Compressive Multispectral Model for Spectrum Sensing in Cognitive Radio Networks

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***Abstract*—Cognitive Radio (CR) is one of the most promising techniques for optimizing the spectrum usage. However, the large amount of data of spectral information that must be processed to identify and assign spectral resources increases the channel assignment times, therefore worsening the quality of service for the devices using the spectrum. Compressive Sensing (CS) is a digital processing technique that allows the reconstruction of sparse or compressible signals using fewer samples than those required traditionally. This paper presents a model that addresses the Spectral Sensing problem in Cognitive Radio using Compressive Sensing as an effective way of decreasing the number of samples required in the sensing process. This model is based on Compressive Spectral Imaging (CSI) architectures where a centralized spectrum manager selects what power data must be delivered by the different wireless devices using binary patterns, and builds a multispectral data cube image with the geographical and spectral data power information. The results show that this multispectral data cube can be built with only a 50% of the samples generated by the devices and, therefore reducing the data traffic dramatically.**

I. Introduction

In the next generation of radio systems, the efficient usage of the spectrum will be essential. Whilst the data traffic in the wireless networks is so rapidly growing, mainly in the mobile telephone bands (850MHz, 900MHz, 1900 MHz or 2700MHz in GSM, UMTS, LTE or ISM), most of the UHF bands are underused and, therefore, the performance and exploitation of the electromagnetic spectrum is greatly unbalanced [1].

Cognitive Radio (CR) proposes to reuse the portions of the spectrum that are not being used over time [2]. CR depends on the usage of the devices to sense the spectrum in order to identify the unused portions or *spectrum holes*. This spectrum sensing problem, ie., the spectral sensing speed, is one of the most challenging issues in cognitive radio systems today and in the near future because of the enormous increase in the number of devices trying to access the spectrum. As an example, [3] shows the effect of the increase in the amount of data processed during the spectral sensing that generates data package collisions when several cognitive devices send packages with spectral information to a centralized server (if a device sends its data packet and the server is busy, a collision occurs). The larger the packet, more collisions and worse quality of the service.

Compressive Sensing (CS) is a signal processing technique that can be used for reducing the number of samples in the spectral sensing operation. CS allows the reconstruction of a signal using far less samples than those required by traditional approaches [4]. CS has already been used in different areas, such as image processing, medical imaging, seismic data, biological applications, radars, among others [5]. CS is particularly important in the field of telecommunications [6], in areas such as channel estimation, MIMO channels, OFDM channels, UWB systems, sensors networks and antennas [7], [8]. In addition, Compressive Spectral Imaging (CSI) is an interesting CS application where the data of a multispectral image involves a large amount of spatial and spectral information that can be represented with fewer compressive samples; in some cases, the amount of data in CSI can be reduced a 90%. In this field, three of the most remarkable of these CSI architectures are the spatio-spectral encoded compressive HS imager (SSCSI) [9], the coded aperture snapshot spectral imagers (CASSI) [10] and snapshot colored compressive spectral imager (SCCSI) [11].

This work incorporates the advances in CS and CSI to the spectrum sensing in CR with the proposal of a new multispectral model for CR networks where a spectrum manager device built a data cube with the geographical and spectral power information of the wireless devices. This work starts by introducing the CS and CSI concept and then explains the multispectral model for CR networks based on the binary patterns that select the compressive samples that the wireless devices must take. The quality of the data cube greatly varies depending on the number of samples selected by the binary pattern; therefore, the performance of the system is carefully analyzed in terms of the binary pattern structure. Finally, the conclusions of this work are presented.

II. Compressive Sensing and Compressive Spectral Imaging

A signal $\mathbf{s} \in \mathbb{R}^N$ is K-sparse if $\|\mathbf{s}\|_0 = |(\mathbf{s})| = |s_{(k)} \neq 0 : k = 1, ..., N\}| \leq K$, where $\mathbf{s}$ has at most K non-zeros. It is possible that the signal has less non-zeros in another representation basis $\mathbf{\Psi} \in \mathbb{R}^{N\times N}$ where $\mathbf{f} = \mathbf{\Psi s}$. CS takes advantage of the sparsity principle of the signals in order to apply sensing protocols that capture the essential information of the signal with a small number of samples. The sensing process can be represented by

$$\mathbf{g} = \mathbf{\Phi f} = \mathbf{\Phi \Psi s}, \tag{1}$$

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where $\mathbf{\Phi} \in \mathbb{R}^{M \times N}$ is a sampling matrix. Note that (1) is an undetermined linear system if $M \ll N$, but if $\mathbf{f}$ is sparse, it is possible to find a unique solution solving

$$\hat{\mathbf{f}}_{\ell_0} = \arg\min_{\mathbf{f}} \|\mathbf{f}\|_0 \quad \text{subject to} \quad \mathbf{\Phi f{=}g}. \tag{2}$$

