

**Research Article** 

# A MULTIGRID METHOD FOR NUMERICAL SOLUTION OF ELLIPTIC PARTIAL DIFFERENTIAL EQUATIONS

By

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### ABSTRACT

Techniques and analyses of multigrid method for solving elliptic partial differential equations (PDEs) in two dimensions are presented. The focal point of this paper is the applicability of the parametric reaccelerated overrelaxation (PROR) iterative method as a smoother in multigrid solution of elliptic PDEs. The two-dimensional Poisson equation on a unit square domain with Dirichlet boundary conditions is adopted as the model PDE. We present some practical formulae and techniques for building the various multigrid components using Kronecker tensor product of matrices. In addition, we carryout smoothing analysis of the PROR method using Local Fourier Analysis (LFA) and show how optimal relaxation parameters and smoothing factors can be obtained from analytic formulae derived to ensure better convergence. This analysis combines full standard coarsening strategy (doubling) and second order finite difference scheme. The result of PROR smoothing factors in comparison with those of other widely used smoothers is also presented. Results obtained from numerical experiment are displayed and compared with theoretical results.

Keywords: Multigrid, elliptic PDEs, Poisson equation, coarsening strategy, point-smoothing, smoothing factor, local Fourier analysis.

AMS subject classification: 65F10, 65F15, 65M06, 65N55.

### I Introduction

Many real world applications are modeled as partial differential equations (PDEs) on rectangular domains. For instance, the set of Maxwell's electromagnetic equations combined with Ohm's law is used as the basic model for describing the propagation of electromagnetic waves in earth's crust, the Schrodinger equation for scattering applications in quantum mechanics can be transformed in some cases to the Helmholtz equation, a prototype of elliptic PDEs [1]. According to [2], multi-dimensional PDEs have diverse applications in many applied science fields such as financial engineering [3], molecular



biology [4], and quantum dynamics [5, 6]. In addition, the Poisson equation in particular, occurs frequently in electromagnetism, fluid dynamics among others.

It is common and often easier to express PDEs as systems of linear equations, a procedure known as discretization. Although, it may be possible to use direct methods such as matrix inversion, Gaussian elimination, and the likes, to exactly solve these systems of equations, they tend to take far too long to be practicable for very large and sparse linear systems. In general, it is a difficult if not impossible task to solve many PDEs exactly via direct methods. Except in simple cases, numerical method is best, if not the only, way of obtaining a solution satisfying certain boundary conditions [7].

The ubiquity of elliptic PDEs in the field of applied sciences, coupled with the difficulty in the use of direct methods for solving large systems obtained from discretizing PDEs, has led to the development of many suitable indirect (iterative) techniques for a wide range of specific applications and problems. [8] suggested that iterative methods are preferred and such techniques remain the leading approach for solving very large linear systems.

Classical iterative methods such as the Jacobi [9], Gauss Seidel [10], Successive overrelaxation (SOR) [11], accelerated overrelaxation (AOR) [12] methods have all been deployed in the solution of PDEs. Other recent variants of SOR and AOR include preconditioned SOR [13], reaccelerated overrelaxation (ROR) [14], and parametric reaccelerated overrelaxation (PROR) [15] methods. The classical iterative methods are however seldom used as stand-alone methods for solving very large linear systems today due to their slow convergence properties. However, when used as smoothers in a multigrid method, the convergence rate of the whole solution process is sped up rapidly.

Multigrid methods are a class of iterative techniques called multi-resolution methods which are very efficient for problems exhibiting multiple scales of behavior. Multigrid methods typically solve the system of equations on a "coarse" grid, and "refine" the solution to the desired accuracy instead of trying to solve the discrete system at full resolution as obtained in classical iterative methods [16]. Many multigrid methods and applications where multigrid have been applied abound in literature; these include multigrid methods for solution of two dimensional (2-D) Poisson problem [17, 18], multigrid smoothing factors for red-black Gauss-Seidel relaxation applied to a class of elliptic operators [19], red-black SOR smoothing in multigrid [20], multigrid solution of three dimensional (3-D) Poisson equation [21], a book on various multigrid treatments and applications [22], multigrid method for higher dimensional PDEs[2], multigrid method based on L-shaped coarsening for PDEs on stretched grids [23], multigrid solution of Poisson equation on irregular voxelized domains with mixed boundary conditions [24], high order compact difference scheme (HOC) and a multigrid solution of 2-D elliptic problems with variable coefficients [25], multigrid method in distributed control problems modeled by Stokes equations [26], fourth-order compact difference scheme in multigrid solution of 2-D elliptic boundary value problems [27], multigrid method with eighth-order compact finite difference scheme for Helmholtz equation [28], multigrid method for solving optimal control problems governed by stochastic PDEs [29], application of tweed and wireframe relaxation methods as smoothers in multigrid solution of elliptic PDEs on stretched, structured grids [30], multigrid strategies for the solution of elliptic PDEs discretized by the Hybrid High-Order method (HHO) [31], and many others.

Although numerous multigrid methods have been developed and/or applied to solving a wide range of problems, most of the existing multigrid methods for solving elliptic partial differential equations often employed Jacobi, Gauss-Seidel, SOR iterative methods and some of their variants as the relaxation schemes (smoothers). The AOR method and its variants have hardly been explored as smoothers in multigrid methods. Thus, the focus of this paper is the use of a recent version of the AOR iterative method as a smoother in multigrid solution of the 2-D Poisson equation chosen as the model problem for elliptic PDEs.



In section 2, we present the discretization of the continuous problem (model PDE) and show how this can be done with Kronecker tensor products. Section 3 gives smoothing and coarsening strategies and grid transfer strategies. Next, we provide the LFA for the PROR method and present some results of smoothing factors and optimal relaxation parameters in section 4. In section 5, we present and discuss the results of numerical experiments and reveal the multigrid convergence result that we get. Lastly, a summary of the work is presented in the form of conclusion in the last section.

