

JAN 16 1990

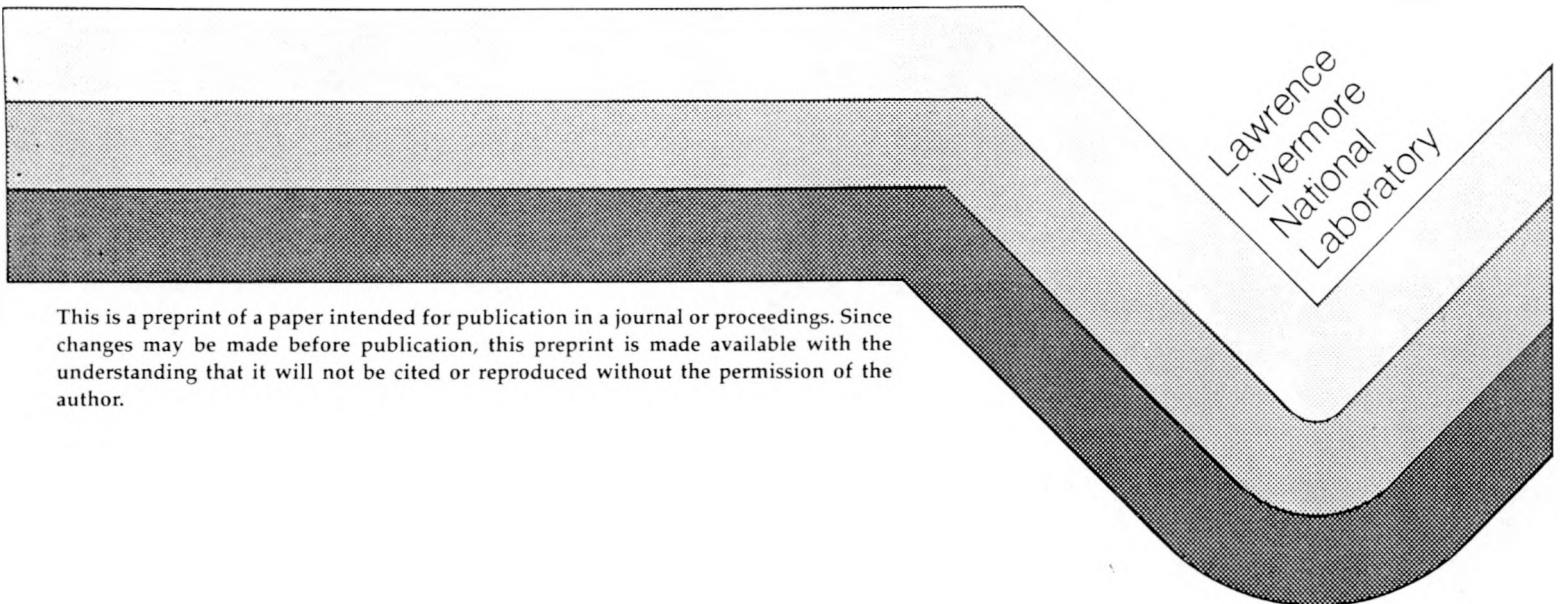
A PARALLEL ITERATIVE METHOD FOR SOLVING 3-D  
ELLIPTIC PARTIAL DIFFERENTIAL EQUATIONS\*

Anne Greenbaum  
New York University  
Courant Institute of Mathematical Sciences  
251 Mercer Street  
New York, NY 10012

Edna Reiter  
Department of Mathematics and Computer Science  
California State University at Hayward  
Hayward, CA 94542

Garry Rodrigue  
Department of Applied Science  
University of California, Davis  
P. O. Box 808  
Livermore, CA 94550

To appear in Proceedings of the NATO  
Supercomputer Workshop  
Trondheim, Norway  
June 19-23, 1989



This is a preprint of a paper intended for publication in a journal or proceedings. Since changes may be made before publication, this preprint is made available with the understanding that it will not be cited or reproduced without the permission of the author.

