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RESEARCH

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Blind signal separation based on widely linear complex autoregressive process of order one

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Abstract

In this paper, the blind signal separation problem of complex baseband signal is addressed. A widely linear complex autoregressive process of order one is employed to represent the temporal structure of complex sources. We formulate a new contrast function by a convex combination of generalized autocorrelations and the statistics of the innovation. And the proposed contrast function is optimized by gradient method. Simulation results show that the proposed algorithm is better than the comparison algorithm in convergence speed and convergence accuracy.

Keywords: Blind source separation, Complex auto-regressive model, Generalized autocorrelation, Gradient learning

1 Introduction

For the next generation mobile communication system (5G) which aims at achieving more than 10 times spectrum efficiency compared with the current communication system (4G) [1], spectrum efficiency is a critical performance index. Since radios must either transmit or receive on the same channel, but not simultaneously, in previous wireless communication systems, the spectrum is not utilized sufficiently. Fortunately, an emerging technique, Co-frequency and Co-time full-duplex (CCFD) [2, 3], is able to address this issue. CCFD enables radios to transmit and receive signals on the same channel simultaneously and thus, theoretically, can double the spectrum efficiency. CCFD technique claims to be the most potential duplex scheme for the 5G network. But, there is a challenge which lies in the application of CCFD technique, i.e., mitigating the local self-interference (SI) [2, 3]. Since the transmit and receive antenna work on the same frequency band, traditional interference cancellation techniques are invalid. As [4] shown, blind source separation (BSS) [5] has a big advantage in addressing this issue.

The problem of blind source separation has been widely researched [6, 7] since it is able to estimate original signals from their observed sensors signals without knowing both the mixing process and the sources. Separation of complex-valued signals is a frequently arising problem, such as performing BSS in baseband for communication signals or in frequency domain for time domain convolutive signals [8]. Many BSS algorithms estimate the original signals by some priori information, such as non-Gaussianity [9], sparseness [10], boundedness [11]. Although these methods have been proved useful in many applications, it is also worth noticing that the separation accuracy and the convergence of these algorithms have reached to saturation so it is hard to be further improved. Therefore, other prior information should be considered in the contrast function or the algorithm, such as linear predictability [12], linear autocorrelation [13] or temporal predictability [14], etc.

From a practical point of view, the sources are usually temporal dependent in many realistic applications. Is it possible to improve the separation accuracy by exploiting the temporal dependency? It is quite an interesting topic. Right now, several studies have been published based on that idea. Specifically, [15, 16] exploited the contributions of temporal dependency of source signals by using an autoregressive model to represent sources and using joint matrix diagonalization to achieve BSS. An AR-MOG model is employed in [17] to describe the temporal dependency of source signals, in which the temporal dependency is represented by autoregressive structure, but the probability distribution of the innovation is not Gaussian but mixture of Gaussian. By this way, the temporal and statistics information of sources are fully taken into consideration [18, 19] constructed contrast function based on generalized autocorrelations (linear or nonlinear autocorrelations). Although the above methods successfully applied BSS and achieved good performance, they are all proposed for real-valued signals. There is a very small amount of open research on BSS methods using temporal dependency of complex value signals [13]. However, their performance is similar with the methods using only independency and other methods [20].

In this paper, a widely linear complex autoregressive process of order one [21] is employed to represent the temporal structure of complex sources. Using some temporal information like in [17], we formulate contrast function by a convex combination of generalized autocorrelations and the statistics of the innovation. By doing this, we hope lead to a new complex BSS algorithm with higher separation accuracy compared with other methods using only the independency. The proposed contrast function is optimized by gradient method. As the simulation results shown, the proposed algorithm converges fast and performs a better separation performance than the comparing algorithms.

This paper is organized as follows. First, the BSS problem is formulated in Sect. 2. We then introduce the new contrast function based on the generalized autocorrelations of source signals and derive a gradient-based algorithm in Sect. 3. The performance of the algorithm is demonstrated with simulations in Sect. 4. Conclusions are drawn in Sect. 5.

