IMPROVED MULTI-TAG RADIO-FREQUENCY IDENTIFICATION SYSTEMS BASED ON NEW SOURCE SEPARATION NEURAL NETWORKS

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ABSTRACT

Electronic systems are progressively replacing mechanical devices or human operation for identifying people or objects in everyday-life applications. Especially, the radio-frequency contactless identification systems available today have several advantages, but they cannot handle easily several simultaneously present items. This paper describes a solution to this problem, based on source separation techniques. The effectiveness of this approach is experimentally demonstrated, using workstation and real-time DSP-based implementations of the proposed system. More precisely, various source separation methods are compared, and the new proposed approaches are shown to be the most attractive ones, thanks to their good performance and self-normalized (i.e. "automated") operation.

1. INTRODUCTION

Many real-world situations require to identify people, animals or objects. Typical examples are owner identification before starting car engines, access control for restricted areas, cattle identification or control of the flow of manufactured products in factories. 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, cattle or products in the above examples). These approaches are progressively being replaced by various types of electronic systems, and especially by systems based on radio-frequency (RF) communication.

Such an RF system [1] is shown in Fig. 1. It consists of a base station inductively coupled to portable identifiers (or "tags") which contain 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 a single 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 [2]. The overall identification system then checks these data and controls its actuators accordingly.

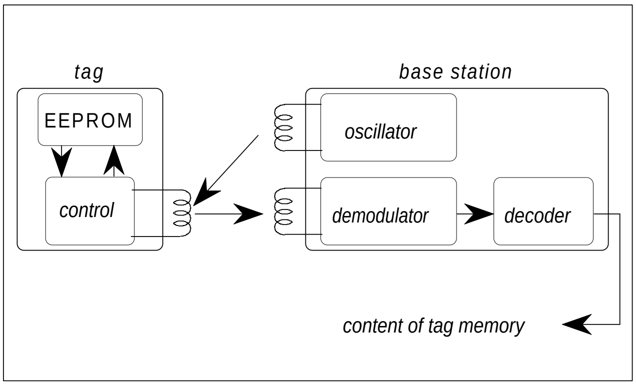

Figure 1: Single-tag RF identification system.

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), and because it operates with battery-less tags. However, when two tags are placed in the RF field of the base station, both tags answer this station. The demodulated signal determined 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 type of problem have been presented in the literature. Some consist in making the base station and tags communicate according to a predefined protocol, so that each tag successively provides its contents This approach is not attractive because it entails slow operation and yields a complex system, since significant circuitry must be added to the base station and tags in order to implement the communication protocol. Another approach consists in using tags which operate at different frequencies. This again yields complex circuitry and requires a large frequency band to be allocated to the system, which is not always possible. The approach presented in this paper aims at avoiding all these drawbacks. This is achieved by resorting to blind source separation techniques.

The remainder of this paper is organized as follows. The overall structure of the proposed system is presented in Section 2. Alternative approaches for its source separation unit are depicted in Section 3. The experimental performance of the resulting versions of this system is reported in Section 4. Conclusions and prospects are presented in Section 5.

2. OVERALL PROPOSED SYSTEM

The system that we propose for simultaneously handling two tag signals is an extension of the standard system described above. It relies on a base station containing two reception antennas and two demodulators, which yield two mixed signals. These mixed signals are processed by a source separation unit, which extracts the two components corresponding to the two tags. Then, by decoding these separated signals, the memory contents of the two tags are obtained independently[1].