## **DISCLAIMER**

**This report was prepared as an account of work sponsored by an agency of the United States Government. Neither the United States Government nor any agency thereof, nor any of their employees, makes any warranty, express or implied, or assumes any legal liability or responsibility for the accuracy, completeness, or usefulness of any information, apparatus, product, or process disclosed, or represents that its use would not infringe privately owned rights. Reference herein to any specific commercial product, process, or service by trade name, trademark, manufacturer, or otherwise does not necessarily constitute or imply its endorsement, recommendation, or favoring by the United States Government or any agency thereof. The views and opinions of authors expressed herein do not necessarily state or reflect those of the United States Government or any agency thereof.**

---

## **DISCLAIMER**

**Portions of this document may be illegible in electronic image products. Images are produced from the best available original document.**

# A Parallel Iterative Method for Solving 3-D Elliptic Partial Differential Equations\*

Anne Greenbaum  
New York University  
Courant Institute of Mathematical Sciences  
251 Mercer Street  
New York, NY 10012

Edna Reiter  
Department of Mathematics and Computer Science  
California State University at Hayward  
Hayward, California, 94542

Garry Rodrigue  
Department of Applied Science  
University of California, Davis  
P.O. Box 808  
Livermore, California, 94550

## 1 Domain Decomposition

In this paper, we will consider the parallel solution of the Dirichlet problem for a second-order uniformly elliptic equation in two and three dimensions. Specifically, we shall consider the problem

$$\begin{aligned} L(u) &= f \text{ in } \Omega \\ u &= g \text{ on } \Gamma \end{aligned} \tag{1}$$

where

$$L(u) = - \sum_{j=1}^3 \frac{\partial}{\partial x_j} \left( a_j \frac{\partial u}{\partial x_j} \right)$$

---

\*This work was performed under the auspices of the U.S. Department of Energy at the Lawrence Livermore National Laboratory under Contract W-7405-Eng-48 and at the Courant Institute of Mathematical Sciences under Contract DE-AC02-76ER03077

**MASTER**

with  $a_i$  positive, bounded, and piecewise smooth on bounded  $\Omega$  with boundary  $\Gamma$ . For sake of exposition, we will assume the equation is 2-dimensional, however, the extension to 3-dimensions of the numerical methods to be described will be obvious.

The solution of elliptic problems such as those given by (1) arise quite often on supercomputers when they are used to numerically simulate problems arising in mechanical systems. They are often solved when the steady state of dissipative systems as in gas dynamics is desired. These equations are particularly difficult to solve on a computer because their discrete representation on a computational grid yields a linear system of equations where the number of unknowns is equal to the number of grid points on the lattice and, in 3-dimensions, the number of unknowns can be very large, (e.g.  $10^6$ ).

A general framework for developing parallel algorithms for solving the elliptic equation (1) on a multiprocessing supercomputer is provided by a technique that has come to be known as *domain decomposition*. For time-independent problems such as (1), the technique of domain decomposition begins by subdividing the *global* domain  $\Omega$  into a union of subdomains:

$$\Omega = \bigcup_{i=1}^n \Omega_i.$$

Again, for ease of exposition, we will assume  $\Omega = [0, 1] \times [0, 1]$  is the unit cube and the subdomains are themselves cubes,  $\Omega_i = [\alpha_i, \beta_i] \times [\gamma_i, \delta_i]$ . Examples of such decompositions are given in Figure 1.

For a given decomposition, numerical methods are constructed by solving equation (1) on each of the subdomains and then piecing together the sub-solutions in some manner to provide an approximation to the global solution,[3]. This seems quite straightforward provided there is some mechanism for defining appropriate boundary conditions on each of the subdomain problems. The first attempts at providing subdomain boundary conditions were based around the classical Schwarz alternating method. Here, an initial guess is provided for the boundary conditions and then each sub-problem is solved numerically in some sequential order. Boundary conditions are updated whenever sub-solutions are computed on subdomains containing neighboring subdomain boundaries. As an example, let us consider the

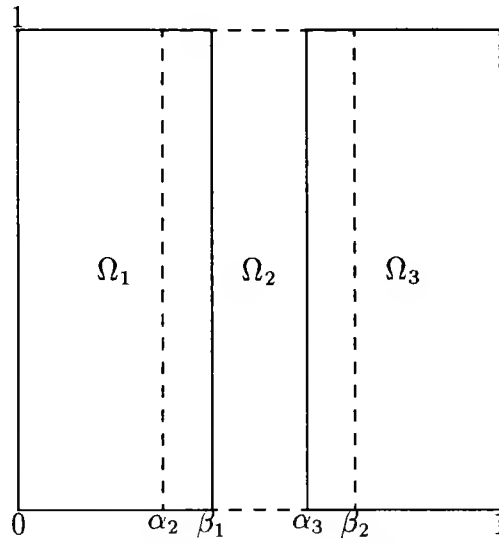


Figure 1: Three Subdomains

solution of (1) using a decomposition such as the one given in Figure 1. Let  $u_i^{(0)}$  be given initial guesses for the solution  $u$  on each of the subdomains  $\Omega_i$ . Then for  $k = 1, 2, \dots$ , define the sequence of sub-solutions  $\{u_i^{(k)}\}$  as follows:

$$Lu_i^{(k)} = f \Big|_{\Omega_1} \quad \text{on } \Omega_1,$$

$$u_i^{(k)} = g \text{ on } \Gamma \cap \Gamma_i,$$

$$u_i^{(k)} = \begin{cases} \left. u_2^{(k-1)} \right|_{\Gamma} & \text{if } i = 1, \\ \left. u_{i-1}^{(k-1)} \right|_{\Gamma_{i-1}} & \text{if } 1 < i < n, \\ \left. u_{i+1}^{(k-1)} \right|_{\Gamma_{i+1}} & \text{if } 1 < i < n, \\ \left. u_{n-1}^{(k-1)} \right|_{\Gamma_n} & \text{if } i = n. \end{cases}$$

Convergence of the above procedure to the global solution follows from the maximum principle. The numerical analog of the previous algorithm is obvious and has been shown to be equivalent to a block-Jacobi matrix iterative method, and consequently, often results in slow convergence, [3]. Specifically, the matrix iteration takes the form

$$\hat{x}^{(k+1)} = M^{-1}N \hat{x}^{(k)} + \hat{q} \quad (2)$$

where  $M$  is a block-diagonal matrix and  $N$  is a non-symmetric matrix. Consequently, a major effort over the past few years has been to develop iterative methods based around domain decomposition that will converge faster than the Schwarz methods.

## 2 Conjugate Gradient Acceleration

The easiest and, probably, the most popular way of accelerating an iteration of the form (2) is by the method of conjugate gradients (or, Krylov subspace methods),[2]. Basically, an additive splitting  $A = M - N$  of a symmetric, positive-definite, matrix is given. Then, the following iteration is used to solve the matrix equation  $A\hat{x} = \hat{b}$ .

Let  $\hat{x}^{(0)}$  be an initial guess and  $\hat{r}^{(0)} = \hat{b} - A\hat{x}^{(0)}$ . Then, for  $k = 0, 1, \dots$ , define

$$\begin{aligned}
 i) \quad M\hat{z}^{(k)} &= \hat{b} - A\hat{x}^{(k)}; \\
 ii) \quad \beta_k &= \begin{cases} 0, & k = 0; \\ \frac{\hat{z}^{(k)t} M \hat{z}^{(k)}}{\hat{z}^{(k-1)t} M \hat{z}^{(k-1)}}, & k \geq 1; \end{cases} \\
 iii) \quad \hat{p}^{(k)} &= \hat{z}^{(k)} + \beta_k \hat{p}^{(k-1)}; \\
 iv) \quad \alpha_k &= \frac{\hat{z}^{(k)t} M \hat{z}^{(k)}}{\hat{p}^{(k)t} A \hat{p}^{(k)}}; \\
 v) \quad \hat{x}^{(k+1)} &= \hat{x}^{(k)} + \alpha_k \hat{p}^{(k)}.
 \end{aligned} \tag{3}$$

The convergence of this iteration in a finite number of steps is guaranteed if the matrix  $M$  is symmetric and positive-definite. In fact, it is known that

$$E(x^{(k)}) \leq 2 \left( \frac{\sqrt{\kappa} - 1}{\sqrt{\kappa} + 1} \right)^k E(x^{(0)}) \tag{4}$$

where

$$\begin{aligned}
 \kappa &= \frac{\lambda_{max}}{\lambda_{min}}, \\
 \lambda_{max} &= \text{largest absolute eigenvalue of } M^{-1}A, \\
 \lambda_{min} &= \text{smallest absolute eigenvalue of } M^{-1}A, \\
 E(x) &= (x^t A x)^{1/2}.
 \end{aligned}$$

Consequently, convergence will be rapid if the matrix  $M$  is *spectrally* close to  $A$  in the sense that  $\kappa$  should not be large. The literature on the choice of  $M$  is vast especially for the case when the matrix  $A$  represents a discrete approximation to (1). However, it is not until recently that reasonable choices of  $M$  have been provided that make efficient use of a decomposed domain. The difficulty of using domain decomposition methods in conjugate gradient lies in the origin of each of the two ideas. The conjugate gradient method has its foundation in linear algebra whereas

domain decomposition is embedded in the theory of differential equations, and at the present time a unified mathematical connection between the conjugate gradient method and differential equations has not been established.

