Full-Duplex Self Cancellation Techniques Using Independent Component Analysis

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***Abstract*—Independent component analysis (ICA) has been shown as a promising means for solving the self-interference cancellation (SIC) problem for in-band full duplex systems. This paper presents a detailed analysis of the interference suppression capability and computational complexity of several different ICA algorithms, operating at either real-valued or complex-valued domain. In addition, on the basis of the setup of the full-duplex system, we show that a much simplified complex-valued ICA algorithm that only performs whitening and decorrelation processes are sufficient to separate the signal of interest from the mixed signal. Extensive simulation results are presented in this paper to illustrate the performance and complexity of various ICA approaches applying to the full-duplex system.**

***Index Terms*—In-band Full Duplex, MIMO, Self-Interference, Independent Component Analysis (ICA)**

I. Introduction

In-band full duplex wireless communication systems, where the wireless transceiver transmits and receives data simultaneously using the same frequency resources, has gained significant attention and interest due to its enhanced spectral efficiency [1]–[3]. Moreover, the aggregation of full duplex and Multi-Input-Multi-Output (MIMO) techniques [4] makes it more lucrative for achieving greater spectral efficiency [4]. In the in-band full duplex system, the signal of interest (SOI) is mixed with the self interference (SI) signal at the receiving end of the transceiver node and leads to numerous problems including, saturation of the front-end, non-linear effects, as well as loss of dynamic range. Therefore, an effective scheme for removing the SI from the mixed signal is crucial for a practical realization of the In-band full duplex system. In addition, the self-interference cancellation (SIC) problem becomes more critical and challenging in MIMO full duplex systems since the dimension of the problem grows exponentially. Several approaches have been reported to solving the SIC problem in full duplex systems [5]–[7]. Most SIC cancellation approaches rely on the estimation of the SI channels and removing the inference signals based on the estimated channels. However, the estimation of SI channels requires the utilization of training symbols that inherently degrade spectral efficiency. On the other hand, in [6] independent component analysis (ICA) was proposed as a blind source separation (BSS) techniques [8] that can be applied to separate the mixed signals in the full duplex system without using any training data. The system setup and the modified Fast ICA algorithm based on the real domain were presented in [6]. Experimental results show that the Signal to Noise Ratio (SNR) is improved by up to 6 dB compared to another all-digital scheme based on the least-squares (LS) interference cancellation method [7]. Various types and modifications of ICA algorithms operating on different dimensions of the signal space, e.g., complex vs. real have been proposed in literature [9]–[12]. Typical ICA algorithms depend on iterative vector and matrices computations and thus usually lead to very-high complexity and extended latency [13]. As a result, it is worth further investigating the trade-offs and efficiency of different variations of ICA algorithms for the SIC cancellation in full duplex systems.

In this paper, we investigate the application of ICA approaches towards solving the SIC problem for in-band full duplex systems. To be specific, we analyze the performance and complexity of different variations of ICA algorithms operating at the either real-valued domain or complex-valued domain. Furthermore, the trade-offs between the performance and complexity for different ICA algorithm is studied in this paper. In addition, we show that only conducting the whitening and decorrelation steps in the ICA algorithm are sufficient to separate the SOI from the mixed signals. This approach simplifies the computational complexity of the ICA algorithm. Extensive simulation results are presented in this paper to illustrate the performance and complexity of various approaches applying to the full-duplex system.

II. Prior Work

The in-band full-duplex (IBFD) system transmits and receives signals at the same time, using the same frequency band [1]. Due to the simultaneous transmission and reception, spectral efficiency of IBFD can be doubled compared to the half-duplex communication scheme [2], [3]. The main challenge of IBFD system lies in the cancellation of the signal of interference (SI) caused by the transmitted signal at the receive antenna of the same transceiver node. In order to successfully mitigate the SI and to achieve full-duplex communication, several IBFD system models have been proposed in literature [1]–[3]. Specifically, an all-digital interference cancellation scheme is presented in [7] and the IBFD system model that is proposed therein is shown in Fig.1. In this system, during the training phase, training symbols are transmitted and at the receiver a least-square (LS) channel estimation approach is

