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Television channel spectrum sensing using independent component analysis

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Paulo Ixtanio Leite Ferreira[1] ✉, *Glauco Fontgalland*[2], *Bruno Barboso Albert*[2], *Edmar Candeia Gurjão*[2]

[1]*Department of Electrical Engineering, Federal Institute of Science and Technology of Paraíba, Princesa Isabel, Brazil*
[2]*Department of Electrical Engineering, Federal University of Campina Grande, Campina Grande, Paraíba, Brazil*
✉ *E-mail: paulo.ferreira@ee.ufcg.edu.br*

Abstract: Spectrum reuse has been proposed as a method to solve frequency bands scarcity. Detection of unused channels in a given frequency band is the main problem to reuse the spectrum. Various methods are proposed in the literature to perform this spectrum sensing. In this study, the authors apply independent component analysis (ICA) to estimate the available bands in the TV band spectrum when analogue and digital TV channels are in operation. Each component recovered by ICA is in a specific frequency band, then the other bands are considered free to reuse, that is, the absence of transmitters in a channel means there are unused bands. A measurement setup was implemented to validate the use of ICA as a spectrum detection method. The results also show the feasibility of using ICA for wideband spectrum sensing with low computational costs.

1 Introduction

The necessity for more bandwidth in wireless systems is always growing, especially to satisfy the demand of connectivity between people via social networks and data processing in the cloud accessed through mobile devices. In spite of this need, the spectrum has not been effectively used [1]. For example, a measurement in a spectrum snapshot in New York City shows that the maximum total spectrum occupancy is only 13.1% from 30 MHz to 3 GHz frequency range [2]. The variation in the spectrum occupancy has been found to be < 1% in the Amateur Radio Band (1240–1300 MHz) and 77% in the television (TV) bands of channels 7–13 (174 –216 MHz), which indicates the necessity of improving spectrum usage [3]. To solve the scarcity and the underuse of the spectrum, the cognitive radio (CR) technology has been considered. This technique detects and utilises portions of the spectrum always avoiding interference with users assigned in close channels.

The analysis of the spectrum utilisation, spectrum sensing, is normally performed in two steps: sensing the channels and using the obtained information to decide which channels are empty. Owing to their broadband and low occupancy, the spectrum for TV channels has been proposed for spectrum reutilisation. It implies a new challenge for spectrum detection methods, since there are different bandwidths used in TV channels [4].

Some methods are being proposed to spectrum sensing; energy detection method is the classical spectrum sensing method, but because of its simplicity it has low performance in a noisy environment [5]. The matched filtering method matches the received signal with a template of possible transmissions. Although more accurate than the energy detection, it requires previous information about the user signals characteristics [6, 7]. Stochastic methods are implemented by analysing some statistical characteristics of the signal [8]. The accuracy and good performance of these methods, even in noisy environment, come from their high computational complexity.

Independent component analysis (ICA) is a blind source separation method that has been proved very efficient in various scenarios. It has been applied in areas such as image processing [9], communications [10], among others. In this paper, the ICA is applied for spectrum sensing in TV channel bands. The advantages of applying the ICA lies in its frequency and bandwidth independence, good performance in presence of low signal-to-noise ratio (SNR) (see Table 1) and low computational complexity [11]. Therefore, and with the advantage of not requiring prior information about the sources occupying the monitored spectrum [12], the ICA may be used to overcome the issues of previously spectrum detection methods.

In [13, 14], ICA was applied for spectrum detection. The simulated data were used to determine the spectrum occupancy based on the determination of the Kurtosis of the signals after separation. The drawback is that the methods based on the use of Kurtosis are susceptible to outliers [15]. In this paper, the method is applied with data obtained from measurements, which making use of the negentropy turns it immune to outliers.

In the remainder of this paper, a brief description of ICA method is given in Section 2 and the FastICA algorithm in Section 3. Section 4 describes the proposed method. Section 5 presents the experimental setup, and in Section 6 the results and discussion are shown. Finally, the conclusions are drawn in Section 7.

