Classifying the Quality of Point-Spread Functions with Contrast-To-Noise Ratios

Using an automated method for region of interest and background detection

EMVi-R-83

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August 2018

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Contents

Abstract

In microwave imaging, the data acquired at different frequency intervals are fed into reconstruction algorithms. However, the quality of data at each frequency varies, and using frequencies with low contrast-to-noise ratio (CNR) can be detrimental to the overall quality of the reconstruction. An algorithm is developed to classify the quality of the point-spread function data by evaluating the CNR at each frequency. Validation is performed on the algorithm with simulated and experimental datasets.

1 Introduction

A microwave imaging system is being developed at McMcaster University for use as a breast cancer screening tool. Malignant breast tissue and normal breast tissue differ with respect to their electric permittivities. In order to derive the electric permittivities of imaged tissue, complex-valued S-parameter data are acquired by the imaging system. The data are then processed and fed into reconstruction algorithms to determine complex permittivity. Quantitative microwave holography (QMH) [2,3] is the reconstruction algorithm used in conjunction to the work described in this report, which employs the use of Born's approximation (BA) or Rytov's approximation (RA) to linearize the forward model of scattering.

The acquisition scans are performed across the x, y, and z planes at a range of frequencies. The quality of the data can vary with frequency. Consequently, frequencies with low CNR can lead to poor final image quality. The datasets are usually inspected prior to reconstruction in order to identify and remove the poor quality frequencies. With large datasets, this critical step can be time-consuming.

Measurement acquisition conducts three seperate scans: a reference object (RO), a calibration object (CO), and an object-under-test (OUT). The system point-spread functions (PSFs) are derived from the CO and RO measurements. In this report, an algorithm is developed to classify the quality of the PSF at each sampling frequency. It is important to note that the quality of the PSF at a particular frequency does not have an exact correlation to the quality of the OUT at the same frequency. The algorithm is adapted into a function (Matlab 2017a) that can be called to classify the good frequencies, and feed them into the reconstruction algorithms. Compared to manual identification, the execution of the algorithm is faster, and largely autonomous.

The normalized PSFs are the minimum required inputs for the algorithm to execute (see Eq. (20) in [2]). The general function call, with no optional inputs used, is: `[freq_good] = PSF_classification(CO)`, where CO is the normalized PSF data. The algorithm can be described in two parts. The first is the automated detection of the defined areas of interest for the CNR calculations - a region of interest (ROI) and an exclusion zone. The second is using the area definitions to perform a series of CNR and/or signal-to-noise ratio (SNR) calculations, which are used to determine the quality of the PSFs.

2 Region of Interest Detection

The algorithm first detects and defines two regions - the ROI and an exclusion zone. Automated detection of these regions supports a more robust and data-driven algorithm. The ROI is defined as a cluster of points that contain the signal of interest, and is consistent across all frequencies but varies across z-planes. The exclusion zone is defined as a circular region that omits the ROI and potential interference patterns around it. The area outside of the exclusion zone is defined as the background of the image, which theoretically contains only noise.

2.1 Inversion

To determine a general ROI across all frequencies, a frequency summation of the magnitude of the complex-valued PSFs is performed. The signal is expected to be constant across all frequencies, while the noise is expected to be stochastic. This summation therefore leads to an enhancement of the signal while supressing the noise.

At each frequency, the algorithm determines if the PSF is a depressed signal relative to its background. The PSF is first estimated to be within 5% of the center of the image. If the average signal in the estimated PSF region is lower than the average signal outside of the region, then inversion will be performed to retrieve the desired elevated signal. The data is inverted according to (1),

$$PSF_{\text{inverted}} = (|PSF| - 1) \times (-1). \tag{1}$$

2.2 ROI Cluster Detection

The ROI is defined as a cluster of points that have a value higher than 3 dB, with the maxima of the signal in the frequency summation as a reference point. If the user wishes to use a different threshold point (ie. to 3.5 dB), it can be changed in the function call: `PSF_classification(C0, 'cluster_threshold', 3.5)`. The algorithm checks for a cluster within a 25% distance from the center of the image (on both sides, spanning 50% of image). If multiple clusters are detected, the cluster closest to the center of the image is selected. If a cluster is not found within 25% of the center, the algorithm iterates in 5% increments until it reaches the size of the image. A warning is issued to the user if the distance is over 25%, as it is indicative of an off-centered ROI. See Fig. 1 for an initial cluster ROI detection.

An abnormal cluster ROI is defined as a cluster with a radius that results in the exclusion zone exceeding image dimensions. If the detected cluster is abnormal, the algorithm reverts to the alternative fixed-sized ROI detection method, which is more robust but less accurate. The fixed-sized method is described in section 2.3.

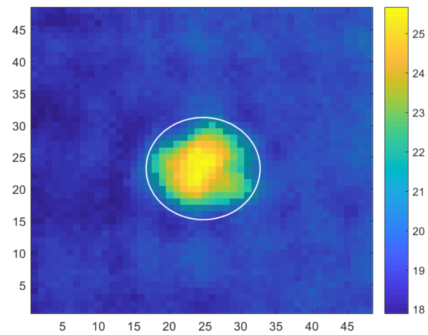


Fig. 1. An image of the frequency summations of the PSFs. The cluster ROI is shown with highlighted pixels. The initial exclusion zone is shown inside the white circle, and the initial background is shown outside the white circle.

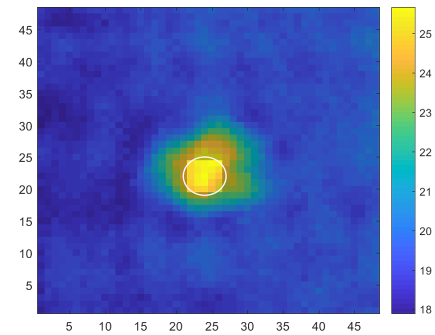


Fig. 2. An image of the frequency summations of the PSFs. The fixed-sized ROI is shown with highlighted pixels. The initial exclusion zone is shown inside the white circle, and the initial background is shown outside the white circle.

The initial exclusion zone is defined as a circle that fully encompasses the ROI. The centroid of the cluster is taken as the center point of the circle, (x_0, y_0). The radius, ρ, is defined as the maximum distance of the centroid to a point on the boundary of the cluster, (x_b, y_b), as shown in (2),

$$\rho = \sqrt{(x_0 - x_b)^2 + (y_0 - y_b)^2}. \tag{2}$$

2.3 Alternative Fixed-Sized ROI Detection

In the case of an abnormal cluster ROI, the algorithm defaults to an alternative fixed-sized ROI detection method. The user can also select this method in the function call: `PSF_classification(C0, 'maxima_ROI', 1)`. In this method, the maxima of the frequency summation is used as the center-point of a boxed region. The region dimensions can be defined by the user. A default size of 10x10mm is implemented to mimic the size of a scattering probe. The user can change the millimeter size of the fixed-sized ROI in the function call: `PSF_classification(C0, 'maxima_ROI', 1, 'probe_size', [20, 20])`. See Fig. 2 for the fixed-sized ROI definition.

The initial exclusion zone definition is the same as the cluster method, except it takes the coordinate points of the maxima as the center of the circle.

2.4 Exclusion Zone Refinement

The exclusion zone is defined at each frequency in order to accurately determine the background of the image. The algorithm searches for the smallest exclusion zone that encompasses the ROI and any surrounding interference patterns or signal leaks. To do so, the algorithm increments the radius of the exclusion zone by 5% of its x range, $range_x$, as seen in (3). If the change in the background variance is less than 4% between two iterations, the algorithm will select the previous iteration's exclusion zone. The convergence criteria is defined in (4),

$$\rho = \rho + ((range_x) \times (0.05)) \tag{3}$$

$$\frac{\mathrm{var}(A_{BGnext}) - \mathrm{var}(A_{BG})}{\mathrm{var}(A_{BG})} \times 100\% < 4\%. \tag{4}$$

For a vectorized image, A, we define its variance, $\mathrm{var}(A)$, in (5) and its mean, $\mathrm{mean}(A)$, in (6). In this report, A is the complex-valued image for an S-parameter at a particular frequency and z-plane. A_{BG} is the defined background in the current iteration, and A_{BGnext} is the variance of the background in the next iteration. A small change in variance indicates that increasing the exclusion zone will not have a significant change in CNR and/or SNR calculated values.

$$\mathrm{var}(A) = \frac{1}{N-1} \sum_{i=1}^{N} (|A_i - \mathrm{mean}(A)|)^2 \tag{5}$$

$$\mathrm{mean}(A) = \frac{1}{N} \sum_{i=1}^{N} A_i. \tag{6}$$

3 Evaluating the Quality of PSFs

3.1 CNR and SNR Calculations

The established ROI and exclusion zone definitions are fed into the algorithm's evaluation of PSF quality. The two quality metrics are CNR and SNR, outlined by (7) and (8). CNR uses a contrast signal, taken as the difference of the mean of the ROI signal and the mean of the background. SNR simply takes the mean of the ROI signal. Both methods evaluate noise as the standard deviation of the background,

$$CNR = \frac{|\mathrm{mean}(A_{ROI}) - \mathrm{mean}(A_{BG})|}{\mathrm{std}(A_{BG})} \tag{7}$$

$$SNR = \frac{\mathrm{mean}(A_{ROI})}{\mathrm{std}(A_{BG})} \tag{8}$$

where A_{ROI} is the defined ROI, A_{BG} is the defined background, and $\mathrm{std}(A)$ is defined in (9),

$$\mathrm{std}(A) = \sqrt{\frac{1}{N-1} \sum_{i=1}^{N} (|A_i - \mathrm{mean}(A)|)^2}. \tag{9}$$

To evaluate the CNR and/or SNR of a complex-valued dataset, the dataset is processed into its magnitude, phase, real and imaginary components. Then, each of these individual components, along with the complex-valued component, are fed into the general equations above to produce a variety of values. The evaluated CNRs and SNRs are magnitude, phase, the average of real and imaginary, and complex magnitude.

