IEEE Access
Multidisciplinary : Rapid Review : Open Access Journal

Received November 18, 2021, accepted December 1, 2021, date of publication December 6, 2021, date of current version December 24, 2021.

Digital Object Identifier 10.1109/ACCESS.2021.3133336

Fast and Robust Spectrum Sensing for Cognitive Radio Enabled IoT

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This work was supported by the National Natural Science Foundation of China.

ABSTRACT The development of spectral efficient solutions for internet of things (IoT) face challenges primarily due to the large-scale placement of an immense number of sensors and devices. Cognitive radio (CR) technology is considered as a potential solution to resolve the spectrum scarcity problems of IoT. Incorporation of CR in IoT encounters various challenges including fast response and efficient spectrum sensing even in low signal to noise ratio. In this study we integrate the basic functionalities of the both CR and IoT technology and present a five layered framework for CR enabled IoT. In addition to the framework we also proposed and develop a spectrum sensing algorithm for CR-based IoT architecture, meeting the efficiency and time sensitivity requirements. The proposed algorithm is more accurate, robust to noisy environment and four times faster than existing approaches. The developed algorithm is compared with existing blind spectrum sensing techniques in term of detection performance, optimization methods and computational complexity. Experimental evaluations with real wireless microphone signals demonstrate the effectiveness of the proposed scheme and show superiority over existing ones.

INDEX TERMS Cognitive radios, Internet of Things, principle component analysis, spectrum sensing.

I. INTRODUCTION

The interconnection of different objects via internet brings the concept of IoT. These objects are integrated with different sensors and the communication units [1], [2]. The communication range, data bandwidth, and the spectrum resources are the key concerns for IoT [3], IoT applications generate huge data to the network, most of it could be redundant and causes spectrum and other resource wastage, cognitive radio seems to be a potential solution to such issues due to its cognition capability [4], [5]. CR is a key enabling technology for next generation wireless communication networks, since it offers a promising solution to address the problem of the spectrum scarcity [6], [7]. Each node in CR network has the ability of fast switching and keep knowledge about the channel condition. Dynamic spectrum access (DSA) empowers a CR node to adjust its parameters according to network situations [8]. Spectrum sensing helps these nodes to utilize the spectrum without interfering to the licensed/primary user (PU) [9]–[11].

Spectral efficient methods are required to be incorporated to improve connectivity and competent functioning of massive number of heterogeneous devices in IoT networks. Wi-Fi, mobile networks, and other technologies uses the licensed free ISM bands and ever increasing IoT objects causing ISM to be extremely crowded soon. CR ability in IoT will help to provide enough spectrum for future networks.

CR-IoT will permit the current IoT to build the high-level intelligence [12] and It can learn recent network conditions, analyze the data, take smart decisions, and adapt accordingly to maximize the network performance. CR capable sensor nodes in an IoT network can reuse the spectrum and enhance the spectrum utility efficiency.

CR-IoT devices would have better access to other networks and services that make the system more scalable [12]. IoT devices could achieve better connectivity as CR nodes are capable of communicating to multi-frequency devices. In addition, self-configuration property of the CR nodes can make the IoT wireless network more efficient and robust [13].

The associate editor coordinating the review of this manuscript and approving it for publication was Francesco Benedetto.

TABLE 1. List of acronyms.

Acronym	Meaning
CR	Cognitive radios
IoT	Internet of things
SNR	Signal to noise ratio
PU	primary user
SU	secondary user
PCA	principle component analysis
RPCA	Robust principle component analysis
MOG	mixture of Gaussian
USRP	Universal Software Radio Peripheral
M2M	Machine to machine
SISO	single input single output
SIMO	single input multiple output
APG	Accelerated Proximal Gradient
IALM	Inexact Augmented Lagrange Multiplier
FFT	Fast Fourier transform
ISM	Industrial, Scientific and Medical
RRE	Relative reconstruction error
P_d	probability of detection
P_f	probability of false alarm

Due to above discussed benefits, current research trends are supporting the incorporation of CR into IoT to support devices from manufacturing, health care, smart grid, to buildings, and so on [14]. Considering the vigorous importance of spectrum sensing in CR-IoT, this paper exploits the spectrum sensing a vital part of this paradigm, analyze the existing spectrum sensing techniques and present an efficient, robust yet fast spectrum sensing algorithm that suits best for time sensitive IoT applications [15], [16].

Paper presents the need of CR capability in IoT and proposed a five layered framework for CR-IoT, comprises of perception layer, virtual object layer, composite virtual objects, communication layer, and consumer layer. Being a vital component of CR spectrum sensing is an important element of CR-IoT [4], [17]. We have examined the detection performance and complexity of the blind detection techniques based on principle component analysis (PCA) and Robust PCA for low SNR scenarios, experienced by the various IoT applications [18]. Moreover, a novel and more efficient sensing algorithm is proposed considering a complex noise model (i.e. mixture of Gaussian). In addition, experimental test bed was established with USRP2 kit and GNU Radio to evaluate the proposed algorithm. Specific contributions of the paper are as follows.

A. CONTRIBUTIONS

- This paper discusses the standing of CR capability for IoT network and investigates the two main issues faced by CR-based IoT that is time sensitivity and spectrum scarcity.
- Presented a five layered framework for CR-IoT, comprises of perception layer, virtual object layer, composite virtual objects, communication layer, and consumer layer. The proposed framework integrates the main functions of both CR and IoT.
- Considering the requirements of CR-IoT nodes we put effort to propose a spectrum sensing algorithm for CR enabled IoT nodes which is fast (low convergence time) and robust (RPCA with complex noise model). The proposed algorithm employed Inexact ALM that is five time faster than the existing approach with APG to decompose the covariance matrix. Moreover, new approach achieves higher precision and requires less storage.
- Sensing ability of the proposed and existing RPCA algorithms is analyzed under a low SNR (< -20 dB) scenario with two different noise models (Gaussian noise model and Complex noise model). The effect of number of receive antennas and number samples on the sensing performance is also analyzed. In addition, computational complexity is computed and compared mathematically.

The rest of the paper is organized as follows. Cognitive Radio-IoT Framework is presented in section II. A brief discussion on the related work is presented in section III Section IV describes the system model and the PCA based existing spectrum sensing techniques. The proposed algorithm is presented in Section V along with a discussion on computational complexity of the algorithms. Details about the experimental set up and the discussion on the results are provided in Section VI. Finally, Section VII concludes the paper with future research directions.

II. COGNITIVE RADIO ENABLED IOT FRAMEWORK

There are various frameworks for CR-IoT has been proposed in the literature most of them focused on a specific application, and existing literature yet to be merged into a reference framework model. In this section we have discussed few models and proposed a framework based on these references.

