A post processing method to solve the problem of Disjoint Component Analysis in the case of Secondary Surveillance Radar replies separation

Sara ZAGHLOUL* Nicolas PETROCHILOS

CReSTIC, University of Reims, BP 1039, 51687 REIMS Cedex2, France

*sara.zaghloul@univ-reims.fr

Résumé – Nous proposons une méthode de post-traitement pour résoudre le problème de séparation par analyse en composantes disjointes (DCA) dans le cas de signaux SSR (Radar de Surveillance Secondaire) complexes. DCA est un critère de séparation aveugle de sources (BSS) réelles qui calcule la disjonction entre les sources, la minimisation de ce critère permet la récupération des signaux d'origine. L'adaptation pour des données complexes du critère a montré de bonnes performances en cas de mélange de signaux SSR, mais l'algorithme utilisé est coûteux en calcul. Nous avons donc proposé d'utiliser une des versions réelle de l'algorithme qui présente parfois un des problèmes suivants : la répétition d'une des sources estimées, l'ajout d'une relation linéaire entre les sources estimées et donc la perte d'une source en fin de séparation, voire deux sources non-séparées. Nous ajoutons donc une étape finale basée sur des considérations d'algèbres linéaire pour récupérer les signaux perdus. Cette méthode est comparée à d'autres algorithmes de la littérature.

Abstract – We propose a post-processing method to solve the disjoint component analysis (DCA) separation problem for complex SSR (Secondary Surveillance Radar) signals. DCA is a blind source separation criterion (BSS) that calculates the disjunction between sources, the minimization of this criterion allows the recovery of the original signals. Adapting the criterion for complex data has shown good performance in the case of mixing of the two modes of SSR signals, but the algorithm is computationally expensive. Therefore, we propose to use the original real-valued algorithm which sometimes has one of the following problems: the repetition of one of the estimated sources, or the addition of a linear relationship between the estimated sources and therefore the loss of a source at the end of the separation, or even two non-separated sources. We therefore add a final step based on linear algebra considerations to recover the lost signals. This method is compared to other algorithms in the literature.

1 Introduction

Blind Source Separation (BSS) consists of separating a set of mixed signals into their original source signals without knowing the sources nor the mixing processes. BSS is used in a variety of applications, such as speech recognition, image processing, and biomedical signal analysis. Separation can be based on different measures such as source independence as in ICA [1] and its enhanced version fast-ICA [2], or the temporal correlation as in [3], Constant-modulus property as in [4] and finally the Disjointness of signals [5].

Our research focuses on the source separation from the secondary surveillance radar, which operates in a question-response mode. The radar operates with two types of response, namely mode A/C that allows the exchange of the aircraft's identity and altitude, and mode S that enables the transmission of longer messages (i.e. more information). Nowadays, the two modes co-exist and have different characteristics, making the separation problem quite difficult.

P. Comon was the first to apply source separation to mode A/C using ICA [6], while AJ. van der Veen later proposed the AZCMA that use the Zero/Constant Modulus properties of the replies to separate two or more mode S replies [4]. An extension of the AZCMA algorithm, the MS-ZCMA, and an algorithm based on the Manchester encoding of the data, the MDA, were later proposed to solve a mixture of only mode S replies [7]. In [8], M. Zhou proposed an extension to overcome the MDA's weakness for large time delays between the leading and trailing reply, then a simplified version was proposed in [9]. Note that these algorithms can only separate a mixture of mode S. In [11], the problem of a mixture of various modes (A/C +S) was resolved via an oblique projection method based on non-fully overlapping replies using the Extended Projection Algorithm (EPA), and later in [10], an exhaustive method based on DCA and Givens rotations was proposed to solve the same problem, which is more robust than EPA but computationally expensive.