2 Independent component analysis

ICA is a statistical technique for revealing hidden factors that underlie sets of random variables, measurements or signals [15]. It allows recovering statistically independent signals from compositions of these signals, called mixture signals [16]. The ICA does not require any prior information about the sources or their environment, which makes it a powerful tool in several fields of applications. In [10, 17–19] was shown that the ICA is somewhat resistant to noisy environments, which makes it a good fit to solve issues on underused portion of the spectrum.

2.1 Mathematic model of ICA

The ICA model is a generative model; it describes how the observed data are generated by a mixture of signal sources. Let us consider a vector of n source signals $\boldsymbol{s} = [s_1, s_2, \ldots, s_n]^{\mathrm{T}}$ and a vector of m measured signals $\boldsymbol{x} = [x_1, x_2, \ldots, x_m]^{\mathrm{T}}$, where each signal x_i $(i = 1, \ldots, m)$ is a linear combination of the n source signals [15]

$$\begin{bmatrix} x_1 \\ x_2 \\ \vdots \\ x_i \end{bmatrix} = \begin{bmatrix} a_{11} & a_{12} & \cdots & a_{1j} \\ a_{21} & a_{22} & \cdots & a_{2j} \\ \vdots & \vdots & \ddots & \vdots \\ a_{i1} & a_{i2} & \cdots & a_{ij} \end{bmatrix} \begin{bmatrix} s_1 \\ s_2 \\ \vdots \\ s_j \end{bmatrix} \tag{1a}$$

Table 1 Parameters of individual channel sources

Primary users	Parameters		
	Reserved bandwidth, MHz	Maximum power, dBm	Signal noise-rate – SNR, dB[a]
channel 21	512–518	–78.98	06.02
channel 23	524–530	–55.91	29.09
channel 25	536–542	–78.17	06.83

[a]Average noise power was considered in the calculation of SNR (SNR = P_{Max}–$P_{Med.Noise}$).

where each element of this matrix can be written as

$$x_i = a_{i1}s_1 + a_{i2}s_2 + \cdots + a_{ij}s_j, \quad \text{for all } i = 1, \ldots, m \text{ and } j = 1, \ldots, n \tag{1b}$$

The a_{ij} are coefficients that give the mixing weights. From (1a) and using matrix notation, the mixing model can be written in a compact form $\boldsymbol{x} = \boldsymbol{As}$, where $\boldsymbol{A}$ is a mixing matrix. Typically, the number of measurements sensors (output data vector $\boldsymbol{x}$) is considered equal to the number of sources (input data vector $\boldsymbol{s}$); however, it can be different since the number of sources may be an unknown parameter. In this paper, we consider $n < m$ to obtain the best ICA performance, as presented in [20].

The main application of ICA is for the case where $\boldsymbol{s}$ and $\boldsymbol{A}$ are unknown. Therefore, the objective is to obtain a separation matrix $\boldsymbol{W}$ to recover the signals sources, by doing

$$y_i = w_{i1}x_1 + w_{i2}x_2 + \cdots + w_{ij}x_j \quad i = 1, \ldots, n \text{ and } j = 1, \ldots, m \tag{2}$$

The coefficients w_{ij} represent the weights in the separation matrix. The problem can then be restated by determining the coefficients w_{ij} in (2). This linear transformation can then be expressed as a multiplication of the matrix of weights coefficients and the measured signals (3)

$$\begin{bmatrix} y_1 \\ y_2 \\ \vdots \\ y_i \end{bmatrix} = \begin{bmatrix} w_{11} & w_{12} & \cdots & w_{1j} \\ w_{21} & w_{22} & \cdots & w_{2j} \\ \vdots & \vdots & \ddots & \vdots \\ w_{i1} & w_{i2} & \cdots & w_{ij} \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \\ \vdots \\ x_j \end{bmatrix} \tag{3}$$

In matrix notation one writes $\boldsymbol{y} = \boldsymbol{Wx}$. The matrix $\boldsymbol{W}$ is defined as the (pseudo) inverse of the matrix $\boldsymbol{A}$ ($\boldsymbol{W} = \boldsymbol{A}^{-1}$). The diagram in Fig. 1 describes the procedure used to test (simulation) and apply (real case) the ICA method.

