Performance Analysis of Incoherent RF Tomography Using Wireless Sensor Networks

Gianluca Gennarelli and Francesco Soldovieri, Senior Member, IEEE

Abstract—This paper addresses the problem of imaging targets using radio signals transmitted by the nodes of a wireless sensor network. The sensors are assumed to be simple wireless communication devices, e.g., Wi-Fi cards, which are capable to measure only the received signal power. A fully incoherent linear inverse scattering approach is herein tackled, and a Rytov-based model is considered. The main contribution of this paper is concerned with the evaluation of the imaging performance achievable when phase information is not exploited in the inversion stage. The analysis is worked out with the singular value decomposition tool, in order to foresee the resolution limits for a given network arrangement and noise level on data. The popular coherent inverse scattering model of Born approximation is also considered as benchmark for comparison purposes. Numerical results based on full-wave data are reported to highlight the actual capabilities of the incoherent tomography.

Index Terms—Incoherent tomography, rytov approximation, singular value decomposition (SVD), wireless sensor networks (WSNs).

I. INTRODUCTION

T
HE technological advances in wireless communications, microelectromechanical systems, and digital electronics have triggered, in recent years, the rapid development of wireless sensor networks (WSNs). These networks are composed of autonomous nodes connected over wireless links that sense some physical parameters of interest in the surrounding environment [1]. As it is well known, the main characteristics of a WSN are the reduced sensor size, low power consumption, low cost, and scalability. These peculiar features have motivated the diffusion of WSNs in military and civil application areas. Typical examples are the environmental monitoring [2], homeland security [3], structural monitoring [4], healthcare [5], building automation [6], industrial process monitoring [7], volcano eruption detection [8], etc. (see [9], for an exhaustive overview).

One of the most challenging problems in the framework of WSNs deals with the localization and tracking of static or moving targets (e.g., people) from the knowledge of signals collected by sensor nodes [10]. The targets can be either cooperative (active), i.e., equipped with a transponder device connected to other nodes [11] or noncooperative (passive) [12]–[14]. In the former case, they take actively part in the localization/tracking process, and several methods have been devised based on the analysis of various features of the radio-frequency (RF) signal emitted by the transponder, e.g., time of arrival, direction of arrival, and received signal strength (RSS) (see [10] and references therein). When targets are noncooperative, the problem is solved by exploiting the variations of the RF signal scattered by the targets. Various approaches have been proposed and tested in several scenarios of practical interest [12]–[14].

In recent times, pioneering studies have been focused on tomographic techniques capable of imaging an investigation region, possibly following its spatial variations over time [15]–[21]. For instance, the radio tomographic imaging (RTI) proposed in [15], drawing from the concept at the basis of X-ray computed tomography, permits imaging the attenuation of objects in a scene using RSS measurements. A differential RTI strategy can be exploited as well, when time-varying phenomena need to be monitored. The imaging approach proposed in [16] exploits an electromagnetic inverse source modeling and a customized classification procedure based on support vector machine. A strategy based on Rytov wave models has been adopted in [17] to show experimentally see-through-wall capabilities from power measurements using wireless local area network cards installed on mobile robots.

The concept to image an area by wireless devices has been addressed likewise in the frame of wireless tomography [18]–[21]. Wireless tomography stems from the need to integrate remote sensing functionalities into large-scale wireless communication networks, with the goal to reduce costs and leverage wireless industry investments in future years. As wireless portable devices (e.g., smartphones) are largely available over the world, the idea is to replace ad hoc devices for RF tomography with cheaper sensors not designed for remote sensing purposes. Accordingly, incoherent, coherent, and self-coherent imaging strategies have been discussed in [18]. Specifically, as phase information is generally difficult to achieve with communication components, research efforts have been devoted mostly on self-coherent strategies, which combine phase retrieval algorithms with standard coherent tomographic processing [18], [19]. A single-step approach for self-coherent tomography using semidefinite relaxation has been proposed in [20]. Moreover, a hybrid system combining few advanced sensors having phase measurement capability with simple sensors detecting only the amplitude of total field has been reported in [21].

In this paper, we address the imaging of targets in a scene by using a WSN consisting of simple nodes, which are capable to measure only the RF signal power. In a possible operative
scenario, the collected data are sent to a fusion center, which handles the signal processing necessary for the imaging task. Accordingly, a centralized RF tomography is considered.