### 3 Additive Schwarz Method

Because the convergence rate of the conjugate gradient method depends on the relationship between the matrix  $A$  that approximates equation (1) and the preconditioning matrix  $M$ , it may be possible to build a matrix  $M$  from a domain decomposed differential equation that is related to equation (1). We do so by first splitting the global solution of (1) into the sum of a *homogeneous* solution and a *particular* solution. That is,  $u = u^{(H)} + u^{(P)}$  where

$$L(u^{(H)}) = 0 \text{ on } \Omega, \tag{5}$$

$$u^{(H)} = g \text{ on } \Gamma,$$

and

$$L(u^{(P)}) = f \text{ on } \Omega, \tag{6}$$

$$u^{(P)} = 0 \text{ on } \Gamma.$$

Now, let

$$\Omega = \bigcup_{i=1}^n \Omega_i \tag{7}$$

be a decomposition of  $\Omega$  and define the subproblems

$$L(u_i) = f \Big|_{\Omega_i} \text{ on } \Omega_i, \tag{8}$$

$$u_i = \begin{cases} g & \text{on } \Gamma \cap \Gamma_i, \\ u & \text{on } \Gamma_i - \Gamma. \end{cases}$$

Clearly,  $u = u_i$  on  $\Omega_i$ . Again,  $u_i = u_i^{(H)} + u_i^{(P)}$  where

$$L(u_i^{(H)}) = 0 \text{ on } \Omega_i, \quad (9)$$

$$u_i^{(H)} = \begin{cases} g & \text{on } \Gamma_i \cap \Gamma, \\ u & \text{on } \Gamma_i - \Gamma, \end{cases}$$

and

$$L(u_i^{(P)}) = f \Big|_{\Omega_i} \text{ on } \Omega_i, \quad (10)$$

$$u_i^{(P)} = 0 \text{ on } \Gamma_i.$$

Clearly, each of the "particular" problems defined by (10) can be solved in parallel. Thus, we take as an approximation to  $u^{(P)}$  the function  $\nu^{(P)}$  where

$$\nu^{(P)} = \sum_{i=1}^n \nu_i^{(P)} \quad (11)$$

and

$$\nu_i^{(P)} = \begin{cases} u_i^{(P)} & \text{in } \Omega_i, \\ 0 & \text{in } \Omega - \Omega_i. \end{cases} \quad (12)$$

Then,

$$u \simeq u^{(H)} + \nu^{(P)} \quad (13)$$

and

$$\mathcal{L}(u) \simeq L(u) \quad (14)$$

where

$$\mathcal{L}(u) = L(u^{(H)}) + \left( \sum_{i=1}^n L(\nu_i^{(P)}) \right). \quad (15)$$

We now carry out the numerical equivalent of the above construction. To do so, we overlay the global domain  $\Omega$  by a grid  $G$  such that the boundaries  $\Gamma_i$  of the subdomains are contained in  $G$ . Now, suppose the grid  $G^{(H)}$  also overlays the domain  $\Omega$  with  $G^{(H)} \subset G$ . Let

$$G_i = G \cap \overline{\Omega}_i$$

where  $\bar{\Omega}_i$  is the closure of  $\Omega_i$ ,  $\hat{u}$  the discrete representation of the function  $u$  on grid  $G$  and  $\hat{v}_i$  the restriction of  $\hat{u}$  on  $G_i$ . If  $A_i$  is the matrix representation of the equation (10) on  $G_i$ , then define the matrix  $\mathcal{A}_i$  on  $G$  by

$$\mathcal{A}_i \hat{u} = \begin{cases} A_i \hat{v}_i, & \text{on } G_i \\ 0, & \text{otherwise.} \end{cases}$$

