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Application of blind source separation techniques to multi-tag contactless identification systems

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SUMMARY Electronic systems are progressively replacing mechanical devices or human operation for identifying people or objects in everyday-life applications. Especially, the 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 blind source separation techniques. The effectiveness of this approach is experimentally demonstrated, especially by using a real-time DSP-based implementation of the proposed system.
key words: blind source separation, Hérault-Jutten algorithm, higher-order statistics, identification systems, neural networks.

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]-[4] 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 content is specific to each tag and allows to identify the tag-bearer (person or object). The basic mode of operation of this system may be represented 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, modulated by its encoded memory content. The base station receives this signal, demodulates it, and decodes it so as to determine the memory content (details of the coding scheme are presented in Section 3). It then checks these data and controls the actuators of the system 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), 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 pre-defined protocol, so that each tag successively provides its content [5]. 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 [6]. 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, which form an emerging area of signal processing.

The remainder of this paper is organized as follows. The overall structure of the proposed system is presented in Section 2. Its source separation module is depicted in Section 3. The experimental performance of this system is reported in Section 4. Finally, conclusions and perspectives are presented in Section 5.

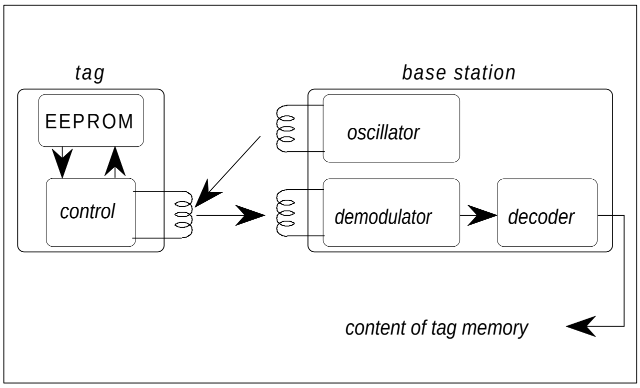

Fig. 1 Single-tag RF identification system.

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2. Proposed system

The system proposed in this paper (Fig. 2) 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 module, 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.

More precisely, the modulation/demodulation scheme used in this system is such that the mixed signals are restricted to their simplest possible form, i.e. they are linear instantaneous mixtures of the components corresponding to the two tags. It is now well known (see e.g. [7]) that the separation of unknown types of source signals based on linear instantaneous mixtures of these signals cannot be performed by using only the second-order statistics of the available signals. Therefore, one has to resort to the higher-order statistics of these signals, which results in using nonlinear algorithms for estimating the mixture parameters. Various source separation algorithms based on these principles have been reported in the literature. A survey of the earliest approaches may be found in [8]. Since then, many other approaches have been proposed, including e.g. [9]-[19]. Among all these approaches, the one which has been selected in this investigation is the Hérault-Jutten neural network, which is depicted in Section 3. This choice is motivated by several considerations. First, the convergence properties of this network are now well defined [20]-[23], and they are such that this network does apply to the type of sources considered in this application, as will be shown in the subsequent sections of this paper. In addition, this network is based on an adaptative algorithm, which makes it able to track easily evolving mixtures which occur in our application when tag-bearers are moving. Finally, this network uses very simple computations, which makes it attractive for the final real-time implementation targetted in this investigation.

It should be noted that this system 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. Principles and suitability of the Hérault-Jutten neural network

In the simplest source separation problem (which corresponds to the application considered in this paper), two sensors provide measured signals $E_1(t)$ and $E_2(t)$, which are unknown linear instantaneous mixtures of two unknown source signals $X_1(t)$ and $X_2(t)$, i.e:

