RADIO-FREQUENCY INTERFERENCE SEPARATION AND SUPPRESSION FROM ULTRA-WIDEBAND RADAR DATA VIA LOW-RANK MODELING

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ABSTRACT

Radio-frequency interference (RFI) is the most common, and also the most challenging type of interference or noise source that has a direct impact on the performance of ultra-wideband radar systems in various practical application settings. Existing techniques for RFI suppression either employ filtering (notching) which introduces other harmful side-effects such as side-lobe distortion and target-amplitude reduction or RFI modeling/estimation/tracking which requires complicated narrow-band modulation models or even direct RFI sniffing. In this paper, we propose a robust and adaptive technique for the separation and then suppression of RFI signals from ultra-wideband (UWB) radar data via modeling RFI as low-rank components in a joint optimization framework. More specifically, we advocate a joint sparse-and-low-rank recovery approach that simultaneously solves for (i) UWB radar signals as sparse representations with respect to a dictionary containing transmitted waveforms; and (ii) RFI signals as a low-rank structure. The proposed technique is completely adaptive with highly time-varying environments, and does not require any prior knowledge of the RFI sources (other than the low-rank assumption). Both simulated data and real-world data measured by the U.S. Army Research Laboratory (ARL) Ultra-Wideband (UWB) synthetic aperture radar (SAR) confirm that the proposed RFI separation/suppression technique successfully recovers UWB radar signals embedded in large-amplitude RFI signals.

Index Terms— Synthetic aperture radar (SAR), ultra-wideband (UWB) radar, radio frequency interference (RFI), low-rank, matrix recovery, sparse representations

1. INTRODUCTION

We are interested in low-frequency ultra-wideband (UWB) radar and communications systems which have played important roles in many practical applications. The U.S. Army Research Laboratory (ARL) has been developing low-frequency UWB radar systems to detect difficult targets in various applications such as foliage penetration (FOPEN) [1], ground penetration for improvised explosive device (IED) detection [2], and sensing-through-the-wall (STTW) [3]. These systems must operate in the low-frequency spectrum that spans from under 100 MHz to several GHz in order to achieve the penetration capability while maintaining high imaging resolution. The most critical challenge for any UWB system is that it must be able to operate in the presence of others: collected radar information is corrupted in both time and frequency domain by various RFI. This is a notoriously challenging problem due to the dynamic and unpredictable nature of the noise sources, not to mention the strength of the noisy signals. Previous work in this RFI-suppression area includes parametric noise modeling [4], spectral decomposition [5], and adaptive filtering [6]-[8], all with limited successes. Most can only provide acceptable results with one particular source of RFI. Several past efforts have taken advantage of the low-rank RFI property to extract them via eigen-decompositions [9]-[10]. However, these techniques heavily depend on the quality of the orthogonal subspaces and cannot distinguish signal-versus-noise if they happen to have the same power within the same subspace. Recent sparsity-based approaches tend to focus on obtaining sparse scenes directly, hence computationally expensive [11]-[12].

Our previous attempt in solving the RFI problem models both the raw SAR signal of interest \(x\) as well as the interference \(e\) to be sparse with respect to well-designed dictionaries [13]-[14]. The signal dictionary \(D_x\) is obtained from discrete time-shifted versions of the transmitted radar signal \(s(t)\) whereas the RFI dictionary \(D_{ri}\) is constructed from real observed RFI collected from the environment with the radar transmitters turned off (we call this process RFI sniffing). Hence, the observed data record \(y_i\) at aperture \(i\) is modeled as \(y_i = D_x x_i + D_{ri} e_i + n_i\) where \(n_i\) represents the typical unstructured dense noise with small variance. Popular sparse recovery algorithms such as OMP or \(\ell_1\)-minimization variants can be employed to solve for \(x_i\) and \(e_i\). This technique processes each data record independently and requires prior knowledge of RFI via sniffing.

This paper demonstrates that the RFI problem can be solved if SAR signals are sparse while the RFI sources satisfy only one single assumption – low-rank. This RFI property results from our focus on batch-processing of data collected from sensors within a small spatial-temporal window. Finally, this approach processes raw SAR data directly without involving the costly image formation step. Hence, it can be incorporated into most existing systems as a pre-processing module prior to other popular signal processing and image formation steps.
2. SPARSE SIGNALS AND LOW-RANK RFI MODEL

We propose the following joint-sparse-representation-plus-
low-rank signal model as follows
\[ Y = D_x A + L + N \]  
(1)
where columns of \( Y \) contain observed SAR signals within a
small spatial-temporal window, is the sparsifying dictionary
for SAR signals as previously mentioned, \( A \) contains the
sparse coefficients (so, \( D_x A \) describes the signals of interest
\( X \)), \( L \) represents the RFI corruption embedded in the
observed data, and \( N \) is the typical dense Gaussian noise
with low bounded power.