Once the values of the elements of the vectors $\boldsymbol{w}_i$ of the matrix $\boldsymbol{W}$ are determined, the resulting output vector $\boldsymbol{y}$ can be obtained as an optimal approximation of vector $\boldsymbol{s}$. The detail of this procedure is described in [11].

Among the available algorithms to implement the ICA [19], in this paper the FastICA is used, as described in Section 3.

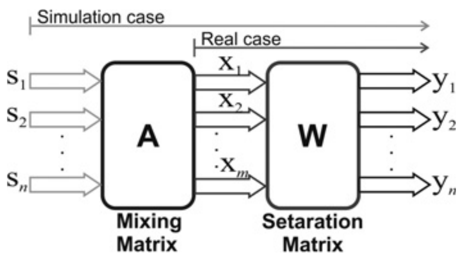

Fig. 1 *ICA block diagram*

3 FastICA algorithm

Owing to its high convergence speed and satisfactory performance in a wide variety of applications, FastICA is one of the most popular iterative methods for ICA. The FastICA is a fixed-point algorithm that seeks to maximise the non-gaussianity of mixed signals [21]. It is based on the optimisation of a non-linear contrast functions $g(\cdot)$, by maximisation of the negentropy (or kurtosis) as a non-gaussianity measures and by applying symmetric or deflationary orthogonalisation [11, 21]. The cost functions $g(\cdot)$ used in FastICA are [15]

$$g_1(y) = \tanh(a_1 y) \tag{4}$$

$$g_2(y) = y\,\exp(-y^2/2) \tag{5}$$

$$g_3(y) = y^3 \tag{6}$$

where $1 \le a_1 \le 2$ is a suitable constant, often taken as $a_1 = 1$. In this paper, we use the FastICA algorithm with non-linear contrast function g_3 with maximisation of the negentropy, and symmetric orthogonalisation.

The steps for recovering sources signals are as follows [12]. First, centring the data to make its mean zero; next, data whitening to obtain the vector $\boldsymbol{z}$; define the number of independent components m, to be estimated; choose randomly the initial values for the $\boldsymbol{w}_i$, $i = 1, \ldots, m$, each of unit norm; and then maximise the output negentropy of $\boldsymbol{y}_i = \boldsymbol{w}_i\boldsymbol{x}$ using (7)

$$\boldsymbol{w}_i \leftarrow E\{zg(\boldsymbol{w}_i^{\mathrm{T}}z)\} - E\{g'(\boldsymbol{w}_i^{\mathrm{T}}z)\}\boldsymbol{w} \tag{7}$$

The next step is to organise the columns vectors $\boldsymbol{w}_i$ in $\boldsymbol{W} = [\boldsymbol{w}_1, \boldsymbol{w}_2, \ldots, \boldsymbol{w}_m]^{\mathrm{T}}$, and to perform the symmetrical orthogonalisation process

$$\boldsymbol{W} \leftarrow (\boldsymbol{W} \times \boldsymbol{W}^{\mathrm{T}})^{-1/2} \cdot \boldsymbol{W} \tag{8}$$

The final step it to check the convergence. If it has not reached, the process returns to step in (7). Convergence means that the old and new values of vector $\boldsymbol{w}$ point in the same direction, that is, the absolute value of their dot product is (almost) equal to 1 [15].

It is important to highlight that this algorithm has most of the advantages of neural algorithms: parallel computation, small memory storage, fast convergence [11] and there is no learning rate or other adjustable parameters, which makes it easy to use and more reliable [15].

The FastICA convergence is cubic (or at least quadratic), under the assumption of the ICA data model; the algorithm finds directly independent component of (practically) any non-Gaussian distribution using any non-linearity g (e.g. (4), (5) or (6)) [11]. In general, four iterations were necessary for convergence.