### II The Continuous Problem and Its Discretization

#### 2.1 The Model PDE

Consider the standard 2-D Poisson PDE:

$$-\left(\frac{\partial^2}{\partial x^2} + \frac{\partial^2}{\partial y^2}\right)u(x, y) = f^{\Omega}(x, y)x, y \in \Omega = \prod_{i=1}^2 (a_i, b_i)$$
(1)

with Dirichlet boundary conditions:

$$u(x, y) = g(x, y)x \in (a_1, a_2), y \in (b_1, b_2)$$
(2)

According to [23], the 2-D Poisson equation in (1) provides a consistent model upon which new numerical solvers can be tested without digging too deeply into the complications of many application problems. Therefore, it serves well as a model problem in the study of convergence behaviour of elliptic partial differential equation, hence its adoption as the model PDE in the design of the multigrid method in this thesis.

In order to simulate Dirichlet boundary conditions (2), let u be a test function (whose boundary values are defined as g) given as follows:

$$u(x, y) = \frac{\sin(c_1 \pi x) + \sin(c_2 \pi y)}{c_2 + x + y}, \quad c_{1,c_2,c_3} \in \mathbb{R}$$
(3)

To simulate the right hand side, the negative Laplacian in (1) is computed from the prescribed test function to give f(x, y) as follows:

Differentiating (3) partially with respect to x, we obtain:

$$\frac{\partial u}{\partial x} = \frac{(c_1 \pi) \cos(c_1 \pi x)(c_3 + x + y) - (\sin(c_1 \pi x) + \sin(c_2 \pi y))}{(c_3 + x + y)^2}$$
(4)

Also, the second derivative of (3) with respect to rwith further simplification yields:

$$\frac{\partial^2 u}{\partial x^2} = \frac{(c_1 \pi)^2 \sin(c_1 \pi x)}{(c_3 + x + y)} + \frac{2(c_1 \pi) \cos(c_1 \pi x) + 2u}{(c_3 + x + y)^2}$$
(5)

Similarly,  $\frac{\partial^2 u}{\partial y^2}$  is obtained by differentiating (3) twice with respect y leading to:



$$\frac{\partial^2 u}{\partial y^2} = \frac{-(c_1\pi)^2 \sin(c_1\pi y)}{(c_3 + x + y)} + \frac{-2(c_1\pi)\cos(c_1\pi y) + 2u}{(c_3 + x + y)^2}$$
(6)

Then, the source function, f(x, y) becomes:

$$f = \frac{(c_1\pi)^2 \sin(c_1\pi y) + (c_1\pi)^2 \sin(c_1\pi y)}{(c_3 + x + y)} + \frac{2(c_1\pi)\cos(c_1\pi y) + 2(c_1\pi)\cos(c_1\pi y) - 2u}{(c_3 + x + y)^2}$$
(7)

to complete the prescription of the model problem,[see 23].

The continuous problem prescribed above is represented in operator notation as:

$$Lu(x, y) = f^{\Omega}(x, y) \tag{8}$$

where *L* is the Laplacian.

Thus, we obtain the discrete equivalent of (8) as:

$$L_h u_h(x, y) = f_h^{\Omega}(x, y) \tag{9}$$

The discretization of the Laplacian,  $L_{i}$  is taken to be  $O(h^2)$  accurate, leading to a 5-point stencil in two dimensions. The number of cells in the discretization grid along the *i*th dimension (given by  $N_i$ ) may not necessarily be equal to the number of cells along *j*th dimension. Thus, the grid size along *i*th dimension is given by:

$$h_i = (b_i - a_i)/N_i \tag{10}$$

and the one-dimensional (1-D) variant of this stencil is:

$$\frac{\partial^2 u}{\partial x^2}|_{x=x_i} \equiv \frac{1}{h_i^2} \begin{bmatrix} 1 & \underline{-2} & 1 \end{bmatrix} u_i + O(h^2)$$
(11)

The discrete equation given by (9) can be represented in matrix notation as:

$$A_h u_h = b_h \tag{12}$$

## 2.2 The Discretization Matrix, A<sub>k</sub>

The coefficient matrix,  $A_h$  is an  $(M \times M)$  matrix with M –unknowns where M is the order of  $A_h$  given by:

$$M = \prod_{i=1}^{2} (N_i - 1)$$
(13)

Let the discretization grid be G, that is:

### $G = [N_1, N_2](14)$

Then, applying the d –dimensional tensor product formula proposed in [2], matrix  $A_h$  is constructed using the tensor product formula:



$$A_{h} = \sum_{i=1}^{2} \{ j_{=i}^{1} \otimes I_{(2+i-j)} \otimes L_{i} \otimes j_{=1}^{i-1} \otimes I_{(i-j)} \}$$
(15)

where 🛞 is the Kronecker tensor product of matrices and 🛞 is the cumulative Kronecker tensor product. For instance,

Also, in (15),  $I_m$  ( $m \in \{1,2\}$ ) is the identity matrix of order  $N_m - 1$  and  $L_i$  is the one dimensional discrete Laplacian operator in the *i*th dimension.  $L_i$  is obtained using the 1-D stencil in (11). The stencil is applied to each point, including the boundaries, to obtain  $L_i$ . The left and right boundary vectors are however sorted and integrated into the right hand side,  $b_h$  of the linear system (12) as earlier stated (eliminated boundary). The following matrix is obtained for  $L_i$  in (15) for  $G = \{5, 5\}$  to illustrate how matrix is  $A_h$  is constructed:

$$L_{i} - \frac{1}{h^{2}} \begin{bmatrix} 2 & -1 & 0 & 0 \\ -1 & 2 & -1 & 0 \\ 0 & -1 & 2 & -1 \\ 0 & 0 & -1 & 2 \end{bmatrix}$$
(16)

Similarly, the 1-D Laplacian operator is used to construct the Laplacian for the *j*th dimension and replaced back in to (15) to obtain the full 2-D discretization matrix,  $A_{p}$ .

