

Computational Fluid Dynamics
Prof. Sreenivas Jayanti
Department of Computer Science and Engineering
Indian Institute of Technology, Madras


Lecture – 51
Alternating Direction Implicit (ADI) method

In the last lecture we have seen the successive over relaxation method as a simple means of increasing the rate of convergence over Gauss-Seidel method for the specific case, where A is diagonally dominant.

(Refer Slide Time: 00:34)

Improved Convergence Rate: Successive Overrelaxation (SOR)

- The rate of convergence of SOR depends on its spectral radius, as before
- The optimal relaxation factor, when A is symmetric and positive definite, is given by
$$\omega_{opt, GSOR} = 2 / [1 - \rho^2(P_{Jac, opt})]^{0.5}$$
- The spectral radius for the optimal relaxation factor is given by
$$\rho_{GSOR} = \omega_{opt} - 1$$
- For the case of the Laplace equation with Dirichlet boundary conditions, the spectral radius of the Jacobi iteration matrix is $\cos(\pi/M)$; therefore ω_{opt} for the GS-SOR is
$$\omega_{opt} = 2 / [1 + \sin(\pi/M)] \approx 2(1 - \pi/M)$$
- Hence the spectral radius at optimum relaxation is given by
$$\rho_{GSOR} = 2(1 - \pi/M) - 1 = 1 - 2\pi/M$$
- For large M and in the asymptotic limit, the number of iterations required to reduce error by an order of magnitude varies as $n^{0.5}$ and that the total number of arithmetic operations required to reduce error by a decade varies as $n^{1.5}$, compared to n^2 for GS
- In the general case, ω_{opt} changes with A and one may need to estimate it numerically!




We made the point that the optimal SOR can have tremendous increase over the Gauss-Seidel method because it would take only square root of n number of arithmetic operations for in terms of the asymptotic rate of convergence. As opposed to n for the Gauss-Seidel method, therefore the total number of arithmetic operations varies as n rise for 1.5 compared to n square for the Gauss-Seidel method.

When n is large, that is, when the number of grid points is large, then the variation of n to the power one point five or n square can make a huge difference. But, this kind of great improvement is possible only for the case where we have the optimal SOR parameter,

optimal value of the SOR parameter, and that something that is not known in the general case. So, we have to keep that in mind and then try to estimate the value of the optimal value. And then, see how it can be how the rate improves.

There are; there is a different approach for acceleration of the solution of $Ax = b$. And that method, one such method which is known as the alternating direction implicit method is what we will examine in this lecture.

(Refer Slide Time: 01:57)



NPTEL

The Alternating Direction Implicit (ADI) Method: Peaceman and Rachford (1955)

- Combination of iterative and direct methods; takes advantage of the goodness of TDMA
- Consider the elliptic partial differential equation in Cartesian coordinates with Dirichlet b.c.:

$$\frac{\partial}{\partial x} [A(x, y) \frac{\partial u}{\partial x}] + \frac{\partial}{\partial y} [C(x, y) \frac{\partial u}{\partial y}] + G(x, y)u = S(x, y)$$

where A and C are positive functions for the equation to be elliptic.

- Assuming G to be non-negative and considering a uniform mesh spacing of h and k in the x- and y-directions, the equation can be discretized as

$$(H + V + D)u = q$$

where

$$Hu(x, y) = -a(x, y)u(x+h, y) + 2b(x, y)u(x, y) - c(x, y)u(x-h, y)$$

$$Vu(x, y) = -d(x, y)u(x, y+k) + 2e(x, y)u(x, y) - f(x, y)u(x, y-k)$$

$$Du(x, y) = hkG(x, y); \quad q = hKS(x, y)$$

with $a = k/h^2 A(x+h/2, y); \quad c = k/h^2 A(x-h/2, y); \quad 2b = a+c$
 $d = h/k^2 C(x, y+k/2); \quad e = h/k^2 C(x, y-k/2); \quad 2f = d+e$

- Nothing but central differencing in a slightly different disguise ("builds character" to do the familiar thing in an unfamiliar way!)

The original formula is proposed by Paceman and Rachford in 1955. It is a combination of the iterative method and the direct method. Specifically, the, it takes advantage of the goodness of the tridiagonal matrix algorithm, goodness in the sense that it takes only n number of k times n number of arithmetic operations to get a solution of $Ax = b$, where A is tridiagonal. So, it takes advantage of that. But, it puts that in the context of an iterative method.