More precisely, the modulation/demodulation scheme used in this system is such that the mixed signals provided by the demodulators are restricted to their simplest possible form, i.e. they are linear instantaneous mixtures (as defined in Subsection 3.1) of the components corresponding to the two tags (this is shown from a theoretical and experimental point of view in [2]). Various source separation approaches suited to such mixtures have been proposed since the eighties. A survey of this field may be found in [3]. In this paper, we consider some of these approaches which are based on similar principles, and we investigate their performance when applied to the proposed system. We also introduce modified versions of this type of approaches and we benchmark them against the considered classical solutions. All these approaches are described in Section 3. They were selected in this investigation for the following reasons. First, their convergence properties are well defined and they are such that these approaches do apply to the type of sources considered in this application, as will be shown in the subsequent sections of this paper. In addition, these approaches are based on adaptive algorithms, which makes them able to track easily evolving mixtures which occur in our application when tag-bearers are moving. Finally, they use very simple computations, which makes them attractive for the final real-time implementation targetted in this investigation.

It should be noted that the system thus obtained meets the requirements defined in Section 1: 1) it yields fast operation by allowing two tags to communicate simultaneously with the base station; 2) all the tags 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; 3) the system uses a single carrier frequency.

3. SOURCE SEPARATION PROBLEM AND SOLUTIONS

3.1. Problem statement

In the "simplest configuration" of the blind source separation problem, two signals $E_1(t)$ and $E_2(t)$ are available, and these signals are unknown linear instantaneous mixtures of two unknown supposedly independent source signals $X_1(t)$ and $X_2(t)$, i.e:

$$E_1(t) = a_{11}X_1(t) + a_{12}X_2(t) \quad (1)$$

$$E_2(t) = a_{21}X_1(t) + a_{22}X_2(t), \quad (2)$$

where the terms a_{ij} are unknown mixture coefficients. The goal is then to estimate the source signals $X_j(t)$ from the mixed signals $E_i(t)$. As stated above, this generic problem is faced in the system considered in this paper, where the mixed signals are the demodulator outputs, whereas the sources to be restored are the encoded tag memory contents. The remainder of this section describes all the solutions to this generic problem which are considered in this paper.

3.2. Classical neural networks

Three related approaches available from the literature are considered in this paper. The first one is the recurrent neural network proposed by Hérault and Jutten [4], whose weights c_{12} and c_{21} are updated according to[2].

$$\frac{dc_{ij}(t)}{dt} = -af[s_i(t)]g[s_j(t)], \quad (3)$$

where a is a positive adaptation gain, $s_i(t)$ and $s_j(t)$ are the (estimated) zero-mean signals corresponding to the network outputs $S_i(t)$ and $S_j(t)$, and f and g are odd functions. When arbitrary odd nonlinear functions f and g are used, the network is only able to separate (some types of) symmetric sources [2]. As shown e.g. in [2], this restriction may be avoided by using either $f = (.)$ or $g = (.)$ (and not both because this would result in using only the second-order statistics of the signals and it would not guarantee that this algorithm reaches separation [4]). Especially, two sets of functions are attractive, due to their simplicity and to the type of sources to which they apply, i.e:

$$f = (.)^3 \quad \text{and } g = (.), \quad (4)$$

and

$$f = (.) \quad \text{and } g = (.)^3. \quad (5)$$

The choice between these two sets of functions is to be made depending on the considered type of sources (to ensure that the network weights converge to values which yield separated signals at the network outputs): (4) applies to globally sub-gaussian sources (see e.g.[5]), i.e. to sources such that $R < 9$, where R is the ratio defined as:

$$R = \frac{E\{x_1^4\}E\{x_2^4\}}{(E\{x_1^2\})^2(E\{x_2^2\})^2}, \quad (6)$$

and where $x_j(t)$ are the zero-mean versions of the sources $X_j(t)$ and $E\{\}$ stands for mathematical expectation. It may be shown[3] that (5) applies to globally super-gaussian sources, i.e. to sources such that $R > 9$.

[1] A more detailed description of this extended system may be found in [2].

[2] As compared to the original papers by Hérault and Jutten, the signs of the weights c_{12} and c_{21} have been changed here, in order to be homogeneous with the subsequent approaches considered in the current paper. The network structure is modified accordingly.

[3] This may be shown e.g. by adapting the approach of [5] to the functions defined in (5).

