A Novel Method for Sparse Array Antenna Through-the-wall Imaging Radar Wall Clutter Elimination Using Independent Component Analysis

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Abstract— A wall clutter elimination method for the through-the-wall imaging radar (TWIR) with sparse array antenna is presented in this paper. Unlike the synthetic aperture radar (SAR) processing techniques, we scan the elements of the array periodically to create a range profile (RP) matrix for each transmit/receive antenna pair. Then, based on analysis of the weak fluctuation among RP signals, we apply independent component analysis (ICA) on each RP matrix to decompose the signal components and remove the wall clutter. The experimental results show that the proposed method can separate targets and wall clutter components, and improve the signal-to-clutter ratio (SCR) of final image effectively.

1. INTRODUCTION

Through-the-wall imaging radar (TWIR) emits electromagnetic waves to image and localise objects or people behind walls, which can assist actions in many area such as military, antiterrorism and rescues [1]. However, the serious interference caused by the reflections from walls is the main difficulty against revealing a scene [2]. To mitigate the wall clutter, a direct approach is to subtract the background from the measured data. But sometimes the empty room data is unavailable in the real scenarios. The statistical techniques like singular value decomposition (SVD) and principal component analysis (PCA) can project the echo into targets and clutters subspaces and abandon the latter according to the magnitude of the singular value or eigenvalue without other priori information [3, 4]. However, when the reflections of targets are weak, the characteristic of targets subspace is unobvious. In contrast, based on the hypothesis that the observed signal is a linear combination of independent components, i.e., source signals which are statistically independent from each other, the independent component analysis (ICA) algorithm can separate target signals and clutters more effectively.

ICA method has been reported to process a B-scan matrix which is formed through the movement of monostatic radar alone the crossrange in synthetic aperture radar (SAR) imaging approach [3, 4]. While the single-output multiple-input or multiple-input multiple-output processing techniques are suitable for multistatic system using an array antenna. In this case, a B-scan-like two-dimensional matrix can be formed by scanning the elements of the array one antenna pair at a time [5]. But sometimes, the sparsity of array elements limits the number of range profiles (RP), i.e., observed signals obtained in one single scanning. This will hinder the effectiveness of ICA method. To overcome the issue, a multiple scanning based ICA method is proposed based on the analysis of the weak fluctuation among RP signals in different periods, which implements multiple scanning of the array antenna, then applies ICA to a RP matrix for each transmit/receive antenna pair and remove the wall clutter components.

The formation of RP is briefly introduced in Section 2, as well as ICA model. Then the multiple scanning based ICA method for sparse array antenna is discussed in Section 3. To examine the feasibility of the proposed method, a four-element fixed array antenna is employed to detect two trihedrals in a room in Section 4 The experimental results show that the proposed method can separate target and wall clutter components effectively. The signal-to-clutter ratio (SCR) is promoted in final image after removing the wall clutter components.

2. SIGNAL REPRESENTATION

For a one-dimensional fixed array, RP is obtained for each antenna pair by scanning the elements of array. The wideband signal waveform is synthesized by stepped-frequency continuous wave (SFCW) with a finite number K of frequency points, be denoted as $f_k = f_0 + (k-1)\,\Delta f$, $k = 0, 1, \ldots, K-1$, where f_0 denotes the start frequency and Δf represents the frequency step size. Inverse discrete

Fourier transform is implemented to generate the time-domain signal given by

$$r_n^l = \sum_{k=0}^{N-1} u_k^l \exp\left(j\frac{2\pi n}{N}k\right), \quad 0 \leq n \leq N-1 \tag{1}$$

where u_k^l is the frequency-domain data at f_k, n denotes the range cell index. Let $\mathbf{R}^l = [r_0^l, r_1^l, \ldots, r_{N-1}^l]$ represents the RP in the field of view of lth antenna pair in matrix notation, $l \in \{1, 2, \ldots, L\}$.

In [3], a few statistical techniques for wall clutter elimination are reported based on monostatic system using SAR imaging approach. Among them, the ICA algorithm is attractive due to its relatively good signal decomposition performance. ICA models the observed signal as a linear combination of independent source signals as follows [6]

$$\mathbf{X} = \mathbf{AS} \tag{2}$$

here $\mathbf{X} = [x_1, x_2, \ldots, x_M]^T$ is the observed signals matrix in rows of N samples, $\mathbf{A}$ denotes a $M \times P$ constant mixing matrix which has full column rank, and $\mathbf{S} = [s_1, s_2, \ldots, s_P]^T$ is the matrix of independent source signals. Both $\mathbf{A}$ and $\mathbf{S}$ are unknown. The task of ICA is to determine a full rank separating matrix $\mathbf{W}$ to estimate the source signals as

$$\mathbf{S} = \mathbf{WX} \tag{3}$$

In SAR mode, the observed signal represents the RP obtained at antenna position m. Then $\mathbf{X}$ is equivalent to the so called B-scan matrix.

