Wave-Oriented Signal Processing of Dispersive Time-Domain Scattering Data

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Abstract—Phase-space data processing is receiving increased attention because of its potential for furnishing new discriminants relating to classification and identification of targets and other scattering environments. Primary emphasis has been on time-frequency processing because of its impact on transient, especially wideband, short-pulse excitations. Here, we investigate the windowed Fourier transform, the wavelet transform, and model-based superresolution algorithms within the context of a fully quantified and calibrated test problem investigated by us previously: two-dimensional (2-D) short-pulse plane wave scattering by a finite periodic array of perfectly conducting coplanar flat strips. Because the forward problem has been fully calibrated and parametrized, some quantitative measures can be assigned with respect to the tradeoffs of these time-frequency algorithms, yielding tentative performance assessments of the tested processing algorithms.

Index Terms—Scattering, signal processing, time-domain analysis.

I. INTRODUCTION

INCREASED attention within the electromagnetics community has been given recently to phase-space signal processing techniques [1]–[11] for dealing with propagation and scattering in complex environments. Experiments have usually been carried out in the time-frequency subdomain of the full configuration (space-time)—spectrum (wavenumber-frequency) phase space, although some work has also been done in the space wavenumber phase space [3], [5], [11]. Demonstrations of utility have primarily (and understandably) been supported by results that reflect favorably on the particular technique used for a particular problem, but there have yet to emerge more general criteria as to how the phase space should be systematically parametrized and calibrated. In this paper, we make an attempt to move in this direction.

Two useful classifiers of propagation and scattering are whether the event is local or global. The wave objects associated with local and global events in the time domain are wavefronts and space-time resonances, respectively. Having made this basic classification, the question arises as to how the corresponding phase-space footprints are parametrized and how these footprints can “best” be extracted from propagation and scattering data. Because the phase space is accessed most effectively from the data by windowed transforms, the window shape and size is one of the essential parameters. Because phase-space distributions are subject to the configuration-spectrum tradeoff imposed by the uncertainty relation [12], the relative emphasis on configuration or spectrum is a second parameter. Quantitative assessment of the influence of these parameters requires analytical and numerical experimentation, with the goal of arriving at criteria that may eventually serve as standards (benchmarks) for testing wave-oriented data processing algorithms. The analytical-numerical experiments are best carried out for problems which can be solved under fully controlled conditions.

Our controlled problem has been a finite array of perfectly conducting coplanar flat strips arranged periodically along $z$ in the $z = 0$ plane (Fig. 1), with subsequent generalization to include perturbations around this periodic prototype [13]–[15]. This test configuration involves several scales (strip width, strip separation, and array size), collective effects due to periodicity, and edge scattering due to the individual strip edges, as well as the truncation edges of the array. Under short-pulse plane wave excitation, the corresponding time-domain scattered fields can be parametrized phenomenologically either as a sum of time-gated primary and multiple scatterings due to individual strips or as collective scattering from the entire “aperture” of the periodic array. The latter yields a sum of dispersive sustained wavetrains (time-domain Floquet modes) each of which accounts via its characteristic frequency profile for the global effects of infinite periodicity, complemented by Floquet-mode modulated edge diffractions due to the truncations. For the phenomenology-based (wave-oriented) data processing of this fully calibrated scattering model, we have utilized the short-time Fourier transform, the wavelet transform, and a windowed superresolution algorithm, without and with the addition of white Gaussian noise.

For the present discussion, we return to this canonical problem to address more critically the phase-space calibration issues detailed above. Our earlier studies, as those of others, have shown that phase-space processing can work, but these studies have not dwelled on the usually painstaking trial and error that has to be pursued to make them work. A fully
parametrized and calibrated forward scattering problem is the basis for quantitative parametrization of the wavefront and resonance alternatives that characterize, respectively, the early- and late-time scattered fields at the observer. We show in the paper how critically the processing window size influences the phase-space footprints, and how conclusions from these trials could not have been stated with reasonable confidence without the backup of a forward calibrated model.

The remainder of the paper is organized as follows. The forward model for the target under study is summarized in Section II, highlighting information that is relevant for the subsequent phase-space processing. The fixed resolution, multiresolution, and superresolution algorithms used for time-frequency processing are summarized in Section III, with results presented in Section IV. Conclusions are summarized in Section V.