### 2.3 Right Hand Side, **b**<sub>h</sub>

The column vector,  $b_h$  is built in a similar manner using Kronecker tensor products following [2]. It consists of the source function  $f_h^{\Omega}$  and the boundary function  $f_h^{\Gamma}$ .

Importantly, we define a consistent listing of grid points. Let  $\mathfrak{T}$  be an index matrix which denotes the set of indices in the computational grid, where each row (a 2-tuple) represents the index of a grid point and counts in descending order, from right to left, for the ascending order of the dimensions. Then, we have grid coordinates as a pair  $(i_2, i_1)$ . That is:

$$\mathfrak{T} = [\tau_2 \tau_1] \tag{17}$$

where each  $\tau_k$  is a column vector of length *M*.

Also, we consider the following definitions required for building the index set for the interior and the boundary points:

$$\gamma_i : \gamma_i = [1, 2, \dots, (N_i - 1)]^T, i = (1, 2)$$

$$1_i : 1_i = [1, 1, \dots, 1]^T$$

$$(18)$$

Now, the column of 3 are formed using the Kronecker tensor product:

$$\tau_i - \underset{j=i}{\overset{1}{\longrightarrow}} \otimes \mathbf{1}_{(2+i-j)} \otimes \gamma_i \otimes \underset{j=1}{\overset{i-1}{\longrightarrow}} \otimes \mathbf{1}_{(i-j)}$$

$$\tag{19}$$

to complete the construction of the index set. The vector of the source function for each row of  $\mathfrak{T}$  denoted by  $\mathfrak{S}$ , can then be computed. This is represented as:

$$S = f_{\mathcal{X}}^{\Omega}$$
 (20)

In addition, to complete the specification of  $b_n$ , contribution of boundaries to  $b_n$  needs to be computed. We recall that two column vectors; the left and the right boundary-coefficient vectors were isolated from the 1-D Laplacian operators in each

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dimension, Now, considering the *i*th dimension, let the left and the right boundary-coefficient vectors be  $l_i$  and  $r_i$ , respectively, then the *i*th 2-D left and right boundary-coefficient vectors respectively denoted by  $\mathcal{L}_i$  and  $\mathcal{R}_i$  are given by the Kronecker tensor formulae:

$$\mathcal{L}_{i} =_{j=i} \otimes \mathbb{1}_{(2+i-j)} \otimes l_{i} \otimes \frac{i-1}{j=1} \otimes \mathbb{1}_{(i-j)} \\ \mathcal{R}_{i} =_{j=i} \otimes \mathbb{1}_{(2+i-j)} \otimes n_{i} \otimes \frac{i-1}{j=1} \otimes \mathbb{1}_{(i-j)}$$

$$(21)$$

Also, let the contribution from the left boundary and the right boundary in  $b_k$  be represented as  $\mathcal{B}_{l}$  and  $\mathcal{B}_{R}$ , respectively, where  $\mathcal{B}_{l}$  is the cumulative sum of the two left boundaries while  $\mathcal{B}_{R}$  is the sum of the two right boundaries. Worthy of note is that if any  $\tau_{i}$  in (3.17) is replaced by a vector of left boundary value, a left boundary index set is obtained, and if it is replaced by a vector of right boundary value, we get a right boundary index set. That is, if:

$$\mathfrak{T}_{L_{i}} = \left[\tau_{2}\tau_{1}\ldots\tau_{(i-1)}\overline{a}_{i}\ \tau_{(i+1)}\ldots\tau_{2}\tau_{1}\right]$$
  
$$\mathfrak{T}_{R_{i}} = \left[\tau_{2}\tau_{1}\ldots\tau_{(i-1)}\overline{b}_{i}\tau_{(i+1)}\ldots\tau_{2}\tau_{1}\right]$$
(22)

then:

$$\mathcal{B}_{L} = \sum_{i=1}^{2} (\mathcal{L}_{i} \circ f_{\mathcal{I}_{L_{i}}}^{\Gamma}) \\
 \mathcal{B}_{R} = \sum_{i=1}^{2} (\mathcal{R}_{i} \circ f_{\mathcal{I}_{R_{i}}}^{\Gamma})$$
(23)

where • is the component-by-component multiplication of the operand column vectors. Thus we obtain the right side of discrete problem as:

$$b_n = S + \mathcal{B}_L + \mathcal{B}_R \tag{24}$$

to obtain the complete discretization of the model PDE

### III Design of the Method

### 3.1 Multigrid Based on Point Relaxation

Multigrid methods consists of essential components such as grid coarsening and smoothing strategies, grid transfer schemes, the smoothing method and the coarse grid correction. The famous algorithm of multigrid is presented in [22] and has been used by many other authors in literature.

The technique of relaxation (smoothing) in multigrid is mainly classified into point relaxation and block relaxation methods. Although block relaxation methods (line and plane smoothing) are mostly used for anisotropic PDEs, they are quite expensive in terms of CPU-time because each relaxation step consists of solving a small linear system exactly (or to a satisfactory level of accuracy). Fortunately, point smoothing works well in most cases, particularly for standard coarsening. More so, in most situations, block smoothing can be substituted with point-relaxation methods with some modifications. Thus point relaxation approach is adopted as the smoothing strategy in the multigrid method discussed in this research.

