A Linearization Approach for Blind Signal Recovery in Multipath MIMO Systems with Signal Misalignment

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Abstract This paper deals with blind deconvolution for signal recovery in multipath multiple-input multiple-output (MIMO) systems, where the delays of different paths of each source signal from transmit antenna to receive antenna are random. Such a problem is often solved in an ideal state in literature, i.e., each transmitted signal arrives at the receive antennas simultaneously and the arrival time intervals of two adjacent paths are identical. However, the ideal case could not be satisfied in most applications. To address this issue, we propose a blind signal recovery algorithm. Specifically, by using Taylor series expansion to approximate sources, the convolutive MIMO signal recovery problem is transferred into instantaneous blind source separation (BSS) problem. Building on the ideas of second-order blind identification (SOBI), an extended SOBI algorithm is developed to recover the extended sources (including original sources and their derivatives). The simulation results illustrate the well performance and the interest of the proposed algorithm in comparison with other approaches.

Keywords Blind signal recovery · Multipath MIMO · Signal misalignment · Blind source separation · Taylor series approximation.

1 Introduction

Multiple-input and multiple-output (MIMO) is a significant diversity technique to improve system capacity in communication systems. However, the source signals are mixed through wireless channel and inter-frequency interference (ICI) is introduced which leads to the deterioration of the system performance. Existing MIMO mixing channel models can be divided into two categories. One is that there is only one transmission path at each antenna pair between transmitter and receiver. However, in wireless communications, it is oversimplified. In general, since the radio propagation environment is open, signal reflections are introduced by surroundings. In this case, the mixing channel is modeled as multipath. That
is, the source signals suffer from not only ICI but also inter-symbol interference (ISI). One objective in MIMO systems is to mitigate the ISI and the ICI so as to recover source signals. It can be realized by introducing training signals but extra bandwidth is needed for the training signals. However, in blind methods, the advantages lie in the fact that blind signal recovery algorithms do not require allocating extra bandwidth to training signals.

In this paper, we consider a MIMO context where source signals are mixed through a multidimensional convolutive channel. And blind approach is explored to recover source signals. Here, “blind” means the mixing system is unknown and no other information is required.

Blind MIMO signal recovery problem can be considered as blind source separation (BSS) problem. For convolutive BSS algorithms, it can be divided into two categories, i.e., time domain algorithms [1][2][3] and frequency domain algorithms [4][5][6]. Theoretically, dealing with signals in the frequency domain is quite easily performed compared with processing in time domain. The received signals are split into many frequency bins, and in each bin, mixtures can be treated as instantaneous. Complex instantaneous BSS algorithms can be employed to separate such mixtures. However, due to the permutation problem generated by the complex instantaneous BSS algorithm, there remains the problem of grouping all frequency components of each source signal. For time domain approaches, the permutation problem does not need to be considered for the received data do not split into pieces, but the algorithm complexity is relatively high. Furthermore, for both frequency domain and time domain methods, an assumption lies in the algorithms that each transmitted signal arrives at the receive antennas simultaneously and the arrival time intervals of two adjacent paths are identical. In most situations, this assumption cannot be satisfied, and the problem of source recovery in that case is more complex. In this study, we address the general case of convolutive mixture problem: multidimensional convolutive mixture of sources with random delays. We propose an effective time domain convolutive blind signal recovery algorithm based on second-order statistics.

Inspired with [7][8], where Taylor series approximation is taken to effectively realize multipath self-interference cancellation in full-duplex radios, we also take this point to linearize delayed sources. It will be shown that by linearizing delayed sources based on Taylor series approximation, the convolutive mixture problem can be transferred into linear problem (instantaneous mixture). And a simple extension of second-order blind identification (SOBI) algorithm [9] is employed to deal with this problem. In the simulations, the proposed algorithm will be compared with two blind convolutive signal recovery algorithms based on ideal convolutive mixture models. One is fast fixed-point independent vector analysis (FIVA) [4], which is an effective frequency domain convolutive BSS algorithm. The other one is a time domain convolutive BSS algorithm, general algebraic algorithm for blind extraction (GABE) [1]. It will be shown that the two comparison algorithm are invalid when the delays of different signals are random, but the proposed algorithm performs an interesting result.