2 Methods/experimental

3 Problem formulation

Considering there be N sensors and N independent sources, the instantaneous linear mixtures of these sources are observed at the sensors:

$$\mathbf{x}(t) = \mathbf{A}\mathbf{s}(t) \tag{1}$$

where $\mathbf{s}(t) = [s_1(t), s_2(t), \ldots, s_N(t)]^{\mathrm{T}}$ (superscript T denotes transpose) is a vector of unknown zero mean and unit-variance source signals, $\mathbf{x}(t) = [x_1(t), x_2(t), \ldots, x_N(t)]^T$ is the observation vector, and $\mathbf{A}$ is the unknown $N \times N$ mixing matrix. We impose another assumption on the source signals that the source signals have specific temporal structures-linear or nonlinear autocorrelations.

4 The proposed algorithm

In general, pre-processing operations of observed signals are needed before performing BSS algorithm. Two common pre-processing operations are removing mean and whitening. The whitening matrix $\mathbf{Q}$ can be obtained using the eigenvalue decomposition of covariance matrix $\mathbf{R}_x = E\left[\mathbf{x}(t)\mathbf{x}(t)^{\mathrm{H}}\right]$ (superscript H denotes conjugate transpose, $E[\bullet]$ denotes expectation).

$$\mathbf{Q} = \mathbf{D}^{-\frac{1}{2}}\mathbf{V}^{\mathrm{H}} \tag{2}$$

where $\mathbf{D}$ and $\mathbf{V}$ are the eigenvalue matrix and the eigenvector matrix of the covariance matrix $\mathbf{R}_x$. The observations are whitened by $\mathbf{Q}$,

$$\mathbf{z}(t) = \mathbf{Q}\mathbf{x}(t) \tag{3}$$

Then, $\mathbf{R}_z = E\left[\mathbf{z}(t)\mathbf{z}(t)^{\mathrm{H}}\right] = \mathbf{QAR}_s(\mathbf{QA})^{\mathrm{H}}$, due to $\mathbf{R}_s = \mathbf{I}$, $\mathbf{R}_z = \mathbf{I}$, and $\mathbf{QA}$ is a unitary matrix which imposes unitary constraint on the demixing matrix $\mathbf{W}$. The sources can be estimated by

$$\mathbf{y}(t) = \mathbf{W}\mathbf{z}(t) \tag{4}$$

where $\mathbf{y}(t) = [y_1(t), y_2(t), \ldots, y_N(t)]^T$ is the estimation of $\mathbf{s}(t)$.

We use widely linear complex autoregressive process of order one to describe complex-valued signals [21]

$$s_n(t) = b_1 s_n(t-\tau) + b_2 s_n^*(t-\tau) + \nu_n(t) \tag{5}$$

where $\nu_n(t)$ denotes the innovation of the signal $s_n(t)$, b_1 and b_2 are the complex autoregressive coefficients, τ is a delay in time, $s_n^*(t-\tau)$ designates the complex conjugate of $s_n(t-\tau)$. For simplicity, the time index t is omitted in the following, i.e., $s_n(t) = s_n$, $s_n(t-\tau) = s_{n\tau}$.

Then, we define a contrast function considering both the temporal characteristics of the signals and the probability distribution of the innovations.

$$\begin{aligned} J_0(\mathbf{w}_n) = {} & \varepsilon E\left\{ G\left(\left|\mathbf{w}_n^{\mathrm{H}}\mathbf{z}\right|^2\right) G\left(\left|\mathbf{w}_n^{\mathrm{H}}\mathbf{z}_\tau\right|^2\right)\right\} + (1-\varepsilon) \\ & \times E\left\{ F\left(\left|\mathbf{w}_n^{\mathrm{H}}\mathbf{z} - b_1\mathbf{w}_n^{\mathrm{H}}\mathbf{z}_\tau - b_2\mathbf{w}_n^{\mathrm{H}}\mathbf{z}_\tau^*\right|^2\right)\right\} \end{aligned} \tag{6}$$

where ε is a balance factor between 0 and 1, $\mathbf{w}_n^{\mathrm{H}}$ is the *nth* row vector of demixing matrix $\mathbf{W}$ and $|\mathbf{w}_n|^2 = 1$, τ is a delay in time, G is a differentiable function which measures the generalized autocorrelation degree of the source signal, F is also a differentiable function which is associated with the probability distribution of the innovations. Finding the extrema of a contrast is a well-defined problem only if the function is real. So we let our contrast functions operate on absolute values rather than complex values. Examples of choices are $G_1(u) = u$, $G_2(u) = u^2$, $G_3(u) = \log[\cosh(u)]$, $F(u) = \log[\cosh(u)]$.