CS generally involves solving

$$\hat{\mathbf{f}}_{\ell_1} = \arg\min_{\mathbf{f}} \|\mathbf{f}\|_1 \quad \text{subject to} \quad \|\mathbf{\Phi f{-}g}\|_2 \leq \epsilon. \tag{3}$$

or the equivalent convex unconstrained optimization problem:

$$\min_{\mathbf{f}} \left(\frac{1}{2} \|\mathbf{\Phi f{-}g}\|_2^2 + \lambda \|\mathbf{f}\|_1 \right). \tag{4}$$

where $\|\cdot\|_2^2$ is the Euclidean norm and $\|\cdot\|_1$ is the ℓ_1 norm.

In CSI the multispectral image is modeled as a data cube $f \in \mathbb{R}^{M \times N \times L}$ where $M \times N$ are the spatial dimensions and L is the number of spectral bands. CSI measurements can be modeled as equation (1) and the signal can be reconstructed by solving the optimization problem (4). In this case, the sampling matrix $\mathbf{\Phi}$ corresponds to a optical system. For instance, CASSI system [10] is an architecture that attains CSI measurements, in three main steps: first encoding the information with a code aperture pattern, second using a prism as a dispersive element that shifts the spectral information and finally impinging in a focal plane array (FPA) detector.

III. Compressive Spectrum Sensing Multispectral Model

It is possible to model the radio-spectrum data as a $M \times N \times L$ data cube where $M \times N$ corresponds to the spatial location of the power transmitted by wireless devices, and L are the possible spectrum slot bands, following the same idea as in the multispectral image with spatial information in different spectral bands.

Figure 1 shows several Software Defined Radios (SDR) located in a geographical area, with all the users transmitting at 20 dbm in their spectral bands. Figure 1 also shows users transmitting in bands B1, B2, B3 and B4. If we assume that the wideband wireless network has L consecutive spectrum bands, we can define an image $\mathbf{f}_k$, where $1 \leq k \leq L$, as the power handling image in the k frequency. The grayscale pixels of each image represent power levels, where white is the highest power level and black the lowest one. Each image on the right represents one frequency band, therefore L images.

With every SDR sensing the spectrum, it is easy to build a data cube $f(\mathbf{x}, \mathbf{y}, \lambda)$ where (x, y) is one SDR geographical position and λ a frequency value. Figure 2 shows how the data cube is built using the samples sent from each SDR.

The data cube construction process is carried out by an spectral manager, generally called *spectrum broker* (SB), that defines the roles of the devices (what and when to sample and how and when to send the information back to the SB). Algorithm 1 describes this process in detail.

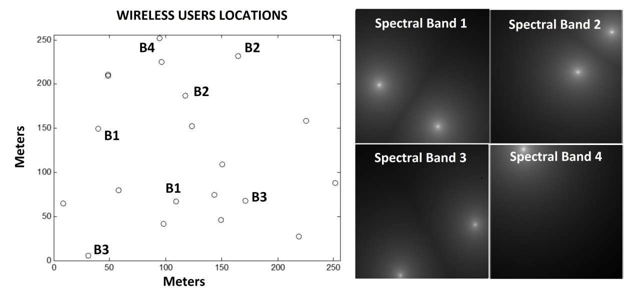

Fig. 1. Power handling images in 4 frequency bands.

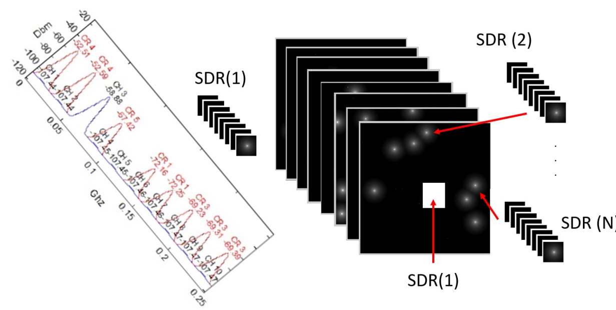

Fig. 2. Data cube construction based on the spectral information of the SDRs.

