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BLIND DECONVOLUTION OF SIGNALS USING A COMPLEX RECURRENT NETWORK

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Abstract– An algorithm for the separation of mixtures of signals was derived recently by Jutten and Herault under the assumption that the signals are independent. This algorithm is based on higher order moments and has also been applied to deconvolving signal mixtures. In practical problems where the order of the convolving filter may be high, frequency domain approaches are known to provide a more computationally efficient method of deconvolution. In this paper, we introduce a complex recurrent network structure for performing blind deconvolution. The aim is to investigate the performance of this approach for separating unknown, convolved signals which may occur in a situation such as the well-known 'cocktail-party problem'.

INTRODUCTION

Adaptive filtering techniques have been widely applied to noise cancellation and blind deconvolution problems, where the aim is to obtain an enhanced signal based on some knowledge of the signal or noise [20, 23, 35]. More recently, the problem of separating mixtures of signals has been considered. In this case, the only assumption made is that the signals are independent. In addition, there are multi-sensors which record the signal. This situation is commonly encountered in practice, e.g. in the "cocktail-party" problem, where the aim is to listen to a desired signal (speech) and other signals are considered as noise. In such cases, traditional methods for adaptive noise cancellation (e.g. [35]) are insufficient to solve the problem.

A novel method to overcome the problem of blind separation of sources has been proposed recently by Jutten and Herault [21]. They proposed an algorithm which only assumes that the sources are statistically independent. The blind separation of sources problem consists of a mixture model, with a number of unknown input signals, and a desired method of estimating those signals. The mixture model is described by

$$x_j(t) = \sum_{i=0}^{M} a_{ji} u_i(t) \tag{1}$$

where $u_i(t)$ is the ith signal source, a_{ji} is the (amplitude) weighting applied to the signal from the ith source and received by the jth sensor, and $x_j(t)$ is the sum of received signals at the jth sensor. Based on this model, Jutten and Herault proposed a method to estimate values for $u_i(t)$. **??**. The model developed by Jutten and Herault may be described as follows

$$Y(t) = X(t) - WY(t) \tag{2}$$
$$Y(t) = [y_0(t), y_1(t), ..., y_M(t)]^T \tag{3}$$
$$X(t) = [x_0(t), x_1(t), ..., x_M(t)]^T \tag{4}$$

$$W = \begin{bmatrix} 0 & w_{01} & \cdots & w_{0M} \\ w_{10} & 0 & \cdots & w_{1M} \\ \vdots & \vdots & \vdots & \vdots \\ w_{M0} & w_{M1} & \cdots & 0 \end{bmatrix}$$

Where it is tacitly assumed that the number of sensors is equal to the number of sources, and the time constant of the network is small compared to that of the incoming signals, and that the network is stable. Thus, the network output can be described as

$$Y(t) = (I + W)^{-1} X(t) \tag{5}$$

where I is the identity matrix. We define the vector of zero mean output signals as

$$\underline{y}(t) = [\underline{y}_0(t), \underline{y}_1(t), ..., \underline{y}_M(t)]^T \tag{6}$$

The weights w_{ji} are updated by a stochastic gradient descent algorithm, a cost criterion (for each output) is defined as

$$J_i(t) = \underline{y}_i^2(t) \tag{7}$$

$$= y_i^2(t) - E[y_i^2(t)] \tag{8}$$

which is the power of the zero mean output signal. The algorithm obtained by this process is modified to update the weights using nonlinear functions which provide the test for higher order moments [21]. Thus, we have

$$\Delta w_{jk} = \eta f(\underline{y}_j(t)) g(\underline{y}_k(t)) \tag{9}$$

where η is a learning rate constant, and $f(x)$, $g(x)$ are odd nonlinear functions. For the simulations reported in Section 4 we used $f(x) = x^3$, and $g(x) = \arctan(x)$.

