



# 2.29 Numerical Fluid Mechanics

## Fall 2011 – Lecture 10

### REVIEW Lecture 9:

- Direct Methods for solving linear algebraic equations
  - Gauss Elimination
  - LU decomposition/factorization
  - Error Analysis for Linear Systems and Condition Numbers
  - Special Matrices: LU Decompositions
    - Tri-diagonal systems: Thomas Algorithm (Nb Ops:  $8O(n)$ )
    - General Banded Matrices
      - Algorithm, Pivoting and Modes of storage
      - Sparse and Banded Matrices
    - Symmetric, positive-definite Matrices
      - Definitions and Properties, Choleski Decomposition

$$\begin{aligned} p & \text{ super-diagonals} \\ q & \text{ sub-diagonals} \\ w & = p + q + 1 \text{ bandwidth} \end{aligned}$$



# 2.29 Numerical Fluid Mechanics

## Fall 2011 – Lecture 10

### REVIEW Lecture 9, Cont'd:

- Direct Methods
  - Gauss Elimination
  - LU decomposition/factorization
  - Error Analysis for Linear Systems and Condition Numbers
  - Special Matrices (Tri-diagonal, banded, sparse, positive-definite, etc)
- Iterative Methods:
$$\mathbf{x}^{k+1} = \mathbf{B} \mathbf{x}^k + \mathbf{c} \quad k = 0, 1, 2, \dots$$
  - Convergence
    - Nec. & Suf.:  $\rho(\mathbf{B}) = \max_{i=1 \dots n} |\lambda_i| < 1$ , where  $\lambda_i = \text{eigenvalue}(\mathbf{B}_{n \times n})$  (ensures  $\|\mathbf{B}\| < 1$ )
    - Jacobi's method, Gauss-Seidel iteration



# TODAY (Lecture 10): Systems of Linear Equations IV

- Direct Methods
  - Gauss Elimination
  - LU decomposition/factorization
  - Error Analysis for Linear Systems
  - Special Matrices: LU Decompositions
- Iterative Methods
  - Concepts, Definitions and Convergence
  - Jacobi's method
  - Gauss-Seidel iteration
  - Stop Criteria
  - Example
  - Successive Over-Relaxation Methods
  - Gradient Methods and Krylov Subspace Methods
  - Preconditioning of  $\mathbf{Ax}=\mathbf{b}$



# Reading Assignment

- **Chapter 11 of “Chapra and Canale, Numerical Methods for Engineers, 2006/2009.”**
  - Any chapter on “Solving linear systems of equations” in CFD references provided. For example: chapter 5 of “J. H. Ferziger and M. Peric, Computational Methods for Fluid Dynamics. Springer, NY, 3<sup>rd</sup> edition, 2002”



# Linear Systems of Equations: Iterative Methods Element-by-Element Form of the Equations

$$\begin{matrix} 0 & \mathbf{x} & \mathbf{x} & 0 & \mathbf{x} \\ 0 & 0 & \mathbf{x} & 0 \\ & \mathbf{x} & 0 & \mathbf{x} & 0 \\ \mathbf{x} & 0 & 0 & \mathbf{x} & 0 \\ \mathbf{x} & \mathbf{x} & 0 & \mathbf{x} \end{matrix}$$

Sparse (large) Full-bandwidth Systems (frequent in practice)

Iterative Methods are then efficient

Analogous to iterative methods obtained for roots of equations,  
i.e. Open Methods: Fixed-point, Newton-Raphson, Secant

Rewrite Equations

$$\begin{matrix} 0 & & & & 0 \\ & 0 & & & 0 \\ & & 0 & & 0 \\ & & & 0 & 0 \\ 0 & & & & 0 \end{matrix}$$

$$\bar{\mathbf{A}}\bar{\mathbf{x}} = \bar{\mathbf{b}} \Leftrightarrow \sum_{j=1}^n a_{ij}x_j = b_i$$

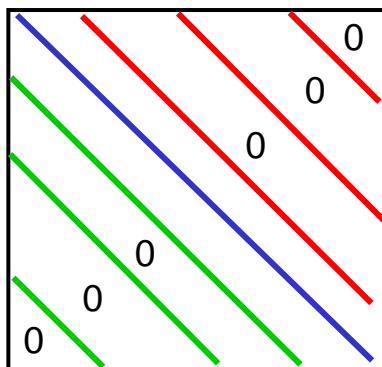
$$a_{ii} \neq 0 \Rightarrow x_i = \frac{b_i - \sum_{j=1}^{i-1} a_{ij}x_j - \sum_{j=i+1}^n a_{ij}x_j}{a_{ii}}, \quad i = 1, \dots, n$$



# Iterative Methods: Jacobi and Gauss Seidel

Sparse, Full-bandwidth Systems

0	x	x	0	x
0	0	x	0	
	x	0	x	
x	0		x	0
x		x	0	x



Rewrite Equations:

$$\bar{\bar{\mathbf{A}}}\bar{\mathbf{x}} = \bar{\mathbf{b}} \Leftrightarrow \sum_{j=1}^n a_{ij}x_j = b_i$$

$$a_{ii} \neq 0 \Rightarrow x_i = \frac{b_i - \sum_{j=1}^{i-1} a_{ij}x_j - \sum_{j=i+1}^n a_{ij}x_j}{a_{ii}}, \quad i = 1, \dots, n$$