II. STATEMENT OF THE PROBLEM

The test problem involves a pulsed plane wave incident normally upon a finite periodic array of perfectly conducting flat, infinitesimally thin, coplanar strips (Fig. 1). For the specific problem parameters here, we have taken strips arranged with period $d$ and width $w = 0.64d$. The fields are observed at a distance of $29.58d$ directly above the left-most edge of the array for TE polarization (electric field parallel to the strip edges). The Rayleigh pulse in Fig. 2 describes the incident pulse shape with time and frequency normalized to $T = d/c$, where $d$ is the array period (see Fig. 1) and $c$ is the speed of light in vacuum.

From (1) it is seen that as $t \rightarrow \infty$ the modal resonant frequency $f_m \rightarrow cm/d$, the cutoff frequency of the $m$th Floquet mode under conditions of normal incidence; similar behavior has been observed in other scattering scenarios [1], [6], [7], [10]. The expression in (1) applies to the infinite periodic array which generates infinitely extended nontruncated plane wave trains. Nevertheless, as the calibrated forward model shows [13]–[15], the truncations for the finite array do not noticeably affect the Floquet-mode frequencies in (1) over those portions of the array where these modes can be separately resolved (i.e., away from $t \approx z/c$).

III. PROCESSING OPTIONS

As stated earlier, we consider three processing options: the short-time Fourier transform, the wavelet transform, and a windowed superresolution algorithm. The particular superresolution algorithm involves an eigenvector-based matrix-pencil method [16], which is similar in spirit to the matrix-pencil method developed by Hua and Sarkar [17], [18], and is one example of several parametric techniques [19], [20] that can be applied to time-frequency processing. These processing options are reviewed briefly below and, in Section IV, they are applied to the problem discussed in Section II for noiseless as well as noisy data. Concerning the choice of the processing window, narrow windows emphasize temporally localized, wideband phenomena (wavefronts) while wide windows emphasize temporally prolonged narrowband phenomena (modes or resonances), with corresponding alternative parametrizations of the scattering process. The definition of “wide” or
“narrow” is tied to characteristic scales of the target. For our prototype strip array, there are two relevant characteristic scales: the strip width and the array period; the third scale, the overall size of the array, is not relevant for the near-zone observations in this problem. To isolate edge diffractions, the window size must be small relative to the travel time $w/c$ between the edges of each strip. To resolve individual strips but not individual edges, the window size should lie between $w/c$ and $d/c$, where $d$ is the array period. To accommodate near-zone collective effects as expressed by the time-domain Floquet modes, we have previously [4] found that the window size should be large enough to include the scattered fields (at the observer) from at least three strips; this last condition is consistent with the minimum number that places the center strip in a locally periodic environment, and it suffices (though possibly with poor resolution) to exhibit the Floquet-mode footprints of an infinite periodic array with that interstrip spacing. Tuning the window size to extract a particular parametrization from data presents difficulties even for fully controlled model problems with a priori knowledge. Nevertheless, it is hoped that some insights and guidelines can emerge from this study for dealing with data derived from unknown scattering configurations.

A. Short-Time Fourier Transform

The Gaussian-windowed short-time Fourier transform (STFT) of a function $g(t)$ is expressed as

$$G(\omega, \tau; \sigma) = \frac{1}{(2\pi)^{1/2}\sigma} \int_{-\infty}^{\infty} g(t) \exp(j\omega t) \times \exp\left[-(t - \tau)^2/2\sigma^2\right] dt$$

where $\tau$ is the center position of the sliding Gaussian window with standard deviation $\sigma$. The well-parametrized phenomenology pertaining to the diffraction problem in Section II allows us to investigate the accuracy of the STFT footprints throughout the phase space, for early and late times, varying window size, and additive noise.

B. Wavelet Transform

The continuous wavelet transform [21], [22] of a function $g(t)$ is given as

$$W(s, \tau) = \frac{1}{\sqrt{s}} \int_{-\infty}^{\infty} g(t) \psi\left(\frac{t - \tau}{s}\right) dt$$

where $s$ is the “scale” and $\psi(t)$ is the “mother wavelet.” The wavelet transform behaves as a bank of bandpass filters (one for each scale), and if the filter response is narrow enough the scale $s$ can be related to frequency, generating a time-frequency distribution. Under such conditions, small scales ($s$) correspond to high frequencies (narrow time resolution and wide frequency resolution) and large scales correspond to low frequencies (wide time resolution and narrow frequency resolution). To extract time-dependent spectra, the mother wavelet should have good filtering properties in the spectral domain; we have utilized the Morlet-type mother wavelet [21]

$$w(t; \omega_0, \sigma) = \frac{1}{(2\pi)^{1/2}\sigma} \cos(\omega_0 t) \exp(-t^2/2\sigma^2).$$

For scale $s = 1$, the frequency $\omega_0$ identifies the center frequency of the equivalent bandpass filter [21], [22], and the parameter $\sigma$ determines the time-frequency resolution at that scale (frequency); the center frequencies of wavelet filters for $s \leq 1$ are $\omega_0/s$. Although (4) is expressed as a two-parameter transform ($\sigma$ and $\omega_0$), in practice it is described by a single parameter: the number of oscillations desired for the Gaussian modulation (this can be realized by varying $\sigma$ for a fixed $\omega_0$, or vice versa).