The proposed model in (1) and the corresponding
recovery algorithm described in the next section rely on two
key assumptions: (i) SAR signals of interest are sparse or
jointly sparse – hence, \( A \) is either a sparse or a structured-
sparse matrix); (ii) RFI components contain a high degree of
correlation – hence \( L \) is low-rank. The sparse nature of radar
signals have been well established in the compressed
sensing community [11]-[19]. The low-rank assumption on
\( L \) is confirmed and illustrated in Figure 2, where a snapshot
of a modern-day RFI spectrum is depicted. Although there
are multiple interference sources ranging from AM to FM
radio, from digital TV broadcast to cellular phone
communications, the RFI is relatively sparse in frequency.
Let \( x[n] \) be the many collected segments of RFI in time
domain, Figure 2 (bottom left) shows the autocorrelation
sequence \( c[m] = E(x[n] x^*[n-m]) \) with the lag coefficient \( m \)
in the \( \pm 1 \text{ms} \) range. We can see that the RFI signal is
relatively stationary with a steady decrease in magnitude of
the correlation coefficient. Moreover, Figure 2 also illustrates
that the magnitude of singular values of the pure-RFI matrix
\( L \) decays very quickly, indicating that \( L \) is low-rank. The
majority of the RFI power concentrates within the top 10% of
its components. If observed signals are collected and
processed within a small spatial-temporal neighborhood, we
believe that the RFI low-rank assumption is always valid.

3. RECOVERY ALGORITHM

The next question is how to separate the sparse signal \( X \) and
the low-rank interference \( L \) from the observed mixture \( Y \).
Recently, there have been a lot of similar efforts from the
matrix factorization community and our proposed model is
closest to the sparse-plus-low-rank model in [20]-[22].
However, we enjoy the additional benefit of the sparsifying
signal dictionary \( D_x \). It can be proven that the key to
successful noise-source separation here depends on the
incoherence level between atoms in \( D_x \) and the subspace
basis of the RFI. In an active sensing application like SAR,
the dictionary is known, under control, and has been proven
very effective [11]-[19].

We propose to separate and extract the RFI
components \( L \) from the observed SAR data \( Y \) via solving
the following optimization problem
\[
\min_{A,L} \|L\|_* + \tau \|A\|_1 + \mu \|Y - D_x A - L\|_F^2
\]
where \( \|L\|_* \) is the nuclear norm of \( L \) (approximating its
rank), \( \|A\|_1 \) is the \( l_1 \) entry norm of \( A \), and the last term with
the Frobenius norm enforces the consistency of the observed
data. The optimization is solved based on the alternating
direction method of multipliers (ADMM) on the augmented
Lagrangian multipliers (ALM) [23] as shown in Algorithm
1. Once the optimal \( A \) and \( L \) have been found, we can either
recover the SAR signal via direct representation as \( X = D_x A \)
or via RFI-suppression as \( X = Y - L \). Depending on the noise
level and the setting of the parameter \( \mu \), there is a subtle
difference between \( X = D_x A \) and \( X = Y - L \) – small targets are
often better preserved with the latter (our preference) while
objective error measure is slightly better with the former.

Figure 2. A typical example of a modern-day RFI spectrum. Top left: RFI spectrum with the red line depicting the level of
RFI suppression via the notching scheme described in Section 4, resulting in roughly 10% spectrum loss. Top right: two RFI
segments in time-domain 1 ms apart. Bottom left: auto-correlation of normalized RFI within a 2-ms window. Bottom right:
fast decay of singular values of RFI \( L \) matrix whose 1500-sample columns are selected randomly within a 2-ms window.
In this section, we validate the proposed signal model and the joint-sparse+low-rank recovery algorithm above with several RFI-suppression experiments on two different data sets. In both cases, the RFI involved is real – RFI was collected on the ARL ground as shown in Figure 2. All parameters are empirically tuned to our best effort to achieve the highest possible SNR for each method.

