Blind Source Separation: A Novel Range Ambiguity Suppression Method in Multichannel SAR

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ABSTRACT

In this paper, we introduce a blind source separation (BSS) method as a novel approach to suppress range ambiguities in Synthetic Aperture Radar (SAR). The method is described and applied to a SAR image with simulated range ambiguity. Statistical analysis of the input image data is done to determine suitability of BSS implementation. The result is analyzed and there is a significant improvement in recovering the original image. The paper shows that the BSS method is promising enough to be further extended to more realistic range ambiguous SAR scenario.

Index Terms – Range Ambiguities, Blind Source Separation, Multiple Elevation Beams

1. INTRODUCTION

A major challenge in the implementation of High Resolution Wide Swath (HRWS) Synthetic Aperture Radar (SAR) is the suppression of the range ambiguities. It is due to tradeoff between the desired wide swath on one side and the high PRF required to avoid azimuth ambiguity on the other. Several approaches have been developed in the past years such as SCORE [1] [2], Azimuth Phase Coding [3] [4] , Staggered SAR [1] [5] [6] and shown to be useful to suppress or mitigate the effect of range ambiguities. The communality between these approaches is that they require *a priori* information about the topography [7] and are not scene-adaptive in the sense that they do not rely on measured backscatter statistics in eliminating range ambiguities. The complexity of getting accurate *a priori* information of topography motivates search of an alternative method that does not rely on information on topography.

Blind source separation (BSS) is a technique of separating mixed signals back to its original signal without knowing the characteristic of original signal and how they are mixed [8]. This motivates introducing a new technique that requires no information about the topography. To begin with, it has to be made sure that the problem of range ambiguity in multichannel SAR is similar to the problem of BSS. Next, it is important to investigate the statistics of the SAR image, because the method relies on the assumption that the source signals are non-Gaussian and independent from one another [9]. In reality, the measured backscattered signals will neither pure Gaussian nor pure non-Gaussian, different scene will also have different statistics, so the successful implementation in one scene might be not working in another scene. Hence, the thorough analysis the statistic in different domain (range compressed, focused) is needed, to propose where the BSS is best implemented.

This method will be performed *a posteriori* on-ground using multichannel Scan-on-Receive (SCORE) [1] [2] data as input. The approach followed here combines on-board SCORE with on-ground BSS [7]; this maintains efficiency of data transferred to the ground, while enabling more robust range ambiguity suppression because topography information is no longer required.

2. PROBLEM PHENOMENON

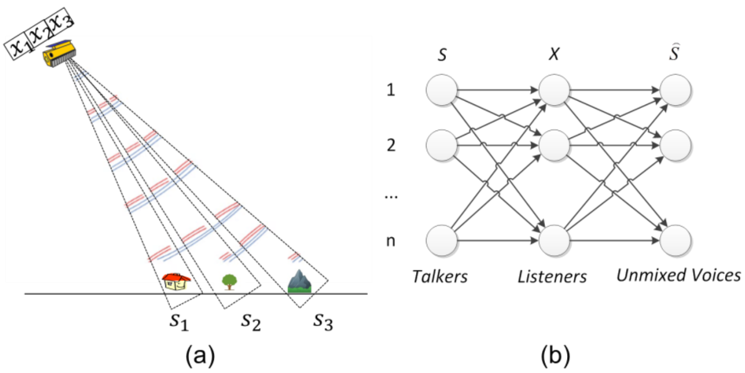

Fig. 1. (a) SAR Multiple Elevations Beams (b) Cocktail party problem where several listeners listen to several talkers that talk concurrently

Multiple elevations beams are created from multichannel SAR in order to obtain wider swath and maintain high resolution, known as HRWS, as illustrated in Fig. 1(a). The number of elevation beams is equivalent to the number of sub-swath illuminated. The range ambiguities will arise from backscatter signals that simultaneously come from

different sub-swaths; due to sidelobe, significant topography height difference, etc. and it will be added to the desired signal with a certain complex weighting. This phenomenon is similar to the cocktail party problem in Fig. 1(b), a classical example of BSS where a number of people talk simultaneously and a same number of microphones listen to the mixed voice. BSS is used to isolate the voice of single person.
The goal of BSS (separating mixed voice to obtain the desired one in cocktail party problem) is similar to removing range ambiguity by separating mixed backscatter from several areas and recovering only the desired signal. This can be written in equation (1).

