A multi-tag radio-frequency identification system using a new blind source separation method based on spectral decorrelation

H. Saylani, Y. Deville, S. Hosseini, M. Habibi

Abstract— **In recent years, electronic systems have progressively replaced mechanical devices and human operation for identifying people or objects in many everyday-life applications. This includes systems which perform contactless identification by using radio-frequency tags. Although the latter systems are efficient, they are often unable to easily identify several simultaneously present tags. A solution to this problem, based on blind source separation (BSS) techniques which use artificial neural networks, has been reported in the literature. It yields attractive results but is not able to achieve identification when the signals to be processed contain less than about 1000 samples. In this paper, we use instead a BSS method which was quite recently developed in our team. This approach is based on frequency-domain decorrelation and applies to mutually uncorrelated non-stationary (especially cyclo-stationary) signals. The resulting identification system achieves much higher performance than the previous one in terms of required signal size and insensitivity to the positions of the tags to be identified.**

I. Problem statement

Systems for identifying people or objects are now widespread. Typical examples are owner identification before starting car engines or access control for restricted areas. In the past, the approaches used to perform such identifications were mainly based on mechanical devices (such as keys for starting car engines) or human operation (e.g. visual inspection of people for access control). These approaches are progressively replaced by various types of electronic systems, and especially by systems based on radio-frequency (RF) communication.

Fig. 1 shows such an RF system, which was e.g. considered in [1]. It consists of a base station inductively coupled to a portable identifier. This identifier (called a "tag") contains an LC resonator, a controller and non-volatile programmable memory (EEPROM). The memory contents are specific to each tag and allow to identify the tag-bearer (person or object). The basic mode of operation of this system may be modelled as follows. The base station emits an RF sine wave, which is received by the tag. The tag is thus powered and answers by emitting a sine wave at the same frequency (due to inductive coupling), modulated by its encoded memory contents. The base station receives this signal, demodulates it, and decodes it so as to determine the memory contents.

H. Saylani, Y. Deville and S. Hosseini are with Laboratoire d'Astrophysique de Toulouse-Tarbes, Observatoire Midi-Pyrénées - Université Paul Sabatier Toulouse 3, 14 Av. Edouard Belin, 31400 Toulouse, France hsaylani , ydeville , shosseini@ast.obs-mip.fr

H. Saylani and M. Habibi are with Laboratoire d'Automatique et de Micro-Ondes, Faculté des Sciences, Université Ibn Tofail, 14000 Kénitra, Maroc mohamed.habibi@caramail.com

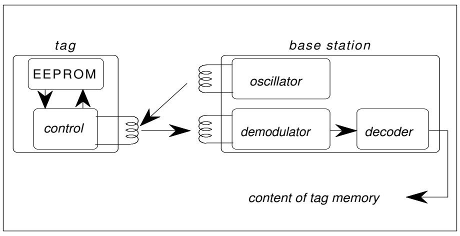

Fig. 1. Single-tag RF identification system.

The overall identification system then checks these data and controls its actuators accordingly.

This type of system is attractive because it yields contactless operation between the base station and tags, thus avoiding constraints on the positions of the tag-bearers. However, when two tags are placed in the RF field of the base station, both tags answer this station. The demodulated signal derived by this station is then a mixture of two components, and cannot be decoded by this basic station. This system is therefore unable to identify two simultaneously present tag-bearers.

A few attempts to solve this problem have been presented in the literature [2],[3]. To avoid their drawbacks (which are e.g. described in [1]), an alternative approach using Blind Source Separation (BSS) techniques based on Artificial Neural Networks (ANNs) was proposed in [1]. It makes it possible two separate two tag signals when two mixtures of these signals are available. The second mixture is obtained by inserting an additional reception antenna and an additional demodulator in the base station (see Fig. 2). The tags thus have the same simple structure as in the standard single-tag system, and the added complexity only appears in the base station, i.e. in a single location of the system, so that its cost is limited.