The research in [19] have proposed a CR-IoT architecture and they have categorized the nodes into three levels, device level nodes, gateway nodes and access nodes, the gateway nodes are connecting the other two levels. Al-Fuqaha *et al.* [20] have deliberated five-layer framework for IoT, device layer, abstraction layer, service management layer, application layer, business layer. Authors in [21] also presented a five-tier model consisting of application, service, communication, abstraction and perception layer and discussed the functionalities of each layer. CR-based IoT framework with three levels has been presented in [4]. First level is the virtual objects (main elements are VO and VO registry), second is the composite virtual objects (CVOs) level consisting of the CVOs, CVO registry and perform task related to situation, and the third level is the consumer level.

Various main functionalities of the IoT and the CR are same, authors in [21] have identified and summarized the similarities between the functionalities of the CR and IoT paradigm.

We present a five layered framework for CR-IoT, comprises of perception layer, virtual object layer, composite virtual objects, communication layer, and consumer layer as depicted in Figure 1. The proposed framework integrates the functionalities of both technologies CR and IoT. The layered approach makes it easy to combine similar attributes and

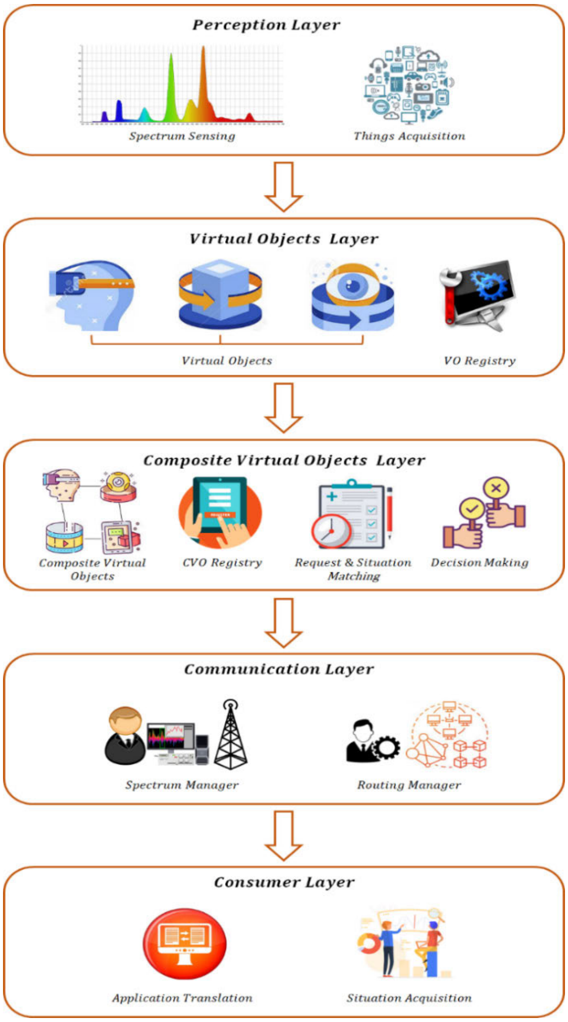

FIGURE 1. Cognitive radio-IoT framework.

help to make the development process independent. Each layer consists of many sub-modules that performs the functionalities of CR and IoT correspondingly. For example, the spectrum sensing module in the perception layer is responsible for finding the underutilized spectrums, and the things acquisition module handles the similar type of functionalities for IoT.

A. VIRTUAL OBJECT LAYER (VOL)

The main units of the VOL are virtual objects and its registry. This layer hides the device heterogeneity, location mobility issues from the other layers of the framework. VOL deals all the sensors, actuators as a virtual object.

B. COMPOSITE VIRTUAL OBJECTS LAYER (CVO)

At this layer, CVOs & their registry, demand and state similarity, and decision taking are the main elements.

C. COMMUNICATION LAYER

This layer handles the data transmission between the nodes and connection to the internet. Communication layer is responsible to provides intelligent routing, and managing spectrum issues.

D. PERCEPTION LAYER

It comprises of two submodules named as things acquisition and spectrum sensing. Things acquisition submodule is to gather the information from the environment while spectrum sensing is responsible to detect underutilized free spectrum frequencies via any spectrum detection technique.

E. CONSUMER LAYER

This layer is responsible for application translation and situation acquisition, it also handles the creation and management of the required services.

III. RELATED WORK

Spectrum sensing is necessary to determine the spectrum capacity and to enable the IoT device communication over unutilized radio spectrum. Work in [22] has discovered underutilization of FM radio spectrum in urban areas, and present it to be utilized by the low powered and short ranged CR-IoT devices. The study in [23] considered the standing of spectrum utilization by unlicensed user for the future IoT infrastructures. [15] Introduce the concept of cognitive M2M communication, started with motivate to integrate cognitive radio technology in IoT from technical, applications, industry support, and standardization aspects. Then, they have proposed cognitive M2M network architecture.

[24] discusses the recent advance in cognitive M2M communications from a protocol stack perspective. They cover the standardization and the latest developments on protocols for cognitive M2M networks for IoT. [25] Investigate implementation of CR technology for a narrowband IoT. They elaborate the important of reducing the spectrum sensing overhead to maximizing the network throughput, authors derive a set of optimal sensing parameters to get the maximum throughput of a narrowband cognitive radio IoT network. Authors in [26] presented a short review on the most recent spectrum sensing methods. They analyze and express the conditions when spectrum sensing is an appropriate and cost-effective option especially in the future intelligent IoT systems [27] Proposed an energy and spectrum efficient architecture of CR sensor networks for IoT. Their approach enables the IoT nodes to access the spectrum opportunistically and harvest energy via ambient radio-frequency sources. [28] present a comprehensive survey on spectrum sensing techniques for cognation radio networks with a particular focus on wide band sensing. They also present the narrow band spectrum sensing techniques and their pro and cons. As we proposed the spectrum sensing for CR enabled IoT systems using blind sensing techniques that are covariance based, previous work in that direction is discussed below.

Blind detection methods are quite useful for signal detection in low signal to noise ratio (SNR) because they did not require any prior knowledge about the signal or channel [6], [10], [29].

To overcome the issue of noise power uncertainty, the covariance based detection (CBD) algorithms were suggested in [30]. Signal and noise generally have different statistical covariance, this property has been exploited for covariance-based spectrum sensing in [10]. When the PU is absent, off diagonal elements of the covariance matrix is zero, while it is non-zero when the signal is present. This technique did not require prior information of the primary user signal, channel or noise [31]. Recently, principle component analysis (PCA) has been used for spectrum sensing and signal classification in cognitive radio networks [32].

