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August 2004

Technical Report DIT-04-071

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Abstract

Genetic algorithms (GAs) are well known optimization strategies able to deal with nonlinear functions as those arising in inverse scattering problems. However, they are computationally expensive thus offering poor performances in terms of general efficiency when compared with inversion techniques based on deterministic optimization methods. In this paper, a parallel implementation of an inverse scattering procedure based on a suitable hybrid genetic algorithm is presented. The proposed strategy is aimed at reducing the overall computational burden in order to make the approach competitive with gradient-based methods (GCs) in terms of runtime by preserving the capabilities of escaping from local minima. This results is achieved by fully exploiting the natural parallelism of evolutionary techniques and the searching capabilities of the hybrid approach. The effectiveness of the proposed implementation is demonstrated by considering a selected numerical benchmark related to a two-dimensional scattering geometry.

Index Terms - Microwave imaging, inverse scattering, genetic algorithms, parallel implementation.

1 Introduction

The solution of inverse scattering problems is usually very difficult due to their inherent non linear nature and ill-posedness. Now-a-day, the leading way to face them is to recast the original problem into an optimization one, which is successively solved by means of a minimization technique (see for example [1], [2], [3], [4] and references cited therein). Unfortunately, the use of iterative procedures often makes the reconstruction process computationally expensive or inaccurate.

From a computational point of view, deterministic techniques (e.g., conjugate gradient procedures [5], [6]) result very attractive. However, when local-type inversion procedures are adopted, accurate and reliable results can be obtained only if the starting trial solution is close enough to the "actual" solution. In many practical cases, such a starting point is not available and some inaccuracies or artifacts in the resulting reconstruction occur due to the presence of false solutions corresponding to local minimum points of the cost function.

The use of global optimization techniques [7], [8], [9], [10] would in principle avoid such a circumstance. However, the overall computational burden can become easily unacceptable in serial implementations. This could prevent their use in real-time or quasi-real time applications.

In order to limit these drawbacks, the following strategies can be taken into account:

- the reduction of the number of problem unknowns by recurring to a suitable parameterization of the unknown scatterer [12] or by considering a multi-zooming strategy [11];
- the hybridization of the global optimization procedure with deterministic procedures [13], [14], [15];
- the use of fast solver for the iterative computation of electric field solution [16] in order to limit the number of unknowns handled by the global optimization procedure

to the parameter describing the physical properties of the scatterer under test;

- the exploitation of the intrinsic parallelism of global optimization procedures by considering a parallel implementation.

As far as serial implementations are concerned and since the birth of computers, the computational speed of even the most advanced and expensive computer systems has been regarded as a limiting factor even though state-of-the-art computers have played a significant role in many scientific and technical areas. The gigantic increase in computational performances of computer systems is mostly related to advances in electronic devices. In this way, the microprocessors of today are getting more and more powerful while retaining a reasonable cost-to-performance ratio. On the other hand, to produce processors with considerably higher speeds by using special-purpose fast electronics is extremely expensive. As a consequence, one way to increase the speed of computer systems without extreme costs is to connect many standard, off-the-shelf processing units to form a parallel computer system. This solution seems to offer the best trade-off between computational speed and cost of the system.

Moreover, one of the most attractive feature of the optimization procedures based on GAs is their parallelism that allows a so effective sampling of the solution space. The GA presents an *implicit* and an *explicit* parallelism. On the one hand, the term "implicit parallelism" (and the closely related term "building block") refers to the fact that the effective number of *schemata* [17] processed by the GA is greater than the number of individuals processed at each iteration (i.e., the population dimension I). This property guarantees that, also in a serial implementation, several characteristics of the solution are processed in a parallel way. A well known result is the Holland's inequality stating a lower bound of the order of $\frac{I^3}{c_1\sqrt{\ell}}$ to the number of schemata processed in a population of $I = c_1 2^\ell$ strings, being c_1 a small integer [18]. This result has been generalized in [19] where it has been showed that, for a population of $I = 2^{\beta\ell}$ individuals, this bound is a monotonically decreasing function of β and that for $\beta \geq 1$ its value is optimal up to

a constant and that with probability $\left(1-2e^{-\ell}\right)$ the number of schemata propagated is greater than one half of the value of the lower bound.

On the other hand, the parallelism of the GA is guaranteed also by the *multiple-agent* nature of the optimization procedure. At each iteration, a number of sample points, equal to the population dimension, is processed to effectively look for the optimal solution. In order to fully exploit also this characteristic, a parallel implementation of the procedure is mandatory. Consequently, the expected advantages coming from the parallelization of a GA can be summarized as follows:

- parallel search from multiple points in the solution space;
- more efficient search, even when no parallel hardware is available;
- higher efficiency than sequential implementation;
- easy hybridization with other search procedures (deterministic as well as stochastic);
- speedup due to the use of multiple CPUs.

