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Research Article

A Nonlinear Prediction Approach to the Blind Separation of Convolutive Mixtures

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We propose a method for source separation of convolutive mixture based on nonlinear prediction-error filters. This approach converts the original problem into an instantaneous mixture problem, which can be solved by any of the several existing methods in the literature. We employ fuzzy filters to implement the prediction-error filter, and the efficacy of the proposed method is illustrated by some examples.

1. INTRODUCTION

The problem of blind source separation has attracted a lot of attention in the last years due to its applicability to many fields, such as digital communications, pattern recognition, and biomedical engineering [1].

Since the pioneering work by Hérault et al. [2], a myriad of different techniques for source separation has been developed. In the great majority of the works, the mixing process is modeled as an instantaneous linear system. Despite its simplicity, an analysis of the vast literature on the subject clearly attests that this simple linear instantaneous model can be applied to a large number of scenarios with good results. Even highly complex systems, such as those found in biomedical signal processing, can be surmised to suit a framework of this sort (see, for instance, [1, 3, 4] and references therein for more details on applications and reviews about the existing separation criteria). However, some mixing systems are of a more complex nature, and, as a consequence, cannot be modeled simply as linear combination of the instantaneous source signals (which originates the notation *instantaneous mixture*). Indeed, there are practical instances in which the measured signals must necessarily be understood as being formed by a combination of different sources and *delayed* versions of them. A model of this kind bears a strong resemblance with the idea of convolution and, in the case of blind source separation, this is exactly the reason why it is usually designated by the name of *convolutive mixture*.

A typical situation in which convolutive mixtures are found arises, for instance, when a set of microphones is used to detect different sources in a reverberant environment; the most accurate description of the traditional *cocktail party problem* [3]. Another application emerges in digital communication systems wherein several users transmit wideband signals. When the coherence time of the channel is greater than the propagation time of the multiple signals, the phenomenon of intersymbol interference (ISI) will be a relevant factor and, consequently, the notion of convolutive mixture will be of paramount importance in the process of modeling the mutual influences of the different users (cochannel interference) and the ISI [5].

Convolutive mixtures are much more difficult to separate, since the usual assumption of independence between the sources must be augmented by hypotheses concerning the statistical independence (or dependence) between the delayed versions of a given source. The complexity of the overall separation problem can be "measured" by the number of proposed solutions thereto in the literature, which is considerably smaller than the number of techniques belonging to the context of instantaneous mixtures. Most of the approaches are related to the use of contrast functions based on the cumulants of the pertinent signals [6–9] or on some sort of modification in the information-maximization criteria to allow dealing with the delayed copies of the source signals [10]. A common factor shared by all these approaches is that they employ the same structure of the mixture to perform the separation of the signals.

In this paper, we propose a two-step technique for the case in which all sources are i.i.d., that is, based on a prediction paradigm, thus exploring the temporal structure of the observed samples. Our approach makes use of nonlinear prediction-error filters (NPEFs) to convert the convolutive problem into an instantaneous one. Therefore, the use of a nonlinear predictor can be understood as a preprocessing stage of a more general separation method. In contrast with related approaches found in [5, 11], we apply an independent nonlinear error-prediction filter to each observed sequence, hence being a useful preprocessing technique for underdetermined mixtures or even a single-channel case.

The paper is structured as follows. In Section 2, we discuss the fundamentals of the problem of source separation of convolutive mixtures. In Section 3, we review some concepts about nonlinear prediction and present our approach to solve the convolutive problem. In Section 4, the adopted nonlinear structure and training algorithm are presented. The simulation results are shown and discussed in Section 5, and, in Section 6, our conclusions and final remarks are stated.

2. PROBLEM STATEMENT

Let $s_1(n), s_2(n), \ldots, s_M(n)$ denote M mutually independent source signals and let $x_1(n), x_2(n), \ldots, x_N(n)$ be mixtures of the original sources, that is,

$$x_i(n) = \Phi[s_1(n), \ldots, s_M(n)], \quad i = 1, \ldots, N, \tag{1}$$

where Φ represents a function with or without memory. The main goal of blind source separation consists of recovering the original source signals based solely on the observed samples of the mixtures.