Although this multi-tag approach is attractive, the performance of the BSS units used in [1] highly depends on the mixing conditions, so that the quality of the identification

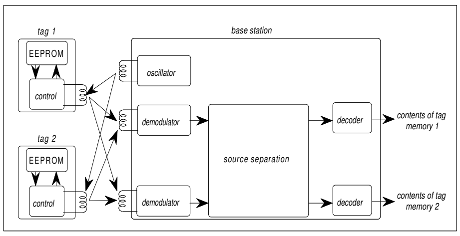

Fig. 2. Multi-tag RF identification system.

of tag-bearers is quite sensitive to their positions. Moreover, this performance degrades for short tag signals, which limits the ability of this system to achieve short reponse times. In this paper, we therefore aim at achieving higher performance in this identification application, by using a BSS method which was developed quite recently in our team (see [4]; related approaches were also described in [5],[6]). This method is based on spectral decorrelation and exploits source non-stationarity (especially cyclo-stationarity). We selected it because it is suited to the type of sources and mixtures considered in our application[1] and due to its advantages: (1) its performance has a low sensitivity with respect to the mixing coefficient values and therefore with respect to the positions of tag-bearers, and (2) this BSS method yields good performance even for very short signals, as confirmed below in this paper.

II. Goal of BSS

Let us assume that two observations $x_1(n)$ and $x_2(n)$ are available and that they are noiseless mixtures of two unknown discrete-time sources $s_1(n)$ and $s_2(n)$. Let us denote $\mathbf{x}(n) = [x_1(n),\, x_2(n)]^T$ and $\mathbf{s}(n) = [s_1(n),\, s_2(n)]^T$ the observation and source vectors. These vectors are linked by the following relationship when considering linear instantaneous mixtures:

$$\mathbf{x}(n) = \mathbf{A}\,\mathbf{s}(n), \tag{1}$$

where $\mathbf{A} = [a_{ij}]$ is the unknown 2x2 so-called "mixing matrix". This matrix is assumed to be real-valued and invertible.

BSS methods aim at providing an estimate of the mixing matrix $\mathbf{A}$, or of it inverse $\mathbf{A}^{-1}$. More precisely, in this blind context where neither the sources nor the mixing matrix are known, $\mathbf{A}$ or $\mathbf{A}^{-1}$ can only be estimated up to a permutation matrix $\mathbf{P}$ and a diagonal matrix $\mathbf{D}$ [7]. BSS methods therefore estimate a matrix $\mathbf{B} = \mathbf{PDA^{-1}}$ (or a matrix $\mathbf{B}' = \mathbf{PDA}$).

Using (1), the output vector $\hat{\mathbf{s}}(n)$ of a BSS system is therefore defined as

$$\begin{aligned}\hat{\mathbf{s}}(n) &= \mathbf{B}\mathbf{x}(n) &(2)\\ &= (\mathbf{PDA}^{-1})(\mathbf{A}\mathbf{s}(n)) &(3)\\ &= \mathbf{PD}\mathbf{s}(n). &(4)\end{aligned}$$

The matrix $\mathbf{B}$ therefore allows us to restore the sources $s_1(n)$ et $s_2(n)$ up to permutation and scale factors. These indeterminacies are not a problem for the application studied in this paper: by applying the two signals $\hat{\mathbf{s}}_i\, (i = 1, 2)$ thus obtained to the decoders of the considered identification system, we anyway get the memory contents of the two tags.

III. Frequency-domain BSS

Now consider the frequency-domain representation of the above BSS problem, which is e.g. used in the specific BSS method described in Section IV. The sources $s_1(n)$ et $s_2(n)$ are assumed to be stochastic, real-valued, zero-mean, non-stationary [4] and mutually uncorrelated. Applying the Fourier transform[2] to Eq. (1) yields

$$\mathbf{X}(\omega) = \mathbf{A}\mathbf{S}(\omega), \tag{5}$$

where $\mathbf{X}(\omega) = [X_1(\omega), X_2(\omega)]^T$, $\mathbf{S}(\omega) = [S_1(\omega), S_2(\omega)]^T$ and where $S_i(\omega)$ and $X_i(\omega)$ $(i = 1, 2)$ are resp. the Fourier transforms of $s_i(n)$ et $x_i(n)$. The frequency-domain observations $X_i(\omega)$ are therefore linear instantaneous mixtures of the frequency-domain sources $S_i(\omega)$.

