

Cognitive ISAR for Congested RF Environments via Waveform Design and Data Recovery Strategies

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Abstract—This paper proposes and analyzes the concept of a cognitive inverse synthetic aperture radar (ISAR) ensuring spectral compatibility in crowded electromagnetic environments. To realize the cognitive paradigm, the perception is carried out by a spectrum sensing module providing the relevant spectral parameters of the sources in the environment. The action stage employs a tailored signal design process, synthesizing a radar waveform with bespoke spectral notches, enabling ISAR imaging over a wide spectral bandwidth without interfering with the other radio frequency (RF) sources. A key enabling requirement for the proposed application is the capability to successfully recover possible gaps in the collected data. This process is carried out resorting to advanced methods based on compressed sensing recovery strategy. The capabilities of the proposed system are assessed exploiting a dataset of drone measurements in the frequency band between 13 GHz and 15 GHz. Results highlight the effectiveness of the devised architecture to enable spectral compatibility while delivering high-quality ISAR images.

Index terms— ISAR, cognitive radar, compressed sensing, spectral compatibility, drone imaging, missing data.

I. INTRODUCTION

The electromagnetic spectrum is a valuable and highly dynamic resource that is yet to be fully harnessed by radar systems [1]. Accordingly, an essential requirement for a next-generation radar system is the ability to operate in a congested electromagnetic spectral environment and guaranteeing compatibility with overlaid emitters by agility in the exploitation of the dynamically available frequency bands. Recent research emphasizes the importance of the waveform design and diversity (WDD) paradigm [2]–[5] as a means of addressing this challenge. This approach, when implemented within a cognitive radar architecture, involves alternating between two key steps: a perception stage, where the radar detects emitters within its band of interest [6,7], and an action stage, where a spectrally-shaped waveform is designed and transmitted to minimize interference with the aforementioned sources and to enhance spectrum efficiency by optimizing the signal-to-interference-plus-noise ratio (SINR) [1,8]–[12].

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In the context of radar imaging, a cognitive inverse synthetic aperture radar (ISAR) imaging system, fulfilling specific spectral requirements, is here proposed. As part of the radar operations workflow, a perception mode provides awareness of the emitters in the surrounding environment via specific radio frequency (RF) sensing modules [6,7,13]. This allows the synthesis and transmission of a tailored radar waveform encompassing spectral notches to avoid interference with overlaid systems, realizing the so-called *perception-action cycle*. Consequently, the radar is able to perform ISAR imaging over a wide bandwidth without inducing and experiencing interference from coexisting emitters.

Nevertheless, the presence of spectral notches in the transmitted waveform inevitably results in frequency domain gaps, which may eventually lead to spurious and high sidelobes in the resulting ISAR image if not adequately accounted for. To overcome such drawbacks, a data recovery process is demanded at the image formation stage in order to successfully accomplish ISAR imaging even in the presence of missing data [14]–[16]. In the past decade, the compressed sensing framework has shown to be remarkably powerful in tackling this kind of problem, with numerous algorithms proposed in the open literature [17]–[19]. For the problem at hand, the well-known 2D-SL0 algorithm [15,20] is applied to retrieve the missing data in the considered ISAR application. Furthermore, a low-rank recovery process is formulated to reconstruct the data based on the assumption of a limited amount of dominant modes in the image. Approximating the rank with its tightest convex description, the problem is optimally solved by resorting to the iterative Majorization Minimization (MM) algorithm [21].

To assess the performance of the proposed cognitive ISAR system, an extensive numerical analysis has been conducted employing a dataset of drone measurements in the frequency band [13,15] GHz and HH polarization [22,23]. The results highlight the radar capability to operate within a congested spectrum while producing high-quality ISAR images, also under low SINR regime, if the system is equipped with tailored waveforms and signal processing algorithms.

The remainder of this work is organized as follows. Sec-

tion II introduces the waveform design framework for spectral compatibility applications. Section III discusses the ISAR imaging technique in the presence of incomplete data. In Section IV, numerical analysis on a dataset comprising returns from a commercial drone is reported and discussed considering several scenarios of practical relevance. Finally, Section V concludes the paper¹.