The real and imaginary CNR is evaluated separately and then combined as an average to capture the behaviour of the complex-valued dataset. The complex-valued datset is used to evaluate complex magnitude CNR by first evaluating the complex mean of the ROI and background, as seen in (7), and then taking the absolute magnitude of both means before the subtraction. This will result in a different CNR from the magnitude CNR. A similar approach is taken to evaluate the real and imaginary, and complex magnitude SNR.

3.2 Classifying 'Good' Frequencies

Complex magnitude CNR is the default evaluation of the algorithm because it most simply accounts for the nature of a complex-valued dataset. CNR is used in place of SNR due to two possible situations The first case is when the ROI and background have similar signal strengths. In this case, the CNR will be a low value and indicative of the data quality, whereas the SNR would result in a false positive. The second case is when the ROI has a depressed signal strength (for real, imaginary, complex-valued, phase) relative to the background noise, but the PSF is still visually noticable. In this case, the CNR will be a high value and indicative of the data quality, whereas the SNR would result in a false negative.

Once the complex magnitude CNRs are calculated, a user-defined threshold is used to classify a PSF as 'good' or 'bad'. The default threshold used by the algorithm is CNR $\geq$ 3 dB - which is justified in section 4 with experimental validation. For example, If the PSF of a dataset at a certain frequency evaluates to a complex magnitude CNR at or above 3 dB, it is classified as a good quality PSF that can be used with the reconstruction algorithms. If the PSF evaluates to a complex magnitude CNR below 3 dB, it is thrown away and not used in reconstructions. If the PSFs have more than 1 z-plane, the average complex magnitude CNR across all z-planes is evaluated and used in the thresholding process.

The user can select their desired calculation modes by assigning the corresponding linear ratio thresholds in the function call. For example, to evaluate the phase and complex magnitude CNRs with a 1 and 2 dB threshold, respectively, the user must call: `PSF_classification(CO, 'CNR_thresholds', [0 1.2589, 0, 1.5849])`. To evaluate the SNR values, the same logic applies but the user must use the `'SNR_thresholds'` input.

4 Validation of Classification Algorithm on a Simulated Dataset

To evaluate the performance of the algorithm, 3 dB white Gaussian noise is created and added to a simulated dataset consisting of RO, CO and OUT measurements. The PSFs are acquired by subtracting the RO from the CO, according to BA [2]. The noisy PSFs are then submitted to the algorithm to check whether the systematically added 3 dB noise evaluates to a complex magnitude CNR of approximately 3 dB.

After confirming the accuracy of the CNR estimate, white Gaussian noise is added to a select number of frequencies. Reconstruction with Born-based QMH (BA-QMH) is performed on three cases. The first case adds noise to randomly selected frequencies, the second adds noise to only the lower frequencies, and the third adds noise to the higher frequencies. The default reconstruction, which uses all frequencies, is compared to the reconstructions that use the algorithm's 'good' frequencies, classified by a 3 dB threshold.

4.1 Generating White Gaussian Noise

The generated noise must be scaled to the contrast signal, which is defined in the algorithm as the numerator in (7). The analogous contrast signal, C, for CO and RO measurements is defined in (10) as the difference between the mean of the ROI of the CO (the 'central signal') and the mean of the RO. The average contrast signal is taken across all z-planes of the CO.

The `wgn` MATLAB function is used to create an N_{x} by N_{y} complex-valued white Gaussian noise matrix. The real and imaginary components are scaled to have half power, shown in (11). The power of the noise is calculated in (11) for each frequency and S-parameter in order to achieve a desired, consistent 3 dB CNR.

$$C = |\mathrm{mean}(ROI_{CO})| - |\mathrm{mean}(RO)| \tag{10}$$

$$power = 10 * \log_{10}(C^2) - 3. \tag{11}$$

After adding noise to the RO, CO and OUT, the PSFs for each S-parameter are fed into the classification algorithm. The results of the CNR evaluations are shown in Fig. 3. The average complex magnitude CNR across all z-planes is approximately around or under 3 dB. This is consistent with the noise addition, which was scaled in accordance to the contrast signal to output a predicted CNR of 3 dB.

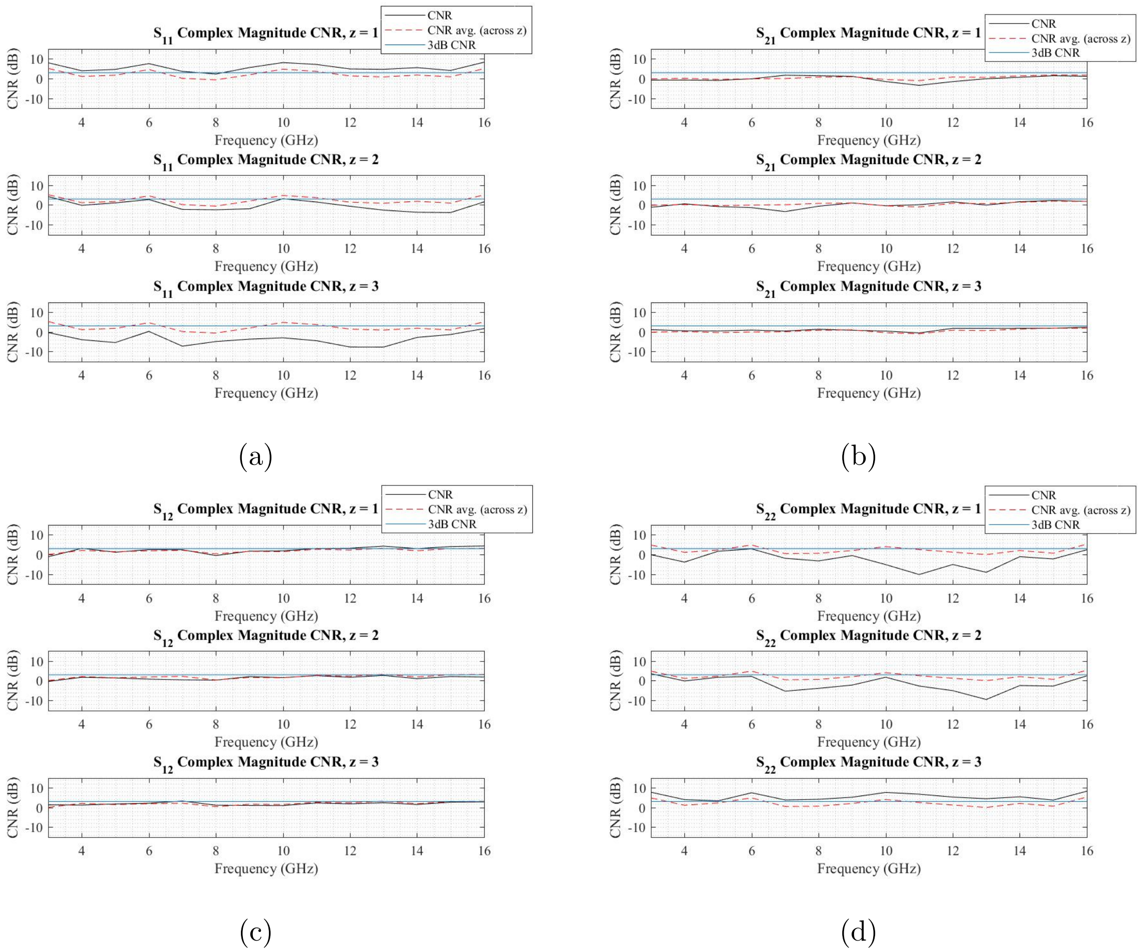


Fig. 3. Complex magnitude CNR values for the PSF of (a) S_{11} (b) S_{21} (c) S_{12} (d) S_{22} with noise added to dataset. All S-parameters show average CNR values across all z-planes of approximately 3 dB.

4.2 Corrupting Frequencies with White Gaussian Noise

4.2.1 Corrupting Random Frequencies

In the first case, white Gaussian noise is added to the dataset at 5, 11 and 15 GHz. Fig. 4 shows the complex magnitude CNR calculations for each S-parameter PSF. The CNR at the intended frequencies show a significant drop in quality. The default reconstruction is shown in Fig. 5 and is noticably affected by the addition of white Gaussian noise. The reconstruction is then performed with the good frequencies, as classified by the algorithm using a 3 dB threshold (see Table 1). The resulting reconstruction is shown in Fig. 6 and is seen to be an improvement from the default reconstruction.