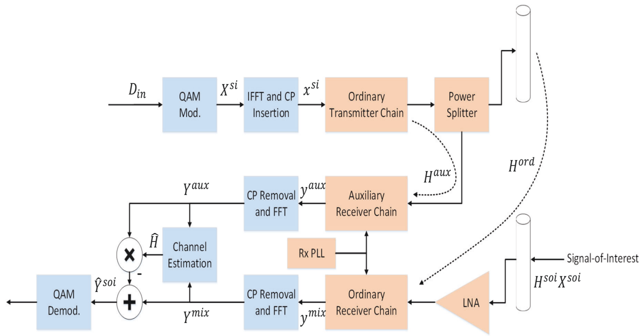

Fig. 1. The IBFD system with the LS-based SIC scheme.

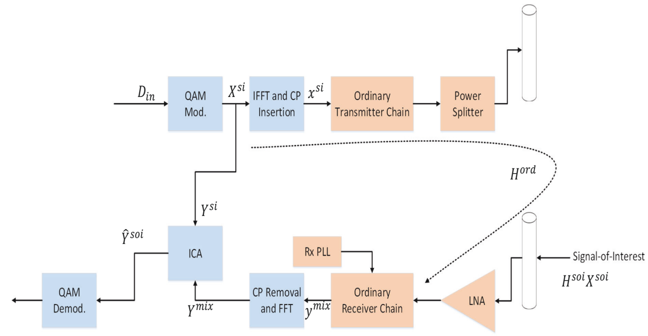

Fig. 2. The IBFD system based on the BSS scheme and the ICA-based SIC algorithm presented in [6].

performed to estimate the SI channel. The estimated channel is then utilized in the transmission phase for cancelling the actual SI signal. Clearly, the more training is performed, the better the channel estimate, at the expense of reduced data throughput. The performance of the LS-based channel estimated is illustrated in [6].

On the other hand, the blind source separation (BSS) [8] is a technology that is widely used for separating mixed signals. In the BSS problem, the mixed signal $\mathbf{Y}$ can be formulated as follows

$$\mathbf{Y} = \mathbf{H}\mathbf{X} \tag{1}$$

where $\mathbf{H}$ and $\mathbf{X}$ are the mixing matrix and the source signal respectively. Furthermore, the essence of the BSS is to generate a demixing matrix such that the source signal can be recovered after applying to the mixed signal as shown in the following

$$\hat{\mathbf{X}} = \mathbf{W}\mathbf{Y} \tag{2}$$

where $\mathbf{W}$ is the demixing matrix and $\hat{\mathbf{X}}$ is the recovered signal which should ideally be equal to $\mathbf{X}$. A digital cancellation scheme based on the concept of BSS is presented in [6] where the system model is shown in Fig. 2. This system does not require training symbols for the channel estimation as the conventional approaches. Instead, the signal of interest (SOI) is separated from the mixed signal by using the independent component analysis (ICA) algorithm which is widely used in BSS problems [8]. It is shown in Fig.2 that, in this system setup, the received signal, containing the mixture of SOI and SI in addition to noise, along with the direct feedback from the digital transmitted signal are the input to the ICA algorithm. In other words, the BSS problem can be formulated as follows

$$\begin{bmatrix} Y^{si} \\ Y^{mix} \end{bmatrix} = \begin{bmatrix} 1 & 0 \\ H^{ord} & H^{soi} \end{bmatrix} \begin{bmatrix} X^{si} \\ X^{soi} \end{bmatrix} \tag{3}$$

where Y^{si} and Y^{mix} are the two input signals to the ICA algorithm. Furthermore, the signal Y^{si} is the direct input from the SI signal X^{si} and Y^{mix} is the mixture of the SI and the SOI signal X^{soi}. Moreover, the H^{ord} and H^{soi} denote the SI and SOI channels respectively.

