

# To Be Decided

André Costa Batista, Ricardo Adriano, and Lucas S. Batista

**Abstract**—To be written.

**Index Terms**—Keyword 1, keyword 2, keyword 3. **Remember:** alphabetical order.

## I. INTRODUCTION

HERE we go.

## II. PROBLEM STATEMENT

Let  $D \in \mathbb{R}^2$  denote the Domain of Interest (DOI) embedded within a homogeneous, isotropic, nonmagnetic ( $\mu = \mu_0 = 4\pi \times 10^{-7}$  H/m), and lossless ( $\sigma = \sigma_0 = 0$  S/m) background medium with permittivity  $\epsilon_b = \epsilon_{rb}\epsilon_0$ , where  $\epsilon_0 \approx 8.85 \times 10^{-12}$  F/m. We consider a 2D Transverse Magnetic (TMz) polarization where the DOI is illuminated by incident plane waves and assume the time convention  $e^{j\omega t}$ . All scatterers are located within the DOI, and the scattered field  $E_z^s$  at point  $\rho \in S$  outside  $D$  is evaluated according to the following integral equation [1]:

$$E_z^s(\rho) = -\frac{k_b^2}{4} \int_D H_0^{(2)}(k_b|\rho - \rho'|) \chi(\rho') E_z(\rho') dS' \quad (1)$$

where  $k_b = \omega\sqrt{\epsilon_b\mu_0} = 2\pi/\lambda_b$  is the background wave number,  $\lambda_b$  is the wavelength of the incident wave,  $H_0^{(2)}$  is the zero-order Hankel function of the second kind,  $E_z$  is the total electric field in the DOI, and  $\chi$  is the contrast function given by

$$\chi(\rho) = \frac{\epsilon_r(\rho)}{\epsilon_{rb}} - 1 - j \frac{\sigma(\rho)}{\omega\epsilon_b}, \quad (2)$$

which maps the relative permittivity  $\epsilon_r(\rho)$  and conductivity  $\sigma(\rho)$  distributions within  $D$ . It should be noted that the term  $(-jk_b^2/4)H_0^{(2)}(k_b|\rho - \rho'|)$  corresponds to the Green's function in free space.

In electromagnetic inverse scattering problems, we aim to recover the contrast function  $\chi$  using a set of  $N_M$  measurements of the scattered field collected for each of the  $N_S$  sources. Additionally,  $E_z$  is also unknown in  $D$  and must be solved. For our formulation, the  $N_S$  sources correspond to  $N_S$  incidence angles of the plane wave, and the  $N_M$  measurements are taken at  $N_M$  points in  $S$ , arranged in a circular, equidistant array situated far from the center of the DOI by a radius

$R_O$ . By discretizing the DOI into  $N_X \times N_Y = N$  pixels, the inverse problem is solved numerically according to the following equation:

$$E_{ms}^s = - \sum_{n=1}^N G_{mn}^S \chi_n E_{ns} \quad (3)$$

where  $G^S$  is given according to the Richmond discretization [2], [3]. Equation (3) can also be expressed in matrix form:

$$\mathbf{E}^S = \mathbf{G}^S \chi \mathbf{E} \quad (4)$$

where  $\mathbf{E}^S$  is the  $N_M \times N_S$  scattered field matrix,  $\mathbf{G}^S$  is the  $N_M \times N$  Green's function matrix,  $\chi$  is the  $N \times N$  contrast diagonal matrix, and  $\mathbf{E}$  is the  $N \times N_S$  total electric field matrix.

It is important to highlight that, although assumptions are made regarding the scattered field domain and the incident field, the proposed indicators do not depend on these assumptions. They can be applied in any scenario where these entities are defined, and the assumptions in this paper serve only to clearly establish the context in which the indicators are tested.

## III. INDICATORS

Once the result of the contrast function reconstruction is obtained by a given algorithm, the error in recovering the shape and location of the objects can be measured by comparing it with the original images. This means that the application of these metrics is relevant in studies where the exact response is known. Although in many real-world scenarios the imaged scatterer is unknown, applying these metrics to known cases can be valuable for comparing the performance of different algorithms and for estimating a confidence interval for the average performance of an algorithm in a given configuration. Therefore, these metrics are relevant tools that can contribute to the investigation and evaluation of algorithms for the problem.

For the two indicators that will be explained below, the image of the original contrast function of the problem and the image reconstructed by any algorithm will be denoted by the matrices  $\bar{\chi}_o$  and  $\bar{\chi}_r$ , both of size  $N_X \times N_Y$ . In other words, the elements of these matrices represent the pixels of the images.

### A. Shape Error

The contrast function has complex values when the medium or the scatterers have losses. Therefore, the first step is to account for the possibility that the elements of the matrices  $\bar{\chi}_o$  and  $\bar{\chi}_r$  have real and imaginary parts. The simplest approach is to use the magnitude of the complex variables as the value of each pixel. This choice does not eliminate the possibility that objects with different contrasts might have

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A. C. Batista, R. Adriano, and L. S. Batista are with the Department of Electrical Engineering, Universidade Federal de Minas Gerais, Belo Horizonte, MG 31270-901, Brazil (e-mail: andre-costa@ufmg.br; rluiz@ufmg.br; lusoba@ufmg.br). A. C. Batista and L. S. Batista are also with Operations Research and Complex Systems Laboratory (ORCS Lab), Belo Horizonte, MG, Brazil.

the same magnitude. However, in cases involving only lossless materials, this approach is not problematic because the contrast is purely real. Since the primary objective is to verify the shape of the scatterers, the critical aspect is distinguishing between the background medium and the scatterer, with the background medium having zero contrast. Thus, this approach to simplifying the methodology for measuring shape error should not have significant consequences in performance verification scenarios for the algorithm.