Now let  $P$  be an operator that maps grid functions on  $G^{(H)}$  into grid functions defined on  $G$  by bilinear interpolation. If  $A^{(H)}$  is the matrix approximation to equation (5) on  $G^{(H)}$ , then define

$$\mathcal{A}^{(H)} \hat{u} = A^{(H)} P \hat{u}, \text{ on } G^{(H)}.$$

Now, if  $M$  is the preconditioning matrix to be used in the conjugate gradient method, then we carry out the computation of step (3i) by

$$\begin{aligned} z^{(k)} &= M^{-1} r^{(k)} \\ &= \mathcal{A}^{(H)*} r^{(k)} + \left( \sum_{i=1}^n \mathcal{A}_i^\dagger r^{(k)} \right) \end{aligned}$$

where the matrices  $\mathcal{A}_i^\dagger$  are the pseudo-inverses of  $\mathcal{A}_i$ , i.e.,

$$\mathcal{A}_i^\dagger r^{(k)} = \begin{cases} A_i^{-1} r^{(k)} & \text{on } G_i, \\ 0 & \text{otherwise.} \end{cases}$$

and

$$\mathcal{A}^{(H)*} r^{(k)} = P A^{(H)-1} P^t r^{(k)}.$$

Again, we see that  $M$  is symmetric and positive-definite. The above method of constructing  $M$  is called the additive Schwarz method, [1],[4],[5].

## 4 Computational Example

We apply the above the previously described to compute a numerical solution to the 3-dimensional Poisson equation

$$L(u) = \frac{\partial^2 u}{\partial x^2} + \frac{\partial^2 u}{\partial y^2} + \frac{\partial^2 u}{\partial z^2} = f \quad (16)$$



$\Delta_c$	$\Delta_f$	$t_s$	$t_p$
1/3	1/16	.243	.199
1/3	1/24	.76	.51
1/3	1/32	2.33	1.25

Table 1: Timings on NMFEC Cray-II

of  $\Omega$ . Let this decomposition be given by

$$\Omega = \bigcup_{i=1}^n R_i.$$

On the closure of each subdomain  $R_i$  define a grid  $G_f$  of mesh-size  $\Delta_f$ . Extend the internal boundaries of the regions  $R_i$  by  $\Delta_f$  in each coordinate direction to obtain a larger sub-domain  $\Omega_i$ . Clearly,  $\Omega = \bigcup_{i=1}^n \Omega_i$ . We use the conjugate gradient method given in (3) where the preconditioner  $M$  is defined by the additive Schwarz method. The calculations were executed on the Cray-II located at the NMFEC in the Lawrence Livermore National Laboratory.  $t_s$  refers to time in minutes without multiprocessing and  $t_p$  refers to the time in minutes with multiprocessing. The banded version of the LU-factorization algorithm was used to solve the linear systems involving  $\mathcal{A}_i$  and  $\mathcal{A}^{(H)}$  in step (3i) of the conjugate gradient method.

## 5 Summary

We have described an iterative algorithm for solving linear systems arising from the discretization of elliptic partial differential equation. The algorithm combines domain decomposition techniques and the conjugate gradient method in order to achieve rapid convergence and parallelism. Subdividing the domain allows us to solve 3-dimensional problems in an efficient manner. Table 1 indicates the timings that were achieved on the Cray-II located at the NMFEC. Although the maximum speedup we achieved was 1.9, the parallel performance of the algorithm was disappointing. The idealized timing which assume we receive all four processors

simultaneously should produce speedups in the range of 3.5-3.8. We are continuing to research the cause of this poor performance and will be the subject of a future paper.

## References

- [1] P.E.Bjorstad, Multiplicative and Additive Schwarz Methods: Convergence in the Two-Domain Case, Proc. of the 2nd Int. Symp. on Domain Decomposition Methods, Los Angeles, Calif., Jan. 14-16,1988, SIAM Publications, Philadelphia, Pa., pp.147-159.
- [2] G.Golub and C.Van Loan, Matrix Computations, Johns Hopkins University Press, Baltimore, Maryland, 1983.
- [3] G. Rodrigue, Inner/Outer iterative methods and numerical Schwarz methods, Journal of Parallel Computing, 2, 1985, pp. 205-218.
- [4] O. Widlund, Optimal iterative refinement methods, Proc. of the 2nd Int. Symp. on Domain Decomposition Methods, Los Angeles, Calif., Jan. 14-16, 1988, SIAM Publications, Philadelphia, Pa., pp. 114 - 126.
- [5] A. Greenbaum, C. Li, and H.Z. Chao, Parallelizing Preconditioned Conjugate Gradient Algorithms, Computer Physics Communications, 53, 1989, pp. 295-309