The rest of this paper is organized as follows. Sections II develops the problem formulation and basic idea. Section III presents the derivations of the proposed algorithm. To demonstrate the effectiveness of the proposed blind signal recovery algorithm, simulations and performance comparisons are given in section IV. Conclusions are given in section V.
2 Problem Formulation and Basic Idea

2.1 Problem Formulation

Assume there are $N$ sources $s(t) = [s_1(t), s_2(t), \cdots, s_N(t)]^T$, they propagate through a multidimensional convolutive channel and are observed by a set of sensors $x(t) = [x_1(t), x_2(t), \cdots, x_M(t)]^T$, according to a common convolutive mixture model,

$$x(t) = \sum_{k=0}^{L} A(k) s(t - k\tau) + \xi(t)$$

where $A(k)$ is the $M \times N$ matrix corresponding to the impulse response of the convolutive mixing system, $L$ is the channel response length, $\tau$ is the arrival time interval of two adjacent paths, $\xi(t) = [\xi_1(t), \xi_2(t), \cdots, \xi_M(t)]^T$ is i.i.d. additive white Gaussian noise (AWGN) vector with zero-mean and variance $\sigma^2$ and uncorrelated with $s(t)$.

We extend this convolutive mixture model to a more general case: the delays of different paths of each signal are random. Then, the signal observed by the $j$th sensor is

$$x_j(t) = \sum_{n=1}^{N} \sum_{k=0}^{L} A_{j,n}(k) s_n(t - \tau_{j,n}(k)) + \xi_j(t)$$

where $\tau_{j,n}(k)$ is the delay of the $k$th path from the $n$th transmitter to the $j$th sensor.

2.2 Basic Idea

Inspired by [7][8], we introduce a linear approximation technique for the multipath signals which will form the basis of our new blind convolutive signal recovery.

The first order Taylor series approximation for the delayed signal $s_n(t - \tau_{j,n}(k))$ can be written as

$$s_n(t - \tau_{j,n}(k)) = s_n(t) - s_n'(t) \tau_{j,n}(k) + e_1[\tau_{j,n}(k), t]$$

where $e_1[\tau_{j,n}(k), t]$ is the residual error, $s_n'(t) = \frac{ds_n(t)}{dt}$ is the derivative of $s_n(t)$. The error term heavily relies on the delays $\tau_{j,n}(k)$. Generally, $e_1[\tau_{j,n}(k), t]$ decreases with the decrease of $\tau_{j,n}(k)$. Substituting (3) into (2), we have

$$x_j(t) = \sum_{n=1}^{N} \sum_{k=0}^{L} A_{j,n}(k) s_n(t - \tau_{j,n}(k)) + \xi_j(t)$$

$$\approx \sum_{n=1}^{N} \sum_{k=0}^{L} A_{j,n}(k) s_n(t) - s_n'(t) \tau_{j,n}(k) + \xi_j(t)$$

$$= - \sum_{n=1}^{N} \left( \sum_{k=0}^{L} A_{j,n}(k) \tau_{j,n}(k) \right) s_n'(t) + \xi_j(t)$$

$$+ \sum_{n=1}^{N} \left( \sum_{k=0}^{L} A_{j,n}(k) \right) s_n(t)$$




The mixture model of (2) can be transferred into

\[ \mathbf{x} (t) = \mathbf{A} \tilde{\mathbf{s}} (t) + \xi (t) \]  

where \( \tilde{\mathbf{s}} (t) = [s_1 (t), s_2 (t), \ldots, s_N (t), s'_1 (t), s'_2 (t), \ldots, s'_N (t)]^T \) is the augmented source vector, and \( \mathbf{A} \) denotes the augmented mixing matrix (6).

