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A NOVEL WIDEBAND SPECTRUM SENSING FOR COGNITIVE RADIO USING SPARSE APPROXIMATION

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Abstract- The demand for radio frequency (RF) spectrum is always expanding due to the fast expansion of new wireless communication services and applications. The majority of the available RF spectrum has already been licensed to current wireless services. On the other side, it has been discovered that spectrum is substantially underused owing to static frequency allotment to devoted users, resulting in spectrum voids or spectrum opportunities. A CR is a device that scans the spectrum of licensed users (also known as main users) for available spectrum opportunities and sends data only when the spectrum is not used. The CR should be able to detect spectrum occupancy rapidly and accurately in order to maximize spectrum use while minimizing interference to licensed users. This makes spectrum detection one of the cognitive radio's primary functions. The simulation results are shown to demonstrate the usefulness of the suggested strategy. The approach is data-driven and does not need any previous knowledge of the signal. Finally, simulation findings reveal that the technique outperforms alternative spectrum sensing methods. The approach, in particular, improves detection probability.
Keywords – Cognitive radio, spectrum sensing, cooperative wideband spectrum sensing, Sparse Approximation

I. INTRODUCTION

One of the most important needs of SU is to monitor use behavior in the licensed spectrum in order to exploit underutilized spectrum (referred to as spectrum opportunity or spectrum gaps) without interfering with the PUs. Furthermore, PUs are under no duty to share or adjust their operational characteristics in order to share spectrum with SUs. As a result, SU should be able to identify spectrum gaps without the assistance of PUs; this capacity is known as spectrum sensing, and it is regarded as one of the important components of cognitive radio networks [1]. Spectrum sensing is a critical enabler technology for cognitive radio (CR), providing critical information on spectrum availability. However, because to significant wireless channel fading and route loss, the primary user (PU) or secondary user (SU) signals received at the CR or SU might be virtually too faint for accurate identification. Spectrum sensing (SS) by spectrum-sensing providers (SSPs) is critical for dynamic spectrum access and preventing interference with licensed main users. Before using the licensed spectrum, SUs must determine if the band is already in use by a PU. SUs must continually check if any PU has become active in a particular licensed band while using that band, and if so, the SUs must abandon that band. (PUs). Spectrum sensing is the assumption and cornerstone of cognitive radio technology for addressing spectrum shortage. Non-licensed users in cognitive radio (CR) networks utilize available resources dynamically in order to avoid interfering with licensed users. As a result, non-licensed or secondary users (SUs) must use spectrum sensing (SS) techniques to reliably identify the presence of signals sent by licensed or main users (PUs). Spectrum sensing is a crucial technology used in cognitive radio (CR)-based IoT networks to determine idle spectrum. Because of the large range of applications and widespread use of Internet-connected device networks, adaptability, receptiveness, and accuracy are the steeplechases. By making efficient use of spectral gaps, CR aids in dynamically distributing unlicensed frequency bands to Internet of Things (IoT) devices.

II. PROPOSED ALGORITHM

To forecast spectrum consumption, the cognitive radio system evaluates all levels of flexibility (time, frequency, and space). There are a few spectrum sensing techniques available. Spectrum sensing is a technology that determines whether or not a certain frequency band is in use. Varieties of methods are offered to identify the existence of signal transmission and may be used to increase detection likelihood.

To address the l1-norm regularized least square problem of sparse PU signal retrieval, this paper presents an Sparse approximation with a unique pre-conditioner. This methodology would retrieve a signal $x \in \mathbb{R}^{\eta}$ from its noisy measurements. General sparse approximation can be estimated as,

$$\mathfrak{b} = \mathcal{A}x + n \in \mathbb{R}^{\mathrm{M}} \qquad (1)$$

Where $\mathcal{A} \in \mathbb{R}^{\mathrm{MxN}}$ and $n \in \mathbb{R}^{\mathrm{M}}$ is the environmental noise.

The traditional Least Squares (LS) approach necessitates a large number of observations.

$\mathcal{M} \geq \mathcal{N}$,and $\mathcal{A}$ has full rank $\mathcal{N}$ to recover $\dot{x} = (\mathcal{A}^{\mathcal{T}}\mathcal{A})^{-1}\mathcal{A}^{\mathcal{T}}\mathfrak{b}$. Current Compressed Sensing (CS) techniques could recreate x from a much smaller number of observations $\mathcal{M} \leq \mathcal{N}$. As long as the PU signal appears sparse, the aforementioned basis pursuit's denoising dilemma can be solved:

$$\min_{xe\mathbb{R}^N} \frac{1}{2}\|Ax - b\|^2 + \tau\|x\|_1 \qquad (2)$$

Where $\tau > 0$ is a specified normalization coefficient, $\|x\| = \sqrt{\sum_{i=1}^{N} x_i^2}$ and $\|x\|_1 = \sqrt{\sum_{i=1}^{N} |x_i|}$ denote the l_2 and the l_1 norms of x, respectively,

Including the constraint clearly defines the solution key space in (6) the pseudo recovery, proposed methodology would use a simple optimization strategy to get them out.

