Clutter Suppression in Synthetic Aperture Radar Targets using the DFRFT and Subspace Methods with Rank Reduction

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***Abstract*—SAR based vibration estimation using discrete Fractional Fourier transform (DFRFT) analysis methods has gained attention in recent work on vibrometry. In the presence of significant clutter however, this estimation becomes challenging due to the presence of clutter induced peaks in the vibration spectra. In this paper, we incorporate rank reduction and filtering into a subspace DFRFT approach that results in significant peak enhancement along with an accompanying reduction in the associated mean square estimation errors when applied to simulated SAR and synthetic chirp data. The approach is further applied to vibration data gathered from a real GA-Lynx system and shown to produce a corresponding peak enhancement and clutter suppression in the vibration spectrum.**

***Index Terms*— synthetic aperture radar, discrete fractional Fourier transform, micro-Doppler effect, vibration estimation, clutter suppression, subspace methods, rank-reduction.**

I. Introduction

In recent years, the DFRFT [7], [8], [9], [6] has become a useful time-frequency tool for multiple chirp parameter estimatiolin [5] and in particular it has been successfully applied to the problem of vibration estimation using SAR [2], [3], [4]. Direct DFRFT based estimation of the vibration frequency involves application of the DFRFT to the target return signal, peak coordinate location and translation of the peak coordinates to center-frequency and chirp-rate estimates using the peak-to-parameter mapping. This direct approach works well when the SNR is high and the SCR is high and above 15 dB. However in the presence of significant clutter produced from reflections of surrounding objects, accurate location of the peak becomes difficult due to the presence of clutter-induced side-lobes in the DFRFT spectra.

Prior application of subspace methods for estimation of vibrations using SAR and the DFRFT approach [5] involved the use of the cross-hair approach, where the a cross-hair is placed on the location of the DFRFT peak. The vertical and horizontal slices are frequency variables and are transformed into time-domain quantities using the inverse DFT. The transformed slices are used as the input to the various subspace methods via an eigenvalue decomposition of the underlying correlation matrices decomposed into 3 parts for convenience:

$$\mathbf{R}^{cf} = \mathbf{V}_s^{cf}\mathbf{\Lambda}_s^{cf}{\mathbf{V}_s^{cf}}^H + \mathbf{V}_n^{cf}\mathbf{\Lambda}_n^{cf}{\mathbf{V}_n^{cf}}^H + \mathbf{V}_c^{cf}\mathbf{\Lambda}_c^{cf}{\mathbf{V}_c^{cf}}^H$$

$$\mathbf{R}^{cr} = \mathbf{V}_s^{cr}\mathbf{\Lambda}_s^{cr}{\mathbf{V}_s^{cr}}^H + \mathbf{V}_n^{cr}\mathbf{\Lambda}_n^{cr}{\mathbf{V}_n^{cr}}^H + \mathbf{V}_c^{cr}\mathbf{\Lambda}_c^{cr}{\mathbf{V}_c^{cr}}^H$$

where the subscripts s, c, n are used to indicate the signal, clutter, and noise subspaces. Signal subspace approaches use the information from $\mathbf{V}_s$, whereas noise subspace approaches use the information from $\mathbf{V}_n$.

Ideally if the peak in the DFRFT spectrum corresponding to a single chirp had been a delta function, then the subspace signals would be sinusoidal. However, the fact that we only have approximations of G-H functions in the form of DFT eigenvectors, these will deviate from sinusoidal signals as depicted in Fig. (1). Prior work in [2], [3] did not incorporate rank-reduction and filtering of the subspace signals to remove clutter that manifests as high-frequency noise in the center-frequency and chirp-rate slices. Rank reduction employs correlation matrices that retain just the signal or noise subspace, thereby rejecting noise and clutter prevalent in the other subspaces [1].

II. Application to Synthetic Data

To justify the anticipated improvement in vibration estimation, we first apply the filtering and rank reduction combination to synthetic SAR data [3][4]. Simple binomial smoothing is applied on the subspace slices to remove clutter and noise present in the form of high-frequency fluctuations. Rank reduction is subsequently incorporated into several subspace approaches such as MUSIC, min-norm, eigenvector, principle components Blackman-Tukey (PC-BT) methods [1].