3. MULTIPLE SCANNING BASED ICA

Naturally, a similar representation of observed signal can be introduced into the multistatic system with array antenna, but here$m$ denotes the transmit/receive antenna pair index, i.e., l. For an array antenna with Q elements where all of the antennas are used to both transmit and receive, one can obtain $L = Q \times (Q-1)$ combinations of antenna pair at most. If the element is sparsely distributed, which means that Q is small, the number of observed signals M will be limited. On the other hand, from Equations (2), (3) and properties of rank of matrix, the following relationship can be derived

$$\min(M, N) \geq rank(X) = rank(S) = P \tag{4}$$

Usually the number of discrete sample points is greater than the antenna pair index. So, this is equivalent to $M \geq P$. That means ICA needs more (at least equal) observed signals than the latent sources to make the estimation feasible. Consider the large amount of latent sources in real senarios, the condition may not be satisfied.

To overcome this issue, we scan the array antenna periodically and observe the RP obtained in every scanning. Let $\mathbf{R}_m^l$ represents the RP obtained in mth scanning of lth antenna pair, which is shown in Figure 1. Ideally, if the target is stationary, $\mathbf{R}_m^l$ will not change with m. However, in practice, the RP exists weak fluctuation due to issues involving multipath, slight change of enviroment, and unstability of TWIR system. Figure 2 shows the mean removal magnitde samples of $\mathbf{R}_m^l$ at different range cells n in 50 scanning.

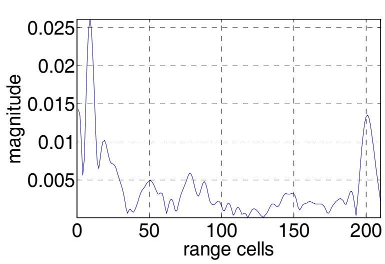

Figure 1: The RP of one antenna pair.

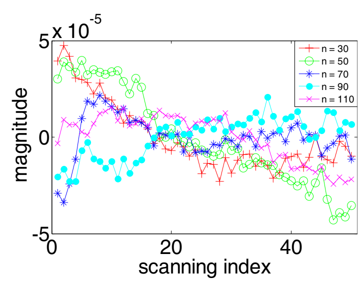

Figure 2: The fluctuation of RP in practical.

As seen, $\mathbf{R}_m^l$ always has a random variation (about 0.1% of the mean) at different range cells with m. So $\mathbf{R}_m^l$ can be used as the observed signal and rewrite the ICA model as follows

$$\mathbf{x}_m^l = \sum_{p=1}^{P} a_{m,p}^l \mathbf{s}_p^l \tag{5}$$

here m denotes the scanning index, $\mathbf{x}_m^l$ represents $\mathbf{R}_m^l$, $\mathbf{s}_p^l$ is the pth source signal of the lth antenna pair, and $a_{m,p}^l$is the corresponding mixing coefficient which also relates to l. This means we apply ICA to a RP matrix, $\mathbf{X}^l = \left[\mathbf{R}_1^l, \mathbf{R}_2^l, \ldots, \mathbf{R}_M^l\right]^T$, for each antenna pair l individually, $l = 1, 2, \ldots, L$. In this way, the lack of observed signals can be overcomed by implementing multiple scanning of the array antenna such that the condition $M \geq P$is satisfied. After decomposition, the wall clutter related signal components which are parts of terms in the sum on the left side of (5) can be removed. The sum of remaining components that contain target information is keeped, which is denoted as $\mathbf{x}_{tar,m}^l$. After $\mathbf{x}_{tar,m}^l$ is obtained for every antenna pair, a two-dimensional matrix represented by $\mathbf{B}_m = \left[\mathbf{x}_{tar,m}^1, \mathbf{x}_{tar,m}^2, \ldots, \mathbf{x}_{tar,m}^L\right]$ is formed for beamforming.

4. EXPERIMENTAL RESULTS

To examine the feasibility of the multiple scanning based ICA approach, experimental data is collected with a four-element Vivaldi array antenna placed parallel to the wall, as shown in Figure 3. The array is 3 m long with an inter-element spacing of 1m and located at a distance of 6.6 m from the exterior wall at the height of 1 m. A 3.2 m × 7 m room surrounded by brick wall with 0.35 m thickness is used for imaging. Two trihedrals of different size are located at same height as that of the array. The one of size 30 cm is located at (−1.4 m, 8.7 m), the other of size 20 cm is located at (1.2 m, 8.1 m). The middle of array is defined as coordinate origin. Wideband signal waveform is synthesized by SFCW which starts from 317 MHz and ends at 1815MHz with steps of size 2 MHz.

First of all, the empty room data is collected which is used as background. Then, the scene is scanned 50 times with the array in the presence of targets such that a 50 × 200 RP (the part of RP outside the imaging field is truncated) matrix, $\mathbf{X}^l$, is formed for each antenna pair. The ICA algorithm is applied to each $\mathbf{X}^l$. Take the 9th pair (antenna 3 transmits, antenna 4 receives) as an example, Figure 4 shows parts of the signal components of $\mathbf{x}_{25}^9$ after decomposition. The background-subtracted RP is indicated by the magenta lines marked with asterisk in Figures 4(b), (c). Notice that the first two peaks which represent trihedral 2 and 1 coinside with component 2 and 3 (the solide blue lines) respectively. Besides, reflections of the exterior and interior walls contribute to component 1 and 4 respectively. This can be verified by observing original RP of the 9th antenna pair which has been shown in Figure 1. The wall clutter related components like component 1 and 4 can be removed according to their peak position.

