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Parzen window entropy based spectrum sensing in cognitive radio[☆]

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ABSTRACT

In this paper, we propose a Parzen window entropy based spectrum sensing algorithm for enhancing the signal-to-noise ratio (SNR) wall of cognitive radio primary user detection. We compute the information entropy using a non-parametric Kernel Density Estimation (KDE) method. Single node sensing is extended to cooperative sensing using the weighted gain combining (WGC) fusion method. The weights of WGC technique are computed using a Differential Evolution(DE) algorithm and compared with the log-likelihood ratio (LLR) method. In addition, the detection performance of the proposed Parzen window entropy is compared with Shannon entropy and energy detection techniques. We consider a DVB-T signal with Additive White Gaussian Noise (AWGN) subjected to Rayleigh fading under noise uncertainty as a primary user signal for simulation. The simulation result reveals that in the case of a single node and cooperative sensing, the proposed method achieves SNR wall of -19 dB and -24 dB respectively at the probability of false alarm 0.1.

1. Introduction

Cognitive Radio provides a promising solution to overcome the spectrum scarcity problem in wireless communications [1]. It supports the dynamic spectrum allocation feature to drive next generation communication. Spectrum sensing is the most prominent function that detects the presence of a signal in a radio channel in Cognitive Radios. There are many sensing algorithms reported in the literature [2], including matched filtering, cyclostationary detection and energy detection. Energy detection is the simplest blind detection technique which does not require apriori information of the signal. However, it fails to detect the signal in the presence of noise uncertainty [3]. If the characteristics of the signal are known apriori, then matched filtering gives ideal results. On the contrary, cyclostationary detection senses the primary user signals under noise uncertainty by exploiting the cyclic properties of the signal at the cost of more computational complexity. The Entropy detection technique seems to be a powerful technique which detects very-low-SNR signals with reasonable complexity in less time [4,5]. In entropy based detection technique, sensing performance is exploited in both time and frequency domains [5,6]. In the time domain, entropy is constant (independent of SNR) and cannot distinguish between signal and noise. As

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an alternative, the frequency domain can be used to detect low-SNR signals in the presence of noise uncertainty. In these methods, the average probability density function (*pdf*) is characterized by histogram bin-width and a number of bins. The main drawback of histogram bins is that they are not smooth and their performance often relies on the two extreme points of the histogram. In the present paper, to counteract this effect, estimation of the density directly by the kernel *pdf* is proposed. Furthermore, Renyi entropy is found to be a more generalized form that increases the overall detection performance, in comparison to Shannon entropy.

Multiple Cognitive Radios are deployed for sensing to mitigate the effects of fading and shadowing. In cooperative sensing, the sensing reliability is increased by combining the individual decisions at the fusion center [7,8]. The sensing data sent by each cognitive user may not be reliable for detection, due to different channel characteristics. The sensing data are aggregated at the fusion center based on different fusion rules, i.e., soft and hard fusion techniques. In the case of hard fusion technique, each node sends binary decision value to the fusion center (FC), and the FC takes a decision by using either binary logic such as AND, OR or majority. In the case of soft fusion technique, the fusion center receives true information about the signal in contrast to binary values and applies rules such as random weights, equal gain combining (EGC) and weighted gain combining (WGC) to take the final decision. Among these, the WGC assigns the weights based on the SNR of each node giving optimum results. If the signal and noise variances are known apriori, then log-likelihood ratio test (LLR) is simple to implement [9]. In the LLR method, the weight of each node is calculated using received signal-to-noise ratio (SNR). If SNR is not known a priori, then evaluation of weight is critical. However, it is not always practical to expect that the receiver node will have a priori information about noise characteristics such as variance. In this scenario, an improper approximation to weight values will lead to performance degradation.

In this paper, we propose a Parzen window-based entropy for spectrum sensing in cognitive radio. We investigate the effect of kernel-based entropy estimation for evaluating the detection performance in the frequency domain. Parzen window-based entropy estimation is robust because the primary user signal can be detected by considering fewer-samples compared to the Shannon entropy detection method in the presence of noise uncertainty with lower-false-alarm probability. The Differential Evolution algorithm is used to compute the weights of each node in cooperative sensing as it does not require a priori information about the noise characteristics.

The rest of the paper is organized as follows. Section 2 presents the single node sensing using Parzen window entropy. Section 3 presents the cooperative spectrum sensing using Parzen window entropy along with the DE algorithm for weight estimation. Section 4 summarizes the proposed algorithm results and comparison with state-of-the-art solutions. Finally, Section 5 concludes the paper.

2. Spectrum sensing using Parzen window based entropy

2.1. Single node sensing model

In this section, we review the spectrum sensing model of cognitive radio. The binary hypothesis test for single node sensing is modeled as

$$H_0 : x(z) = w(z)$$
$$H_1 : x(z) = h.s(z) + w(z), z = 0, 1, 2 \ldots N-1$$

where Hypothesis H_0 is the null hypothesis having only noise component *w(z)* and H_1 is the true hypothesis indicating the presence of primary user signal *s(z)* and noise. *'h'* is the channel gain that constitutes fading parameters and N is the number of samples used for sensing. The noise is assumed to be complex-Gaussian, independent and identically distributed (i.i.d) samples with zero mean and variance σ_w^2 represented as $\mathcal{N}(0, \sigma_w^2)$. Similarly, the signal also exhibits the Gaussian distribution with zero mean and variance $\sigma_w^2 + \sigma_s^2$ represented as $\mathcal{N}(0, \sigma_w^2 + \sigma_s^2)$.

2.2. Proposed Parzen window entropy estimation

In statistics, the *pdf* of a finite set of samples can be evaluated using non-parametric models. Kernel density estimation is one of the non-parametric approaches to estimate the *pdf*, p(x) for a specific point from a sample p(x_n) without requiring any prior knowledge about the underlying distribution. It is also named as the Parzen–Rosenblatt window method. Let (x_1, x_2,..., x_n) be the samples of a random variable X. The Parzen window estimator of samples (x_1, x_2 ... x_n) that are independent and identically distributed having an unknown *pdf* of f is [10,11]

$$f_X(x) = \frac{1}{n}\sum_{i=1}^{n} K_h(x_k - x_i) \tag{1}$$

where n is the number of Gaussian samples, $K_h(.)$ is scaled kernel defined as $K_h(x) = \frac{1}{h}K\left(\frac{x}{h}\right)$ and h is the width of the kernel. The most dominant parameter that affects the density is the width of the kernel. It is also called as a smoothing parameter and is analogous to the histogram bin-width.

The *pdf* of a kernel function is assumed to have zero mean and symmetric around the axis [12]. Several kernel functions like Gaussian, Skewed Unimodel, Kurtotic Unimodel, Bimodel, Trimodel, Claw, and Comb densities having different mean