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

and

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

where a_{11}, a_{12} ... are the unknown mixture coefficients. The problem is then to estimate the source signals $X_j(t)$ from the measured signals $E_i(t)$. Hérault and Jutten are considered as having proposed the first solution to this problem. This solution has been described in various papers (especially [7], [24]), and therefore we only include here the minimum information on this topic needed for understanding the current paper. The solution proposed by Hérault and Jutten requires statistically independent sources $X_j(t)$. It consists in using the recursive neural network shown in a block of Fig. 2, which provides the following output signals:

$$S_1(t) = \frac{E_1(t) - c_{12}E_2(t)}{1 - c_{12}c_{21}} \tag{3}$$

and

$$S_2(t) = \frac{E_2(t) - c_{21}E_1(t)}{1 - c_{12}c_{21}}, \tag{4}$$

where c_{12} and c_{21} are the adaptive weights of the neural network. These weights are updated according to the following nonlinear unsupervised learning rule, based on the higher-order statistics of the output signals:

$$dc_{ij}/dt = af[s_i(t)]g[s_j(t)], \tag{5}$$

where a is a positive adaptation gain, $s_i(t)$ and $s_j(t)$ are the (estimated) centered signals corresponding to the network outputs $S_i(t)$ and $S_j(t)$, and f and g are odd functions. Briefly, the motivation for this learning rule is to force the network outputs $S_1(t)$ and $S_2(t)$ to become (almost) statistically independent, thus making them become respectively proportional to the sources $X_1(t)$ and $X_2(t)$, or *vice-versa*.

When arbitrary odd nonlinear functions f and g are used, the network is only able to separate (some types of) symmetric sources [23]. This restriction may be avoided by using either $f = (.)$ or $g = (.)$ [23] (and not both because, as stated above, this would result in using only the second-order statistics of the signals and it would not guarantee separation if no assumption is made on the color of the sources [7]). Especially, two sets of functions are attractive, due to their simplicity and to the type of sources to which they apply, i.e:

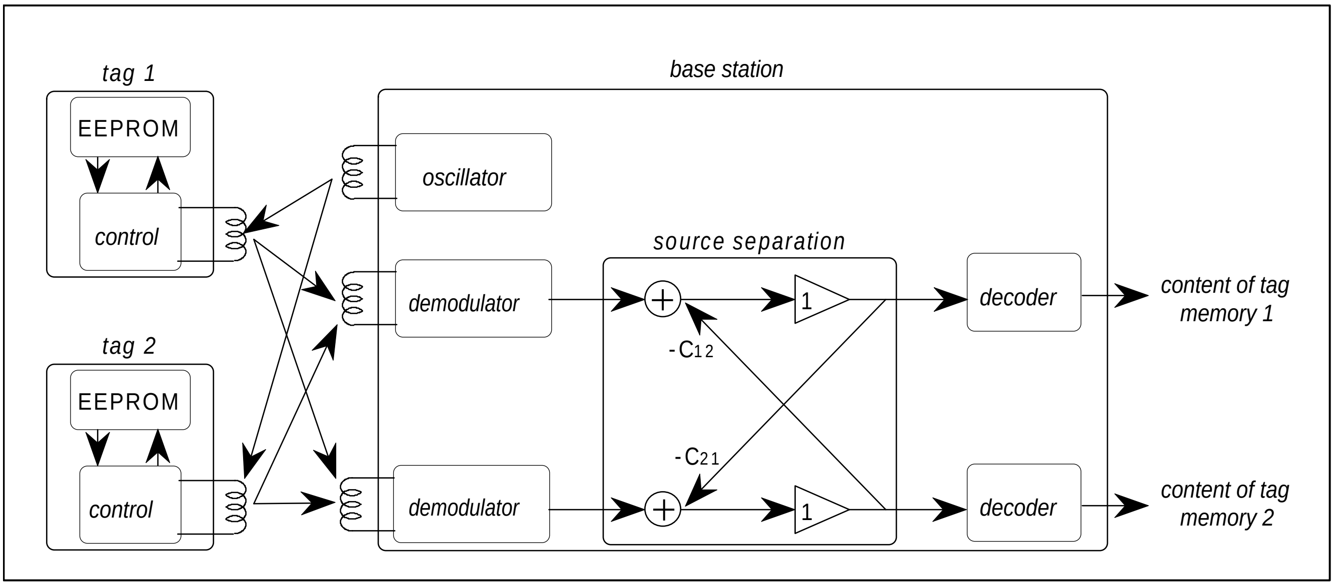

Fig. 2 Multi-tag RF identification system.