4.2.2 Corrupting Low Frequencies

In the next case, white Gaussian noise is added to the low frequency range. The frequencies chosen are 3 - 9 GHz. Fig. 7 shows the complex magnitude CNR calculations at each

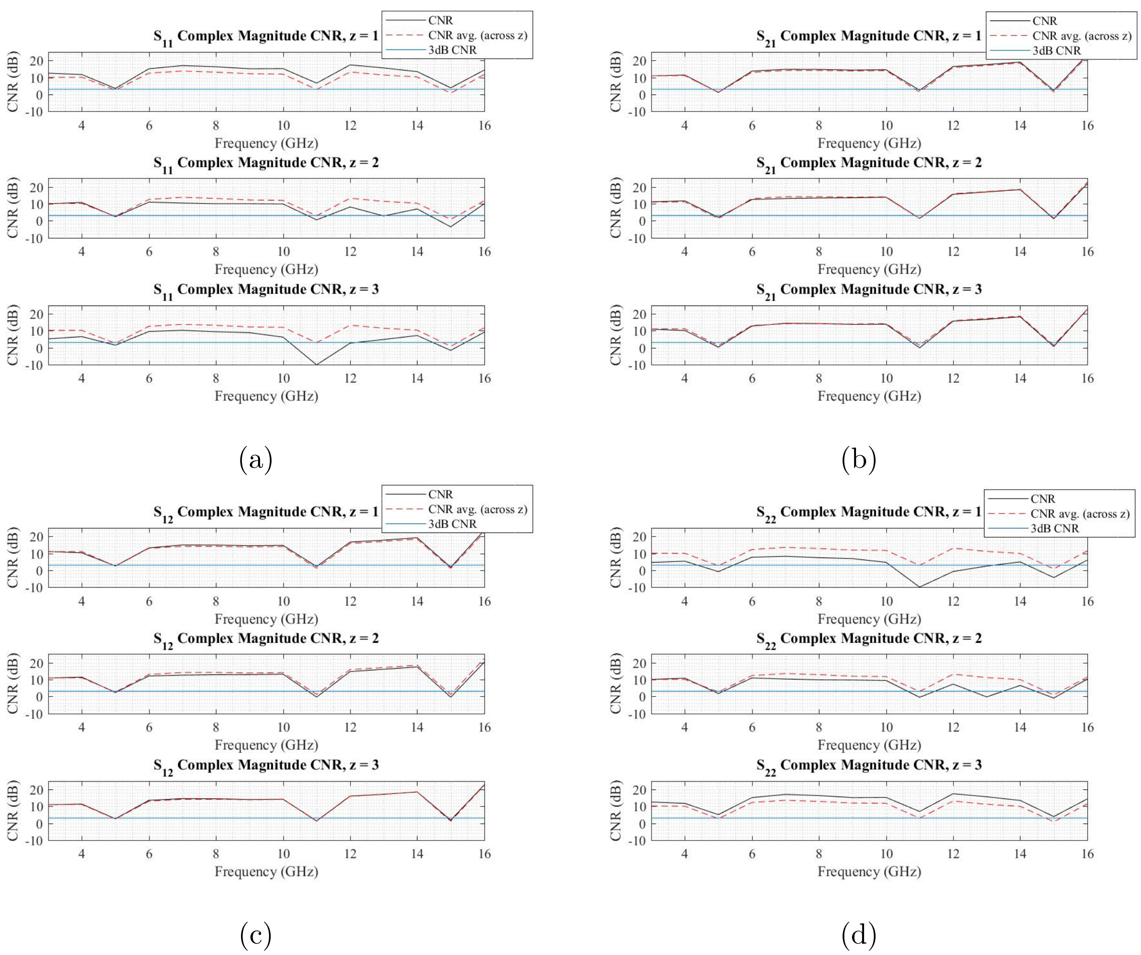


Fig. 4. Complex magnitude CNR values for the PSF of (a) S_{11} (b) S_{21} (c) S_{12} (d) S_{22} with noise added at 5, 11 and 15 GHz. At those select frequencies, all S-parameters show CNR values of approximately 3 dB.

S-parameter	'Good' Frequencies (GHz)	'Bad' Frequencies (GHz)
S_{11}	3, 4, 6, 7, 8, 9, 10, 12, 13, 14, 16	5, 11, 15
S_{21}	3, 4, 6, 7, 8, 9, 10, 12, 13, 14, 16	5, 11, 15
S_{12}	3, 4, 6, 7, 8, 9, 10, 12, 13, 14, 16	5, 11, 15
S_{22}	3, 4, 6, 7, 8, 9, 10, 12, 13, 14, 16	5, 11, 15

Table 1. Classification of frequencies for simulated dataset with noise added at random frequencies.

S-parameter PSF. The CNR at the intended frequencies show a significant drop in quality. The default reconstruction is shown in Fig. 8. Reconstruction is then is performed with the classified good frequencies in Fig. 9 (see Table 2). The reconstruction performed after the classification algorithm demonstrates improvement.

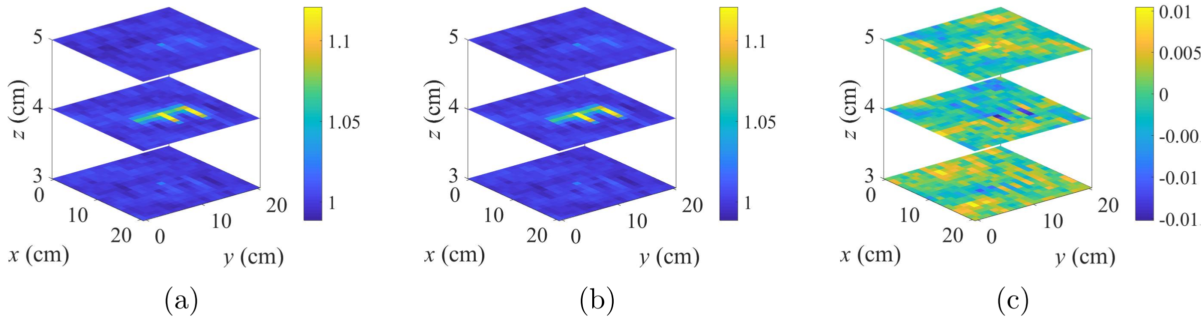


Fig. 5. Reconstructions of the (a) magnitude (b) real part (c) imaginary part of the permittivity of the simulated OUT with 3 dB noise added to 5, 11 and 15 GHz.

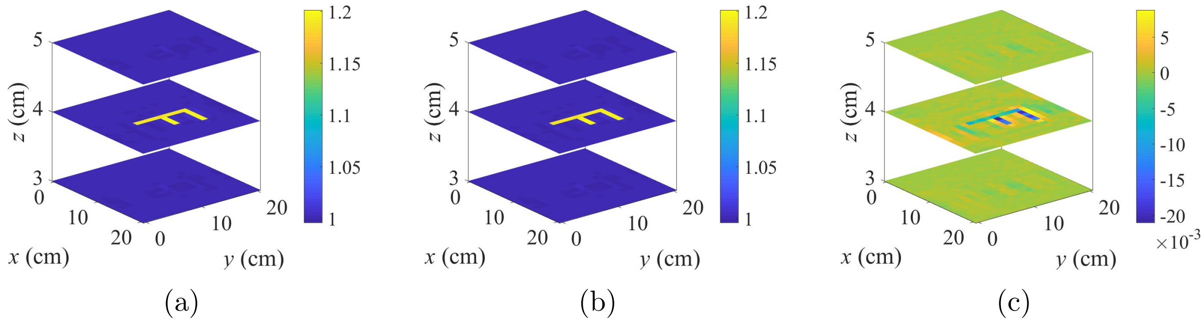


Fig. 6. Reconstructions, with classification algorithm, of the (a) magnitude (b) real part (c) imaginary part of the permittivity of the simulated OUT with 3 dB noise added to 5, 11 and 15 GHz.

S-parameter	'Good' Frequencies (GHz)	'Bad' Frequencies (GHz)
S_{11}	3, 6, 10, 11, 12, 13, 14, 15, 16	4, 5, 7, 8, 9
S_{21}	10, 11, 12, 13, 14, 15, 16	3, 4, 5, 6, 7, 8, 9
S_{12}	10, 11, 12, 13, 14, 15, 16	3, 4, 5, 6, 7, 8, 9
S_{22}	3, 6, 10, 11, 12, 13, 14, 15, 16	4, 5, 7, 8, 9

Table 2. Classification of frequencies for simulated dataset with noise added at low frequencies.

4.2.3 Corrupting High Frequencies

In the final case, white Gaussian noise is added to high frequencies. The frequencies chosen are 10 - 16 GHz. Fig. 10 shows the complex magnitude CNR calculations at each S-parameter PSF. The CNR at the intended frequencies show a significant drop in quality. The default reconstruction is shown in Fig. 11. Reconstruction is performed with the classified good frequencies in Fig. 12 (see Table 3). The reconstruction performed after the classification algorithm demonstrates improvement.