In the system considered in this paper, the sources are globally sub-gaussian, as shown (from a theoretical and experimental point of view) in [2]. All the source separation experiments reported in this paper were therefore performed with networks operating with the functions defined in (4).

Two extensions of the Hérault-Jutten network were also proposed in the literature for performing linear instantaneous source separation. The first one, introduced by Moreau and Macchi [6], is based on a direct (i.e. non-recurrent) version of the Hérault-Jutten network, adapted with the same rule (3) as the latter network. This direct network is attractive because it avoids the matrix inversion which must be performed with the recurrent version in order to derive the network outputs from its inputs and weights. Moreau and Macchi also studied the convergence properties of this network in the "simplest configuration". They especially showed that, for this network too, the functions defined in (4) allow to separate sub-gaussian signals.

Cichocki et al. [7] then defined neural networks which may be considered as extensions of the above-defined ones. The Cichocki networks contain additional self-adaptive weights c_{11} and c_{22}, which are updated so as to normalize the "scales" of the network outputs, according to the rule:

$$\frac{dc_{ii}(t)}{dt} = -a[f[s_i(t)]g[s_i(t)] - 1]. \qquad (7)$$

These networks were claimed to be thus able to process ill-conditioned mixtures and badly-scaled source signals to which the Hérault-Jutten network would not apply. Both the direct and recurrent versions of this type of neural networks were described, and it was also proposed to cascade them in a multilayer neural network in order to improve performance. In this paper, we only consider the direct version of these networks, as it yields the same advantage as the Moreau-Macchi network over the corresponding recurrent structure. Moreover, we focus ourselves on the single-layer version of this network. We showed [8] that, for this network too, the functions defined in (4) allow to separate sub-gaussian signals.

3.3. New self-normalized neural networks

In this paper, we also propose another type of self-normalized source separation neural networks. Before describing them, we would like to justify in more detail the need for introducing a normalization in the Hérault-Jutten and Moreau-Macchi networks.

The latter networks are adapted according to the rule (3). The value selected for the adaptation gain a of this rule has a major influence on the speed and accuracy of the convergence of these networks, as will now be shown. Let us first consider the case when the gain a is high. The increments of the network weights, which correspond to the right term of (3), are then large. This has two consequences. On the one hand, the weights may thus converge quickly towards the values for which these networks provide separated signals, which is a desirable feature. But on the other hand, the fluctuations of these weights around their equilibrium values once convergence has been reached remain large. The networks thus provide "noisy" partly mixed signals on their outputs instead of cleanly separated sources, which may be a problem: in the considered application, these signals may then entail decoding errors if they are too noisy. On the contrary, a low adaptation gain a yields well separated source signals, but the latter signals are obtained only after a long convergence time, which may not be acceptable in applications where (near-)real-time operation is required. This phenomenon corresponds to the classical convergence speed/accuracy trade-off encountered in adaptive systems.

To solve the above problem, one could think of selecting the value of the gain a when designing the considered system, so as to trade-off the convergence speed and accuracy of the network, depending on the requirements set on these two parameters in the considered application. However, in addition to the gain a, the achieved convergence trade-off also depends on two other types of parameters. The first one consists of the functions f and g of the rule (3). This rule shows that the achieved convergence trade-off depends on the overall nature of these functions. In particular, multiplying any of these functions by a given scaling factor is equivalent to multiplying the adaptation gain a by this factor, which modifies the convergence speed and accuracy as explained above. Due to this equivalence, one could think of selecting these functions and the gain a altogether during system design, to achieve the desired convergence trade-off. However, (3) shows that the convergence compromise also depends on the magnitudes of the output signals (through the resulting values of $f[s_i(t)]$ and $g[s_j(t)]$) and therefore on the magnitudes of the mixed signals. For instance, if the functions f and g are set to (4), applying a scaling factor λ to both mixed signals (and therefore to $s_i(t)$ and $s_j(t)$) is equivalent to applying a factor λ^4 to the adaptation gain a. This means that these signal magnitudes have a huge influence on the convergence trade-off. Unlike the previous parameters, these magnitudes are not fixed when designing the considered system: in many applications, the tag locations are not predefined, so that the magnitudes of the mixed signals are unkwown, as they depend on the tag-antenna distances. Consequently, the convergence speed and accuracy of the network are not controlled, which is a major drawback of the Hérault-Jutten and Moreau-Macchi networks. A practical system should therefore include some additional means for ensuring that its operation does not depend on the magnitudes of the mixed signals. In the solution to this problem proposed below, this feature is inherently provided by the considered source separation neural networks.