$$f = (.)^3 \quad \text{and } g = (.), \tag{6}$$

and

$$f = (.) \quad \text{and } g = (.)^3. \tag{7}$$

The choice between these two sets of functions is to be made according to the type of sources considered: (6) applies to globally sub-gaussian sources [21], i.e. to sources such that $R < 9$, where R is a ratio defined as:

$$R = \frac{E\{x_1^4\}E\{x_2^4\}}{(E\{x_1^2\})^2(E\{x_2^2\})^2}, \tag{8}$$

and where $x_j(t)$ are the centered versions of the sources $X_j(t)$. Similarly, (7) applies to globally super-gaussian sources, i.e. to sources such that $R > 9$.

These principles are applied as follows to the system considered in this paper. Each source to be processed by the neural network consists of a succession of frames. Each frame contains a synchronisation sequence followed by data, and these data are encoded by using a standard coded diphase procedure, which is defined hereafter.

As a first step, let us consider only the ideal operation of the system for encoded data (i.e. excluding synchronisation sequences). Ideally, each data bit equal to 0 is encoded as a voltage equal to a value $+V$ during half a cycle, followed by the opposite voltage $-V$ during the other half of the cycle. The bits equal to 1 are encoded by alternating values, i.e. a voltage equal to $+V$ during a complete cycle for one bit equal to 1, and a voltage equal to $-V$ during a complete cycle for the next bit equal to 1. This ideal signal may be represented as a random stationary source, taking the values -1 and 1 (in units defined by the voltage $+V$) with a probability 1/2, whatever the values of the bits that it encodes. As a result, the couple of sources to be separated may be shown to be such that $R = 1$. It is therefore strongly sub-gaussian, so that the version of the network that should be used to process such signals is the one corresponding to (6).

In the real identification system, the source signals are significantly distorted and are therefore not binary valued. In addition, they contain synchronisation sequences which are not symmetric. The corresponding ratio R may therefore be somewhat different from its theoretical value $R = 1$, but is expected to remain significantly lower than the threshold value $R = 9$. The version of the network corresponding to (6) is therefore expected to be able to separate the real signals. This is confirmed experimentally in the next section.

4. Experimental results

4.1 Experimental setup

The experimental setup used for checking the effectiveness of the proposed approach is represented in Figure 3, which provides a vertical section of this setup. The antennas and tags each consist of a horizontal disk (with a diameter of 52 mm for the antennas and 28 mm for the tags). The tags lie on a horizontal plastic plane, while the antennas correspond to horizontal planes resp. situated at distances h_1 and h_2 below the tag plane.

As explained above, the tags, antennas and demodulators used in these experiments are those available in the current standard commercial system. The emission/reception range of this system is limited, i.e. each tag should be at a distance lower than 60 mm from a base station to be detected. In our setup, this required us to put the tags close to the antennas i.e: $h_1 = 35$ mm

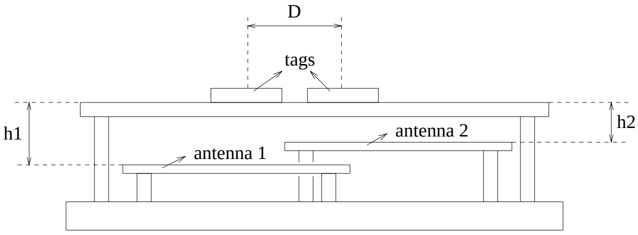

Fig. 3 Vertical section of the experimental setup.

and $h_2 = 25$ mm. This setup should therefore be considered as a preliminary down-scaled version of the target system, from which the real system will then be derived by using longer-range emission/reception units.

The distance D between the tags was varied in the experiments. When the tags are close one to the other (i.e. D close to the tag diameter), the standard system fails to identify the tags, so that the source separation module presented in this paper is required. This is the configuration considered in the remainder of this section.