In general, a phase retrieval approach could be used to determine the phase of the scattered field from only amplitude data and, after a coherent processing, could be carried out for the imaging. However, phase retrieval involves a nonlinear optimization problem (see [18] and [22]–[25]), which is affected by the local minima issue and is computationally demanding for real-time applications. Therefore, we deal with a fully incoherent linear inverse scattering approach. The model is based on the Rytov approximation similar to the one exploited in [17]. The main objective of this work is to provide an investigation on the imaging performance that can be achieved when the phase information is not taken into account in the inversion process. The problem is stated as a linear inverse one, and the singular value decomposition (SVD) of the incoherent scattering operator is computed to analyze its spatial filtering properties, in terms of the spectral content and point spread function (PSF). The coherent Born model is considered as benchmark for comparison purposes.

This paper is organized as follows: Section II addresses the problem statement of the mathematical formulation of the RF tomography by WSNs. In Section III, the resolution analysis is performed, while reconstruction results based on full-wave data are reported in Section IV. Concluding remarks follow in Section V.

II. PROBLEM STATEMENT AND INVERSION APPROACH

For simplicity, we consider the 2-D free-space scenario shown in Fig. 1. Simple sensor nodes are deployed around a scattering scene D, wherein targets are supposed to reside. Their presence is described by the complex relative permittivity ε(r′) = εr( r′) − jσ( r′)/ωε0, with r′ being a generic point in D, εr the relative permittivity (ε0 is the free-space permittivity), σ the electric conductivity, and ω the angular frequency. The nodes are modeled as electric line sources directed along the z-axis (transverse magnetic polarization). They are arranged along a closed curve Γ and are supposed to operate in both transmitting and receiving modes. More specifically, when a transmitting node located at a known position r0 illuminates the scene, each node in the WSN at r0 ∈ Γ records the RF signal. The same operation is repeated by varying the transmitter position r0, so that a multiview/multistatic setup is considered.

In view of the narrow band nature of common wireless devices, the sensors are assumed to work at fixed frequency ω. The exp(jωt) time dependence is assumed and suppressed from this point on.

A. Incoherent Rytov Approach

The sensors are capable to measure only the RF signal power. Therefore, it is not possible to apply conventional linear inversion approaches, e.g., based on migration, diffraction tomography, or inverse filtering [26]–[29], since these last require the complex (amplitude and phase) scattered field.

According to the idea originally introduced in [30] and recently exploited in [17], a linear scattering model can be established within the framework of Rytov approximation [26], [30].

The starting point to derive the Rytov approximation is to represent the incident field as

\[ E_i(r_o) = e^{\phi_i(r_o)} \] (1)

where \( \phi_i(r_o) \) is the complex incident phase function, which encodes the information about the phase and the amplitude of the incident field. Similarly, the total field \( E_t \) is cast as

\[ E_t(r_o) = e^{\phi(r_o)} \] (2)

where the total complex phase function is written as \( \phi(r_o) = \phi_i(r_o) + \phi_s(r_o) \), and \( \phi_s \) is the scattered phase function.

Under Rytov approximation, holding when \(|\chi| \gg |(\nabla\phi_s)^2|/k_0^2\), \( \phi_s \) can be expressed in terms of an integral relationship [26], as follows:

\[ \phi_s(r_o) \approx \frac{k_0^2}{E_i(r_o)} \int_D g(r_o, r') E_s(r', r_o) \chi(r') dr'. \] (3)

In the aforementioned formula, \( k_0 = 2\pi/\lambda_0 \) is the propagation constant in free space (\( \lambda_0 \) is the wavelength);

\[ \chi(r') = \varepsilon_r(r') - 1 - j\frac{\sigma(r')}{\omega\varepsilon_0} = \chi_{re}(r') + j\chi_{im}(r') \] (4)

is the complex contrast function accounting for the presence of targets in \( D \) (\( \chi_{re} \) and \( \chi_{im} \) are its real and imaginary parts, respectively); and

\[ g(r_o, r') = \frac{j}{4} H^{(2)}_0 \left( k_0 |r_o - r'| \right) \] (5)
is the free-space Green’s function, with $H_0^{(2)}$ being the Hankel function of second kind and zero order. Moreover, $E_i(\mathbf{r'}, \mathbf{r})$ is the incident field in $D$ radiated by the transmitting node located at $\mathbf{r}_o$.