To be specific, the FastICA algorithm that is originally proposed in [9] is utilized in the work of [6]. Since the FastICA algorithm assumes real-valued signals, the complex-valued BSS problem expressed in Eq. (3) needs to be decomposed into real-valued dimensions before the FastICA algorithm is applied. The Eq. (3) is decomposed as follows

$$\begin{bmatrix} Y_r^{si} \\ Y_i^{si} \\ Y_r^{mix} \\ Y_i^{mix} \end{bmatrix} = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ H_r^{ord} & -H_i^{ord} & H_r^{soi} & -H_i^{soi} \\ H_i^{ord} & H_r^{ord} & H_i^{soi} & H_r^{soi} \end{bmatrix} \begin{bmatrix} X_r^{si} \\ X_i^{si} \\ X_r^{soi} \\ X_i^{soi} \end{bmatrix} \tag{4}$$

where the subscript r denotes the real part and the subscript i represents the imaginary part of the signal. Therefore, based on Eq. (2) and Eq. (4), the separated signals and demixing matrix can be expressed as

$$\begin{bmatrix} \hat{X}_r^{si} \\ \hat{X}_i^{si} \\ \hat{X}_r^{soi} \\ \hat{X}_i^{soi} \end{bmatrix} = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ w_{31} & w_{32} & w_{33} & w_{34} \\ w_{41} & w_{42} & w_{43} & w_{44} \end{bmatrix} \begin{bmatrix} Y_r^{si} \\ Y_i^{si} \\ Y_r^{mix} \\ Y_i^{mix} \end{bmatrix} \tag{5}$$

The approach to addressing the ambiguity and scaling problem is also illustrated in [6]. Figure 3 shows the simulation result of the output SINR (OSINR) for different frame lengths with input SINR (ISINR) = -10dB in [6]. The effect of nonlinearity is modeled by using the third harmonic power ratio (HPR_3) and the simulation results for a typical HPR_3 = -50dB are shown in the figure. As the frame length increases the performance of the ICA algorithm improve accordingly. It is noted that the ICA approach is based on the concept of BSS and no training symbol is required.

In addition, several topics related to the ICA-based SIC cancellation for the IBFD system worth further studying. For example, a FastICA algorithm that is operating directly on the complex domain (C-FastICA) is proposed in [11]. Furthermore,variations of ICA algorithm have appeared in the literature such as the recently published complex-domain ICA through the entropy bound minimization(CICA-EBM) [12].

III. The Performance and Complexity of ICA Algorithms

The FastICA algorithm employed in [6] is conducted to extract the desired signal from the mixed signal that are both presented in the real-valued domain. However, the SIC problem in the IBFD wireless communication systems presented in

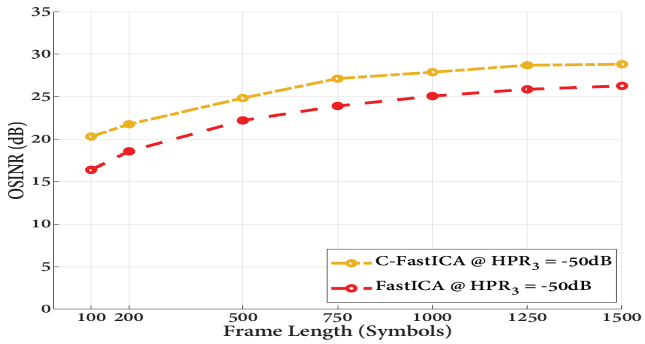

Fig. 3. The OSINR with different frame lengths for FastICA and C-FastICA algorithms.

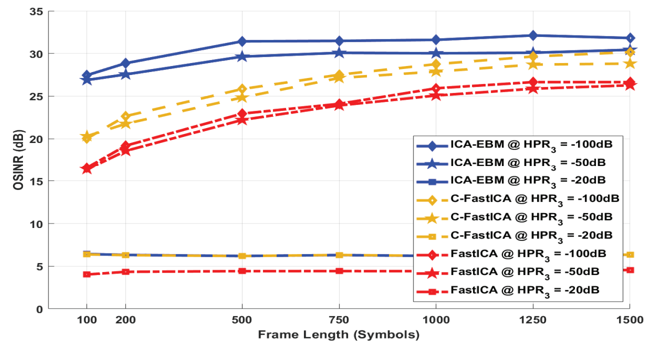

Fig. 4. The OSINR with different frame lengths for FastICA, C-FastICA, abd ICA-EBM algorithms.