In this paper, a parallel implementation of the inversion procedure based on a hybrid GA is proposed. To the best of our knowledge, this implementation represents a novelty in the framework of microwave imaging GA-based procedures and in general for inverse scattering methods (except the paper presented by J. Mallorqui *et al.* [20]). The paper is organized as follows. In Section II, the mathematical statement and the considered two-dimensional geometry are presented. In Section III, a detailed description of the GA-based procedure and its parallel implementation is proposed, while in Section IV selected numerical results of an exhaustive numerical assessment are presented in order to show the computational effectiveness and the reconstruction capabilities of the parallel GA-based approach.

2 Mathematical Formulation

Let us consider the 2D scalar configuration where an incident TM-polarized time-harmonic wave at angular frequency ω (the time factor $exp(j\omega t)$ is omitted in the following) illuminates a cylindrical target with arbitrary cross-section Θ. The target is supposed to lie in an investigation domain D whose object function is defined as follows

$$\tau(x,y) = \begin{cases} \tau_\Theta(x,y) & (x,y) \in \Theta \\ \tau_0 & otherwise \end{cases} \tag{1}$$

where $\tau_0 = 0$ and $\tau_\Theta(x,y) = \varepsilon_r(x,y) - 1 - j\frac{\sigma(x,y)}{\omega\varepsilon_0}$, ε_r and σ being the dielectric permittivity and conductivity of the target, respectively.

The inverse problem consists in retrieving the object function in the investigation domain starting from the resulting electric field, $F(x,y)$, measured by a set of receivers displaced around D in the observation domain O. In the spatial domain, this problem can be described by means of the following integral equations. For the v-th incidence

$$F_{scatt}^{(v)}(x,y) = k_0^2 \int_D G_0(x,y;x',y') F^{(v)}(x',y') \tau(x',y')\, dx'dy' \quad (x,y) \in O \quad (Data\ Equation) \tag{2}$$

$$F_{inc}^{(v)}(x,y) = F_{inc}^{(v)}(x,y) - k_0^2 \int_D G_0(x,y;x',y') F^{(v)}(x',y') \tau(x',y')\, dx'dy' \quad (x,y) \in D \quad (State\ Equation) \tag{3}$$

where $F_{scatt}^{(v)} = F^{(v)} - F_{inc}^{(v)}$ is the scattered field, $F_{inc}^{(v)}$ being the incident field; G_0 is the two-dimensional free-space Green function given by $G_0(x,y;x',y') = \frac{j}{4} H_0^{(2)}\left(k_0\sqrt{(x-x')^2 + (y-y')^2}\right)$, $H_0^{(2)}$ being the Hankel function of zero order and second kind.

In order to solve eqs. (2) and (3), a complete nonlinear approach is needed. By applying Richmond's method [21], discretized counterparts of the inverse scattering integral equations are obtained. The problem unknowns (i.e., the object function τ and $F^{(v)}$ in D) are represented through a linear combination of rectangular basis functions

$(R_n(x,y),\ n=1,...,N)$ as follows

$$\tau(x,y)=\sum_{n=1}^{N}\tau_n R_n\,(x,y)\qquad (x,y)\in D \tag{4}$$

$$F^{(v)}(x,y)=\sum_{n=1}^{N}\psi_n^{(v)} R_n\,(x,y)\qquad (x,y)\in D \tag{5}$$

Then, the inverse problem is cast into the global minimization of the cost function Φ

$$\Phi(\underline{f})=\frac{\sum_{m=1}^{M}\sum_{v=1}^{V}\left|F_{scatt}^{(v)}(x_m,y_m)-\Im_{Data}\left\{\tau_n,\psi_n^{(v)}\right\}\right|^2}{\sum_{m=1}^{M}\sum_{v=1}^{V}\left|F_{scatt}^{(v)}(x_m,y_m)\right|^2}+\frac{\sum_{q=1}^{N}\sum_{v=1}^{V}\left|F_{inc}^{(v)}(x_q,y_q)-\Im_{State}\left\{\tau_n,\psi_n^{(v)}\right\}\right|^2}{\sum_{q=1}^{N}\sum_{v=1}^{V}\left|F_{inc}^{(v)}(x_q,y_q)\right|^2} \tag{6}$$

where $\underline{f}=\left\{\tau_n,\psi_n^{(v)};\ n=1,...,N;\ v=1,...,V\right\}$ and M is the number of points of the observation domain where F is measured; $\Im_{Data}$ and $\Im_{State}$ indicate the discretized form of the right-hand-side terms of equations (2) and (3), respectively. The solution of (6) is obtained by constructing a sequence $\left\{\underline{f}_k,\ k=1,...,K\right\}$, k being the iteration number, which converges to $\underline{f}^{opt}=arg\left\{min\left[\Phi(\underline{f})\right]\right\}$. To this end, a suitable parallel GA-based procedure is used.