And, we will see that for the specific case of elliptic partial differential equation in Cartesian coordinates with Dirichlet boundary conditions and two dimension problem, which is written in this. Rather unfamiliar, but more generic form, where you are writing it as $\frac{\partial}{\partial x} [A(x, y) \frac{\partial u}{\partial x}] + \frac{\partial}{\partial y} [C(x, y) \frac{\partial u}{\partial y}] + G(x, y)u = S(x, y)$

y of another function C, which can again be a function of x and y times $\frac{\partial u}{\partial x} + \frac{\partial u}{\partial y} + G u$, u is the unknown variable here, like our phi, G which is again a function of x and y equal to S, which is a function of x and y. So, this is a generic elliptic partial differential equation in Cartesian coordinates in two dimension. And, a and c have to be positive functions for the equation to be elliptic

So, if G is assumed to be non-negative, and considering uniform mesh spacing of h and k in the x and y directions, this equation can be discretized as $H u + V u + D u = q$, where H, V and D are operators. So, we have $H u = u(x+h, y) - u(x, y)$; is given by $-a(x, y) u(x, y) + b(x, y) u(x, y) - c(x, y) u(x, y)$. Now, this is, this looks a bit complicated. Essentially what we are using is central differencing here. And, so this is, this becomes $u_{i+1, j} + u_{i-1, j} + u_{i, j+1} + u_{i, j-1} - 4u_{i, j} + \dots$ and that is what this is $x \pm h$; h is a Δx equal to Δx here. And, k is equal to Δy . It is just unfamiliar notation.

And, one would say that it is nothing but central differencing in a slightly different disguise. And, I would like to mention the point that sometimes we have to go in to unfamiliar territory. And, if we work it out by ourselves, then it actually enables us to look at what somebody else is saying and it helps us understanding what somebody else is saying, may be in a slightly different language. And, we should always be receptive to those kind of ideas from other people, who may not speak in the same languages as us.

So, in that sense that is why I put up so as to build character. And, so I would like you to just follow it up and see that this is nothing but central differencing. And, applied where, since you have A and C and also G and x are functions of x and y. They take, they can vary here. And that is what this is saying And, but what you have in $H u$ is variation with respect to x. So, you have $u(x+h, y) - u(x, y)$ and $u(x, y) - u(x-h, y)$. Similarly $V u$, H is for the horizontal and V is for the vertical, horizontal meaning x variation and V vertical meaning y variation.

And, similarly we can see that $V u$ is $u(x, y+k) - u(x, y)$. So, that is $y \pm k$. And, again we have $y \pm k$ here and then you have u at y . So, this is $u_{i, j+1} + u_{i, j-1} - 2u_{i, j} + \dots$. And, you have corresponding coefficients here because this

coefficients of variations of x and y . You also have this. And, $D u$ is $h \times k$ times $G \times y$. So, that is coming from here, and q is coming from here. So, q is right hand side term and D is a diagonal term, which involves value of u only at i, j point. And, so that is given by this one here. So, when you put all these things together, then you can put it in this particular form. So, a is k times k divide by h times A at x plus h by two. So, that is a at i plus half j and c is i minus half j and d is i, j plus half and e is i, j minus half. So, in our notation these are all fairly simple things to follow. And, we can write it like this, but we would like to have the practice of doing it in a different way and that is how we have put it.

There is also another reason for doing it, that is, we have the general case. And, we have the general case and we have not assume this to be constant. And, a general case can give us, can extend our range of applicability. So, what we have done so far is nothing but discretization of our elliptic equation, general form of elliptic equation in Cartesian coordinates.

