Faculty of Engineering Civil Engineering

**Numerical Methods** 



## **Special Matrices and Gauss-Siedel**

## Introduction

- Certain matrices have particular structures that can be exploited to develop efficient solution schemes.
- A **banded matrix** is a square matrix that has all elements equal to zero, with the exception of a band centered on the main diagonal. These matrices typically occur in solution of differential equations.
- The dimensions of a banded system can be quantified by two parameters: the band width BW and half-bandwidth HBW. These two values are related by BW=2HBW+1.

### **Banded matrix**



# Tridiagonal Systems

• A tridiagonal system has a bandwidth of 3:

$$\begin{bmatrix} f_1 & g_1 & & \\ e_2 & f_2 & g_2 & \\ & e_3 & f_3 & g_3 \\ & & e_4 & f_4 \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \\ x_3 \\ x_4 \end{bmatrix} = \begin{cases} r_1 \\ r_2 \\ r_3 \\ r_4 \end{bmatrix}$$

• An efficient LU decomposition method, called *Thomas algorithm*, can be used to solve such an equation. The algorithm consists of three steps: decomposition, forward and back substitution, and has all the advantages of LU decomposition.

#### (a) Decomposition

DO 
$$k = 2$$
, n  
 $e_k = e_k/f_{k-1}$   
 $f_k = f_k - e_k \cdot g_{k-1}$   
END DO

#### (b) Forward substitution

 $DO \ k = 2, \ n$  $r_k = r_k - e_k \cdot r_{k-1}$  $END \ DO$ 

#### (c) Back substitution

$$x_n = r_n / f_n$$
  
 $DO \ k = n - 1, 1, -1$   
 $x_k = (r_k - g_k \cdot x_{k+1}) / f_k$   
END DO

## **Cholesky Decomposition**

 This method is suitable for only symmetric systems where:

$$a_{ij} = a_{ji}$$
 and  $A = A^T$   $[L] = \begin{bmatrix} l_{11} & 0 & 0 \\ l_{21} & l_{22} & 0 \\ l_{31} & l_{32} & l_{33} \end{bmatrix}$ 

$$A = L * L^{T}$$

$$\begin{bmatrix} a_{11} & a_{12} & a_{13} \\ a_{21} & a_{22} & a_{23} \\ a_{31} & a_{32} & a_{33} \end{bmatrix} = \begin{bmatrix} l_{11} & 0 & 0 \\ l_{21} & l_{22} & 0 \\ l_{31} & l_{32} & l_{33} \end{bmatrix} * \begin{bmatrix} l_{11} & l_{21} & l_{31} \\ 0 & l_{22} & l_{32} \\ 0 & 0 & l_{33} \end{bmatrix}$$

### **Cholesky Decomposition**

$$a_{ki} - \sum_{j=1}^{i-1} l_{ij} \cdot l_{kj}$$

$$l_{ki} = \frac{l_{ki} - \sum_{j=1}^{i-1} l_{ij} \cdot l_{kj}}{l_{ii}} \quad for \quad i = 1, 2, \dots, k-1$$

$$l_{kk} = \sqrt{a_{kk} - \sum_{j=1}^{k-1} l_{kj}^2}$$

### Pseudocode for Cholesky's LU Decomposition algorithm (cont'd)

```
DO k = 1.n
 DO i = 1. k - 1
   sum = 0.
   DO \ j = 1, \ i - 1
      sum = sum + a_{i,j} \cdot a_{k,j}
    END DO
   a_{ki} = (a_{ki} - sum)/a_{ii}
  END DO
  sum = 0.
  DO \ j = 1, \ k - 1
   sum = sum + a_{ki}^2
  END DO
 a_{kk} = \sqrt{a_{kk} - sum}
FND DO
```

### **Gauss-Siedel**

- Iterative or approximate methods provide an alternative to the elimination methods. The Gauss-Seidel method is the most commonly used iterative method.
- The system [A]{X}={B} is reshaped by solving the first equation for x<sub>1</sub>, the second equation for x<sub>2</sub>, and the third for x<sub>3</sub>, ...and n<sup>th</sup> equation for x<sub>n</sub>. We will limit ourselves to a 3x3 set of equations.