Now, we begin to derive the complex gradient algorithm for complex signals under the model (1). The problem given in (6) can be written as the following Lagrangian function:

$$J(\mathbf{w}_n) = J_0(\mathbf{w}_n) + \lambda\left(\|\mathbf{w}_n\|^2 - 1\right) \tag{7}$$

where the Lagrangian multiplier λ is a real number. The complex gradient of the contrast function J with respect to $\mathbf{w}_n$ can be obtained as

$$\frac{\partial J(\mathbf{w}_n)}{\partial \mathbf{w}_n^*} = \frac{\partial J_0(\mathbf{w}_n)}{\partial \mathbf{w}_n^*} + \lambda \mathbf{w}_n \tag{8}$$

$$\begin{aligned}\frac{\partial J_0(\mathbf{w}_n)}{\partial \mathbf{w}_n^*} = {} & \lambda E\left\{g\left(\left|\mathbf{w}_n^{\mathrm{H}}\mathbf{z}\right|^2\right)G\left(\left|\mathbf{w}_n^{\mathrm{H}}\mathbf{z}_\tau\right|^2\right)\mathbf{w}_n^T\mathbf{z}^*\mathbf{z}\right. \\ & \left. + G\left(\left|\mathbf{w}_n^{\mathrm{H}}\mathbf{z}\right|^2\right)g\left(\left|\mathbf{w}_n^{\mathrm{H}}\mathbf{z}_\tau\right|^2\right)\mathbf{w}_n^T\mathbf{z}_\tau^*\mathbf{z}_\tau\right\} \\ & + (1-\lambda)E\left\{f\left(|\varphi|^2\right)\left[(\mathbf{z} - b_1\mathbf{z}_\tau)\varphi^* - b_2^*\mathbf{z}_\tau\varphi\right]\right\}\end{aligned} \tag{9}$$

where $\varphi = \mathbf{w}_n^{\mathrm{H}}\mathbf{z} - b_1\mathbf{w}_n^{\mathrm{H}}\mathbf{z}_\tau - b_2\left(\mathbf{w}_n^{\mathrm{H}}\mathbf{z}_\tau\right)^*$, the function g and f are the derivations of G and F, respectively. Thus, the complex gradient-based update rule of $\mathbf{w}_n$ can be written as

$$\begin{aligned}\mathbf{w}_n &= \mathbf{w}_n - \mu\left[\frac{\partial J_0(\mathbf{w}_n)}{\partial \mathbf{w}_n^*} - \mathrm{Re}\left\{\mathbf{w}_n^{\mathrm{H}}\frac{\partial J_0(\mathbf{w}_n)}{\partial \mathbf{w}_n^*}\right\}\mathbf{w}_n\right] \\ \mathbf{w}_n &= \frac{\mathbf{w}_n}{\|\mathbf{w}_n\|}\end{aligned} \tag{10}$$

where $\mu > 0$ is the real-valued step-size.

The complex autoregressive coefficients $[b_1, b_2]$ in the algorithm can be estimated simply by a least-squares method as [22]

$$\mathbf{B} = \mathbf{C}_\tau\mathbf{C}^{-1} \tag{11}$$

where $\mathbf{B} = \begin{bmatrix} b_1 & b_2 \\ b_2^* & b_1^* \end{bmatrix}$, $\mathbf{C}_\tau = E\left\{\begin{bmatrix} y_n \\ y_n^* \end{bmatrix}\begin{bmatrix} y_{n\tau} \\ y_{n\tau}^* \end{bmatrix}^{\mathrm{H}}\right\}$, $\mathbf{C}_\tau = E\left\{\begin{bmatrix} y_{n\tau} \\ y_{n\tau}^* \end{bmatrix}\begin{bmatrix} y_{n\tau} \\ y_{n\tau}^* \end{bmatrix}^{\mathrm{H}}\right\}$.