The objective of the PCA is to reduce dimensionality of the data and to identify new underlying meaningful variables. The work in [33] used the PCA to enhance the spectrum sensing by deriving the new SNR attained after applying PCA. It can be taken as a pre-processing step for a classical Spectrum Sensing algorithm PCA is also exploited in modulation classification, [34] suggested an advance automatic modulation classification method for CR using PCA. Authors used two-dimensional property of the spectral correlation function (SCF) to recognize the modulation of the signal. In energy based spectrum sensing (EBSS), the procedure for the threshold computation lacks the clarity and defined steps; an effort has been made in [35] to improve the conventional BESS technique using PCA. A correction factor is proposed to the conventional PCA. The covariance matrix of the white noise is similar to the identity matrix while signal has a low rank matrix. In [36] a PCA based spectrum sensing algorithm was proposed that uses the dimension reduction property of the PCA to reduce the sensing time. Dimension reduction is achieved by discarding the data that did not impart much about the signal's presence or absence. This dimension reduction saves the sensing time but also degrade the sensing efficiency. RPCA has been used to recover the low-rank matrix in [37]. Spectrum sensing using RPCA was also presented in previous studies that is further discussed and analyzed in Section 4.

IV. SPECTRUM SENSING USING PCA AND RPCA

A. SYSTEM MODEL

SISO (single input single output) and SIMO (single input multiple output) antenna systems considered in this paper are represented in Figure 2. Let us define the received signal as $y(n) = y(nT_s)$ and the primary users signal as $s(n) = s(nT_s)$ while $w(n) = w(nT_s)$ represents the Additive white Gaussian noise. Assuming that W is the bandwidth of the received signal, the sample rate is defined as $fs \gg W$. Equation (1) shows the complex baseband samples. Where N is the total number of samples for SISO system.

$$\mathrm{Y} = [y_1(n), y_1(n-1), \ldots, y_1(n-N+1)] \tag{1}$$

N Complex baseband samples with M RF front ends can be represented as [29].

$$\begin{aligned}\mathrm{Y} = [&y_1(n), \ldots, y_M(n), y_1(n-1), \ldots, y_M(n-1),\\ &y_1(-N/M+1), \ldots, y_M(-N/+1)]\end{aligned} \tag{2}$$

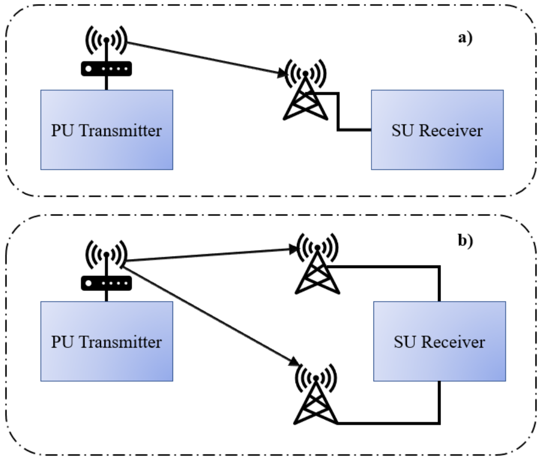

FIGURE 2. a) SISO system, b) SIMO system.

The spectrum sensing needs to discriminate the two hypotheses $\boldsymbol{H_1}$ that indicate the primary user's signal and $\boldsymbol{H_0}$ specify absence of PU is as define below.

$$y(n) = \begin{cases} \boldsymbol{H_0} : w(n) \\ \boldsymbol{H_1} : s(n) + w(n). \end{cases} \tag{3}$$

Performance of the spectrum sensing process is evaluated by two important parameters names as the probability of detection P_d and the probability of false alarm P_f. P_d and P_f are defined as the probability to declare H_1 when the PU exists (H_1) or does not exist (H_0).

$$P_d = P\left(\frac{H_1}{H_1}\right) \tag{4}$$

$$P_f = P\left(\frac{H_1}{H_0}\right) \tag{5}$$

B. PU DETECTION WITH PCA

Principal component analysis was performed for PU signal detection by using the following steps [38]:

- Calculation of the sample covariance matrix as $S_x = \frac{1}{N_s}\sum_{i=1}^{N_s} x_i x_i^T$
- Decomposition of the covariance matrix into eigenvectors.
- Generation of the principal components. $C_{ji} = F^T x_i$ Where F contains the most significant eigenvectors.
- Calculation of the test statistic D as in equation 4.
- Decision between $\boldsymbol{H_1}$ and $\boldsymbol{H_o}$ by comparing the D with the threshold ψ (predetermined at the desired P_f).

The test statistic D which is used to discriminate between PU signal and noise is calculated as follows [32].

$$D = \frac{1}{N}\sum_{j=1}^{g} C_{j1}^2 + C_{j2}^2 + C_{j3}^2 + \cdots + C_{jN}^2 > \psi \tag{6}$$

where C_{ji}^2 is the i^{th} element of the j^{th} principal component and ψ is the detection threshold. PU is detected if $D > \psi$.

C. PU DETECTION WITH RPCA

Suppose that M is the sum of low rank matrix L and a sparse matrix S. An entirely corrupted low rank matrix can be recovered with a theoretical frame work namely RPCA [39]. Both low-rank and sparse matrices are recoverable with PCs, pursuit from their summation under very broad conditions (low SNR, interference and other environmental effects) [40], [41]. The covariance matrix of the signal at receiver is the combination of a sparse and a low-rank matrix under hypothesis H_1 with the assumption that signal and white noise are independent [37], [42].

Let $\hat{x}(n)$ is a concatenation of L consecutive received vectors and is defined as

$$\begin{aligned}\hat{x}(n) &= \left[x^T(n), x^T(n-1), \ldots, x^T(n-L+1)\right]^T \\ &= \begin{bmatrix}\mathbf{H_0}\\ \mathbf{H_1}\\ \vdots \\ \mathbf{H_{L-1}}\end{bmatrix}\begin{bmatrix} s(n) \\ \vdots \\ s(n-L-N_{ch}+1)\end{bmatrix} + \begin{bmatrix}\eta_1(n)\\ \vdots \\ \eta_M(n) \\ \vdots \\ \eta_1(n-L+1) \\ \vdots \\ \eta_M(n-L+1)\end{bmatrix} \\ &= \hat{\boldsymbol{H}}\begin{bmatrix} s(n) \\ \vdots \\ s(n-L-N_{ch}+1)\end{bmatrix} + \begin{bmatrix}\eta_1(n)\\ \vdots \\ \eta_M(n) \\ \vdots \\ \eta_1(n-L+1) \\ \vdots \\ \eta_M(n-L+1)\end{bmatrix}\end{aligned}$$

$$\hat{\boldsymbol{H}}s(n) + \eta(n) = \bar{s} = (n) + \eta(n) \tag{7}$$

Size of $\hat{x}(n)$ is $M \times L$ *and* the channel matrix $\mathbf{H}$ is $M \times L + N_{ch}$ is Further, the three different approaches are discussed below to apply RPCA in spectrum sensing scenario.