The rank-reduced correlation matrices exhibit better conditioning and result in sharper peaks in the corresponding pseudo-spectra as indicated in Fig. 2. Simulations results indicate that signal subspace methods result are more robust to the addition of clutter than the noise subspace methods. Specifically in the case of the min-norm method we actually observe that before rank reduction the chirp-rate peaks are barely visible as depicted in Fig. 2(c,d). While there is peak

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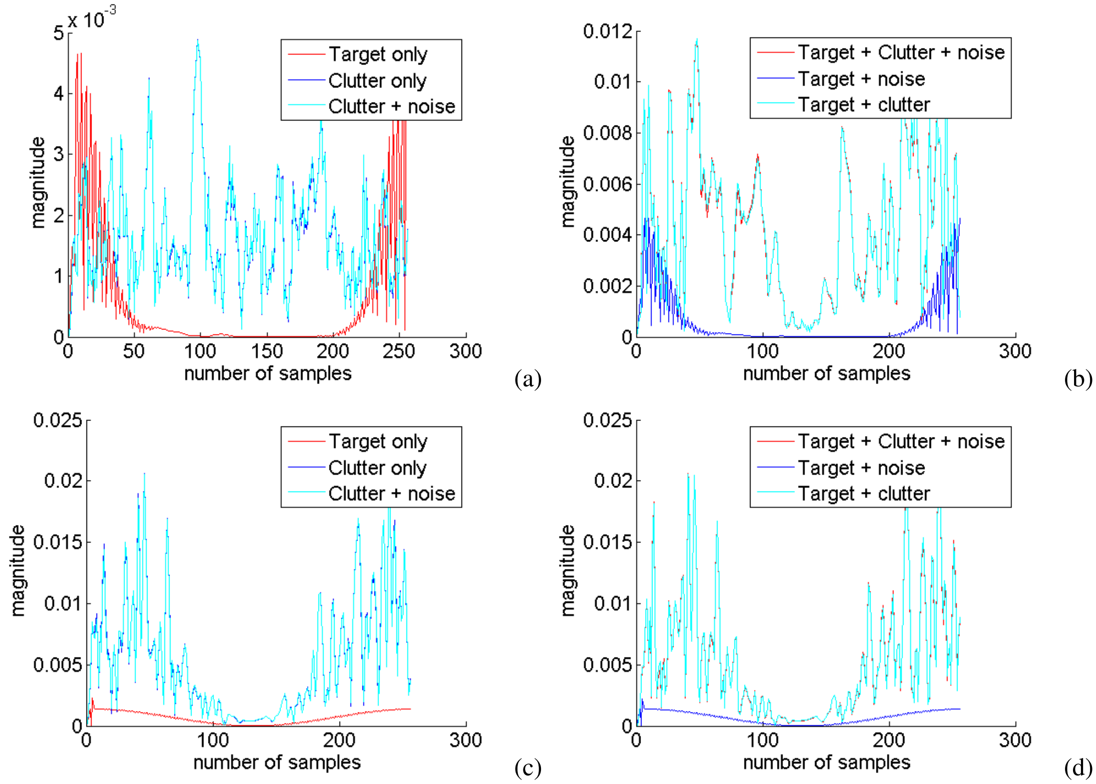

Fig. 1: DFRFT center-frequency (a,b) and chirp-rate (c,d) slices for a synthetic chirp depicting waveforms with clutter manifesting as high-frequency noise. Simple binomial smoothing of these slices reduces the effects of clutter and noise in the signal.

enhancement seen in the pseudo-spectra for the EVEC method in Fig. 2(e,f), the improvement in terms of peak enhancement is the most pronounced in the case of the PC-BT method as described in Fig. 2(g,h).