(Refer Slide Time: 08:14)

The Alternating Direction Implicit (ADI) Method:
Peaceman and Rachford (1955)

$$\partial/\partial x [A(x, y)\partial u/\partial x] + \partial/\partial y [C(x, y) \partial u/\partial y] + G(x, y)u = S(x, y)$$

- Peaceman & Rachford (1955) proposed a two-step solution for the case $G = 0$ and $D = \tau_i$:

$$(H + \tau_1^n)u^{n+1/2} = q - (V - \tau_1^n)u^n$$

$$(V + \tau_2^n)u^{n+1} = q - (H - \tau_2^n)u^{n+1/2}$$

where, τ_1^n and τ_2^n are iteration parameters and I is the identity matrix

- Scheme would converge if τ_1^n and τ_2^n are positive. Going from u^n to u^{n+1} requires the solution of two tridiagonal system of equations (\Rightarrow TDMA can be used), one representing the function dependence in x and the other in y . Hence the name A-D-I
- Scheme expected to be faster than GS but not as fast as Optimum SOR. Faster results can be expected if the operators H, V, D commute, i.e.,
if $HV = VH; HD = DH$ and $DV = VD$ or if $A(x, y) = A(x); C(x, y) = C(y)$ and $G(x, y) = G$
- Then τ_1^n and τ_2^n can be chosen (Axelsson, 1994) such that the asymptotic rate of convergence is asymptotic rate of convergence rate of $O(\log h^{-1})$, compared to $O(h^{-1})$ for Optimum SOR and $O(h^{-2})$ with GS

So, that is our equation here. And Peaceman, Rachford proposed A 2-step solution for the case where G is equal to zero and D is a constant τ_i . So, this discretized equation H plus V plus D times u equal to q . They proposed to solve as two separate equations in A 2

step process. As you go from n to $n + 1$, you first evaluate u at $n + \frac{1}{2}$ by taking the horizontal derivative and constant τ_1 , and vertical derivative is evaluated at n value, and horizontal derivative is evaluated $n + \frac{1}{2}$. So, this will involve, for example, the first equation will involve u at $i + 1, j$, u at i, j and u at $i - 1, j$. So, that makes it implicit in x direction. All values given was at $n + \frac{1}{2}$. And, this part which is $V u_n$ are the y derivative terms are coming in this. And, these are being evaluated explicitly.

So, the first equation is implicit in x , but explicit in y . And having done this, having evaluated the x derivatives at implicitly at $x + \frac{1}{2}$ at $n + \frac{1}{2}$ here, you now come to the vertical derivatives. So, these are evaluated as implicitly because $V u_{n+1}$ will be $u_{i,j+1}$, $u_{i,j}$ and $u_{i,j-1}$. All these things are evaluated implicitly because that is how we have put as u_{n+1} . And here, we have H derivative also contributing to this. And, these are evaluated at the latest values that are available here. So, that is $H u_{n+1, y, n+1}$. And, what we notice that the right hand side terms can be evaluated because these are in the previous time step of previous half time step values. And, only the left hand side terms are implicitly evaluated.

And, the first equation evaluates implicitly the derivatives and variations coming in the x direction. And second one, takes care of the variations in the y direction. But, since each time we are only considering one dimensional variation, so that is at best $\Delta x^2 u$ by $\Delta x^2 u$ here and $\Delta y^2 u$ by $\Delta x^2 u$ here. We have a tridiagonal matrix for each of this. The tridiagonal matrix represent in the first case, the second derivative and other variations in the x direction.

And in the second case, it represents variations in the y direction. And, this is also such that we can get diagonal dominants. So, we can make use of TDMA scheme; and, since as we go from iteration n to iteration $n + 1$, we first evaluate the derivatives in the x direction implicitly. And then, we evaluate the derivatives in the y direction, again implicitly. This is called an implicit method and alternating direction implicit; because you alternating in x direction and alternating and then in y direction, before you complete the step from n to $n + 1$. So, that is why this is alternating direction implicit method.

This scheme is expected to be faster than Gauss-Seidel method, but not as fast as the optimal SOR method. So, in the specific case where the operators H , V and D commute, so that is $H V$ equal to $V H$ and $H D$ equal to $D H$ and $D V$ equal to $V D$, which also essentially means that if A of $x y$ is just a function of x and C of $x y$, which is coming in the y derivative term here. If that is only a function of y here and G of $x y$ which is coming here is not a function of x and y . So, in this particular case we can get much faster results than approaching; in fact, even better than the optimal SOR methods. And, I would like to refer you to the book by Axelsson. It is a mathematical book. It is mathematical base book.

And, in this condition when you have this kind of commutativity of the $H V D$ operators or if we have your equation in which A is a function x only and C is the function of y only and G is constant, then in such a case it is possible to generate a series of numbers τ_1, τ_2 , such that you have an asymptotic rate of convergence, which is of the order of $\log h$ inverse one compared to h inverse one. So, it is one by Δx here and this one by \log of one by Δx .