Let us compute the square amplitude of total field in (2), i.e.,

$$|E_i(\mathbf{r}_o)|^2 = \left| e^{i\phi_s(\mathbf{r}_o)} \right|^2 = |E_i(\mathbf{r}_o)|^2 e^{2\text{Re}[\phi_s(\mathbf{r}_o)]}. \quad (6)$$

Since the RF power detected by sensor nodes is proportional to the square amplitude of the electric field, $P_i(\mathbf{r})$ can be expressed in decibels as follows:

$$P_{i\text{dB}}(\mathbf{r}_o) = P_{i\text{dB}}(\mathbf{r}_o) + (20 \log_{10} e) \text{Re}[\phi_s(\mathbf{r}_o)] \quad (7)$$

where Re[.] is the real-part operator. In the aforementioned formula, $P_{i\text{dB}}$ and $P_{o\text{dB}}$ denote the powers received by the sensors in the presence or absence of targets in $D$, respectively.

Before going on, it is convenient to adopt the more compact operator notation. In particular, (3) is rewritten as

$$\phi_s = \mathcal{T} \chi \quad (8)$$

where $\mathcal{T} : U \to V$ is a compact linear operator mapping $U$ into $V$. Specifically, $U = \mathcal{L}^2(D)$ and $V = \mathcal{L}^2(\Gamma)$ are the complex Hilbert spaces of unknown and data, respectively. Note that $\phi_s$ in (8) represents the data in the coherent inverse scattering model based on Rytov approximation [26].

In view of (8) and due to the linearity of the problem, it is possible to cast (7) as

$$\Delta P = \mathcal{T}_{\text{re}} \chi_{\text{re}} - \mathcal{T}_{\text{im}} \chi_{\text{im}} = \tilde{\mathcal{T}} \tilde{\chi} \quad (9)$$

where $\Delta P = (P_{i\text{dB}} - P_{o\text{dB}})/20 \log_{10} e$, $\mathcal{T}_{\text{re}}$ and $\mathcal{T}_{\text{im}}$ are the real and imaginary parts of the operator $\mathcal{T}$, respectively; $\tilde{\chi} = [\chi_{\text{re}}, \chi_{\text{im}}]$ is the vector of unknown functions $\chi_{\text{re}}$ and $\chi_{\text{im}}$; and $\tilde{\mathcal{T}} : \tilde{U} \to \tilde{V}$. In detail, $\tilde{U} = \mathcal{L}^2(D) \times \mathcal{L}^2(D)$ is the Hilbert space composed of vectors of unknowns, and $\tilde{V} = \mathcal{L}^2(\Gamma)$ is the Hilbert space of data. The tilde symbol has been used in (9) to stress that the operator $\tilde{T}$ and the spaces $\tilde{U}$ and $\tilde{V}$ formally differ from $\mathcal{T}$, $U$, and $V$ introduced previously for (8).

Equation (9) defines a linear inverse problem, and the goal is to retrieve $\tilde{\chi}$, i.e., the real and imaginary parts of $\chi$, from the knowledge of $\Delta P$. This problem is ill-posed, which implies that the solution may not exist and may not depend continuously on data [28].

For that reason, a generalized solution is found by minimizing the norm of the error between the model and actual data, i.e.,

$$\tilde{\chi} = \inf \| \tilde{\mathcal{T}} \tilde{\chi} - \Delta P \|^2. \quad (10)$$

By considering the SVD of the operator $\tilde{T}$, the solution to the problem in (10) can be written as

$$\tilde{\chi} = \sum_{n=1}^{\infty} \frac{(E_s, \tilde{u}_n)}{\sigma_n} \tilde{v}_n \quad (11)$$

where $(\cdot, \cdot)$ denotes the scalar product; $\sigma_n$ is the set of singular values sorted in decreasing order; and $\tilde{u}_n$ and $\tilde{v}_n$ are the singular functions, which represent orthonormal bases in the space of data and unknowns, respectively.