1) FIRST APPROACH (RPCA-1)

Sample covariance matrix (SCM) $S_x(N_s)$ is derived as defined in equation (8) where N_s is number of samples. The received signal is partitioned into two segments and the RPCA is applied to recover the low rank matrices.

$$S_x(N_s) = \frac{1}{N_s}\sum_{n=L-1}^{L-2+N_s}\hat{x}(n)\hat{x}^\dagger(n) \tag{8}$$

$$S_{x1} = \frac{1}{N_s}\sum_{n=L-1}^{L-2+N_s}\hat{x}_1(n)\hat{x}_1^\dagger(n) \tag{9}$$

$$S_{x2} = \frac{1}{N_s}\sum\nolimits_{n=L-1}^{L-2+N_s}\hat{x}_2(n)\hat{x}_2^\dagger(n) \tag{10}$$

S_{x1}, S_{x2} represents the SCM for each segment and the low rank matrices recovered from S_{x1}, S_{x2} by RPCA are $\tilde{S}_{s1}$, $\tilde{S}_{s2}$. The divergence between $\tilde{S}_{s1}$ and $\tilde{S}_{s2}$ should be insignificant when primary signal exists, hence the PU is detected if [43].

$$\left\|(\tilde{S}_{s1}/\left\|\tilde{S}_{s1}\right\|_F)(\tilde{S}_{s2}/\left\|\tilde{S}_{s2}\right\|_F)\right\|_F < T_{RPCA} \tag{11}$$

where $\|.\|_F$ is the Frobenius norm of the matrix and T_{RPCA} is a pre-defined threshold at 10% probability of the false alarm.

2) SECOND APPROACH (RPCA-2)

Here RPCA is adopted as a de-noising process for the SCM of the received signal. In case of H_1 the recovered low-rank matrices $\tilde{S}_{s1}$ and $\tilde{S}_{s2}$ are nearly equal to the SCM of the PU signal. The leading eigenvectors $\tilde{\sigma}_1$ and $\tilde{\sigma}_2$ of low rank matrices $\tilde{S}_{s1}$ and $\tilde{S}_{s2}$ are derived by eigen-decomposition. The PU signal will be identified if [44], [45].

$$\max_{l=0,1,\ldots,d}\left|\sum_{k=1}^{d}\tilde{\sigma}_1[k]\tilde{\sigma}_2[k+l]\right| > T_{RPCA-le} \tag{12}$$

where $T_{RPCA-le}$ *is* the threshold value and the dimension $d = 32$.

3) THIRD APPROACH (RPCA-3)

This methodology combines the power of low-rank (L) and sparse matrix (S). RPCA via Accelerated Proximal Gradient (APG) is used to decompose a sample covariance matrix of the received signal into signal and noise components [37]. Let us define covariance matrix as

$$S\_x = E[\bar{x}(n)\bar{x}(n)\dagger] \tag{13}$$

$$S_x = S_{\bar{s}} + S_\eta \tag{14}$$

S_x is the sum of signal and noise, where, $S_{\bar{s}}$ and S_η are defined as,

$$\begin{cases} S_{\bar{s}} = E[\bar{s}(n)\,\bar{s}\left(n\right)^\dagger] \\ S_\eta = E[\eta(n)\,\eta\left(n\right)^\dagger] \end{cases} \tag{15}$$

$$R_x(N_s) = \frac{1}{N_s}\sum_{n=L-1}^{L-2+N_s}\hat{x}(n)\hat{x}^\dagger(n) \tag{16}$$

After decomposing the covariance matrix into L and S that is low rank and sparse matrices respectively, power ratio

TABLE 2. Comparison of the optimization techniques of RPCA algorithm with rank 20.

Algorithm	Relative estimation error (sec)	Time (s)
Singular Value Thresholding	3.4×10^{-4}	877
Accelerated Proximal Gradient	2.0×10^{-5}	43
APG (partial SVDs)	1.8×10^{-5}	8
Dual Method	1.6×10^{-5}	177
Exact ALM	7.6×10^{-8}	4
Inexact ALM (IALM)	4.3 × 10-8	2
Alternating Direction Methods	2.2 x 10-5	5

between L and S is calculated as [43],

$$T = \frac{tr\left(LL^{\dagger}\right)}{tr\left(SS^{\dagger}\right)}. \tag{17}$$

The PU signal is detected if

$$T > \gamma,$$

where γ is empirically calculated at a desired P_f.

V. PROPOSED SPECTRUM SENSING ALGORITHM (RPCA-CN)

All the PCA based spectrum sensing techniques (discussed in section 4) considered the Gaussian noise model or the sparse noise, which makes them flabby for the real time IoT applications, as in the real environment the noise is much more complex [46]. For the efficient detection of the PU there is a need to consider that complex nature of the noise. The proposed algorithm is based on the RPCA while considering complex noise (mixture of Gaussian (MOG)) model to make the sensing more efficient and well working in all kinds of real environments. Before going to the details of proposed methodology, a brief overview of the optimization methods for RPCA and synthetic data analysis of noise models (in term of relative reconstruction error) has been be discussed.

The optimization methods for RPCA were compared with the intention to choose the best one. APG, Augmented Lagrange Multiplier (ALM) Method, Dual Method and Singular Value Thresholding (SVD) were considered in the assessment, details of these methods could be found in [47], [48]. All the methods are compared in term of relative reconstruction error and the convergence time as presented in Table 2. The relative reconstruction error and the convergence time are important parameters in the context of sensing time [49]. Algorithms were tested on a rank-20 matrix with 5% of its entries corrupted by the enormous errors. It could be observed in Table 2 that the Inexact ALM has the least relative error in estimation and faster convergence as compared to other methods. Due to its fast convergence and accuracy, Inexact ALM has been incorporated in our proposed methodology.

Relative reconstruction error for PCA, RPCA and MOG-RPCA under different noise models is presented in Table 3.

It is clear from the Table that MOG-RPCA has the least RRE under complex noise models. RPCA work well with sparse and Gaussian case as compare to MOG-RPCA, while

TABLE 3. Synthetic data analysis in term of RRE (relative reconstruction error).