III. Application to Synthetic Chirp Signals

Figure 3(a,b) are the MSE's of the PC-BT approach before and after the application of the filtering and rank reduction combination on noisy synthetic chirps in the presence of clutter after averaging over 100 experiments. The simulated clutter is assumed to have a Gamma distribution with a signal to clutter ratio of 5 dB. They depict a significant reduction in the clutter after the application of the filtering and rank reduction combination. A similar improvement in the MSE of around 15 dB is observed with the min-norm method after application of the filtering rank reduction combination as depicted in Figure 3(c,d). Figure 3(e,f) further depict a minimum SCR threshold of -10 dB to -12 dB for the filtering rank reduction to effect a reduction in the center-frequency and chirp-rate MSE's.

This improvement is consistent with the peak enhancement seen with synthetic SAR data depicted in the previous section. Upon demonstrating that we obtain an improvement in the MSE performance with the filtering rank reduction combination on synthetic signals, we can now proceed to claim that a similar improvement in performance is anticipated with real data, since we are decomposing each frame of the target return signal into multicomponent chirps using the DFRFT.

IV. GA-Lynx SAR Data

In this section, we apply the filtering rank reduction combination to real SAR data obtained from a GA-Lynx system operating at a carrier frequency of 15.7 GHz imaging a target that is vibrating at frequency of 2.5 Hz [12]

Lynx is a high resolution, synthetic aperture radar (SAR) with a slant range of 30 km (in 4 mm/hr rain) operating in the Ku band within range 15.2 GHz to 18.2 GHz, and capable of 0.1 m resolution in spotlight mode [12]. The Lynx SAR was designed for operation on a wide variety of manned and unmanned aircraft, i.e., Predator, I-GNAT, and Prowler II platforms.

In Spotlight Mode, the coordinates of a point on the ground can be specified and the SAR dwells on that point until the imagery geometry is exceeded. This mode allows for finer resolution, in addition to its auto-zooming features for accurate image formation. Image formation is accomplished by stretch processing, i.e, de-ramping the received chirp prior to sampling. The motion measurements are received from an Inertial Measurement system mounted on the back of the antenna augmented by carrier-phase GPS measurements and a combined Kalman filter to accurately estimate position and velocity information. Transmitted waveform parameters are adjusted, as well as pulse timing, to optimally collect data