In its simplest form, the mixing process is modeled as a linear, memoryless system, and it is assumed to have the same number of sources and mixtures (in contrast with the underdetermined case, in which $N < M$), that is,

$$\mathbf{x}(n) = \mathbf{A} \cdot \mathbf{s}(n), \tag{2}$$

where

$$\begin{aligned} \mathbf{x}(n) &= \left[x_1(n), x_2(n), \ldots, x_M(n)\right]^T, \\ \mathbf{s}(n) &= \left[s_1(n), s_2(n), \ldots, s_M(n)\right]^T, \end{aligned} \tag{3}$$

and $\mathbf{A}$ corresponds to the mixture matrix whose dimension is $M \times M$.

Thus, in order to recover the sources, one can devise a separation system that consists of a matrix $\mathbf{W}$ such that the vector $\mathbf{z}(n) = \mathbf{W} \cdot \mathbf{x}(n)$ contains estimates of the original signals. Under the aforementioned independence hypothesis, it is possible to understand this problem as being equivalent to that of finding the matrix $\mathbf{W}$ which renders the components of $\mathbf{z}(n)$ as independent as possible. This approach, known as independent component analysis (ICA) [12], ideally permits the recovery of the latent sources up to scaling and permutation ambiguities [1].

Even though the model presented in (2) has been studied thoroughly in a number of practical contexts [1], it may not be suitable for some applications in which the mixing process is known to be of a "convolutive" nature (as in the case of a digital communication channel) rather than being a simple linear combination of the present samples of the sources. This limitation gave rise to the convolutive mixture model, which can be understood as an extension of the instantaneous model (2) to the case wherein each observed signal $\mathbf{x}(n)$ depends not only on the present value of $\mathbf{s}(n)$, but also on delayed samples of the sources

$$\mathbf{z}(n) = \sum_{k=0}^{L-1} \mathbf{A}_k \cdot \mathbf{s}(n-k), \tag{4}$$

where $\mathbf{A}_k$ denotes the mixing matrix associated with delay k. Thus, each observed signal $x_i(n)$ can be written as

$$x_i(n) = \sum_{k=0}^{L-1} \sum_{l=1}^{M} \mathbf{A}_k^{(i,l)} s_l(n-k), \tag{5}$$

with $\mathbf{A}_k^{(i,l)}$ denoting the element (i, l) (row, column) of the mixing matrix $\mathbf{A}_k$. Consequently, the observed signal $x_i(n)$ is composed of a linear combination of filtered versions of the sources.

The solution in this case consists of a set of matrices $\mathbf{W}_k$ that produces an estimate of the sources in accordance with the following equation:

$$\mathbf{z}(n) = \sum_{k=0}^{M-1} \mathbf{W}_k \cdot \mathbf{x}(n-k). \tag{6}$$

As in the case of an instantaneous mixture, independence of the components of $\mathbf{z}(n)$ is still a sufficient condition to ensure effective separation [12]. However, it is important to note that the problem is a little more involved than the instantaneous one. In addition to the scaling and permutation ambiguities, there may be a filtering ambiguity as well [1, 3, 4]. This is the reason why we will henceforth tacitly assume that the discrete-time source signals are composed of i.i.d. samples.

3. LINEAR AND NONLINEAR PREDICTION APPROACHES

The rationale of the prediction task is, in simple terms, to estimate future samples of a given time series from its present

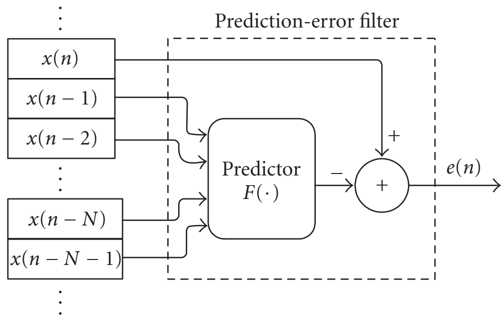

FIGURE 1: Prediction-error filter.

and past values. In signal processing, this task is usually understood as a filtering problem whose essence is the project of a device called *predictor*. In mathematical terms, a predictor is characterized by an input-output relationship of the form

$$y(n) = F[x(n-1), x(n-2), \dots, x(n-N)], \tag{7}$$

where $x(n)$ is the input signal, $N-1$ is the order of the predictor, and $y(n) = F(\cdot)$ is a mapping chosen in accordance with the idea of minimizing the expected value of the square of

$$e(n) = x(n) - y(n), \tag{8}$$

which is called *prediction error*. The adoption of this supervised Wiener-based approach [9] allows us to establish yet another relevant concept: that of a *prediction-error filter*, the output of which is the signal defined in (8). These ideas are depicted in Figure 1.