Case	Parameter	PCA	RPCA	MOG-RPCA
No Noise	RRE	$1.04e^{-15}$	$3.33e^{-8}$	$5.03e^{-5}$
Sparse Noise	RRE	0.768	$1.33e^{-7}$	$8.17e^{-5}$
Gaussian Noise	RRE	$3.11e^{-2}$	$5.95e^{-2}$	$3.11e^{-2}$
Mixture Noise	RRE	$7.7e^{-2}$	$4.96e^{-2}$	$1.90e^{-2}$

with no noise case PCA is better than all other approaches, but this scenario does not exist in real environment.

We proposed RPCA under a Bayesian frame work by assuming noise as a mixture of Gaussian. Such noise modeling presented in [42], [50]. MOG is the universal approximation to any continuous probability distribution, the use of such complex noise model in spectrum sensing scenario makes it able to suite a widespread series of noise such as Laplacian, Gaussian, Sparse and a mixture of these. Suppose that M is the sum of low rank matrix L and a sparse matrix S. The covariance matrix of the signal at receiver is the combination of a sparse and a low-rank matrix under hypothesis H_1 with the assumption that signal and noise are independent [37], [42].

Let $\hat{x}(n)$ is a concatenation of L consecutive received vectors and is defined as

$$\begin{aligned}
\hat{x}(n) &= \left[x^T(n), x^T(n-1), \ldots, x^T(n-L+1)\right]^T \\
&= \begin{bmatrix} \mathbf{H_0} \\ \mathbf{H_1} \\ \vdots \\ \mathbf{H_{L-1}} \end{bmatrix} \begin{bmatrix} s(n) \\ \vdots \\ s(n-L-N_{ch}+1) \end{bmatrix} + \begin{bmatrix} \eta_1(n) \\ \vdots \\ \eta_M(n) \\ \vdots \\ \eta_1(n-L+1) \\ \vdots \\ \eta_M(n-L+1) \end{bmatrix} \\
&= \hat{H} \begin{bmatrix} s(n) \\ \vdots \\ s(n-L-N_{ch}+1) \end{bmatrix} + \begin{bmatrix} \eta_1(n) \\ \vdots \\ \eta_M(n) \\ \vdots \\ \eta_1(n-L+1) \\ \vdots \\ \eta_M(n-L+1) \end{bmatrix}
\end{aligned}$$

$$\hat{H}s(n) + \eta(n) = \bar{s} = (n) + \eta(n)$$

Size of $\hat{x}(n)$ is $M \times L$ *and* the size of the channel matrix **H** is $M \times L + N_{ch}$.

Considering RPCA as generative model with Y the original data matrix, L the low rank components matrix and E the sparse component matrix.

$$Y = L + E \tag{18}$$

It is assumed that the entries of E are drawn independent of a Laplacian distribution and the singular values of the L are drawn from another Laplacian distribution. RPCA can be interpreted as a MAP estimation with the Laplacian noise. Noise components are modeled with the assumption that each e_{ij} in E follows MOG distribution as in [47].

$$e_{ij} \sim \sum_{k=1}^{K} \Pi_k N\left(e_{ij} \middle| \mu_k, \tau_k^{-1}\right), \tag{19}$$

where, Π_k is mixing portion with value greater than zero and $\sum_{k=1}^{K} \Pi_k = 1$, K is Gaussian component number and $N\left(e_{ij} \middle| \mu_k, \tau_k^{-1}\right)$ is Gaussian distribution with μ mean and τ precision. To complete the Bayesian model conjugate priors over the parameters of Gaussian component μ_k, τ_k and Π as:

$$\mu_k, \tau_k \sim N(\mu_k \left| \mu_0 \left(\beta_0 \tau_k^{-1}\right)\right) Gam\left(\tau_k | c_0, d_0\right), \tag{20}$$

$$\Pi \sim Dir(\pi | \alpha_0), \tag{21}$$

where, $Gam(\tau_k | c_0, d_0)$ is the Gamma distribution with parameters c_0 and d_0, and $Dir(\pi | \alpha_0)$ denotes the Dirichlet distribution. This Distribution is parameterized by $\alpha_0 = \alpha_{01}, \alpha_{02}, \ldots, \alpha_{0k}$. Low rank component modeling is done via ARD (automatic relevance determination) due to its speed and scalability.

$$D_x = A_k + E_k \tag{22}$$

The mathematical model for approximating the low-dimensional subspace is to discover a low rank matrix A from the observation matrix D, while minimizing the discrepancy between A and D. The proposed RPCA-CN could be summarized as follow.

- Obtaining the sample covariance matrix

$$D_x = \frac{1}{N_s} \sum_{n=L-1}^{L-2+N_s} \hat{x}(n)\, \hat{x}^{\dagger}(n)$$

- Recovery of low rank matrix A_k and error matrix E_k from the sample covariance matrix D_x of the received signal with RPCA via Inexact ALM as described in Algorithm 1.
- Calculation of the detection test static

$$S = \frac{tr\left(A_k A_k^{\dagger}\right)}{tr\left(E_k E_k^{\dagger}\right)}$$

- PU signal will be detected if

$$S = \frac{tr\left(A_k A_k^{\dagger}\right)}{tr\left(E_k E_k^{\dagger}\right)} > \gamma, \tag{23}$$

where, threshold γ is calculated empirically at a pre-defined P_f. In our experiments we consider two cases for P_f that is $P_f = 1\%$ and $P_f = 10\%$.

Algorithm 1 : RPCA via Inexact ALM

Input: observations matrix $D_x \in R^{m \times n}$, λ
1: $Y_0 = \frac{D}{J(D)}$; $E_0 = 0$; $\mu_0 > 0$; $\sigma > 1$; $k = 0$.
2: **while** not converged **do**
3: // step 4-5 solve $A_{k+1} = \arg\min L\left(A, E_k, Y_k, \mu_k\right)$
4: $(U, S, V) = svd\left(D - E_k + \mu_k^{-1} Y_k\right)$;
5: $A_{k+1} = US_{u_k} - 1[S]V^T$
6: // step 7 solve $E_{k+1} = \arg\min L\left(A_{k+1}, E, Y_k, \mu_k\right)$
7: $E_{k+1} = US_{u_k} - 1[D - A_{k+1} + \mu_k^{-1} Y_k]$
8: $Y_{k+1} = Y_k + \mu_k(D - A_{k+1} + E_{k+1})$
9: Update μ_k to μ_{k+1}
10: $k \leftarrow k + 1$
11: **end while**
Output: (A_k, E_k)

A. COMPUTATIONAL COMPLEXITY

Complexity of the PCA based spectrum sensing algorithm comes from two phases, first is the calculation of the SCM and the second is the decomposition of the SCM. In first part (M^2FN_s) multiplications and $O(M^2F(N_s - 1))$ additions are required, here M represent the number of antennas at the receiver, while F is smoothing factor and number of samples are represented by N_s. In the second step $O(M^3F^3)$ multiplications and additions are involved [39], [51]–[53]. We can summaries as,

Complexity of the PCA: $O(M^2FN_s) + O(M^3F^3 + V^2)$. Complexity of the RPCA: $O(M^2FN_s) + O(M^3F^3)$. Complexity of the RPCA per iteration with MOG:

$O((m+n)R^3 + KmnR + mnR^2)$ Where,

- m is the dimensionality.
- n size of the input data.
- K MOG number.
- R is the Rank.