II. WAVEFORM DESIGN FOR SPECTRAL COMPATIBILITY

In this section, the problem of designing spectrally-shaped waveforms is briefly introduced with reference to a cognitive radar system. To this end, let us consider a radar operating in the presence of K emitters, each of them transmitting over a frequency band $\Omega_k = [f_1^k, f_2^k]$, $k = 1, \dots, K$, within the radar frequency support range, where f_1^k and f_2^k denote the lower and upper normalized frequencies (with respect to the sampling rate) for the k th source, respectively.

Let $c(t)$ be the baseband equivalent of the radar transmitted waveform whose complex sequence $\mathbf{c}$ (corresponding to samples of $c(t)$ picked up at the frequency rate equal to the radar bandwidth) is $c(i)$, $i = 1, \dots, N$. To ensure spectral compatibility with the overlaid emitters, the cognitive radar has to suitably shape the spectrum of the transmitted signal to manage the amount of interfering energy produced in the shared frequency intervals. The average signal energy transmitted on the k th band Ω_k is given by [24]

$$\frac{1}{f_2^k - f_1^k} \int_{f_1^k}^{f_2^k} S_c(f) df, \quad (1)$$

where $S_c(f) = \left| \sum_{n=1}^N c(n) e^{-j2\pi f(n-1)} \right|^2 = N |\mathbf{c}^\dagger \mathbf{p}_f|^2$, with $\mathbf{p}_f = \frac{1}{\sqrt{N}} [1, \exp(-j2\pi f), \dots, \exp(-j2\pi(N-1)f)]^T$ the temporal steering vector tuned to the normalized frequency f . That said, each frequency band Ω_k is substantially discretized by taking the normalized frequencies $f_i = i/N$, $i = 0, \dots, N-1$ falling in Ω_k itself. Then, denoting by

$$\mathbf{F}_N(m, n) = \frac{1}{\sqrt{N}} e^{-\frac{j2\pi(m-1)(n-1)}{N}} \quad (2)$$

the $N \times N$ Fourier matrix scaled by $1/\sqrt{N}$, a viable means to quantify the average energy level injected on Ω_k is through

$$\frac{N\Delta f}{f_2^k - f_1^k} \sum_{f_i \in \Omega_k} |\mathbf{c}^\dagger \mathbf{p}_{f_i}|^2 = \frac{1}{f_2^k - f_1^k} \sum_{f_i \in \Omega_k} |\mathbf{c}^\dagger \mathbf{p}_{f_i}|^2 = \mathbf{c}^\dagger \mathbf{R}_N^k \mathbf{c}, \quad (3)$$

where $\mathbf{R}_N^k = \frac{1}{f_2^k - f_1^k} \mathbf{Q}_N^k \mathbf{Q}_N^{k\dagger}$, with $\mathbf{Q}_N^k$ the submatrix of $\mathbf{F}_N$ whose columns correspond to the discrete frequencies

¹**Notation.** Boldface is used for vectors $\mathbf{a}$ (lower case), and matrices $\mathbf{A}$ (upper case). The transpose, the conjugate, and the conjugate transpose operators are denoted by the symbols $(\cdot)^T$, $(\cdot)^*$ and $(\cdot)^\dagger$, respectively. For any complex number x , $|x|$ indicates the modulus of x . For any matrix $\mathbf{A}$, $\|\mathbf{A}\|_F$, and $\|\mathbf{A}\|_*$ denote the Frobenius and nuclear norm, respectively, whereas $(\mathbf{A})^+$ represents its pseudoinverse. Moreover, for any real matrix $\mathbf{B}$, $(\mathbf{B})_+$ denotes the rectified linear unit operator, which replaces all negative entries of $\mathbf{B}$ with zero. In addition, the rank and the Shannon-rank of $\mathbf{A}$ are denoted by $\text{rank}\{\mathbf{A}\}$ and $\text{rank}_S\{\mathbf{A}\}$, respectively. Finally, $\mathbb{A}[\cdot]$ represents the spatial mean operator, whereas the letter j represents the imaginary unit (i.e. $j = \sqrt{-1}$).

belonging to Ω_k . Thus, indicating by E_I^k , $k = 1, \dots, K$, the acceptable level of interference on Ω_k , which is related to the quality of service demanded by the k th licensed emitter, the transmitted radar waveform has to comply with the constraints

$$\mathbf{c}^\dagger \mathbf{R}_N^k \mathbf{c} \leq E_I^k, \quad k = 1, \dots, K. \quad (4)$$

By doing so, a detailed control of the interference energy produced on each shared frequency bandwidth is enforced.