Although prediction itself is a very important research topic, here our interest lies specifically on its relation with another classical filtering problem: that of *blind equalization*. In order to clarify this connection, the relevance of which will soon become patent, let us briefly present the fundamentals of the equalization problem.

Suppose that a transmitted signal $s(n)$ is sent through a given communication channel and received as a distorted version $x(n)$. The receiver can use a filter, the *equalizer*, to produce an estimate as reliable as possible of the original message. The problem of designing an equalizer without resorting to supervised training (i.e., a blind equalizer) has been a major research topic for many years. See, for instance [13] and references therein. A fairly well-known fruit of these efforts is exactly the key to relate a prediction-error filter to an equalizer. Suppose that the transmitted signal, $s(n)$, is formed by i.i.d. samples, and that the channel is modeled as a linear filter whose impulse response is $h(n)$. In this case, it is possible to show that *a linear prediction-error filter can play the role of an equalizer if the channel is minimum phase* [9, 14, 15]. This restriction is, in a certain sense, an emblematic expression of the limited applicability of second-order statistics to unsupervised problems. Nonetheless, as shown in [16, 17], this limitation can be overcome if the predictor and, consequently, the prediction-error filter are *nonlinear structures*. In other words, it is possible to use nonlinear prediction-error filters as equalizers of nonminimum phase channels (notice that, in this case, there will be an implicit use of higher-order statistics), which reveals that the aforementioned restriction is related to the nature of the adopted filtering structure, and not to the solidity of the prediction criterion.

In order to analyze the viability of using nonlinear prediction-error filters as equalizers, let us consider the input-output relationship of a linear channel:

$$\begin{aligned} x(n) &= h_0 s(n) + h_1 s(n-1) + \cdots + h_{L-1} s(n-k) \\ &= \sum_{k=0}^{L-1} h_k s(n-k). \end{aligned} \tag{9}$$

If we return to (7), it will become clear that the output of a predictor with N inputs will be

$$\begin{aligned} y(n) &= F[x(n-1), x(n-2), \dots, x(n-N)] \\ &= P[s(n-1), s(n-2), \dots, s(n-N-L+1)]. \end{aligned} \tag{10}$$

Notice that the output is a function $P(\cdot)$ of $s(n-1)$, $s(n-2)$, and so forth, *but not of* $s(n)$. Notwithstanding, as attested by (8), this device will be designed in accordance with the idea of minimizing an error signal that is a function of $s(n)$. Given the i.i.d. character of this signal, we are led to the following conclusion.

If the predictor is a structure endowed with a sufficient degree of flexibility, the prediction error will tend to be equal to the signal $s(n)$ *[16], the "only information" to which the predictor "has no access."*

This section would be no more than a review of the present state of the literature if it were not for a noticeable degree of similarity between (5) and (9), which allows us to comprehend the model of a convolutive mixture as an extension of the classical scenario of SISO (single-input/single-output) equalization to the case of multiple sources and sensors [4]. This can be promptly verified if we consider the signal provided by the ith sensor according to (5) with $M = 1$.

If we assume, in agreement with the spirit of our previous discussion, that, apart from being mutually independent, the sources are composed of i.i.d. samples, it is straightforward to conceive a direct extension of the prediction-based equalization framework to the context of source separation. Let us suppose that there is a prediction-error filter with $N+1$ inputs connected to the output of each sensor. From (5), we obtain

$$\begin{aligned} y_i(n) &= F[x_i(n-1), x_i(n-2), \dots, x_i(n-N)] \\ &= P[\mathbf{s}(n-1), \mathbf{s}(n-2), \dots, \mathbf{s}(n-N-L+1)]. \end{aligned} \tag{11}$$

Since the prediction error would be, in this case,

$$\begin{aligned} e_i(n) &= x_i(n) - y_i(n) \\ &= \Phi[\mathbf{s}(n), \mathbf{s}(n-1), \dots, \mathbf{s}(n-N-L+2)] \\ &\quad - P[\mathbf{s}(n-1), \mathbf{s}(n-2), \dots, \mathbf{s}(n-N-L+1)], \end{aligned} \tag{12}$$

