Blind Signals Separation in wireless communications based on Compressive Sensing

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Abstract — **The algorithm for separation of signals from two different wireless standards (Bluetooth and IEEE 802.11b standard), operating within the same frequency band is proposed in this paper. The components separation is performed using the time-frequency representation and the concept of Compressive Sensing. Knowing the signals nature, it is possible to select just a small set of time-frequency points that entirely belongs to the IEEE 802.11b signal. These points are extracted from the original time-frequency representation and are used to recover the full signal by using Compressive Sensing method. Once when the components of IEEE 802.11b signal are known, it is possible to reconstruct the remaining components in the band, belonging to the Bluetooth signal. Unlike the conventional separation methods, such as windowing or filtering, this approach works well even in the case of overlapping signals as well. The theory is proved with experimental results.**

Keywords — **Bluetooth, Compressive Sensing, IEEE 802.11b, separation, time-frequency**

I. Introduction

THE common challenge that appears in wireless communication systems is distinguishing between the signals that use same frequency band [1]-[4]. There is a number of wireless standards, in the first instance, the Wireless Personal Area Network – WPAN, Wireless Metropolitan Area Network (WMAN); Wireless Local Area Network – WLAN and Wireless Wide Area Network – WWAN. They differ in energy consumption, operation distance, data rates, types of modulations, and occupied frequency band [2]. This paper is focused on two modes that use Industrial, Scientific and Medical (ISM) frequency band: frequency hopping code division multiple access and direct sequence code division multiple access. Moreover, we consider the signals belonging to the standards based on modes – IEEE 802.11b (direct sequence) and Bluetooth (frequency hopping). The identification of the standard to which the signal belongs is important in applications related to wireless communications. Usually, the time-frequency (TF) methods have been used for the identification of the two standards at a certain time and frequency point [2]. TF blocks are implemented in order to extract signal parameters, and accordingly, to identify signal mode. In this paper, we have also used TF to represent wireless signals. However, instead of standard identification based on extracted signal parameters from the TF representation, the signals which belong to different standards are separated in the TF plane and then classified. The commonly used methods for component separation, like filtering or windowing require knowledge on the signal structure and may be complex for realization. Like an eigenvalue decomposition method, [5], [6], the signal separation methods often assume that components do not overlap in time or frequency. We propose the method which can deal even with highly overlapping signal components, by combining the TF, Compressive Sensing and L-statistics approach.

Compressive Sensing (CS) [7]-[20] deals with signals sampled at the rates far lower than that defined by Shanon-Nyquist theorem. In other words, the signal is highly under-sampled where available samples (observations or measurements) are chosen randomly. However, the missing samples may also occur by intentionally omitting some of the signal samples. This is the case with noisy signals where we omit corrupted samples using robust estimation techniques such as the L-statistics [9]-[13]. The removed noisy samples could be recovered by using CS reconstruction algorithms. The reconstruction is done from small set of available samples by using complex mathematical algorithms – optimization algorithms [7], [11], [14]-[16]. CS requires signal to satisfy certain conditions, such as sparsity in its own or certain transform domain.

II. Standard Compressive Sensing formulation

The important information for majority of real signals is concentrated in a small number of transform domain signal coefficients having large values, while the rest of coefficients can be set to zero. This property is called sparsity and it is imposed in the Compressive Sensing scenarios. The signal, which is sparse in one domain, needs to be dense in another domain, similarly as the sinusoid is sparse in the Fourier domain while it is dense in the time domain. Such kind of signals, can be reconstructed from a small incomplete set of samples, taken randomly form the dense representation. Let us illustrate the CS procedure on