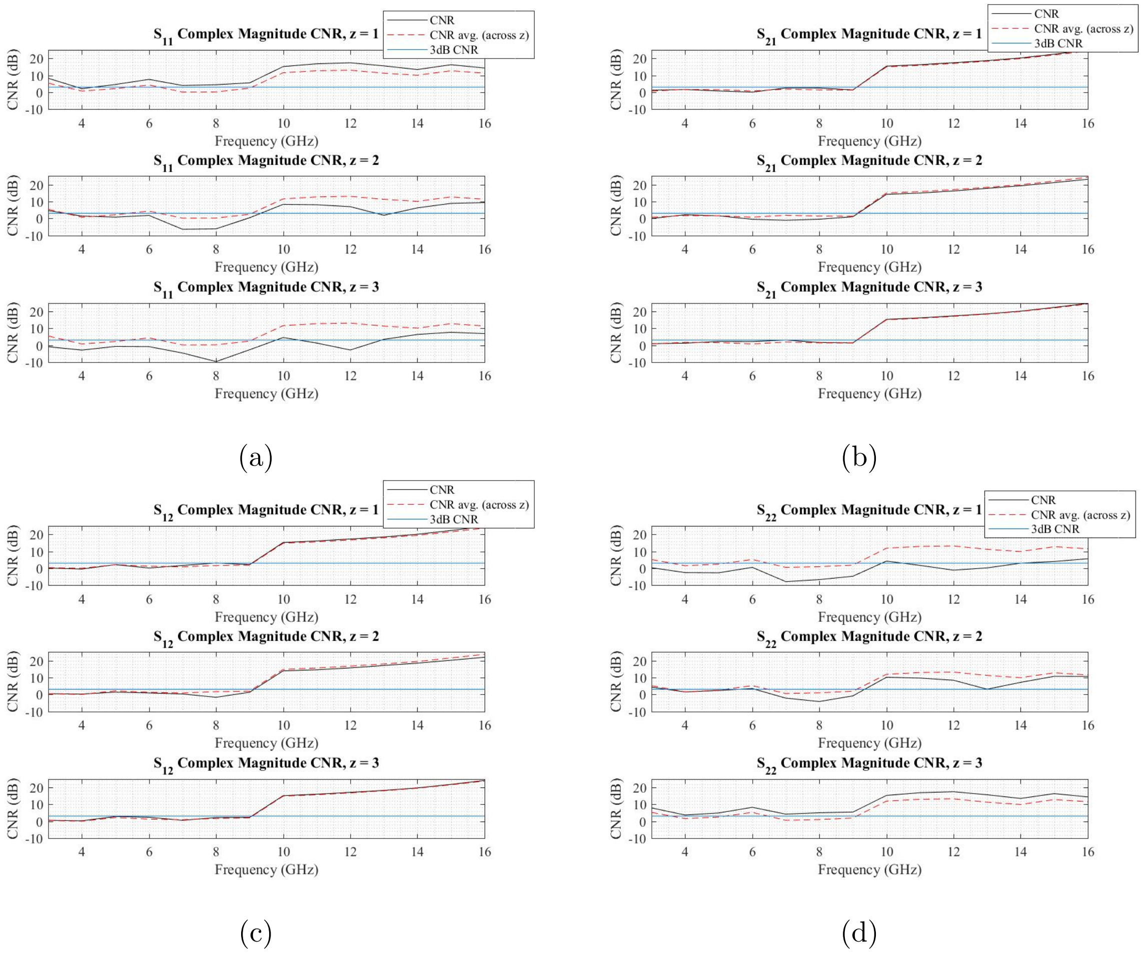
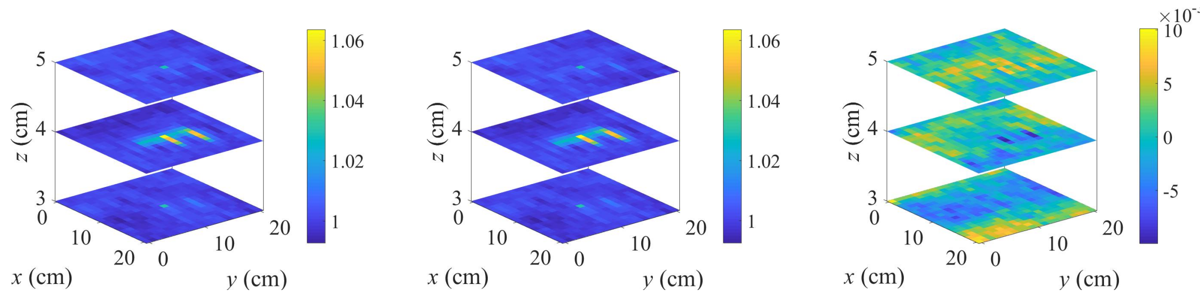


Fig. 7. Complex magnitude CNR values for the PSF of (a) S_{11} (b) S_{21} (c) S_{12} (d) S_{22} with noise added at 3 - 9 GHz. At the low frequency range, all S-parameters show average CNR values across all z-planes of approximately 3 dB.

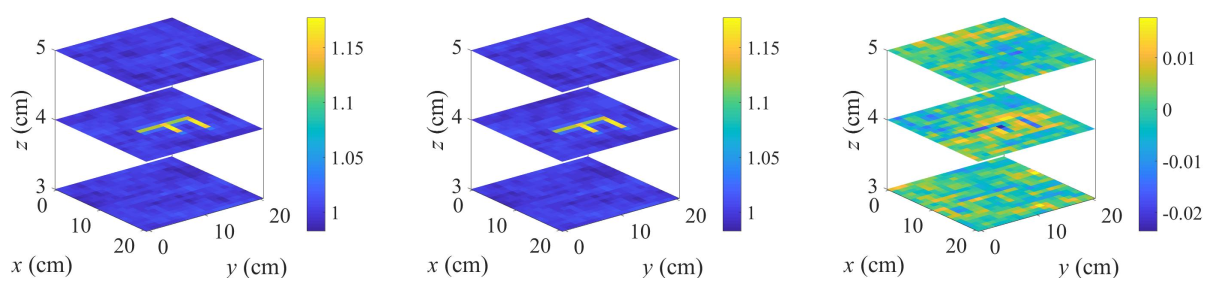
S-parameter	'Good' Frequencies (GHz)	'Bad' Frequencies (GHz)
S_{11}	3, 4, 5, 6, 7, 8, 9, 10, 16	11, 12, 13, 14, 15
S_{21}	3, 4, 5, 6, 7, 8, 9	10, 11, 12, 13, 14, 15, 16
S_{12}	3, 4, 5, 6, 7, 8, 9	10, 11, 12, 13, 14, 15, 16
S_{22}	3, 4, 5, 6, 7, 8, 9, 10, 16	11, 12, 13, 14, 15

Table 3. Classification of frequencies for simulated dataset with noise added at high frequencies.



(a) (b) (c)

Fig. 8. Reconstructions of the (a) magnitude (b) real part (c) imaginary part of the permittivity of the simulated OUT with 3 dB noise added to 3 - 9 GHz.



(a) (b) (c)

Fig. 9. Reconstructions, with the classification algorithm, of the (a) magnitude (b) real part (c) imaginary part of the permittivity of the simulated OUT with 3 dB noise added to 3 - 9 GHz.

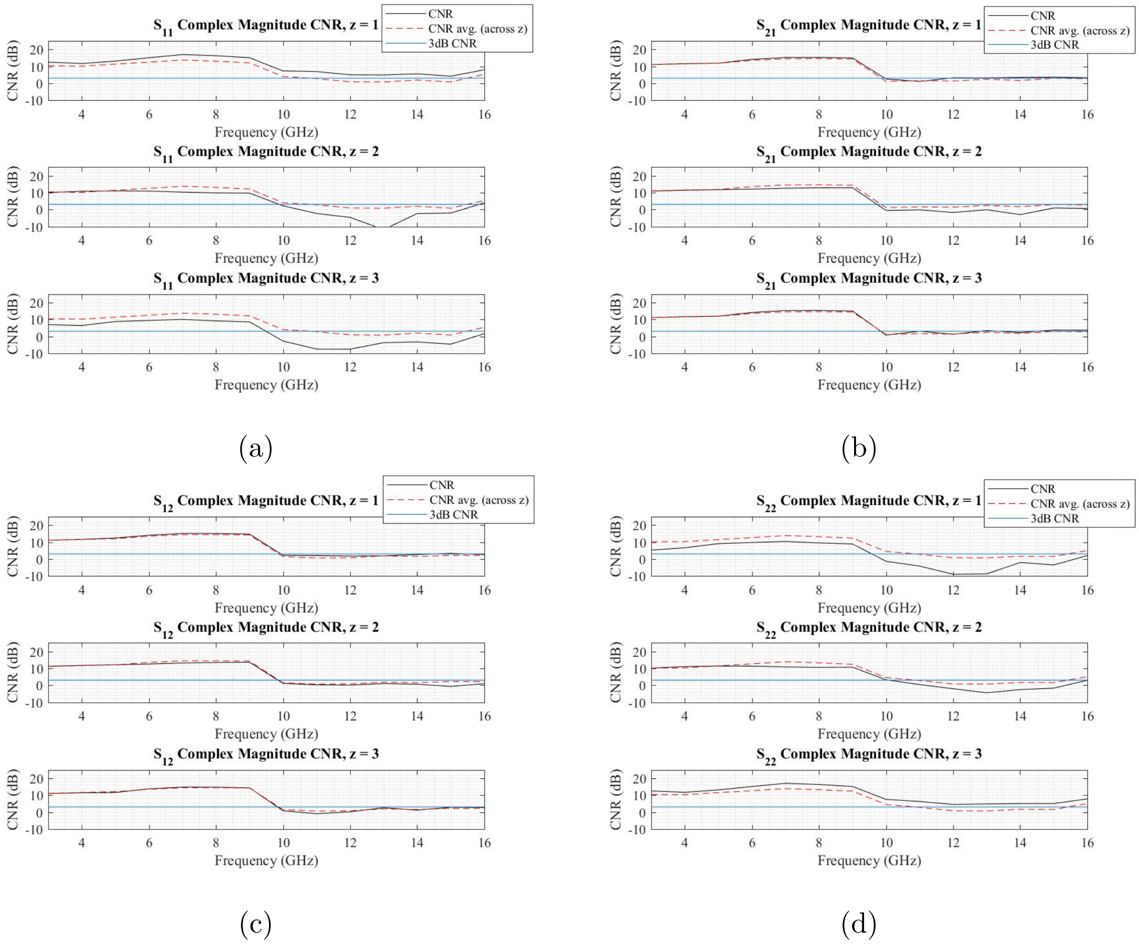


Fig. 10. Complex magnitude CNR values for the PSF of (a) S_{11} (b) S_{21} (c) S_{12} (d) S_{22} with noise added at 10 - 16 GHz. At the high frequency range, all S-parameters show average CNR values across all z-planes of approximately 3 dB.