3 GA-Based Solution Strategy and Its Parallel Implementation

Evolutionary algorithms are known as robust optimization techniques able to effectively explore very large nonlinear parameter spaces. However, they generally present a low convergence rate and require a large number of cost function evaluations to achieve a satisfactory convergence threshold. Consequently, they result computationally expensive especially when compared to deterministic optimization methods. From a computational point of view, in order to make GA-based procedures competitive with deterministic

methods (while maintaining their favorable features), the following key points should be addressed:

- to improve the convergence rate of the iterative procedure;
- to reduce the computational time for the cost function evaluation.

3.1 Hybrid GA Strategy: Step-by-Step Procedure

Concerning the first issue, an effective strategy is the hybridization aiming at fully exploiting the complementary advantages of deterministic and stochastic techniques. The simplest way to implement a hybridized version of a GA is that of considering a *two-stage optimization*. Firstly, the minimization is carried out with a GA (or a deterministic technique). Subsequently, a deterministic procedure (or a stochastic technique) is employed. In this framework, different strategies have been proposed. In [22], a μ-GA has been coupled with a deterministic method proposing a criterion for switching from the stochastic to the deterministic optimizer and vice versa. Moreover, Ra *et al.* [13] proposed a hybrid method in which the Levenberg-Marquardt algorithm (LMA) is used to localize a minimum and the minimization process switches to the GA in order to climb local minima until the global minimum of the cost function is reached. On the contrary, in [14], the iterative process operates as a real-coded GA (RGA) in order to locate the *attraction basin* of the global optimum. When a satisfactory "order of closeness" to the global minimum is attained then a standard Polak-Ribière conjugate gradient algorithm is applied in order to refine and improve the current solution.

The main drawback of these approaches is the need of evaluating the "quality" of a minimum and/or the "closeness" of the solution to the attraction basin of the global minimum. This requires either an accurate knowledge of the cost function, which generally is not available, or an heuristic definition of the "degree" of accuracy of the current solution. Moreover, a closer coupling between stochastic and deterministic optimizers could provide better reconstruction results. In this framework, the coupling can be obtained by means

of the *step-by-step optimization* (SbSGA) described in the following.

As a reference, let us consider the real-coded version of the GA presented in [14] where a gene is the optimization parameter itself and the chromosome $\underline{c}_k$ directly codes the unknown array ($\underline{c}_k = \underline{f}_k$). The RGA requires the definition of a population of trial solutions $P = \left\{\underline{f}^{(i)};\ i = 1, ..., I\right\}$ and a rank of the solutions according to their *fitness* (defined as the corresponding cost function value). Then, new populations of trial solutions are iteratively obtained by applying the standard genetic operators (namely the selection, the mutation and the crossover) and by introducing a genetic operator which performs a gradient-like based minimization. More in detail, for each iteration, firstly a *mating pool* is chosen through a stochastic binary tournament selection ς [23]

$$P_{k(\varsigma)} = \varsigma\left\{P_k\right\} \subset P_k \tag{7}$$

Then, by considering a *generational model* (in which a whole new population of I individuals replaces the old one), a new temporary population $\widetilde{P}_k$ is generated applying the arithmetical crossover C and the RGA-mutation M [4]:

$$\begin{gathered} \widetilde{P}_k = P_{k(C)} \cup P_{k(M)} \\ P_{k(C)} = C\left\{P_{k(\varsigma)}\right\} \qquad\qquad P_{k(M)} = M\left\{P_{k(\varsigma)}\right\} \end{gathered} \tag{8}$$

Moreover, in order to insure a monotonic decrease of the best fitness in the population during the iterative process, the elitism [24] is activated. The best solution of the temporary population (i.e., $\underline{f}_k^* = arg\left\{min_{i=1,..,I}\left[\Phi(\underline{\tilde{f}}_k^{(i)})\right]\right\}$, $\underline{\tilde{f}}_k^{(i)} \in \widetilde{P}_k$) undergoes to the deterministic-minimization operator. More in detail, a sequence of successive approximations is generated as follows

$$\underline{f}_h^* = \underline{f}_{h-1}^* + \varphi_h \underline{d}_h \quad h = 0, ..., H \tag{9}$$

where $\underline{f}_0^* = \underline{f}_k^*$. The step length φ_h and the search direction $\underline{d}_h$ are chosen according to

the alternating direction implicit method [25]. The sequence length H is adaptively tuned iteration-by-iteration. H is increased ($H \leftarrow H+1$) when the *stationary condition* holds

$$\frac{\left| K_{window}\Phi_k^{(opt)} - \sum_{j=1}^{K_{window}} \Phi_j^{(opt)} \right|}{\Phi_k^{(opt)}} \leq \gamma_{st} \tag{10}$$

where $\Phi_k^{(opt)} = min_{i=1,..,I}\left\{\Phi(\underline{f}_k^{(i)})\right\}$, K_{window} and γ_{st} are a fixed number of iterations and a fixed numerical threshold, respectively. On the contrary, H is decreased ($H \leftarrow H-1$) when the *static conditions* are satisfied

$$\begin{gathered} \Phi_{k-K_{window}}^{(opt)} = ... = \Phi_k^{(opt)} \\ \left|\nabla\Phi_k^{(opt)}\right| \leq \gamma_{th} \end{gathered} \tag{11}$$