4 Proposed method

Consider a scenario with various sources transmitting into a given spectrum bandwidth, where each source is a channel with specific central frequency and fixed bandwidth. The received signal in the CR is composed by a mixture of transmitted signals. On the basis of the idea that the CR must detect the occupied bandwidths (signal sources), the proposed method uses the received signal to analyse the spectrum availability using the FastICA algorithm and then declaring the locations of the unused channels. That is, after signal separation by ICA, a visual inspection of the obtained independent components is performed and occupied frequency bands are determined, therefore, by complement unused channels are identified.

TV signals are generated by different TV stations (in different band frequencies) with different contents and may therefore be considered as statistically independent signals in most cases. To prove statistical independence in a formal way, it is very difficult to do, if not impossible [22, 23]. The unique form to do that is to obtain the joint probability distribution of the signal sources and to show that it is equal to the product of individual distribution of each signal.

The identification of the empty channels is performed observing in the estimated spectrum by ICA the power level, one channel is declared empty if the power level is below a certain threshold. FastICA is a fixed-point algorithm that implements the ICA; it aims to find the elements of the separation matrix $\boldsymbol{W}$ using (7) and (8). When convergence is achieved, the matrix $\boldsymbol{W}$ is multiplied by the matrix elements $\boldsymbol{x}$, resulting in independent components $\boldsymbol{y}$. As long as the occupied bands (source signals) are identified, the tracks that are empty can be observed in a complementary way.

It should be noted that the ICA is based on the statistical independence and not the power spectrum format of the users. Therefore, even if two or more users have similar spectra, but have statistical independence, the separation can be performed. Compared with the three main energy spectrum categories, it should be noted that ICA combines low complexity with good results, and energy methods have low complexity, but low performance, matched filtering methods also have low complexity; however, precise characteristics of the signal must be known a priori, and statistical methods have best results but they have high complexity.

5 Experimental setup

To validate the use of ICA for spectrum sensing, it was implemented an experimental setup for measurement of the Brazilian's TV spectrum channel. The three measured channels, one digital TV, one analogue TV and one continuous wave (CW) from a microwave generator, are taken as the original sources transmitters. The mixture signals are received by a broadband antenna connected to a spectrum analyser. Once captured, the data are recorded and used in a semi-automatic implementation of ICA.

Fig. 2 shows the measurement setup with three primary sources (channels) and up to four measurements positions. The channels 21 and 23 are allocated for transmission of digital and analogue TVs, respectively. The channel 25 was a CW signal with the same TV bandwidth generated to emulate the spectrum of the third TV channel. This channel can be placed at random distances (d_i, $i = 1, 2, 3, 4$) from the receiver (Rx) antennas, once the far-field condition was assured. The four measurements positions are chosen as: $d_1 = 2.30$ m, $d_2 = 2.00$ m, $d_3 = 2.64$ m and $d_4 = 3.20$ m.

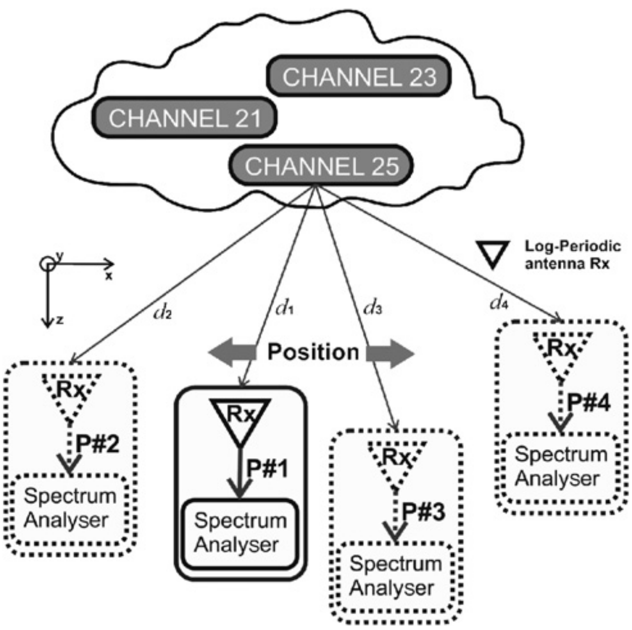

Fig. 2 *Measurement setup to capture the TV open channels*

In Fig. 2, the dashed blocks indicate the displacement sequence of the Rx system for measurement in positions P#2, P#3 and P#4.