In this work, we adopt a truncated SVD (TSVD) strategy to regularize the inverse problem. The TSVD scheme neglects in (11) the singular values after a truncation index $N_t$, which acts as regularization parameter. This last is typically chosen at the knee of the curve defined by the singular values. However, depending on the behavior of singular values and noise level on data, the choice of $N_t$ is not trivial. In this work, we adopt the popular L-curve method that selects the optimal regularization parameter in correspondence to the knee exhibited by the curve of the discrepancy norm of the solution as the parameter varies [31].

### B. Coherent Born Approach

The linear inverse scattering model provided by the first-order Born approximation [26] has been successfully applied in past years to solve many inverse scattering problems (e.g., see [27]–[29] and [32]–[34]).

Under the Born approximation, the scattering phenomenon is governed by a linear integral equation [26]

$$E_s(\mathbf{r}_o) = k_0^2 \int_D g(\mathbf{r}_o, \mathbf{r}') E_i(\mathbf{r}', \mathbf{r}_o) \chi(\mathbf{r}') d\mathbf{r}' \quad (12)$$

which must be solved in terms of $\chi$ given the complex scattered field data $E_s$. The Born approximation holds for weak scatterers, but its limits of validity can be significantly extended as far as qualitative reconstructions are considered sufficient to characterize the targets in the scene [29].

The Born model is not directly applicable for RF tomography by WSNs due to the lack of phase information. Therefore, it is considered here only as a reference model, with the intention to test the performance of the incoherent Rytov approach. It must be also said that the coherent Rytov model in (8) could have served this purpose as well. However, it requires the application of sophisticated phase unwrapping procedures to evaluate the scattered phase $\phi_s$ [35]. For that reason, its use in realistic inverse scattering applications has been much more limited, with respect to the Born model.

Looking at practical WSN applications, it must be noticed that the sensor nodes may operate in complex multiscreening environments. For instance, the targets may be not in line of sight with the sensors or may be illuminated only by direct waves but also from fields scattered by the objects in the scene (e.g., buildings, earth, etc.). In those cases, it is necessary to account for multipath phenomena, in order to develop an accurate forward model. To this end, as done in [36]–[38], the exact incident field and Green’s function of the scenario involved in (12) may be evaluated by means of numerical techniques. This strategy requires the knowledge of the geometrical and electromagnetic properties of the scenario.

### III. Imaging Performance of the Incoherent Rytov Approach

An effective way to analyze the spatial filtering of the operator $\tilde{T}$ defined in (9), i.e., the class of retrievable object profiles,
is provided by the SVD tool, owing to the concept of spectral content [32]–[34]. The spectral content has allowed evaluating the retrievable information from the data under different measurement configurations for 2-D (e.g., see [32]) and 3-D inverse scattering problems [33], [34].

For the TSVD inversion scheme, the spectral content is defined as the sum of the square amplitude of the Fourier transforms of the complex singular functions corresponding to the retained singular values, i.e.,

\[
sp(k_x, k_y) = \sum_{n=1}^{N_t} |\tilde{v}_n(k_x, k_y)|^2
\]

(13)

\[
\tilde{v}_n(k_x, k_y) = \int_{-\infty}^{+\infty} \int_{-\infty}^{+\infty} \tilde{v}_n(x, y) e^{-j(k_xx+y_y)dxdy}
\]

(14)

\[
\tilde{v}_n(x, y) = \tilde{v}_{n}^{re}(x, y) + j\tilde{v}_{n}^{im}(x, y)
\]

(15)

where \(\tilde{v}_{n}^{re}\) and \(\tilde{v}_{n}^{im}\) are the real singular functions corresponding to \(\chi_{re}\) and \(\chi_{im}\), respectively.

Another figure of merit usually adopted to appreciate the achievable resolution is the PSF, i.e., the regularized reconstruction of a pointlike target [28]. This last is evaluated by generating the data, according to the forward model for an impulsive contrast function. Then, the data are inverted by the TSVD scheme.

Since the singular spectrum of the operator \(\tilde{T}\) cannot be worked out in closed form, we examine its filtering properties by discretizing (9) with the method of moments [39]. The numerical implementation is based on a point matching in data space, while the unknown function is represented with rectangular basis functions.