#### **3.2** The Relaxation Scheme



The core of the multigrid method proposed in this research is the relaxation scheme deployed as a smoother. Other components are essentially some simple and basic choices existing in literature. As will be shown in section 4, the smoothing analysis of the PROR method in [15], which we now denote by  $\alpha, r, \omega$  –PROR, proves its admirable smoothing effect for problems of the Poisson type and is thus chosen as the smoother for our proposed multigrid method. Also, although we do not provide the smoothing analysis of the PROR method in the red-black setting (abbreviated as  $\alpha, r, \omega$  –RBPROR), it will be considered in the implementation. The $\alpha, r, \omega$  –RBPROR method consists of two partial steps, each step being an  $\alpha, r, \omega$  –PROR sweep. The first step applies to and updates only the red (odd) points while the second one applies to and updates only the black (even) points in the grid. From an implementation angle, this red-black smoothing procedure depends upon a partitioning process by which the grid **G** can be separated into the red part (**G**<sub>R</sub>) and the black part (**G**<sub>R</sub>). The grid-point listing employed in the implementation scheme is such that the points are arranged in a column vector and listed out in lexicographic order. We also make use of optimal relaxation parameters ( $\alpha_{opt}, r_{opt} and \omega_{opt}$ ) in the relaxation (smoothing) process. The error-smoothing effect of the relaxation method can be enhanced by the use of optimal relaxation and acceleration parameters [see, 20].

The  $\alpha_{r} r_{\mu} \omega$  –PROR method is given as follows:

$$x^{(n+1)} = [(1+\alpha)I - \omega L)]^{-1} \{ [(1+\alpha - r + r\omega)I + (r - \omega - r\omega)L + (r - r\omega)U] x^{(n)} + (r - r\omega)b \} (25)$$

with iteration matrix:

 $L_{\alpha r.\omega} = [(1+\alpha)I - \omega L)]^{-1} \{ [(1+\alpha - r + r\omega)I + (r - \omega - r\omega)L + (r - r\omega)U]$ (26)

where  $\alpha$  is a fixed parameter and r and  $\omega$  are acceleration and relaxation parameters respectively.

### **3.3** Coarsening Strategy

For the coarse grid H, standard full coarsening strategy is applied to the 2-D model problem. It involves doubling the grid size of the fine grid, h in both direction, i.e. H = 2h. In two dimensions and standard coarsening, the relation between the coarse and fine grid is given by:

$$\Omega_{2h} = \frac{1}{4}\Omega_h \tag{27}$$

#### 3.4 Discretization of the Coarse Grid

A very vital component in the coarse-grid correction process is the choice of the coarse-grid operator,  $L_{II}$  According to [1], re-discretizing the differential operator (i.e. the Laplacian, in the case of the model PDE in this work) on the coarse grid is sufficient as the approximation to the discrete operator on the coarse grid in many situations. This means that the direct equivalent of the fine grid operator on the coarse grid, H is used. As soon as the next coarser grid is decided, the Laplacian is discretized using the same discrete stencils as presented in section 2. This is traditionally known as the discrete operator on the fine grid operator (DCG). Thus, in this work, the DCG operator, which is the coarse grid operator (GCG). However, using the



GCG is disadvantageous in that it is usually denser than the DCG operator except special transfer operators are employed to generate the coarse-grid operators which is not the case in this paper.



### 3.5 Grid Transfer Operators

The full weighting (FW) restriction and the bilinear interpolation operators in two dimensions are used for the inter-grid transfers (restriction and prolongation respectively) of the grid functions. The 2-D FW restriction operator is given by:

$$I_{h}^{2h} = \frac{1}{16} \begin{vmatrix} 1 & 2 & 1 \\ 2 & 4 & 2 \\ 1 & 2 & 1 \end{vmatrix}_{h}^{2h}$$
(28)

while the bilinear prolongation is given by the 9-point stencil:

$$I_{2h}^{h} = \frac{1}{4} \begin{vmatrix} 1 & 2 & 1 \\ 2 & 4 & 2 \\ 1 & 2 & 1 \end{vmatrix}_{2h}^{h}$$
(29)

The generation of the FW restriction and bilinear prolongation operator matrices via Kronecker tensors is presented next. We note that the 2-D FW restriction (28) is the Kronecker tensor product of the 1-D FW operators in  $x_1$  and  $x_2$  directions given below:

$$\begin{pmatrix} I_{\hbar}^{2h} \end{pmatrix}_{x_{1}} = \frac{1}{4} \begin{bmatrix} 1 & 2 & 1 \end{bmatrix} \\ \begin{pmatrix} I_{\hbar}^{2h} \end{pmatrix}_{x_{2}} = \frac{1}{4} \begin{bmatrix} 1 \\ 2 \\ 1 \end{bmatrix}$$
 (30)

We construct the 2-D FW restriction operator matrix, **R** via the Kronecker tensor products formulae:

$$\mathbf{R} = \prod_{i=1}^{2} (\mathbf{R}_{i})^{k_{i}}$$

$$(\mathbf{R}_{i})^{k_{i}} = \prod_{l=0}^{k_{i}} \left[ \begin{array}{c} 1 \\ j=i \otimes \mathbf{I}_{N_{(2+i-j)}} \otimes \mathbf{O}_{[N_{i}/2^{(k_{i}-l-1)}]} \otimes \begin{array}{c} i-1 \\ j=1 \otimes \mathbf{I}_{[N_{(i-j)}/2^{k_{(i-j)}}]} \end{array} \right]$$
(31)

The quantities in (31) are given as follows:

 $I_{\alpha}$  is the identity matrix of order  $(\alpha - 1) \times (\alpha - 1)$ .

 $I_{\alpha}$  is the 1-D FW restriction matrix of order  $\left(\frac{\alpha}{2}-1\right) \times (\alpha-1)$ .

 $T = [k_1, k_2]$  is the coarsening request;  $k_i$  is the count of  $(h \rightarrow 2h)$  transfers along the *i*th dimension where  $\alpha$  is any dummy subscript.

Next, given the prescription of the 2-D FW restriction operator matrix, the prolongation (bi-linear interpolation) operator matrix can then be obtained with the following relation:

(32)

$$\boldsymbol{P} = 2^{\left(\sum_{i=1}^{2} k_i\right)} (\boldsymbol{R}^T)$$

to complete the specification of the grid transfer operators.

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Worthy of note is that the restriction operator in (31) is a generalized one which gives us the leverage to experiment with different types of coarsening strategies depending on the grid. Also, it offers the required matrix for any number of coarsening along any number of dimensions for an abstract d-dimensional problem [see 2].