Since this variation is smaller than this variation, we can get much faster rate of convergence than in the case of Gauss-Seidel method or optimal SOR method. And, what this functional variation where A is function of x only and C is a function of y only, makes the equation here like a variable separable. The solution is like variable separable type of format.

So, if you have that kind of elliptic equation with an arbitrarily complex variation of A in terms of x , which makes the solution probably more difficult analytically, if A is function of x only, but it can be any complicated function. And, we are evaluating it numerically. So, there is no problem here. So, when we look at the numerical solution here, we are going to evaluate the small a in which a functional form is put in is evaluated numerically. So, it can be any kind of arbitrary complexity in x only. So, in such a case we can get tremendous rate of improvement of the alternating direction implicit over the Gauss-Seidel method or even optimal SOR method.

(Refer Slide Time: 15:18)

The ADI for Parabolic Problem

- If the coefficient matrix A in equation $Ax = b$ is decomposed into $A = A_1 + A_2$, then solution:

$$(1 + \tau_1 A_1) x^{n+1} = (1 - \tau_2 A_2) x^n + \tau_1 b$$

$$(1 + \tau_2 A_2) x^{n+1} = (1 - \tau_1 A_1) x^n + \tau_2 b$$
- For stationary ADI, τ_1 and τ_2 do not change from iterations to iteration. If A_1 and A_2 are positive definite, the method would converge if τ_1 and τ_2 are positive and if A_1 and A_2 commute, then a sequence of τ_1^n and τ_2^n can be generated to give a fast convergence rate.
- For extension to parabolic equations, consider the unsteady diffusion problem in 2-D:

$$\partial u / \partial t = \alpha (\partial^2 u / \partial x^2 + \partial^2 u / \partial y^2)$$
- Implicit FTCS differencing:

$$U^{n+1} - U^n = \Delta t (S_x + S_y) U^{n+1} \quad \text{or} \quad [1 + \Delta t (S_x + S_y)] U^{n+1} = U^n$$
 where $S_x U^{n+1} = (\alpha / \Delta x^2) (u^{n+1}_{i+1,j} - 2u^{n+1}_{i,j} + u^{n+1}_{i-1,j})$
 and $S_y U^{n+1} = (\alpha / \Delta y^2) (u^{n+1}_{i,j+1} - 2u^{n+1}_{i,j} + u^{n+1}_{i,j-1})$
- Split the LHS into two 1-D problems:

$$[1 + \Delta t (S_x + S_y)] U^{n+1} = (1 - \Delta t S_y) (1 - \Delta t S_x) U^{n+1} - \Delta t^2 S_x S_y U^{n+1} \approx (1 - \Delta t S_y) (1 - \Delta t S_x) U^{n+1}$$
- Solve in two half-time steps, each 1-D with possibility of use of TDMA:

$$(1 - \Delta t S_y) U^{n+1} = (1 + \Delta t S_x) U^n \quad (1 - \Delta t S_x) U^{n+1} = U^{n+1/2} - \Delta t S_y U^n$$
- Or

$$u^{n+1}_{i,j} - \beta_x (u^{n+1}_{i+1,j} - 2u^{n+1}_{i,j} + u^{n+1}_{i-1,j}) = u^{n+1/2}_{i,j} + \beta_y (u^{n+1/2}_{i,j+1} - 2u^{n+1/2}_{i,j} + u^{n+1/2}_{i,j-1})$$

$$u^{n+1/2}_{i,j} - \beta_y (u^{n+1/2}_{i,j+1} - 2u^{n+1/2}_{i,j} + u^{n+1/2}_{i,j-1}) = u^{n+1/2}_{i,j} - \beta_x (u^{n+1/2}_{i+1,j} - 2u^{n+1/2}_{i,j} + u^{n+1/2}_{i-1,j})$$
- Unconditionally stable for transient diffusion but stability needs to be investigated for the general case

So, we can generalize this ADI method. If we take $Ax = b$ and then decompose it into $A = A_1 + A_2$, then we can put it in this particular form, where one plus tau 1 A 1 x n plus half equal to one minus tau A 2 x n plus tau 1 b and one plus tau 2 A 2 x n plus one equal to 1 minus tau 2 A 1 x n plus half b. Now, what this one is saying that this A 2 part of this is being evaluated explicitly and A 1 part of this is being evaluated implicitly. And having done this, how you come to the other part A 2, which is being done explicitly, in the implicitly in the second step of the equation.