IV. Binary Pattern Architectures

A. Binary patterns and transmittance

In a typical CSI architecture the samples are acquired based on an aperture code $\mathbf{T}_{(x,y)}$, where black elements block the light and white elements let the light to go through [12]. Similarly, in this paper we propose a binary pattern architecture where the SB generates patterns that define which samples to take in the spatial and frequency domain. In general, binary patterns are block-unblock masks. Specifically, we have a matrix $\mathbf{D} = (d_{i,j}) \in \mathbb{C}^{n_1 \times n_2}, d_{i,j} \in \{0, 1\}$ where $d_{i,j} = 1$ represents a transmissive element and $d_{i,j} = 0$ represents a block element. The transmittance values are calculated as

$$t_r = \sum_{i=0}^{n_1-1} \sum_{i=0}^{n_2-1} \frac{d_{i,j}}{n_1 n_2}, \tag{5}$$

where n_1 are the horizontal pixels and n_2 the vertical pixels of the binary pattern.

For example, $t_r = 0.2$ means that the 20% of the binary pattern are transmissive and the remaining 80% are blocking. Figure 3 shows three binary patterns with different transmittance values.

Figure 4 shows an example of a 16 pixels' binary pattern that defines the samples to take in the λ spectral band. Note that the binary pattern discards 9 samples.

B. Compressive multispectral sensing architectures

In this work, we propose three binary pattern-based architectures in order to perform the compressive multispectral sensing. The first architecture (Figure 5) applies the same binary pattern to all the bands of the multispectral data cube.

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Algorithm 1 *The general process for building the data cube*

Require: There are s SDR's in the area. There are L spectral bands. There are $M \times N$ geographic points.

A $\mathbf{SDR}_{new}$ requires service.
The $\mathbf{SDR}_{new}$ sends a request to **SB**.
The **SB** defines the samples to request from the $\mathbf{SDR}_{new}$ using a binary pattern.
The **SB** requests the samples from the $\mathbf{SDR}_{new}$
for $k \leftarrow 1, s$ **do**
  The **SB** defines the samples to request from the $\mathbf{SDR}_k$ using a binary pattern.
  The **SB** request the samples from the $\mathbf{SDR}_k$
end for
The **SB** builds the model of the equation 1.
The **SB** solves the optimization problem of the equation 4.
With the data cube **f**, the **SB** assigns spectral resources to the $\mathbf{SDR}_{new}$
$s \leftarrow s + 1$

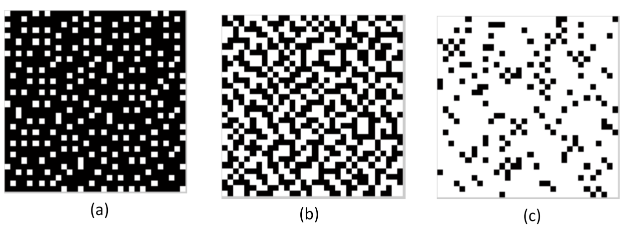

Fig. 3. Three binary patterns with different transmittance (a) $t_r = 0.2$ (b) $t_r = 0.5$ (c) $t_r = 0.9$.

Note in Figure 5 that, exactly like in the CSI architectures, the 3D data is mapped into a 2D *Power Plane Array* (PPA) that corresponds to a $\mathbf{P}_{(x,y)}$ matrix, where every pixel is a linear combination of the data cube pixels and the binary pattern pixels. This can be expressed by

$$P_{jl} = \sum_{k=0}^{L-1} F_{jlk} T_{jl} + \omega_{jl}, \tag{6}$$

where P_{jl} is a measure proportional to the spectral signature registered by the SDR's in the geographical position j, l, mapped in the PPA $\mathbf{P} \in \mathbb{R}^{M \times N}$, L is the number of spectral bands, T_{jl} is the binary pattern and ω_{jl} is the noise of the system.

In Architecture 1, the power level information of several geographical points in all the bands is discarded, so therefore, it is possible to have an ill-conditioning problem.

The second proposed architecture, shown in figure 6 has different binary patterns for each spectral band. This mean that Architecture 2 selects different samples of different bands and different geographical points.

