Microwave Tomography based on Time-Domain Solver and Adaptive Optimization

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***Abstract*—Microwave tomography is an ill-posed inverse problem. It is a non-linear multimodal optimization problem. As such, microwave tomography is highly computationally intensive and needs advanced optimization methods to be solved quickly. In contrast to typical approach based on faster local optimization coupled with linearization or regularization methods, the solution presented in this paper uses adaptive global optimization methods for more precise resulting images. Also, proposed solution uses time-domain solver to obtain measurement on multiple frequencies, for easier solving of the ill-posed problem. A two-dimensional numerical prototype is implemented. Few optimization methods are compared, yielding the covariance matrix adaptive hybrid method to be most effective.**

***Index Terms*—Microwave tomography, microwave imaging, inverse scattering problem, optimization, FDTD, CMA-ES, ACiD.**

I. Introduction

Microwave tomography (MWT) [1] is an inverse scattering problem used for object imaging by means of electromagnetic (EM) waves. Object under imaging is illuminated by the EM waves, the object scatters EM waves and output scattered waves are measured. Output scattered waves are practically a function of dielectric properties distribution in the object under imaging. Generally, that distribution is unknown and it represents the final target of the imaging process. Obtaining scattering function i.e. image of the dielectric distribution from input and output EM waves is an inverse scattering problem which is solved numerically.

Microwave tomography is an interdisciplinary field, involving electromagnetic, measurement, numeric and optimization. For effective imaging, interoperability between aforementioned fields is needed. Application of microwave tomography is also diverse, including: biomedical scanning [2], nondestructive material testing, subsurface imaging [3] [4] and more.

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Because EM scattering occurs multiple times, inverse scattering is an ill-posed problem, meaning it has multiple solutions. Few methods exist to tackle this optimization problem. First method for solving this problem is the linearization of inverse problem by introducing approximation in EM scattering equations and solving the problem with local (convex) optimization methods. Examples are Born and Rytov approximations [5] [6]. These approximations limit the use of microwave tomography to problems with small contrast in dielectric distribution [7] [8]. Second method is the application of regularization in optimization, also enabling usage of local optimization methods. Drawback of regularization is a blurred resulting image, because regularization acts as a low-pass filter of objective function. Third method is the application of global optimization methods, which are more computationally intensive, but could yield images of better quality. Forth method is the indirect optimization of the dielectric image. Instead of optimizing values of the image pixels, geometry and dielectric values of some regions are parametrized and these parameters are tuned by global optimization methods. This approach demands a priori knowledge about the geometry of the object under imaging and it is more functional than structural type of imaging.

In this paper, the global optimization methods are selected for the solving of the inverse scattering problem. Using findings from previous work [9] and knowledge from literature [10] few optimization heuristics are selected: global optimization heuristics Artificial Bee Colony (ABC) [11] [12] and Evolution Strategy with Covariance Matrix Adaptation (CMA-ES) [13] [14] [15], as well as hybrid of global with local optimization heuristics ABC hybrid with Hooke-Jeeves [16] [17] (ABC/HJ) [9] and CMA-ES hybrid with Adaptive Coordinate Descent [18] (CMA-ES/ACiD). Final experimental comparison yields CMA-ES/ACiD hybrid methods to be the best method. Finite-Difference Time-Domain (FDTD) [19] [20] is used as a solver and multiple frequencies are used for comparison of output scattered waves. Currently, only two-dimensional (2D) FDTD with soft-source is implemented, while 3D FDTD with accurate antenna and measurement chamber modeling is work in progress [21].

In Chapter II short survey of existing solutions is presented. Implementation of the proposed solution is described in Chapter III. Experimental results with comparison are given in Chapter IV. Chapter V includes final conclusions and future research directions.

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II. Related work

The fastest possible method for inversion is diffraction tomography [22]. It is based on linearization of scattering equations by the Born or Rythov approximation. As mentioned before, this linearization works only when the contrast in dielectric distribution is small. When contrast is large, multiple scattering occurs, introducing non-linearity. In typical microwave tomography applications, contrast is considerably large and linearization cannot be applied [7] [8].

Quantitative non-linear methods are most commonly used in microwave imaging. First class of these methods does not use the EM forward solver. These are gradient methods; for example Contrast Source Inversion (CSI) [23] [24] [25]. Second class of these methods are iterative ones. They start with the Born linearized solution and iteratively improve it by simulating additional scattering through the forward solver [26] [27] [28] [29] [30].