=> Iterative, Recursive Methods:

Jacobi's Method

$$x_i^{(k+1)} = \frac{b_i - \sum_{j=1}^{i-1} a_{ij}x_j^{(k)} - \sum_{j=i+1}^n a_{ij}x_j^{(k)}}{a_{ii}}, \quad i = 1, \dots, n$$

Computes a full new  $\mathbf{x}$  based on full old  $\mathbf{x}$ , i.e.  
Each new  $x_i$  is computed based on all old  $x_i$ 's

Gauss-Seidel's Method

$$x_i^{(k+1)} = \frac{b_i - \sum_{j=1}^{i-1} a_{ij}x_j^{(k+1)} - \sum_{j=i+1}^n a_{ij}x_j^{(k)}}{a_{ii}}, \quad i = 1, \dots, n$$

New  $\mathbf{x}$  based most recent  $\mathbf{x}$  elements, i.e.  
Each new  $x_{i-1}^{k+1}$  directly used to compute next element  $x_i^{k+1}$



# Iterative Methods: Jacobi's Matrix form

Iteration – Matrix form

$$\bar{\mathbf{x}}^{(k+1)} = \bar{\bar{\mathbf{B}}} \bar{\mathbf{x}}^{(k)} + \bar{\mathbf{c}}, \quad k = 0, \dots$$

Decompose Coefficient Matrix

$$\bar{\bar{\mathbf{A}}} = \bar{\bar{\mathbf{D}}} + \bar{\bar{\mathbf{L}}} + \bar{\bar{\mathbf{U}}}$$

with

$$\bar{\bar{\mathbf{D}}} = \text{diag } a_{ii}$$

$$\bar{\bar{\mathbf{L}}} = \begin{cases} a_{ij}, & i > j \\ 0, & i \leq j \end{cases}$$

**Note: this is NOT LU-factorization**

$$\bar{\bar{\mathbf{U}}} = \begin{cases} a_{ij}, & i < j \\ 0, & i \geq j \end{cases}$$

Jacobi's Method

$$x_i^{(k+1)} = \frac{b_i - \sum_{j=1}^{i-1} a_{ij} x_j^{(k)} - \sum_{j=i+1}^n a_{ij} x_j^{(k)}}{a_{ii}}, \quad i = 1, \dots, n$$

$$\bar{\mathbf{x}}^{(k+1)} = -\bar{\bar{\mathbf{D}}}^{-1}(\bar{\bar{\mathbf{L}}} + \bar{\bar{\mathbf{U}}}) \bar{\mathbf{x}}^{(k)} + \bar{\bar{\mathbf{D}}}^{-1} \bar{\mathbf{b}}$$

Iteration  
Matrix form

$$\left\{ \begin{array}{l} \bar{\bar{\mathbf{B}}} = -\bar{\bar{\mathbf{D}}}^{-1}(\bar{\bar{\mathbf{L}}} + \bar{\bar{\mathbf{U}}}) \\ \bar{\mathbf{c}} = \bar{\bar{\mathbf{D}}}^{-1} \bar{\mathbf{b}} \end{array} \right.$$



# Convergence of Jacobi and Gauss-Seidel

- Jacobi:

$$\mathbf{A} \mathbf{x} = \mathbf{b} \Rightarrow \mathbf{D} \mathbf{x} + (\mathbf{L} + \mathbf{U}) \mathbf{x} = \mathbf{b}$$

$$\mathbf{x}^{k+1} = -\mathbf{D}^{-1}(\mathbf{L} + \mathbf{U}) \mathbf{x}^k + \mathbf{D}^{-1}\mathbf{b}$$

- Gauss-Seidel:

$$x_i^{(k+1)} = \frac{b_i - \sum_{j=1}^{i-1} a_{ij}x_j^{(k+1)} - \sum_{j=i+1}^n a_{ij}x_j^{(k)}}{a_{ii}}, \quad i = 1, \dots, n$$

$$\mathbf{A} \mathbf{x} = \mathbf{b} \Rightarrow (\mathbf{D} + \mathbf{L}) \mathbf{x} + \mathbf{U} \mathbf{x} = \mathbf{b}$$

$$\mathbf{x}^{k+1} = -\mathbf{D}^{-1}\mathbf{L} \mathbf{x}^{k+1} - \mathbf{D}^{-1}\mathbf{U} \mathbf{x}^k + \mathbf{D}^{-1}\mathbf{b} \quad \text{or}$$

$$\mathbf{x}^{k+1} = -(\mathbf{D} + \mathbf{L})^{-1}\mathbf{U} \mathbf{x}^k + (\mathbf{D} + \mathbf{L})^{-1}\mathbf{b}$$