$$X = AS \tag{1}$$

$$\begin{bmatrix} x_1(t) \\ \vdots \\ x_N(t) \end{bmatrix} = \begin{bmatrix} a_{11} & \cdots & a_{1n} \\ \vdots & \ddots & \vdots \\ a_{N1} & \cdots & a_{NN} \end{bmatrix} . \begin{bmatrix} s_1(t) \\ \vdots \\ s_N(t) \end{bmatrix}$$

Where $x_n(t)$ denotes (mixed) observed signals, a_{ij} is complex mixing factors, and $s_n(t)$ are original signals that contains no ambiguity.

$$\hat{S} = BX \tag{2}$$

The task is to recover the original signal, i.e. finding the unmixing matrix B as written in equation (2).

3. BLIND SOURCE SEPARATION – THE METHOD

Independent Component Analysis (ICA) is the most used technique in BSS that allows separation of original signal from complex mixture of signals based on 2 assumptions: the original signals need to be non-Gaussian and independent from each other. There are 3 processing steps of ICA as depicted in Fig. 2.

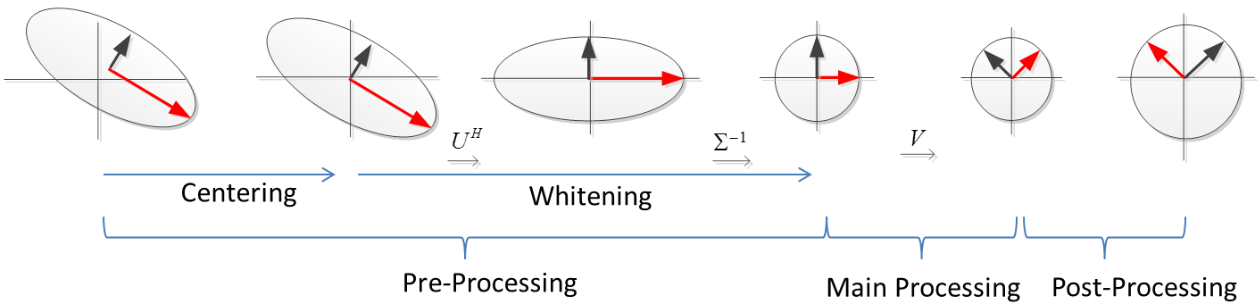

Fig. 2. The graphical illustration of full processing of ICA. Red and black arrow represent vector of the principal component of the joint distribution of the input data

3.1. Pre-Processing

Pre-processing consist of centering and whitening. Centering is a step to center the input by subtracting the mean of all signals. The main strategy of ICA is to decompose matrix B in equation (2) into smaller operations and solve it one by one. According to Singular Value Decomposition (SVD) [10], any matrix can be decomposed into smaller operations: a rotation U^H, a stretch along axis Σ^{-1}, and a second rotation V as shown in Fig. 2. It can be written that:

$$B = \mathrm{U}^H \Sigma^{-1} \mathrm{V} \tag{3}$$

Whitening consists of decorrelation and normalization. Decorrelation is a step to rotate the observed signals X to align the eigenvectors of the covariance matrix X along the cartesian basis by multiplying with a rotation matrix U^H, this step has familiar name: Principal Component Analysis (PCA). The eigenvectors of the covariance of X shows the principal components of X. Projecting X onto its principal components removes linear correlations and provides a strategy for dimensional reduction. Normalization is aimed to normalize the variance along all dimensions by multiplying by a scaling matrix Σ^{-1}. A more detailed explanation on how to obtain U^H and Σ^{-1} can be found in [9] [10].