The contrast function reconstructed by many algorithms – such as BIM, DBIM, CSI, SOM, among others – is commonly a discretized approximation of a continuous surface. Therefore, even if the original image contains only objects with well-defined boundaries and homogeneous contrast, the image of these objects obtained by the algorithms will have frequently smooth edges, i.e., the contrast value gradually varies between the background medium and the object's value. Consequently, identifying a contour in the resulting image is heuristic because it requires selecting a criterion to define the contrast value at which a pixel can be considered as belonging to the object. For simplicity, the threshold  $T$  for considering a pixel in the recovered image to be within an object's contour will be defined as half of the total contrast variation in the image, i.e.:

$$T = \min(|\bar{\chi}_r|) + \frac{1}{2} [\max(|\bar{\chi}_r|) - \min(|\bar{\chi}_r|)] \quad (5)$$

This approach has advantages and disadvantages. If the reconstructed image contains multiple scatterers, and one or more of them has a contrast below this threshold, the methodology will fail to detect the contour of these objects. However, in scenarios where there is only one scatterer in the image, this approach is simple and effective. In fact, a single scatterer is the most objective way to test an algorithm's potential in recovering geometry, since the presence of multiple scatterers can degrade the algorithm's performance due to the influence of the induced currents in each scatterer on the scattering of the other. Furthermore, this approach poses no issues for algorithms capable of accurately capturing contours, such as machine learning-based methods. Moreover, instead of using the values from the original image, it is more beneficial to use only the values from the reconstructed image, both to isolate the influence of error in the contrast estimate and to apply the metric to qualitative methods that do not estimate contrast. If, for some reason, the original contrast function involves soft boundaries of the objects, the threshold might also be applied to the original image.

Once the thresholding step is applied, the contours of the scatterers can be determined. One of the techniques suitable for this task is the Marching Squares algorithm [4]. This algorithm efficiently returns a set of points that delineate each contour. It is important to note that hollow objects may have two or more contours. Additionally, if the imaging algorithm fails to detect an object, a discrepancy will arise in the number of contours between the original and reconstructed images.

For these reasons, instead of comparing the geometries through calculations based on the points of each contour, we prefer to perform the comparison based on the number of

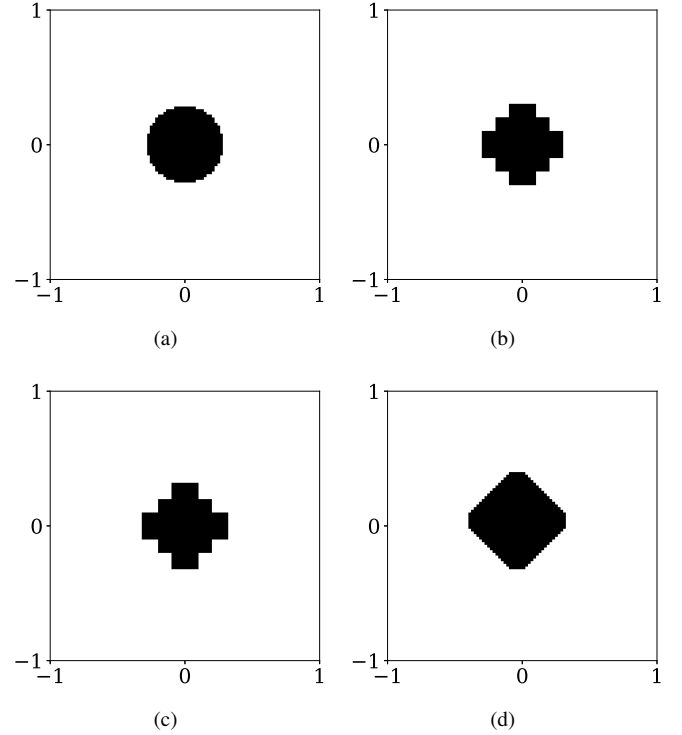


Fig. 1. An example illustrating the differences between nearest neighbor interpolation and the adopted contour detection methodology. (a) Original image of the scatterer (resolution 100x100); (b) Image reconstructed by an imaging algorithm after thresholding (20x20); (c) Image reconstructed to the original resolution using nearest neighbor interpolation; (d) Image reconstructed to the original resolution using contour identification.

pixels that were misclassified. Specifically, after identifying which pixels fall within each contour in each image, we can determine which pixels belonged to the scatterers in the original image but were not captured in the reconstructed image (false negatives) and which pixels did not belong to the scatterers in the original image but were classified as such in the reconstructed image (false positives).

A potential question that may arise from this choice is why not directly calculate false positives and false negatives immediately after thresholding. One reason is that original and reconstructed images typically have different resolutions. While the nearest neighbor interpolation method is an alternative for addressing this issue, the chosen approach may be more effective for capturing and preserving object contours, particularly when the resolution of the reconstructed image is significantly lower. This is illustrated in Fig. 1.

#### B. Position Error

### IV. COMPUTATIONAL EXPERIMENTS

#### A. Shape Recovering Study

- 1) *Single scatterer:*
- 2) *Varying contrast:*

#### B. Average performance

#### C. Position Detection Study

- 1) *Single scatterer:*

- 2) *Multiple scatterers:*
- 3) *Average performance:*

## V. CONCLUSION

A conclusion section is not required. Although a conclusion may review the main points of the paper, do not replicate the abstract as the conclusion. A conclusion might elaborate on the importance of the work or suggest applications and extensions. [5]

## ACKNOWLEDGMENT

Use the singular heading even if you have many acknowledgments. In most cases, sponsor and financial support acknowledgments are placed in the unnumbered footnote on the first page, not here.

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