In this second architecture, the pixels of the PPA are calculated by

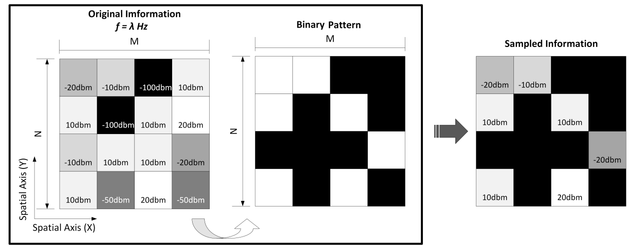

Fig. 4. Binary pattern in one spectral band.

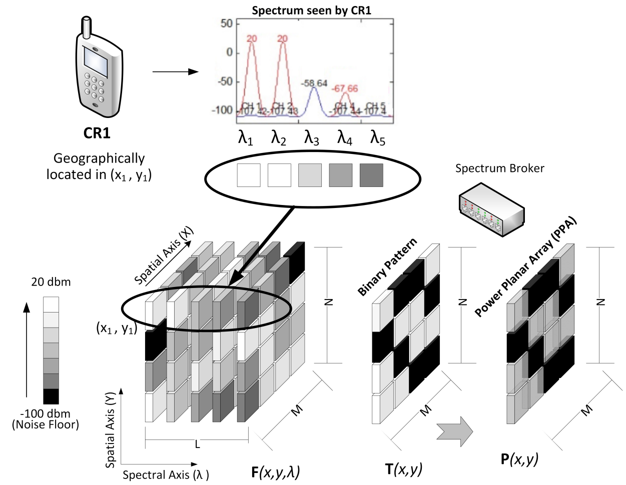

Fig. 5. Architecture 1 for compressive multispectral sensing.

$$P_{jl} = \sum_{k=0}^{L-1} F_{jlk} T_{jlk} + \omega_{jl}, \tag{7}$$

where in this case, T_{jlk} is a data cube with the binary patterns for $0 < k < L - 1$.

Finally, in order to get a closer analogy with the CASSI system, we propose Architecture 3 (Figure 7), where the PPA is calculated by the linear combination of displaced data samples. The model of the $\mathbf{P}$ array is

$$P_{jl} = \sum_{k=0}^{L-1} F_{j(l+k)k} T_{j(l+k)} + \omega_{jl}, \tag{8}$$

C. The Data Cube Construction

In all the architectures, the PPA is represented by a one-dimensional vectorized array and $\mathbf{P}$ is modeled by

$$\mathbf{P} = \mathbf{\Phi f} = \mathbf{\Phi \Psi s} \tag{9}$$

that corresponds to the equation 1. In this work $\mathbf{\Psi}$ is the Kronecker representation basis, and the data cube is built solving the optimization problem

$$\min_{\mathbf{f},\mathbf{w} \in \mathbb{R}^{N}, \mathbf{v} \in \mathbb{R}^{M}} \|\mathbf{w}\|_1 + \iota_{E(\epsilon, \mathbf{I}, 0)}(\mathbf{v}) \quad \text{subject to} \quad \mathbf{w}=\mathbf{f} \quad \mathbf{v}=\mathbf{\Phi f}\text{-}\mathbf{P}, \tag{10}$$

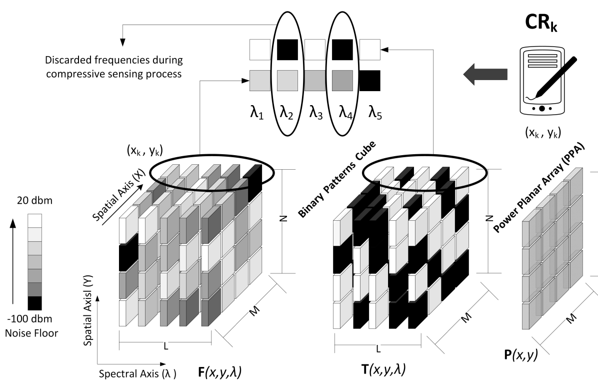

Fig. 6. Architecture 2 for compressive multispectral sensing.