Note that in the Jutten and Herault formulation, the network architecture used is a recurrent network [21]. A related situation is that involving a convolutive model for dispersive media, this was considered by Nguyen, Jutten [26, 22], Platt and Faggin [16], Lacoume and Ruiz [24], Soon, Tong et. al. [30, 31] and Van Gerven and Van Compernolle [28] (Figure 1). In this case,

$$x_j(t) = \sum_{i=0}^{M} \sum_{k=0}^{P} a_{jik} u_i(t - d_k) \tag{10}$$

In a similar manner to that given by Jutten and Herault, Platt and Faggin gave a weight update equation for their model as

$$\Delta w_{ikj} = \eta f(\underline{y}_i(t)) g(\underline{y}_k(t - d_j)) \tag{11}$$

where the best reported results were obtained with $f(x) = |x|$, and $g(x) = x$. Previously, there has been significant work done on this topic, closed form solutions have been presented in [3, 6, 7, 33, 34], while other models have been considered in [30, 31].

The models developed by Jutten and Herault, Platt and others are based on real signals. In some situations however, it is desirable to be able to use complex signals. It is well known, for example, that frequency domain adaptive filters can have advantages over time-domain filters [17], (though for some adaptive noise-cancelling applications,

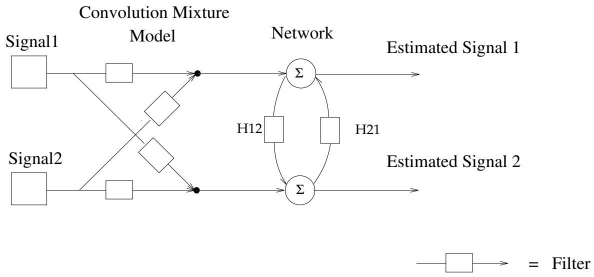


Figure 1: Convolutive mixture model and the network proposed by Platt and Faggin. In this case, each of the synapses is a filter. Note that we show only a two neuron network. In practice, the principles discussed here apply to any size network, (provided there are at least as many inputs as outputs).

these advantages are not apparent [9]). For conventional filter structures, frequency domain adaptive filters (using complex signals) have advantages in two main areas. The use of the Fast Fourier Transform (FFT) for complex weight update leads to a reduction[1] in computation with increased data [36]. Secondly, it is known that for the usual stochastic gradient algorithms, the convergence rate is proportional to the eigenvalue spread of the inputs [37]. This serves as a limiting factor in the time-domain filter. In a frequency-domain filter, the use of frequency bins provides an approximate orthogonalization of the data [17], and the learning rate in each frequency bin can be adjusted according to the power level present. This overcomes the problem of eigenvalue spread [19]. In effect, a normalized algorithm can be applied in each frequency bin [17], allowing the convergence rate to be improved for dependent inputs such as speech. For those applications where a frequency domain implementation does offer advantages, we present the algorithm contained herein.

For these reasons, we present a complex algorithm for blind source separation. The complex algorithm is derived in Section 2. Computational complexity details are given in Section 3, simulation results are given in Section 4 and conclusions are given in Section 5.

A COMPLEX ALGORITHM FOR BLIND SOURCE SEPARATION

The algorithm is developed by considering a complex model analogous to the real case. Figure 2 the case of two mixture inputs and two outputs. The same techniques are applicable to larger network structures. From (3), we define

$$\bar{Y}(t) \quad = \quad [Y(t), Y(t-1), ..., Y(t-N+1)] \tag{12}$$

Taking the Fourier transform, and noting that the sampling rate in the frequency domain is reduced by a factor of N, where N is the number of points in the FFT (assuming no zero padding to overcome the problem of circular convolution), we have

$$\begin{aligned} \bar{\mathbf{Y}}(n) &= \text{FFT}\left[\bar{Y}(t)\right] \qquad\qquad t = nN \qquad (13) \\ &= \begin{bmatrix} \mathbf{y}_{00}(n) & \mathbf{y}_{01}(n) & \cdots & \mathbf{y}_{0N-1}(n) \\ \mathbf{y}_{10}(n) & \mathbf{y}_{11}(n) & \cdots & \mathbf{y}_{1N-1}(n) \\ \vdots & \vdots & \vdots & \vdots \\ \mathbf{y}_{M0}(n) & \mathbf{y}_{M1}(n) & \cdots & \mathbf{y}_{MN-1}(n) \end{bmatrix} \end{aligned}$$

[1]The computational advantages are dependent on which scheme is used for processing, that is, whether the algorithm implements a circular convolution [11], or linear convolution [10], [12] .