DCA is a criterion for measuring the overlap between signals, this criterion is designed for real-valued signals separation. The implementation uses either a gradient based optimizer [5] to converge to the separation parameters or suite of a Givens rotations [12] to find the optimal direction of separation. In this paper we propose a post processing method to solve the SSR signals separation problem when using the real version algorithm of DCA [5] on the complex-valued signals by converting the complex-valued signals into real-valued signals.

The following section presents the data model and the different DCA algorithms as well as our proposed method. We then compare the performance of the different algorithms via simulation.

2 Data Model

We consider the linear mixing model of p sources received on p antennas as follows:

$$X = MS + N \quad (1)$$

X, S and N made up of k samples and p sources (size of the matrices equal to $p \times k$), where X is the observed mixed signals, S is the original signals, N is the noise vector and M is an unknown mixing matrix of size $p \times p$. The reconstruction of the estimated source from the observation X is performed as follow:

$$Y = WX \simeq \widehat{S} \quad (2)$$

with W is the separation matrix of size $p \times p$ and $\hat{S}$ are the estimated sources.

In SSR Mode S, the message transmitted is either 56 (short) or 112(long) bits of information encoded by a Manchester code with a symbol period equal to 1 µs A bit equal to 0 is coded by a rising edge [0,1], and a bit equal to 1 by a falling edge [1,0]; preceded by an 8 µs preamble:

p_e = [1, 0, 1, 0, 0, 0, 0, 1, 0, 1, 0, 0, 0, 0, 0, 0] followed by the encoded data : b_S = [p_e, b_1, b_2,..., b_{56}/ b_{112}] of total length equal to 128 (short) or 240 (long) bits corresponding to 64 or 120 µs, depending on the number of bits transmitted. The preamble is used to synchronize the received signal in time (detection of the start of a packet). The signal is then modulated by pulse amplitude modulation (PAM) and has the following form:

$$b_S(t) = \sum_{n=0}^{127/239} b[n] p_S(t - nT) \quad (3)$$

where T=1 µs and $p_S(t)$ is a rectangular pulse.

Before emitting the signal, the ICAO (International Civil Aviation Organization) requires to up-convert the signal to the frequency f_0 = 1090 MHz, with a ±1 MHz tolerance. After down-conversion to base band, a residual frequency f_r remains, adding a progressive phase rotation to the transmitted symbols. The received base band signal become:

$$s(t) = g b_S(t) exp(j2\pi f_r t) \quad (4)$$

where g contains the received power and a phase which is the bulk delay at the reception of the first symbol.

3 Algorithms for the DCA criteria

In [5] a source separation method is proposed for real signals which is based on the maximization of the disjointness between each sources (the minimization of the overlap between the sources):

$$H(W) = \frac{1}{2} \sum_{i \neq j} O_{ij} = \frac{1}{2} \sum_{i \neq j} E(|Y_i||Y_j|) \quad (5)$$

with E(.) the mathematical expectation. If two estimated sources $\{Y_i, Y_j\}$ are disjoint, where Y_i is the i^{th} row of Y, then O_{ij} will be equal to 0. The criterion to be minimized will be the sum of all the O_{ij}. The minimization is performed based on gradient descent optimizer (DCA-RGD) with a renormalization to avoid converging to the zero solution.

Another algorithm for real-valued signals was proposed in [12], this algorithm is based on real Givens rotations (DCA-RGR). It minimizes the DCA criterion in one direction at each time by rotating the data pairwise, where it uses the Golden section method to estimate the rotation angle that minimize O_{ij}.

In [10] the criterion was extended to complex-valued data, this algorithm is based on complex Givens rotations (DCA-CGR) which parameters are estimated by an exhaustive search. Due to this, the algorithm is computationally expensive but it demonstrates the effectiveness of DCA complex criterion in separating SSR signals.

The DCA performs well for SSR sources because H(W), eq.5, is time-independent. Assume two overlapping SSR replies, as in fig.1: on the left side, the replies are represented as they are received, while on the right side we reshuffles the time axis so that when one source is null, it is pushed to either side. By doing so, the value of H(W) remains unchanged, but the right representation reveals partially disjoint sources.