### **Gauss-Siedel**

$$\begin{aligned} a_{11}x_1 + a_{12}x_2 + a_{13}x_3 &= b_1 \\ a_{21}x_1 + a_{22}x_2 + a_{23}x_3 &= b_2 \end{aligned} \implies \begin{aligned} x_1 &= \frac{b_1 - a_{12}x_2 - a_{13}x_3}{a_{11}} \\ x_2 &= \frac{b_2 - a_{21}x_1 - a_{23}x_3}{a_{22}} \\ a_{22} \end{aligned} \\ x_1 &= \frac{b_3 - a_{31}x_1 - a_{32}x_2}{a_{33}} \end{aligned}$$

Now we can start the solution process by choosing guesses for the x's. A simple way to obtain initial guesses is to assume that they are zero. These zeros can be substituted into  $x_1$  equation to calculate a new  $x_1 = b_1/a_{11}$ .

## **Gauss-Siedel**

• New  $x_1$  is substituted to calculate  $x_2$  and  $x_3$ . The procedure is repeated until the convergence criterion is satisfied:

$$\left|\varepsilon_{a,i}\right| = \left|\frac{x_i^{new} - x_i^{old}}{x_i^{new}}\right| 100\% < \varepsilon_s$$

#### Jacobi iteration Method

An alternative approach, called *Jacobi iteration*, utilizes a somewhat different technique. This technique includes computing a set of new x's on the basis of a set of old x's. Thus, as the new values are generated, they are not immediately used but are retained for the next iteration.

#### **First Iteration**



#### The Gauss-Seidel method

The Jacobi iteration method

#### **Convergence Criterion for Gauss-Seidel Method**

- The gauss-siedel method is similar to the technique of fixed-point iteration.
- The Gauss-Seidel method has two fundamental problems as any iterative method:
  - 1. It is sometimes non-convergent, and
  - 2. If it converges, converges very slowly.
- Sufficient conditions for convergence of two linear equations, u(x,y) and v(x,y) are:

$$\left| \frac{\partial u}{\partial x} \right| + \left| \frac{\partial u}{\partial y} \right| < 1$$
$$\left| \frac{\partial v}{\partial x} \right| + \left| \frac{\partial v}{\partial y} \right| < 1$$

### Convergence Criterion for Gauss-Seidel Method (cont'd)

• Similarly, in case of two simultaneous equations, the Gauss-Seidel algorithm can be expressed as:



## Convergence Criterion for Gauss-Seidel Method (cont'd)

Substitution into convergence criterion of two linear equations yield:  $\left| \frac{a_{12}}{a_{11}} \right| < 1, \quad \left| \frac{a_{21}}{a_{22}} \right| < 1$ 

$$\begin{aligned} a_{11} > |a_{12}| & \text{For n equations} \\ a_{22} > |a_{21}| & |a_{ii}| > \sum_{j=1}^{n} |a_{i,j}| \end{aligned}$$

That is, the diagonal element must be greater than the offdiagonal element for each row.

#### **Gauss-Siedel Method-Example 1**

$$\begin{bmatrix} 3 & -0.1 & 0.2 \\ 0.1 & 7 & -0.3 \\ 0.3 & -0.2 & 10 \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \\ x_3 \end{bmatrix} = \begin{bmatrix} 7.85 \\ -19.3 \\ 71.4 \end{bmatrix} \Rightarrow x_1 = \frac{7.85 + 0.1x_2 + 0.2x_3}{3}$$
$$\Rightarrow x_2 = \frac{-19.3 - 0.1x_1 + 0.3x_3}{7}$$
$$x_3 = \frac{71.4 - 0.3x_1 + 0.2x_2}{10}$$

• **Guess**  $x_1, x_2, x_3$  = zero for the first guess

Iter.	<b>x</b> <sub>1</sub>	<b>X</b> <sub>2</sub>	X <sub>3</sub>	ε <sub>a,1</sub> (%)	ε <sub>a,2</sub> (%)	ε <sub>a,3</sub> (%)
0	0	0	0	-	-	-
1	2.6167	-2.7945	7.005610	100	100	100
2	2.990557	-2.499625	7.000291	12.5	11.8	0.076

## Improvement of Convergence Using Relaxation

$$x_{i}^{new} = \lambda \cdot x_{i}^{new} + (1 - \lambda) \cdot x_{i}^{old}$$

- Where  $\lambda$  is a weighting factor that is assigned a value between [0, 2]
- If  $\lambda = 1$  the method is unmodified.
- If  $\lambda$  is between 0 and 1 (under relaxation) this is employed to make a non convergent system to converge.
- If  $\lambda$  is between 1 and 2 (over relaxation) this is employed to accelerate the convergence.