### IV Local Fourier Analysis of the $\alpha_1 r_1 \omega$ –PROR Method

Local Fourier Analysis (LFA) is a tool for investigating the convergence behavior of multigrid methods introduced by Brandt [32] with contributions from other notable authors such as Stuben [33], [34], [35], [36], and [22]. Much details, including the validity of LFA alongside related theorems and proofs, are presented in [35]. In what follows in this section, we focus on the design of a Fourier representation for  $\alpha$ , r,  $\omega$  —PROR Method applied to the discrete operator of the model PDE ( Laplacian) given in section 2.1, the definition of the smoothing factor and the estimation of relaxation and acceleration parameters. It is assumed that the reader is familiar with the basics of the LFA tool as can be found in [22, 33, 34, 35, 36]. Also, we adopt the definitions and notations as obtainable in [19, 20, 22, 36] to carry out our analysis in this section.

Consider the Laplacian operator given in (1) as follows:

$$-\left(\frac{\partial^2}{\partial x^2} + \frac{\partial^2}{\partial y^2}\right) \tag{32}$$

The continuous partial derivatives in (32) are discretized by second-order finite difference in (11), to give their discrete equivalents, denoted by  $L_{h}$ . Although we stated in section 2.1 that the grid spacing may not necessarily be equal, for the purpose of this analysis, we assume equal grid spacing in both directions, i.e.  $h_1 = h_2 = h$ . LFA considers only the 'local nature' of the discrete operator, i.e. any general discrete operator, nonlinear, with non-constant coefficients, can be linearized locally and can be replaced locally (by freezing the coefficients) by an operator with constant coefficients. Thus for an effective analysis through LFA tool, we must have constant coefficients, and also neglect the effects of the boundaries. More specifically, all arising operators are extended to an infinite grid given by:

$$G_h = \{x = kh = (k_1h_1, k_2h_2), k \in \mathbb{Z}^2\}$$
 (33)

where his the grid size.

The fundamental quantities in LFA are the discrete eigen-functions (also known as Fourier components or Fourier modes) of the resulting infinite grid operators. These grid functions are given by:

$$\varphi(\boldsymbol{\theta}, \boldsymbol{x}) = e^{i\boldsymbol{\theta}\boldsymbol{x}/h} = e^{i\boldsymbol{\theta}_1\boldsymbol{x}_1/h_1}e^{i\boldsymbol{\theta}_2\boldsymbol{x}_2/h_2} \quad \text{for } \boldsymbol{x} \in G_h(34)$$

where  $\theta$  varies continuously in  $\mathbb{R}^2$ . We note that:

$$\varphi(\theta, x) \equiv \varphi(\theta', x)$$
 for  $x \in G_h$  iff  $\theta = \theta' \pmod{2n}$  (35)

That is, (3.5) holds if the difference of multiples of  $2\pi$  is between all the components of the 2-tuple,  $(\theta \otimes \theta')$ . Thus it is sufficient to consider these grid functions only for  $\theta \in [-\pi,\pi)^2$  which can be written as  $-\pi \leq \theta < \pi$ , where  $\theta$  refers to both components  $\theta_1$  and  $\theta_2$ . For  $-\pi \leq \theta < \pi$ , these functions,  $\varphi(\theta, x)$  are linearly independent on  $G_h$ . Also,  $\varphi(\theta, x)$  are sometimes written as  $\varphi_h(\theta, x)$  for clarity purpose since they are defined on  $G_h$  and in that way, depend on h.

#### 4.1 High and Low Fourier Frequencies

In LFA, two distinct kinds of Fourier components; the high frequency components and the low frequency components are distinguishable with respect to the grids  $G_{\mathbb{N}}$  and  $G_{\mathbb{H}}$ . In a 2-grid setting, the classification of the frequencies  $\theta = (\theta_1, \theta_2)$  as either high or low is dependent upon the coarsening strategy that is employed. However, for the purpose of this paper, it is



sufficient to discuss only the case of standard (full) coarsening. Furthermore, the classification into this two categories of frequency components is based on the fundamental observation that only those frequency components  $\varphi(\theta_{n})$  on  $G_{h}$  with  $-\frac{\pi}{2} \le \theta < \frac{\pi}{2}$  are distinguishable on  $G_{H}$ . For each  $\theta' \in [-\frac{\pi}{2}, \frac{\pi}{2}]^2$ , three other frequency components  $\varphi(\theta_{n})$  on  $G_{h}$  with  $\theta \in [-\pi, \pi)^2$  coincide on  $G_{H}$  with  $\varphi'(\theta_{n})$  and not visible on  $G_{H}$ . Evidently, the following identity holds:

 $\varphi(\theta, \mathbf{x}) \equiv \varphi(\theta', \mathbf{x}) \text{for} \mathbf{x} \in G_H \text{ iff } \theta = \theta'(\text{mod}\pi)$  (36)

leading to the definition below

DEFINITION 1 (high and low frequencies for full coarsening): An element  $\theta_j$  ( $j \in \{1,2\}$ ) of a Fourier frequency  $\theta$  is termed low if  $-\frac{\pi}{2} \leq \theta_j < \frac{\pi}{2}$  for  $\theta \in [-\pi, \pi)^2$ . Otherwise it is called high. We say we have a low Fourier frequency  $\theta$ , if all of its elements are low. Otherwise it is called a high frequency. Therefore,  $\varphi(\theta_{i,i})$  is called a low frequency mode if:

$$\boldsymbol{\theta} \in T^{low} := \left[-\frac{\pi}{2}, \frac{\pi}{2}\right]^2 \tag{37}$$

and  $\varphi(\boldsymbol{\theta}_{..})$  is called a high frequency mode if:

$$\boldsymbol{\theta} \in T^{high} := \left[-\pi, \pi\right)^2 \setminus \left[-\frac{\pi}{2}, \frac{\pi}{2}\right]^2 \tag{38}$$

The distinction described above clearly depends on the coarsening strategy, as, for different coarsening strategies, different sets of Fourier frequencies are visible on the coarse grid.