5 Results and discussion

The proposed algorithm is compared with three competitive complex ICA algorithms: complex FastICA [23], EBM [24] and EASI [20]. FastICA is a Newton-based ICA algorithm which converges fast. EBM is a conjugate gradient-based algorithm. EASI is a relative gradient-based algorithm. In general, Newton method converges faster than conjugate gradient and relative gradient methods, and relative gradient method converges slowest. The performance index is defined as (12) which means the average inter-symbol-interference of the estimation sources.

$$\begin{aligned}PI = \frac{1}{2N}&\left[\sum_{k=1}^{N}\left(\sum_{l=1}^{N}\frac{|U_{kl}|^2}{\max_n|U_{kn}|^2} - 1\right)\right. \\ &\left. + \sum_{l=1}^{N}\left(\sum_{k=1}^{N}\frac{|U_{kl}|^2}{\max_n|U_{nl}|^2} - 1\right)\right]\end{aligned} \tag{12}$$

where $\mathbf{U} = \mathbf{WQA}$ is the combined separation-whitening-mixing matrix, and U_{kl} is the (k, l)th entry of $\mathbf{U}$.

Figure 1 shows the constellation figures of two original 8PSK signals, their mixtures and the estimations using the proposed algorithm employing the function $G_1(u) = u$,