Eq. (1) and (5) are equivalent. Transposing the BSS problem into the frequency domain is attractive because the sources $S_i(\omega)$ thus obtained have new properties, which may be exploited by powerful BSS methods. We then aim at estimating the matrix $\mathbf{B}$ by processing the linear instantaneous mixtures $X_i(\omega)$ of the sources $S_i(\omega)$, instead of the mixtures of the sources $s_i(n)$. The estimates of the time-domain sources $s_i(n)$ are then derived from the matrix $\mathbf{B}$, using Eq. (2).

As the sources $s_1(n)$ and $s_2(n)$ are assumed to be zero-mean and mutually uncorrelated in the time domain, it may be shown easily that

$$E\big\{S_1(\omega_1)S_2(\omega_2)\big\} = E\big\{S_1(\omega_1)S_2^*(\omega_2)\big\} = 0 \quad \forall\, \omega_1, \omega_2. \tag{6}$$

The BSS method described below therefore aims at providing two uncorrelated frequency-domain output signals. This approach is then referred to as a "spectral decorrelation BSS method" and denoted "SpecDec" hereafter.

The following notations are used below

$$\begin{cases} \mathbf{R}_X(\omega) = E\big\{\mathbf{X}(\omega)\mathbf{X}^H(\omega)\big\} \\ \mathbf{Q}_X(\omega) = E\big\{\mathbf{X}(\omega)\mathbf{X}^T(\omega)\big\} \end{cases} \tag{7}$$

where $\mathbf{X}^H$ and $\mathbf{X}^T$ are resp. the Hermitian transpose and transpose of vector $\mathbf{X}$.

IV. Spectral decorrelation BSS method

The SpecDec BSS method used in this paper is based on the following theorem, whose proof is provided in [4].

Theorem: Suppose the sources $s_1(n)$ et $s_2(n)$ are real-valued, zero-mean and mutually uncorrelated. If there exists a frequency ω_0 such that

$$\begin{cases} E\{|S_i(\omega_0)|^2\} \neq 0 \quad ,i = 1, 2 \\ \frac{E\{S_1^2(\omega_0)\}}{E\{|S_1(\omega_0)|^2\}} \neq \frac{E\{S_2^2(\omega_0)\}}{E\{|S_2(\omega_0)|^2\}} \end{cases} \tag{8}$$

denoting $\mathbf{V}$ a complex-valued matrix whose columns are the eigenvectors of the matrix $\mathbf{R}_X^{-1}(\omega_0)\mathbf{Q}_X(\omega_0)$, i.e. $\mathbf{R}_X^{-1}(\omega_0)\mathbf{Q}_X(\omega_0) = \mathbf{V\Lambda V^{-1}}$ where $\mathbf{\Lambda}$ is a diagonal matrix), then we have

$$\mathbf{V}^T = \mathbf{PDA}^{-1}, \tag{9}$$

where $\mathbf{D}$ is a complex diagonal matrix and $\mathbf{P}$ is a permutation matrix.

Therefore, when Condition (8) is met for a given frequency ω_0, determining the eigenvectors of the matrix

[1] As shown in [1], the demodulator outputs are linear instantaneous mixtures of the components corresponding to the two tags.

[2] The Fourier transform of a discrete-time stochastic process $u(n)$ is a stochastic process defined as $U(\omega) = \sum_{n=-\infty}^{\infty} u(n)e^{-j\omega n}$ [8].