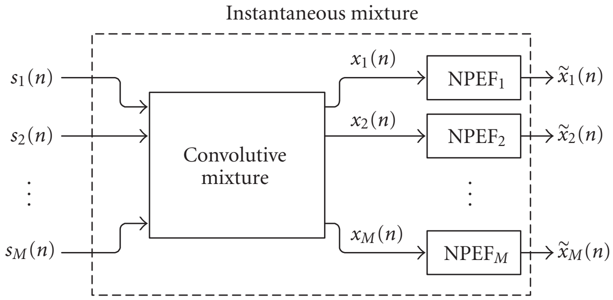

Figure 2: Converting a convolutive mixture problem to an instantaneous one.

it is licit to conclude that, if a sufficiently flexible structure to conclude the separation was employed, the error would tend to be equal to

$$e_{i,\text{opt}}(n) = \tilde{x}_i(n) = \sum_{l=1}^{M} \mathbf{A}_0^{(i,l)} s_l(n), \tag{13}$$

or, equivalently,

$$\mathbf{e}_{\text{opt}}(n) = \mathbf{A}_0 \cdot \mathbf{s}(n), \tag{14}$$

where $\mathbf{e}_{\text{opt}}(n) = [e_{1,\text{opt}}(n), e_{2,\text{opt}}(n), \ldots, e_{M,\text{opt}}(n)]^T$.

In (14), we find the essence of our proposal: *effective prediction-error filters can "transform" a convolutive mixture into an instantaneous one*. In other words, the project of a bank of nonlinear prediction-error filters (one per sensor, as indicated in Figure 2) in accordance with this spirit engenders a sort of "preprocessing" which, ideally, allows the influence of past samples of the sources to be eliminated from the problem. After this preprocessing step, conventional ICA methods would be able to conclude the separation.

It is possible to consider the convolutive problem as a kind of instantaneous problem with more sources than sensors (the idea, in this case, is to think of each independent signal or delayed version as a source) [4]. However, this conception does not take advantage of the relationship between a signal and its delayed versions, which, on the other hand, is exactly the basis of the prediction approach. This fact intuitively explains how a problem that appears to be "subparametrized" can, at least from a theoretical standpoint, be transformed into a conventional ICA problem.

4. FUZZY PREDICTION-ERROR FILTER

Having thus exposed the fundamentals of our proposal, it is time to consider in more detail some aspects of its implementation. A natural first step in this direction is to choose an adequate filtering structure to play the role of the nonlinear predictor. In this paper, our choice fell on a *fuzzy filter*, a fact that can be a priori justified on two capital bases.

(1) Fuzzy filters are flexible structures endowed with universal approximation capability [18].
(2) Fuzzy filters were employed with success in the related context of prediction-based nonlinear equalization [17].

In simple terms, a fuzzy filter is a nonlinear filtering structure capable of processing information in conformity with a basis of logical rules that employ nonbinary membership functions (fuzzy sets) [18]. If these membership functions are Gaussian, product inference and centroid defuzzification are utilized, it is possible to obtain an input-output mapping of the form

$$y(n) = \frac{\sum_{l=1}^{N_r} w_1 \prod_{j=1}^{m} \exp\left(-\left|x_j - c_{j,l}\right|^2 / 2\sigma_{j,l}^2\right)}{\sum_{l=1}^{N_r} \prod_{j=1}^{m} \exp\left(-\left|x_j - c_{j,l}\right|^2 / 2\sigma_{j,l}^2\right)}, \tag{15}$$

where N_r and m are the numbers of rules and inputs of the fuzzy system. In (15), it is noticeable that the free parameters of this structure are the centers of the Gaussian membership functions, $c_{j,l}$, their variances, $\sigma_{j,l}^2$, and the "output weights," w_l. The manifold nature of these parameters suggests a training process divided into two distinct stages, namely, choosing centers and variances and finding the adequate set of output weights. According to our previous discussion, our aim is to choose these parameters in order to minimize the mean-square value of the prediction-error signal defined in (8). Let us now discuss how we will attempt to fulfill this task.

4.1. *Learning algorithms*

The problem of choosing the centers of membership functions is typically associated with that of finding regions of the input space which are representative of the available data. In the context of digital communications, since the source samples belong to a finite alphabet and, moreover, the mixing process involves a limited number of delayed versions, the observed signal will also be restricted to a finite alphabet. Therefore, if we wish to process this signal using a filter, its input vector will necessarily be contained in a finite set of possibilities, the elements of which are called *channel states*.