A demonstration of the wavelet transform has been provided by Kim and Ling [6], [7]. They applied the transform in the frequency domain for which case it corresponds in the time domain to a variable-window-size STFT; the window scaling was chosen so as to satisfy the “wavelet condition” and, at early times, the window size was made small to emphasize temporally narrow, spectrally wide wavefront returns, while at late times, the window size was made progressively wider to emphasize temporally wide, spectrally narrow target resonances. The manner in which their scale-based scheme accommodates both extremes simultaneously seems to work best when the early-time and late-time portions of the scattered fields are “clean”; however, this is frequently not the case, especially with noisy data. The Morlet wavelet transform in (3) and (4), which we have used, is implemented directly in the time domain, but parametrized in terms of the sampling frequency $\omega_0$, which determines its filtering properties. We have found this multiresolution scheme to be robust even in the presence of moderate noise levels (see Section IV-B).

C. Windowed Superresolution Algorithms

The windowed Fourier transform and the wavelet transform are well suited to extracting wave phenomenology from data, but the achievable time-frequency resolution is subject to the uncertainty relation [12]. The resolution achieved with these first-pass algorithms can be improved by fitting properly chosen model-based algorithms locally to the data. We concentrate here on models that relate to oscillatory wave phenomena. The time-domain Floquet modes are characterized by dispersive wavetrains with time-dependent frequency [see (1)] and algebraic damping [13], [14]. To extract the time-varying modal strength and time-dependent oscillation frequency, we apply model-based superresolution to locally windowed portions $g_0(t; \tau)$ of the data $g(t)$, using a constant amplitude window $q(t)$ with finite support

$$g_0(t; \tau) = g(t)q(t - \tau); \quad q(t) = 1, \quad t \in [-T_0/2, T_0/2];$$
$$q(t) = 0, \quad t \not\in [-T_0/2, T_0/2].$$

We have also considered several other types of window functions. An obvious choice, consistent with our STFT, is a Gaussian window; however, it was found that the Gaussian-modulated data could no longer be well represented as a sum of damped sinusoids as assumed in the model and, therefore, the phase-space results were inaccurate. Phase-space results were found to be most reliable when the model-based schemes are applied to the unmodulated data [i.e., with a rectangular window, as in (5)].
Proceeding with the superresolution processing above for sampled time-domain data $g[n]$, we have

$$g_0[n; i] = g[n]g[n - i] = \sum_{m=1}^{M_i} a_m \zeta^m_m = \exp[(j\omega_m(i) - \alpha_m(i))\Delta t]$$

where $M_i$ is the number of modes contributing inside each window (usually unkown), $g[n-i]$ is the rectangular window function in (5) centered at $i$, the sampling rate $\Delta t$ is set by the Nyquist criterion, and $\omega_m(i) - \alpha_m(i)$ is the complex frequency of the $m$th mode inside the $i$th window (corresponding to a modal pole in the complex frequency plane). Many parametric algorithms [19], [20] can deal with data of the form in (6). We have found the matrix-pencil method developed by Hua and Sarkar [17], [18] to be particularly useful for noisy data and have utilized a modified form of this algorithm [16]. It should be noted that in addition to being useful for the extraction of modal information, parametric algorithms have also found utility for the estimation of wavefront arrivals [24], [25].

IV. RESULTS

A. Noise-Free Data

**Short-Time Fourier Transform (STFT):** We first consider the scattering scenario discussed in Section II under noise-free conditions. Fig. 3 displays the time-frequency distribution resulting from application of the STFT in (2), for a Gaussian window-size $\sigma = 1.2T$, which ensures that scattered fields due to at least three strips reach the observer for nearly all window positions. The time-domain scattered field is shown in the bottom plot, the global Fourier transform of the scattered field, and the center plot is the STFT of the scattered field using a Gaussian window with standard deviation $\sigma = 1.14T$ (the real part of the modulated Gaussian window is shown inset for frequency $f = 2.14/T$). The instantaneous Floquet mode frequencies $\omega_m(t)$ from (1) are shown by the solid curves.