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the discrete time domain signal x. In terms of the transform domain coefficients, the signal could be represented as [7]:

$$x = \sum_{l=1}^{L} \psi_l s_l = \mathbf{\Psi} s \,, \tag{1}$$

where ψ_l and s_l denote basis vectors and transform domain coefficients, and L is the full signal length (when sampled according to the sampling theorem). The signal is assumed to be sparse in the domain $\mathbf{\Psi}$. The available samples (signal measurements) are randomly acquired from the dense domain, by using properly defined measurement matrix $\boldsymbol{A}$. The measurement vector is:

$$m_{M\times 1} = \boldsymbol{A}_{M\times L} \mathbf{\Psi}_{L\times L} x_{L\times 1} = \boldsymbol{A}^{CS}_{M\times L} x_{L\times 1} \tag{2}$$

where m is measurement vector, M is number of acquired samples (M<<L), $\boldsymbol{A}_{M\times L}$ is the measurement matrix and $\boldsymbol{A}^{CS}$ is the CS matrix. The CS matrix could be formed from the matrix $\mathbf{\Psi}$, as follows:

$$\boldsymbol{A}^{CS} = \mathbf{\Psi}(1:\nabla(1:M),1:L)) \,, \tag{3}$$

where ∇ denotes the operator performing random permutations of M positions. The CS matrix is formed as random partial Fourier transform matrix. It has been known from the literature that such random partial Fourier matrix lead to fast recovery algorithms, and it satisfies a near optimal RIP with high probability [21]-[22]. The system of equations (2) can be solved by using ℓ_1 norm minimization [7], [15]:

$$\min_{x} \|x\|_{l_1} \quad subject \;\; to \;\; m = \boldsymbol{A}^{CS} x \,. \tag{4}$$

III. Problem Formulation

Consider the signal that consists of the sum of signals belonging to the considered wireless standards – Bluetooth and IEEE 802.11b:

$$x = x_{FHSS}(n) + x_{802.11b}(n) \,. \tag{5}$$

The signal x Fourier transform could be written as:

$$X(k) = X_{FHSS}(k) + X_{802.11b}(k) \,. \tag{6}$$

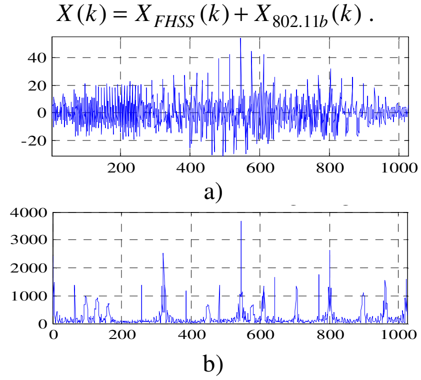

Fig. 1. a) Time and b) frequency domain of the signal

Time and frequency domain representation of the signal x are shown in Fig.1. It is important to note that distinguishing between the two different types of signal components is difficult, in some situations impossible, by observing time or frequency domain, separately. Therefore, in the applications we use the joint TF domain in order to provide suitable representation of the signal, and to localize regions in the TF plane that belong to the certain standard. As overlapping components can exist in the band, separation by using conventional techniques (filtering, eigen/singular value decomposition, etc.) become ineffective. Therefore, we use CS approach to extract signals of interest.

The overlapping TF regions may have high or low energy values, depending on the phases of overlapping components. Therefore, we considered removing the certain percent of the lowest and highest energy TF regions and then recovering these regions by using the CS concept. Having in mind that separation is done in the TF domain, CS procedure will be modified compared to the standard CS approach described in Section II.

IV. CS Based Separation of Wireless Signals in the TF Domain

The wireless signals, both Bluetooth and IEEE 802.11b, consist of sinusoidal components and therefore can be considered as sparse in the Fourier domain. Sinusoidal nature of these signals makes them appropriate candidates for the CS application. Unlike the common CS algorithms, where the measurements are taken in the time domain, here the measurements are selected from the TF domain. Since the components of Bluetooth signal have shorter time duration compared to the IEEE 802.11b signals, [1]-[4], [18], [19], they will produce lower sum of energy along a certain frequency in the TF plane. It means that sorting along the frequency axis in TF plane will completely condense the Bluetooth components in the lower part of sorted TF plane. In order to discard Bluetooth components and overlapping points, we have used the L-statistics approach - the highest and lowest components in the sorted TF plane are removed. Thus, we are left with the certain part of middle frequency region which actually belongs solely to IEEE 802.11b. Note that, depending on the phases of components the intersection points may have largest or smallest values. Using just a small number of selected points belonging to the IEEE 802.11b signal, the full signal is recovered using the CS procedure, as described in the sequel.