And, A 1 part is now being evaluated x explicitly again. If you do this in the case of stationary ADI, so that is tau 1 and tau 2 are constant. They do not change from iteration to iteration, if this decomposition is such that A 1 and A 2 are positive definite. Then the method would converge, if tau 1 into tau 2 are positive and if A 1 and A 2 commute, then a sequence of tau 1 and tau 2 can be generated to give a fast convergence rate.

So, the idea here is to say that there is no one approaches to the solution of $Ax = b$. So, the idea here is not to say that this is the method by which we can solve. There can be different approaches for different things. When a mathematician looks at $Ax = b$, then he will see many possibilities. And, in some cases if we are aware of those kinds of possibilities, then we can take advantage of that and then get a solution. And,

sometimes when we by looking for alternative ways of getting a solution, we may get some specialized method which will apply for special classic problems. So, it is in that sense we would like to have background to the solution $Ax = b$. And, it is not a trivial problem. And, people have had spent their career, trying to look for various methods. And, this module is just it is an important part of CFD solution.

And, this module is looking at how many different ways or what are the different kinds of successful approaches that people have adopted for the solution $Ax = b$. So, it is in that context we are looking at it, not in the sense of trying to solve our simple problem. We are trying to get good view of good prospective of the field of CFD from especially in the context of solution of $Ax = b$, which we realize is very important problem when we have large number of grid points, which we need to have in order get confidence in a CFD solution. So, it is in that context I am putting this up; not from an examination point of view, not from a solution point of view for a specific problem, but, as a general matter of academic significance.

So, we can extend the ADI method, even for parabolic equations. But, we have to do in a careful way. So, let us consider this parabolic equation when you have $\frac{du}{dt} = \alpha \frac{\partial^2 u}{\partial x^2} + \frac{\partial^2 u}{\partial y^2}$. And, this is an unsteady two dimensional problem with constant α . Earlier, in this case we have put some diffusivity, which is especially varying here. And, here we are looking at constant α , which is the same in the two directions.

We can use over implicit FTCS as differencing for stability. We know that explicit means that there is conditional stability. But, implicit will make it unconditionally stable. But, in the process we get an equation which is, which has five diagonals. And, five diagonals mean that we cannot solve it using the TDMA method. So, now, in order to bring in the TDMA possibility, we would like to pose it in this particular form where we take only the x direction and only the y direction variables.

Now, how can this be done when we have this time derivative also. So, for that we write it symbolically as $u^{n+1} - u^n = \Delta t (S_x + S_y) u^{n+1}$. So, S_x and S_y are operators in the sense that you do not have S_x without u . So, we

define $S_x u_{n+1}$ as $\alpha \frac{\Delta x}{2} (u_{i+1}^{n+1} - u_{i-1}^{n+1})$ which is a time index and which subscripts $i+1, j$, i, j and $i-1, j$. So, this whole thing is representing $\frac{\Delta x}{2} \frac{\partial u}{\partial x}$. And, the right hand side is being evaluated at $n+1$ time step. So, in a way we know the difference between explicit and implicit. And, this is an implicit way of dealing with the space derivative; because your time derivative involves this u_{n+1} here. And, when we put this, evaluate this set u_{n+1} , this makes it implicit. And, that is why we call this as FTCS implicit

And similarly, $S_y u_{n+1}$ is now taking care of the y derivative $\alpha \frac{\Delta y}{2} (u_{i,j+1}^{n+1} - u_{i,j-1}^{n+1})$. So, in that sense this is again like what we have written previously in a straight forward way for a FTCS. Now, we are putting it in more symbolical language. And, once you put it like this, you can bring in the, we can club this operational u_{n+1} with this. And, write it as $1 + \Delta t S_x + \Delta t S_y$, there must be a minus here, $1 - \Delta t S_x + \Delta t S_y$ equal to u_n . We take this on the other side. We bring this on to this side and we will be getting $1 - \Delta t S_x - \Delta t S_y$ here.

Now, we can split this thing here into $(1 - \Delta t S_x)(1 - \Delta t S_y)$ times u_{n+1} . This is the full expansion of this, and because this is Δt^2 and these are Δt . We can neglect this as a higher order term. And then, we can write this as $(1 - \Delta t S_x)(1 - \Delta t S_y) u_{n+1}$. So, now we are writing this one with a minus sign here as $1 - \Delta t S_x - \Delta t S_y$ and this.