**Fig. 3.** Short-time Fourier transform (STFT) of the time-domain fields scattered from the array in Fig. 1; the bottom plot is the time-domain scattered field, the left plot is the global Fourier transform of the scattered field, and the center plot is the STFT of the scattered field using a Gaussian window with standard deviation $\sigma = 1.14T$ (the real part of the modulated Gaussian window is shown inset for frequency $f = 2.14/T$). The instantaneous Floquet mode frequencies $\omega_m(t)$ from (1) are shown by the solid curves.
window sizes than that in Fig. 4 up to the regime, where the Floquet mode dispersion bands begin to overlap to such an extent that they are no longer distinguishable. Instead, the STFT now tends to isolate individual strip scatterings with short time support and wide frequency spread. For an unknown scattering environment, where one does not know the appropriate scales a priori, we suggest sampling the data for wave phenomenology content by sliding a range of fixed window sizes across it. If a particular window size appears to extract a recognizable local- or global-phase space signature from the sampled portion of the scattered field, processing algorithms with better resolution can be applied locally there to hone in on the suspected wave phenomenology.

Wavelet Transform: In the STFT, for each fixed-window pass the spectral content at different frequencies is extracted by the corresponding variable modulation of the Gaussian window. On the other hand, the Morlet wavelet transform keeps the number of oscillations in the modulated Gaussian fixed, but shrinks the scale to extract high-frequency information and dilates the scale to extract low-frequency information. In Figs. 5 and 6, the Morlet mother wavelets have been tuned so that at frequency $f = 2.14/T$, they have exactly the same shape as the real part of the modulated Gaussian used in the STFT results of Figs. 3 and 4, respectively (i.e., the Morlet-wavelet basis at $f = 2.14/T$ (shown inset) is identical to the real part of the modulated Gaussian in Figs. 3 and 4 at the same frequency). Thus, at frequency $f = 2.14/T$ the results of the STFT and Morlet-wavelet processing are identical (strictly speaking, these transforms are not identical since the STFT is complex, and the Morlet wavelet, as defined, is real; however, the real part of the STFT is the same as the Morlet-wavelet transform and, if desired, the Morlet-wavelet transform could be redefined in terms of a complex exponential). In other regions of the time-frequency phase space, the results of STFT and wavelet processing are fundamentally different because of the different parametrizations in these respective algorithms. The Morlet-wavelet transform results in Fig. 5 reveal time-domain Floquet mode bands as in Fig. 3, but now the time-frequency resolution changes as one moves through the phase space; in particular, the variable resolution of the wavelet transform causes a distortion of the $m = 0$ specular response. As one improves the frequency resolution by increasing the number of oscillations in the mother wavelet, there is a commensurate reduction in temporal resolution and vice versa. This is demonstrated in Fig. 6, where the Morlet wavelet at $f = 2.14/T$ corresponds to the modulated Gaussian in the STFT results in Fig. 4. In this case, because of the reduced number of oscillations and the corresponding reduced frequency resolution, the time-domain Floquet modes are not as easily distinguished whereas, due to the increased temporal resolution, the temporally localized $m = 0$ specular response is more sharply defined.

Along the lines discussed above, one may establish other interesting relations between the STFT and Morlet-wavelet transform responses. When the large Morlet wavelet in Fig. 5 is shrunk for the extraction of high-frequency components, there is a frequency for which the results of the wavelet processing correspond to STFT processing with the small window in Fig. 4; this frequency is $f = 5.46/T$ (we recall that at scale $s$ the Gaussian in the Morlet wavelet has standard deviation $\sigma_s$ and the modulation frequency is $f_0/s$, where $\sigma$ and $f_0$ are the standard deviation and frequency at scale $s = 1$; by adjusting the scale $s$, the Gaussian in the Morlet wavelet can be compressed to correlate to the size of the narrow STFT window, and the scale required for this translation
determines the frequency \( f_0 = 5 \times 10^6 / T \) at which the wavelet transform and STFT are similar). Similarly, when the small Morlet wavelet considered in Fig. 6 is dilated to extract low-frequency information, there is a frequency \( (f = 0.583) / T \) for which the wavelet processing is equivalent to STFT processing with a large window (Fig. 3). These properties underscore the interrelationship between the Morlet wavelet and the STFT, which may be exploited when deemed useful.