\[
\mathbf{A} = \begin{bmatrix}
\sum_{k=0}^{L} A_{1,1} (k) & \cdots & \sum_{k=0}^{L} A_{1,N} (k) & - \sum_{k=0}^{L} A_{1,1} (k) \tau_{1,1} (k) & \cdots & - \sum_{k=0}^{L} A_{1,N} (k) \tau_{1,N} (k) \\
\sum_{k=0}^{L} A_{2,1} (k) & \cdots & \sum_{k=0}^{L} A_{2,N} (k) & - \sum_{k=0}^{L} A_{2,1} (k) \tau_{2,1} (k) & \cdots & - \sum_{k=0}^{L} A_{2,N} (k) \tau_{2,N} (k) \\
\vdots & \ddots & \vdots & \ddots & \ddots & \vdots \\
\sum_{k=0}^{L} A_{M,1} (k) & \cdots & \sum_{k=0}^{L} A_{M,N} (k) & - \sum_{k=0}^{L} A_{M,1} (k) \tau_{M,1} (k) & \cdots & - \sum_{k=0}^{L} A_{M,N} (k) \tau_{M,N} (k)
\end{bmatrix}
\]

Then, the generalized convolutive blind recovery problem is transferred into the linear instantaneous mixture blind recovery problem, which is the basic idea of this paper.

For large delay, a better approximation of the delayed signal can be realized by using high-order Taylor series, i.e.,

\[
s_n (t - \tau_{j,n} (k)) = s_n (t) + \sum_{p=1}^{P} \frac{(-1)^p}{p!} s_n^{(p)} (t) \tau_{j,n}^p (k) + \epsilon_p [\tau_{j,n} (k), \ell] \]

where \( P \) is the Taylor series order, \( \epsilon_p [\tau_{j,n} (k), \ell] \) is the residual error. And the high-order approximation mixture model is similar to (5) and (6). For convenience, we take the first-order Taylor approximate for example in the follows.

\[\text{3 Algorithm Derivations}\]

In the extended model (5), besides the \( N \) original sources, their first-order derivatives are also treated as sources. So, we take a further assumption that \( M \geq 2N \) (for high-order Taylor approximation, \( M \geq PN \)). As in the previous SOBI method [9], BSS can be realized in two steps: whitening and rotation. Whitening is to find a matrix to whiten the observations, whose function is to achieve dimension reduction, if \( M > 2N \) (\( M > PN \)), and normalize the variance of the components; rotation is to recover the sources from the whitened observations.

According to [9], the whitening matrix \( \mathbf{W} \) can be obtained as follows.

The covariance matrix of the observation vector can be written as

\[ \mathbf{R}_{\mathbf{x}} (t_0) = E [\mathbf{x} (t) \mathbf{x} (t + t_0)^T] = \mathbf{A} \mathbf{R}_{\tilde{\mathbf{s}}} (t_0) \mathbf{A}^T + \sigma^2 \delta (t_0) \mathbf{I} \]

where \( E[\mathbf{x}] \) denotes the expected value, \( \delta (t_0) \) is Dirac delta function and \( \sigma^2 \) is the noise variance.
Note that the covariance matrix of the extended source signals is

$$R_s(t_0) = \begin{bmatrix} R_{ss'}(t_0) & R_{ss'}(t_0) \\ R_{ss'}(t_0) & R_{ss'}(t_0) \end{bmatrix}$$

(9)

where

$$R_{ss'}(t_0) = \text{diag} \left[ R_{ss_1}(t_0), R_{ss_2}(t_0), \ldots, R_{ss_{SN}}(t_0) \right],$$

$$R_{ss'}(t_0) = \text{diag} \left[ R_{ss_1'}(t_0), R_{ss_2'}(t_0), \ldots, R_{ss_{SN}'}(t_0) \right],$$

$$R_{ss'}(t_0) = \text{diag} \left[ R_{ss_1}(t_0), R_{ss_2}(t_0), \ldots, R_{ss_{SN}}(t_0) \right],$$

$$R_{ss'}(t_0) = \text{diag} \left[ R_{ss_1'}(t_0), R_{ss_2'}(t_0), \ldots, R_{ss_{SN}'}(t_0) \right]$$

and $\text{diag}[\mathbf{d}]$ denotes the diagonal matrix with diagonal vector $\mathbf{d}$.