The aforementioned spectral constraints are accounted for in several waveform design algorithms described in the open literature [1,24], which could be employed at the action stage of the proposed architecture.

III. ISAR IMAGING IN THE PRESENCE OF MISSING DATA

ISAR imaging is a technique used to generate high-resolution images of moving targets. Conventional imaging techniques rely on the coherent integration of received echoes over a range of aspect angles, generally resorting to Fourier-based methods (downstream a careful compensation stage). However, in the presence of missing samples in the frequency domain, for instance due to spectral notches in the transmitted waveform, ISAR images obtained with the standard range-Doppler (RD) algorithm [25] may be distorted or exhibit a coarse final image resolution due to the degradation of the matched filter response. Therefore, to provide high-quality images in this context, the processing stage could include a strategy to retrieve any missing measurements within the available collected data. In particular, let $\mathbf{S}$ be the observed *incomplete* matrix in the frequency domain and $\mathbf{I}$ the ISAR image, the goal is to minimize the displacement term (quantified via the Frobenius norm), i.e.,

$$\min_{\mathbf{I}} \|\mathbf{S} - \Theta_x \mathbf{I} \Theta_y^\dagger\|_F^2, \quad (5)$$

where Θ_x and Θ_y are the corresponding undercomplete Fourier matrices (obtained by zeroing specific rows of the DFT matrix corresponding to the missing frequencies/pulses samples) [15], which can be computed starting from the parameters of the cognitive waveform spectral notches and the location of possible temporal gaps. Unfortunately, Problem (5) is ill-posed since the missing entries of $\mathbf{S}$ cannot be uniquely determined without making assumptions on the matrix $\mathbf{I}$. A viable method to overcome this limitation is to reformulate the inference task as a bi-objective optimization problem, where one figure of merit is the squared norm of the displacement while the other is a regularization function. As to the latter, in the open literature the ℓ_0 norm of $\mathbf{I}$ has been employed, and the bi-objective problem is handled by minimizing it under a constraint on the maximum amount of displacement. In this regards, the CS framework (with bespoke approximations of the ℓ_0 norm) has been successfully applied to this retrieval problem (see Subsection III-A). An alternative method is to consider the rank of $\mathbf{I}$ as the regularization term and to tackle the optimization problem via the scalarization framework [26] (see Subsection III-B).

A. Compressed-Sensing Recovery

CS represents a powerful signal processing tool capable of reconstructing signals from a small amount of measurements, under the assumption that a limited number of unknowns leads to the available observations. It has been successfully applied to accomplish ISAR imaging, yielding noteworthy improvements in the context of data reduction as well as resolution enhancement [15]. The key principle underlying CS-based ISAR imaging lies in its ability to leverage the sparsity assumption of scatterers in the image domain [15].

Accordingly, the CS approach reconstructs the ISAR image $\mathbf{I}$ by solving the following optimization problem

$$\hat{\mathbf{I}} = \arg \min_{\mathbf{I}} \|\mathbf{I}\|_0 \text{ s.t. } \|\mathbf{S} - \Theta_x \mathbf{I} \Theta_y^\dagger\|_F^2 \leq \epsilon, \quad (6)$$

where ϵ is a user-defined tuning parameter accounting for the noise level in the measured data.

Notably, in [15], the 2D-SL0 algorithm [20] has been successfully employed to handle (6), obtaining a sparse solution consistent with the observed data.

B. Rank-Minimization (RM) Recovery

In this subsection, a different regularization function is considered, i.e., the rank of $\mathbf{I}$ which rules the amount of modes describing the image. As a consequence, the figure of merits involved in the inference problem are

- $\|\mathbf{S} - \Theta_x \mathbf{I} \Theta_y^\dagger\|_F^2$, which controls the fitting of the recovered image with the available measurements;
- $\text{rank}\{\mathbf{I}\}$, which accounts for the amount of modes required to faithfully describe the image.