Eq. (3) inherently contains the signals in the complex-valued domain. As a result, the complex-valued mixing matrix in the full duplex system is underwent a real-valued decomposition so that the real-valued FastICA algorithm can be applied. This inevitably increases the dimension of the problem as shown in Eq. (3) and Eq. (4) . On the other hand, the modified FastICA algorithm that is directly operating on the complex-valued domain (C-FastICA) is presented in [11]. This C-FastICA algorithm can be directly applied to the complex-valued mixing matrix in full duplex system without performing the real-valued decomposition. In other words, the separated signals and demixing matrix obtained by C-FastICA can be expressed as follows.

$$\begin{bmatrix} \hat{X}^{si} \\ \hat{X}^{soi} \end{bmatrix} = \begin{bmatrix} 1 & 0 \\ w_{21} & w_{22} \end{bmatrix} \begin{bmatrix} Y^{si} \\ Y^{mix} \end{bmatrix} \tag{6}$$

In order to compare the performance of interference cancellation between the real-valued FastICA algorithm and the complex-valued C-FastICA algorithm, extensive simulations are conducted. Figure 3 compares the OSINR between the real-valued FastICA algorithm and the complex-valued C-FastICA algorithm with different frame lengths for the ISINR=-10dB. Furthermore, simulations results for HPR$_3$ = -50dB is also assumed in this figure. It can be observed from the simulation results that the C-FastICA algorithm achieves better OSINR than FastICA throughout different frame lengths. This can be attributed to the fact that the C-FastICA algorithm is applied to the complete complex-valued mixing matrix instead of operating on the real and imaginary parts of the signal separately.

Although the real-valued ICA algorithm can be extended for complex signals, the additional dimension and various distributions could lead to performance degradation. The ICA algorithm that is specifically designed for separating complex signals have been reported in the literature based on different optimization objectives such as entropy bound minimization or negentropy maximization. Specifically, a novel complex-valued ICA algorithm by entropy-bound minimization algorithm (ICA-EBM) is presented in [12]. This algorithm uses a novel differential entropy estimator for the complex signals. The proposed entropy estimator is adopted with the noncircularity and the non-Gaussianity of sources. Furthermore, the ICA-EBM algorithm exploits multiple measuring functions during the signal separation so that the entropy for a wide class of distributions can be approximated. The experimental results reported in [12] show that the ICA-EBM algorithm achieves promising performance with comparable complexity. This ICA-EBM algorithm is applied in the IBFD system and extensive simulations have also conducted to comparing the performances between the FastICA, C-FastICA, and ICA-EBM algorithms. Figure 4 illustrates the OSINR between the real-valued FastICA algorithm, the complex-valued C-FastICA algorithm, and complex-valued ICA-EBM algorithm with different frame lengths. Furthermore, simulations results for HPR$_3$ = -20dB, HPR$_3$ = -50dB and HPR$_3$ = -100dB are also illustrated in this figure. It can be observed from the simulation results that the ICA-EBM algorithm achieves better OSINR than other ICA algorithms. This could mainly due to the fact that multiple cost functions are used for approximating different variations of statistical distributions.

Algorithms	FastICA	C-FastICA	ICA-EBM
preprocessing stage			
Addition	3.1×10^4	8.6×10^3	8.6×10^3
Multiplication	3.8×10^3	3.3×10^3	3.3×10^3
Division	24	14	14
Square Root	8	4	2
main processing stage			
Addition	3.2×10^5	1.3×10^5	3.1×10^5
Multiplication	3.3×10^5	1.3×10^5	3.0×10^5
Division	2.1×10^3	1.1×10^4	7.7×10^4
Square Root	3.6×10^2	1.1×10^4	5.4×10^2
Log	0	0	1.6×10^2

Fig. 5. Computational complexity for different ICA algorithms.