**Windowed Superresolution Processing:** The time-dependent dispersion bands extracted in Figs. 3–5 straddle the time-dependent dispersion curves predicted by (1). In fact, for our simple test example, the resolution of the STFT or wavelet transform suffice for discrimination of the different well-separated time-domain Floquet modes. As a comparison, we choose here an alternative route with broader implications, namely, model-based windowed superresolution processing that is applied to the data in Figs. 3–6. In particular, we use the windowed eigenvector pencil method [16].

The superresolution results are shown in Fig. 7. The modal poles extracted from the windowed data in (6) are plotted as dots in the phase space at the time corresponding to the center of the sliding window, and they are weighted (see shading) by the modal excitation strength (spectral residue). The window size in (5) was set to \( T_0 = 1.2T \), which is comparable to the size of the Gaussian window used in Fig. 3 for the STFT computations; concerning the window size, if the window is made too small (in efforts to improve temporal resolution), the amount of data available for accurate model performance may be insufficient, whereas if the window is made too large, one will sacrifice temporal resolution and thereby compromise the benefits of superresolution processing. The model order was determined by performing a singular-value decomposition (SVD) at each window position and setting the model order for that window position equal to the number of nonzero singular values. As shown by the results in Fig. 7, this technique works very well for the noise-free data considered here; however, highly noisy data require more sophisticated techniques [23]. We see that over most of the range, the windowed superresolution processing (dots) is in close agreement with the expected \( m \neq 0 \) Floquet-mode time-frequency dispersion curves in (1). Whereas the STFT and wavelet transforms extract bands that are centered about the predicted curves, the windowed superresolution scheme homes in on these curves as such. Additionally, the model-based algorithm extracts the weakly excited \( m = 6 \) mode, which was not seen in either the STFT or wavelet results. Note, however, that the specularly reflected \( m = 0 \) Floquet mode is not extracted in Fig. 7 while the nonmodel-based STFT and wavelet transforms extract this mode easily (Figs. 3–6). The failure occurs because the superresolution model is based on spectra of the form in (6), which does not match the \( m = 0 \) mode physics. This illustrates the limitations of model-based algorithms: their performance is contingent upon matching the model to the phase-space parameters that characterize the data. If the underlying phenomenology is not known a priori, we have sought to establish it via the STFT and/or the wavelet transform. When this sorting out indicates the possible presence of previously explored model-based phenomenologies, the appropriate algorithms can be invoked to improve resolution. This strategy is pursued in Section IVB for noisy data.

**B. Noisy Data**

**STFT and Wavelet Transform:** Most previous investigations of the STFT and wavelet transform have dealt with noise-free synthetic data [1]–[10] or data measured in a very-low-noise anechoic chamber [11]. In practice, the data will be contaminated with noise. To account for this, we reconsider the test problem investigated in Section IV-A, adding white Gaussian noise. Up to 10-dB SNR additive noise, we have found that the STFT and Morlet-wavelet transforms continue to resolve the underlying phenomenology provided that one uses a “proper” STFT window size and Morlet wavelet as discussed earlier. However, for 5-dB SNR, the performance of STFT and wavelet processing degrades, even for the “proper” choice.

These observations are substantiated in Figs. 8 and 9 which show results of STFT and Morlet-wavelet processing on the 5-dB SNR data using the same parameters as in Figs. 3 and 5, respectively; the time-dependent modal dispersion curves from (1) are plotted as previously. Evidently, due to blurring of the phase-space footprints, it is now much more difficult to extract the predicted time-dependent dispersion. The \( m = 1 \) dispersive mode is excited most strongly and is least affected by the noise; the dispersion of the \( m = 2 \) and \( m = 3 \) modes is outlined much less clearly but there is at least a suggestion of bands with confined frequency and extended temporal support. This suffices to hypothesize that the underlying data is characterized by time-dependent modes and that the data should, therefore, be subjected to an appropriate model-based algorithm for improved resolution, as done below. It should be noted that the noise-free phase-space results in Figs. 3–7 were plotted down to \(-90 \) dBm, while the noisy results were plotted down to \(-60 \) dBm. If the results in Figs. 8 and 9 are plotted to \(-90 \) dBm, the modal bands are entirely obscured in the present gray-scale format. This points out another difficulty (in addition to window-size selection) in portraying the outcome...
Fig. 8. Short-time Fourier transform of the time-domain fields in Fig. 3–7, with 5-dB additive white Gaussian noise. The Gaussian window size is the same as in Fig. 3, as are plots of the instantaneous frequencies $f_{\nu}(t)$.