Hence, to face with the resulting bi-objective optimization, as already mentioned, the scalarization framework [26] is exploited. However, the resulting optimization problem is NP-hard (due to the rank term) [27]. Hence, to determine a high quality sub-optimal solution, the rank operator is approximated via the plain nuclear norm, which is the closest convex relaxation to the rank function [27,28]. According to the above guidelines, the inference problem becomes

$$\hat{\mathbf{I}} = \arg \min_{\mathbf{I}} f(\mathbf{I}), \quad f(\mathbf{I}) \triangleq \frac{1}{2} \|\mathbf{S} - \Theta_x \mathbf{I} \Theta_y^\dagger\|_F^2 + \lambda \|\mathbf{I}\|_*, \quad (7)$$

which is a convex optimization problem. A viable strategy to minimize the objective in (7) relies on the MM framework [21], which involves the construction of a tailored surrogate function (s.f.) that satisfies specific properties, leveraging on the optimized solution from the previous iteration. The s.f. is then minimized to update the optimized point.

To proceed further, let us denote by $\mathbf{I}_k$ the estimate of $\mathbf{I}$ at the k th iteration; following similar line of reasoning as in [27], a s.f. $g(\mathbf{I}; \mathbf{I}_k)$ for the objective function in (7) is given by the quadratic approximation of $f(\mathbf{I})$, i.e.,

$$g(\mathbf{I}; \mathbf{I}_k) = \frac{\tau}{2} \|\mathbf{I} - \bar{\mathbf{I}}_k\|_F^2 + \lambda \|\mathbf{I}\|_* + f(\mathbf{I}_k) - \frac{1}{2\tau} \|\nabla f(\mathbf{I}_k)\|_F^2 \quad (8)$$

where $\tau \geq \mathcal{L}_f$, where $\mathcal{L}_f$ is the Lipschitz constant for the objective function $f(\mathbf{I})$,

$$\bar{\mathbf{I}}_k = \mathbf{I}_k - \frac{1}{\tau} \Theta_x^\dagger (\Theta_x \mathbf{I}_k \Theta_y^\dagger - \mathbf{S}) \Theta_y, \quad (9)$$

Algorithm 1: MM-based RM algorithm

Input: $\mathbf{I}_0, \lambda, \mathbf{S}, \Theta_x, \Theta_y, k = k_{\text{MAX}}$.

- 1 set $\tau \geq \lambda_{\max}(\Theta_x^\dagger \Theta_x) \lambda_{\max}(\Theta_y^\dagger \Theta_y)$;
- 2 set $k = 0$;
- 3 set $\mathbf{I}_M = \Theta_x^\dagger \mathbf{S} (\Theta_y^\dagger)^\dagger$;
- 4 **repeat**
- 5 set $\bar{\mathbf{I}}_k = \mathbf{I}_k - \frac{1}{\tau} \Theta_x^\dagger (\Theta_x \mathbf{I}_k \Theta_y^\dagger - \mathbf{S}) \Theta_y$;
- 6 compute the SVD of $\bar{\mathbf{I}}_k$: $\bar{\mathbf{I}}_k = \mathbf{U}_k \Sigma_k \mathbf{V}_k^\dagger$;
- 7 set $\Sigma_{k+1} = (\Sigma_k - \frac{\lambda}{\tau} \mathbf{I})_+$;
- 8 set $\mathbf{I}_{k+1} = \mathbf{U}_k \Sigma_{k+1} \mathbf{V}_k^\dagger$;
- 9 set $k = k + 1$;
- 10 **until** $\text{rank}_S\{\mathbf{I}_k\} \leq \text{rank}_S\{\mathbf{I}_M\}$ or $k = k_{\text{MAX}}$;

Output: $\hat{\mathbf{I}} = \mathbf{I}_k$

whereas $\nabla f(\mathbf{I}_k)$ is the gradient of $f(\mathbf{I})$ evaluated at $\mathbf{I}_k$.