Finally, the individuals of the old population P_k are replaced according to the following criterion

$$\begin{gathered} \underline{f}_k^* = \underline{f}_H^* \\ \underline{f}_{k+1}^{(i)} = \underline{\tilde{f}}_k^{(i)} \end{gathered} \tag{12}$$

3.2 SbSGA Parallel Implementation

The basic motivation to implement an evolutionary algorithm in parallel is the reduction of the computational time for cost function evaluations. There are several approaches to GA's parallelization [26]. In the following, the SbSGA parallel implementation will be presented by addressing two specific issues: (a) structuring the parallel implementation and (b) making parallel implementation.

3.2.1 Structuring the Parallel Implementation

From an algorithmic point of view, a relatively easy approach to be implemented is the *global parallelization* [27]. In this type of implementation, a *panmitic* structure is considered. The whole population is dealt with a single pool of individuals as in the serial algorithm. The selection takes place globally and any individual can potentially mate

with any other. Therefore, the behavior of the algorithm (from the serial implementation to the parallel one) remains unchanged, but the fitness evaluation $\Phi(\underline{\tilde{f}}_k^{(i)})$ is explicitly parallelized. According to the *master-slave* paradigm [27], the master processor stores the entire population P_k and applies the SbSGA operations (selection, crossover, mutation, and the deterministic-minimization operator) to produce the next generation P_{k+1}. The slave processors are used to evaluate in parallel the cost function of a fraction of the trial-solution population. The communication between master and slave processors occurs only when different subsets of individuals are sent to different processors or when the processors send back the fitness values. The master processor, after sending the subsets of individuals, waits until it receives the fitness values for all individuals of the population before proceeding into the genetic loop (*synchronous global parallelization*).

3.2.2 Making Parallel Implementation

Since the *global parallelization* model does not assume anything about the computer hardware architecture or software communication tools, it is very natural to consider an implementation strategy able to profit of most usual instrumentation available in universities and research institutes.

Concerning the hardware architecture, a networked computer cluster is considered. This distributed memory architecture requires an exchange of information between master and slave processors. Such a communication is implemented through a message passing procedure which represents the main bottleneck limiting the parallel computing performances. However, the use of high-performance communication networks and the transfer of messages with extremely concise information (e.g., relative to the trial solution and the value of the corresponding cost function) among the processors can overcome these problems.

The message-passing and the process management are realized with the *parallel virtual machine* (PVM) software library [28] which allows the utilization of a heterogeneous network of parallel and serial computers as a single general and flexible concurrent com-

putational resource. Another advantage of PVM is its wide acceptability.

4 Numerical Validation and Effectiveness Assessment

The parallel implementation of the SbSGA computer code has been evaluated on a 25-node Intel Pentium-based cluster. The nodes of the cluster are $1.7\,GHz$ Intel Pentium IV with $256\,MB$ of RAM. The operating system is the Linux Red Hat 8.0. The processors are connected to a $100\,\frac{Mbit}{sec}$ Ethernet communication network and the implementation 3.4.4 of the PVM software library is used as communication protocol.

In order to evaluate the computational effectiveness of the proposed implementation, three test cases of different sizes are considered. The scattering problem scenario is the so-called dielectric inhomogeneous "Osterreich" configuration [4] where three different homogeneous objects ($\tau_{(1)} = 1.0$, $\tau_{(2)} = 2.5$, and $\tau_{(3)} = 2.0$) belong to a square investigation domain D of side $L = 1.0\,\lambda$. Four different ($V = 4$) incident plane waves with unit amplitudes are employed. The electric field is collected in O along a circle (L in radius) at $M = 80$ measurement points. This geometry has been partitioned differently for each test case: $N = 10 \times 10$ (test case #1), $N = 15 \times 15$ (test case #2), and $N = 19 \times 19$ (test case #3).

It should be pointed out that only one scattering geometry will be taken into account since the main emphasis of this research work is the evaluation of the computational effectiveness of the parallel implementation of the SbSGA-based approach. Consequently, there is no need to present different scattering geometries. On the contrary, different problem dimensions must be considered in order to show the key features and the current limitations of the approach from a computational point of view. As far as the evaluation of the reconstruction accuracy of the SbSGA-based approach is concerned (also in comparison with other deterministic or stochastic techniques), we will provide just some preliminary indications. An accurate and detailed analysis will be proposed in a future paper as a result of an exhaustive research work currently under development.