In addition, we analyze the computation complexity for different ICA algorithms including FastICA, C-FastICA, and ICA-EBM. Figure 5 compares the complexity of different ICA algorithms with preprocessing and main processing stages. It is noted that the complexity of ICA algorithms is higher than the complexity of LS algorithm since iterative matrices and vectors operations are involved in the ICA computations. As previous mentioned, the preprocessing stage include main steps of centering and whitening. Furthermore, the calculations of covariance matrix, the eigenvalue decomposition (EVD) and the computation of whitened signals are the primary parts in the whitening process where the EVD dominates the computational complexity at the entire preprocessing stage. In our evaluation, a Jacobi-based algorithm by using the COordinate Rotation DIgital Computer (CORDIC) operator is assumed for realizing the EVD process [14]. It can be seen from Fig. 5 the computational complexity for the real-valued ICA is higher than that of the complex-valued ICA. This is due to the fact that the dimension of the received matrix is extended in order for the real-valued ICA algorithm to be applied. This increases the complexity of vectors and matrices operations. In particular, it can be observed from Eq. (5) and Eq. (6) that the ICA algorithm in the real-value decomposed problem estimates the demixing matrix containing more rows with more elements in each row. In addition, it is noted that the FastICA algorithm uses more iterations to achieve the convergence than the C-FastICA algorithm. This more iterations along with the extended problem dimension makes the FastICA contain more scalar operations including addition, multiplication than the C-FastICA algorithm. On the other hand, the C-FastICA algorithm requires more division and square-root calculations than the FastICA algorithms due to the utilization of more complex cost functions. Since the realization of the division and square-root calculation in digital circuit is challenging, this could be a bottleneck from designing efficient VLSI circuit. Finally, the ICA-EBM algorithm leads to higher computational complexity since more calculations of the cnotrast functions are contained in this approach.

IV. The Performance and Complexity of the C-FastICA Algorithm

The main idea of the ICA algorithm is to find a demixing matrix by exploiting the statistical independence or non-Gaussianity of the variables. This demixing matrix is then utilized to separate the mixed signal and to recover the desired source signal. A typical ICA algorithm consists of steps including preprocessing, iteratively calculating each part in the demixing matrix, and decorrelating the outputs every each iteration. The general flowchart of the C-FastICA algorithm is shown in Fig.6 as an example. In particular, during the preprocessing stage, centering the received signal to be zero-mean and whitening the received signal are usually performed. The centering process aims to simplify the ICA algorithm by subtracting the observed signal vector from its mean vector, i.e., making a zero-mean vector. Furthermore, the whitening process results in a vector where the components are uncorrelated and with equal unity variances is obtained. In other words, the mixing matrix and demixing matrix are converted into orthogonal matrices through preprocessing. The whitening process can be conducted through the eigenvalue decomposition (EVD) of the covariance matrix of the received signal. The whitening process reduces the parameter to be estimated

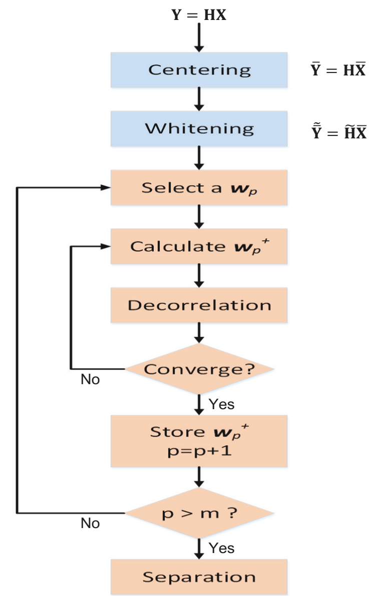

Fig. 6. The flowchart of the C-FastICA algorithm.