So, now this equation, this being made equal to u_n can be solved at two half time steps, each one dimension with the possibility of use of TDMA. So, we can first write this as $(1 - \Delta t S_x) u_{n+1/2} = (1 - \Delta t S_y) u_n$. And from this, we get $u_{n+1/2}$. And, we substitute this here. And then, we put, we solve for $(1 - \Delta t S_y) u_{n+1} = (1 - \Delta t S_x) u_{n+1/2}$. Now, what we claim is that this solution here, this two-step solution here is the same as the solution of this, which is roughly the same as the solution of this within second order accuracy in time.

Now, we are using here this discretization is first order accurate in time. So, the second order terms can be neglected with respect to the first order terms here. And, that is the

argument here. So, this decomposition into two independent steps of this one here is the same mathematical. And, how can we do that? We can do that by substitution, we can pre multiply this by one minus $\Delta t S_x$. And then, we can substitute this expression here and show that this is same. So, it is a bit of exercise that I would like the interested reader to pursue, and show that this is equal to this one. So, there is premultiplication of this one by one minus $\Delta t x \Delta t S_x$. And then, substitution of this thing here, this will actually give us this solution here. Ok.

Now, what is the advantage that we have gained in this? We can write this equation as $u_{n+1/2}^{i,j} - \beta x$, where βx is $\alpha \Delta x^2 \Delta t$ by Δx^2 , which we have seen in simple differencing of this using FTCS implicit. So, this is $-\beta x$ times $u_{n+1/2}^{i,j} - 2u_n^{i,j} + u_{n+1/2}^{i,j} - u_{n+1/2}^{i-1,j} + u_{n+1/2}^{i+1,j} - u_{n+1/2}^{i,j-1} + u_{n+1/2}^{i,j+1}$ equal to $u_n^{i,j} + \beta y$ times $u_{n+1/2}^{i,j} - u_{n+1/2}^{i-1,j} + u_{n+1/2}^{i+1,j} - u_{n+1/2}^{i,j-1} + u_{n+1/2}^{i,j+1}$. So, this is the term that is coming here and this is already known from the pears values.

So, all the right hand side is known. And, the left hand side involves $u_{n+1/2}^{i,j}$ and $u_{n+1/2}^{i-1,j}$. And, you also have $u_{n+1/2}^{i,j}$ term coming here. So, gives us a tridiagonal matrix. And, this can be solve using TDMA scheme to get $u_{n+1/2}^{i,j}$ at all i, j . And, this will bring in here. And then, we write the second part of this equation here to get $u_{n+1}^{i,j}$; now, at $u_{n+1}^{i,j+1}$ and $u_{n+1}^{i,j}$ and $u_{n+1}^{i,j-1}$.

So, once you solve this, this equation, then we gets $u_{n+1}^{i,j}$ at all points. So, this is again a tridiagonal matrix, involving u values at $n+1$ times step at i, j , for all of them. And, this involves again a tridiagonal matrix, but involving u at $n+1/2$ time step, not at n . So, this two times step solution enables us to take, to break up this pentadiagonal matrix into two tridiagonal matrix solutions. Now, this pentadiagonal matrix is not 5 adjacent diagonals, but this with the 5 diagonals with some zeros in between.

So, this particular decomposition of this scheme into this is unconditionally stable for transient diffusion. Even in three dimension, we can extend this to three dimension. And, have three successive one dimension solutions. But, the stability is guaranteed for

transient diffusion, but if you bring in some advection terms into this, then we have to look for stability and we have to see whether it is stable or not.

So, for the general case where you have other terms that are coming, then we have to look at this stability. But, otherwise this breaking up of essentially pentadiagonal matrix into two tridiagonal matrix or seven diagonal matrix. For the three dimension case of this transient diffusion problem into three one dimension problems is unconditionally stable. And, we can just go ahead and get solution for this. And, the overall scheme is expected to be faster than trying to use a Gauss-Seidel method for the same pentadiagonal or seven diagonal equation.

And so, this is a way, an innovative way of making use of the goodness of the tridiagonal matrix algorithm for the solution of matrix which is not tridiagonal. But, what this also tells us is that it is not trivial extension. We cannot just take it up into anything. We cannot factorize it and then take it up. This is part of operating splitting kind of approach and it has to be done properly.