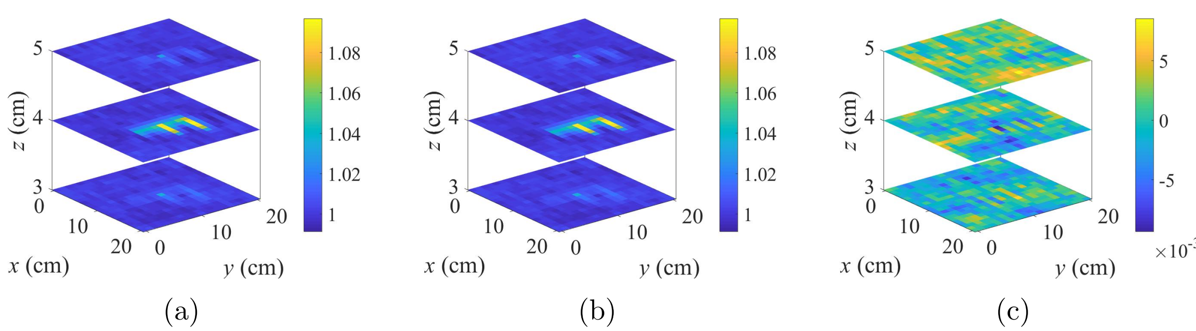


Fig. 11. Reconstructions of the (a) magnitude (b) real part (c) imaginary part of the permittivity of the simulated OUT with 3 dB noise added to 10 - 16 GHz.

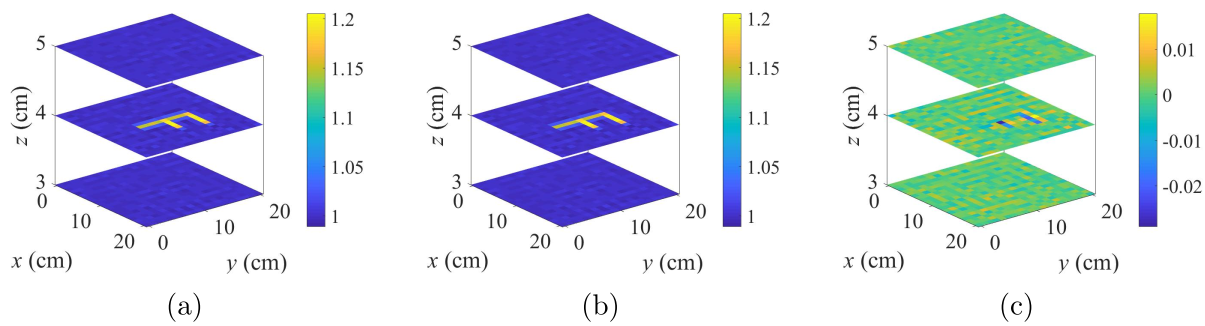


Fig. 12. Reconstructions, with the classification algorithm, of the (a) magnitude (b) real part (c) imaginary part of the permittivity of the simulated OUT with 3 dB noise added to 10 - 16 GHz.

5 Validation of Algorithm on Experimental Datasets

In order to determine an appropriate default threshold for use in the classification algorithm, two experimental datasets are used for validation. BA-QMH and Rytov-based QMH (RA-QMH) are used for reconstruction to determine any differences the algorithm makes in their usages. Different thresholds of 0, 1, 2 and 3 dB for the complex magnitude CNR are used to analyze the differences in reconstructions and select a good threshold.

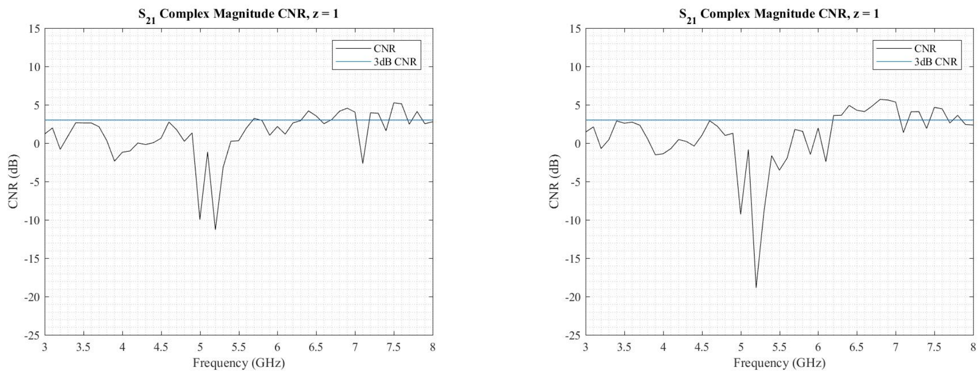
5.1 Alginate Reconstruction

The first experimental dataset is a scan of a phantom with alginate embedded within a peanut-butter and jam (PBJ) mixture as shown in Fig. 13 [3]. The reconstructions are performed with BA-QMH and RA-QMH, separately. The CNR calculations for the PSFs are shown in Fig. 14 and indicate higher CNR values for higher frequencies in both BA-QMH and RA-QMH.

Fig. 13. An OUT constructed from absorber sheets, a PBJ mixture, and alginate embedded on the side.

The BA-QMH reconstructions of the alginate phantom are shown in Fig. 15. Each reconstruction uses a set of frequencies, determined by the classification algorithm as having an average complex magnitude CNR across all z-planes above 0, 1, 2 and 3 dB. The total number of good and bad frequencies for each threshold is reported in Table 4. Similar reconstructions for the alginate phantom using RA-QMH are shown in Figure 16.

BA-QMH shows clear improvement with the classification algorithm. With an imposed 3 dB threshold, it outputs a reconstruction with visible alginate, and decreased rippling.



(a) (b)

Fig. 14. Complex magnitude CNR of the alginate experimental dataset for (a) S_{21} PSF, using BA. (b) S_{21} PSF, using RA.

Threshold	Number of 'Good' Frequencies		Number of 'Bad' Frequencies	
	Born	Rytov	Born	Rytov
0 dB	41	37	10	14
1 dB	33	32	18	19
2 dB	25	24	26	27
3 dB	12	14	39	37

Table 4. Thresholding results for experimental alginate dataset.

RA-QMH does not show significant improvement with any threshold. This may be due to the phase wrapping issues commonly associated with RA, which would affect the accuracy of the calculated CNR.

5.2 Bowtie Reconstruction

The second experimental dataset uses bowtie antennas to scan a 5 layer, 5.5 cm thick phantom. The layer of interest is the second layer, which consists of a PBJ mixture within absorber sheets, and two blueberries embedded on the side. The phantom is shown in Fig. 17. The reconstructions are performed with BA-QMH and RA-QMH, separately. The dataset includes five separate CO measurements, labelled as S_{31a}, S_{31b}, S_{31c}, S_{31d} and S_{41}, with each having measurements for five depth layers. Fig. 18 shows the CNR calculations for each CO measurement at z-plane 2 using BA-QMH. Similar CNR calculations with RA-QMH are shown in Fig. 19.

The reconstruction of the final images using the second z-plane of each CO measurement are shown in Fig. 20 and Fig. 21 for BA-QMH and RA-QMH, respectively. Each reconstruction uses a set of frequencies, determined by the classification algorithm as having an average complex magnitude CNR across all CO measurements above 0, 1, 2 and 3 dB. The thresholding results for BA-QMH and RA-QMH are reported in Table 5 and Table 6.