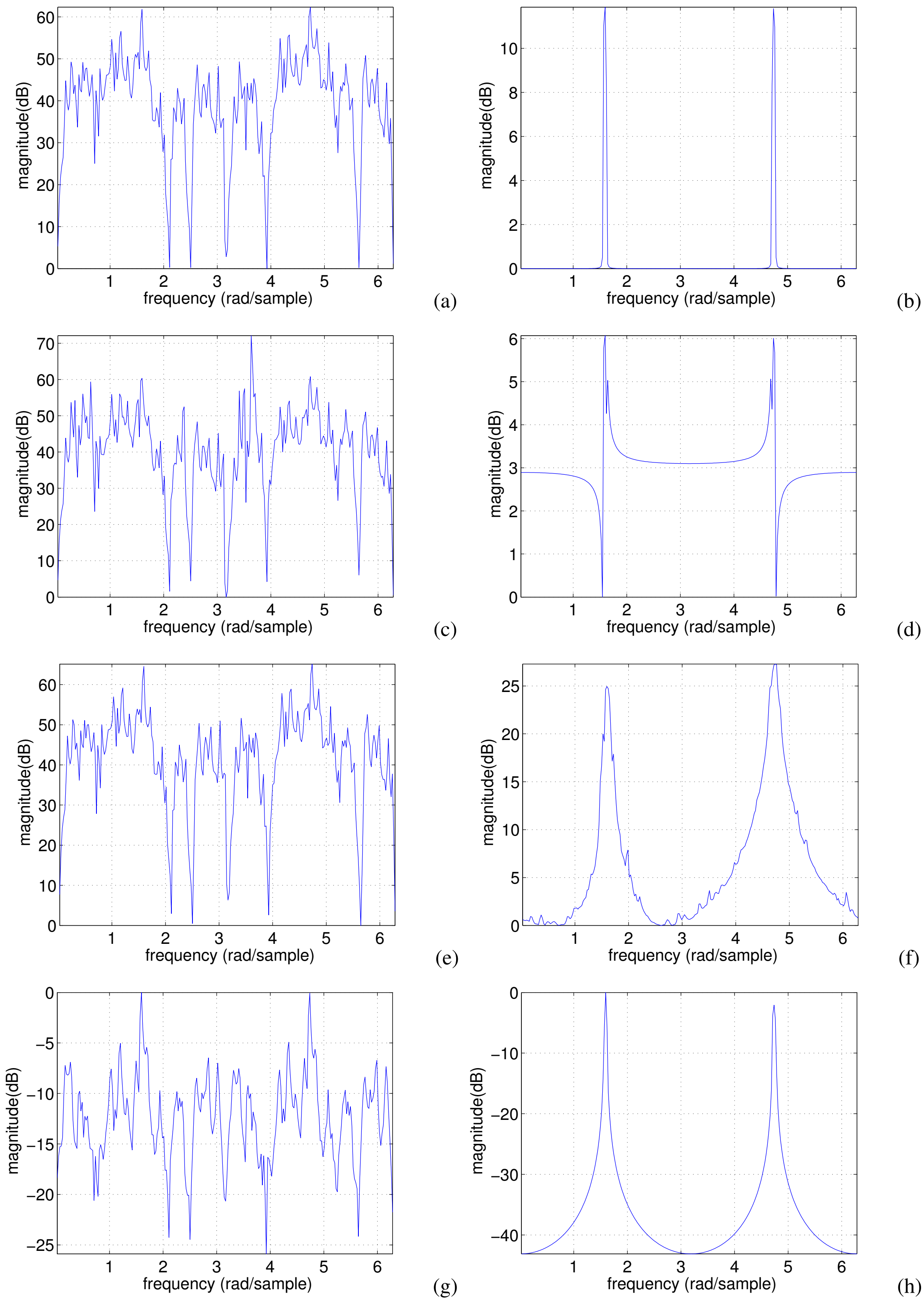

Fig. 2: Synthetic chirp results: (a,b) pseudo-spectra for MUSIC before and after filtering and rank-reduction, (c,d) pseudo-spectra for min-norm before and after filtering and rank-reduction, (e,f) pseudo-spectra for EVEC before and after rank-reduction, (g,h) PC-BT before and after rank reduction.