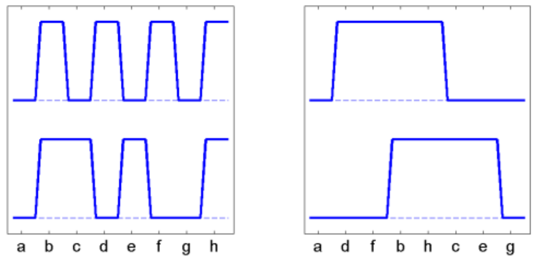

Figure 1 – Case of two fully overlapping signals before and after time reshuffling.

4 Proposed Method

We consider the case of two complex-valued mixed signals, i.e SSR. Since DCA-RGD only deals with real-valued signals, we convert each complex signal into two real signals by separating their real and imaginary components. This yields a total of four real signals, two for each complex signal, on which we apply DCA-RGD.

It delivers either the desired output or one of the problems: missing source or correlated sources, signal loss which can be seen as a repeated output or the rest of a mixed signal, and correlated signal that can be seen as a linear dependency.

We propose a post-processing method based on linear algebra, that use singular value decomposition (SVD) to ensure the linear independence of the separated signals (in case of correlated sources), and Gram-Schmidt orthogonalization (QR decomposition) to recover any lost signals, which flow chart is summarized in fig.3.

First, to detect any remaining mixed signal, as in fig.(2.c), we have a test that counts the number of zeros in each signal. Mixed signals are distinguished by their relatively higher number of non-zeros, typically higher than ≈ 500 compared to separated signals. If a mixed signal is detected, we remove it from Y and we form Y_S of size (3×k) containing only the desired output. We recover the missing output by performing a QR on the compound matrix $[Y_S^T X^T]$ (see eq. 6), where we partition Q into its 3 first columns to obtain Q_1 of size (3×k) and Q_2 of its 4 last columns of size (4×k), then R_1, R_2 and R_3 are automatically deduced, and are respectively of size (3×3), (3×4), and (4×4).

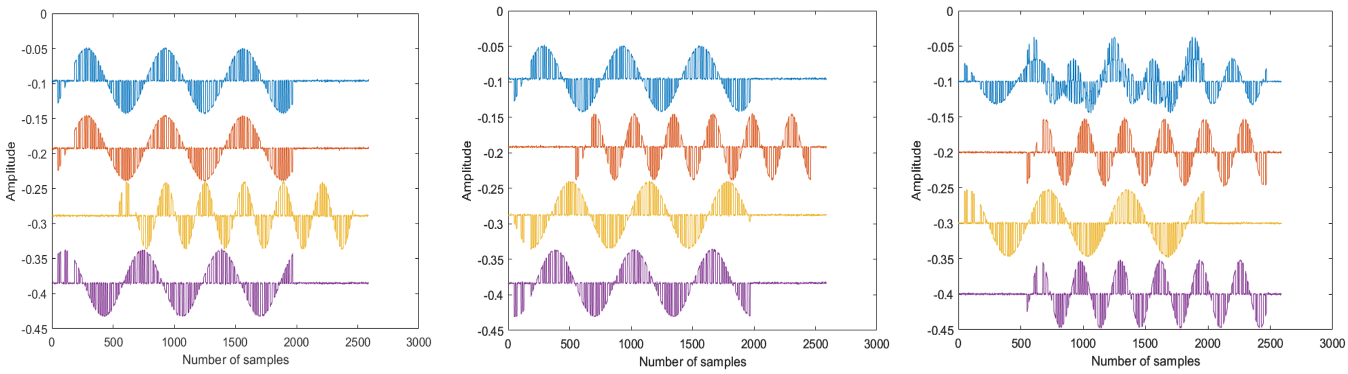

Figure 2 – The output of DCA-RGD which consists of 4 real-valued time series signals that can exhibit typical problems: (a-left) repeated signal, (b-middle) linear relationship, (c-right) mixed signal.