Let us now focus on the minimization of $g(\mathbf{I}; \mathbf{I}_k)$. To this end, let $\mathbf{U}_k \Sigma_k \mathbf{V}_k^\dagger$ be the Singular Value Decomposition (SVD) of $\bar{\mathbf{I}}_k$ and $\mathbf{U} \Sigma \mathbf{V}^\dagger$ that of $\mathbf{I}$, with the singular values in Σ_k and Σ sort in descending order; hence, based on [29, Corollary 7.4.1.5],

$$\|\mathbf{I} - \bar{\mathbf{I}}_k\|_F^2 \geq \|\Sigma - \Sigma_k\|_F^2 \quad (10)$$

with the equality if $\mathbf{I} = \mathbf{U}_k \Sigma \mathbf{V}_k^\dagger$. As a consequence, the left and right singular vectors of a minimizer for the objective in (8) are the same as $\bar{\mathbf{I}}_k$. Therefore, assuming that $\bar{\mathbf{I}}_k$ has r non-zero singular values $\{\bar{\sigma}_k^{(i)}\}_{i=1}^r$, the optimization problem at hand reduces to computing the singular values as solution of the optimization problem

$$\min_{\sigma^{(1)} \geq 0, \dots, \sigma^{(r)} \geq 0} \tilde{g}(\mathbf{I}; \mathbf{I}_k) \triangleq \sum_{i=1}^r \left[\frac{\tau}{2} \left(\sigma^{(i)} - \bar{\sigma}_k^{(i)} \right)^2 + \lambda \sigma^{(i)} \right] \quad (11)$$

where $\sigma^{(i)}, i = 1, \dots, r$, are the possible non zero singular values of $\mathbf{I}$. As a consequence, a minimizer of (8) is

$$\mathbf{I}_{k+1} = \mathbf{U}_k \Sigma_{k+1} \mathbf{V}_k^\dagger \quad (12)$$

with $\Sigma_{k+1} = (\Sigma_k - \frac{\lambda}{\tau} \mathbf{I})_+$.

The procedure is detailed in **Algorithm 1**, wherein $\mathbf{I}_0$ is the initialization matrix (e.g., the output of the 2D-SL0 algorithm), whereas $\tau \geq \lambda_{\max}(\mathbf{C}^\dagger \mathbf{C}) = \lambda_{\max}(\Theta_x^\dagger \Theta_x) \lambda_{\max}(\Theta_y^\dagger \Theta_y)$ [27], with $\mathbf{C} = \Theta_y^\star \otimes \Theta_x$. Finally, denoting by $\mathbf{I}_M = \Theta_x^\dagger \mathbf{S} (\Theta_y^\dagger)^\dagger$ the ISAR image computed on the incomplete data, the procedure terminates when either the condition $\text{rank}_S\{\mathbf{I}_k\} \leq \text{rank}_S\{\mathbf{I}_M\}$ is met or the maximum number of iterations k_{MAX} is reached, where $\text{rank}_S\{\mathbf{I}\} = \exp \left[- \sum_{i=1}^r \frac{\sigma_i(\mathbf{I})}{\|\sigma\|_1} \log \left(\frac{\sigma_i(\mathbf{I})}{\|\sigma\|_1} \right) \right]$ is the Shannon effective rank of $\mathbf{I}$ [30], with $\sigma = [\sigma_1(\mathbf{I}), \dots, \sigma_r(\mathbf{I})]^\text{T}$ the vector comprising the singular values of $\mathbf{I}$.

C. RD-based Imaging

After the reconstruction stage performed by means of the 2D-SL0 or **Algorithm 1**, leveraging the conventional Fourier dictionaries Ψ_x and Ψ_y that account for the range compression and the cross-range compression, respectively, it is

possible to reconstruct the slow-time/frequency domain data as $\hat{S}_c = \Psi_x \hat{I} \Psi_y^\dagger$ which allows to realize the ISAR imaging by means of the conventional RD algorithm applied on $\hat{S}_c$ [15].

IV. NUMERICAL ANALYSIS

In this section, the effectiveness of the proposed procedure is investigated by comparing the image obtained with the proposed cognitive ISAR process with those resulting from an ideal case (receiving only the useful target contribution without spectral holes) as well as a standard ISAR operating in the presence of interference. The comparison is conducted both visually and numerically by resorting to specific quantitative metrics such as

- **Image Contrast (IC):** It evaluates the relative intensity variations in the image, providing an indication of its overall clarity and sharpness. It is defined as $IC(I) = \sqrt{\mathbb{A}[(\|I\| - \mathbb{A}[\|I\|])^2] / \mathbb{A}[\|I\|]}$.
- **Normalized Mean Squared Error (NMSE):** It represents the normalized error between the obtained image and the reference as $NMSE(I, I_R) = \frac{\|I - I_R\|_F}{\|I_R\|_F}$.