The full signal x of length L can be represented by using the full length discrete Fourier transform (DFT) vector X as [9], [20]:

$$x = \boldsymbol{D}_{L\times L}{}^{-1} X \,, \tag{7}$$

where $\boldsymbol{D}_{L\times L}{}^{-1}$ denotes inverse DFT matrix of size (L×L). On the other side, the Short-Time Fourier Transform (STFT) of the windowed signal x can be written in the matrix form as follows [13]:

$$\boldsymbol{S} = \begin{bmatrix} S_N(0) \\ S_N(N) \\ \\ S_N(L-N) \end{bmatrix} = \begin{bmatrix} \boldsymbol{D}_N & \mathbf{0}_N & \dots & \mathbf{0}_N \\ \mathbf{0}_N & \boldsymbol{D}_N & \dots & \mathbf{0}_N \\ \dots & \dots & \dots & \dots \\ \mathbf{0}_N & \mathbf{0}_N & \dots & \boldsymbol{D}_N \end{bmatrix} \begin{bmatrix} x(0) \\ x(1) \\ \dots \\ x(L-1) \end{bmatrix}, \tag{8}$$

$$\boldsymbol{S} = \boldsymbol{D}x$$

where N is size of non-overlapping window, while

$$\boldsymbol{D}_N = \exp(-j2\pi sk/N) \tag{9}$$

is N×N DFT matrix, s=0,…,N-1, k=0,…,N-1.

In order to obtain $\boldsymbol{D}$ matrix of size L×L ($\boldsymbol{D}_{N\to L}$), the following relation is used:

$$\boldsymbol{D} = \boldsymbol{I}_{L/N} \otimes \boldsymbol{D}_{N\times N} \,. \tag{10}$$

Matrix $\mathbf{I}_{L/N}$ is (L/N)×(L/N) identity matrix and ⊗ denotes Kronecker product. Combining relations (7) and (8) it follows:

$$\boldsymbol{S} = \boldsymbol{D}x = \boldsymbol{D}\boldsymbol{D}_{L\times L}{}^{-1}X = \boldsymbol{\Psi}X. \tag{11}$$

After calculating the STFT, the sorting operation along is performed along the frequency (for each k):

$$S_{SORT}(n,k) = sort\{S(n,k)\}, \tag{12}$$

where $n=0, \ldots, L-1$. The sorting operation is performed in ascending order. The percentage P of low value coefficients and percentage Q of high value coefficients are removed from the sorted STFT vector [13]:

$$S_{CS}(k) = \{S_{SORT}(n,k), n = P, P+1, \ldots, L-Q\}, \tag{13}$$

where $S_{CS}(k)$ denotes the vector of available STFT coefficients at frequency k. When considering all frequencies k, the vector of all $S_{CS}(k)$ is denoted by S_{CS}. Now, based on (12) the vector of all available STFT points can be written as:

$$\boldsymbol{S}_{CS} = \boldsymbol{\Psi}_{CS} X\ , \tag{14}$$

where the matrix $\boldsymbol{\Psi}_{CS}$ is formed by omitting the rows which corresponds to the removed STFT values. The coefficients that remain in the TF plane (S_{CS}) will be used in CS reconstruction procedure. Similar to the standard CS reconstruction formulation, here we also use ℓ_1 norm minimization to reconstruct DFT vector X, which is further used to obtain time domain representation. The reconstruction can be written as the minimization problem [13], [20]:

$$\min \|X\|_{\ell_1} \text{ subject to } \boldsymbol{S}_{CS} = \boldsymbol{\Psi}_{CS} X\ . \tag{15}$$