And, what we would like to show here is that that this problem broken up into, written up in this way and approximated at this way. And then, this is equal to u_n . So, that problem is broken up into two steps which are given by this. And, this break up is such that this result in problem is given like this. Example, why we are writing it like this and why we are writing in a different way. Here is; part of the decomposition is a problem. Only doing this way will mean that this two-step solution is same as this one-step solution.

So, we would like to be aware of this that it is not to trivial solution. It requires some thought into the properly composition. And, in the general case it also requires stability analysis.

With this, we would like to conclude this presentation of this alternating direction implicit method. This is, as we can see is a different approach to accelerating the solution over the Gauss-Seidel method. And, the solution in this particular case is trying to take advantage of the fastness of the tridiagonal matrix algorithm. But this has, this works

only in certain cases in a straight forward way. And even then, we have to be careful about the decomposition.


In the next lecture we will look at yet another way of accelerating over the Gauss-Seidel method. And, this again looks that it incorporates a different philosophy, different philosophy, in the sense that any iterative method like solving $Ax = b$ as an iterative method like this.

(Refer Slide Time: 31:00)

Convergence Analysis of the Basic Iterative Schemes

- In iterative methods, $Ax = b$ is solved as $x^{k+1} = Px^k + q$ $k \geq 0$
- Define error, ϵ , as $\epsilon = \bar{x} - x$ where \bar{x} is the exact solution, i.e., $A\bar{x} = b$ and $\bar{x} = P\bar{x} + q$
- At the k^{th} iteration, we have, $\epsilon^k = \bar{x} - x^k$ and $Ax^k = b^k$ and $x^{k+1} = Px^k + q$
- The residual at the k^{th} iteration can be evaluated as $\delta^k = b - b^k = b - Ax^k$: if residual is zero, the solution has converged
- For error reduction, through subtraction, we get $\epsilon^{k+1} = P\epsilon^k$
- Thus, at the end of m iterations, we have, $\epsilon_m = P^m \epsilon^0$
- For convergence, $\rho(P) < 1$ where $\rho(P)$ is the spectral radius of iteration matrix P and is given by $\rho(P) = \max \{ |\lambda_i| \}, 1 \leq i \leq n$ where λ_i are the eigenvalues of $P_{n \times n}$.
- For central differencing of the Laplace equation in 2-D with Dirichlet boundary conditions, with uniform spacing in x and y and having $M \times M = M^2$ no of grid points, the spectral radius of the iteration matrix with the Jacobi scheme is given by

$$\rho(P_J) = \cos(\pi/M) \approx 1 - \pi^2/2M^2 \quad \text{for large } M$$
- For the GS scheme, $\rho(P_{GS}) = \cos^2(\pi/M) \approx 1 - \pi^2/M^2$ for large M




The convergence of the iterative method is faster if the breaking up of A into M and N .

(Refer Slide Time: 31:18).

Iterative Solution Methods

- In iterative methods, we do not solve $Ax = b$
- Rather, we solve repeatedly the equation $Qx^k = (Q-A)x^{k-1} + b$ and approach the solution asymptotically
- In the Jacobi method, $Q = \text{diagonal of } A$ and we write iterative scheme as
$$x^k = Q^{-1}(Q-A)x^{k-1} + b = (I-Q^{-1}A)x^{k-1} + Q^{-1}b = Mx^{k-1} + N$$
- In the Gauss-Seidel method, $Q = \text{lower triangular part of } A \text{ including the diagonal elements, and we write the iterative scheme as}$
$$x^k = Q^{-1}(Q-A)x^{k-1} + b = (I-Q^{-1}A)x^{k-1} + Q^{-1}b = Mx^{k-1} + N$$
- In actual computations, we do not do matrix inversion and solve directly as follows



We are putting x equal to M and N here. And, part of this M is being evaluated in an implicit way. So, the idea we will introduce in the next class that if M is very close to A , then this becomes solution which is implicit. So, the idea of making; we cannot take fully implicit solution of $Ax = b$ because that would involve n (Refer Time: 32:00) number of mathematical operations. But if we can do it approximately, but as close to a fully implicit method, then we get a faster iteration, faster convergence; is the idea behind the strongly implicit procedure method, which we will see in the next class.