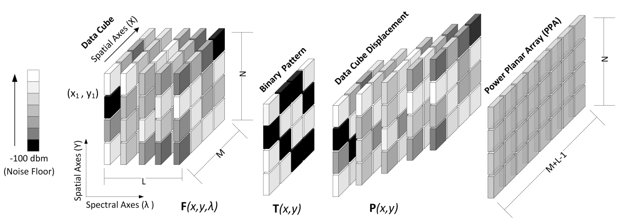

Fig. 7. Architecture 3 for compressive multispectral sensing.

with the *constrained - split augmented Lagrangian shrinkage algorithm: C-salsa*, [13]. $E(\epsilon, \mathbf{\Phi}, \mathbf{P})$ is an ellipsoid that corresponds to the feasible set in problem (3),

$$E(\epsilon, \mathbf{\Phi}, \mathbf{P}) = \{\mathbf{f} \in \mathbb{R}^N \colon \|\mathbf{\Phi f}\text{-}\mathbf{P}\|_2 \leq \epsilon\} \tag{11}$$

In equation 10, $E(\epsilon, \mathbf{I}, 0)$ is a closed ϵ radius Euclidean ball centered on the origen of $\mathbb{R}^D$, and $\iota_S \colon \mathbb{R}^D \to \overline{\mathbb{R}}$ denotes the indicator function of set $S \subset \mathbb{R}^D$,

$$\iota_S(\mathbf{s}) = \begin{cases} 0 & \text{if } \mathbf{s} \in S \\ +\infty & \text{if } \mathbf{s} \notin S \end{cases} \tag{12}$$

The algorithm presented in [13] was implemented for the data cube construction.

V. Results

All the proposed architectures were implemented with the 0.5 transmittance binary pattern shown in Figure 8-a. The simulation runs on a geographical area of 256×256 cells with 30 SDR's transmitting at 20 dbm distributed in in all 8 possible bands. Figure 8-b shows the PPA calculated with the linear combination of the compressive samples and binary pattern pixels.

Figure 9 compares the ideal data cube with the data cube built for the spectral bands λ_1 and λ_3 in terms of the *Peak Signal to Noise Ratio* (PSNR), that corresponds to the ratio between the maximum possible power of a original data cube and the power of corrupting noise that affects the fidelity of its reconstruction. The data cube was built using the PPA $\mathbf{P}$ matrix and solving the optimization problem of equation (10).

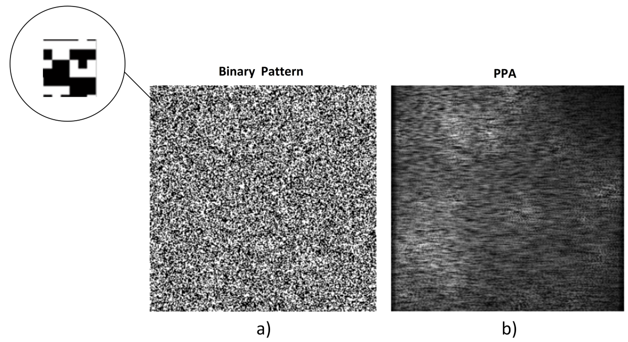

Fig. 8. a) Binary pattern used in the simulations. b) PPA calculated in the simulation.

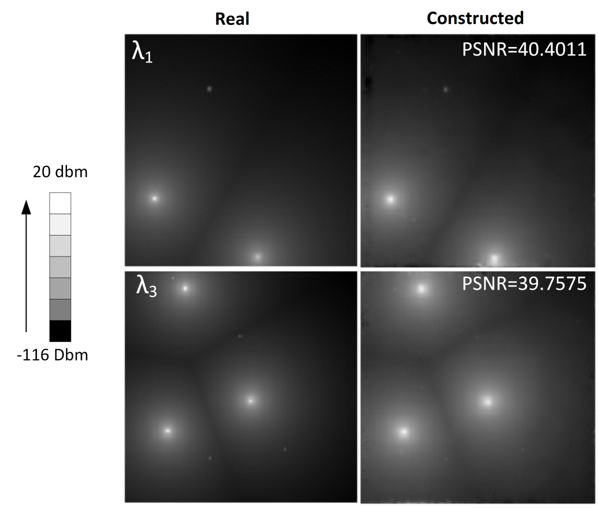

Fig. 9. Data Cube Constructed by the SB.