In the presence of additive noise, this scenario becomes somewhat more complicated, since, as a rule, there will be a *continuum* of possible input vectors. Nevertheless, it is still possible to assume that there are "clouds of noisy samples" around the very same channel states. For instance, consider a situation in which two binary independent source signals are filtered by the FIR models $1 + 0.6z^{-1}$ and $0.5 + 1.2z^{-1}$ and combined to form a mixture $x_1(n)$. Suppose that we wish to use a filter with two inputs, $x_1(n-1)$ and $x_1(n-2)$, to process this signal. In this particular case, there will be 64 distinct two-dimensional channel states, all of which are represented in Figure 3. In this figure, it is also shown how the presence of additive white Gaussian noise (AWGN) of variance equal to $\sigma^2 = 0.01$ would originate "clouds" of data around these deterministic states.

Under these circumstances, it is quite appealing to deem representative a situation wherein each state is associated with a multidimensional Gaussian, with variances proportional to the dispersion of each "cloud" around the real states, given by the variance of the noise σ^2. This, apropos, is a most relevant step in the project of the celebrated Bayesian equalizer [19]. In the problem at hand, that is, that of nonlinear prediction in the eventual presence of AWGN, it is possible

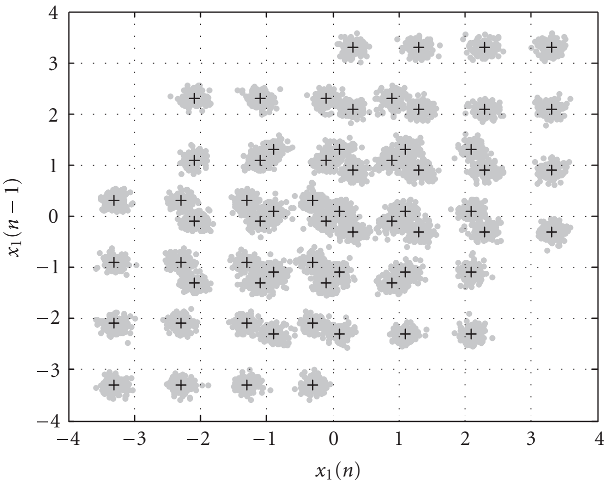

FIGURE 3: Channel states and noisy data.

to demonstrate that this option is not only intuitive, but also solid from a theoretical standpoint [17]. As a consequence, the first stage of the training process of the nonlinear predictor will consist of estimating the states generated by the convolutive mixture.

In signal processing applications, a task of this sort is usually accomplished with the aid of a clustering technique. Given a set of data vectors $\{\mathbf{x}(1), \mathbf{x}(2), \ldots, \mathbf{x}(n)\}$, the objective of a clustering algorithm is to find the set of centroids $R = \{\mathbf{r}_1, \mathbf{r}_2, \ldots, \mathbf{r}_k\}$ that minimizes the following cost function:

$$J = \sum_{j=1}^{K} \sum_{i \in C_j} ||\mathbf{x}_i - \mathbf{r}_j||^2, \tag{16}$$

where C_j corresponds to the jth cluster, and

$$\mathbf{r}_j = \frac{1}{N} \sum_{i \in C_j} x_i. \tag{17}$$

Ideally, the solution R obtained from the minimization of (16) should be identical to the set of channel states. However, traditional optimization methods, such as the k-means algorithm [19], may not converge to the optimal solution due to the multimodal character of the cost function (16), as pointed out by Merz [20].

Since the filtering problem is, from the "standpoint of the output weights" (15), linear in the parameters, it is of capital importance that the choice of the centers of the nonlinear membership functions be successful. In other words, an appropriate estimation of the channel states is of vital importance to the design of a fuzzy predictor. Consequently, the efficiency of the proposed training strategy will strongly depend on the ability of the adopted clustering algorithm to avoid convergence to local minima. Motivated by this crucial issue, we decided to resort to a robust clustering technique based on the concept of iterated local search (ILS) [20], which will be described in the sequel.

```
Begin
    Initialization: Create Starting solution R;
    R = Local search (R);
    Repeat
        R' = R+ Random Disturbance (Mutation);
        R' = Local search (R');
        If J(R') < J(R) then R = R';
    Until the stop criterion is met
    Return R;
End
```

ALGORITHM 1: ILS algorithm.