The obtained vector X denotes DFT of the IEEE 802.11b signal. The DFT of the Bluetooth signal can be easily obtained by eliminating the IEEE 802.11b signal components from the original DFT of the signal. Having separated DFTs of the signals, time domain and TF domain of the signals can be calculated, as well. Compared to the standard ℓ_1 reconstruction algorithms , the proposed algorithm is extended with STFT calculation and sorting operation. Complexity of the STFT calculation is T<(3/4)$\log_2$M-2, where M denotes window width. Sorting operation could be performed using bitonic sort. Bitonic sorting complexity is O($N_S \log_2 N_S$), where N_S denotes square root of the signal length.

V. Experimental Results

A. *Example 1*

Consider the signal in the form defined with relation (5), where the $x_{802.11b}$ signal is defined as:

$$x_{802.11b}(n) = \sum_{i=1}^{p_1} M_i e^{j(\pi nK/L+\varphi_i)}\ , \tag{16}$$

while x_{FHSS} is defined:

$$x_{FHSS}(n) = \sum_{i=1}^{p_2} M_i e^{j(\pi nK/L)} e^{-[(n-\delta_i)/d_i]^{\varepsilon}}\ . \tag{17}$$

Parameters p_1 and p_2 denote number of components in the corresponding signals, M_i denotes component amplitude, while K,φ, δ and ε are constants. Both signals are defined as sum of complex sinusoids. Parameter d_i in the FHSS signal definition determines component duration [13]. The signal with 7 IEEE 802.11b and 17 Bluetooth components is observed. Time domain and Fourier transform of the signal is shown in Fig. 2. The STFT of the sum of these two signals is shown in Fig. 3a, while the sorted values of the STFT are shown in Fig. 3b. The STFT that remains after the sorting and selection certain STFT region is shown in Fig. 3c. The reconstructed STFT of the IEEE 802.11b signal is shown in Fig. 4a. The STFT of the Bluetooth signal is obtained by subtracting reconstructed IEEE 802.11b STFT from the STFT of original signal, and is shown in Fig. 4b.

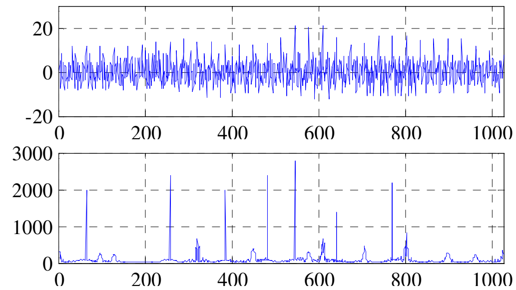

Fig. 2. Time (first row) and frequency (second row) domain of the sum of signals (16) and (17)

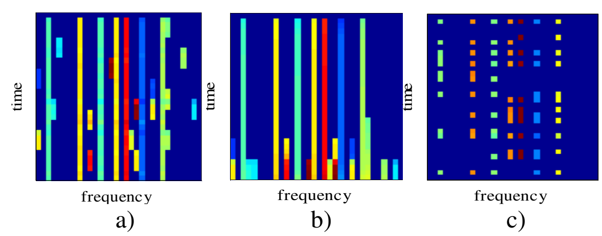

Fig. 3. a) STFT of the original signal, b) sorted STFT, c) remain STFT after choosing certain region from the sorted STFT

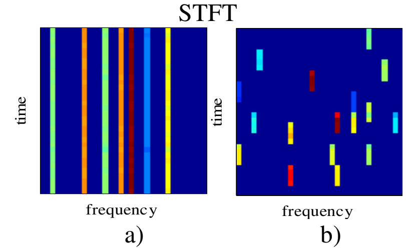

Fig. 4. a) Reconstructed STFT of the IEEE 802.11b, b) STFT of the Bluetooth signal