Third class of methods uses forward solver to simulate scattered fields. Scattered fields are compared with measured ones by calculate Mean Square Error (MSE). Optimization methods are used to find best match between measured and simulated fields. Most of these methods use local optimization, usually Gauss-Newton [25] [31] or Conjugate-Gradient [32] [33] or similar gradient-based heuristic. These local heuristics need some kind of regularization to make objective function convex. Still, these methods could miss the solution if they are not provided with a good initial solution and good regularization term. Also, these methods are criticized due to smoothing out resulting image, because low-pass filtering of objective function through regularization [1].

Better approach from aforementioned local heuristics assumes using global heuristics. In comparison with local methods, stochastic global optimization methods explore the search space better and the probability of getting stuck in a local sub-optimal solution is lower. Drawback of these methods is slow convergence. Typical global heuristics are: evolutionary based like Genetic Algorithm (GA) [34], swarm based like Particle Swarm Optimization (PSO) [35] [1], Artificial Bee Colony (ABC) [11], Ant Colony Optimization (ACO) [36], and others [12]. For faster convergence hybridization with local heuristics is often used [9]. Adapting search direction to objective landscape instead to coordinate axes could also yield better convergence and exploration [13] [18] [10] [3] [4].

Broad range of solvers is used in literature. One method assumes solving Electric-field Integral Equation (EFIE) by Methods of Moments (MoM) [37]. Very popular method is Finite Element Method (FEM) [31] [10]. Alongside the aforementioned frequency based methods, Finite-Difference Time-Domain (FDTD) is a referent time-domain based method [34] [32] [33] [31]. FDTD simulates propagation of EM waves in discrete space, with discrete time steps. Because FDTD is time-domain method it is possible to excite the simulation with an EM wave with broad frequency spectrum. It is experimentally proven that using multiple frequencies

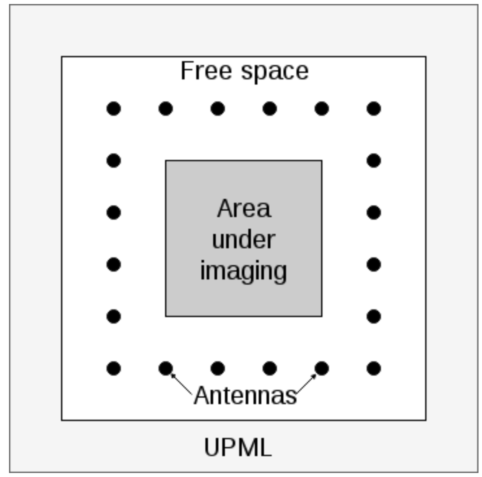

Fig. 1. FDTD solver configuration

makes inverse scattering a less ill-posed problem and helps faster convergence of the inversion [38] [39] [29]. Many others solvers exist.

III. Implementation

In previous research [9], analysis of inverse objective function's landscape is conducted. Analysis is done on the similar FDTD forward solver used in this paper, without any approximations or regularization on objective function. Analysis has shown that objective function is very rugged and composed of narrow valleys. Valleys have steep sides and mild axial slope. They are usually not directed alongside coordinate axes, but stretched in some diagonal direction. Typical (local) heuristic which searches alongside coordinate axes fails to propagate through such valleys. Attempt to solve this problem was searching in diagonal directions, but the number of search directions rises exponentially with the number of pixels optimized, further slowing down the optimization.

Such rugged landscape of the objective function is also not usable for calculating the gradient. Steep sides of valleys will misled optimization heuristic in the wrong direction. This is one reason why regularization is needed. For example, one implementation of inversion using FDTD solver and gradient optimization applies regularization just on gradient information, but not on the entire objective function [32]. Such approach brings less filtering applied on objective function and inversion could give better results.

One solution which could help with such a landscape is utilization of adaptive optimization methods. CMA-ES and ACiD are typical methods and these are used in this paper.

In this paper CMA-ES is hybridized with ACiD. First, the ACiD local optimization is run, for the fast exploitation i.e. fast cost (fitness) decrease towards minimum. At some point ACiD stops being effective, due to intense ruggedness of the landscape at smaller step size. After that, CMA-ES proceeds using covariance information from ACiD, doing exploration in the nearby. Another hybrid is ABC with HJ executed on every

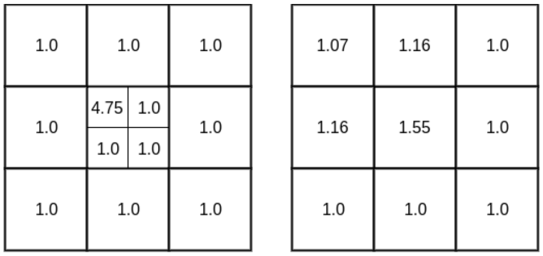

Fig. 2. Area under imaging: object under imaging and best match

bee [11], to raise exploitation [9]. Also, standalone CMA-ES and ABC are used for comparison.