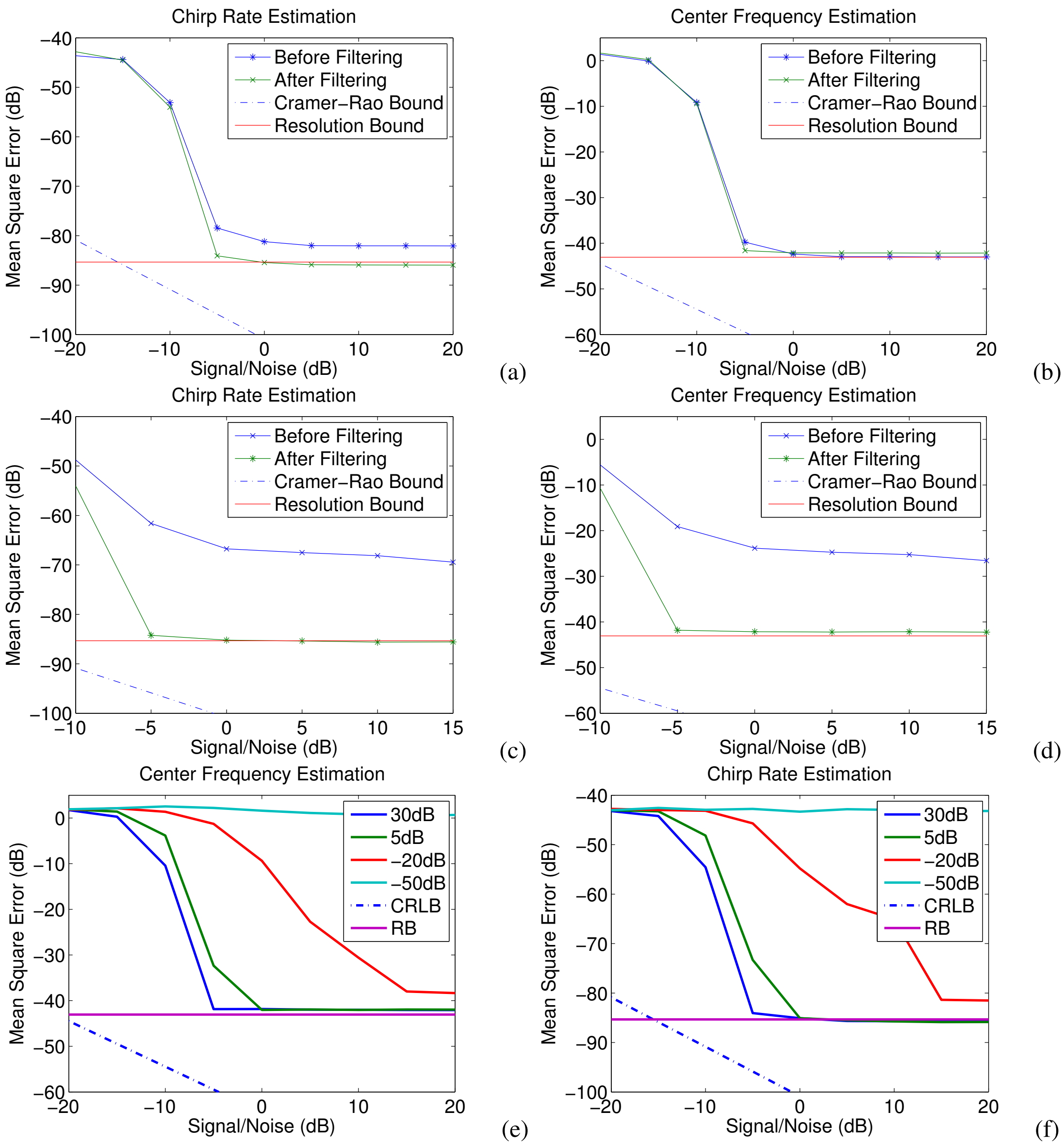

Fig. 3: MSE performance before and after rank reduction and filtering for a SCR of 5 dB obtained by averaging over 100 experiments: (a,b) MSE of the estimates of the PC-BT approach, 3(c,d) MSE of the estimates of the min-norm approach, 3(e,f) MSE for different clutter levels for the PC-BT approach.The combination of binomial smoothing and rank reduction produces an improvement of around 15 dB on average for the minimum norm method with both parameters. The filtering rank reduction combination also produces a reduction in the MSE for the PC-BT method which is clearly more robust in the presence of clutter. A SCR threshold in the vicinity of -12 dB is needed for the filtering rank reduction combination to produce a reduction in the MSE with the PC-BT method.

on the desired space-frequency grid prior to digital sampling and minimizing the need for subsequent data interpolation. During image formation, residual spatially variant phase errors are compensated as spatial coordinates becomes available and errors due to unsensed motion are mitigated by an autofocus operation.

Clutter manifests as noise in the acceleration estimates and as significant side-lobes in the vibration spectra. Incorporating filtering and rank reduction significantly reduces the effects of noise and clutter and produces enhanced peaks in the vibration spectra in comparison to direct application of the DFRFT as depicted in Fig. 4 and Fig. 5. Furthermore we are able to see that signal subspace approaches such as the PC-BT approach are more robust to the addition of clutter than noise subspace approaches such as the min-norm method.