The PSNR value is approximately 39 dB for the images that represent the real and constructed data cubes in all the bands; this is a proof of the good quality of our approach. The data cube construction only needs 50% of the samples of the real data cube because the binary pattern transmittance is 0.5. This means that each SDR only sends 50% of its spectral information (data cube spectral axis) and that the SB has only to calculate 50% of the power levels in the geographical positions (data cube spatial axis).

To compare the influence of the binary patterns transmittance values in the different architectures, we carried out a whole set of simulations. Figure 8 shows these results in terms of the PSNR for the ideal and constructed data cubes. The results show that there is a value of transmittance that gets the best data cube construction for each architecture. Not only that, but also that there is a point where the quality is no longer improved even with the increment of the transmittance. Therefore, in compressive multispectral architectures this proves that taking more samples not necessarily means getting better quality results. Architecture 1 has by far the worst performance, because all the bands' samples in specific geographical points are discarded.

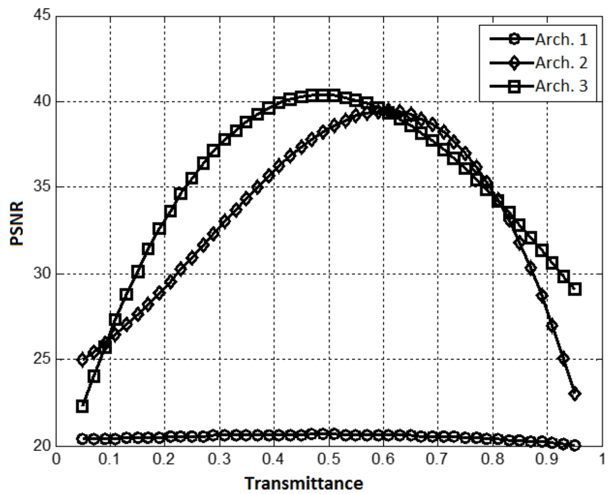

Fig. 10. Transmittance analysis of the three architectures.

Figure 11 compares the mean square error (MSE) of the original power spectral signal with the reconstructed, for one SDR. In this case, the simulation was done with a 150 SDR's - 48 bands data cube.

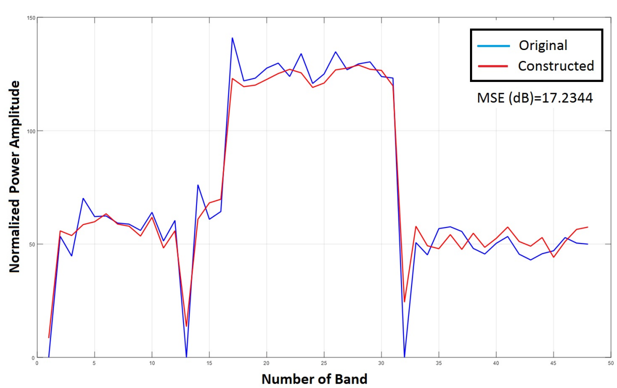

Fig. 11. SDR Spectral Signal Constructed

In order to compare the results with the sampling rate used in previous works, a decimated rate (DR) is defined as $DR = \frac{DN}{NS}$, where DN corresponds to the total number of original data and NS is the amount of data used before the data cube construction. We select a model that uses spatial interpolation [14], and other that uses compressive sensing to create cartography maps solving the "Orthogonal Matching Pursuit" (OMP) algorithm [15].

TABLE I
DECIMATED RATE IN THE CONSTRUCTION OF DATA CUBE FOR THREE MODELS - 8 SPECTRAL BANDS.

	DN	NS	DR
CS Multispectral Model	524.288	32.768	16
CS - OMP model	5.000	400	12.5
Spatial Interpolation Model	80.000	20.000	4

VI. CONCLUSION

This paper presented a new model of compressive multispectral sensing for cognitive radio based on Compressive Spectral Imaging Techniques. In this model, a Power Plane Array (PPA) is built using the compressive samples of the power information in the different spectral bands of the SDR's. The samples were extracted with the help of binary patterns, in a way that reduced the data sampled by half. Using the PPA, The Spectrum Broker (SB) constructs the data cube with the spatial and spectral information of the SDR's to perform spectrum sensing and assignment for cognitive radio networks. This model is our first approximation, and is considering that the SB is able to know the exact placement of all the users, and that the users are SDRs to sense the spectrum. This is a plausible near future scenario, therefore this model will allow to greatly condense the spectral information of big areas into small data packages.

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