Among other solutions also based on CMA-ES [10], uses FEM as forward solver, [3] [4] use CG-FFT, while solution proposed in this paper utilizes FDTD. Also, CMA-ES is used for parameter optimization in electromagnetic problems [40] [41].

In this paper 2D TM-mode (Ez-mode) FDTD algorithm is used as a solver. Entire space is represented by 2D rectangular grid. In Fig. 1 solver configuration is presented with defined area under imaging which should contain the object under imaging. Permittivities of the grid's cells in the area under imaging are input values for the solver. Dual free space layers with an array of point antennas surrounds this area. 6 layers of Uniaxial Perfectly Matched Layer (UPML) are set around, to absorb waves going out of imaging space. The discretization constant of space is set to 16th part of smallest wavelength, while space and time discretization constant are connected by Courant-Friedrichs-Lewy (CFL) condition.

Simulation is done through iterations. While a single antenna is transmitting, others receive the scattered waves. This is repeated until all antennas took the role of a transmitter. All received fields represent the output from the solver. Soft point source is used for the excitation, emulating transmit antennas. In the same positions the field is sampled, emulating receive antennas.

For the excitation, a signal specially optimized for FDTD is used [42]. Main characteristics of this signal include wideband, DC-less, short bandwidth product (excitation/simulation time) and continuity of derivatives in FDTD formulas for better precision.

At first, the solver is used for measurement simulation. The target solution is set in the area under imaging and output is used as a measured field. This output could be the field measured in real world. Afterwards, the solver is repeatedly called by the optimization algorithm, with some trial as input and giving simulated field as output. Cost i.e. fitness of objective function is the sum of the squared difference between measured and simulated fields.

IV. Results

Comparison is done on 3 by 3 optimization cells (9 degrees of freedom), where every optimization cell is a 2 by 2 FDTD cell. Simple object is imaged, with geometry defined by FDTD cells instead of using optimization cells, to partially avoid

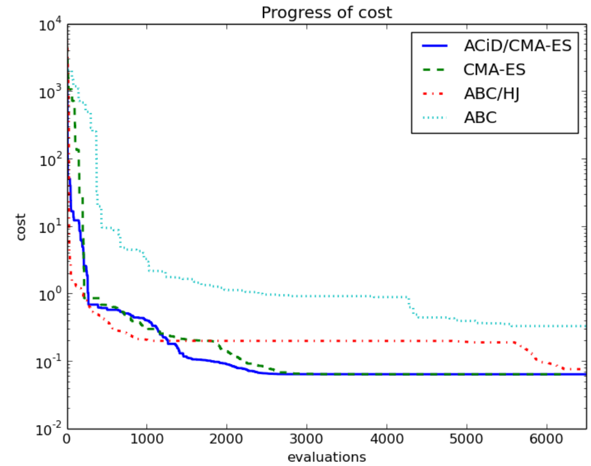

Fig. 3. Cost progress comparison for four heuristics

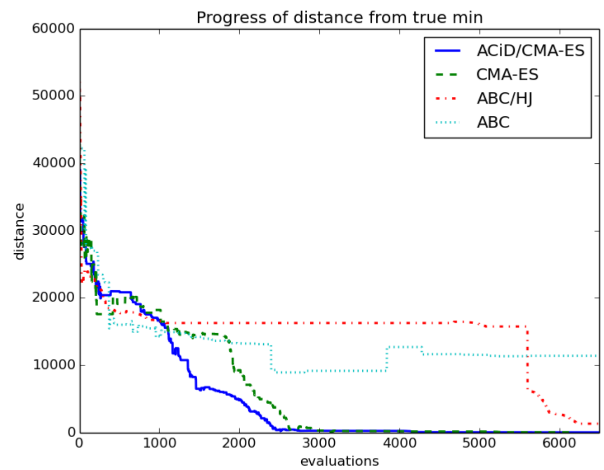

Fig. 4. Advancement progress comparison for four heuristics

inverse crime. Fig. 2 shows cell values of area under imaging. Object under imaging used in measurement simulation is show on the left and best possible match by the optimization is shown on the right. Every cell (larger are optimization and smaller FDTD cells) contains value of relative permittivity ϵ_r. Range of ϵ_r of the object under imaging is between 1.0 and 4.5, while for heuristics variate optimization cells between 1.0 to 1.93. Such smaller range is possible because optimization cells could not have values larger than object's FDTD cells average. This experimental setup measure 20 frequencies in range between 300 MHz-1 GHz. FDTD cell is around 5 mm x 5 mm in dimensions.