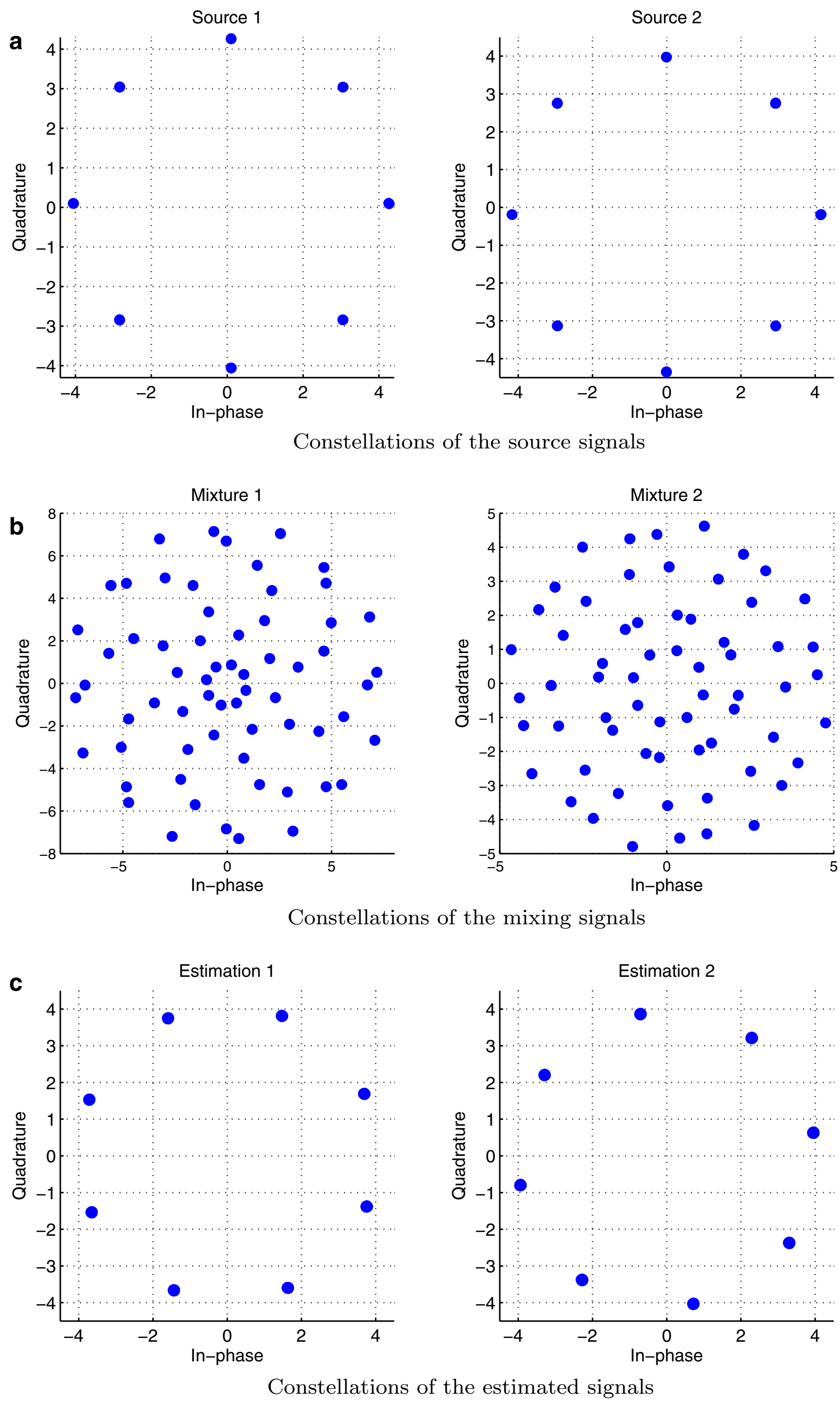

Fig. 1 Simulation result of the proposed algorithm for mixtures of two 8PSK signals, time delay $\tau = 1$

$\lambda = 0.3$. In this simulation, the two 8PSK are with the following parameters: symbol rate $R_s = 198$ kBps and raised cosine filter which has 0.35 roll-off factor, sampling frequency is $16R_s$. The mixing matrix is randomly generated as

$$\mathbf{A} = \begin{bmatrix} 0.5559 - 0.4087i & -0.3675 + 0.9735i \\ -0.4565 + 0.1023i & -0.6240 - 0.3897i \end{bmatrix} \tag{13}$$

From Fig. 1, we can see that the source signals are properly estimated. As most complex BSS algorithms, there are with some ambiguities including amplitude, order, and phase ambiguities. The combined separation-whitening-mixing matrix is estimated as

$$\mathbf{U} = \begin{bmatrix} -0.0042 - 0.0003i & \mathbf{0.4022 - 0.9156i} \\ \mathbf{-0.9841 - 0.1778i} & 0.0049 - 0.0006i \end{bmatrix} \tag{14}$$

In order to illustrating the influence of time delay τ to the proposed algorithm, the separation performance of the proposed algorithm with different time delay τ is simulated. As shown in Fig. 2, the PI values obtained by the proposed algorithm using function $G_1(u)$ is minimum at $\tau = 8$, the PI value obtained by using $G_3(u)$ increases with the increase of time delay τ and the PI curve with employing $G_2(u)$ is relative flat compared with that by using the other two nonlinear functions. This simulation result indicates that the separation performance of the proposed algorithm relies heavily on the selections of function $G(u)$ and time delay τ. In the rest simulations, we set $\tau = 1$.

Figure 3a shows the convergence speed of different algorithms. The sources are two 8PSK signals with the same parameters as previous and the mixing matrix is randomly generated. It is clear that the convergence speed of EASI is slower than other algorithm since EASI is a relative gradient-based algorithm. FastICA and EBM have a similar convergence speed and the convergence value of FastICA is lower than EBM, which means the residual inter-symbol-interference of EBM is higher than FastICA. For the proposed algorithm, we can see that its convergence speed is similar with FastICA and EBM. In