3.2. Main Processing

After pre-processing, the degree of freedom is reduced from $(N^2 - 1)$ to $N(N-1)/2$ where N equals to the number of signals. Main processing is a step to find rotation matrix V that maximize the independence between the signals. From the central limit theorem, it can be derived that a sum of two independent random variables tends to be more Gaussian than the original. This implies that independence can be obtained by maximizing non-Gaussianity.
The algorithm used here is Joint Approximation Diagonalization of Eigen-matrices (JADE). This algorithm works by exploiting the 4th order moment (cumulant) of the signals where iterative process is used to find the rotation matrix V that diagonalize set of cumulant's eigenpairs; maximizes auto-cumulant and minimizes cross-cumulant eigen-matrices [11] [12].

3.3. Post-Processing

The post processing step is required to recover scaling and permutation uncertainties. Otherwise, equation (1) will not have unique solutions because there are 2 unknowns; A and S. In order to do that, in this case it is assumed that $\{a_{xx}|1 \leq x \leq N\} = 1$, this is supposedly a valid assumptions because a mixed signal is consist of an original signal and several ambiguity that have lower coefficient.

4. SIMULATION APPROACH AND STATISTICS EVALUATION OF INPUT DATA

In this section, a SAR image data with range ambiguity is simulated and their statistics are evaluated to know how independent and non-Gaussian the input data is. This is essential because the performance of the method is heavily affected by how good the requirements are fulfilled

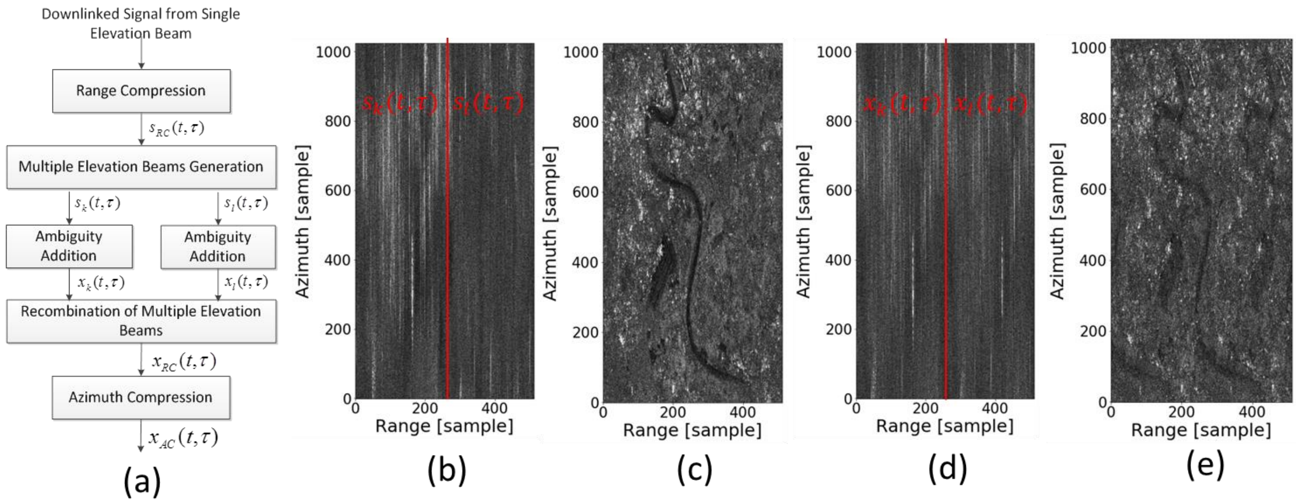

Fig. 3. (a) Range Ambiguity Simulation Design (b) Original Range Compressed (c) Original Focused (d) Normalized Ambiguous Range Compressed (e) Normalized Ambiguous Focused

As shown in Fig. 3(a), each range ambiguous (observed) signal in multichannel SAR is simulated as a weighted sum of the original signal and arbitrary weighted unwanted signals coming from different ranges as given in (4)

$$\begin{bmatrix} x_k(t,\tau) \\ x_l(t,\tau) \end{bmatrix} = \begin{bmatrix} w_{11} & w_{12} \\ w_{21} & w_{22} \end{bmatrix} \cdot \begin{bmatrix} s_k(t,\tau) \\ s_l(t,\tau) \end{bmatrix} \quad (4)$$