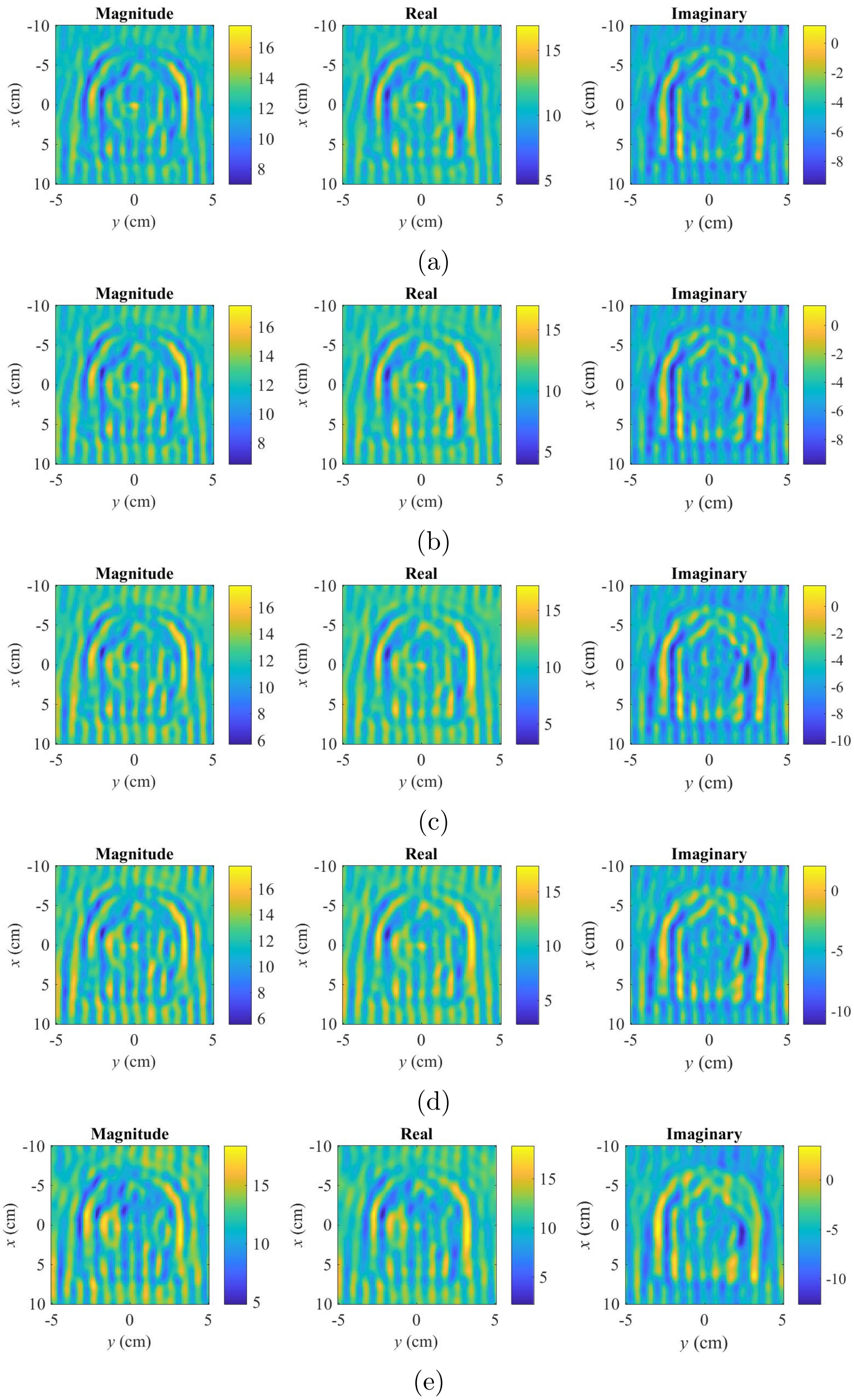


Fig. 15. (a) BA-QMH reconstructions of the alginate experimental dataset with all frequencies. BA-QMH reconstructions of the alginate experimental dataset using frequencies with an average complex magnitude CNR above (b) 0 dB (c) 1 dB (d) 2 dB (e) 3 dB.

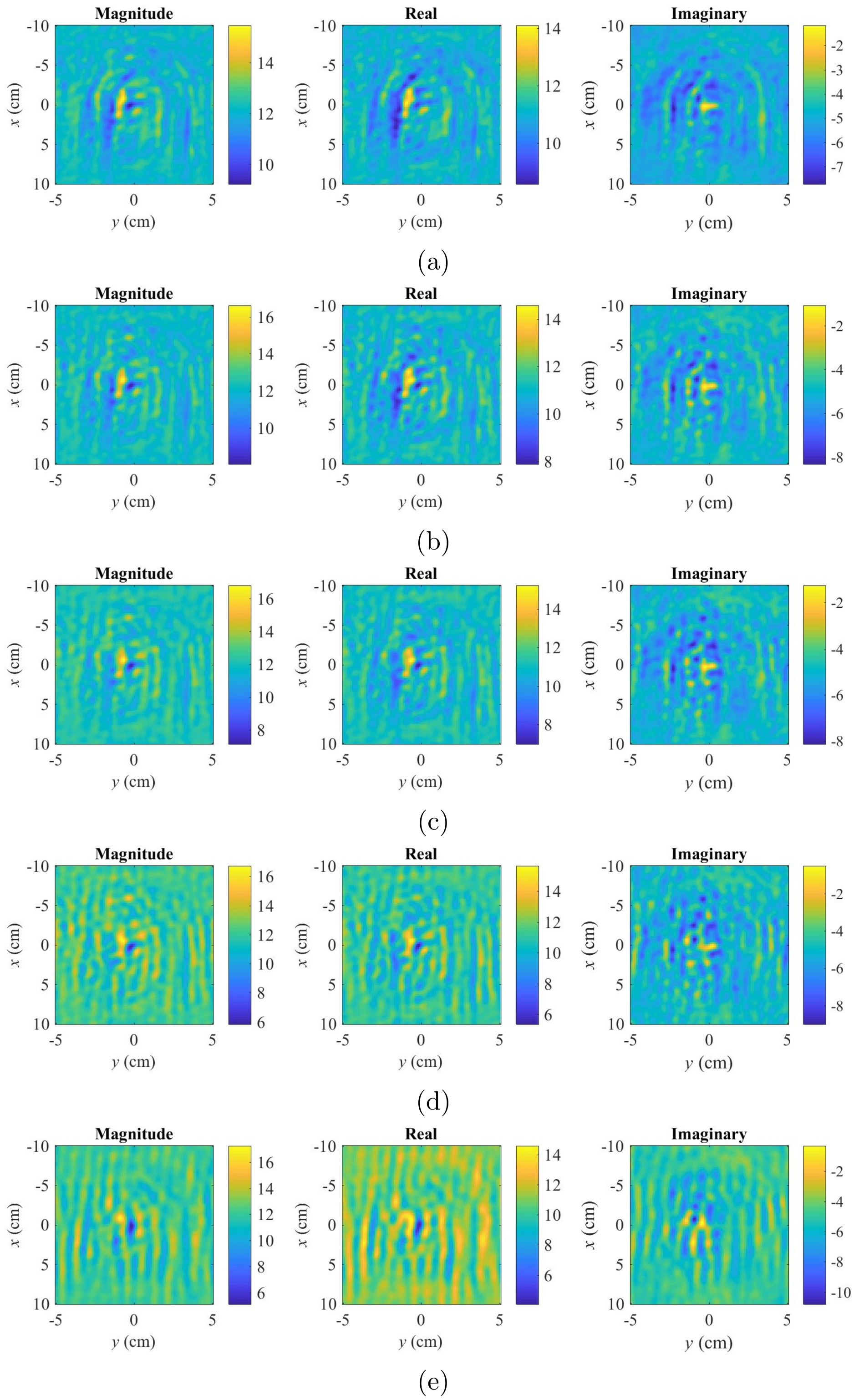


Fig. 16. (a) RA-QMH reconstructions of the alginate experimental dataset with all frequencies. RA-QMH reconstructions of the alginate experimental dataset using frequencies with an average complex magnitude CNR above (b) 0 dB (c) 1 dB (d) 2 dB (e) 3 dB.

Fig. 17. The second layer of an OUT constructed from absorber sheets, a PBJ mixture, and two blueberries embedded on the side.

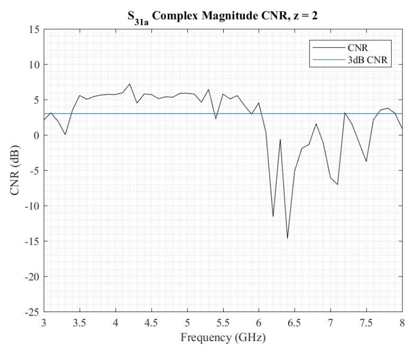
Threshold	Number of 'Good' Frequencies					Number of 'Bad' Frequencies				
	S_{31a}	S_{31b}	S_{31c}	S_{31d}	S_{41}	S_{31a}	S_{31b}	S_{31c}	S_{31d}	S_{41}
0 dB	40	46	37	38	45	11	5	14	13	6
1 dB	37	46	35	33	45	14	5	16	18	6
2 dB	34	46	35	33	41	17	5	16	18	10
3 dB	30	42	28	24	36	21	9	23	27	15

Table 5. Thresholding results for experimental bowtie dataset, z-plane = 2, using BA.

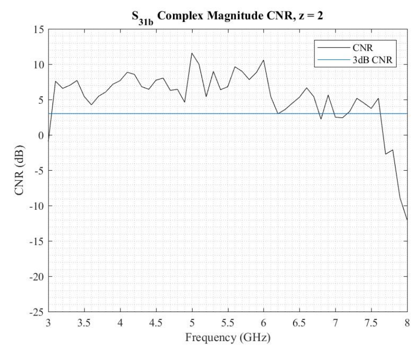
BA-QMH shows clear improvement with the classification algorithm. At the 3 dB imposed threshold, the reconstruction of the imaginary permittivity shows the structure of the two blueberries, which is not evident in the reconstruction with all frequencies.