The complexity of the proposed method is slightly high as compare to the existing RPCA algorithms however, modern day devices are can afford this complexity.

VI. EXPERIMENTAL RESULTS

To validate the proposed algorithm and evaluate its performance, we perform a series of experiment using both simulated and real microphone signals in this section.

A. EXPERIMENTAL SETUP

Two receiver systems SISO and SIMO were setup for the reception of correlated signals, transmission constraints were

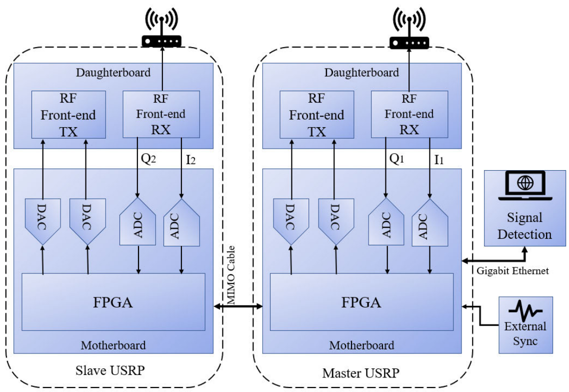

FIGURE 3. Correlated signal reception system.

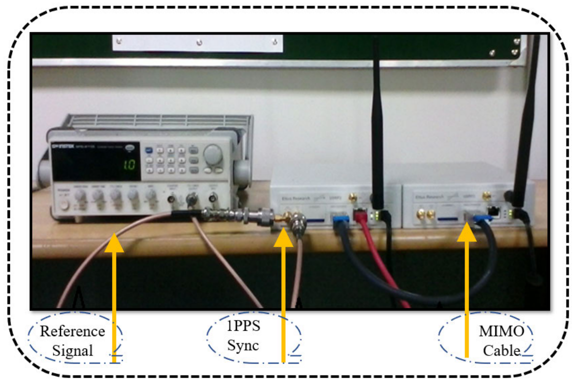

FIGURE 4. Testbed setup, USRPs master/slave configuration.

FIGURE 5. GNU radio environment.

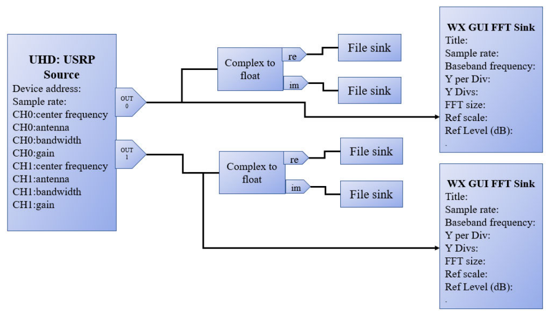

FIGURE 6. GNU radio companion flow graph for SIMO system.

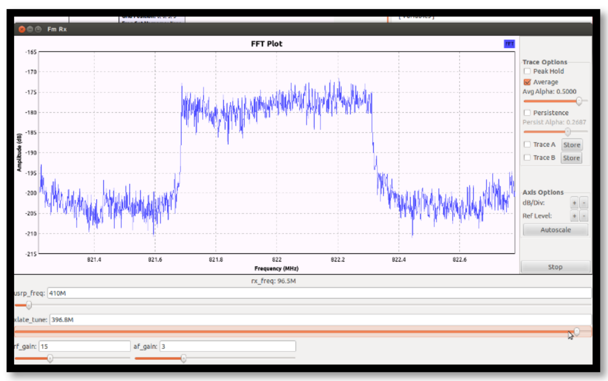

FIGURE 7. FFT plot of the received signals.

fixed as in [54]. USRP2 is a high performance SD, it contained a single pair of Tx and Rx antenna and keeps a widespread range of 50 MHz to 2.2 GHz [54]. The two USRPs were connected in a master/slave configuration, the master USRP was connected with the personal computer via the ethernet interface. They were inter-linked with a MIMO cable, that ensured fully coherent signal reception. Synchronization between USRPs is established with two reference signals at the master USRP, one is a 10 MHz signal to provide a single frequency reference and the other is 1 PPS signal to synchronize the sample time across the USRPs.

Figure 3 shows the block diagram of the signal reception system. The data sets are the synchronized signals from both I and Q channels of the two different RF front ends. Testbed setup comprises of USRPs is depicted in the Figure 4.

The PU is a FM (frequency modulation) signal with 410 MHz frequency and a bandwidth of 200 kHz. R and S SMF100A microwave signal generator was used to transmit the signal. The SNR was varied by tuning the transmit power at the signal generator. The sampling rate is set to 6.25 Mega samples/sec. The received signals were fed into the host computer and stored into MATLAB readable files with the help of GNU radio, where the detection and performance analysis was done, Figure 5 and Figure 6 shows the GNU radio environment and GNU radio companion flow graph respectively. FFT plot of the received signal is shown in Figure 7.

SNR of the recorded signal was calculated by turning off the signal generator and measuring the noise at each RF front end. The power of the signal at M_{th} front end is estimated by equation 24 and the SNR is calculated as in equation 25.

$$P_M = \frac{1}{N\sum_{n=1}^{N} |X_M(n)|^2} \tag{24}$$

$$SNR_M = 10log_{10}\left[\frac{P_{M,1} - P_{M,0}}{P_{M,0}}\right] \tag{25}$$

$P_{M,1}$ and $P_{M,0}$ represent the power of signal and the noise respectively. After collecting the data set we additionally incorporate different noise distributions (as detailed in section 5) to the data matrix to generate the different data sets for evaluation. Evaluations for P_d were performed for $N = 60,000$ and $L = 6$ at 10% and 1% probability of false alarm. Noise uncertainty $U = 0.5$ and is defined

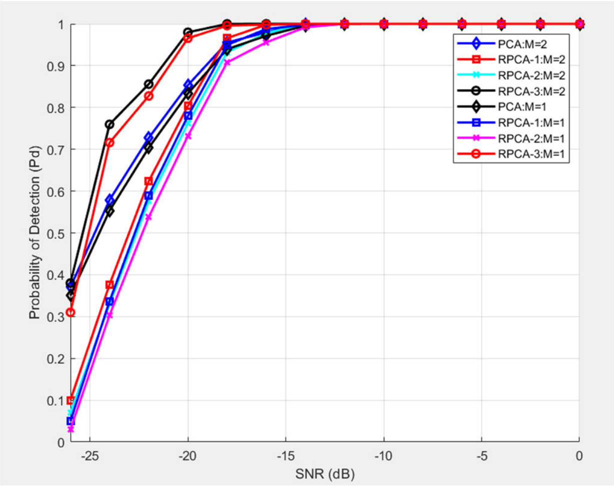

FIGURE 8. P_d at 10 % P_f, with single and multiple antennas ($M = 1, 2$).