More precisely, the type of networks that we propose is based on the same structures as above: they may contain one or several layers, and each layer may have a recurrent or a direct forms. The proposed networks differ from the previous ones in the algorithm used to update their weights, which here reads:

$$\frac{dc_{ij}(t)}{dt} = -a\frac{f[s_i(t)]}{\sqrt{E[f^2(s_i)]}}\;\frac{g[s_j(t)]}{\sqrt{E[g^2(s_j)]}} \qquad (8)$$

where the normalizing terms $\sqrt{E[f^2(s_i)]}$ and $\sqrt{E[g^2(s_j)]}$ are estimated in practical situations, using first-order low-pass filtering. The variance of the correcting term $\frac{f[s_i(t)]}{\sqrt{E[f^2(s_i)]}}\;\frac{g[s_j(t)]}{\sqrt{E[g^2(s_j)]}}$ of this rule is equal to one when source separation is achieved, thanks to the normalizing terms. This value is independent from the scales (and statistics) of the source and mixed signals, which is the main motivation for introducing this rule here, as explained above. Moreover, this variance is also independent from the separating functions. The adaptation gain a may therefore be selected independently from all these parameters when designing the system, so as to achieve the desired convergence trade-off. Moreover, this rule is well-suited to non-stationary situations, which occur e.g. when tag-bearers are moving: in this case, using short-term estimates of $\sqrt{E[f^2(s_i)]}$ and $\sqrt{E[g^2(s_j)]}$ makes it possible to automatically track the evolution of the characteristics of the considered signals. These networks lead to the same type of considerations as above about the functions f and g to be selected, e.g. among (4) and (5), depending on the type of sources to be processed [9], [10].

4. EXPERIMENTAL RESULTS

The results presented below were obtained with the experimental setup defined in [2]. More precisely, we here restrict ourselves to the versions of this setup in which the source separation algorithms were implemented on a workstation. The results thus obtained were then confirmed by implementing some of these source separation algorithms on a real-time DSP-based setup [2].

4.1. Separation from artificial mixtures

The first set of source separation experiments was performed with artificial mixtures of real sources, successively applied to each one of the five types of neural networks defined in Section 3, i.e:

- the Hérault-Jutten network,
- the Moreau-Macchi network,
- the single-layer direct Cichocki network,
- the two single-layer versions of the networks that we proposed in this paper, resp. based on a recurrent and a direct structure, and resp. denoted NWUr and NWUd below (where "NWU" refers to the Normalized Weight Updating algorithm used in these networks).

The goal of these experiments was twofold. On the one hand, they aimed at checking that all these networks can actually separate the source signals which occur in the real considered system, assuming these signals are mixed in a linear instantaneous way. On the other hand, they allowed us to compare the performance of all these networks in various situations and to select the best networks.

