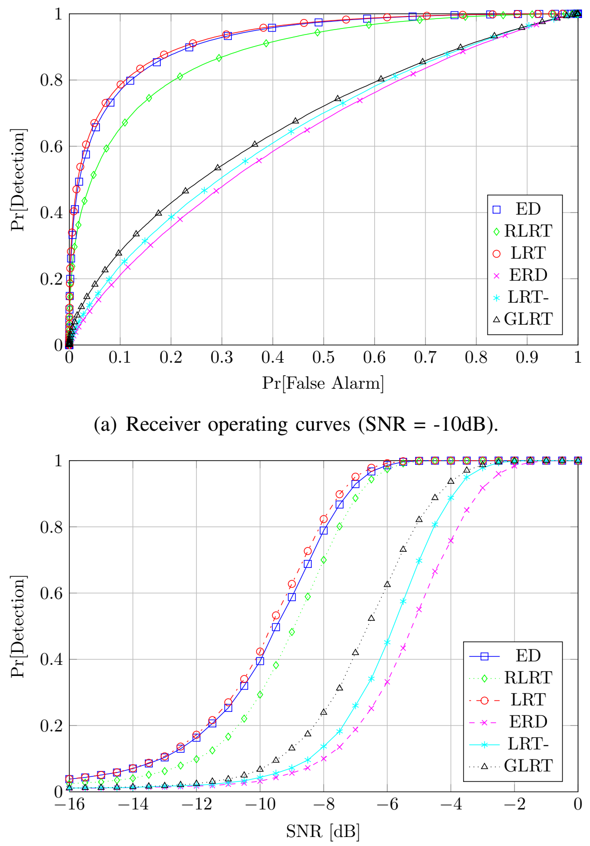
1) Receive K(N_c+N_d)+N_d samples
2) Perform (17) over captured samples
3) Record the correlation maximum and its index i
4) Copy only correlation noise values from function in 2. by excluding values that have index in the range $i - N_c < i < i + N_c$
5) Decide if channel is occupied by evaluating the following metric:

$$\frac{\max R_{xx}^{(CP)}[n,\tau]}{\tilde{R}_{xx}^{(CP)}[n,\tau]} \gtrless \gamma \tag{18}$$

In order to obtain the curve plotted in Fig. 5, we firstly have calculated the threshold γ. To reproduce H_0, white Gaussian distributed input noise samples were considered. In this way the γ value at which the $P_{FA} = 10^{-2}$ can be evaluated. We used a Monte Carlo approach over 1000 repetitions for K=1 (1 symbol). Once the threshold γ has been set, we varied the input SNR during H_1 tests to plot the corresponding P_D function.

IV. Results

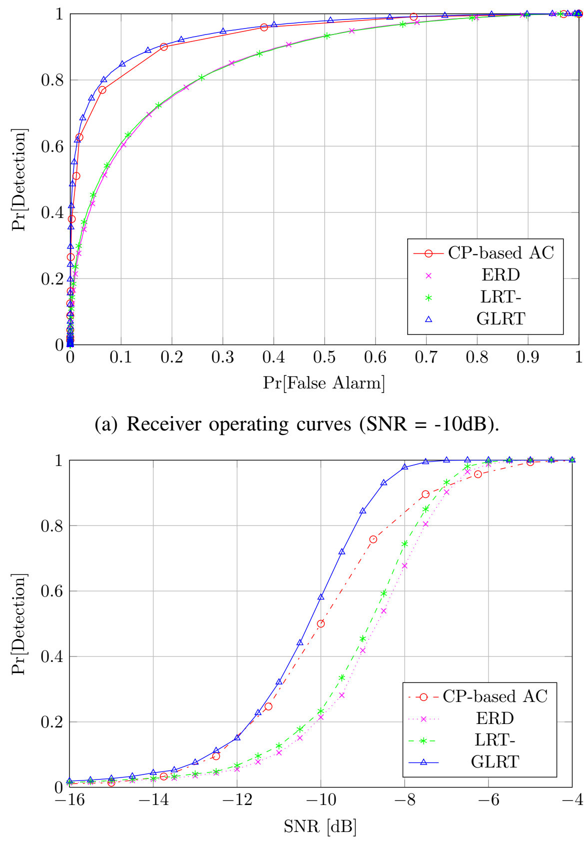
The results obtained for the DVB-T signal under linear mixture models provided by flat fading Rayleigh channel are reported in Fig. 2. First, we report the ROC (Receiver Operating Characteristic) curve obtained by plotting the detection probability versus the false alarm one. Then by fixing the false alarm rate to 0.01, we plot the detection probability as a function of the signal-to-noise ratio. By fixing the detection probability, this allows to evaluate the differences in terms of SNR between the algorithms, at the parity of detection and false alarm probability.