Fig. 9. Morlet-wavelet transform of the time-domain fields in Fig. 8 using the same Morlet wavelet as in Fig. 5. Instantaneous frequencies $f_{\nu}(t)$ as in Fig. 3.

of phase-space processing: the plots are often sensitive to the scaling used in the graphics. While the results in Figs. 8 and 9 are for a specific 5-dB noise realization (and therefore could be termed qualitative), their quality is typical of results found on an ensemble of other test examples.

Windowed Superresolution Processing: Applying the windowed eigenvector pencil method to the data in Figs. 8 and 9, we note that for these high-noise conditions, it is difficult to rely on a SVD of the data matrix to determine the model order. We have, therefore, followed the procedure discussed by others when model-based algorithms are applied to noisy data [26], [27]: the model order has been set to a value larger than appropriate for the scattered signal in the absence of noise. It has been found that the higher order model mitigates against the effects of the noise and that the additional spurious poles often lie outside the band of the true system poles [27]. For the results in Fig. 10, the model order was set to 12 for all window positions and the window size was 1.2$T$; we also considered model orders up to 20, and found little variation of the phase-space signatures in the vicinity of the dispersion curves of modes $m = 1$, 2, and 3. However, the signatures were relatively strongly perturbed when considering various model orders less than ten.

The results in Fig. 10 show that our superresolution processing accurately extracts the $m = 1$ mode dispersion over much of the time-frequency range; the $m = 2$ and $m = 3$ modes are also extracted, but somewhat less accurately due to their relatively weak excitation strength compared to the $m = 1$ mode. We note that the SNR has been defined with respect to the entire scattered waveform; however, the local SNR degrades with increasing time because the scattered field decays with time (see the bottom of Fig. 3): at early times, the SNR is greater than 5 dB, while at late times, the SNR is significantly smaller (after $t \approx 42T$, the SNR is less than 0 dB). Thus, in Fig. 10, the poles extracted by the pencil method are in relatively good agreement with the dispersion curves of the $m = 1$, 2, and 3 modes for $t < 42T$ while, for later times, the agreement diminishes considerably.
To quantitatively assess the properties of a superresolution algorithm for noisy data, one must consider algorithm performance for an ensemble of realizations, relative to the Cramer–Rao lower bound [28]. In the context of the windowed superresolution algorithm considered in this paper, we have performed such an analysis for a similar problem [29].

V. CONCLUSION

In this paper, we have taken some first steps toward a systematic assessment of the performance of time-frequency phase space processing schemes for extraction of footprints associated with time-domain target scattering. Such information is useful for classification of forward target scattering phenomenology, and for extraction of this phenomenology from scattering data for the purpose of target identification. Our demonstrations have been for the particular canonical example of a truncated periodic array of flat coplanar perfectly conducting strips illuminated by a normally incident short-pulse plane wave, but the methodology and conclusions, so far, should be applicable as well to other scattering scenarios. We have emphasized the importance of fully validated and calibrated forward scattering algorithms, parametrized in terms of robust wave physics. Assessment of the performance of the various schemes for our particular example has been given at appropriate places in the text. We have tried to distinguish procedures based on detailed or at least partial knowledge of the connection between the target geometry and corresponding forward scattering data from procedures advocated when there is no a priori information. Resolution is the principal issue throughout, and is strongly dependent on the sampling window size. Our test conditions have been purposely selected so as to highlight signatures with short-time wideband phase-space footprints versus those with long-time narrowband footprints, which are associated with weakly dispersive and strongly dispersive wave phenomena, respectively. Even these favorable conditions—where the various wave types do not overlap and, thus, can be individually identified—are accompanied by resolution tradeoff and other difficulties inherent in the time-frequency phase space. It is here that fully calibrated forward scattering models can help substantially toward the understanding of features and resolution ambiguities arising in the inverse treatment of the data, thereby suggesting that consideration might be given to eventual benchmarking of phase-space methodologies.

In this paper, we have taken what we regard as some first steps toward this goal. Trials similar to those reported by us here have undoubtedly been carried out also by other phase-space practitioners. However, the detailed execution and calibration, if any, of these trials has generally not been reported. We hope that such reporting will become part of the phase-space literature so that experiences and quantitative assessments can be shared and critically compared. Calibration of phase-space methods becomes ever more important if these methods are to be applied to real-target scattering scenarios of substantial complexity. While we have concentrated here on time-frequency processing, similar considerations apply to space-wavenumber processing.

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