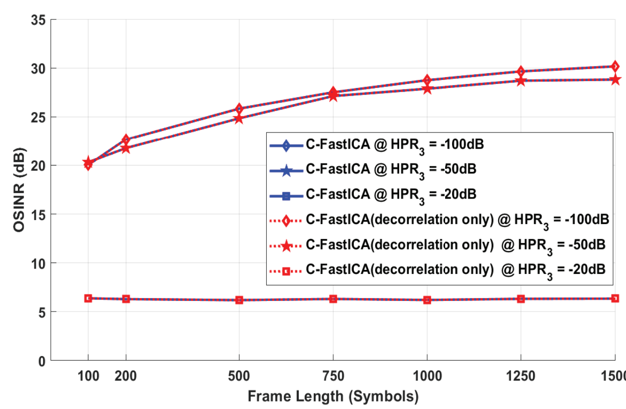

Fig. 7. The OSINR with different frame lengths for C-FastICA and C-FastICA without the update of the objective function.

during the ICA process and thus decreases the complexity. In other words, after the whitening, only parameters that are orthogonal need to be estimated. However, since the complex matrix operations are required, the whitening process usually incurs high complexity.

Moreover, the C-FastICA algorithm shown in Fig.6 calculates each row of the demixing matrix iteratively until the convergence. Each time after a new vector is computed, it needs to be decorrelated with the previous vector to avoid the convergence on the same signal. The deflation scheme based on Gram-Schmidt approach is usually used for calculating the decorrelated vector. Furthermore, the targeted vector is updated in each iteration based on the Newton iteration method and certain objective function. This chosen objective function is associated with the distribution of the source signal and usually incurs high computation complexity. This process is conducted several times until a convergence is achieved. To be

Algorithms	C-FastICA	C-FastICA (decorrelation only)
preprocessing stage		
Addition	8.6×10^3	8.6×10^3
Multiplication	3.3×10^3	3.3×10^3
Division	14	14
Square Root	4	4
main processing stage		
Addition	1.3×10^5	42
Multiplication	1.3×10^5	32
Division	1.1×10^4	16
Square Root	1.1×10^4	8
Log	0	0

Fig. 8. Computational complexity for different ICA algorithms.

specific, one of the unique properties of the considered system setup in this works is that one of the input to the ICA algorithm comes from the direct input of the transmit signal and is assumed to be known. Furthermore, due to the whitening of the received signal during the preprocessing stage, the matrix is converted into a whitening matrix which is an orthogonal matrix. Based on this orthogonal matrix with the partially known SI signals, the demixed SOI signals only need to be looked in the orthogonal direction. As a result, the iteratively updating the objective function can be omitted without sacrificing the accuracy of the generated unmixing matrix. In other words, only conducting the whitening and decorrelation steps in the ICA should be sufficient to separating the SOI from the mixed signals. This will much simplify the computational complexity of the ICA algorithm. So we can omit the iterative equation and only do decorrelation. In order to verify this, simulations are conducted and the results are shown in Fig. 7. It can be observed from the simulation results that the OSINR of the approach where only preprocessing and decorrelation are conducted is almost on top of the OSINR of the conventional C-FastICA algorithm.

Furthermore, Figure 8 compares the computation complexity between the C-FastICA algorithm and the simplified C-FastICA algorithm with preprocessing and decorrelation only. It can be seen from this figure that since the calculation of the updated objective function is avoided, the computation complexity can be greatly saved. Moreover, it is noted that the convergence speed is also mush shortened. Based on the experimental results shown in Fig.6 and 8, it can be concluded that based on the ICA approach with preprocessing and decorrelation only can achieve identical performance with much reduced complexity.

V. Conclusion

Extensive investigates have been conducted in this paper for the application of independent component analysis (ICA) approaches on the self-interference cancellation (SIC) problem in in-band full duplex systems. The detailed analyses for the capabilities of interference suppression and computational complexities of real-valued and complex-valued ICA algorithms are presented and discussed. We also show that a much simplified ICA algorithm that only conducts whitening and decorrelation steps are sufficient to separate the signal of interest from the mixed signals.

Acknowledgment

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