$\hat{x} = [x^+; x^-] \in \mathbb{R}^{2N} \geq 0$, and $\hat{A} = [A, -A] \in \mathbb{R}^{M_x 2N}$

(3)

where,

$x_i^+ = \max(x_i, 0)$, and $x_i^- = \max(-x_i, 0)$, the $Ax = \hat{A}\hat{x}$ and, $\|x\|_{1=}\|\hat{x}\|_1$and hence Eq. 6) can be solved with respect to $\hat{A}$ and. $\hat{x} \geq 0$.

As a result, proposed method just need to acknowledge the version of Eq.(6) shown below for $x \geq 0$

$$\min_{x e \mathbb{R}^N} \frac{1}{2}\|Ax - b\|^2 + \tau e^\tau x \qquad (4)$$

$$st x \geq 0$$

Since in Eq.(8) an optimization problem is convex with nothing but linear constraints that fulfills Slater's condition, then this can discover optimized solution by addressing its Karush-Kuhn-Tucker (KKT) system:

$$A^\tau Ax - s - A^\tau b + \tau e = 0 \qquad (5a)$$

$$X.Se = 0 \qquad (5b)$$

$$(x, s) \geq 0 \qquad (5c)$$

Where

$$X = Diag(x) and S = Diag(s)$$

The above equation indicates diagonal matrices consist of primal coefficient x and dual coefficient value x and dual coefficient s, respectively, and 0 and e indicate an entirely zero or all one array whose size should be apparent from reference, respectively. The Inverse Sparse Approximation (ISA) addresses a transformed Karush-Kuhn-Tucker method by merely substituting Eq. (9b) for Eq. (9b) in the basic Karush-Kuhn-Tucker framework.

$$Xse = \sigma\mu e \qquad (6)$$

where

$\mu = x^\tau s/N$ goes to 0 , Whenever it converges, it returns to zero and $\sigma \in [0,1]$is a centeredness element. A σ closer to 1will prompt search results further towards the interior $(x, s) > 0$. Moving from a specific point(x, s), The novel Karush-Kuhn-Tucker system's orientation could be calculated as

$$A^\tau A\Delta x - \Delta s = r_d \qquad (7a)$$

$$S\Delta x + X\Delta s = r_e \qquad (7b)$$

Where r_d indicated the stationary residual and complementary slackness residual $r_e$can be expressed by

$$r_d = s - \nabla h(x) \qquad (8a)$$

$$r_e = \sigma\mu e - XSe \qquad (8b)$$

Here,

$\nabla h(x) = A^{\tau}Ax - A^{\tau}b + \tau e$ is the gradient of the objective function

$$h(x): \frac{1}{2}\|Ax - b^2\| + \tau e^{\tau}x \qquad (9)$$

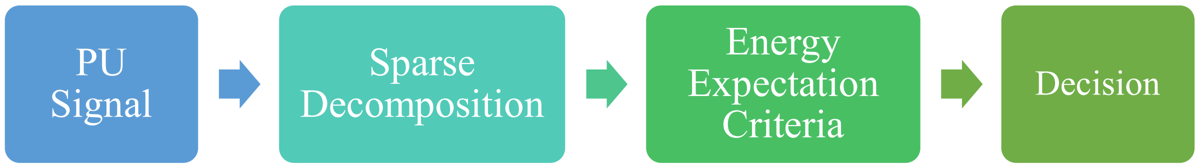

Figure 1:. Proposed SP in PU Signal Detection

In Algorithm 1, the proposed method represents Inverse Sparse Approximation (ISA) with predictor-corrector steps, which employs the Inverse Sparse Approximation (ISA) framework. It can be widely regarded as one of the most effective of the different SAs. To ensure quicker convergence, the proposed ISA uses different initializations, which have simplified but appropriate coefficients, a new pre-conditioner and adaptive tolerance. Although Eq. (9) must be fulfilled at all times, the proposed ISA allows quite versatile x,s that violate Eq. (9) during initial setup and subsequent iterations, that only need Eq. (9) to be fulfilled at convergence.

Algorithm: 1 Inverse Sparse approximation (ISP) Framework

Inputs: ϵ : $Choose\ (x^0, s^0) > 0\ stop\ accuracy\ \epsilon$ (e.g. 1e − 6),
Total Epochs is k_{max}.
$for\ k = 1,2, \ldots \ldots, k_{max}\ do$
Perform Prediction Step : set $\sigma \leftarrow 0.001$
$(x^k, s^k, \alpha_p, \alpha_d) = UPDATE(x^{k-1}, s^{k-1}, \sigma)$
if $\min(\alpha_p, \alpha_d) \leq 0.1$ then
Perform Correction Step: set $\sigma \leftarrow 0.99$.
$if\ \mu_k \leq \epsilon h(\mathrm{x}^k)\ and\ \|\mathrm{r}_d^k\| \leq \epsilon$ then
Break
Output: $\mathrm{x}^{\boldsymbol{k}}$
Function: UPDATE($\mathrm{x}^{k-1}, \mathrm{s}^{k-1}, \sigma$)
Compute $\Delta\mathrm{x}, \Delta\mathrm{s}$ with σ , $\mathrm{x}^{k-1}, \mathrm{s}^{k-1}$
Compute α_p, α_d with $\mathrm{x}^{k-1}, \mathrm{s}^{k-1}, \Delta\mathrm{x}, \Delta\mathrm{s}$
Update $(\mathrm{x}^k, \mathrm{s}^k) \leftarrow (\mathrm{x}^{k-1} + \alpha_p\Delta\mathrm{x}, \mathrm{s}^{k-1} + \alpha_d\ \Delta\mathrm{s})$
return $(\mathrm{x}^k, \mathrm{s}^k, \alpha_p, \alpha_d)$