According to [10], $R_{skk}(t_0)$ has the following properties

$$R_{skk}(t_0) = R_{skk}'(t_0)$$

$$R_{skk}'(t_0) = R_{skk}'(-t_0) = -R_{skk}(t_0).$$

(11)

Also note that $R_{skk}'(0) = 0$. Therefore, $R_s(t_0)$ is a diagonal matrix. When $t_0 = 0$, we obtain

$$R_0(0) = AR_0(0)A^T + \sigma^2 I.$$  

(12)

As presented in [9], the whitening matrix $W$ and noise variance $\sigma^2$ can be estimated using the eigenvalue decomposition of covariance matrix $R_s(0)$. The noise variance estimation can be obtained by taking the average of the $M - 2N$ lowest eigenvalues of covariance matrix $R_s(0)$

$$\hat{\sigma}^2 = \frac{1}{M - 2N} \sum_{k=2N+1}^{M} \lambda_k$$

(13)

where $\lambda_k$ are the descending-ordered eigenvalues of covariance matrix $R_s(0)$. The whitening matrix $W$ can be estimated as

$$W = \begin{bmatrix} (\lambda_1 - \hat{\sigma}^2) v_1 \\ (\lambda_2 - \hat{\sigma}^2) v_2 \\ \vdots \\ (\lambda_{2N} - \hat{\sigma}^2) v_{2N} \end{bmatrix}$$

(14)

where $v_k$ is the corresponding eigenvalue vector of $\lambda_k$.

The observations are whitened by $W$, $z(t) = Wx(t)$, and the covariance matrix of whitened observations can be written as

$$R_z(t_0) = \text{WARR}_s(t_0)(\text{WA})^T + \sigma^2 \delta(t_0) I$$

(15)

For high-order Taylor approximation, since $R_{skk}^{(p)}(t_0) = R_{skk}^{(p)}(t_0)$, $R_{skk}^{(p)}(t_0) = R_{skk}^{(p)}(-t_0) = -R_{skk}^{(p)}(t_0)$, $R_{skk}(0) = 0$, $R_s(0)$ is still a diagonal matrix.
In SOBI algorithm [9], the covariance matrix of source signals is diagonal, thus the rotation consists in joint diagonalization of the covariance matrices of the whitened observations for some nonzero time lags. However, in this paper, the covariance matrices of the extended sources $\mathbf{R}_s(t_0)$ may not be diagonal for $t_0 \neq 0$. Therefore, the SOBI algorithm cannot be directly applied to the extended model.

Observe from (9) to (11), we can conclude that

$$\frac{1}{2} \begin{bmatrix} \mathbf{R}_s(t_0) + \mathbf{R}_s(-t_0) \\ \end{bmatrix} = \frac{1}{2} \begin{bmatrix} \mathbf{R}_{ss}(t_0) & \mathbf{R}_{ss}^\prime(t_0) \\ \mathbf{R}_{ss}^\prime(t_0) & \mathbf{R}_{ss}^\prime(-t_0) \end{bmatrix} = \begin{bmatrix} \mathbf{R}_{ss}(t_0) & \mathbf{0} \\ \mathbf{0} & \mathbf{R}_{ss}^\prime(t_0) \end{bmatrix}$$

Then, combining (15) and (16), we obtain

$$\frac{1}{2} \begin{bmatrix} \mathbf{R}_z(t_0) + \mathbf{R}_z(-t_0) \end{bmatrix} = \mathbf{WA} \begin{bmatrix} \mathbf{R}_{ss}(t_0) & \mathbf{0} \\ \mathbf{0} & \mathbf{R}_{ss}^\prime(t_0) \end{bmatrix} (\mathbf{WA})^T \quad \forall t_0 \neq 0 \tag{17}$$

From (17), it follows that the global matrix $\mathbf{WA}$ can be estimated using joint matrix diagonalization [11] of $\mathbf{R}_z(t_0) + \mathbf{R}_z(-t_0)$ at several values of $t_0$.

