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## Signal Processing

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#### ABSTRACT

Recent work on multiantenna spectrum sensing in cognitive radio (CR) networks has been based on generalized likelihood ratio test (GLRT) detectors, which lack the ability to learn from past decisions and to adapt to the continuously changing environment. To overcome this limitation, in this paper we propose a Bayesian detector capable of learning in an efficient way the posterior distributions under both hypotheses. Our Bayesian model places priors directly on the spatial covariance matrices under both hypotheses, as well as on the probability of channel occupancy. Specifically, we use inverse-gamma and complex inverse-Wishart distributions as conjugate priors for the null and alternative hypotheses, respectively; and a binomial distribution as the prior for channel occupancy. At each sensing period, Bayesian inference is applied and the posterior for the channel occupancy is thresholded for detection. After a suitable approximation, the posteriors are employed as priors for the next sensing frame, which forms the basis of the proposed Bayesian learning procedure. The performance of the Bayesian detector is evaluated by simulations and by means of a CR testbed composed of universal radio peripheral (USRP) nodes. Both the simulations and experimental measurements show that the Bayesian detector outperforms the GLRT in a variety of scenarios.

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Review





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#### 1. Introduction

Cognitive radio (CR) networks [1–3] rely on spectrum sensing as a key operation that secondary users (SUs) must perform in order to identify whether a wireless communication channel is in use by a licensed primary user (PU) or not [4]. A reliable spectrum sensing stage is crucial to detect spectrum holes that can be subsequently filled with transmissions from SU [5]. To this end, detectors employing multiple antennas have received increased attention recently because they do not require prior knowledge about the PU signaling scheme and are able to work with asynchronously sampled signals [6-12]. These multiantenna detectors exploit the fact that under the null hypothesis (only noise) the signals received at the different antennas are spatially uncorrelated, whereas the presence of a PU induces some correlation and/or additional structure in the spatial covariance matrix.

Since the binary hypothesis testing problem involves some unknown parameters (e.g., noise variance and channel), the generalized likelihood ratio test (GLRT) approach has been typically followed to find one-shot detectors in several scenarios [6,7,9,12]. In [12], frequency and timedomain GLRTs have been derived that only exploit the spatial correlation induced by the presence of a PU, whereas the problem of detecting a rank-P primary user signal is addressed in [9,7]. However, these detectors do not take into account the smooth changes in the characteristics of the channel or the noise that can be expected between consecutive sensing frames. More precisely, it is reasonable to assume that the time scale of variation of the statistical parameters involved in the detection problem (for instance, noise variance or space-time PU activity pattern) are much longer than the sensing period. For instance, channel access patterns for primary users have been characterized as slowly time-varying in [13] and more recently in [14]. It is clear that detectors able to learn from past decisions would provide improved performance in these slowly time-varying scenarios. With this goal in mind, in this paper we propose an adaptive Bayesian framework for multiantenna sensing and evaluate its performance both by simulations and by means of a CR testbed.

Adaptive Bayesian detectors for radar applications have been proposed in [15–17], where a training set of data is available for the estimation of noise statistics. For cognitive

radio applications, however, noise-only data is not always available: therefore, these adaptive Bayesian techniques cannot be applied to the scenarios considered in this paper. Bayesian detectors specific for cognitive radios have been previously proposed in [18–22]. Typically, these works assume a prior distribution for the unknown parameters and apply Bayesian inference to come up with improved parameter estimates and, consequently, more reliable detectors. In comparison to these Bayesian approaches, our work presents two main novelties: first, our Bayesian detector places priors directly on the spatial covariance matrices under both hypotheses; and second, it includes learning and forgetting steps that allow to track the variations of the channel and noise characteristics from frame to frame. Our Bayesian approach is able to learn from past sensing frames when the coherence time of the propagation channel [23] is longer than the time elapsed between consecutive sensing periods. We refer to this situation as "smooth channel variations". Let us also remark that the proposed Bayesian detector is specifically tailored for multiantenna cognitive receivers and, consequently, this approach is not directly applicable to singleantenna SUs.

Specifically, our multiantenna Bayesian model uses inverse-gamma and complex inverse-Wishart distributions as conjugate priors for the null and alternative hypotheses, respectively; and a binomial distribution as the prior for channel occupancy. The reason for choosing these priors being that under Gaussian noise they are the conjugate priors for this problem and, therefore, the posteriors can be calculated in closed form. More precisely, the posterior conditioned on the channel state occupancy (idle or busy) adopts the same form as the prior. However, the unconditional posterior (marginalized over the channel state) becomes a convex combination of the priors. Since the marginalized or unconditional posteriors summarize the information gathered so far about the actual CR scenario, they are used as priors for the next sensing period: this represents the learning stage. To keep the learning process simple and scalable, the unconditional posterior (which is a linear combination of complex inverse-Wishart distributions when the PU is present) must be approximated within the family of the prior. Furthermore, the procedure is equipped with a forgetting mechanism based on [24] that allows to work on nonstationary environments.

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