4.2. Iterated local search (ILS) approach for clustering

In order to avoid convergence to local minima, the ILS clustering technique attempts to find the optimal solution by combining concepts drawn from the field of evolutionary computation and efficient local search techniques like the k-means algorithm. A brief description thereof is shown in Algorithm 1.

In a certain sense, the ILS operates on two different levels: one that consists of an efficient local search, performed in our implementation by the k-means algorithm, and another that is founded on an evolutionary-based search, which is responsible for the global search capability inherent to the technique. The combination of these features produces an algorithm with a very good balance between *exploration* and *exploitation* of the search space.

The main drawback of the ILS algorithm is its higher computational complexity when compared to k-means in isolation [20]. As a result, in situations characterized by an elevated number of inputs and sources, as well as by stringent real time requirements, to use the ILS algorithm may be rather impractical.

4.3. Adjusting the weights of the fuzzy predictor

After this initial clustering stage, there remain two issues to be addressed: to choose the variances of the Gaussian functions and the output weights. The first one can be estimated using the results obtained with the ILS algorithm. Once we have the centers of the clusters, it is straightforward to evaluate the dispersion of the data around each cluster, and therefore obtain the variances $\sigma^2_{j,l}$. The second aspect, however, must be considered in more detail. After the determination of both the centers and variances of the Gaussian functions, the output of the predictor can be rewritten as follows:

$$y(n) = \sum_{l=1}^{N_r} w_l \cdot \psi_l, \tag{18}$$

where ψ_l is given, in accordance with (15), by

$$\psi_l = \frac{\prod_{j=1}^{m} \exp\left(-\left|x_j - c_{j,l}\right|^2 / 2\sigma^2\right)}{\sum_{l=1}^{N_r} \prod_{j=1}^{m} \exp\left(\left|x_j - c_{j,l}\right|^2 / 2\sigma^2\right)}. \tag{19}$$

In (18), we show that, at this point, the filtering problem becomes simply a matter of linearly combining a number of *fuzzy-basis functions* ψ in a manner consonant with the spirit of the prediction criterion. This problem, as stated earlier, is *linear in the parameters*, which allows us to resort to a vast amount of tools and results belonging to the classical adaptive filtering framework [18]. In our implementation, we use a recursive least squares algorithm (RLS) to adapt the weights of the nonlinear predictor.

5. RESULTS

In order to analyze the validity of the proposed technique, simulations were conducted in three distinct scenarios. In the first and second one, we considered the existence of two sources and a mixture system with memory equal to two ($L = 2$). In the third, a case with two sources and $L = 3$ was studied.

The output signals of the nonlinear prediction error filters are used as inputs for the fastICA algorithm [1], in order to complete the separation process. In all the situations, the efficacy of the obtained solutions was quantified via the following criterion:

$$\text{MSE}_i = \frac{1}{K}\sum_{n=1}^{K}\{[y_i - s_i]^2\}, \tag{20}$$

where y_i and s_i correspond, respectively, to the ith estimated and true source signal, and K is the number of samples. The rationale of this measure is simply to reveal the degree of effectiveness of the discussed preprocessing followed by a traditional ICA technique in accomplishing the task of recovering the source signals.

In accordance with our previous discussions, the source signals are considered to be independent and identically distributed (i.i.d.) sequences of symbols belonging to a binary $\{\pm 1\}$ alphabet.

5.1. First scenario: paraunitary mixture system with memory $L = 2$

In the first case, there are two sources to be separated from a mixture system with memory $L = 2$, with

$$\mathbf{A}_0 = \begin{bmatrix} 0.79 & -0.55 \\ 0.21 & -0.15 \end{bmatrix}, \qquad \mathbf{A}_1 = \begin{bmatrix} -0.15 & -0.21 \\ 0.55 & 0.79 \end{bmatrix}, \tag{21}$$

and noise variance $\sigma^2 = 10^{-4}$. This is an example of a paraunitary channel, and was generated as indicated in [7].