Since the global matrix $\mathbf{WA}$ is estimated, the extended sources can be estimated by linear transformation of the whitened observations,

$$\hat{s}(t) = (\mathbf{WA})^T \mathbf{z}(t) \tag{18}$$

However, the estimated extended sources contain not only original sources, but also their respective derivatives. Therefore, we need to identify the original sources. Observe from (9) to (11), we can conclude that

$$\frac{1}{2} \begin{bmatrix} \mathbf{R}_s(t_0) - \mathbf{R}_s(-t_0) \\ \end{bmatrix} = \frac{1}{2} \begin{bmatrix} \mathbf{R}_{ss}(t_0) & \mathbf{0} \\ \mathbf{0} & \mathbf{R}_{ss}^\prime(t_0) \end{bmatrix} = \begin{bmatrix} \mathbf{0} & \mathbf{R}_{ss}^\prime(t_0) \\ -\mathbf{R}_{ss}^\prime(t_0) & \mathbf{0} \end{bmatrix} \tag{19}$$

From (16) and (19), we can identify the $N$ pairs original source and respective derivative. Since derivation corresponds to high pass filtering, the signal with lowest mean frequency in each signal pair is detected as original source.

4 Results and Discussion

In this section, three algorithms, i.e., the proposed algorithm, FIVA [4] and GABE [1], are simulated to demonstrate the separation performance for misalignment sources. The two comparison algorithms work in time and frequency domain respectively.
The simulations are set-up as follows. The sources consist of a BPSK signal and a single tone signal with overlapping spectra and unit variances. The misalignment mixtures are generated as described in model (2). \( T_s \) is the symbol period of the BPSK signal. In the simulations, the delays \( \tau_{j,n}(k) \) in model (2) are randomly generated and they are uniformly distributed from zero to the maximal delay. Each source contains 8192 samples.

The performance of these algorithms is evaluated through two performance indexes, i.e., cross-correlation index (CCI) and mean square error (MSE).

\[
CCI = \frac{1}{N} \sum_{k=1}^{N} |R_{s_k \hat{s}_k}|
\]

\[
MSE = \frac{1}{N} \sum_{t=1}^{T} \sum_{n=1}^{N} [s_n(t) - \hat{s}_n(t)]^2
\]

where \( T \) is sample length.

4.1 Experiment 1 – Influence of the Maximal Delay

Fig. 1 and Fig. 2 show the influence of the maximal delay to CCI and MSE. In the two figures, three algorithms are simulated, proposed algorithm, GABE and FIVA, and the influence of multipath orders has also taken into consideration. Observing Fig. 1 and Fig. 2, we notice that performance of FIVA and GABE is susceptible to the value of maximal delay, in other words, they are sensitive to misalignment sources. Especially for FIVA, its CCI performance heavily decreases along with the increase of the maximal delay. However, the performance of the proposed algorithm is much better than the other two comparison algorithms, especially when the maximal delay is small. Even when the maximal delay equals \( T_s \), the CCI performance of the proposed algorithm can reach to 96% with around 43% and 56% gains compared with GABE and FIVA, respectively; and the MSE performance of the proposed algorithm can reach to -11dB, while the MSE performance of GABE and FIVA algorithm are about -1dB. From the two figures, we can also find that the multipath order has a little influence to the algorithms for misalignment sources.

4.2 Experiment 2 – Influence of the Taylor Series Orders

The CCI and MSE indexes are drown versus the number of Taylor series orders in Fig. 3 and Fig. 4, respectively. In Fig. 3, we give the CCI performance of the proposed algorithm for different maximal delays. For small maximal delay, the number of Taylor series orders has little impact on CCI performance; when the maximal delay is higher than \( 3T_s \), the CCI performance increases with the number of Taylor series orders increasing; while when the maximal delay equals \( T_s \), the CCI performance decreases along with the increase of the number of Taylor series orders. Before giving the explanations, it is necessary to note that high order Taylor series approximate of sources can reach a higher accuracy, the separation performance may also be improved through the high approximate accuracy for sources. For the small maximal delays cases, Taylor series expansion can reach a
high level accuracy even at low order for sources, so the CCI performance keeps on a stable level. For large maximal delay cases, high-order Taylor series expansion of sources can reach a higher accuracy for sources, this makes the performance improving with Taylor series orders. When the maximal delay is $T_s$, the proposed
algorithm can reach a good performance at low-order Taylor series expansion. While for high-order Taylor series approximation, although the approximate accuracy for sources may be higher, the accuracy may not good enough to improve the influence of the approximate error of the Taylor series expansion to separation performance but to make the performance worse.