In the following, the parallel implementation of the SbSGA will be evaluated with respect to several computational-performances indices [29], namely

- the speedup S,
- the efficiency $\eta = \frac{S}{U}$, U being the number of cluster nodes (or workers) excluding the master processor, and
- the efficacy $\varepsilon = \eta \times S$.

Since we are dealing with a parallel stochastic iterative procedure, let us consider the *speed-up orthodox weak definition*:

$$S(U) = \frac{\sum_{e=1}^{E} \left\{ T_{ser}^{(e)} \right\}}{\sum_{e=1}^{E} \left\{ T_{par}^{(e)}(U) \right\}} \tag{13}$$

where T_{ser} and T_{par} are the execution time of the serial and the parallel code version, respectively; E is the number of statistically independent runs of the stochastic algorithm. For the comparison, the number of cluster nodes has been varied from $U = 5$, 10, 15, 20, 25 and $E = 20$ independent executions have been carried out in order to have representative time values. Moreover, the following GA's parameters have been adopted: $I = 81$, $K = 10^4$, $P_{cross} = 0.7$ (crossover probability), $P_{mut} = 0.8$ (mutation probability), $K_{window} = \frac{K}{20}$, and $\gamma_{th} = 10^{-4}$ (convergence threshold).

The change of the three key indicators as a function of the number of workers used and for different problem dimensions is presented in Figure 1. The top diagram shows the behavior of the speedup. The *ideal speedup* ($S_{ideal} = U$) is also reported. As it can be observed, the peak overall speedup occurs when running the parallel code on $U = 25$ processors, but the distance between the ideal-speedup curve and S increases with the number of cluster nodes due to the fast-growing communications overhead. As expected [26][30], by implementing a *global parallelization*, the speedup is sub-linear ($S(U) \leq U$).

Moreover, due to the communication overhead and load imbalance among the processors, it results a reduction of the efficiency η with the dimension of the cluster (Fig.

$1(b)$). A more significant decrease takes place in correspondence with the largest problem dimension caused from the augmented information passing among the master and slaves processors.

Relating speedup and efficiency, it is possible to determine the optimum number of nodes which is the maximum of the efficacy curve (Fig. $1(c)$). The slope of the efficacy curve for the different size problems indicates that a number of about $U = 10 - 15$ workers might be efficiently used to solve the problem.

On the other hand, to assess the effectiveness of the proposed parallel approach within the framework of microwave imaging techniques, it is mandatory to compare the computational cost of the SbS parallel implementation both with its sequential implementation and with a standard serial deterministic procedure. It is well known that the main bottleneck preventing a quasi/real-time application of a GA-based procedure is the computational complexity greater than that of a conjugate-gradient-based procedure. The proposed parallel implementation is aimed at making the GA-based approach competitive with deterministic techniques, maintaining the GA key-features in term of reconstruction accuracy. For comparison purposes, Fig. 2 gives an indication of the amount of the average computational time needed for the parallel SbSGA code, for its sequential implementation, and for a standard conjugate-gradient method [31] when the largest size problem is considered (test case #3). The computational cost increases with the increasing of the problem dimension and the parallel implementation allows a dramatic runtime reduction (of about 9 times for the largest case $N = 19 \times 19$) as compared with the serial code. Because of the significant speedup of 6.9 ($U = 10$) (Fig. $1(a)$), the overall runtime of the parallel code turns out to be almost equivalent to that of the deterministic procedure.

As expected, the parallel evolutionary technique maintains its effectiveness in the profile reconstruction as briefly summarized in Fig. 3 where the behavior of the error figures defined in [4] versus the problem size is reported. In general, the genetic-based imaging procedure (i.e., both the RGA-based approach and the hybrid GA method) overcomes the CG method in term of reconstruction accuracy. More in detail, the SbSGA shows a more

significant improvement (if compared with that of the RGA method) as compared with the deterministic technique especially when larger problem sizes are taken into account. However, the last sentence should be considered as a preliminary indication to be further validated with a specific (and out of the scope of the present paper) study.

For completeness, a pictorially representation of the reconstructed profile ($N = 19 \times 19$ - test case #3) is shown in Fig. 4 by considering different methodologies (the dielectric distribution estimated with the hybrid GA based on the "two-stage optimization" [14] is also reported - Fig. $4(c)$).