$\mathbf{R}_X^{-1}(\omega_0)\mathbf{Q}_X(\omega_0)$ allows us to identify the matrix $\mathbf{A}^{-1}$ up to a permutation matrix and a complex diagonal matrix. Moreover, since the matrix $\mathbf{A}$ is assumed to be real-valued, when using Eq. (9) only the real part of the matrix $\mathbf{V}^T$ should be considered. More precisely, let us denote $\mathbf{D} = \mathbf{D}_R + j\mathbf{D}_I$ where $\mathbf{D}_R$ and $\mathbf{D}_I$ are resp. the real and imaginary parts of the matrix $\mathbf{D}$. Eq. (9) then reads: $\mathbf{V}^T = \mathbf{P}(\mathbf{D}_R + j\mathbf{D}_I)\mathbf{A}^{-1}$. Hence, $\Re\{\mathbf{V}^T\} = \mathbf{P}\mathbf{D}_R\mathbf{A}^{-1}$. The matrix $\mathbf{A}^{-1}$ is therefore equal to the real part of the complex matrix $\mathbf{V}^T$ up to a permutation matrix and a *real* diagonal matrix. The sources are thus estimated up to a permutation and a real scale factor, as shown by the following equation:

$$\Re\{\mathbf{V}^T\}\mathbf{x}(n) = \mathbf{P}\mathbf{D}_R\mathbf{A}^{-1}\mathbf{x}(n) = \mathbf{P}\mathbf{D}_R\mathbf{s}(n). \tag{10}$$

The practical implementation of this BSS method requires one to compute the matrices $\mathbf{R}_X(\omega)$ and $\mathbf{Q}_X(\omega)$ defined in (7) and therefore to estimate mathematical expectations. If the signals are cyclo-stationary, a realization of the temporal mixture over a given window yields almost the same spectral shape in sub-windows whose size is a multiple of the least common multiplier of the cyclo-stationarity periods of both sources. Mathematical expectations may therefore be estimated by computing the Fourier transforms of the mixtures on each sub-window and then averaging other all sub-windows. As shown in [4], the set of equations (8) can only be satisfied at frequencies ω_0 which are multiples of $\omega_c/2$, where ω_c is the cyclo-stationarity frequency of one of the two sources.

V. Test results

The two tag signals used herefater are similar to those considered in the tests reported in [1]. They contain 8000 samples. We consider the same artificial mixtures and performance criterion as in [1] in order to compare our following results to those in [1]. We thus first process signals with a low mixture ratio, corresponding to the mixing matrix $A_1 = [1\ 0.4; 0.3\ 1]$ and then signals with a high mixture ratio, associated to $A_2 = [1\ 0.98; 0.98\ 1]$. Our performance criterion is the Signal to Interference Ratio Improvement ($SIRI$) defined as: $SIRI = (SIRI_1 + SIRI_2)/2$, where

$$SIRI_i = 10.\log_{10}\left[\frac{E\{(x_i(n) - s_i(n))^2\}}{E\{(\hat{s}_i(n) - s_i(n))^2\}}\right] \qquad i = 1, 2 \tag{11}$$

is the improvement of the signal to interference ratio for source s_i on output i, expressed in dB. In (11), we consider a version of $\hat{s}_i(n)$ rescaled so that it has the same variance as $s_i(n)$.

For each mixing matrix, we vary the number N of samples of observed signals actually used in our method, and we determine the corresponding performance. For each value of N, we take advantage of all available 8000 samples however, by using a statistical approach for measuring $SIRI$: we compute the mean value of the $SIRIs$ corresponding to all N-sample windows obtained by sweeping over our complete signals, with a $N/2$-sample overlap between adjacent windows. This mean of $SIRI$ is denoted $\overline{SIRI}$. We alo compute the standard deviation σ of $SIRI$.

TABLE I

Mean (dB) and standard deviation (dB) of $SIRI$ (denoted $\overline{SIRI_1}$ and σ_1 for a low mixture ratio and $\overline{SIRI_2}$ and σ_2 for a high mixture ratio) vs. number N of samples, for SpecDec.