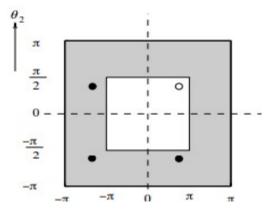


Figure. 1: high and low frequencies in 2-D

### 4.2 Fourier Representation of *a*, *r*, *w* – PROR

#### Lemmas

Lemma 1 (see [22])



For  $-\pi \leq \theta < \pi$ , all grid functions  $\varphi(\theta, x)$  are (formal) eigenfunctions of any discrete operator which can be described by a difference stencil  $L_h = [s_k]_h$  ( $k = (k_1, k_2) \in \mathbb{Z}^2$ ). Then, the following relation holds:

$$L_h \varphi(\boldsymbol{\theta}, \boldsymbol{x}) = \tilde{L}_h(\boldsymbol{\theta}) \varphi(\boldsymbol{\theta}, \boldsymbol{x}) \qquad (\boldsymbol{x} \in G_h)$$
(39)

where  $\tilde{L}_{h}(\boldsymbol{\theta})$  is the corresponding eigenvalue (formal) or the symbol of  $L_{h}$  given by:

$$\widetilde{L}_{h}(\boldsymbol{\theta}) = \sum_{k} s_{k} e^{i\boldsymbol{\theta}.k}$$
(40)

*Lemma* **2** (see [22])

Suppose a relaxation method can be written locally as:

$$L_h^+ \overline{w}_h + L_h^- w_h = f_h(41)$$

where  $w_h$  corresponds to the old approximation of  $u_h$  and  $\overline{w}_h$  is the new approximation, then the

relaxation is characterized by the splitting:

$$L_h = L_h^+ + L_h^-(42)$$

Under the assumption in (41) and (42), all grid functions,  $\varphi(\boldsymbol{\theta}_{h})$  with  $\tilde{L}_{h}^{+}(\boldsymbol{\theta}) \neq 0$  are eigenfunctions of  $S_{h}$  such that:

$$S_h \varphi(\boldsymbol{\theta}, \boldsymbol{x}) = \tilde{S}_h(\boldsymbol{\theta}) \varphi(\boldsymbol{\theta}, \boldsymbol{x}) (-\pi \le \boldsymbol{\theta} < \pi) (43)$$

where  $\bar{S}_h(\theta)$  is the amplification factor given by:

$$\tilde{S}_{h}(\boldsymbol{\theta}) \coloneqq -\frac{\tilde{L}_{h}^{-}(\boldsymbol{\theta})}{\tilde{L}_{h}^{+}(\boldsymbol{\theta})}(44)$$

Now, the PROR method (25) can be rewritten in a notation consistent with [22]as follows:

$$[(1+\alpha)D - rL)]u^{n} - [(1+\alpha-\omega+r\omega)D + (\omega-r-r\omega)L + (\omega-r\omega)U]u^{n-1} + (\omega-r\omega)\overline{b}(45)$$

where D denotes the diagonal part, L and U are the lower and upper parts of the iteration matrix (26) respectively. Equation (45) further simplifies to:

$$\frac{1}{\omega - r\omega} [(1+\alpha)D - rL]u^n = \left[\frac{(1+\alpha - \omega + r\omega)}{\omega - r\omega}D + \frac{(\omega - r - r\omega)}{\omega - r\omega}L + U\right]u^{n-1} + \overline{b}(46)$$



$$\frac{1}{\omega(1-r)} [(1+\alpha)D - rL]u^n = \left[\frac{(1+\alpha-\omega(1-r))}{\omega(1-r)}D + \frac{(\omega(1-r)-r)}{\omega(1-r)}L + U\right]u^{n-1} + \overline{b}(47)$$

Also, the discrete equivalent of the model problem is of the form:

$$L_h u_h = f_h \tag{48}$$

where  $L_h$  represent the discrete Laplacian operator given by:

$$-\Delta_h = -\frac{1}{h^2} \left( \frac{\partial^2}{\partial x^2} + \frac{\partial^2}{\partial y^2} \right) (49)$$

and the stencil representation of (49) is as follows:

$$-\Delta_h = \frac{1}{h^2} \begin{bmatrix} 1 & 1 \\ -1 & 4 & -1 \end{bmatrix} (50)$$

If the PROR relaxation method conforms with (41) and (42), then we obtain:

$$L_{h}^{+} = \frac{1+\alpha}{\omega(1-r)}D - \frac{r}{\omega(1-r)}L$$
(51)

and in view of (50),  $L_h^{\dagger}$  in stencil form is given as:

$$L_{h}^{+} = \frac{1}{h^{2}} \begin{bmatrix} -\frac{r}{\omega(1-r)} & 4\left(\frac{1+\alpha}{\omega(1-r)}\right) & 0\\ & -\frac{r}{\omega(1-r)} \end{bmatrix}$$
(52)

Also, from (47):

$$L_{h}^{-} = -\left[\frac{\left(1+\alpha\right)-\omega(1-r)\right)}{\omega(1-r)}D + \frac{\omega(1-r)-r}{\omega(1-r)}L + U\right](53)$$
$$= \left(1-\frac{1+\alpha}{\omega(1-r)}\right)D - \left(1-\frac{r}{\omega(1-r)}\right)L - U(54)$$

Again, using (50), we obtain the stencil form of  $L_h^-$  as:

$$L_{h}^{-} = \frac{1}{h^{2}} \begin{bmatrix} \left(1 - \frac{r}{\omega(1-r)}\right) & 4\left(1 - \frac{1+\alpha}{\omega(1-r)}\right) & -1\\ & \left(1 - \frac{r}{\omega(1-r)}\right) \end{bmatrix}$$
(55)