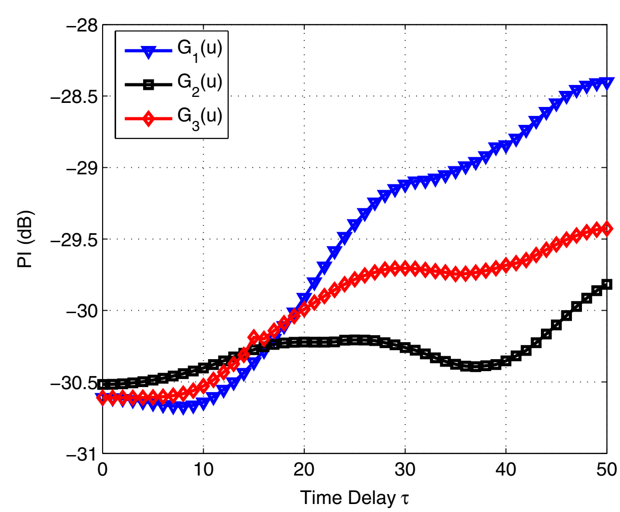

Fig. 2 Separation performance of the proposed algorithm at different time delay τ, sample length is 3000 and $\lambda = 0.3$

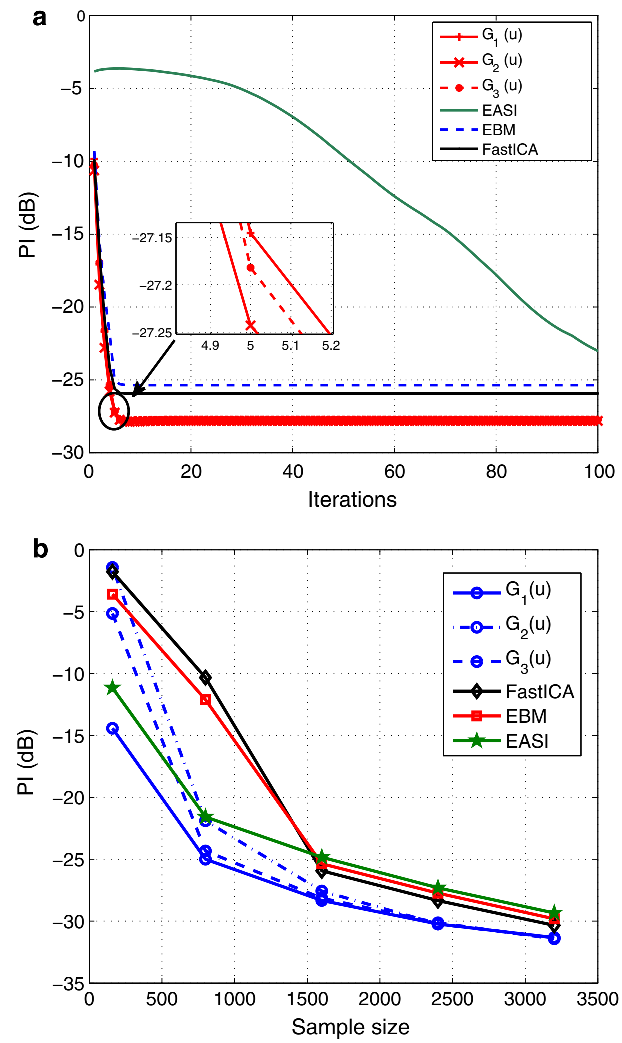

Fig. 3 **a** Comparison of average PIs over 100 independent runs for the four algorithms. **b** Comparison of average PIs of the four algorithms over 100 independent runs at different sample size for 8PSK signals

addition, it can also be seen that the convergence speed and convergence values of the proposed algorithm using the three different function $G(u)$ are similar, and the convergence values of the proposed algorithm are lower than the two comparing algorithms.

Figure 3b shows the averaged PI values for the separation of two 8PSK sources with different sample size. The mixing matrix is randomly generated in every individual experiment. From Fig. 3b, we observe that with the increase of sample size, the PI values decrease. The proposed algorithm using the function $G_1(u)$ is the best, and the proposed algorithm with the three functions show a similar performance when the sample size is bigger than 1600. FastICA and EBM show a similar performance. The performance of EASI is similar with EBM when sample size is bigger than 1600, and performs even better than FastICA and EBM when sample size is smaller than 1600. However, as shown in Fig. 3a, the convergence speed of EASI is so slow that it would not be the first choice to perform sources separation.