In this first scenario, we employed our proposal and also the technique introduced in [8]. The results obtained are exhibited in Table 1, wherein the first row indicates the MSE (20) associated with the pair of predictors in the ideal case, that is, when all channel states are perfectly known, the second row contains the MSE (average of 20 independent experiments) of the two nonlinear prediction-error filters designed in accordance with the method described in Sections 3 and 4, and the third indicates the MSE of the unprocessed signals. The last row indicates the results using the approach described in [8].

Table 1: First scenario.

	MSE_1	MSE_2
Ideal case	0.001	0.002
Adapted case	0.0567	0.0490
Unprocessed	0.4129	0.4141
Algorithm in [8]	0.0548	0.0379

Table 2: Second scenario.

	MSE_1	MSE_2
Ideal case	0.0001	0.0000995
Adapted case	0.00168	0.00136
Unprocessed	0.6242	0.6930

The results show that the nonlinear prediction approach is able to reduce the problem to an instantaneous one, to which the fastICA can be effectively applied. The results also show that the performance is at least equivalent to that presented in [8].

5.2. Second scenario: mixture system with memory $L = 2$

In the first case, there are two sources to be separated from a mixture system with memory $L = 2$, with

$$\mathbf{A}_0 = \begin{bmatrix} 1 & 0.5 \\ 0.8 & 0.6 \end{bmatrix}, \qquad \mathbf{A}_1 = \begin{bmatrix} 0.6 & 1.2 \\ 0.3 & 0.9 \end{bmatrix}, \tag{22}$$

and noise variance $\sigma^2 = 10^{-4}$.

Under these circumstances, from the point of view of each sensor in the separating system, the received signal can be understood as a superposition of SISO transmissions through minimum- and maximum-phase channels (see (5)). It is important to notice that these matrices do not represent a paraunitary mixing system, thus they have not been suitable for direct application of techniques such as that shown in [7, 8].

We evaluated this second scenario using the same structure described for the first scenario. The results are summarized in Table 2, and show that, despite the mixing system is not a paraunitary system, the nonlinear prediction in conjunction with the fastICA algorithm is able to recover the sources.

By analyzing the joint distributions of the relevant signals, one can notice the efficacy of the proposed technique in this situation. In Figure 4, the joint distribution of the sources is depicted, whereas, in Figure 5, the effect of the convolutive mixture on the ideal distribution is shown. It is noticeable that the existence of a superposition of delayed versions is responsible for the creation of an “interference pattern.” Finally, the joint distribution of the prediction-error filters’ outputs is shown in Figure 6. Notice that the joint distribution of the outputs of the bank of filters is clearly a

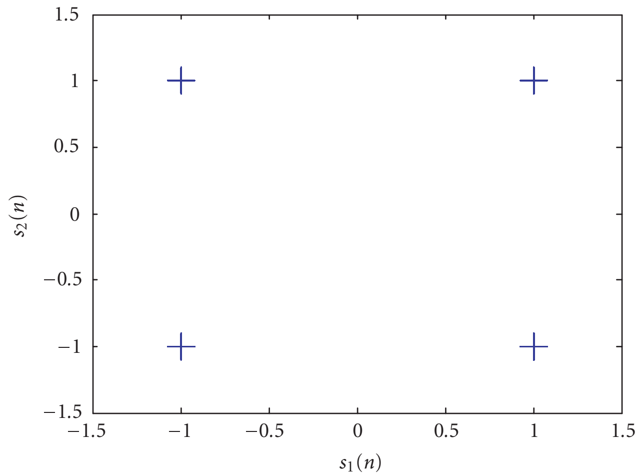

FIGURE 4: Joint distribution of the sources.

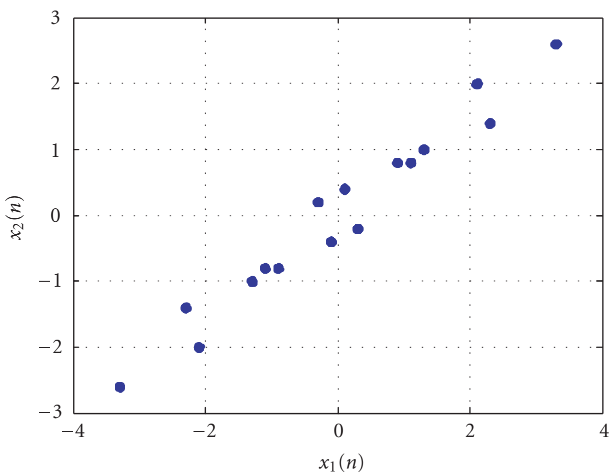

FIGURE 5: Joint distribution of the mixture signals.