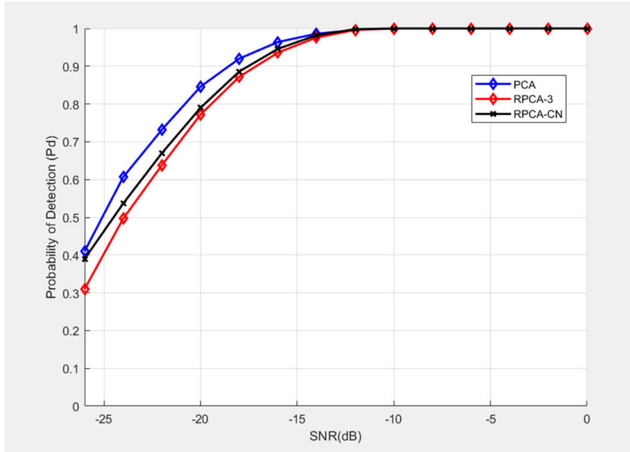

FIGURE 9. P_d at 10% P_f, under gaussian noise model, N = 60000 and M = 2.

in equation 26 where σ_n^2 is the actual noise variance and $\hat{\sigma}_n^2$ is the estimated noise variance.

$$U = \sup \left| 10 \log (\hat{\sigma}_n^2)/(\sigma_n^2) \right| \tag{26}$$

Threshold is calculated empirically at a desired probability of false alarm that is 0.1 and 0.01.

B. RESULTS AND DISCUSSIONS

This subsection provides the results of the experiments which compare the performance of the proposed RPCA-CN algorithm with existing spectrum sensing techniques. Existing PCA and RPCA based approaches presented in section IV are evaluated in term of P_d at 10% P_f. Figure 8 shows the detection ability of the existing algorithms in term of P_d at various SNR with single and multiple receive antenna (one and two receive antennas considered in this paper). Here M show the number of receive antennas, It can be seen that there is significant improvement in probability of detection, as it moved from single to double receive antenna configuration because this configuration improved the correlation between the samples. In this analysis RPCA-3 (with APG) out performs other approaches.

Figure 9 illustrate the comparison of the performance under Gaussian noise model for P_d Vs SNR at 10% probability of false alarm, $N = 60000$ and $M = 2$. Similar experiment was conducted for 1% P_f and the results are shown in Figure 10. PCA has better detection ability in Gaussian noise model than RPCA-3 and RPCA-CN as in this case there are no utilization of parameters (μ_k, τ_k and Π) that are incorporated in RPCA. Evaluations under complex noise model for of P_d at 10% P_f is demonstrated in Figure 11, under complex noise model PCA is not able to perform well and has quite low P_d in low SNR range (-25 to -15 dB).

PCA try to express most possible variability caused by the noise and has sensitivity to outliers. Outliers are the inordinately enhanced classical measures of variance, as PCA follows the maximum variance therefore outlier

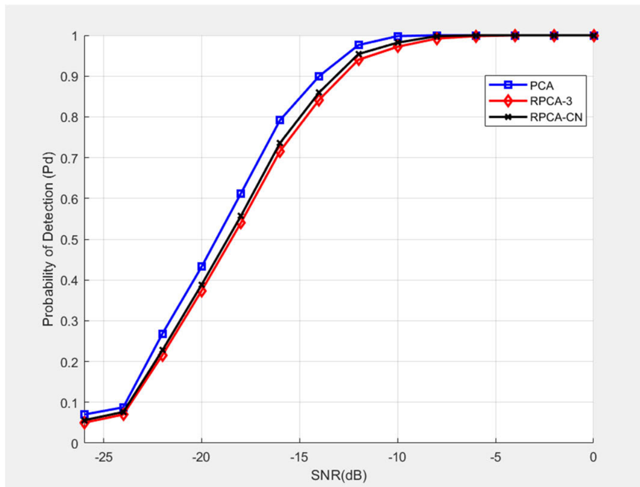

FIGURE 10. P_d at 1% P_f, under gaussian noise model, N = 60000 and M = 2.

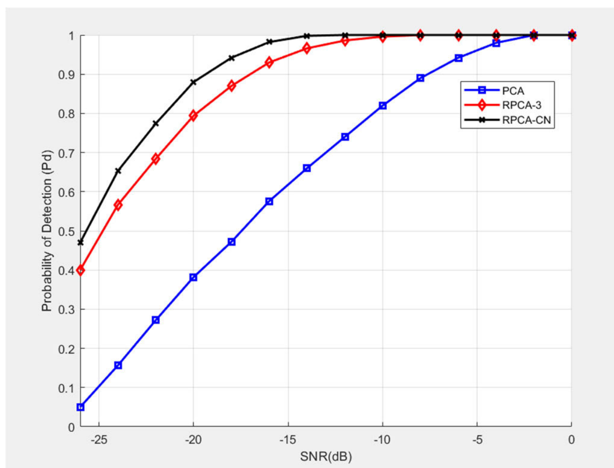

FIGURE 11. P_d at 10% P_f, under complex noise model, N = 60000 and M = 2.

has the capability of artificially increasing the variance in an uninformative direction [39]. In this regard, scaling is

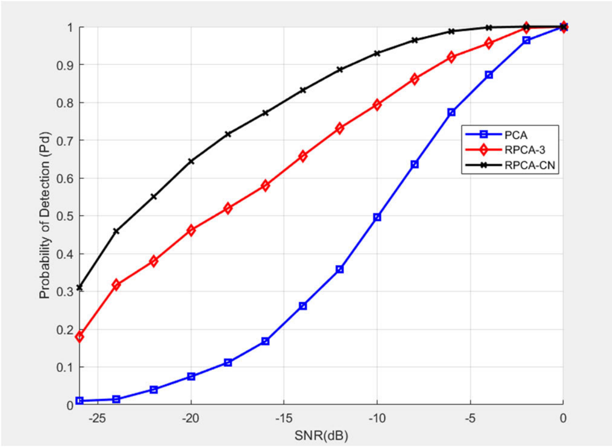

FIGURE 12. P_d **at 1%** P_f**, under complex noise model, N = 60000 and M = 2.**