5.1 Description of measurement setup

In the setup used, the signals captured from the channels 21 and 23 are open broadcasting, whereas the channel 25 was generated using a microwave generator (R&S SMBV 100A) configured for a chirp signal, with 6 MHz bandwidth. A log-periodic antenna (A.H. Systems SAS 510-7) was used to transmit the signal of the channel 25. The Rx placed in positions P#1, P#2, P#3 and P#4 is composed of a spectrum analyser, R&S FSL6 (9 kHz–6 GHz), connected to a high-gain broadband antenna (R&S HL040). The Rx positions (P#1–P#4) were randomly chosen.

5.2 Measurement procedure

The electric field power density generated by the digital and analogue TV systems (channels 21 and 23) are within the power transmission limit required by the Brazilian regulatory agency (ANATEL) National Telecommunication Agency. The 6 MHz bandwidth for the third source (channel 25) is obtained by configuring the microwave generator in single mode; start frequency $F_{st} = 536$ MHz and stop frequency $F_{sp} = 542$ MHz; linear spacing; saw-tooth shape; and 50 kHz for steplin. The Rx (R&S FSL6) was configured to cover from 510 to 544 MHz with RBW = 30 kHz, VBW = 100 kHz, maximum hold in trace mode and 10 000 sweep point.

The reception system was initially calibrated for each channel individually by recording their spectrum and amplitude. For example, first, the spectrum of the channel 21 is measured as a single source; after this, the channel 23 is measured; and finally, the channel 25 is measured. The measured data for each individual spectrum are shown in Fig. 3. These measurements were conducted in free space, covering the band from 510 to 544 MHz (BW = 34 MHz). This total bandwidth is 82.35% larger than the one used in traditional methods, as reported in [24].

6 Results and discussion

Fig. 3 shows the spectrum measured from the three primary users (TV channels) in position P#1, only. The results for the other positions follow the same pattern. These measured data will be used for comparison with the recovered signals by ICA. One can see from these results that the 6 MHz bandwidth requirement was satisfied, although their spectrum amplitudes were different, as expected (digital, analogue and emulate TV channels). The two

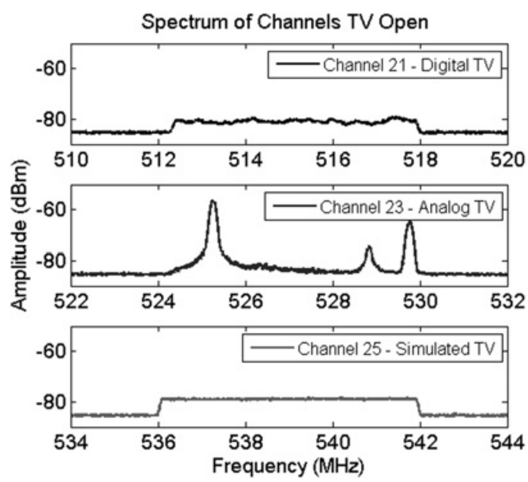

Fig. 3 *Spectrum of the primary users (channels 21, 23 and 25) measured in position P#1*

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broadcasting sources measured (channels 21 and 23) have been presented an additional guard band in the left-hand side of their spectrum band.

The spectra of the received signals (Channel 21 + Channel 23 + Channel 25) in four different positions are shown in Fig. 4. For readability, they are shown in pairs in two pictures. These data have all information required by ICA for identification of the sources, and therefore to spectrum detection.

The picture on the top of Fig. 4 shows the spectrum of the received measurements at positions P#1 and P#2 (Channel 21 + Channel 23 + Channel 25) and the bottom shows the spectrum measured in positions P#3 and P#4. It can be seen that outside of the bandwidths allocated for the primary users there are available unused bands.