As mentioned in introduction, four heuristics are used and compared. In Fig. 3 progress of cost (fitness) of the objective function is shown. It can be observed that the ABC global optimization heuristic has slowest convergence. ABC/HJ hybrid heuristic has a faster convergence in comparison to ABC. Both ABC and ABC/HJ inherit problems with long stagnation

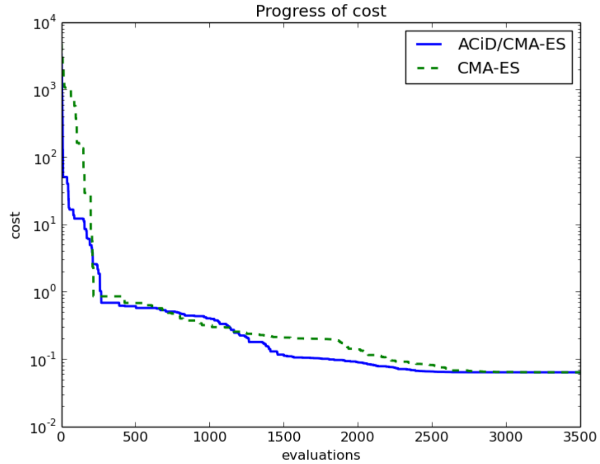

Fig. 5. Cost progress comparison for CMA based heuristics

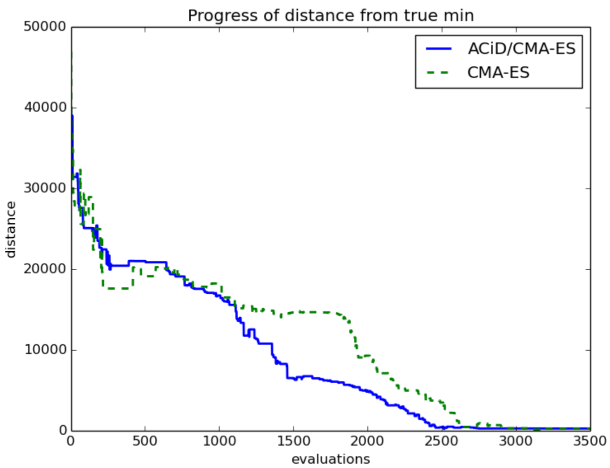

Fig. 6. Advancement progress comparison for CMA based heuristics

periods. Reason for this is the low exploration of search space. On the other hand, CMA-ES and ACiD/CMA-ES have much faster convergence, without severe stagnation.

Fig. 4 shows the progress of distance between the best solution and the true minimum solution. It could be seen that this metric has similar behavior as the cost progress. ABC based methods need few times more objective function's evaluations to converge and still not so close to true minimum as CMA based methods.

Fig. 5 is a closer look to the cost progress between CMA based heuristics. It could be seen that ACiD has fast convergence during first hundred iterations. After ACiD, CMA-ES proceeds and usually comes to the true minimum before CMA-ES only heuristic. Fig. 6 shows that the distance also behaves like the cost and ACiD/CMA-ES is a faster method. It should be noted that because statistical nature of these heuristics these progress curves of ACiD/CMA-ES could be worse on some sections than CMA-ES.

V. Conclusion

A novel solution for microwave tomography is implemented and few heuristics are used for optimization. Covariance matrix adaptive hybrid method is experimentally proven to be the most effective. Time-domain solver with multiple measurement frequencies is advantageous in contrast with single frequency solver. The main disadvantage of the used methods is potentially slower convergence and higher computational burden of global optimization in comparison to local optimization methods with linearization and regularization.

Future research direction would be focused on 3D FDTD development with accurate antenna and measurement chamber model. Advanced modeling requirements will bring additional computation burden and make optimization problem challenging and interesting. Also, additional research direction is implementation of the hardware measurement chamber for realistic measurement and closing a gap between modeling and real world.

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