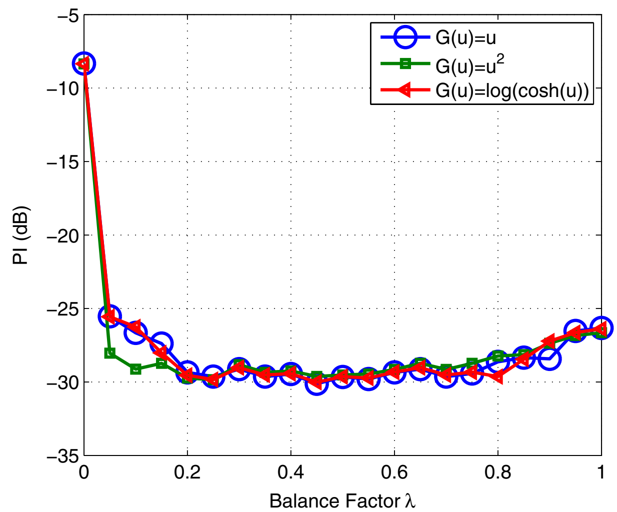

Fig. 4 The performance of the proposed algorithm with different λ

Figure 4 shows the impact of λ on the separation performance of the proposed algorithm. From Fig. 4, we can see that there exists a balance between the innovations and autocorrelations, i.e., no matter which part is dominant, the separation performance will deteriorate. When $\lambda = 0$, i.e., only the innovations are in consideration, the PI values are so high which means the sources are not estimated properly. When $0 < \lambda < 0.2$, the PI values decrease with the increase of λ, that is to say, the separation performance is improved with the increase of λ. Then, the PI line are flat in $0.2 < \lambda \leq 0.7$. When $0.7 < \lambda \leq 1$, the PI values increase with the increase of λ, that is to say, the separation performance deteriorates with the increase of λ.

6 Conclusion

In this paper, we address the complex blind source separation problem by using the temporal characteristics of the sources. A gradient-based algorithm is proposed which takes into account not only the time-structure characteristics of the signal but also the statistical properties of the signal. In the simulations, we perform the proposed algorithm on the mixtures of two 8PSK signals. The simulation results show that although the convergence speed of the proposed algorithm is similar with complex FastICA and EBM algorithms, its convergence value is smaller than the comparing algorithms, which means the averaged signal-to-interference ratio of the estimated signals is higher than the comparison algorithms. In addition, by reasonably selecting the value of balance factor λ, the algorithm can achieve better performance.

Abbreviations

BSS: Blind source separation; CCFD: Co-frequency and co-time full-duplex; SI: Self-interference.

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Authors' contributions

JL participated in the design of the study, performed the simulation analysis and drafting the manuscript. YQ participated in algorithm simulation. MF, XT, LG and JF participated in the English correction and integration of the paper. LC participated in the simulation analysis. All authors read and approved the final manuscript.

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Availability of data and materials
The data used in this article are all randomly generated using Matlab software.

Competing interests
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References