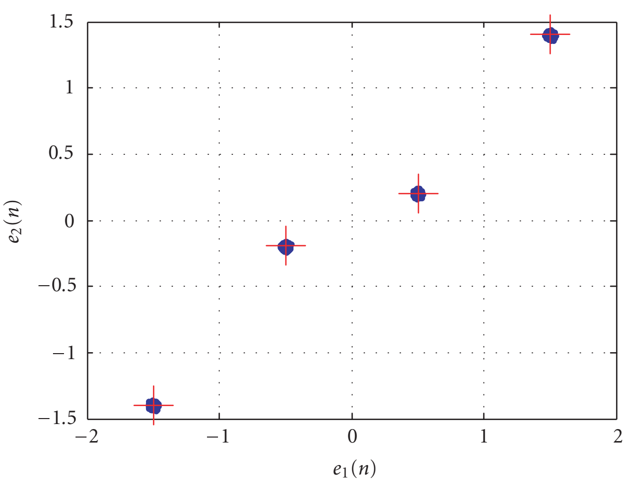

FIGURE 6: Joint distribution of the error-prediction filters outputs; (+) indicates the joint distribution of the corresponding instantaneous problem (14).

TABLE 3: Third scenario.

	MSE_1	MSE_2
Ideal case	0.0001	0.0001
Adapted case	0.00818	0.00669
Unprocessed	0.6621	0.4269

rotated and scaled version of the source signals, thus being suitable for classical ICA algorithm for instantaneous mixtures, for example, fastICA.

5.3. *Third scenario: mixture system with memory* $L = 3$

Consider now a mixture system with memory $L = 3$ described by the following matrices:

$$\mathbf{A}_0 = \begin{bmatrix} 1.12 & 0.53 \\ 0.625 & .04 \end{bmatrix}, \qquad \mathbf{A}_1 = \begin{bmatrix} -1.57 & 0.92 \\ 1.0625 & -2.32 \end{bmatrix}, \qquad \mathbf{A}_2 = \begin{bmatrix} 0.78 & 0.225 \\ -0.375 & 1.22 \end{bmatrix}, \tag{23}$$

and noise variance $\sigma^2 = 10^{-4}$.

All the SISO channels between each source and mixture are nonminimum phase, which is a clear indicative of the difficulty inherent to the problem we will face, since, even in the context of SISO systems, the equalization of such channels using prediction-error filters would require the use of nonlinear structures.

In Table 3, we present the MSE for the ideal and adapted cases. Once more, the MSE in the latter case was obtained from the average of 20 experiments. Furthermore, the order of the employed prediction-error filter was not altered.

The obtained results in the simulated situations allow us to draw two conclusions.

(1) The idea of using a prediction-based preprocessing proved itself to be valid, since, in the ideal case, it is possible to remove virtually all the “convolutive aspect” of the mixture.

(2) The training method proposed in the previous section was able to significantly reduce the MSE, thus being successful in both these tasks.

6. CONCLUSIONS

In this paper, we have proposed a preprocessing technique which, ideally, allows a convolutive mixture be transformed into an instantaneous one. The basis of our approach is to use a bank of nonlinear prediction-error filters to remove the influence of delayed version of the sources, which corresponds to an extension of recent results in the field of nonlinear blind equalization to the wider context of source separation.

In order to implement these ideas, we adopted a fuzzy predictor and a training method whose essence lies in the ILS clustering technique. This approach was tested in two distinct scenarios, and, in both cases, it was possible to attest the efficiency of the proposal *per se* (by analyzing the MSE associated with the ideal predictors) as well as that of the filters obtained via the training method. In other words, the results show that the idea of using a bank of prediction-error filters to remove the "convolutive nature" is viable and, moreover, can be implemented if appropriate structures and algorithms are chosen.

A natural extension of this paper is to consider the even more general case in which the sources are not necessarily digital signals. This idea is feasible, since, albeit this restriction was relevant for the chosen training process, it is, by no means, inherent to the theoretical proposal.

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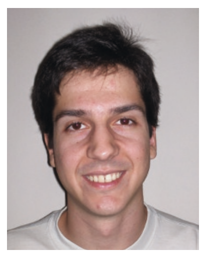

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