The dataset utilized for the analysis is the one detailed in [22], which comprises measurements of various drones acquired in a semi-controlled environment across a frequency range of 8.2-18 GHz, using HH and VV polarizations, and azimuth aspect angles spanning 0-360 degrees with 0.1 degree steps and elevation close to 0 degree. In the following, the data pertaining to the DJI Matrice 100, obtained in HH polarization with a 2 GHz bandwidth from 13 GHz to 15 GHz (considering a frequency step of 4.5 MHz) and with a target rotation of 15 degrees (with an angular resolution of 0.1 degrees), are employed for the analysis.

Five different situations are considered and compared:

- the ideal case, used as a ground truth (GT), which assumes the transmission of a standard linear frequency modulated (LFM) signal (chirp) in the absence of interference;
- the standard case, involving the transmission of a standard chirp in the presence of emitters operating within the same band as the ISAR frequency range;
- the notched case, comprising a perception stage, where the radar recognizes the presence of overlaid emitters, and an action stage, involving design and transmission of a tailored chirp-like signal with spectral notches in the frequency spectra;
- notched + CS case (referred to as N-CS case), wherein the 2D-SL0 algorithm [20] is applied to the data obtained in the notched case to reconstruct the frequency-angle data;
- notched + RM case (referred to as N-RM case), where **Algorithm 1** is employed as recovery method, considering $\lambda = 300$, $\tau = 20\lambda_{max}(\Theta_x^\dagger \Theta_x) \lambda_{max}(\Theta_y^\dagger \Theta_y)$, and $k_{MAX} = 50$.

In the aforementioned scenarios, all the overlaid sources are assumed to be telecommunication emitters (representing the only disturbance contributions).

For the aim of this analysis, the spectrum of each complex high-range-resolution (HRR) target echo signal (provided by

the dataset [22] using the same pre-processing steps), for a given aspect angle θ_i (corresponding to a specific slow-time snapshot), is first multiplied by the transmitted waveform spectrum, as initial step to model (approximately) the data collected by the ISAR receiver. In the ideal and standard cases, the transmitted waveform is a standard chirp; in the other cases, it is a spectrally-shaped cognitive waveform. It should be noted that in the CS and RM cases, prior to the image formation step (using the standard RD algorithm), the data matrix undergoes a frequency-angle data recovery procedure, according to the methods detailed in Section III-A and III-B, respectively. Finally, the obtained data are used for the RD image formation. The sequence of the employed steps is illustrated in the flowchart reported in Fig. 1.

For the synthesis of the spectrally-shaped waveform to transmit in the notched case, a modified version of the waveform design algorithm in [24,31] is used, considering notch depths of 30 dB for the first notch and 40 dB for the second one, respectively.

The five mentioned cases are analyzed and compared in a scenario characterized by two communication sources, with the former operating in the range [13.38, 13.62] GHz with a 240 MHz bandwidth, and the latter in the range [14.53, 14.65] GHz with a 120 MHz bandwidth. Figs. 2 reports the amplitude (dB) of the frequency-time (i.e., frequency-angle) data and the corresponding ISAR image (obtained using the standard RD imaging procedure). The figures clearly show that, if not properly suppressed, interfering signals introduce noticeable spurious in the resulting ISAR image (Fig. 2 (f)). Employing the cognitive approach only and down-streaming the pulse compression, the frequency-angle data results being gapped in the frequency domain (Fig. 2 (c)). The presence of these missing data is deleterious for the imaging process, resulting in high sidelobes appearing as fake scatterers (Fig. 2 (g)). Conversely, leveraging the CS/RM technique (the two recovery strategies achieve indistinguishable results), it is possible to reconstruct the frequency-angle data (Fig. 2 (d)) and obtain an high-quality ISAR image (Fig. 2 (h)), with negligible visual differences from the GT (Fig. 2 (e)) [15].

A. Low signal-to-noise ratio (SNR) Scenarios

In the following, the cognitive ISAR process is investigated in a low SNR regime, such as in the case of distant targets (still detectable) as well as in the presence of some barrage jamming affecting the entire radar bandwidth. In such contexts, the observed data S is significantly corrupted by interference.

