Phaseless near-field techniques from a random starting point

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The phase retrieval problem

Phase retrieval consists in the reconstruction of a signal from only intensity data

Applications in Electromagnetics

- Array diagnostics or antenna diagnostics
- Reconstruction of radiated fields
- Inverse scattering problem

Mathematical formulation

Phase retrieval is a quadratic inverse problem that can be formulated as recovering the unknown vector $\mathbf{x} \in \mathbb{C}^N$ from the set of equations

$$B(\mathbf{x}) = \mathbf{M}^2$$

where $\mathbf{M}^2 = [\mathbf{M}_1^2, \mathbf{M}_2^2, \ldots, \mathbf{M}_N^2]^T \in \mathbb{R}^M$

Quadratic operator that links the unknowns to the data

$$B : \mathbf{x} \in \mathbb{C}^N \rightarrow |\mathbb{L}\mathbf{x}|^2 \in \mathbb{R}^M$$

where $|\mathbb{L}\mathbf{x}|^2 = (\mathbb{L}\mathbf{x}) \odot (\mathbb{L}\mathbf{x})^*$
The question of local minima

**Quadratic inversion method**

\[
\min_{x \in C^N} \phi(x) \quad \text{where} \quad \phi(x) = \|B(x) - M^2\|^2_2
\]

Possible presence of **TRAP POINTS**

Local minima

Saddle points with null gradient
The evaluation of the dimension of data

The dimension of data can be defined as the number of independent functions required to represent the data with a given degree of accuracy.

**How is it possible to evaluate the dimension of data space?**

1. By introducing a linear representation of the data through a redefinition of the unknown space
2. By evaluating the number of relevant singular values of the linear operator that represents the data

\[
B(x) = M^2 \quad \text{System of } M \text{ quadratic equations in } N \text{ unknowns}
\]

\[
A(X) = M^2 \quad \text{System of } M \text{ linear equations in } N^2 \text{ unknowns}
\]

The dimension of data space \( M_{\text{ind}} \) is equal to number of relevant singular values of \( A \)
The origin of local minima

The image of the quadratic operator $B(\mathbf{x})$ represents the manifold of data.

The data vector $\mathbf{M}^2$ is a point of the manifold of data (in absence of noise).

The functional $\phi$ is a measure in the data space of the distance between the point $B(\mathbf{x})$ and the data point $\mathbf{M}^2$.

Local minima arise since the manifold of data has a non zero curvature.

Example for a simple case of 1 real unknown and 2 data.
How to “cure” local minima

If the ratio \( \frac{\text{dimension of data space}}{\text{number of unknowns}} \) is high enough,

the manifold of data is sufficiently large and no trap points appear in the functional.
Strategies to solve local minima question

How to cure local minima?

By increasing the dimension of data

In which way is it possibile to increase $M_{ind}$?

By increasing of the number of scanning surface

By dividing the numerical procedure in more steps, and by searching in each step only a reduced number of unknowns

When is this possible?

This is possible if
1. some components of the unknown vector $x$ are zero or quasi-zero
2. the location of such zeros is known or it can be estimated from data
Curing local minima by increasing the data (1)

Diagrams of the equations

Equations 2 and 3 are quite similar

Manifold of data

Singular values of the lifting operator

Quartic functional

The functional contains local minima
Curing local minima by increasing the data (2)

Diagrams of the equations

All the 3 equations are different each other

Manifold of data

Singular values of the lifting operator

Quartic functional

Local minima disappear
Curing local minima by searching less unknowns

**Numerical procedure to escape from local minima**

*First step of the procedure*

- Localizing the zero or quasi zero components of \( \mathbf{x} \in \mathbb{C}^N \), and creating the vector \( \mathbf{x}_{rel} \in \mathbb{C}^{N_1} \) by deleting from \( \mathbf{x} \) all the zero and quasi-zero components.

- Since the zero components of \( \mathbf{x} \) does not contribute to the data \( \mathbf{M}^2 \), instead, to solve the system \( \mathbf{Lx}^2 = \mathbf{M}^2 \) it is possible to solve the problem
  \[
  \left| \mathbf{L}_{\text{rel}} \mathbf{x}_{\text{rel}} \right|^2 = \mathbf{M}^2
  \]
  where \( \mathbf{L}_{\text{rel}} \) is the matrix obtained by deleting the columns of \( \mathbf{L} \) corresponding to the zero components of \( \mathbf{x} \). The solution of the quadratic system above can be found by minimizing
  \[
  \phi(\mathbf{x}_{\text{rel}}) = \left\| \left| \mathbf{L}_{\text{rel}} \mathbf{x}_{\text{rel}} \right|^2 - \mathbf{M}^2 \right\|^2
  \]

*Second step of the procedure*

- Minimizing the functional \( \phi(\mathbf{x}) = \left\| \left| \mathbf{Lx} \right|^2 - \mathbf{M}^2 \right\|^2 \) starting from an initial guess whose main components are equal to \( \mathbf{x}_{\text{rel}} \) and zero otherwise. *This starting point is in the attraction region !!!*
Geometry of the test cases

2D scalar radiation problem

The data are collected 2 lines circles at points \( (z_i, x_m) \)

The number of phaseless measurements collected on the \( p \)-th circle are \( M_p = 4N_0 + 1 \) with \( N_0 = \frac{\beta a}{\pi} \)

Mathematical model

\[
| E(z_i, x_m) |^2 \approx \left| \sum_{n=-N_0}^{N_0} \left( I(u_n) \psi_n(z_i, x_m) \right) \right|^2 \quad i = 1, \ldots, N_c \quad m = 1, \ldots, M_p
\]

Unknowns (Samples of the radiation integral)

\[
\mathbf{x} = [x_1, \ldots, x_N]^T = [I(u_{-N_0}), \ldots, I(u_{N_0})]^T
\]

with \( N = 2N_0 + 1 \)

Phaseless Data

\[
M^2 = \left[ | E(z_1, x_1) |^2, \ | E(z_1, x_2) |^2, \ldots, \ | E(z_2, x_{M_p}) |^2 \right]
\]
Unknown sequence, and data

Unknown sequence
(Samples of the radiation integral $I(u)$)

Square amplitude of the radiated field in dB on different lines parallel to the source
Results of the numerical analysis

Comparison of the ratio $\frac{\text{dimension of data space}}{\text{number of unknowns}}$ in the first and in the second step of the procedure.

Value of the ratio $\frac{\text{dimension of data space}}{\text{number of unknowns}}$ for which the numerical procedure converges.

The proposed method compared with the classical quadratic inversion method requires a lower number of data. Since it reconstructs $N$ unknowns with the number of data required to reconstruct the $N_1$ non-zero unknowns.