It must be stressed that a correct numerical analysis demands an accurate discretization of the continuous operator \(\tilde{T}\), in order to catch its main characteristics. Moreover, a crucial question is the determination of the optimal number of sensor nodes. According to [40], when square amplitude data are uniformly collected over a circular domain, the optimal number of sensors to collect the scattered field is equal to \((4k_0a)^2\), where \(a\) is the minimum radius enclosing the target. Since no \(a\) priori information is available on the targets’ location other than they are somewhere in \(D\), we consider \(a\) as the radius of the smallest circle enclosing \(D\). It is easily realized that this number rapidly becomes large at high frequencies and/or when a wide area (in terms of wavelength \(\lambda_0\)) needs to be investigated. Therefore, the goal of the following analysis is to highlight the filtering properties of the operator \(\tilde{T}\) in “ideal” conditions, i.e., by assuming a correct sampling of the electromagnetic field. On the other hand, by looking at realistic applications, the case of a WSN whose number of nodes is lower than the optimal one will be examined later on.

We consider the WSN topology shown in Fig. 2, where sensor nodes operating at 2.45 GHz are deployed over a circumference of 1-m radius with a uniform angular spacing of 2.5° (144 nodes). The domain \(D = [-0.5, 0.5] \times [-0.5, 0.5] m^2\) is discretized into square image pixels with sides of 0.025 m.

The solid line plotted in Fig. 3 displays the behavior of singular values for the operator \(\tilde{T}\), where the singular values are normalized with respect to the largest one. As can be seen, they exhibit an abrupt decay after a critical index, i.e., around \(N_t = 1800\). For a comparison, the singular values of the Born operator are also displayed as dashed line. The curve of Born singular values presents a knee at \(N_t = 904\), which is nearly half of the critical index in the Rytov approach. By accounting that, in the Rytov approach, real-value data are considered, whereas under the Born model, we have complex scattered field data, it turns out that the amount of independent information (before the exponential decay of the singular values) is very similar for the two approaches.

The spectral content related to the operator \(\tilde{T}\) has been evaluated for different values of the TSVD truncation index, which are equal to \(N_t = 500\), 1000, and 1500, respectively. The results are shown in Fig. 4, where the superimposed dashed line represents the Ewald circle, i.e., the set of spatial frequencies retrievable by the coherent diffraction tomography (Born model) [26]–[29]. As can be seen, the scattering operator \(\tilde{T}\) acts as a low-pass filter with a circular symmetry; therefore, only a smoothed version of the contrast function can be retrieved. The
spatial filtering is more severe when the truncation index is low, while the spectral content gradually fills the Ewald circle as \( N_t \) increases.

The regularized PSFs of a point target located at \((0, 0)\) m are plotted in Fig. 5, for the chosen regularization parameters \( N_t \). As expected, the spatial resolution \( \Delta \) along a radial direction improves as the truncation index grows. In particular, when \( N_t = 1500 \), it turns out that \( \Delta \approx \lambda_0/4 = 0.3 \) m, which is the classical limit achievable with a multiview/multistatic configuration within the framework of coherent diffraction tomography.

These results suggest that, in principle, it is possible to retrieve from incoherent data similar information as from coherent measurements. However, this possibility ultimately depends on the adopted regularization parameter, which is intrinsically related to the necessity to mitigate the effect of the noise on data. In this respect, it is worthwhile to remark that data involved in (9) and (12) are substantially different. Consequently, a comparison of the two models at hand for the same number of retained singular values has no physical sense. Therefore, in order to perform a fair comparison, we consider the following cases where the signal-to-noise ratio (SNR) on the scattered field is the same for both the approaches. In a first moment, the SNR is assumed constant over each wireless link, i.e., for each TX/RX pair.

We consider a cylindrical target centered at the origin and having a radius of 0.02 m, i.e., smaller than system resolution, in order to emulate a point target (see Fig. 2). The cylinder has a real contrast equal to 0.01, thus acting as a weak scatterer. The scattered field data have been generated by means of the exact analytical solution to the problem involving an electric line source radiating in proximity of a lossless dielectric cylinder [39]. After, the scattered field data have been corrupted with additive white Gaussian noise (AWGN) by increasing progressively the SNR from \(-30\) to 20 dB with a step of 5 dB. The inversions have been performed via TSVD for both the models, and the optimal regularization parameter has been selected by applying the L-curve method [31].