V. Conclusion

With the results achieved from both the simulated data as well as real SAR data, it was demonstrated that the DFRFT method for estimating vibrations using subspace techniques can be augmented with filtering of the subspace signals and

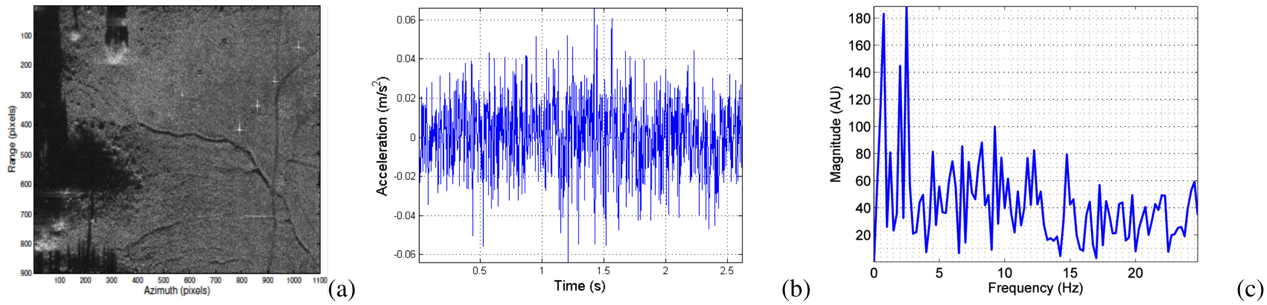

Fig. 4: Direct DFRFT estimates from real data: (a) SAR image used in the experiment, (b) acceleration estimates for SNR of 30 dB and SCR of 5 dB that are considerably noisy and (c) corresponding vibration spectrum depicting a peak at 2.5 Hz corresponding to the vibration frequency in the presence of significant clutter manifested in the form of sidelobes.

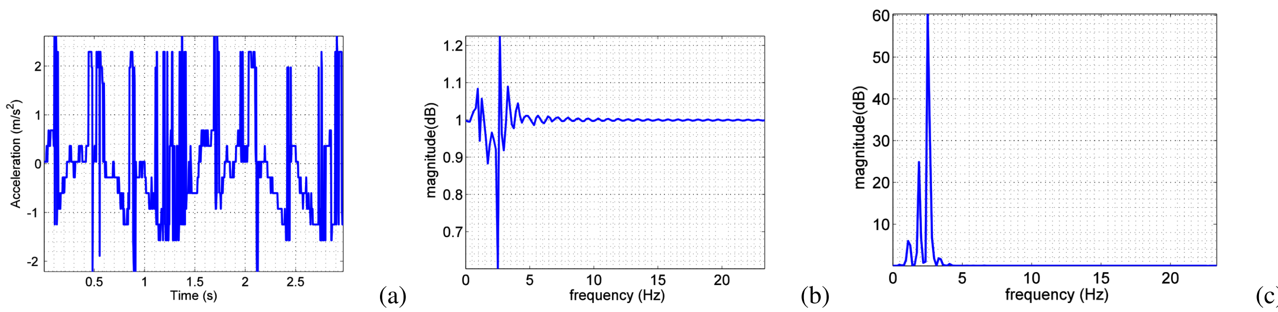

Fig. 5: Subspace estimates incorporating rank reduction on real data: (a) acceleration estimates for SNR = 30 dB and SCR = 5 dB, depicting a clearer picture and (b) vibration spectra for the min-norm method, depicting a sharp null at 2.5 Hz that still incorporates a lot of clutter in the form of sidelobes and (c) the principle component Blackman-Tukey (PC-BT) method, depicting a significantly sharper peak at 2.5 Hz and reduced clutter. Signal subspace methods such as the PC-BT enable more clutter suppression via rank reduction than noise subspace methods such as the min-norm approach.

rank reduction to effectively combat the presence of clutter in the target return signal. The filtering and rank reduction combination when applied to synthetic SAR data and chirp signals was shown to produce significant peak enhancement and an associated 15 dB reduction in the MSE. The augmented subspace DFRFT method when further applied to real SAR data from a GA-Lynx system was shown to accurately estimate the acceleration and vibration spectra even in the presence of significant clutter. The filtering rank reduction combination was also shown to produce a corresponding reduction in the SCR threshold needed to attain a specified performance.

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