5 Conclusions and Future Works

In this paper, the parallel implementation of a GA-based microwave imaging approach has been presented. A strong reduction of the computational burden has been obtained by fully exploiting the natural parallelism of the genetic process. Moreover, the computational saving has been also obtained by improving the convergence rate of the iterative process and by reducing the overall runtime of the GA's ranking procedure. However, it should be pointed out that the use of this parallelized hybrid GA is not different from other parallel methodologies. Its execution efficiency largely depends upon the system architecture, the parallel execution overhead, the number of new population members created at each generation, the population structure, and the parallel *granularity* (i.e., the computational cost of the steps being executed in parallel). Consequently, future advances could be reached by taking into account these factors. In particular, from a computational point of view (which is the main issue of this paper), the following question should be answered: "*it is really possible to get super-linear speedup with a parallelized hybrid GA?*". Probably, the answer is *yes* only if:

- a *structured population* [26] is taken into account in order to obtain not only a faster algorithm but also a superior numerical optimization fully exploiting the *multi-agent* nature of the genetic algorithm;

- some individuals do a different local search (*decentralized local optimization*) in order to improve the convergence rate of the iterative process;
- the genetic process explicitly keeps memory of the chromosomes evolution in order to reduce/avoid the runtime of the fitness evaluation for similar/equal individuals;
- the genetic operators are applied in parallel.

Future researches will be devoted to this aim in order to help for an application of GA-based strategies to real-time industrial applications.

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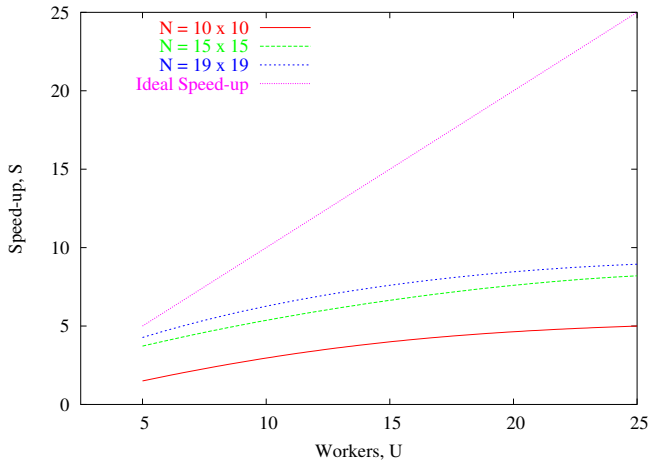
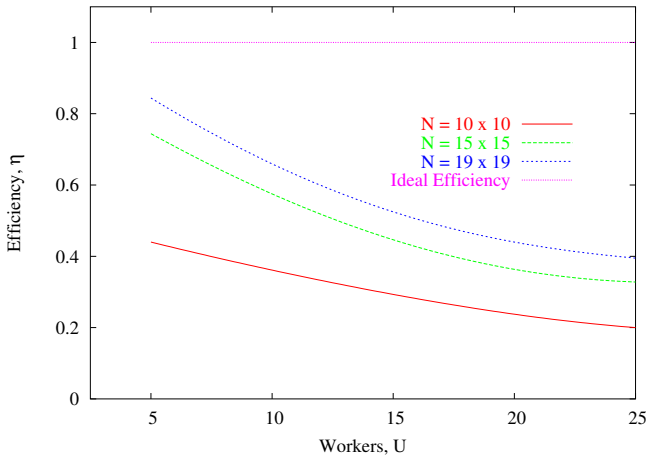
Figure Captions

- Figure 1. Parallel GA - Evaluation of the computational performances: (a) Speedup S, (b) Efficiency η, and (c) Efficacy ε.
- Figure 2. Parallel GA - Normalized runtime versus problem size N.
- Figure 3. Parallel GA - Reconstruction accuracy versus problem size N: (a) external percentage error ξ_{ext}, (b) internal percentage error ξ_{int}, and (c) total percentage error ξ_{tot}.
- Figure 4. Retrieved dielectric profile with the (a) Conjugate-Gradient Method, (b) the RGA-based Approach, (c) the Hybrid GA-based Approach (*Two-Stage Optimization*), and (d) the Hybrid GA-based Approach (*Step-by-Step Optimization* - SbSGA). Problem size: $N = 19 \times 19$.



(a)



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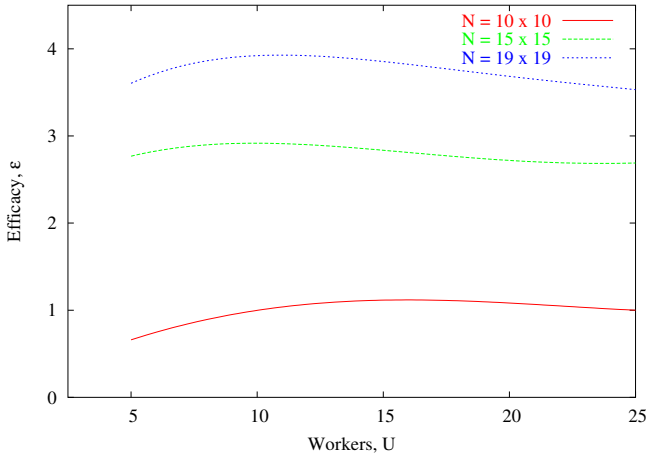


(c)

Figure 1 - A. Massa et *al.*, "Parallel GA-based Approach for ..."