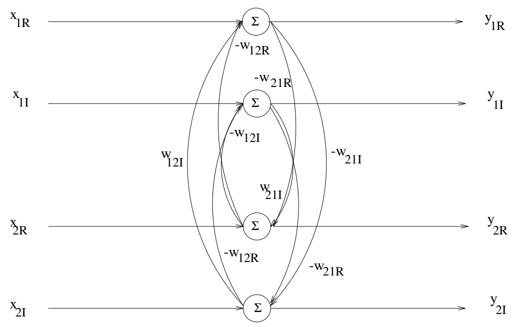


Figure 2: Complex blind source separation model, with two mixture inputs $\mathbf{x}_1$, $\mathbf{x}_2$, and two outputs $\mathbf{y}_1$, $\mathbf{y}_2$. The network is used in every frequency bin.

where n is the new sampling index in the frequency domain and the bold typeface represents variables in the frequency domain (following the convention used in [17]). Define the complex model as using uppervector of complex model outputs (for the jth frequency component) as

$$\begin{aligned}
\mathbf{Y}_j(n) &= \left[\mathbf{y}_{j0}(n), \mathbf{y}_{j1}(n), \cdots, \mathbf{y}_{jM}(n)\right]^T && (14)\\
\mathbf{X}_j(n) &= \left[\mathbf{x}_{j0}(n), \mathbf{x}_{j1}(n), \cdots, \mathbf{x}_{jM}(n)\right]^T && (15)\\
\mathbf{W}_j &= \begin{bmatrix} 0 & \mathbf{w}_{j01} & \cdots & \mathbf{w}_{j0M} \\ \mathbf{w}_{j10} & 0 & \cdots & \mathbf{w}_{j1M} \\ \vdots & \vdots & \vdots & \vdots \\ \mathbf{w}_{jM0} & \mathbf{w}_{jM1} & \cdots & 0 \end{bmatrix} \\
\mathbf{Y}_j(n) &= (I + \mathbf{W})^{-1}\mathbf{X}_j(n) && (16)
\end{aligned}$$

We now derive the weight update equations. For clarity, the j subscript indicating the frequency component index is dropped from the remainder of the paper. Following [36], we minimize both the real and imaginary components of the weights simultaneously. Therefore, the total power $\underline{\mathbf{y}}_i(n)\underline{\mathbf{y}}_i^*(n)$ is minimized, ($*$ represents the complex conjugate), and

$$J_i = \underline{\mathbf{y}}_i(n)\underline{\mathbf{y}}_i^*(n) = \underline{y}_{iR}^2(n) + \underline{y}_{iI}^2(n)$$

The weights are adjusted by minimizing the instantaneous total power,

$$\mathbf{w}_{jk}(n+1) = \mathbf{w}_{jk}(n) - \eta \frac{\partial J_i}{\partial \mathbf{w}_{jk}} \qquad (17)$$

where, $\mathbf{w}_{jk}(n) = w_{jkR}(n) + \jmath w_{jkI}(n)$. Following the procedure used by Jutten and Herault, and updating the complex weights, we have

$$\Delta w_{jkR}(n) = -\eta \frac{\partial J_i}{\partial w_{jkR}}$$

$$\Delta w_{jkI}(n) = -\eta \frac{\partial J_i}{\partial w_{jkI}} \tag{18}$$

$$\frac{\partial \underline{\mathbf{Y}}(n)}{\partial w_{jkR}} = -(I+\mathbf{W})^{-1} \frac{\partial (I+\mathbf{W})}{\partial w_{jkR}} \underline{\mathbf{Y}}(n) \tag{19}$$