Fig. 3 reports the ISAR images obtained under various approaches, assuming a single-pulse SNR of -7 dB. The results show that, in both the standard and notched cases, the target signal is overwhelmed by the disturbance, resulting in practically unusable images. Even the CS-based ISAR method, while capable of recovering missing data induced by spectral notches, fails to produce a high-quality image, as evidenced by the presence of spurious scatterers. In contrast, the proposed N-RM approach demonstrates a strong ability to suppress interference and yield a faithful image of the target. This

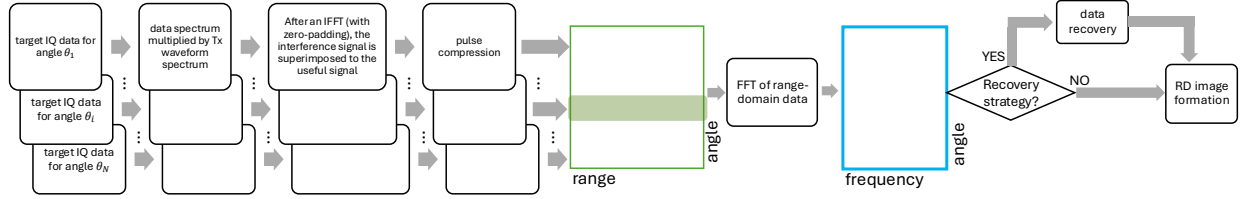


Figure 1: Flowchart depicting the simulation process employed for the numerical analysis of Section IV.

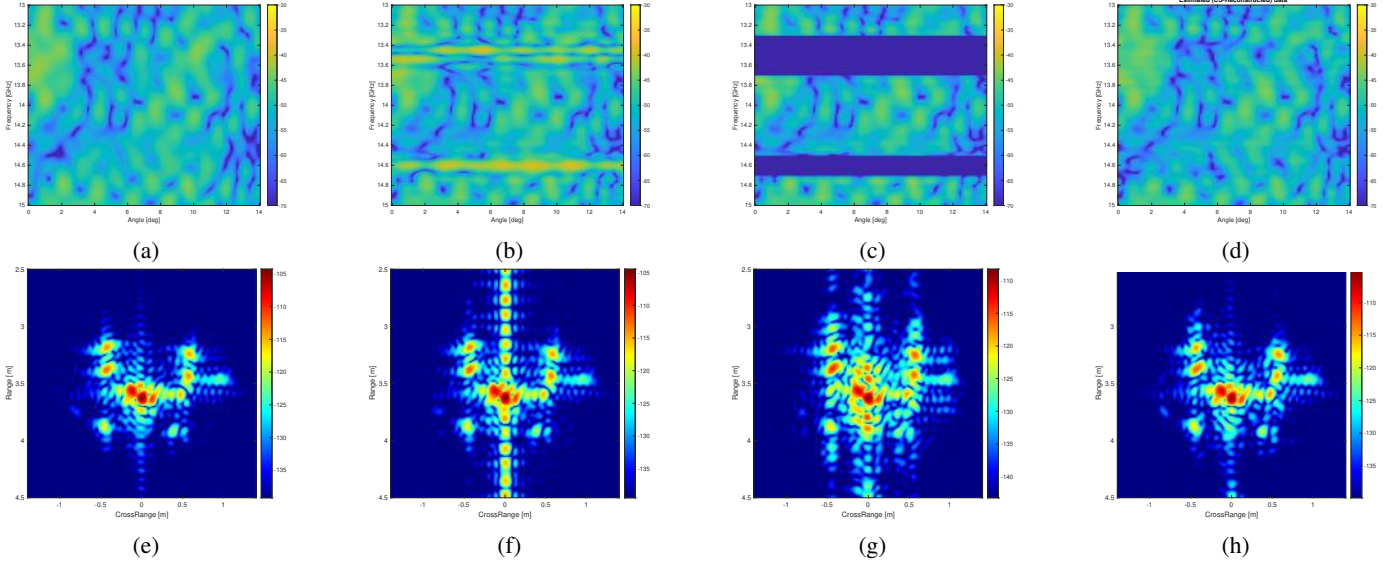


Figure 2: ISAR imaging in the presence of two interferers. (a)-(d): Frequency-angle (dB) spectrum. (e)-(h): ISAR image (dB). (a), (e): GT; (b), (f): standard case; (c), (g): notched case; (d), (h): N-CS/N-RM case.

performance stems from the adopted rank-minimization framework, which enables the reconstruction of slow-time/frequency data by leveraging only the dominant modes in the scene. Furthermore, the image quality, in terms of IC and NMSE metrics achieved by the diverse approaches is illustrated in Fig. 4, for SNR values ranging from -11 dB to 19 dB.