III. EXPERTIMENTS

Figure 2 depicts the detection probability vs the false alarm probabilities when the proposed sparse decomposition and energy-based technique is utilized. Fig. 2 indicates that raising M from 5 to 15, as well as further increasing M to 30, greatly improves sensing performance for the proposed decoding-based fusion rule. This advancement may be attributed to the fact that detection of transmitted bits from CRs is highly dependent on interference induced by non orthogonal transmission. When all of the reporting channels are reasonably strong, the detection performance improves as the interference decreases with longer signature vectors (bigger M). The graph also demonstrates that the theoretical outcome (with M = 15) closely resembles the simulation result.

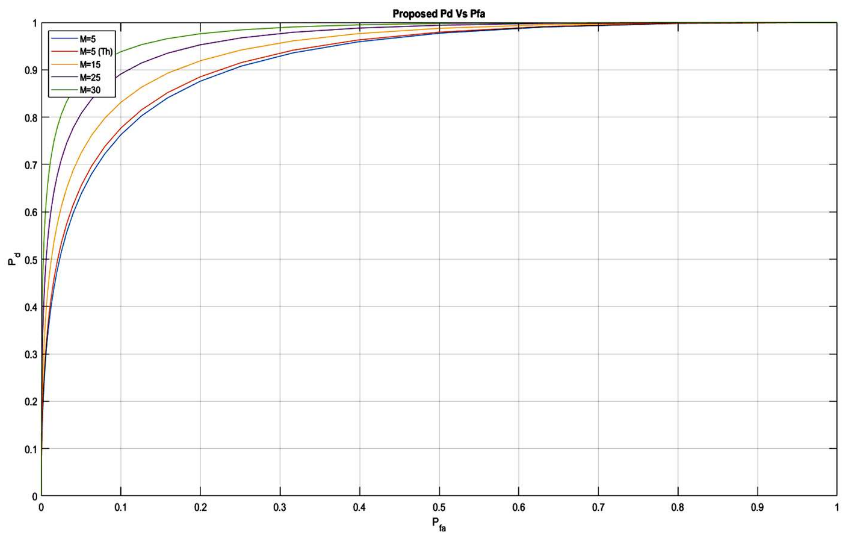

Figure 2: Probability of detection versus probability of false alarm for proposed.

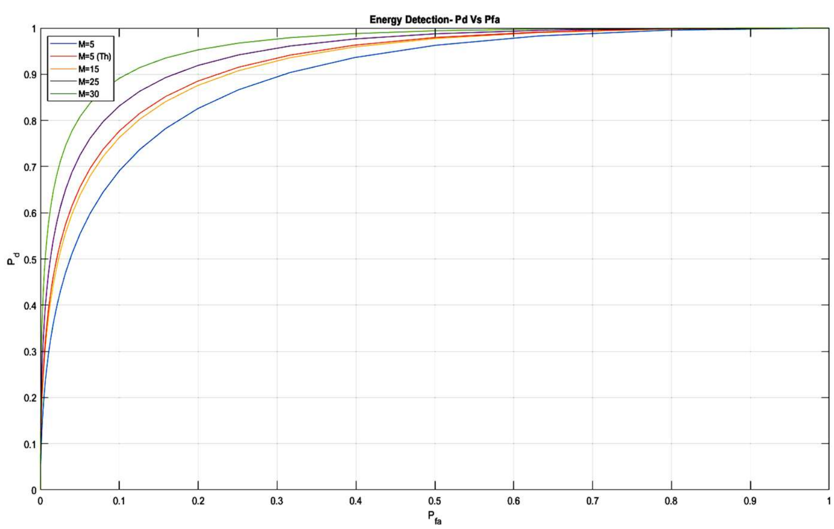

Figure 3: Probability of detection versus probability of false alarm for the energy- based

IV. CONCLUSION

The growing demand for cellular services, along with stagnant frequency distribution regulations, has resulted in wireless spectrum scarcity. Spectrum sensing is a crucial technology used in cognitive radio (CR)-based IoT networks to determine idle spectrum. Because of the large range of applications and widespread use of Internet-connected device networks, adaptability, receptiveness, and accuracy are the steeplechases. By making efficient use of spectral gaps, CR aids in dynamically distributing unlicensed frequency bands to Internet of Things (IoT) devices. The simulation results are shown to demonstrate the efficacy of the suggested strategy. The approach is data-driven and requires no previous knowledge of the signal. Finally, simulation findings reveal that the technique outperforms alternative methods of spectrum sensing. The approach, in particular, improves detection probability.

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