Fig. 6 shows the optimal truncation index \( N_t \) versus SNR on the scattered field.
The entropy defined in (16) is an indicator of the contrast of an image, and it is higher when the image has a poorer resolution. The curves plotted in Fig. 8 display the entropy for both inversion approaches versus the SNR level. As can be seen, they are fully consistent with the images in Fig. 7. Indeed, the

![Fig. 7. Normalized amplitude of the contrast function versus SNR for the incoherent Rytov approach (upper panels) and Born approach (lower panels). Gray scale [0, 1].](image)

<table>
<thead>
<tr>
<th>SNR [dB]</th>
<th>Resolution of incoherent Rytov approach [m]</th>
<th>Resolution of Born approach [m]</th>
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<tbody>
<tr>
<td>-30</td>
<td>0.035</td>
<td>0.028</td>
</tr>
<tr>
<td>-20</td>
<td>0.035</td>
<td>0.028</td>
</tr>
<tr>
<td>-10</td>
<td>0.035</td>
<td>0.028</td>
</tr>
<tr>
<td>0</td>
<td>0.028</td>
<td>0.028</td>
</tr>
<tr>
<td>10</td>
<td>0.028</td>
<td>0.028</td>
</tr>
<tr>
<td>20</td>
<td>0.028</td>
<td>0.028</td>
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</table>

![Fig. 8. Entropy $E$ of the regularized contrast function versus SNR on the scattered field.](image)

![Fig. 9. Curves of singular values in the case of a WSN composed of 18 sensor nodes.](image)
entropy of the Rytov images is mostly larger than that achievable with the Born model, thus implying a lower sharpness. For very noisy data ($\text{SNR} = -30 \, \text{dB}$), both methods produce inaccurate results, and the curves are very close. Then, the difference between them increases as the SNR grows, and finally, the curves become similar for a high SNR.

The investigations performed so far have revealed that the incoherent Rytov approach, in general, yields poorer imaging performance compared to the Born model, for low values of SNR, but the models share similar properties when the noise level is low.

Let us turn now to the case of a more realistic configuration with a number of sensors lower than the optimal one. To this end, the number of nodes in the WSN in Fig. 2 has been decimated by a factor of 8, so that the angular spacing is now $20^\circ$ (18 sensors). The singular values relevant to this new topology are presented in Fig. 9. A significant reduction in the number of singular values before the abrupt decay is observed with respect to the ideal case presented earlier (see Fig. 3). Now, we can state that the amount of information provided by the Rytov model is smaller compared with the one provided by the Born model. This point suggests a major robustness of the Born model when the level of noise on the data is significant also because the Born model has a double piece of information for each singular value.

The tomographic images shown in Fig. 10 confirm this behavior, leading to interesting conclusions. First of all, due to the undersampling of data, a reliable reconstruction can be achieved only when the SNR is larger than 0 dB. Furthermore, the Born model performs better in terms of focusing regardless of the SNR, as established by the lower entropy values (see Fig. 11). Finally, note that the entropy values achieved with this WSN are higher than their counterparts in Fig. 8, particularly for high SNR. This outcome is a direct consequence of the data undersampling and the arising of sidelobes with both inversion approaches (see Fig. 10).

IV. RECONSTRUCTION RESULTS

Numerical tests based on synthetic full-wave data are here presented to assess the reconstruction capabilities of the incoherent Rytov approach. The data are generated by means of the finite-difference time-domain forward solver GPRMax2D [42]. The scattered field is corrupted with AWGN for different noise levels ($\text{SNR} = 0, 20, 40 \, \text{dB}$). The inversions are performed via TSVD, and the regularization parameter is selected by resorting to the L-curve method. The two WSNs already considered in Section III are dealt with for the following analysis.

The first test bed refers to a cylindrical object centered at $(0.25, 0.25) \, \text{m}$ and having a radius of $0.1 \, \text{m}$. Different material properties of the target are taken into account to provide a more solid assessment of the incoherent Rytov approach. The tomographic reconstructions are given, in terms of the amplitude of the contrast function normalized with respect to the maximum.

The scattered field is in the case of a WSN composed of 18 sensor nodes.

Fig. 11. Entropy $E$ of the regularized contrast function versus SNR on the scattered field in the case of a WSN composed of 18 sensor nodes.
This article has been accepted for inclusion in a future issue of this journal. Content is final as presented, with the exception of pagination.