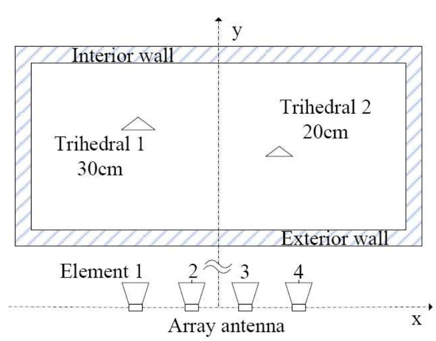

Figure 3: The experimental scene.

As raised above, a two-dimensional matrix represented by $\mathbf{B}_{25}$ is formed for beamforming. Here, the backprojection (BP) algorithm is implemented. Figure 5(a) shows the original BP image without clutter elimination. The heavy wall reflection makes the targets totally invisible. In contrast, using the proposed method, wall clutters are eliminated efficiently and two targets can be observed in Figure 5(b). As mentioned at the beginning of Section 3, we also use the RP of every antenna pair collected in one scanning to form a 12×200 B-scan-like matrix. Then implement ICA

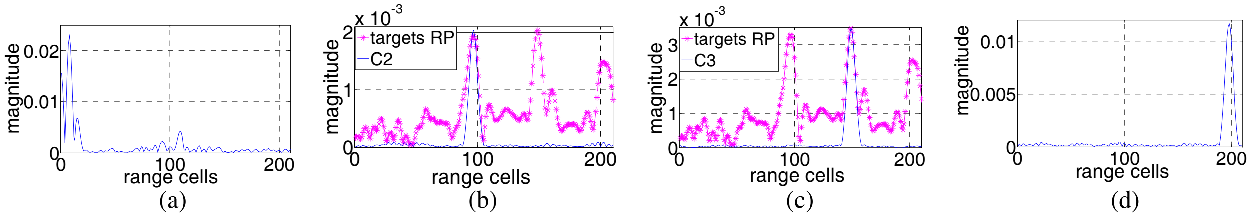

Figure 4: Parts of signal components of observed signal. (a) Component 1. (b) Component 2 (C2). (c) Component 3 (C3). (d) Component 4.

to decompose it and remove the wall clutter related portion. However, as shown in Figure 5(c), the target portion is still invisible in the final beamforming result. The performance of different methods is further compared by calculating the SCR of BP images as follows [7]

$$SCR = N_2 \sum_{(i,j)\in\{A_1,A_2\}} \|I_{ij}\| \Big/ N_1 \sum_{(i,j)\in A_3} \|I_{ij}\| - 1 \tag{6}$$

where N_1 is the number of pixels defining two $0.5\,\mathrm{m} \times 0.3\,\mathrm{m}$ rectangular areas A_1, A_2 around the targets, N_2 is the number of pixels of the entire image area A_3, $\|I_{ij}\|$ denotes the intensity of pixels in corresponding area. It is observed that the BP image processed by multiple scanning based ICA has better SCR performance, as shown in Table 1. However, as shown in Figure 5(b), there are still some ghost targets due to the multipath effects in the scenario.

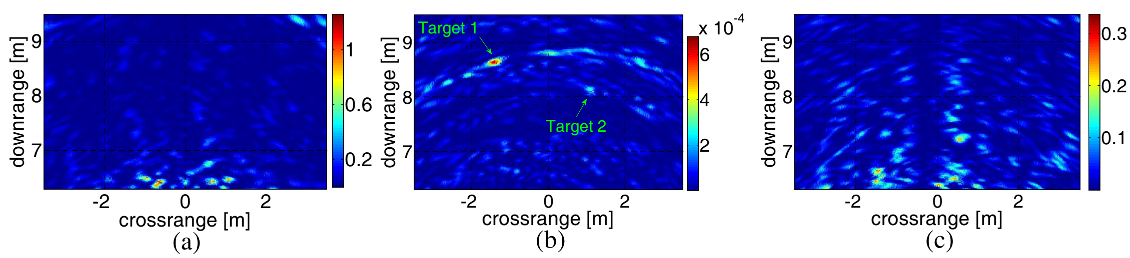

Figure 5: BP image. (a) Original image. (b) Multiple scanning based ICA. (c) Single scanning based ICA.

Table 1: SCR of different BP images.

	Original image	Multiple scanning based ICA	Single scanning based ICA
SCR	0.304	1.93	0.871

5. CONCLUSION

In this paper, we propose a multiple scanning based ICA method for TWIR wall clutter elimination. It can overcome the issue associated with the lack of observed signals for system with sparse array antenna. Experimental results show that the proposed method can separate target and wall clutter components effectively, and the SCR is promoted after removing the latter in final imaging result. Further, the multipath propagation effects should be studied to remove ghost targets in the image.

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