Then, we subtract from a basis space of X, a basis of the space spanned by the separated signal, Y_S, to obtain the lost signal. The resulting matrix X_4 (of rank one), which main vector is orthogonal to the previously obtained sources (eq.7), this vector is combined with Y_S to obtain the correct four separated signals.

$$[Y_S^T X^T] = QR = \begin{bmatrix} Q_1 & Q_2 \end{bmatrix} \begin{bmatrix} R_1 & R_2 \\ 0 & R_4 \end{bmatrix} \tag{6}$$

$$Y_S = Q_1 R_1$$

$$X = Q_2 R_4 + Q_1 R_2$$

$$X = Q_2 R_4 + Y_S R_1^{-1} R_2$$

$$X_4 = X - Y_S R_1^{-1} R_2 = Q_2 R_4 \tag{7}$$

The second test calculates the cross-correlation between output signals. Depending on its value, we either detect a repeated signal (see fig.(2.a)), or a linear relationship between the signals (signal 1, 3 and 4, fig.(2.b)). In the later case, we simply remove the repeat to form Y_S ($3 \times k$). In the former case, We use a SVD on the three linearly dependant sources to extract a basis of the space range, which is used with the last output signal to form again Y_S. The last output source is recovered by the means of a QR with eq. (6-7) in a similar fashion as in the test 1.

5 Simulation

We simulate two long mode S responses where its real and imaginary parts can be represented by a chopped cos(.) and sin(.) functions, with residual frequencies of ±50 kHz, received on a 2-elements antenna array with a direction of arrival (DOA) of {60,120}. We set a threshold of 6 dB for the output Signal-to-Interference-and-Noise-Ratio (SINR), considering the algorithms fail if the SINR falls below this threshold.

Comparing both real implementations, DCA-RGD and DCA-RGR, on SSR signals with a SNR equal to 20 dB for 1000 runs, the failure rates of these two algorithms (see tab.1), are categorized. Most of DCA-RGR failure are signals not separated (computationally expensive to fix), whereas in DCA-RGD the failure is mostly a repetition or a linear relation between the estimated source (easy and cheap to fix), therefore we use our post-processing method on the DCA-RGD result. The high failure rate of the real-data DCA is due to the fact that the algorithms are feed the cosine and sine versions of the same chopped complex source, therefeore the criteria H(W) cannot resolve them properly since they have the exact same time support (and no disjointness).

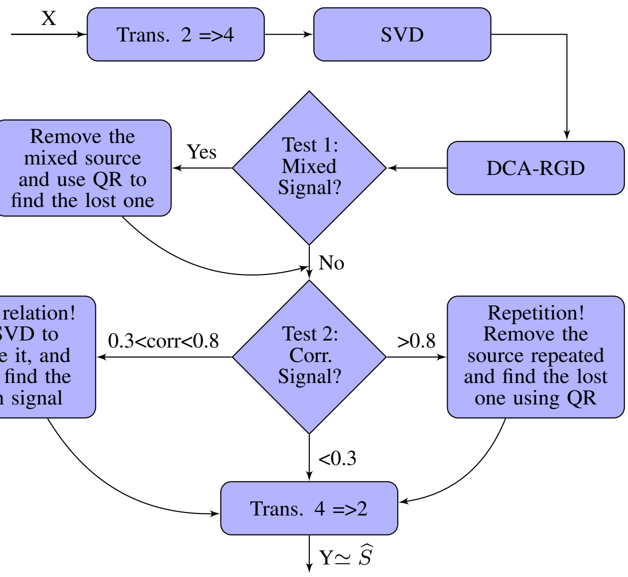

Figure 3 – Our method flow chart

	DCA-RGD	DCA-RGR
Mixed signals	3%	21%
Signal loss	8%	0%
addition of a linear-relation	29%	0%