Threshold	Number of ‘Good’ Frequencies					Number of ‘Bad’ Frequencies				
	S_{31a}	S_{31b}	S_{31c}	S_{31d}	S_{41}	S_{31a}	S_{31b}	S_{31c}	S_{31d}	S_{41}
0 dB	39	46	36	38	44	12	5	15	13	7
1 dB	36	46	36	32	41	15	5	15	19	10
2 dB	31	45	30	30	40	20	6	21	21	11
3 dB	25	45	25	26	38	26	6	26	25	13

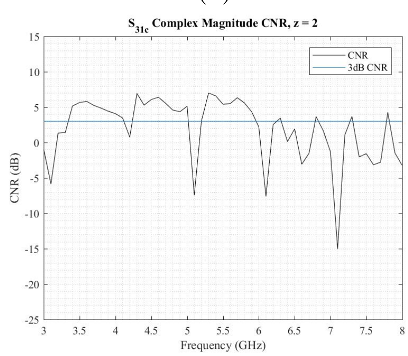
Table 6. Thresholding results for experimental bowtie dataset, z-plane = 2, using RA.



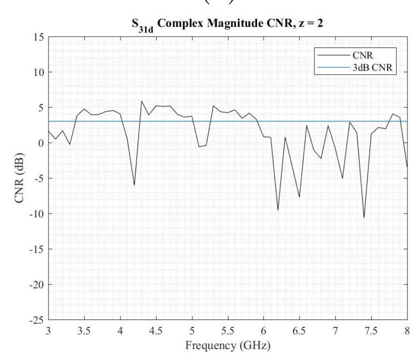
(a)



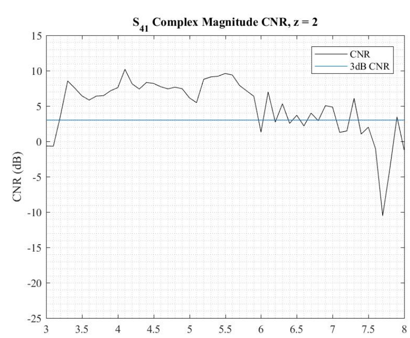
(b)



(c)

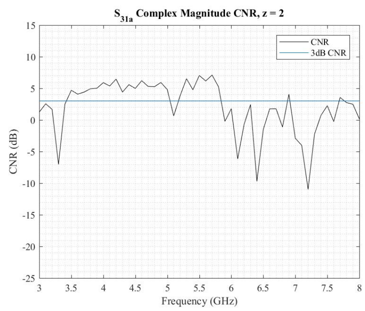


(d)

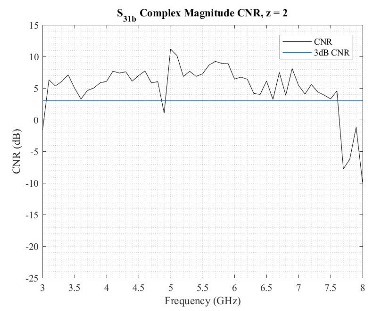


(e)

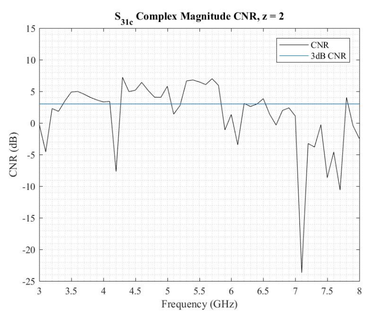
Fig. 18. Complex magnitude CNR for z-plane = 2 of the PSF for (a) S_{31a} (b) S_{31b} (c) S_{31c} (d) S_{31d} (e) S_{41}, using BA.



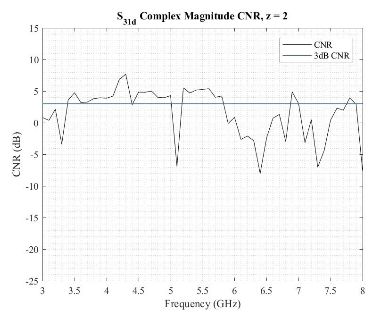
(a)



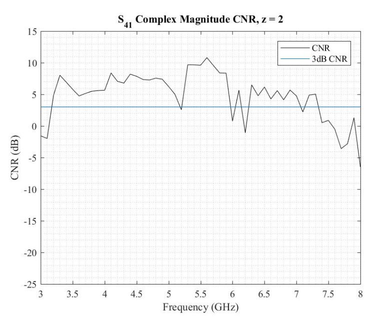
(b)



(c)



(d)



(e)

Fig. 19. Complex magnitude CNR for z-plane = 2 of the PSF for (a) S_{31a} (b) S_{31b} (c) S_{31c} (d) S_{31d} (e) S_{41}, using RA.

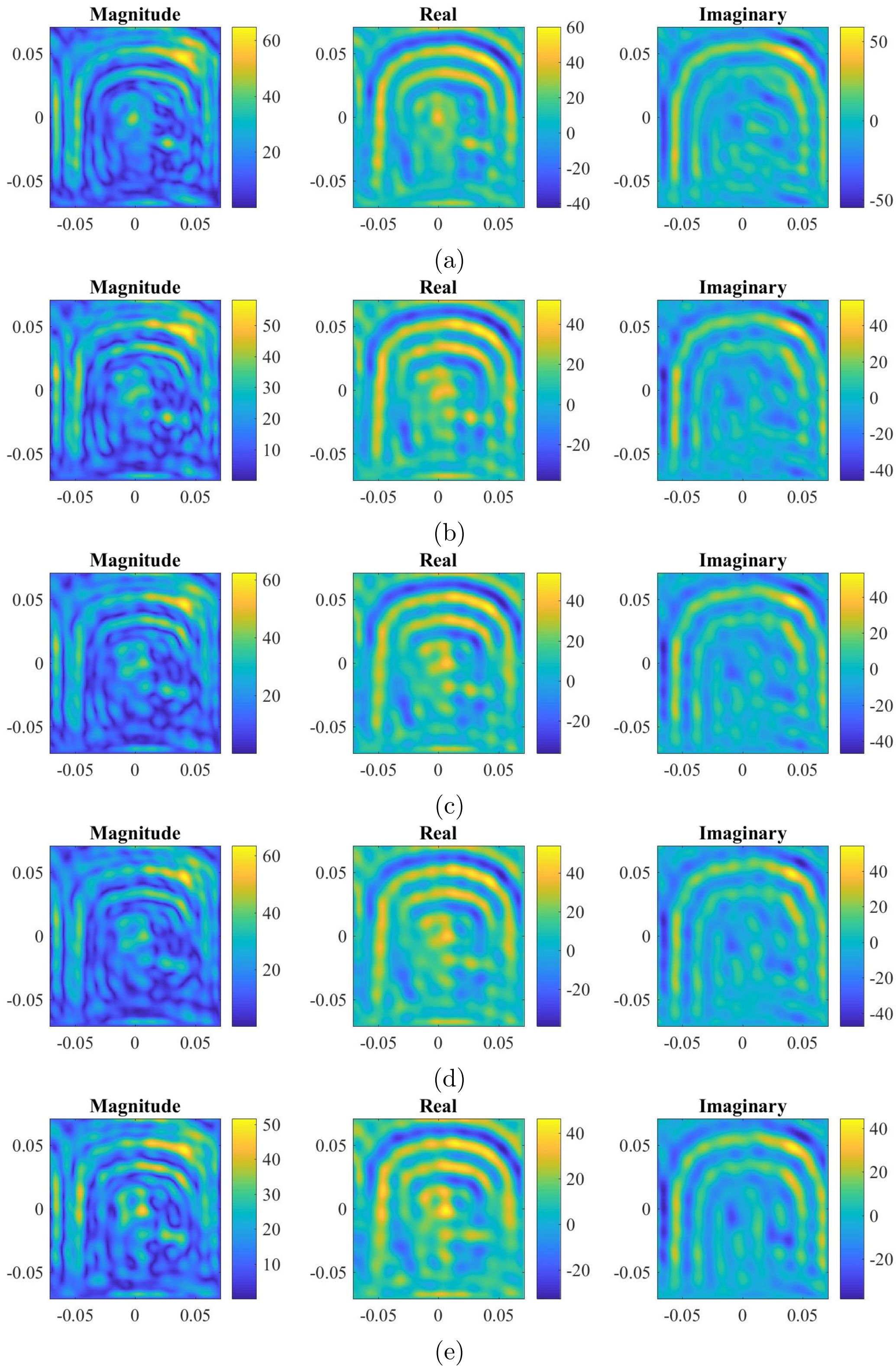


Fig. 20. (a) BA-QMH reconstructions with all frequencies. BA-QMH reconstructions using frequencies with an average complex magnitude CNR above (b) 0 dB (c) 1 dB (d) 2 dB (e) 3 dB.