Applying Lemma 1, we have:



$$\hat{L}_{h}^{+}(\boldsymbol{\theta},\boldsymbol{\alpha},r,\omega) = L_{h}^{+}e^{i\boldsymbol{\theta},\vec{x}/h} = \frac{1}{h^{2}} \begin{bmatrix} -\frac{r}{\omega(1-r)} & 4\left(\frac{1+\alpha}{\omega(1-r)}\right) & 0\\ & -\frac{r}{\omega(1-r)} \end{bmatrix}$$
(56)

 $= [s_k]_h \cdot e^{i\theta \cdot \tilde{x}/h} (57)$ 

where:

$$\hat{L}_{h}^{+}(\boldsymbol{\theta}, \boldsymbol{\alpha}, \boldsymbol{r}, \boldsymbol{\omega}) = \sum_{k} s_{k} e^{i\boldsymbol{\theta}.\boldsymbol{\kappa}}, \quad \boldsymbol{k} = \bar{\boldsymbol{x}}/_{h} = (k_{1}, k_{2}), \boldsymbol{k} \in \mathbb{Z}^{2}(58)$$

Thus, we obtain:

$$\widehat{L}_{h}^{+}(\boldsymbol{\theta},\alpha,r,\omega) = \frac{1}{h^{2}} \left[ 4 \left( \frac{1+\alpha}{\omega(1-r)} \right) - \frac{r}{\omega(1-r)} e^{-i\theta_{1}} - \frac{r}{\omega(1-r)} e^{-i\theta_{2}} \right] (59)$$

Also, similar manipulation in favour of  $L_n^-$  leads to:

$$\hat{L}_{h}(\theta, \alpha, r, \omega) = \frac{1}{h^{2}} \left[ 4 \left( 1 - \frac{1+\alpha}{\omega(1-r)} \right) - \left( 1 - \frac{r}{\omega(1-r)} \right) e^{-i\theta_{1}} - \left( 1 - \frac{r}{\omega(1-r)} \right) e^{-i\theta_{2}} - e^{i\theta_{1}} - e^{i\theta_{2}} \right] (60)$$

Then by Lemma 2:

$$\hat{S}_{h}(\boldsymbol{\theta}, \boldsymbol{\alpha}, \boldsymbol{r}, \boldsymbol{\omega}) = -\frac{\hat{L}_{h}^{-}(\boldsymbol{\theta}, \boldsymbol{\alpha}, \boldsymbol{r}, \boldsymbol{\omega})}{\hat{L}_{h}^{+}(\boldsymbol{\theta}, \boldsymbol{\alpha}, \boldsymbol{r}, \boldsymbol{\omega})} = \frac{\left[4\left(1 - \frac{1+\alpha}{\omega(1-r)}\right) - \left(1 - \frac{r}{\omega(1-r)}\right)e^{-i\theta_{1}} - \left(1 - \frac{r}{\omega(1-r)}\right)e^{-i\theta_{2}} - e^{i\theta_{1}} - e^{i\theta_{2}}\right]}{\left[4\left(\frac{1+\alpha}{\omega(1-r)}\right) - \frac{r}{\omega(1-r)}e^{-i\theta_{1}} - \frac{r}{\omega(1-r)}e^{-i\theta_{2}}\right]}$$
(61)

### 4.3 Smoothing Factor

The smoothing factor of an iterative method's operator (iteration matrix) is the worst factor by which the high frequency errors are reduced per iteration step. In order to measure the smoothing properties of PROR point relaxation method, we adopt the definition of the smoothing factor from [22] as obtained in *Lemma* **2**. Thus, the smoothing factor,  $\mu$ , associated with the PROR iterative method is given by:

$$\mu[\hat{s}_{h}(\theta,\alpha,r,\omega)] = \sup\left\{ \left| \hat{s}_{h}(\theta,\alpha,r,\omega) \right| : \theta \in T^{high} \right\}$$
(62)  
$$= \sup\left\{ \left| -\frac{\left[ 4\left(1 - \frac{1+\alpha}{\omega(1-r)}\right) - \left(1 - \frac{r}{\omega(1-r)}\right)e^{-i\theta_{1}} - \left(1 - \frac{r}{\omega(1-r)}\right)e^{-i\theta_{2}} - e^{i\theta_{1}} - e^{i\theta_{2}} \right] \right|$$
(63)

The smoothing factor can easily be calculated by a computer program which allows for a numerical determination of optimal relaxation and acceleration parameters. Thus, the optimal values of the parameters  $\mathbf{r}$  and  $\boldsymbol{\omega}$  for a fixed value of  $\boldsymbol{\alpha}$  as well as the smoothing factor,  $\boldsymbol{\mu}$  in (63) are obtained over the high frequency Fourier domain,  $\boldsymbol{\theta}$  for different values of  $\boldsymbol{\mu}$  with the aid



of a programme written in MATLAB software and presented alongside those of some other well-known smoothers in the table that follows. We note however that explicit analytical formulae that can be used for determining the optimal relaxation parameters in the case of full coarsening applied to the second-order discretization may be possible [see 20, 37].

C 1.	$\frac{1}{\alpha_{opt} - PROR}  (\alpha_{opt} = 4.00)$							
	[64, 64]	4.00	-1.69	0.4487				
	[128, 128]	4.00	-1.69	0.4489				
	[256, 256]	4.00	-1.69	0.4489				

Smoothing Factors of  $\alpha$ ,  $r_{,\omega}$  – **PRORS** cheme on Various Equidistant Grids. Table 1:

In Table 1, the smoothing factors of  $\alpha_i r_i \omega$  – PROR smoother obtained using optimal relaxation and acceleration parameters, standard full coarsening (doubling) and second order discretization on various equidistant grids are displayed. The table revealed the effect of using  $\alpha$  and optimal parameters in  $\alpha$ ,  $r, \omega - PROR$  relaxation scheme to enhance smoothness.