Table 1 – The failure rate of DCA-RGD and DCA-RGR categorized into three cases: mixed signals, signal loss, and addition of linear relation

Fig. 4 shows the failure rates of Fast ICA, Fold MDA, DCA-CGR, DCA-RGD and our proposed method DCA-RGD+PP in function of the input SNR. We calculate the Zero-Forcing method which can serve as a reference method, by knowing the exact separation matrix. All methods fail for input SNRs lower than 5 dB. However, the success rate gradually increases as the SNR becomes higher, eventually resulting in a complete success for high SNRs. DCA-RGD fails constantly at a rate of 30% for all SNR which confirms the improvement between DCA-RGD and DCA-RGD+PP.

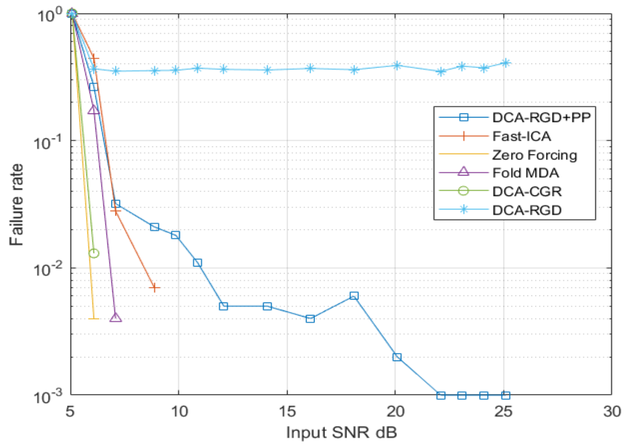

Figure 4 – Failure rate as function of input SNR.

Fig. 5 presents the subtraction of the output SINR from the input SNR for all methods. Except of Fast-ICA, all algorithms performs well for separating mode S responses. Moreover, as shown in [13], the mode S of SSR is pseudo-gaussian, which leads to additional failures for ICA-based algorithms depending on the experimental conditions. Since Fold-MDA cannot handle mode A/C, we conclude that DCA-CGR and DCA-RGD+PP are the most effective algorithms with a difference of less than 1.1 dB from the reference method.

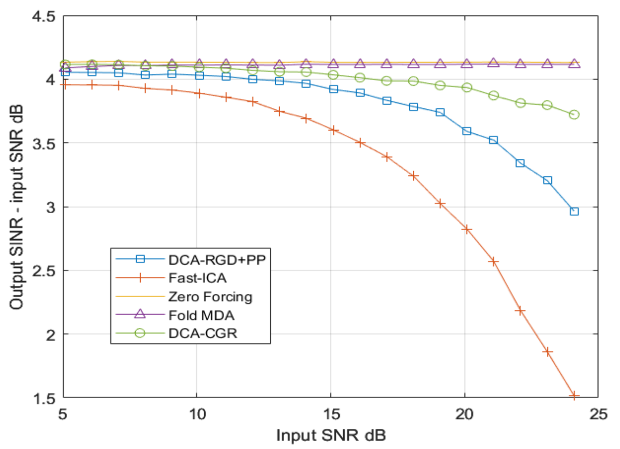

Figure 5 – Output SINR- Input SNR as function of input SNR.

The average processing time of the various DCAs were quasi-constant over the entire range of SINR, we record an average processing time of 0.193s for DCA-CGR and 0.106s for DCA-RGD+PP, therefore DCA-RGD+PP outperforms DCA-CGR with a 45% reduction time.

6 Conclusion

In this paper we propose a post-processing technique that improves the DCA-RGD failure rate when used with complex data mode S SSR signals. Moreover, when compared with DCA-CGR [10], we reduce by half the processing time, while losing less than one dB for SINR; We therefore manage a good trade-off between processing time and signal quality. We plan to further optimize the processing time by revisiting complex data algorithms such as those in [10], which will naturally incorporate the A/C mode into our algorithm.

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