(a) Receiver operating curves (SNR = -10dB).

(b) Detection probability.

Figure 4. DVB-T signal through TU6 channel.



(a) Receiver operating curves (SNR = -10dB).

(b) Detection probability.

Figure 5. Comparison with the CP correlation method [17], [18].

Simulations have been performed assuming $K = 10$ antennas and and observation interval corresponding to $N = 50$ samples. For the CP correlation method, an interval corresponding to one OFDM symbol has been considered. Moreover, in such case, the signal was sampled at 12.5 Msamples/s.

By looking at Fig. 2 we can observe that the best algorithm for known noise variance is the RLRT, while GLRT is the best under unknown variance. It is interesting to note that these results are in agreement with the results providing in the literature for Gaussian signals. As a reference, results for the same algorithms obtained by simulating Gaussian signal samples are reported in Fig. 3 and are essentially identical to the previous one (as expected after verifying the Gaussian properties of the DVB-T signal).

Under a more realistic model, the TU6 channel, the performance of the algorithms are different, as can be observed in Fig. 4. We can see how both GLRT and RLRT lose their predominant position when the received model is different from the linear mixture one: simple energy detection becomes highly competitive in this case. The difference between algorithms with known and unknown noise variance is larger, too.

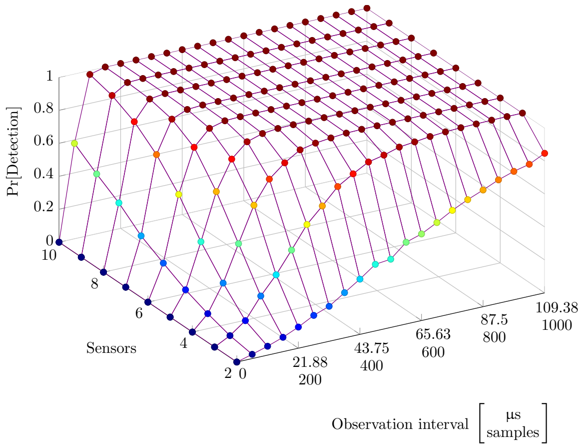
It is important to note that in this work we have supposed a perfect known noise variance for RLRT, LRT and energy detection. Further analysis will be applied to study their performance under imperfect noise variance knowledge, and address its impact for real DVB-T signals (analysis for Gaussian signals can be found, for example, in [19] for energy detection and [7] for RLRT).

Furthermore, we compare the algorithms for unknown noise variance against the technique exploiting the cyclic prefix autocorrelation of the received signal [17], [18] described before. Here, the AWGN channel model is adopted. In this case we can observe that the performance of this algorithm is similar to that of the GLRT. This single-antenna algorithm does not require the computation of the sample covariance matrix eigenvalues, but resorts to a precise knowledge of the signal characteristics.

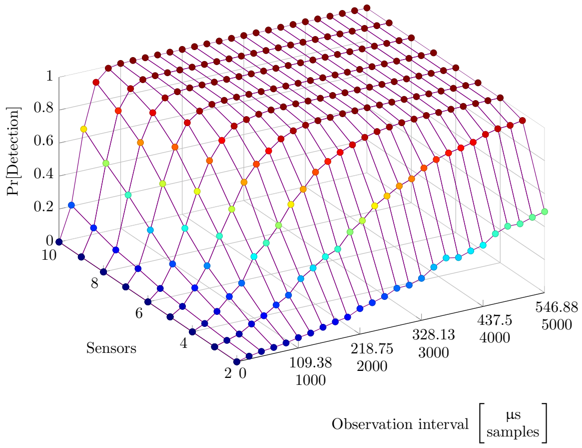
Finally, in Fig. 6 we plot the detection probability of GLRT as a function of the observation interval (expressed both in time units and number of received samples per sensor) and the number of sensors for a specific SNR value of -10dB and -15dB, while the false alarm probability remains fixed to 10^{-2}. The channel is Rayleigh flat-fading. As shown, it is possible to obtain the same performance achieved in Fig. 2 using $N = 10$ sensors even with a lower and hence more realistic number of antennas.

V. CONCLUSIONS

Some of the most important sensing algorithms have been applied to real DVB-T signals and their performance has been assessed considering different channel profiles. The flat fading channel analysis confirms the results



(a) SNR = -10dB, P_{fa} = 0.01.



(b) SNR = -15dB, P_{fa} = 0.01.

Figure 6. GLRT detection probability as a function of time (samples) and sensors through flat-fading channel.

previously obtained by simulation using linear mixture models of Gaussian signals. Under a more realistic multi-path channel model, the performance and hierarchy of the algorithms completely change with respect to the flat-fading case. The obtained results are very useful for the implementation of cognitive systems and networks operating in the digital television white spaces.

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