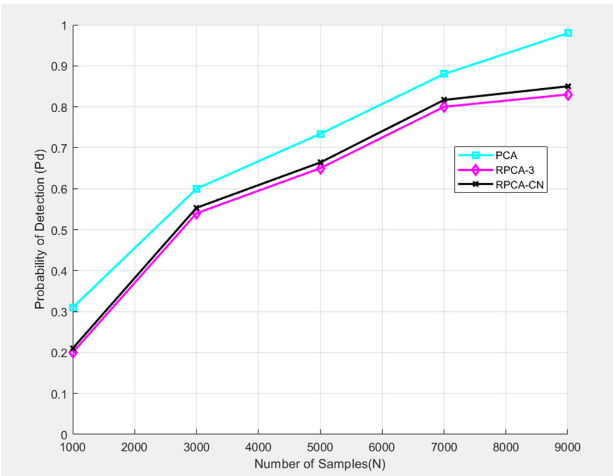

FIGURE 13. P_d **vs N at 10%** P_f**, under gaussian noise model at SNR = −20dB.**

worth discussing, it has some unwanted effects due to similar weights of each variable for PCA, because of it, noise got equal importance as of the variables which represent the actual signal. In such scenario it becomes terrible for PCA to differentiate between useful and redundant information [6], [55]. These factors cause inaccurate results which ultimately degrade the performance in the form of low probability of detection and high probability of false alarm that can be observed from Figure 11. Figure 12 also demonstrate that the RPCA-CN outperforms both PCA and RPCA-3 even in low SNR (−25 dB) and 1% P_f. As RPA-CN employed the IALM (Algorithm 1) that uses significantly smaller number of partial SVDs as compare to exact ALM that is incorporated by RPCA-3 with similar convergence speed, experimental results show that IALM is at least five times faster than APG referring to Table 2. IALM computes the number of non-zeros in error matrix E more accurately than APG, as APG leave several small non-zero terms in E which leads to low P_d.

The effect of varying the number of samples N is analyzed under both noise models, Figure 13 shows the effect of

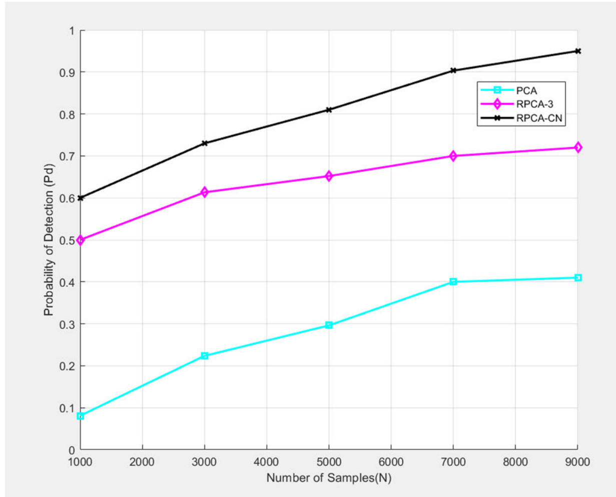

FIGURE 14. P_d **vs N at 10%** P_f**, under complex noise model at SNR = −20dB.**

varying numbers of samples under Gaussian noise model for a fixed $P_f = 10\%$ and SNR $= -20$dB. Increasing the number of samples improve the spectrum sensing performance. With large N PCA performs better than RPCA. Figure 14 demonstrate the effect of N under complex noises model at a fixed $P_f = 10\%$ and SNR $= -20$dB. In this experiment proposed algorithm outperform the PC and RPCA-3 even at highest and lowest number of samples.

Other factor that makes the proposed method more robust and superior than other competitors is that all the parameters involved in the model, including U, V and their ranks can be automatically inferred from the observed data under easy non-informative settings of hyper parameters. Instead of assuming zero-mean data noise in traditional RPCA methods, $V_k s$ is the means of all noise components, left as to-be-estimated parameters, which further enhances the adaptability of our algorithm to real asymmetric noise and results in high P_d.

Percentage of detection efficiency is calculated using equation (27) at SNR −25, −20 and −15dB, RPCA-CN is 18.37% more efficient than RPCA-3 approach even at lowest SNR while as SNR improves to −15 there is less difference between the detection efficiency of the two approaches. As the proposed approach incorporate the IALM for the low rank matrix recovery that has the least convergence time as compare to SVD and APG that are incorporated by the comparative approaches PCA and RPCA-3. If we compare in term of convergence time the proposed approach is four times faster than RPCA-3, as mentioned in Table 3 convergence time for APG is 8 seconds and for IALM is 2 seconds. These evaluations support the statement that the proposed algorithm is fast and more robust in all noise environments and can perform better in real scenario as demanded by the IoT applications.

$$E = [(P_{d(RPCA-CN)} - P_{d(RPCA-3)})/P_{d(RPCA-3)}]100 \quad (27)$$

At SNR $= -25$

$$E_r = \left[\frac{0.58 - 0.49}{0.49}\right] \times 100 = 18.37$$

At SNR $= -20$

$$E_r = \left[\frac{0.90 - 0.82}{0.82}\right] \times 100 = 9.7$$

At SNR $= -15$

$$E_r = \left[\frac{1 - 0.97}{0.97}\right] \times 100 = 3.09$$

VII. CONCLUSION AND FUTURE WORK

IoT objects with cognitive capabilities can efficiently utilize spectrum and fulfill real time applications requirements. Spectrum sensing is the key component of CR and demands special demands when it comes to IoT, including fast and efficient detection of PU. This work presents the need of CR in IoT and a robust spectrum sensing algorithm for CR-based IoT architecture. Proposed algorithm uses the IALM for RPCA with MOG noise model, we made evaluations in real scenario with wireless microphone signals over the air. To validate the improved results, existing RPCA approaches were compared in term of probability of detection and complexity. The performance of the included sensing techniques is also evaluated under varying number of samples. The proposed scheme is more efficient, robust and performs well under actual noise conditions that make it suitable for time sensitive IoT applications. Experimental results and mathematical evaluations demonstrate that the proposed approach is 10.7% improved in term of detection efficiency and at least 4 times faster than existing techniques. Complexity of the proposed RPCA-CN is comparable to existing approaches, which can be one of its limitation. Future work could be done on the complexity reduction of the proposed approach that would be very useful for its implementation on low power IoT devices. We hope that this article would give the readers an insight to the concept of CR based IoT which could help them to follow this emerging research direction.

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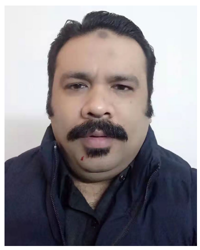

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