The original image is obtained from $N_{beam} = 2$ elevation beams: $s_k(t,\tau)$ and $s_l(t,\tau)$ where $0 \leq k < N/2$ and $N/2 \leq l < N$, N is range sample. The range ambiguity as implied in equation (4) is generated by circularly shifting the original range compressed image and multiplying by a weighted factor W; this is just an arbitrary number to show the existence of range ambiguity as shown in Fig. 3(d) and 3(e). In this simulation, $W = \begin{bmatrix} w_{11} & w_{12} \\ w_{21} & w_{22} \end{bmatrix} = \begin{bmatrix} 1 & 0.6+0.6j \\ 0.6+0.6j & 1 \end{bmatrix}$

Even though range ambiguity is introduced in the range compressed image, the statistical analysis will cover both range compressed and focused version of the range ambiguous image to explore where the method can be better implemented. Independence is measured by examining the joint probability density functions (pdf) of the original signals. The independent signals, either Gaussian or non-Gaussian, will have symmetric distribution, while dependent signals have skewed distribution, as shown in the reference column Fig. 4. The range compressed and original signals evaluated as shown in Fig. 4 takes a signal from range $k = 50$ and $l = 306$ that is mixed and becomes range ambiguity to one another.

While independence can be determined from joint pdf, the gaussianity needs to be further investigated by measuring the excess kurtosis [13]. Excess kurtosis for Gaussian signal is 0 and beyond that value is considered non-Gaussian (super-Gaussian or sub-Gaussian). As shown in Fig. 5, kurtosis of original signals vary highly along the swath; some ranges are extremely non-Gaussian, some ranges tend to be Gaussian. This condition creates performance gaps for the method. Besides that, according to Fig. 4, the original signals are not completely symmetric (independence). Therefore, it is a quite challenging condition even though in general the independence and non-Gaussianity requirements are relatively fulfilled.