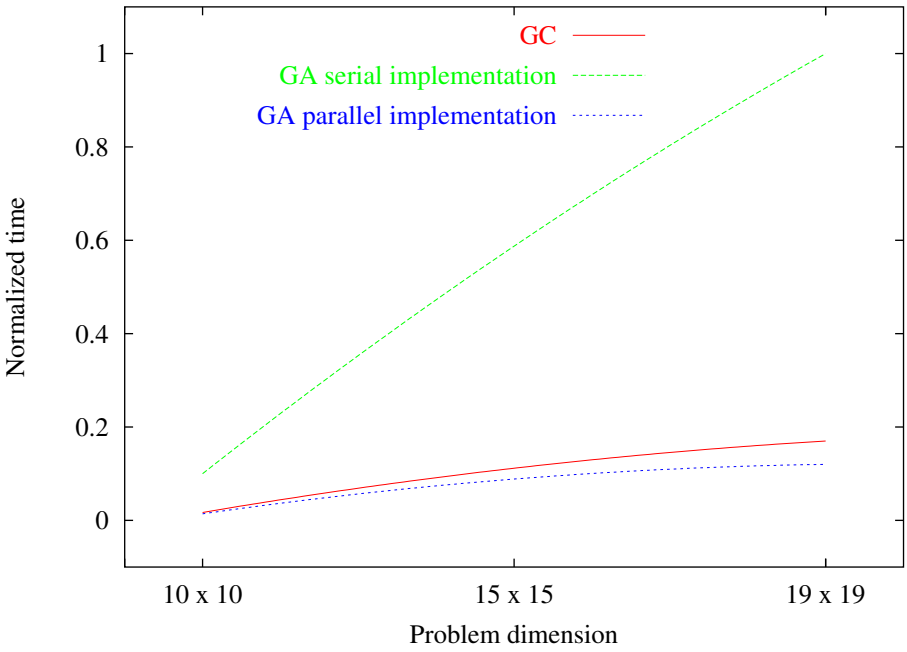
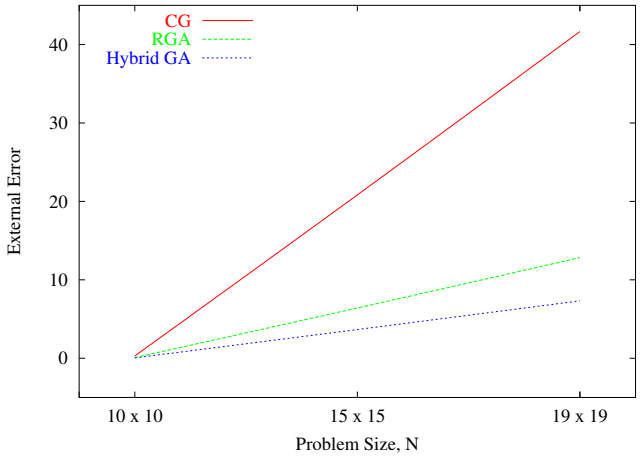
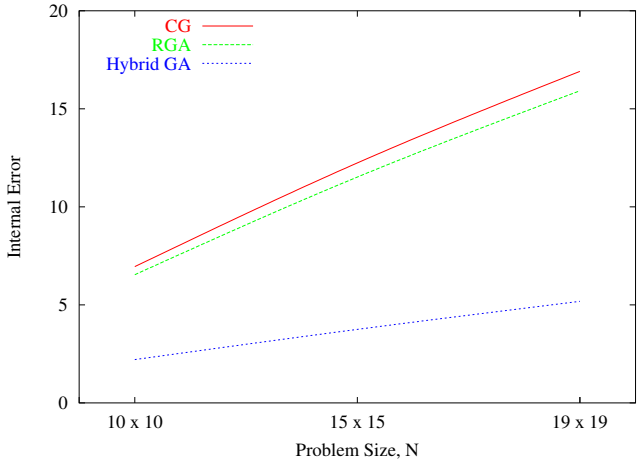


Figure 2 - A. Massa et *al.*, "Parallel GA-based Approach for ..."