N	262	524	1048	2096	3013	4061	5109	6026	7074	7991
$\overline{\mathbf{SIRI_1}}$	16.2	22.8	25.4	31.1	29.6	24.1	27.5	24.9	27.0	30.8
σ_1	9.9	8.4	6.6	8.2	3.3	0.1	0.6	0	0	0
$\overline{\mathbf{SIRI_2}}$	25.2	31.9	34.4	40.3	38.6	33.2	36.5	34.0	36.0	39.7
σ_2	10.0	8.3	6.6	8.3	3.3	0.1	0.6	0	0	0

TABLE II

$SIRI$ (dB) vs. number N of samples for the ANN: low mixture ratio.

N	1200	1400	1450	1500	1600	2000	3000	11500
SIRI	4.8	8.0	9.0	11.2	15.1	17.9	19.9	21.6

The SpecDec method is here implemented by exploiting the fact that the source signals associated to the tags are cyclo-stationary, with the same cyclo-stationarity period, as shown in the Appendix. Therefore, we estimate the matrices $\mathbf{R}_X(\omega)$ and $\mathbf{Q}_X(\omega)$ as explained in Section IV, i.e. we split the considered window in F-sample sub-windows, where F is a multiple of the cyclo-stationarity period N_c of both sources. The latter period is estimated thanks to the maxima of the auto-correlation function of each observed signal, which yields $N_c \simeq 16.357$. In our tests, we use $F = 131$, which is the first multiple of N_c almost equal to an integer ($F \simeq 8.N_c$). The frequency ω_0 is set to $\omega_c/2$, where $\omega_c = \frac{2\pi}{N_c}$ is the cyclo-stationarity frequency of both sources.

The results obtained with the SpecDec method are shown in Table I. This should be compared to the performance of the ANNs used in [1]. Five ANNs were tested in that paper and the best performance was provided by two related networks, based on normalized weight updating. We here present the results obtained with the recurrent version of that type of networks (see Tables II and III). This shows that the SpecDec method is more powerful than these ANNs, especially because it yields a much higher $SIRI$ for a given number N of samples. More precisely:

- For a *low mixture ratio*, when using the considered ANN, $SIRI$ increases with N and is equal to $21.6\,dB$ for $N = 11500$, while the SpecDec method e.g. yields $\overline{SIRI} = 30.8\,dB$ with only 7991 samples. Moreover, the ANN provides a $SIRI$ lower than $10\,dB$ for about $N \leq 1450$, while SpecDec already yields $\overline{SIRI} = 16.2\,dB$ with only 262 samples.
- For a *high mixture ratio*, the $SIRI$ of the ANN again increases with N and is equal to $19.2\,dB$ for $N = 12000$, while SpecDec results in $\overline{SIRI} = 39.7\,dB$ with only 7991 samples. Moreover, the ANN yields a low $SIRI$ when N is low, i.e. $7.7\,dB$ for $N = 900$, while SpecDec provides $\overline{SIRI} = 25.2\,dB$ with only 262 samples.

The SpecDec method therefore yields very good performance even for tag signals containing less than 1000 samples, unlike

TABLE III

$SIRI$ (DB) VS. NUMBER N OF SAMPLES FOR THE ANN: HIGH MIXTURE RATIO.

N	900	1200	2000	4500	12000
SIRI	7.7	9.5	11.4	14.5	19.2

the ANNS considered in [1]. Table I also shows that, for both mixture ratios, the standard deviation of its $SIRI$ tends to be low as compared to the mean value of this $SIRI$ [3].

VI. Conclusion and future work

The results presented in this paper first confirm that BSS makes it possible to identify two simultaneously present RF tags by using a system which is almost as simple as the classical single-tag system. Moreover, they show that our spectral decorrelation BSS method is more efficient that the ANN-based BSS approaches used in [1]. It yields better identification quality thanks to a higher $SIRI$ for a given number N of signal samples, and it guarantees successful identification even for short tag signals, whatever mixture ratio is considered, i.e. $SIRI \geq 20\,dB$ for $N \simeq 300$, while the considered ANNs require at least about 1500 samples to only achieve $SIRI = 10\,dB$. Our future investigations will aim at extending this approach to a higher number of tags.