More precisely, these experiments were performed in the following conditions. In order to create artificial linear instantaneous mixtures of real source signals, a single tag was first placed in the RF field of the base station. The resulting output of one of the demodulators of the base station was sampled, thus providing a single source signal $X_1(t)$. This tag was then removed and a second tag was placed in the RF field of the base station. The same measurement procedure as above was carried out for this second tag, thus providing another source signal $X_2(t)$. Two artificial mixtures $E_1(t)$ and $E_2(t)$ of these two sources were then computed according to (1)-(2). These mixed signals were then provided to software implementations of the considered networks operating with floating-point numbers on a workstation. Two cases were successively considered for the values of the mixture coefficients a_{ij}. In both cases, a_{11} and a_{22} were set to 1. The complexity of the considered mixture was then defined by the values of a_{12} and a_{21}, which were selected as follows:

- The first experiments were performed with $a_{12} = 0.4$ and $a_{21} = 0.3$. These values correspond to a medium mixture ratio, and are similar to the actual values in the experimental setup [2].
- The other experiments were performed with $a_{12} = a_{21} = 0.98$. This corresponds to a very high mixture ratio, which may esp. occur in long-range systems when two tags are very close one to the other as compared to the tag-antenna distances. The sources are then expected to be quite hard to separate, since the two mixed signals $E_1(t)$ and $E_2(t)$ provided to the networks are very similar, as can be seen by applying these values of the mixture coefficients a_{ij} to (1)-(2).

The performance achieved in each experiment is defined by the two parameters considered in Section 3, i.e. the convergence speed and accuracy of the selected network. The convergence speed is measured by the number of samples required for all network weights to have converged to their equilibrium values, which is called the "convergence time" and denoted T_c below[4]. The convergence accuracy is measured by the Signal to Noise Ratio Improvement ($SNRI$) provided by the network. This parameter, which takes large values when the network restores well separated sources, is defined by: $SNRI = (SNRI_1 + SNRI_2)/2$ where $SNRI_i$ denotes the Signal to Noise Ratio Improvement at network output i, expressed in dB. For the Hérault-Jutten and NWUr networks, when source separation is achieved exactly, $S_i(t)$ becomes equal to $a_{ii}X_i(t)$ [4],[10]. For these two networks, $SNRI_i$ is therefore defined by:

$$SNRI_i = 10log_{10}\left[\frac{E\{(E_i(t) - a_{ii}X_i(t))^2\}}{E\{(S_i(t) - a_{ii}X_i(t))^2\}}\right]. \qquad (9)$$

Similar expressions are derived in the same way for the other considered networks.

As explained in Section 3, the overall performance of a given network is defined by the trade-off between T_c and $SNRI$ achieved by this network. This trade-off was determined by performing experiments for various values of the network adaptation gain a, recording the values of T_c and $SNRI$ obtained in these conditions and plotting the resulting variations of $SNRI$ vs T_c. The results thus obtained are shown in Fig. 2 and 3, resp. for the two considered sets of mixture coefficients. The main part of these figures is the one corresponding to the range of values of T_c required in practical applications, which may be defined as follows. The data received from a tag by the base station of a standard single-tag system consists of a series of identical frames, which contain about 2000 samples. Moreover, when the tag enters the field of the base station and progressively

[4] These convergence times were estimated from the plots representing the evolution of the network weights vs time.

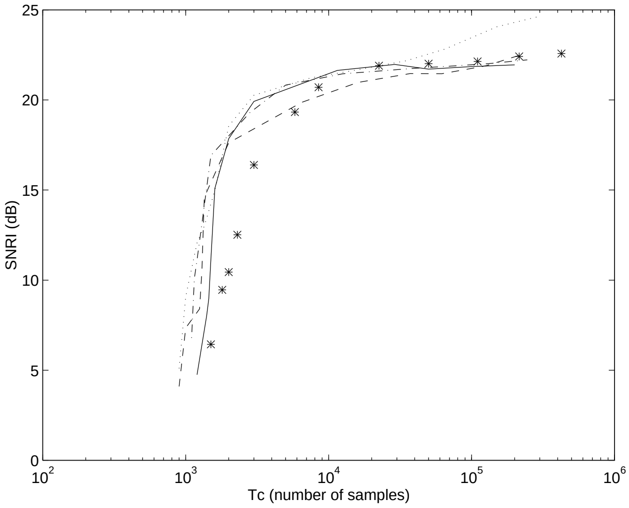

Figure 2: $SNRI$ vs convergence time T_c, when $a_{12} = 0.4$ and $a_{21} = 0.3$. Each plot corresponds to a neural network: Hérault-Jutten: -.-. Moreau-Macchi: .... Cichocki: * * NWUr: — NWUd: - -