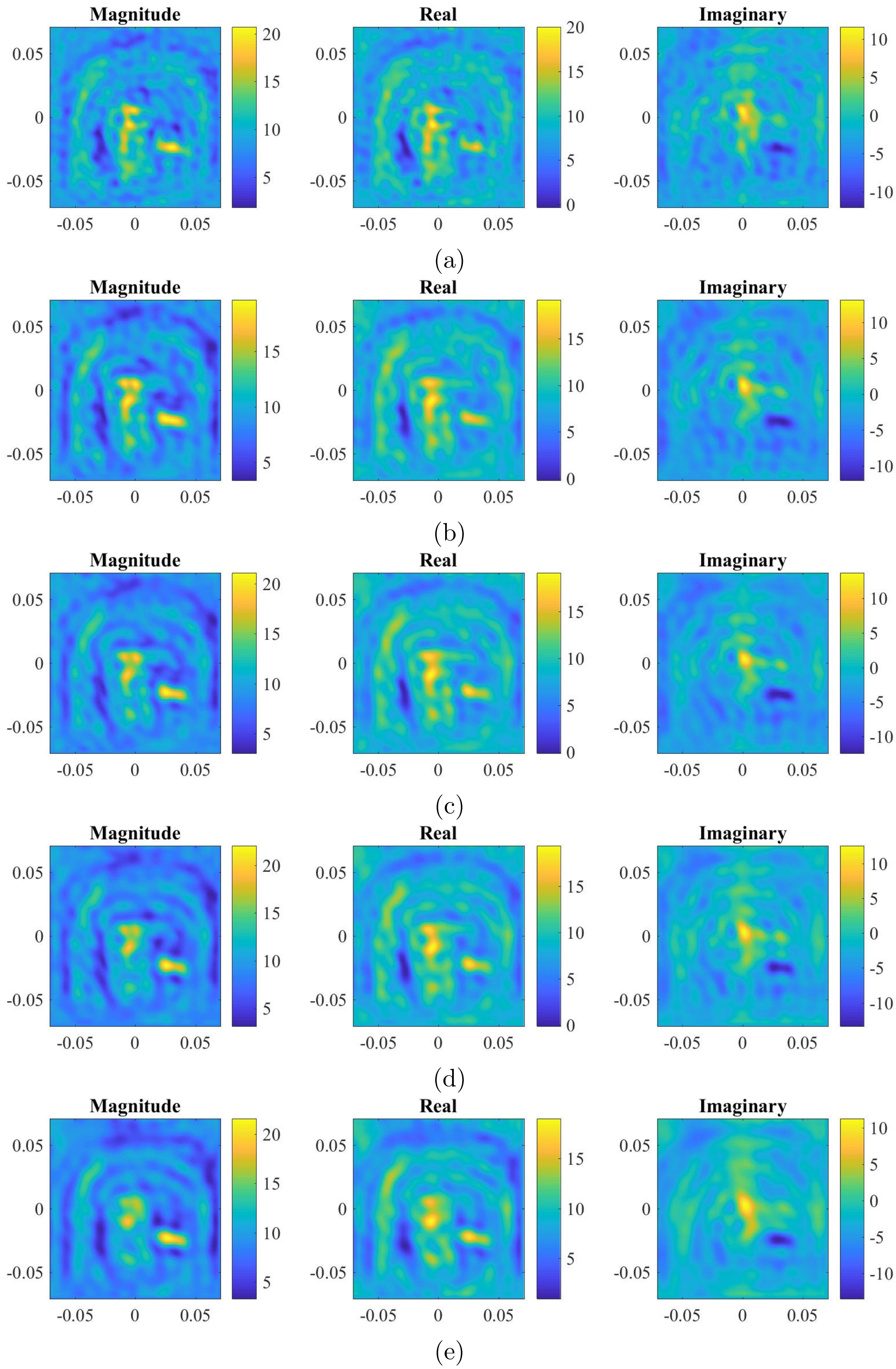


Fig. 21. (a) RA-QMH reconstructions with all frequencies. RA-QMH reconstructions using frequencies with an average complex magnitude CNR above (b) 0 dB (c) 1 dB (d) 2 dB (e) 3 dB.

6 Conclusion

The classification algorithm is able to automatically classify the quality of a PSF dataset at each frequency and improve the reconstructions of experimental datasets with BA-QMH moreso than RA-QMH. The algorithm performs well when executed in its default mode of evaluating complex-magnitude CNR with a 3 dB classification threshold.

References

[1] J. J. McCombe and N. K. Nikolova, "SNR assessment of microwave imaging systems," *2014 IEEE Antennas and Propagation Society International Symposium (APSURSI),* Memphis, TN, pp. 149-150, 2014.

[2] D. Tajik, A. D. Pitcher and N. K. Nikolova, "Comparative study of the Rytov and Born approximations in quantitative microwave holography," *Progress In Electromagnetics Research B,* vol. 79, pp. 1-19, 2017.

[3] D. Tajik, F. Foroutan, D. S. Shumakov, A. D. Pitcher and N. K. Nikolova, "Real-time Microwave Imaging of a Compressed Breast Phantom with Planar Scanning," in *IEEE Journal of Electromagnetics, RF and Microwaves in Medicine and Biology,* 2018.

Appendix A Help documentation for PSF classification algorithm

```
% PSF_CLASSIFICATION Determine frequencies at which PSF quality is
% sufficient for use in image reconstruction.
%
%   [freq_good] = PSF_classification(CO) returns the frequency indices of
%   CO that has CNR or SNR values above the user threshold. The default
%   mode evaluates complex magnitude CNR with a threshold of 2 (linear;
%   3 on dB scale).
%
%   INPUTS:  CO:          Calibration Object dataset, normalized [x,y,f,z]
%
%   ----------------------------------------------------------------------------
%
%   PSF_CLASSIFICATION uses the cluster ROI method by
%   default. The user can use the following optional inputs, written in a
%   'key', value pairing during the function call:
%
%   OPTIONAL INPUTS:
%       'CNR_thresholds', [a b c d]:   Select CNR calculations to execute
%                                      by assigning linear thresholds.
%              a = magn, b = phase, c = avg real/imag, d = complex mag
%              ie. to calculate magn CNR only, feed in 'CNR_thresholds',
%                  [a 0 0 0] where a is the integer threshold for mag CNR.
%
%       'SNR_thresholds', [e f g h]:   Select SNR calculations to execute
%                                      by assigning linear thresholds.
%              e = magn, f = phase, g = avg real/imag, h = complex mag
%
%       'maxima_ROI', 1: Select maxima method to estimate PSF ROI;
%                        default is cluster method.
%
%       'probe_size', [x,y]:  Size of scattering probe [x,y] in mm.
%                             Default is 10x10.
%
%       'peak_signal', 1: Select peak signal method of evaluating CNR/SNR;
%                         default is mean method.
%
%       'plot_ROI_summation', 1: Plot automated ROI against freq summation.
%
%       'cluster_threshold', i: Select threshold cutoff for determining
%                               cluster ROI. Default is 3dB.
%               i = threshold in dB ie. i = 3.5dB, taking signal above
```

```
%                   55% of baseline mininum as potential cluster points.
%
%     'plot_CNR_SNR', 1: Plot CNR and/or SNR against freq index
%                        (default - see 'ftable').
%
%     'dB_scale', 0: Plot CNR and/or SNR in linear scale.
%                    Default is dB scale (10*log10(ratio)).
%
%     'ftable', ftable:  Plot CNR and/or SNR against sampled frequencies.
%               ftable = vector of sampled freq (in GHz) ie. 3.0:0.1:8.0
%
% ---------------------------------------------------------------------
%
% OUTPUTS:
%     freq_good: Structure returning indices of good freqs for a
%                particular calculation. Field will be blank if
%                calculation was not evaluated by the algorithm.
%          ie. if phase CNR was chosen to be evaluated, use
%              freq_good.CNR_phase_i to access the good frequencies.
%
% OPTIONAL OUPUTS:
%     ROI_mask: Cell matrix containing logical ROI mask [f,z]
%
%     exclusion_zone: Structure containing fields ...
%          1) 'Ez_mask' - cell matrix containing logical
%                    exclusion zone mask [f,z]
%          2) 'center_coords' - matrix containing x,y coordinates
%                    of center coordinates of circle
%          3) 'radius' - matrix containing radius of each circle [f,z]
%
%     CO_inversion: Initial magnitude CO dataset with inversion performed
%
% ---------------------------------------------------------------------
%
% Example 1
% ---------
% Evaluate phase SNR (linear threshold = 4) and complex SNR (linear
% threshold = 10) with ROI cluster method. Plot results in dB scale.
%     [freq_good] = SNR_classification(CO, 'plot_ROI_summation', 1,
%     'plot_CNR_SNR', 1, 'SNR_thresholds', [0 4 0 10], 'dB_scale', 1);
%
%
% Example 2
% ---------
% Evaluate real/imag CNR (linear threshold = 5) with ROI maxima method
```

```
%   and specific scattering probe size. Retrieve optional outputs.
%       [freq_good, ROI_mask, exclusion_zone, CO_inversion] =
%       SNR_classification(CO, 'maxima_ROI', 1, 'probe_size', [20,10],
%       'CNR_thresholds', [0 0 5 0]);
%
%
% ---------------------------------------------------------------------
%
%   Written by Jessica Trac, McMaster University, EMVi Lab
%         Adapted from Justin McCombe's SNR GUI code
%         Directory must also have phase_unwrap.m
%
%   Created: May 3 2018
%   Last Revision:  July 23 2018
%
% ---------------------------------------------------------------------
```