Fig. 12. Reconstructions of a dielectric cylinder having a relative permittivity of 1.2 and an electrical conductivity of 0.001 with a WSN composed of 144 sensor nodes. Incoherent Rytov approach (upper panels) and Born approach (lower panels). Gray scale [0.1, 1].

Fig. 13. Reconstructions of a dielectric cylinder having a relative permittivity of 4 and an electrical conductivity of 0.001 with a WSN composed of 144 sensor nodes. Incoherent Rytov approach (upper panels) and Born approach (lower panels). Gray scale [0.1, 1].

The images in Fig. 13 refer to a cylinder with a relative permittivity of 4 and a conductivity of 0.001 and allow testing the methods in the presence of a higher model error due to mutual interactions inside the object. In view of that, the images appear more cluttered with respect to those in Fig. 12. In any case, the Rytov approach still provides reliable results, even if these are slightly worse than those achieved with the Born model. In agreement with the analysis carried out in Section III, Born reconstructions are less sensitive to the noise level.

The next example is concerned with a perfectly conducting cylinder. Note that the Born model rigorously holds for weak scatterers. However, as pointed out in [29], it can be successfully applied also far beyond its limits of validity (e.g., for perfectly conducting targets) to obtain qualitative reconstructions of the targets in the probed scene.

The imaging results obtained in this case are reported in Fig. 14. It is interesting to see that, except when the SNR is equal to 0 dB, the results achieved with Rytov and Born approaches are very similar. Indeed, both methods correctly image only the contour of the cylinder.

The previous numerical experiments have been repeated for the WSN comprising only 18 sensor nodes. The tomographic reconstructions of the cylinder with permittivity of 1.2 and 4 are reported in Figs. 15 and 16, respectively, while those pertaining to the metallic cylinder are shown in Fig. 17. As a general consideration, the quality of the images is now poorer compared...
Fig. 17. Reconstructions of a perfectly conducting cylinder with a WSN composed of 18 sensor nodes. Incoherent Rytov approach (upper panels) and Born approach (lower panels). Gray scale [0.1, 1].

TABLE II

<table>
<thead>
<tr>
<th>Test case</th>
<th>SNR [dB]</th>
<th>Incoherent Rytov approach</th>
<th>Born approach</th>
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<tbody>
<tr>
<td>Cylinder permittivity 1.2</td>
<td>0</td>
<td>7.02</td>
<td>6.65</td>
</tr>
<tr>
<td></td>
<td>20</td>
<td>6.97</td>
<td>6.41</td>
</tr>
<tr>
<td></td>
<td>40</td>
<td>6.99</td>
<td>6.38</td>
</tr>
<tr>
<td>Cylinder permittivity 4</td>
<td>0</td>
<td>7.04</td>
<td>6.75</td>
</tr>
<tr>
<td></td>
<td>20</td>
<td>6.95</td>
<td>6.58</td>
</tr>
<tr>
<td></td>
<td>40</td>
<td>6.93</td>
<td>6.58</td>
</tr>
<tr>
<td>Metallic cylinder</td>
<td>0</td>
<td>7.00</td>
<td>6.91</td>
</tr>
<tr>
<td></td>
<td>20</td>
<td>6.77</td>
<td>6.77</td>
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<tr>
<td></td>
<td>40</td>
<td>6.77</td>
<td>6.77</td>
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</table>

with their counterparts in Figs. 12–14. This outcome is caused by the information loss related to the undersampling of the data. Specifically, as noticed in Section III, the undersampling arises a higher level of artifacts, which are essentially linked to the sidelobes of the PSF (see Fig. 10). In this respect, the Born model appears only more robust than the incoherent Rytov approach, even if a rough indication on the target position and shape can be achieved with both models. The differences between the two methods are almost negligible in the case of the metallic cylinder for high SNR (see Fig. 17). This claim is supported by the comparison between the entropy data summarized in Table II.

In the following, we report the results of another scenario comprising two metallic targets. Specifically, another cylinder centered at \((-0.25, -0.25)\) m and having a radius of 0.05 m is present in the scene, in addition to the previous one. The tomographic reconstructions achieved with the WSN of 144 nodes and 18 nodes are reported in Figs. 18 and 19, respectively. These results confirm that, for a densely populated WSN and data that are not very noisy, the incoherent Rytov approach leads to accurate imaging results that are comparable with those of the Born model. Moreover, if the WSN comprises only few sensors, targets can be less reliably detected with both models, due to presence of artifacts.