1. Q.C. Li, H.N. Niu, A.T. Papathanassiou, G. Wu, 5G network capacity: key elements and technologies. IEEE Veh. Technol. Mag. **9**(1), 71–78 (2014)
2. M. He, C. Huang, Self-interference cancellation for full-duplex massive MIMO OFDM with single RF chain. IEEE Wirel. Commun. Lett. **9**(1), 26–29 (2020)
3. F.J. Soriano-Irigaray, J.S. Fernandez-Prat, F.J. Lopez-Martinez, E. Martos-Naya, O. Cobos-Morales, J.T. Entrambasaguas, Adaptive self-interference cancellation for full duplex radio: analytical model and experimental validation. IEEE Access **6**, 65018–65026 (2018)
4. J. Li, H. Zhang, M.L. Fan, Digital self-interference cancellation based on independent component analysis for co-time co-frequency full-duplex communication systems. IEEE Access **5**(1), 10222–10231 (2017)
5. X. Cai, X. Wang, Z.T. Huang, F.H. Wang, Performance analysis of ICA in sensor array. Sensors **16**(5), 637 (2016)
6. S. Gannot, E. Vincent, S. Markovich-Golan, A. Ozerov, A consolidated perspective on multimicrophone speech enhancement and source separation. IEEE/ACM Trans. Audio Speech Lang. Process. **25**(4), 692–730 (2017)
7. T. Adali, Y. Levin-Schwartz, V.D. Calhoun, Multimodal data fusion using source separation: application to medical imaging. Proc. IEEE **103**(9), 1494–1506 (2015)
8. K. Xie, G. Zhou, J. Yang, Z. He, S. Xie, Eliminating the permutation ambiguity of convolutive blind source separation by using coupled frequency bins. IEEE Trans. Neural Netw. Learn. Syst. **31**(2), 589–599 (2020)
9. S.H. Fouladi, I. Balasingham, K. Kansanen, T.A. Ramstad, Blind source separation using temporal correlation, non-Gaussianity and conditional heteroscedasticity. IEEE Access **6**, 25336–25350 (2018)
10. M. Taseska, E.A.P. Habets, Blind source separation of moving sources using sparsity-based source detection and tracking. IEEE/ACM Trans. Audio Speech Lang. Process. **26**(3), 657–670 (2018)
11. H.A. Inan, A.T. Erdogan, Convolutive bounded component analysis algorithms for independent and dependent source separation. IEEE Trans. Neural Netw. Learn. Syst. **26**(4), 697–708 (2015)
12. A.K. Barros, A. Cichocki, Extraction of specific signals with temporal structure. Neural Comput. **13**(9), 1995–2003 (2001)
13. A. Belouchrani, K.A. Meraim, J.-F. Cardoso, E. Moulines, A blind source separation technique based on second order statistics. IEEE Trans. Signal Process. **45**(2), 434–444 (1997)
14. J.V. Stone, Blind source separation using temporal predictability. Neural Comput. **13**(7), 1559–1574 (2001)
15. A. Boudjellal, K. Abed-Meraim, A. Belouchrani, Separation of dependent autoregressive sources using joint matrix diagonalization. IEEE Signal Process. Lett. **22**(8), 1180–1183 (2015)
16. J. Li, H. Zhang, J. Zhang, Fast adaptive BSS algorithm for independent/dependent sources. IEEE Commun. Lett. **20**(11), 2221–2224 (2016)
17. K.E. Hild, H.T. Attias, S.S. Nagarajan, An expectation–maximization method for spatio-temporal blind source separation using an AR-MOG source model. IEEE Trans. Neural Netw. **19**(3), 508–519 (2008)
18. H.J. Zhang, G.N. Wang, P.M. Cai, Z.K. Wu, S.X. Ding, A fast blind source separation algorithm based on the temporal structure of signals. Neurocomputing **139**, 261–271 (2014)
19. H.J. Zhang, Z.W. Shi, C.H. Guo, Blind source extraction based on generalized autocorrelations and complexity pursuit. Neurocomputing **72**, 2556–2562 (2009)
20. X.L. Li, T. Adali, Complex independent component analysis by entropy bound minimization. IEEE Trans. Circuits Syst. I Regul. Pap. **57**(7), 1417–1430 (2010)
21. A.M. Sykulski, S.C. Olhede, J.M. Lilly, A widely linear complex autoregressive process of order one. IEEE Trans. Signal Process. **64**(23), 6200–6210 (2016)
22. T. Adali, P.J. Schreier, Optimization and estimation of complex-valued signals: theory and applications in filtering and blind source separation. IEEE Signal Process. Mag. **31**(5), 112–128 (2014)
23. Y.F. Liang, J. Harris, S.M. Naqvi, G.J. Chen, J.A. Chambers, Independent vector analysis with a generalized multivariate gaussian source prior for frequency domain blind source separation. Sig. Process. **105**(12), 175–184 (2014)
24. J.M. Ye, H.H. Jin, S.T. Lou, K.J. You, An optimized EASI algorithm. Sig. Process. **89**, 333–338 (2009)

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