The four measurements present in Fig. 4 were the only information used as input data for ICA. We highlight here that only amplitude and frequency were measured, no additional information is needed at the Rx. For instance, the results obtained in [24] assume that the Rx already knows the bandwidth and the carrier frequencies of the channels.

6.1 ICA data processing

As described in the previous section, the measured data in positions P#1–P#4 were used as input of the $\boldsymbol{x}$ vector. Initially, only three measured positions of the spectrum, presented in Fig. 4, were considered as input for ICA. Theoretically, only three measurements are needed to recover the primary sources. The results for the estimated spectrum using FastICA algorithm are presented in Fig. 5. All presented results have undergone a smoothing of 0.001% through the method of moving average [25]. These results were normalised to the maximum value obtained and put in the new scale for easy reading. It is worth to say that the analogue and digital TV signals present their own envelope, as expected. The digital channel 21 has a behaviour close to the theoretical one (channel 25), whereas the analogue channel 23 has a high power concentrated in the video carrier frequency (525.25 MHz) and in the audio carrier frequency (529.75 MHz).

From Fig. 5, one can observe that ICA has been recovered the three occupied bandwidths by the primary users. More specifically, because of the random behaviour of matrix $\boldsymbol{W}$ and the characteristics of the analogue and digital TV signals, one can see in Figs. 5*a* and *c* the presence of channels 21 and 23, only. Therefore the well behaviour of the emulated channel 25, CW signal, is estimated only once (Fig. 5*b*). In the three estimated results shown in Fig. 5, there are no transmissions into other frequency bands. One can clearly identify the four spectral opportunities (empty bands) available to be applied in CR. These opportunities are highlighted in Fig. 6. We must point out that in the frequency frame shown here the two available 6 MHz bandwidths for others possible TV channels, located before and after the channel 23, have been preserved.

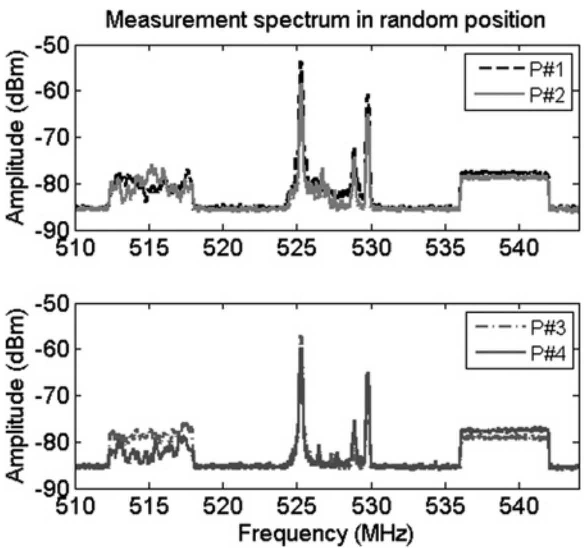

Fig. 4 *Spectra superposition of the three received channels in positions P#1–P#4*

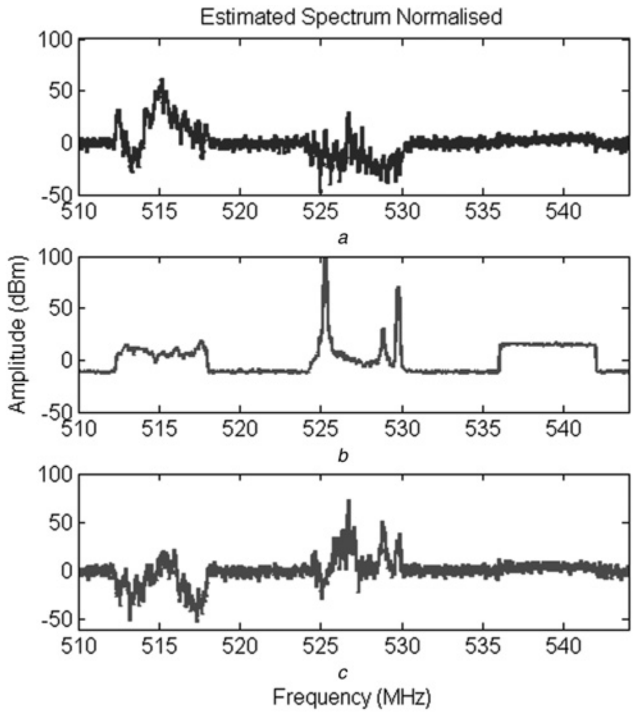

Fig. 5 *Estimated spectrum sensing using ICA, considered only three measurements shown in Fig. 4*