So far, the SNR on data has been assumed constant for each wireless link. However, looking to practical WSN applications, it is interesting to account for the SNR spatial variability among the nodes. With regard to the symmetric WSN made of 18 sensors previously considered, the spatial variability of the SNR has been modeled by defining the SNR as the ratio between the average power of the multiview/multistatic data set and the noise power, which is constant for each channel. The SNR levels here considered are 0, 20, and 40 dB, and the corresponding reconstructions are shown in Fig. 20. As
Regardless of the inversion approach, the imaging results have shown to be less reliable when few sensors are available. This may be a critical issue for the practical implementation of RF tomography by WSNs. In this respect, the results proposed in this work have to be considered only preliminary. Future research activities will address complex scattering scenarios and the development of effective strategies to improve the performance in the case of WSNs having a limited number of nodes. The mutual coupling among sensors caused by their operation in the near field will be also investigated.

Fig. 21. Reconstructions of a perfectly conducting cylinder with an asymmetric WSN composed of 18 sensor nodes. Incoherent Rytov approach (upper panels) and Born approach (lower panels). Gray scale [0.1, 1].

V. CONCLUSION

In this paper, we have addressed the RF tomography by using a WSN consisting of sensor nodes capable to measure only the RF signal power. The main goal was to compare the performance of a fully incoherent inverse scattering approach based on Rytov approximation with the coherent Born model.

The incoherent modeling does not require solving a phase retrieval problem, which suffers from reliability issues (presence of false solutions) and is unpractical for real-time applications. An extensive numerical analysis based on the SVD of the scattering operator has allowed investigating how the absence of phase information in the data impacts the imaging performance. As shown, when the data are not very noisy, the incoherent Rytov approach yields accurate results, which are not very different from those achieved with the coherent Born model. The effect of the number of sensors has been also explored.

REFERENCES


Gianluca Gennarelli was born in Avellino, Italy, in 1981. He received the M.Sc. degree (summa cum laude) in electronic engineering and the Ph.D. degree in information engineering from the University of Salerno, Salerno, Italy, in 2006 and 2010, respectively. From April 2010 to December 2011, he held a Postdoctoral Fellowship at the University of Salerno. Since January 2012, he has been a Research Scientist with the Institute for Electromagnetic Sensing of the Environment of the Italian National Research Council (IREA-CNR), Naples, Italy. In 2015, he was a Visiting Scientist with the Centre for Maritime Research and Experimentation, Science and Technology Organization, North Atlantic Treaty Organization, La Spezia, Italy. He has coauthored over 70 publications in international peer-reviewed journals and conference proceedings. His research interests cover theoretical and applied electromagnetic topics, such as microwave sensors, antennas, electromagnetic inverse scattering problems, radar imaging, diffraction problems, near-field far-field transformation techniques, and electromagnetic simulation. Dr. Gennarelli serves as a reviewer for international journals in the field of antennas and propagation, remote sensing, optics, signal processing, and applied physics.

Francesco Soldovieri (M’10–SM’13) received the Laurea degree in electronics engineering from the University of Salerno, Salerno, Italy, in 1992 and the Ph.D. degree in electronics engineering from the University of Naples “Federico II,” Naples, Italy, in 1996. In 1993, he joined the Electromagnetic Research Group, University of Naples, where he held a Postdoctoral Fellowship in 1998–1999. In 2001, as a Researcher, he joined the Institute for Electromagnetic Sensing of the Environment, Italian National Research Council (IREA-CNR), Naples, where he has been a Senior Researcher since 2006. His main scientific interests include electromagnetic diagnostics, inverse scattering, GPR applications, antenna diagnostics and characterization, and security applications.

Dr. Soldovieri was the General Chair of the 2007 International Workshop on Advanced Ground Penetrating Radar. Since 2002, he has been involved in the Technical Committees of the GPR Conference and the International Workshop on Advanced Ground Penetrating Radar. He has been a Special Guest Editor for issues on the Journal of Applied Geophysics, Near Surface Geophysics, and Advances in Geosciences. He was awarded the 1999 Honorable Mention for the H. A. Wheeler Applications Prize Paper Award of the IEEE Antennas and Propagation Society.