Omitting details, the weight changes (with $i = j$) are

$$\begin{aligned} \mathbf{w}_{jk}(n+1) &= \mathbf{w}_{jk}(n) + \Delta \mathbf{w}_{jk}(n) \\ &= \mathbf{w}_{jk}(n) + -\eta \left(\frac{\partial J_j}{\partial w_{jkR}} + \jmath \frac{\partial J_j}{\partial w_{jkI}} \right) \\ &= \mathbf{w}_{jk}(n) + 2\eta \underline{\mathbf{y}}_k^*(n) \underline{\mathbf{y}}_j(n) \end{aligned} \tag{20}$$

Previously, a higher order independence test was used in the weight update equation, which, if applied in the frequency domain case, would result in an equation of the form

$$\mathbf{w}_{jk}(n+1) = \mathbf{w}_{jk}(n) + 2\eta \mathbf{f}(\underline{\mathbf{y}}_k^*(n)) \mathrm{g}(\underline{\mathbf{y}}_j(n)) \tag{21}$$

where $\mathbf{f}(\cdot)$ and $\mathrm{g}(\cdot)$ are complex functions which operate on real and imaginary components independently, i.e.,

$$\mathbf{f}(x + \jmath y) = f_R(x) + \jmath f_I(y) \tag{22}$$

A function of this type was proposed also by Benvenuto and Piazza [2]. Note that normally $f_R(\alpha) = f_I(\alpha)$. If the above method was used in this case however, the problem of obtaining the correct permutation matrix for the signals would be extremely difficult to solve. The permutations would occur in the frequency domain, and be complicated by an additional multiplication by a diagonal matrix of unit modulus complex values. The approach used in this paper, is to perform the test for independence in the time domain as before and transform the outputs to the frequency domain *before* multiplying them together. Since the signals are not multiplied in the time domain, but the multiplication of $f(y)*g(y)$ is performed in each frequency domain bin, and the problem of permutations between different frequency bands is overcome.

In this way we select a criterion which allows the algorithm to perform a task of essentially the same difficulty as before in the time domain case (down to a permutation matrix in the real valued output signals). The final weight update equations are

$$\mathbf{w}_{jk}(n+1) = \mathbf{w}_{jk}(n) + 2\eta \hat{\mathbf{F}}_k(n) \mathbf{G}_j(n) \tag{23}$$

where the Fourier transform of each block of output signals passed through the non-linear functions is computed, viz

$$\begin{aligned} \mathbf{F}_k(n) &= \mathrm{FFT}\left[f(\underline{y}_k(t))\right] & \mathbf{G}_j(n) &= \mathrm{FFT}\left[g(\underline{y}_j(t))\right] \\ \hat{\mathbf{F}}_k(n) &= \mathrm{FFT}\left[f(\underline{\bar{y}}_k(t))\right] & \hat{\mathbf{G}}_j(n) &= \mathrm{FFT}\left[g(\underline{\bar{y}}_j(t))\right] \end{aligned} \tag{24}$$

where

$$\underline{\bar{y}}_k(t) = \mathrm{FFT}^{-1}\left[\underline{\mathbf{y}}_k^*(n)\right] \tag{25}$$

Note that $\mathbf{F}_k$, $\mathbf{G}_j$, represent vector processes, with the length determined by the number of points in the FFT computation. A method of improving the performance of the standard algorithm, is to include power normalization in each frequency band [17].

Table 1: Computational Complexity Ratios for the Frequency Domain Blind Source Separation Model versus the Time Domain Model with M=2 and L=20.