a Presence of channels 21 and 23
b Repetition of channels 21 and 23, and presence channel 25
c Confirmation of channels 21 and 23

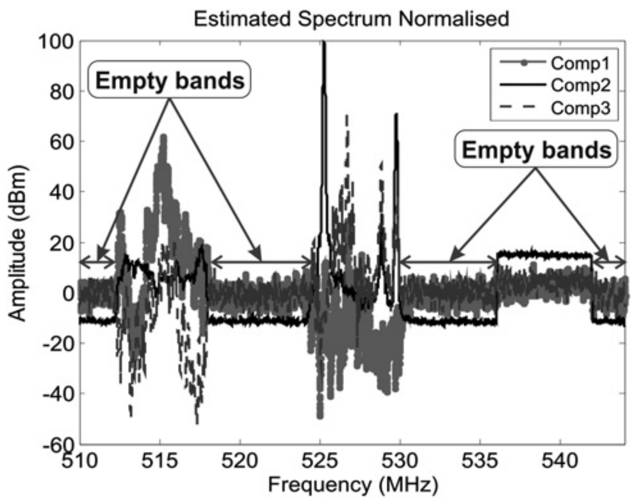

Fig. 6 *Estimated spectrums with occupied and empty bands, obtained by ICA*

Table 2 Recovered spectrum by ICA method for the three measured channels

Bands, MHz							
occupied		512.2–518		524.3–530.2		536–542	
empty	510–512.2		518–524.3		530.2–536		542–544

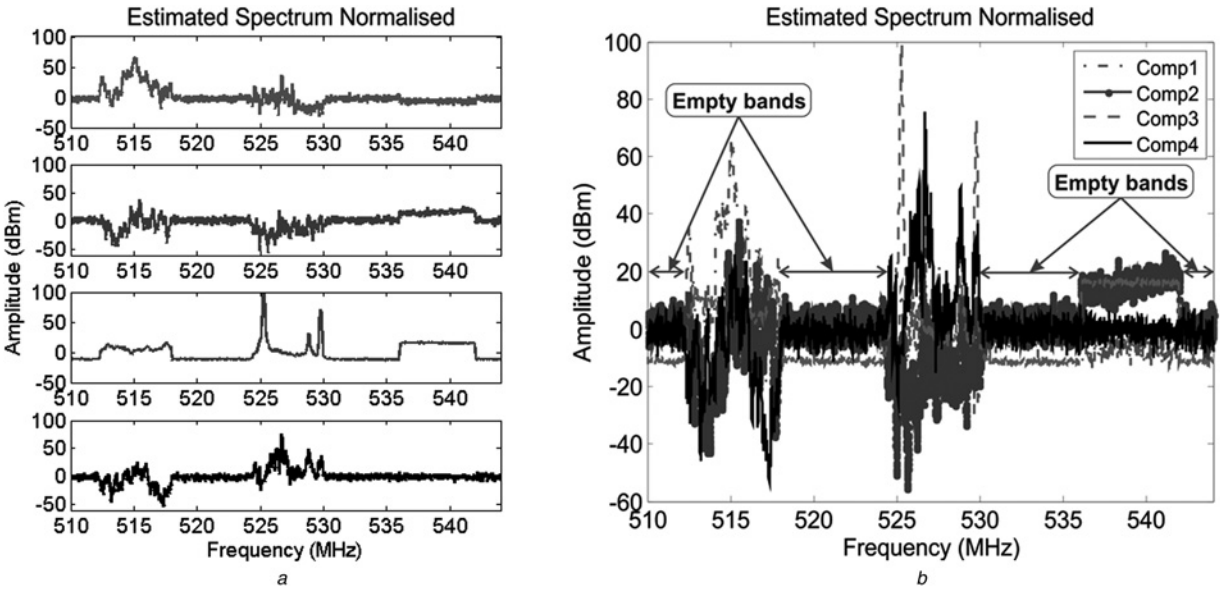

Fig. 7 *Estimated spectrum*

a Estimated spectrums from data shown in Fig. 3, in positions P#1–P#4
b Highlight of the empty bands