Inspection of the curves highlights that the proposed N-RM technique consistently outperforms its counterparts in terms of image fidelity, as reflected by the higher NMSE values attained across the entire SNR range. As compared to IC, N-RM achieves the highest performance for SNR greater than 5 dB, while at lower values, in the standard and N-CS cases, a slightly higher contrast is obtained. However, it is worth remarking that IC solely measures image sharpness and does not reflect fidelity to the ground truth.

Overall, the proposed missing-data retrieval strategies exhibit a robust performance in a variety of practical scenarios, with the N-RM technique being particularly effective in challenging low-SNR conditions.

V. CONCLUSION

In this paper, a cognitive ISAR system designed to guarantee spectral compatibility with possible overlaid emitters has been proposed. To this end, the radar alternates between

perception and action stages, exploiting a spectrum sensing unit to recognize potential emitters within its frequency range and a tailored waveform design process to synthesize radar imaging waveforms with spectral notches used to probe the environment. To mitigate the effects of missing data in the frequency domain, due to spectral notches in the transmitted waveform, a data recovery process is performed prior to the image formation step, either via the CS framework or by solving a RM problem. Experimental numerical analysis, based on drone measurements in the $[13, 15]$ GHz band, have shown that the proposed system is capable of ensuring spectral compatibility while delivering high-quality ISAR images, that are visually comparable to the ground truth.

DATA AVAILABILITY STATEMENT

Data supporting this study cannot be made available due to commercial restrictions.

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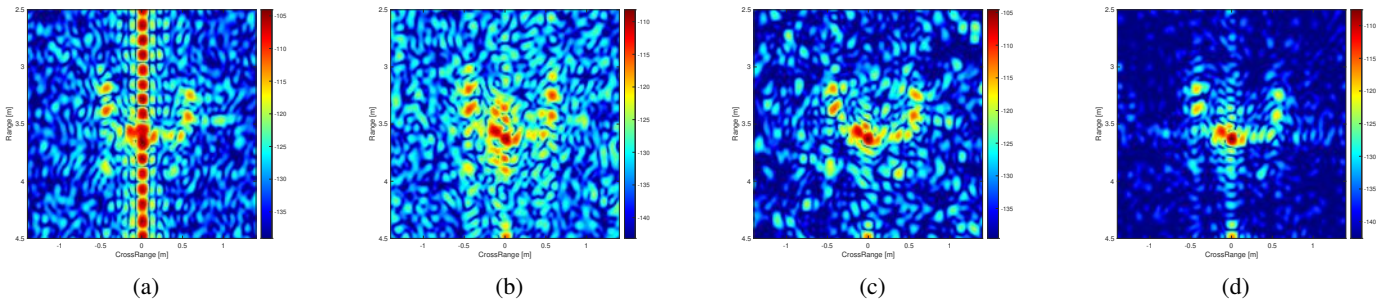


Figure 3: ISAR image (dB) in the presence of two interferers and SNR = -7 dB. (a) standard case (b) notched case (c) N-CS case (d) N-RM case.

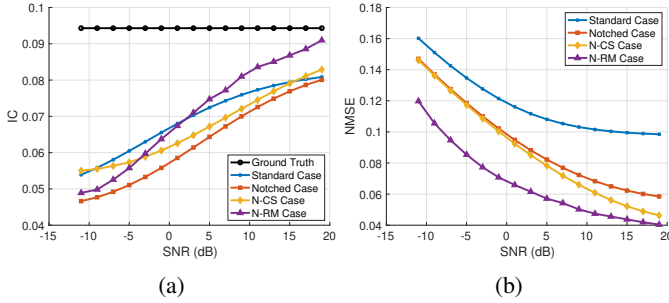


Figure 4: Image quality metrics vs SNR in the presence of two interferers. (a) IC vs SNR (b) NMSE vs SNR.

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