N	8	16	32	64	128	256	512
Complexity Ratio	0.5	0.25	0.12	0.0614	0.0306	0.0153	0.0076

It is possible that minimization of the above criteria may lead to problems of unstable convergence as in the Jutten and Herault algorithm [13]. It is expected that the algorithm presented here and the Jutten and Herault algorithm will have similar properties. For example, convergence is only expected if the probability density functions of the zero mean sources are even, while swapping the $f(\cdot)$ and g$(\cdot)$ functions may cause a stable solution to become unstable [32]. Thus, the presentation of this algorithm does not address some of the more fundamental problems associated with the Jutten and Herault algorithm, but rather introduces a method for overcoming problems of convolved and correlated input signals.

COMPUTATIONAL COMPLEXITY

Consider the convolutive mixture model, where there are N real weights in each filter, M sensors, M model outputs, and the model is applied to N data points.

The computational complexity is determined as the sum of multiplications for both the model outputs and the weight updates. The fast acting recurrent loop [21] is assumed to have L cycles per presentation of input data.

The complexity depends on whether the algorithm uses circular convolution or linear convolution [11], [12], [17], we will only consider the circular convolution here. For the circular convolution case, there are $2M$ FFTs required for the computation of outputs, and $3M$ FFTs required to compute the higher order independence test variables ($\hat{\mathbf{F}}_k$, $\mathbf{G}_j$) (assuming $g(\alpha) \neq \alpha$), giving a total of $5M$ FFTs required for every N data points. To compute the outputs, there will be $4LN(M^2 - M)$ real multiplications required (over L cycles). For the weight updates with real inputs, there will be $6N(M^2 - M)$ real multiplications required, givi ng a total of $5MN \log_2(N) + (6 + 4L)N(M^2 - M)$ real multiplications for every N data points. The method of computing the linear convolution for either the overlap-add or overlap-save methods are described in [17], and are not considered further in this paper. Table 1 shows the comparison between the computational complexity of the time domain with the frequency domain methods. It is expressed as a complexity ratio of the computation required by the frequency domain method and that required by the time domain method.

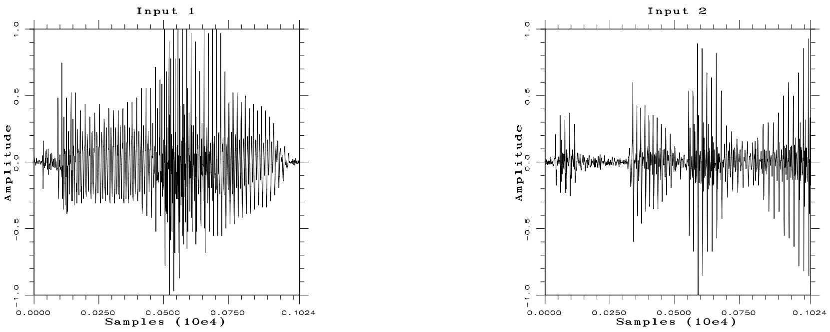
SIMULATION RESULTS

In this section, results are presented in using the above complex algorithm for simulations involving the separation of two speech signals. The voices were digitized at 8kHz and mixed according to the mixture model shown in Figure 1. The actual input voice signals are shown in Figure 3 and the mixture signals are shown in Figure 4

To maintain the symmetry of real outputs for real inputs, the imaginary weights were set to zero [18].

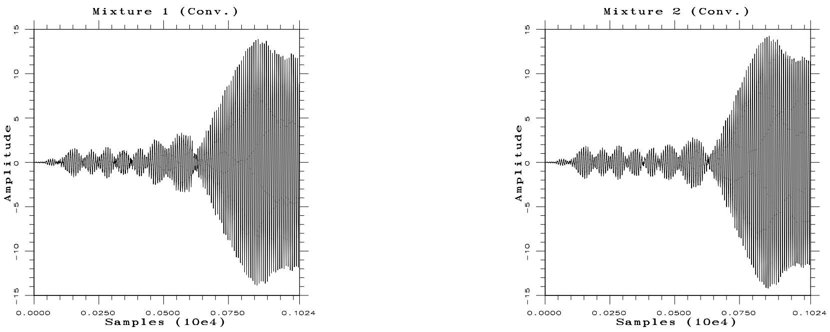
As a means of verifying performance of the complex model, various lengths of data were tried, with the model performing well in the ranges tested (16 - 128). In the results shown, $N = 64$ (Figure 5). 5).