(a)



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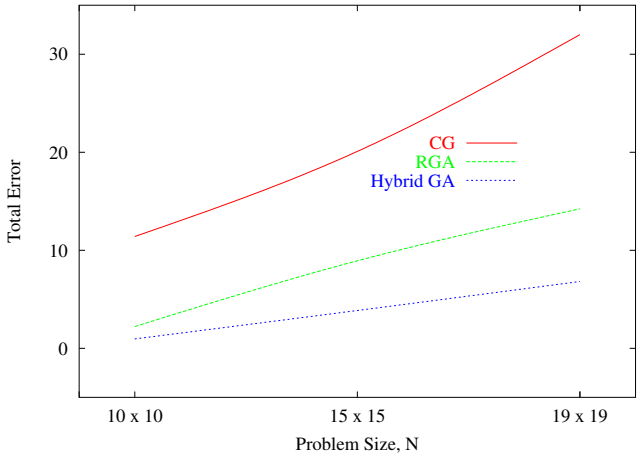

(c)

Figure 3 - A. Massa et *al.*, "Parallel GA-based Approach for ..."

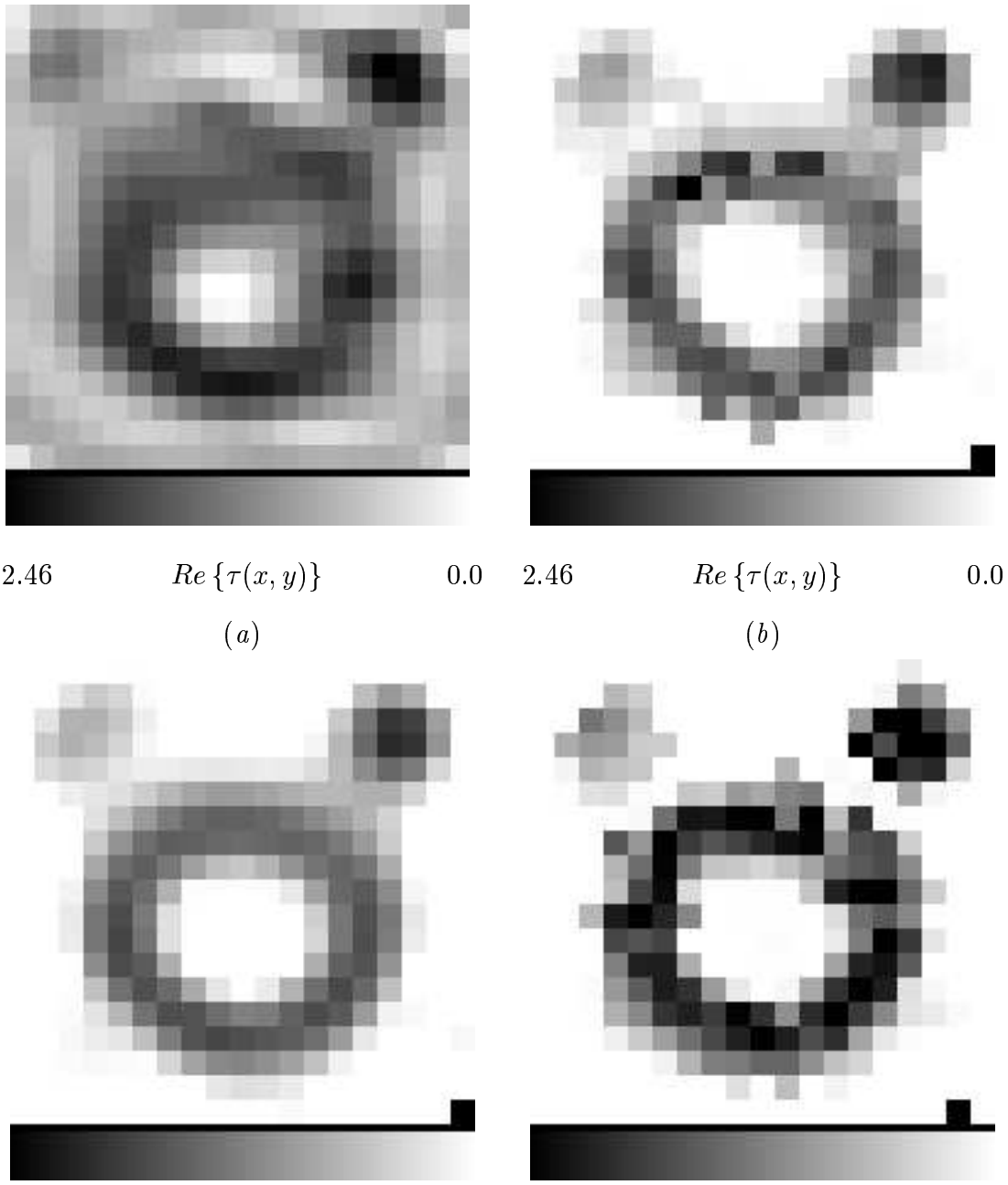

Figure 4 - A. Massa et *al.*, "Parallel GA-based Approach for ..."