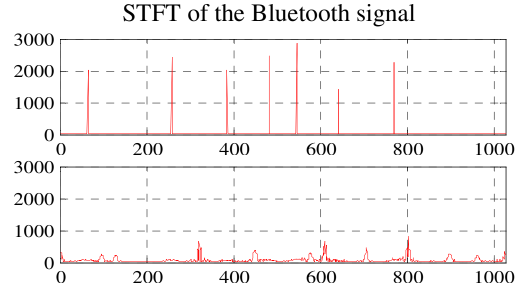

Fig 5. Fourier transform of the reconstructed IEEE 802.11b (first row) and Bluetooth signals (second row)

As it can be seen, all of the components of two signals are preserved and signals are separated in the TF plane. Fig. 5 shows reconstructed DFTs of the wireless and Bluetooth signals, which completely correspond to the components of original signals.

B. Example 2

Let us now consider signal consisted of Bluetooth and IEEE 802.11b signals, with overlapped components. Four components belong to the IEEE 802.11b signal, while twelve components of short duration belong to the Bluetooth signal. The STFT of the original signal is shown in Fig. 6a. Fig. 6b and Fig. 6c shows sorted STFT values and STFT values that remain after the samples removal. As it can be seen from the Fig. 6a, three Bluetooth components overlap with the IEEE 802.11b components.

After CS reconstruction, applied to the STFT from the Fig. 6c, and subtraction from the original signal STFT, the Bluetooth signal STFT is obtained. The corresponding STFTs are shown in Fig. 7. All of the signal components are preserved – 4 components that belong to the IEEE 802.11b signal and 12 Bluetooth signal components (see Fig.7a and Fig. 7b). The DFTs of the original and reconstructed signals are shown in Fig.8. The reconstructed components in DFTs completely correspond to the components of the original signal (see Fig. 8).

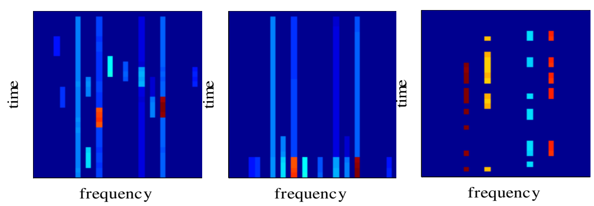

Fig. 6. a) STFT of the original signal, b) sorted STFT, c) remain STFT after choosing certain region from the sorted STFT

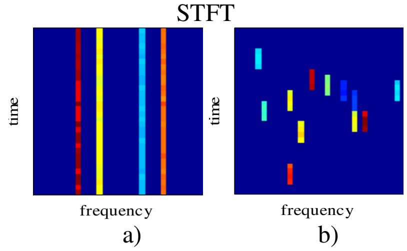

Fig. 7. a) Reconstructed STFT of the IEEE 802.11b, b) STFT of the Bluetooth signal

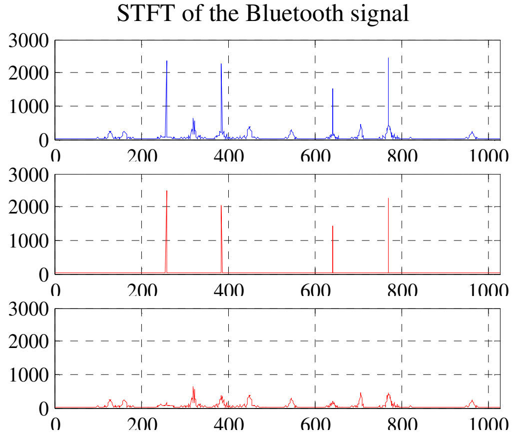

Fig. 8: Fourier transforms of the original signal (first row), and reconstructed IEEE 802.11b and Bluetooth signals (second and third row)

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