While it is possible to implement a linear convolution model, for the example given here, only the circular convolution model was used. The observed results show that the complex model is indeed capable of performing separation of signals mixed in a convolution model. For signal $y_1(t)$, the signal-to-noise ratio (SNR) is 8dB, and for



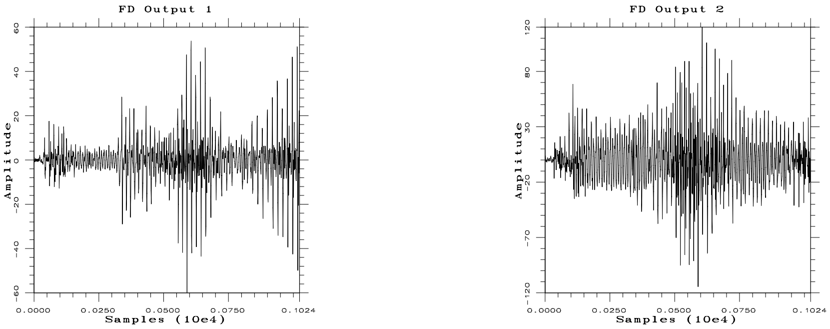
(a) (b)

Figure 3: Input sources of two independent speakers taken while each speaker counted "One .. two .. three ..", (a) u1(t), (b) u2(t). Sampling was done at 8Khz.



(a) (b)

Figure 4: Output from the mixture model, with each signal being a linear combination of both speech signals: (a) x1(t), (b) x2(t).



(a) (b)

Figure 5: Outputs from the frequency domain network which estimate the original input signals: (a) y1(t), (b) y2(t). This test was performed without power normalization and the performance is similar to the original time domain model. For the case shown here, the FFTs used $N = 64$. Learning commenced at the first sample, and occurred over the whole interval shown. Note that the order of the output signals is reversed from that of the input signals, due to the algorithm having no mechanism to sort the outputs in any particular way. Such an addition could be readily implemented.

$y_2(t)$, the SNR is 9.4dB[2]. It should be noted that, as is usual with gradient descent algorithms, better results would be possible by allowing the network to learn for a longer period of time. The results obtained here are less favourable than those reported by Platt and Faggin [16], who obtained around 20dB SNR for separating speech and music using the architecture shown in Fig. 2. In their case however, the mixtures were such that one signal was attenuated; specific details were not given. This contrasts with the results presented here, the estimated signals were of similar magnitudes to the original ones (observe Figures 4(a) and 4(b)). Thus, the simulations presented are not aimed at showing the best performance possible, but simply to verify the operation of the model. It would be interesting to compare the performance of this algorithm with one which uses only second order statistics, however this is not done here.

CONCLUSIONS

The algorithm developed by Jutten and Herault for blind source signal separation has shown promising results for real signals. In many practical situations however, it is desirable to apply an algorithm to complex data. In this paper, we have derived a complex algorithm for blind source signal separation which uses higher-order moments as in the original approach by Jutten and Herault [21], but allows the use of complex coefficients and data. The adoption of this method results in a more efficient implemention of a blind source separation model for convolutive mixtures. Simulations have verified the use of the algorithm for separating real speech signals.

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[2]These results were computed by normalizing the output signals $y_1(t)$, $y_2(t)$ to the same root-mean-square (RMS) value as the corresponding inputs. Thus, we use $y_1'(t) = y_1(t)\gamma_1$, and $y_2'(t) = y_2(t)\gamma_2$ where $\gamma_1 = \tilde{u}_1/\tilde{y}_2$, and $\gamma_2 = \tilde{u}_2/\tilde{y}_1$. The RMS value of x is represented by $\tilde{x}$. Note that in the case presented here, the outputs are reversed with respect to the inputs.

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