4.2 Separation of artificial mixtures

The first set of experiments aimed at checking that the selected Hérault-Jutten network can separate the source signals which occur in the real system, assuming they are mixed in a linear instantaneous way. To this end, a single tag was first placed in the RF field of the base station. The output of one of the demodulators of the base station (Fig. 2) was sampled at 32 kHz, 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) and (2), and provided to a software implementation of the Hérault-Jutten network. The mixture coefficients a_{ij} were chosen so that the mixed signals provided to the network are roughly in the range [-1,1] (in order to ensure convergence) and so that the theoretical convergence values of both weights of this network are equal to 0.4 (which is a typical value occuring in the real system, as shown in Subsection 4.3). Figure 4 shows the evolution of these weights when the learning gain is set to $a = 0.005$, which was selected as a trade-off between the convergence speed and the magnitude of the fluctuations of these weights after convergence. The weights converge towards values which are close to their theoretical values, thus showing the ability of the network to operate with the considered sources. The weight errors after convergence are acceptable, since the resulting network outputs are decoded correctly, as explained below.

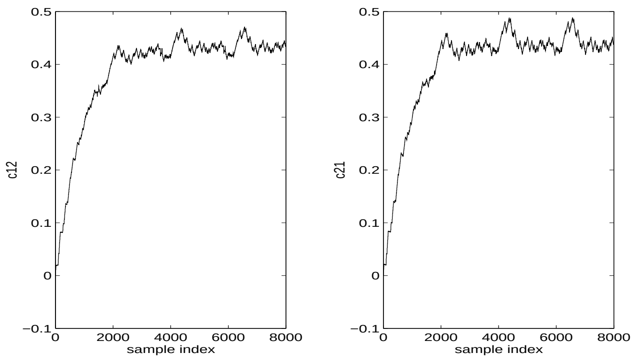

Fig. 4 Evolution of the weights of the network for artificial mixtures.

4.3 Separation of real mixtures

The second set of 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 Hérault-Jutten network. The evolution of the weights of the network, for the same learning gain as above, is shown in Figure 5. The convergence speed of these weights is coherent with the speed obtained in Subsection 4.2. Conversely, this figure does not allow one to know if the network converges to the right solution, since the theoretical weight values are not known here. These theoretical values depend on the unknown mixture coefficients which occur in the real setup. Due to the physical asymmetry of this setup (see Fig. 3), the mixture coefficients are different, so that the network weights converge towards different values (see Fig. 5).

The alternative method used here to check that the network weights converge to the right values consists in providing the network outputs to the decoders of the system. These decoders wait for the first synchronisation sequence in the network outputs, and then provide the restored tag data. Comparing these data with the original data stored in the tags shows that they are exactly the same. In other words: 1) the neural network does not slow down the system, because it converges in a period shorter than a frame (i.e. about 2000 samples), during which the decoders have to wait for a synchronisation sequence anyway, and 2) after convergence it provides a perfect reconstruction of the sources in the sense that it restores the bitstream without any error.

4.4 Real-time implementation

Based on the success of the experiments reported above, we have recently developed a real-time implementation of this approach based on a DSP board. First experi-

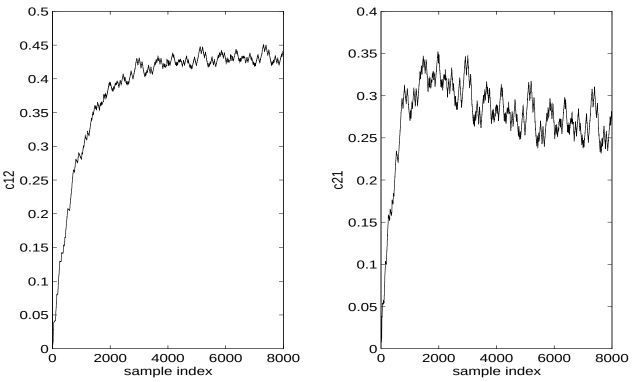

Fig. 5 Evolution of the weights of the network for real mixtures.

ments with this board show that the system, including the source separation neural network, operates correctly when using only fixed-point computations. These experiments also demonstrated the long-term stability of this network.

5. Conclusions and perspectives

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. 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 approach 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 module which would take advantage of this knowledge about the sources to be processed.

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