The strategy adopted to determine the bandwidths is to consider the frequencies where the measured power amplitude is lower than 0 dBm. One can observe that the bandwidths are very close to the original one (Fig. 3). Details about the estimated spectral opportunities by ICA are given in Table 2. For the case presented here, the frequency window from 510 to 544 MHz a total spectral opportunity band of 16.3 MHz was identified.

When comparing the designated bandwidths (6 MHz) for primary users with those bandwidths detected by ICA, the relative errors of 3.33% (channel 21), 1.67% (channel 23) and 0% (channel 25) were obtained. As mentioned before, the well-conditioned signal generated for channel 25 leads ICA algorithm a complete estimation of its bandwidth.

At this point, one can conclude that ICA can determine many broadband signals and, therefore, detect the unused bands. An improvement in the results can be achieved if new measurements are considered in the estimation, as proposed in [26]. Fig. 7 shows the estimated spectrum if four measurements have been taken in positions P#1–P#4. Fig. 7*a* presents the curves for estimation spectrum in separate graphics, where one can see clearly the occupied bands by the primary users and the empty bands. The spectral opportunities are highlighted in Fig. 7*b*.

In the new estimated spectrum, shown in Fig. 7, it can be observed that the frequency bandwidths occupied by primary users are closer to the original spectrum (Fig. 3). The new estimated bandwidths of primary users are 5.86, 5.95 and 6.01 MHz. The obtained relative errors are 2.33, 0.83 and −0.17%, which in overall were dropped below 2.4%. As described previously, once these bands are detected, the channels are used to identify the empty bands. The four unused bands are 512.2–510 MHz (BW = 2.20 MHz); 524.13–518.06 MHz (BW = 6.07 MHz); 535.98–530.08 MHz (BW = 5.9 MHz); and 544–541.99 MHz (BW = 2.01 MHz). As expected, the increase of the input data grows ICA ability to identify more precisely the three primary users and, therefore, any free-frequency bands. This is linked to the fact that ICA has a space of search larger than the previous case (three measurements), which allows greater exploitation of the statistical characteristics of the measured spectrum.

The fact of having more measurements also helps to confirm that there are no other primary users in the investigated bandwidth. This information can be useful to detect unauthorised transmissions in the bandwidth of interest.

The necessity of more input data to improve the estimation does not compromise the computational cost of the FastICA algorithm. The obtained results show that ICA can be applied to spectrum sensing in CR.

The proposed method can be used with TV channels operating with different bandwidths, as proposed for worldwide interoperability for microwave access −700 where one can have channels with 6, 7 or 8 MHz bandwidths. This is one advantage to apply ICA, since the detection method does not need prior information of the channels.

It is important to emphasise here that the accuracy of ICA in detection of users' bandwidth minimises the interference during the allocation of signals in the empty bands.

7 Conclusion

In this paper, it was shown the application of ICA methods for spectrum sensing in the TV channels frequency band. The monitored signals consist of analogue and digital TV channels, and a locally generated signal. The numerical results showed that ICA can be used to identify the presence and absence of primary users. Concurrently, the empty channels in the spectrum can be detected. ICA has advantages over traditional methods for spectrum detection, since it does not require prior information about the channels and can be used for sensing in narrowband and also in broadband spectrum. These characteristics allow the method to determine the existence of users other than the regulated ones (primary users). ICA can sweep wide frequency ranges without penalty in the complexity and speed of the algorithm. The method's accuracy is increased when more measurements are considered in the input data.

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