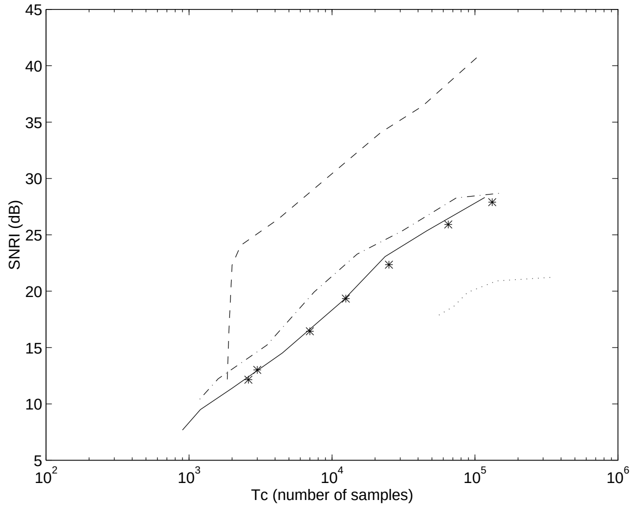

Figure 3: $SNRI$ vs convergence time T_c, when $a_{12} = 0.98$ and $a_{21} = 0.98$. Each plot corresponds to a neural network: Hérault-Jutten: -.-. Moreau-Macchi: .... Cichocki: * * NWUr: — NWUd: - - (for the Moreau-Macchi and Cichocki networks, lower values of T_c than those provided in this figure cannot be reached, as T_c and $SNRI$ then become very sensitive to an increase of the adaptation gain a, and these networks eventually diverge when a is further increased).

starts emitting, the base station has to wait until it receives a clean synchronization sequence (situated at the beginning of a frame) before it can start decoding the received signal. In other words, the base station has an intrinsic latency period of typically one frame. Therefore, in a multi-tag system, one would like the source separation network to converge during this latency period, so that it would then provide separated sources from the first completely clean received frame. Thus, adding such a network to the original single-tag identification system in order to achieve multi-tag capability would not slow this system down. A typical target value for T_c is therefore about one frame, or 2000 samples. Moreover, various applications can accept somewhat higher response times (i.e. typically a few frames), as the duration of a single frame is only about 70 ms, which is quite low as compared to the response times actually required from a user point of view in many identification applications. Therefore, a selection among the considered networks is made hereafter by taking into account their performance not only around $T_c = 2000$ samples, but also in a range typically covering $T_c = 2000$ to 10000 samples (i.e. up to 5 frames).

Fig. 2 and 3 first show that the Moreau-Macchi network should preferably not be used in the considered application, as it cannot achieve the desired T_c for high mixture ratios. The Cichocki network is not attractive either because: i) it cannot reach $T_c \simeq 2000$ samples (or its $SNRI$ is then rather low) and ii) for any T_c in the considered range, its $SNRI$ is lower than or equal to that of the remaining three networks, i.e. Hérault-Jutten, NWUr and NWUd. Among the latter three networks, the preferred ones depend as follows on the main parameter of interest in the considered application. All three networks can reach $T_c \simeq 2000$ samples (with an acceptable $SNRI$), but this is almost the limit achievable by the NWUd network. Therefore, if minimizing T_c is of utmost importance in the considered application, the HJ and NWUr networks should be preferred. On the contrary, if the emphasis is laid on the performance of the network for high mixture ratios, while the value of T_c (within the considered range) is not critical, NWUd should be preferred.