		Table 2:	Comparison of Smo	oothing 1	Factors of S	ome Exi	sting Smooth	ners	
$\alpha, r, \omega$ <b>PROR</b> ( $\alpha_{opt} = 4.00$ )				SOR		ω	<b>ω Jacobi</b> Gauss		s-Seidel
G	ropt	ω <sub>opt</sub>	$\mu(\alpha_{opv}r_{opv}\omega_{opt})$	$\omega_{opt}$	$\mu(\omega_{opt})$	ω <sub>opt</sub>	$\mu(\omega_{\text{opt}})$	ωορτ	$\mu(\omega_{opt})$
[64, 64]	4.00	-1.69	0.4487	1.0	0.4998	0.80	0.6000	-	0.4998
[128, 128]	4.00	-1.69	0.4489	1.0	0.5000	0.80	0.6000	-	0.5000
[256, 256]	4.00	-1.69	0.4489	1.0	0.5000	0.80	0.6000	-	0.5000

Table 2 shows a comparison of the smoothing factors obtained for  $\alpha_{i}r_{i}\omega - PROR$  relaxation scheme with those of SOR, Jacobi and Gauss-Seidel relaxation schemes. The table showed that the  $\alpha$ , r,  $\omega$  – **PROR** demonstrates better smoothing ability than the other iterative methods.

#### V. **Results and Discussion**

We now show the multigrid convergence of the smoother in this work through numerical example. The model PDE (1) is discretized on various equidistant grids using the second order finite difference scheme, and the spectral radius,  $\rho$  of the multigrid iteration operator, M<sub>h</sub> (also the asymptotic convergence factor) is obtained. The only quantity accessible to estimate this factor in a multigrid experiment is the residual (or defect) after the *i*th multigrid cycle denoted by  $r_h^i$ . Thus, the empirical estimate of the multigrid convergence factor  $\rho(M_n)$ , denoted by  $q^m$  and called the contraction number is given as follows:

$$q^{m} = \left(\frac{\|r_{h}^{m}\|}{\|r_{h}^{m-1}\|}\right)$$
(64)

where *m* is the number of iterations or multigrid cycles required for the discrete problem to converge to the numerical solution.



In our experiments, we make two different smoothing choices; one pre- and one post-smoothing, and then two pre- and two post-smoothing steps of the relaxation schemes. Multigrid V-cycle is also deployed as the multigrid control cycle, so that the two different smoothing choices are denoted by V(1, 1) and V(2, 2) respectively. For a correspondence with  $q^m$ , the smoothing factor is presented as a square and compared with the smoothing factor obtained from the LFA analysis presented in Table 1. The contraction number,  $q^m$  is presented against the number of multigrid cycles (iterations) that the experiments took to converge to a tolerance value of  $10^{-10}$ , representing the termination criterion for all of the experiments, That is:

$$\frac{\|b_h - A_h u_h^m\|}{\|b_h\|} \le tolerance \tag{65}$$

This termination criterion is similar to the one based on relative residual reduction since our starting solution (initial guess) in these experiments is an all-zero vector every time. We approximate the test function in (3) for  $c_1 - c_2 - c_3 - 2\pi$  via the numerical solution of the model problem (1). As prescribed in (2), the values of this test function at the boundary are taken as Dirichlet boundary conditions, and its Laplacian obtained analytically in (7) gives the source function for our numerical experiments. The results are displayed in the succeeding tables.

Table 3:	Results of Numerical	Experiment for	V(1, 1) and	V(2, 2) on Equidistant Grid	ls
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$\alpha, r, \omega - PROR  (\alpha_{opt} = 4.00)$								
		$ ho(M_h)=q^m$						
G	$\left[\mu(\pmb{\alpha}_{\texttt{opt}}, r_{\texttt{opt}}, \omega_{\texttt{opt}})\right]^2$	V(1,1)	No of Iter	V(2,2)	No of Iter			
[64, 64]	0.2013	0.1219	8	0.0433	6			
[128, 128]	0.2015	0.1185	8	0.0416	6			
[256, 256]	0.2015	0.1153	8	0.0293	5			

Table 3 presents results of solving model problem using  $\alpha, r, \omega$  – **PROR** methods on various equidistant grids. A close look at the convergence factors clearly shows that the PROR gave appreciable convergence results. In addition, it is observed that the reduction in the multigrid convergence factors as well as in the number of multigrid cycles obtained for V(2, 2) compared to V(1 1) was quite significant, indicating that V(2,2) is a better choice for this problem.

$\alpha, r, \omega - PROR  (\alpha_{opt} = 4.00)$					$\alpha, r, \omega - \text{RB PROR} \ (\alpha_{\text{opt}} = 4.00)$				
	$ ho(M_h)=q^m$					$ ho(M_h)=q^m$			
G	V(1,1)	No of Iter	V(2,2)	No of Iter	V(1,1)	No of Iter	V(2,2)	No of Iter	
[64, 64]	0.1219	8	0.0433	6	0.0539	6	0.0162	5	
[128, 128]	0.1185	8	0.0416	6	0.0517	6	0.0156	5	
[256, 256]	0.1153	8	0.0293	5	0.047	6	0.0087	4	

In Table 4, we display experimental results of using  $\alpha$ , r,  $\omega$  – **PROR** method in comparison with those of PROR in red-black ordering ( $\alpha$ , r,  $\omega$  – RB PROR). It is observed that using the PROR method in red-black setting gave considerably better convergence results than the lexicographic  $\alpha$ , r,  $\omega$  – **FROR** method.



### VI Conclusion

In this paper, we established how acceptable multigrid convergence can be achieved with the use of a newly introduced smoother when used with optimum parameter values in the smoothing process. Through numerical experiments supported by theoretical analysis by means of LFA, we have demonstrated that the PROR method is a viable choice as the relaxation method in multigrid solution of elliptic PDEs discretized on rectangular grids as results revealed the appreciable multigrid convergence that can be achieved with the PROR smoother presented in this work.

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