Fig. 3 CCI vs Taylor series order of the proposed algorithm for misalignment sources. The multipath number is 4.

Fig. 4 MSE vs Taylor series order of the proposed algorithm for misalignment sources. The multipath number is 4.
4.3 Experiment 3 – Influence of Noise

Noise is common in most applications, in this part, we investigate the impact of noise on our proposed algorithm. We firstly define noise level as

$$SNR = \frac{1}{M} \sum_{j=1}^{M} 10\log_{10} \frac{\text{var} \left( \sum_{n=1}^{N} \sum_{k=0}^{L} A_{j,n}(k) s_{n}(t - \tau_{j,n}(k)) \right)}{\text{var}(\xi_{j}(t))}$$

where var(●) denotes calculating the variance of ●. In Fig. 5 and Fig. 6 we display the CCI and MSE performance versus SNR. Three algorithms are compared and three different maximal delay are simulated for each algorithm. From the two figures, we can obtain that the performance of the three algorithms increase with the increase of SNR, and the proposed algorithm is the best of the three algorithms and FIVA is the worst. In addition, for each value of maximal delay, the gains of the proposed algorithm increase with the growth of SNR in comparison with the other two algorithms.

![CCI vs SNR of the proposed algorithm, GABE and IVA for misalignment sources. The multipath number is 4. △: Proposed algorithm; ♦: GABE; ◦: FIVA.](image)

5 Conclusion

In this paper, we have proposed a blind signal recovery algorithm for multipath MIMO. The key novelty of the proposed algorithm is that the delay of each path from transmit antenna to receive antenna is random, i.e., signal misaligning, which
makes the traditional blind signal recovery algorithms invalid. Inspired by [7][8] using Taylor series expansion to approximate sources, and building on ideas developed in [9] for instantaneous blind source separation, our approach transfers the convolutive blind signal recovery problem in MIMO systems into instantaneous blind source separation problem. We extend the SOBI algorithm developed in [9] to address this issue successfully. Simulations have indeed showed that our approach is particularly appealing, since it yields an impressive improvement compared with two comparison algorithms, one (FIVA) process in frequency domain, the other (GABE) process in time domain.

**List of Abbreviations**

BSS: Blind source separation  
MIMO: Multiple-input multiple-output  
SOBI: Second-order blind identification  
ICI: Inter-frequency interference  
ISI: Inter-symbol interference  
FIVA: Fast fixed-point independent vector analysis  
GABE: General algebraic algorithm for blind extraction  
AWGN: Additive white Gaussian noise  
CCI: Cross-correlation index  
MSE: Mean square error
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Availability of data and materials

The datasets used and/or analyzed during the current study are available from the corresponding author on reasonable request.

Authors' contributions

Jiong Li was responsible for all of this paper.

Competing interests

The author declare that they have no conflict of interest.

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**Figure Title and Legend**

Fig. 1 CCI vs maximal delay of the proposed algorithm, GABE and IVA for misalignment sources. The Taylor series order is 1.
Fig. 2 MSE vs maximal delay of the proposed algorithm, GABE and IVA for misalignment sources. The Taylor series order is 1.

Fig. 3 CCI vs Taylor series order of the proposed algorithm for misalignment sources. The multipath number is 4.
**Fig. 4** MSE vs Taylor series order of the proposed algorithm for misalignment sources. The multipath number is 4.

**Fig. 5** CCI vs SNR of the proposed algorithm, GABE and IVA for misalignment sources. The multipath number is 4. △: Proposed algorithm; ◇: GABE; ◦: FIVA.
Fig. 6 MSE vs SNR of the proposed algorithm, GABE and IVA for misalignment sources. The multipath number is 4. △: Proposed algorithm; ◇: GABE; ○: FIVA.