#### **Gauss-Siedel Method-Example 2**

$$-8x_{1} + x_{2} - 2x_{3} = -20$$

$$-3x_{1} - x_{2} + 7x_{3} = -34$$

$$2x_{1} - 6x_{2} - x_{3} = -38$$
Rearrange so that
$$-8x_{1} + x_{2} - 2x_{3} = -20$$

$$-8x_{1} + x_{2} - 2x_{3} = -20$$

R the equations are diagonally dominant

$$2x_1 - 6x_2 - x_3 = -38$$

 $-3x_{1} - x_{2} + 7x_{3} = -34$  $x_1 = \frac{-20 - x_2 + 2x_3}{-8} \quad x_2 = \frac{-38 - 2x_1 + x_3}{-6} \quad x_3 = \frac{-34 + 3x_1 + x_2}{7}$ 

### **Gauss-Siedel Method- Example 2**

iteration	unknown	value	E <sub>a</sub>	maximum $\varepsilon_a$
0	<i>x</i> <sub>1</sub>	0		
	<b>X</b> <sub>2</sub>	0		
	<b>X</b> 3	0		
1	<b>X</b> <sub>1</sub>	2.5	100.00%	
	<i>x</i> <sub>2</sub>	7.166667	100.00%	
	<b>X</b> 3	-2.7619	100.00%	100.00%
2	<i>X</i> <sub>1</sub>	4.08631	38.82%	
	<i>x</i> <sub>2</sub>	8.155754	12.13%	
	<b>X</b> 3	-1.94076	42.31%	42.31%
3	<i>X</i> <sub>1</sub>	4.004659	2.04%	
	<i>x</i> <sub>2</sub>	7.99168	2.05%	
	<b>X</b> 3	-1.99919	2.92%	2.92%

### **Gauss-Siedel Method- Example 2**

The same computation can be developed with relaxation where  $\lambda = 1.2$ 

First iteration:

$$x_1 = \frac{-20 - x_2 + 2x_3}{-8} = \frac{-20 - 0 + 2(0)}{-8} = 2.5$$

Relaxation yields:  $x_1 = 1.2(2.5) - 0.2(0) = 3$ 

$$x_{2} = \frac{-38 - 2x_{1} + x_{3}}{-6} = \frac{-38 - 2(3) + 0}{-6} = 7.333333$$
  
Relaxation yields:  $x_{2} = 1.2(7.333333) - 0.2(0) = 8.8$ 

$$x_3 = \frac{-34 + 3x_1 + x_2}{7} = \frac{-34 + 3(3) + 8.8}{7} = -2.3142857$$

Relaxation yields:  $x_3 = 1.2(-2.3142857) - 0.2(0) = -2.7771429$ 

### **Gauss-Siedel Method- Example 2**

lter.	unknown	value	relaxation	E <sub>a</sub>	maximum $\varepsilon_a$
1	<b>X</b> <sub>1</sub>	2.5	3	100.00%	
	<i>x</i> <sub>2</sub>	7.3333333	8.8	100.00%	
	<b>X</b> <sub>3</sub>	-2.314286	-2.777143	100.00%	100.000%
2	<i>X</i> <sub>1</sub>	4.2942857	4.5531429	34.11%	
	<i>X</i> <sub>2</sub>	8.3139048	8.2166857	7.10%	
	<b>X</b> 3	-1.731984	-1.522952	82.35%	82.353%
3	<i>X</i> <sub>1</sub>	3.9078237	3.7787598	20.49%	
	<i>X</i> <sub>2</sub>	7.8467453	7.7727572	5.71%	
	<b>X</b> 3	-2.12728	-2.248146	32.26%	32.257%
4	<b>X</b> <sub>1</sub>	4.0336312	4.0846055	7.49%	
	<i>X</i> <sub>2</sub>	8.0695595	8.12892	4.38%	
	<b>X</b> <sub>3</sub>	-1.945323	-1.884759	19.28%	19.280%