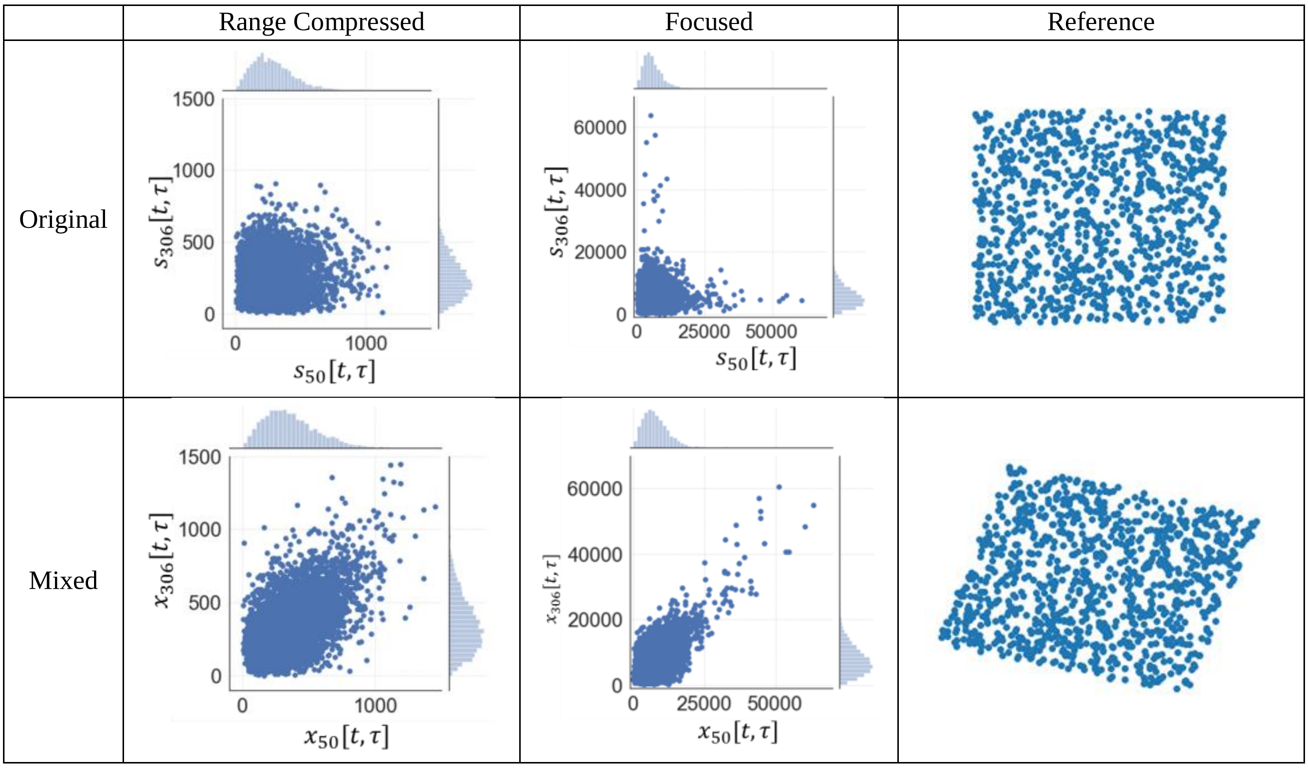

Fig. 4. Joint probability density (pdf) function of 2 signals in range 50 and 306

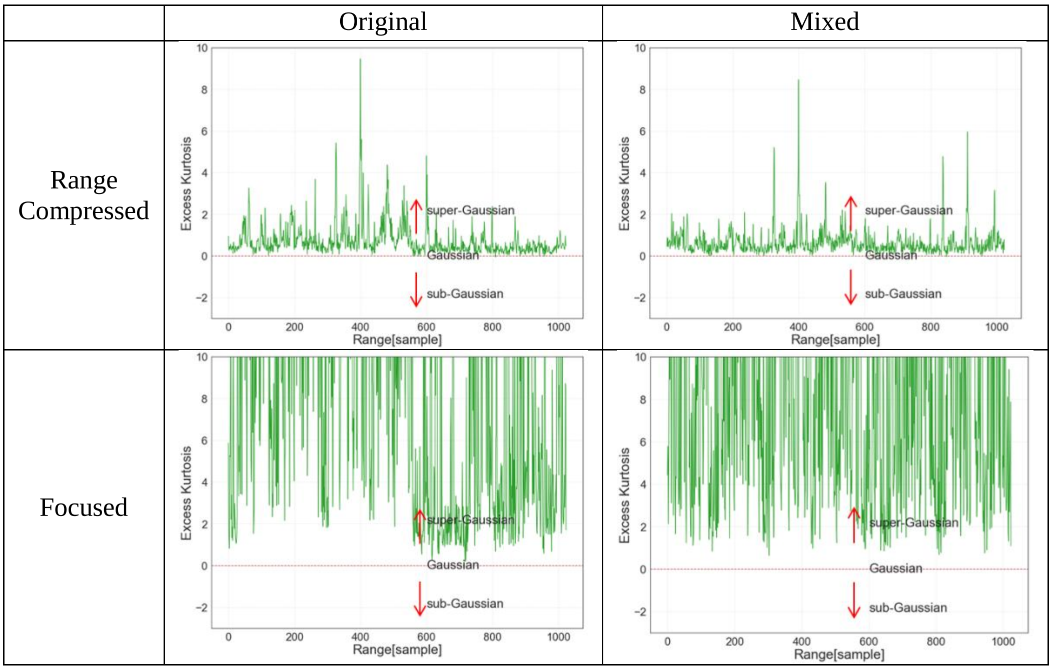

Fig. 5. Kurtosis of SAR Image

5. RESULT AND DISCUSSION

The method is applied to the range compressed and focused image as shown in Fig. 6(a). The Mean Square Error (MSE) and Range-Ambiguity-to-Signal Ratio (RASR) are evaluated as shown in Fig. 6(b)-(e) and shows good performance in both range compressed and focused image. BSS has better performance in the focused image compare to the range compressed image, this due to the non-Gaussianity that is higher in focused image rather than range compressed image. However, in some ranges, the method is not performing well because as discussed in previous section, the independence and non-Gaussianity requirement is not ideally fulfilled.