Up to this point, we only considered the performance (in terms of T_c and $SNRI$) of the considered networks. But, as explained in Section 3, another feature of these networks should also be taken into account, i.e. their ability to operate in a self-normalized (i.e. "automated") way. Then, in addition to the Moreau-Macchi and Cichocki networks which were not accepted above, the Hérault-Jutten network is also rejected here. In other words, the preferred networks in the considered application are NWUr and NWUd (and the eventual selection between these two networks depends whether the emphasis is laid on a low T_c or on high mixture ratios, as explained above). Therefore, only these two networks are considered hereafter. Moreover, their adaptation gain a is set to the value which yields $T_c \simeq 2000$ samples in the experiments with similar mixture coefficients reported above, i.e: $a = 10^{-3}$ for both networks.

4.2. Separation from real mixtures

The second set of source separation experiments was performed with the actual system. To this end, two tags were placed simultaneously in the RF field of the base station, and the resulting mixed output signals $E_1(t)$ and $E_2(t)$ of the two demodulators were measured. These two real mixed signals were then used as the inputs of the software NWUr or NWUd network. Figure 4 shows the evolution of the weights thus obtained for the NWUr network, when its

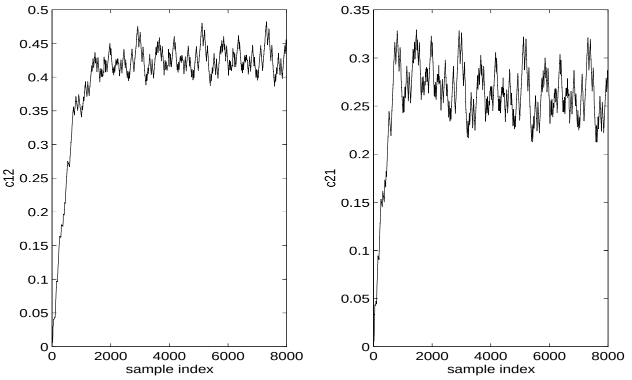

Figure 4: Evolution of the weights of the NWUr network for real mixtures.

learning gain is set to $a = 10^{-3}$. This gain value yields $T_c \simeq 2000$ samples, which is completely coherent with the results obtained with artificial mixtures in Subsection 4.1. The experiments performed with the NWUd network lead to the same results.

Figure 4 also shows that the network weights converge towards different values. This results from the fact that the values of the network weights for which source separation is achieved depend on the values of the mixture coefficients [10], which are here different due to the physical asymmetry of the setup. As these mixture coefficients are unknown here, the theoretical network weight values corresponding to source separation and the experimental $SNRI$ (9) cannot be computed. Another approach should therefore be used to check if the networks succeed in restoring the source signals. The alternative method used here consists in providing the network outputs to the decoders of the system. As explained above, these decoders wait for the first synchronization sequence in the network outputs, and then provide the restored tag data. Comparing these data with the original data stored in the tags (which are only known in these tests) here shows that they are exactly the same. In other words: 1) the NWUr and NWUd neural networks do not slow down the system, because they converge in a period of about one frame, during which the decoders have to wait for a synchronization sequence anyway, and 2) after convergence they provide a perfect restoration of the sources from an application point of view, in the sense that they restore the bitstreams of the tags without any errors.

5. CONCLUSIONS AND PROSPECTS

The investigations presented in this paper demonstrate that source separation techniques make it possible to achieve multi-tag capability with limited means in identification systems. More precisely, among all the source separation methods that we compared, the new approaches that we proposed in this paper were shown to be the most attractive ones, thanks to their good performance and self-normalized (i.e. "automated") operation.

Future activities will concern the separation of a larger number of tag signals, and the use of source separation for reducing background RF noise, thus allowing i) higher distances between the base station and tags, or ii) lower power consumption. Also, the available *a priori* knowledge about the sources was only partly used in the approaches considered up to now. This allowed us to develop a versatile approach, which may be extended to other (identification) systems. However, a fine-tuned approach dedicated to the specific system considered in this paper may also be developed, by using a source separation unit which would take more advantage of this knowledge about the sources to be processed.

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