4.1. UWB Mono-Static Side-Looking Simulation Data

<table>
<thead>
<tr>
<th>RFI to SAR Power Ratio</th>
<th>SAR Signals Corrupted by RFI without Processing SNR (dB)</th>
<th>RFI Notching followed by Spectrum Recovery SNR (dB)</th>
<th>RFI Suppression via Sparse Recovery with Sniffing SNR (dB)</th>
<th>RFI Suppression via Sparse Recovery with Low-rank RFI SNR (dB)</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.25</td>
<td>12.04</td>
<td>16.14</td>
<td><strong>25.01</strong></td>
<td>19.03</td>
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<tr>
<td>0.5</td>
<td>6.02</td>
<td>11.31</td>
<td><strong>18.46</strong></td>
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<td>9.45</td>
<td><strong>9.76</strong></td>
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<tr>
<td>5</td>
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<td>-1.33</td>
<td>4.49</td>
<td><strong>5.47</strong></td>
</tr>
<tr>
<td>10</td>
<td>-20.00</td>
<td>-2.56</td>
<td>0.38</td>
<td><strong>2.43</strong></td>
</tr>
</tbody>
</table>

Table 1. RFI suppression comparison with side-looking mono-static simulation data.

The first experiment is conducted on an UWB simulated data set: mono-static side-looking SAR data are collected from 300 aperture positions in a straight line, imaging a scene with around 40 point targets of random amplitudes at random locations. The signal to noise ratio between the original SAR signals $x$ and the recovered signals $\hat{x}$ as tabulated in Table 1 is defined as the root-mean-square ratio expressed in dB scale: $SNR(x, \hat{x}) = 20 \log_{10} \frac{RMS(x)}{RMS(\hat{x})}$. Compared with latest state-of-the-art notching (which also includes advanced spectrum recovery) [14] and sparse recovery with sniffing techniques [13]-[14], the proposed method remains effective until the RFI level becomes weak, rendering the nuclear norm of $L$ in the optimization ineffective.

4.2. UWB MIMO Forward-Looking Real Data

Next, the proposed spectral recovery technique is tested and evaluated using real-world data from the ARL UWB SAR in forward-looking mode. The SNRs in various RFI-to-SAR power ratios are shown in Table 2. Again, the proposed algorithm proves to be very effective given that RFI sniffing is not needed and the scene of interest is quite complex. Figures 3-5 compare the visual quality of various recovered SAR images in both simulated and real-data cases – our proposed method seems to offer an additional level of denoising advantage (objectively as well as subjectively). In this experiment, we group only 10 neighboring apertures into a batch and each batch is processed independently. So, $Y$ in this case has 160 data columns (this radar configuration has 16 receiving channels per aperture position).

**Table 2.** RFI suppression comparison with forward-looking ARL UWB MIMO real-world data.

We present an effective RFI extraction algorithm based on jointly minimizing the sparsity of the SAR signals and the rank of the RFI. Our technique does not require any specific prior knowledge of the interference sources. Experiments on simulated as well as real UWB SAR data sets show remarkable robustness and confirm the method’s validity.

4. EXPERIMENTAL RESULTS

In this section, we validate the proposed signal model and the joint-sparse+low-rank recovery algorithm above with several RFI-suppression experiments on two different data sets. In both cases, the RFI involved is real – RFI was collected on the ARL ground as shown in Figure 2. All parameters are empirically tuned to our best effort to achieve the highest possible SNR for each method.

Algorithm I: Noise-source separation via joint sparse representation with low-rank interference.
Figure 3. Comparison of RFI suppression performances with side-looking simulated data when RFI power is 5 times that of SAR signals. From left to right: original SAR images of about 40 point targets of different sizes, magnitudes, and locations; RFI-corrupted image without any processing, SNR = –13.98dB; recovered RFI image from RFI notching (based on sniffing information) followed by spectrum recovery, SNR = –1.33dB; RFI-suppressed image via sparse recovery with RFI sniffing, SNR = 4.49dB; RFI-suppressed image via proposed low-rank RFI modeling technique, SNR = 5.47dB.

Figure 4. Comparison of RFI suppression performances with ARL UWB forward-looking real-world data when RFI power is twice that of SAR signals. Clockwise from top left corner: original SAR image of a road with buried targets of interest (in the area enclosed in the red rectangle); recovered RFI image from RFI notching (based on sniffing information) followed by spectrum recovery, SNR = 2.49dB; RFI-suppressed image via sparse recovery with RFI sniffing, SNR = 7.61dB; RFI-suppressed image via proposed low-rank RFI modeling technique, SNR = 7.91dB.

Figure 5. Zoom-in portions of SAR images shown in Figure 4 within the region of interest (red-rectangle region in Figure 4). From left to right: original SAR image; corrupted SAR image without any processing; recovered image from RFI notching; RFI-suppressed image via sparse recovery with sniffing; RFI-suppressed image via proposed low-rank RFI modeling technique without sniffing. One can observe that the proposed low-rank modeling technique yields visually-pleasing recovered SAR image where the two targets of interest stand out clearly from the cluttered background.
6. REFERENCES