The performance is also worse in this condition; the original signal is only slightly non-Gaussian while the range ambiguities are highly non-Gaussian and the magnitude of range ambiguities is high enough compare to the original signal. In that condition, the general rule (derived from the central limit theorem explained in section 3) where the range ambiguous signal is more Gaussian than the original signal is no longer true. Thus, the method will falsely detect the range ambiguity as the original one and vice versa

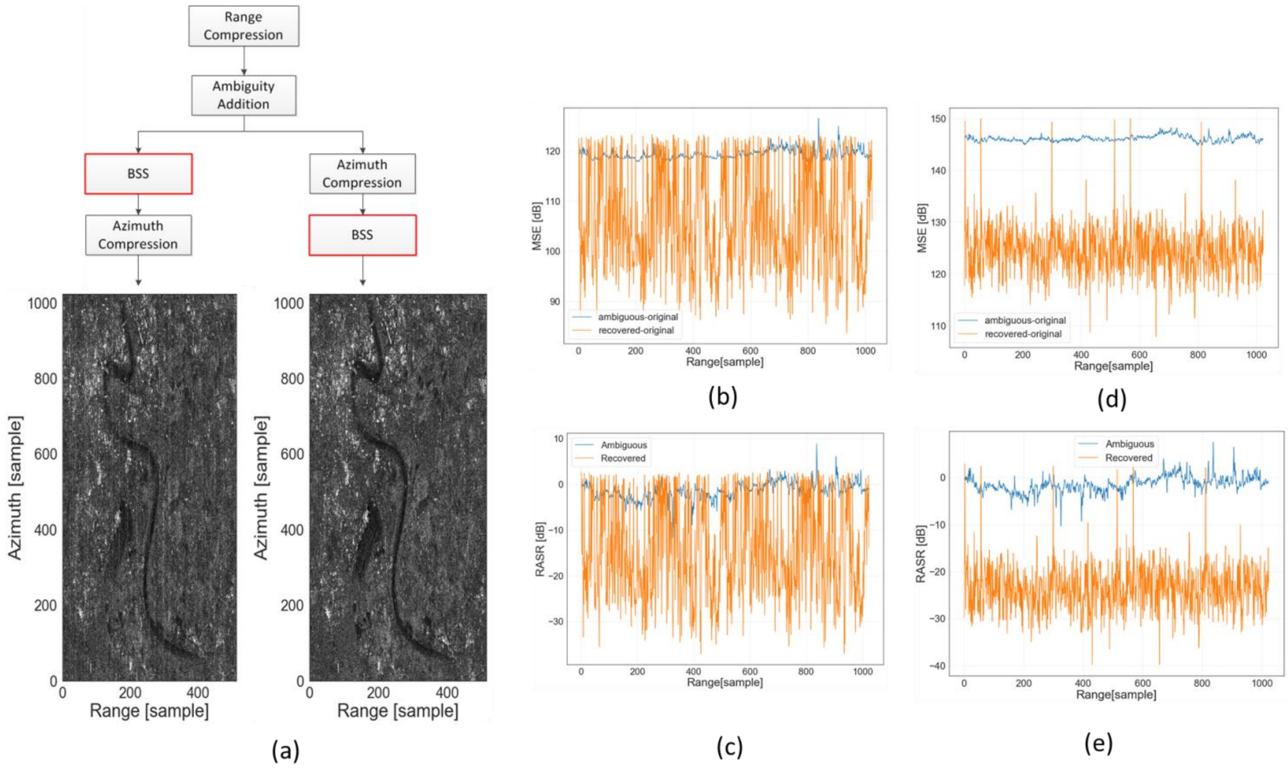

Fig. 6: BSS implemented in different domain (a) left: range compressed, right: focused image. Evaluation of MSE in (b) range compressed and (d) focused image. Evaluation of RASR in (c) range compressed and (e) focused image

6. SUMMARY AND FUTURE WORKS

As of now, according to the statistics and early result presented, the method seems promising enough to be further extended to a more realistic scenario. However, this works is still not complete as it doesn't take into account the noise, range cell migration effect, and contains only two elevation beams. It also becomes more complicated when considering range ambiguity that is extended in azimuth [7]. In the future, those considerations will take into account and will be presented in follow on paper.

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