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Contribution to Working Group 2 Definition of cooperation-based cognitive algorithms, that take advantage of information exchange at a local level

GLRT for Cooperative Spectrum Sensing:
Threshold Setting in Presence of Uncalibrated Receivers

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In order to identify unused portions of spectrum and monitor the activity of primary users (PUs), CR devices must implement spectrum sensing algorithms with highly reliable performance [1]. Many spectrum sensing techniques have been proposed in literature, starting from the traditional algorithms such as the energy detector (ED) and feature-based detectors. These algorithms can be implemented by a single node or by multiple secondary users (SUs) that cooperate sharing their sensing information. However it has been shown that these techniques present some limitations. Indeed, the adoption of the ED in practical scenarios requires the implementation of a proper noise power estimation strategy, and feature detectors can suffer synchronization errors and frequency offsets in realistic environments [2]. Recently, algorithms that exploit the properties of the covariance matrix of the observed signals, often called eigenvalue-based detectors, have attracted a lot of attention providing good performance results without requiring the knowledge of the noise power nor any prior information on the PU signals. These algorithms can be adopted if some kind of diversity is present in the SU system, which typically means that multiple antenna nodes are used or that SUs exploit cooperation. Considering a cooperative SUs network, when there are no PUs, the different nodes receive uncorrelated noise observations, which means that the covariance matrix is diagonal. Otherwise, when primary communications are active, the received signals present a certain degree of correlation and we have a non-diagonal covariance matrix. Therefore a proper detection strategy can be based on the observation of the sample covariance matrix (SCM), denoted with $\mathbf{S}$, in order to discriminate between correlated received signal and white noise, i.e. to distinguish if PUs are present or not.
In cooperative sensing networks nodes are often assumed to have the same noise power level. In this case the generalized likelihood ratio test (GLRT) is the so called sphericity test

$$\mathrm{T}^{(\mathrm{sph})} = \frac{|\mathbf{S}|}{(\mathrm{tr}\{\mathbf{S}\}/n_{\mathrm{R}})^{n_{\mathrm{R}}}} \underset{\mathcal{H}_1}{\overset{\mathcal{H}_0}{\gtrless}} \xi \quad . \tag{1}$$

where n_R is the number of the cooperating nodes.
However, in general, different nodes could experience different temperatures or could even have a

different RF front-end. Therefore we must a more realistic assumption is to consider that the SUs experience different levels of noise. The GLR in this case is the independence test, defined as

$$\mathrm{T}^{(\mathrm{ind})} = \frac{|\mathbf{S}|}{\prod_{k=1}^{n_{\mathrm{R}}} s_{k,k}} \underset{\mathcal{H}_1}{\overset{\mathcal{H}_0}{\gtrless}} \xi \quad . \tag{2}$$

Note that even when multiple antennas are adopted, if they are not properly designed and calibrated, the independence test must be adopted in place of the sphericity test.

In this study we address the analysis of the independence and sphericity tests, studying the threshold setting problem under the Neyman-Pearson framework. We propose in particular to approximate the tests to beta distributed random variables using a moment matching approach and prove simple and analytically tractable expressions easy to use for the computation of the probability of false alarm and for setting the decision threshold. Numerical simulations show that these approximated forms match very well the empirical cumulative distribution function of the tests, even with a small number of samples collected, outperforming the popular chi squared approximation for the GLRT.

References

[1] K. Sithamparanathan and A. Giorgetti, *Cognitive Radio Techniques: Spectrum Sensing, Interference Mitigation, Localization,* Artech House, Sep. 2012.
[2] A. Mariani, *Spectrum sensing algorithms for cognitive radio applications*, Ph.D. thesis, Philosophy Doctoral Program in Electronics, Computer Science and Telecommunications, Alma Mater Studiorum University of Bologna, Cesena, Italy, 2013.