Appendix

The contents of each tag memory may be modelled as a sequence of binary random variables $\{i_n\}$, which are assumed to be independent. Each variable is equal to 0 or 1 with probability $1/2$. As shown in [1], each corresponding tag signal consists of a series of identical frames, composed of a synchronization part followed by the above data, encoded as follows. An encoding rule associates to the sequence $\{i_n\}$ a sequence of stationary random variables $\{C_n\}$ whose values are in a ternary alphabet $\{V_0 = 0, V_1 = 1, V_2 = -1\}$:

$C_n = V_0 = 0$ for $i_n = 0$,
$C_n = V_1 = 1$ for odd occurences of $i_n = 1$
$C_n = V_2 = -1$ for even occurences of $i_n = 1$.

Obviously, $p(C_n = 0) = 1/2$ and $p(C_n = 1) = p(C_n = -1) = 1/4$. Electrical signals $f_j(t)$ $(j = 1, 2, 3)$ are then associated to the values V_j. The signals $f_j(t)$ have a duration T corresponding to the transmission of one bit. Their shapes have no influence on the following discussion. The unmodulated signal $s(t)$ associated to a tag therefore reads

$$\begin{aligned} s(t) \;=\; \sum_{n=-\infty}^{+\infty} & (1 + C_n)(1 - C_n) f_0(t - nT) \\ & + \frac{1}{2} C_n (1 + C_n) f_1(t - nT) \\ & - \frac{1}{2} C_n (1 - C_n) f_2(t - nT). \qquad (12) \end{aligned}$$

[3]The standard deviation of $SIRI$ is zero for $N \geq 5371 = 41.F$, because only one window exists for such values of N.

We aim at showing that the signal $s(t)$ is wide-sense cyclostationary with a cyclostationarity period T, i.e. that

$$\begin{aligned} E\{s(t + kT)\} &= E\{s(t)\}, & (13) \\ E\{s(t_1 + kT)s(t_2 + kT)\} &= E\{s(t_1)s(t_2)\}. & (14) \end{aligned}$$

Due to space limitations, we only provide the proof for Eq. (13). Eq. (14) is shown in a similar way. We have

$$\begin{aligned} E\{s(t + kT)\} = \sum_{n=-\infty}^{+\infty} & E\{s(1 + C_n)(1 - C_n)\} f_0(t - (n - k)T) \\ & + \frac{1}{2} E\{C_n(1 + C_n)\} f_1(t - (n - k)T) \\ & - \frac{1}{2} E\{C_n(1 - C_n)\} f_2(t - (n - k)T). \end{aligned}$$

Denoting $n' = n - k$, we get

$$\begin{aligned} E\{s(t + kT)\} = \sum_{n'=-\infty}^{+\infty} & E\{(1 + C_{n'+k})(1 - C_{n'+k})\} f_0(t - n'T) \\ & + \frac{1}{2} E\{C_{n'+k}(1 + C_{n'+k})\} f_1(t - n'T) \\ & - \frac{1}{2} E\{C_{n'+k}(1 - C_{n'+k})\} f_2(t - n'T). \end{aligned}$$

Since the sequence C_n is stationary, we have

$$E\{C_{n'+k}\} = E\{C_{n'}\} \; and \; E\{C^2_{n'+k}\} = E\{C^2_{n'}\}.$$

Therefore

$$\begin{aligned} E\{s(t + kT)\} = \sum_{n'=-\infty}^{+\infty} & E\{(1 + C_{n'})(1 - C_{n'})\} f_0(t - n'T) \\ & + \frac{1}{2} E\{C_{n'}(1 + C_{n'})\} f_1(t - n'T) \\ & - \frac{1}{2} E\{C_{n'}(1 - C_{n'})\} f_2(t - n'T) \\ & = E[s(t)]. \end{aligned}$$

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