- Both converge if  $\mathbf{A}$  strictly diagonal dominant
- Gauss-Seidel also convergent if  $\mathbf{A}$  symmetric positive definite matrix
- Also Jacobi convergent for  $\mathbf{A}$  if
  - $\mathbf{A}$  symmetric and  $\{\mathbf{D}, \mathbf{D} + \mathbf{L} + \mathbf{U}, \mathbf{D} - \mathbf{L} - \mathbf{U}\}$  are all positive definite



# Sufficient Condition for Convergence Proof for Jacobi

$$\mathbf{A} \mathbf{x} = \mathbf{b} \Rightarrow \mathbf{D} \mathbf{x} + (\mathbf{L} + \mathbf{U}) \mathbf{x} = \mathbf{b}$$

$$\mathbf{x}^{k+1} = -\mathbf{D}^{-1}(\mathbf{L} + \mathbf{U}) \mathbf{x}^k + \mathbf{D}^{-1}\mathbf{b}$$

Sufficient Convergence Condition  $\|\bar{\mathbf{B}}\| < 1$

Jacobi's Method  $b_{ij} = -\frac{a_{ij}}{a_{ii}}, i \neq j$

Using the  $\infty$ -Norm  
(Maximum Row Sum)  $\|\bar{\mathbf{B}}\|_\infty = \max_i \sum_{j=1, j \neq i}^n \frac{|a_{ij}|}{|a_{ii}|}$

Hence, Sufficient Convergence Condition is:

$$\sum_{j=1, j \neq i}^n |a_{ij}| < |a_{ii}|$$

Strict Diagonal Dominance



# Illustration of Convergence (left) and Divergence (right) of the Gauss-Seidel Method

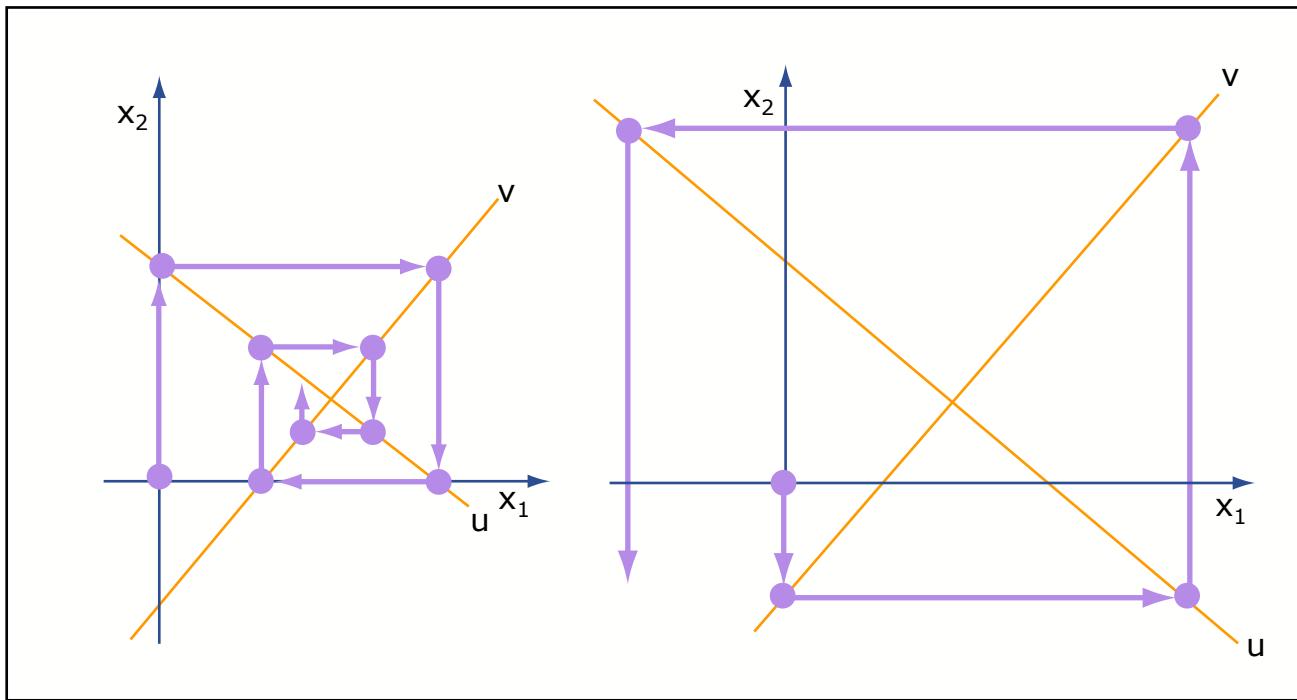


Image by MIT OpenCourseWare.

Since the same functions are plotted in each case, the order of implementation of the equations determines whether the method converges or diverges.



# Special Matrices: Tri-diagonal Systems

Finite Difference

$$\frac{d^2y}{dx^2} \Big|_{x_i} \simeq \frac{y_{i-1} - 2y_i + y_{i+1}}{h^2}$$

Discrete Difference Equations

$$y_{i-1} + ((kh)^2 - 2)y_i + y_{i+1} = f(x_i)h^2$$

Matrix Form

$$\begin{bmatrix} (kh)^2 - 2 & 1 & . & . & . & . & 0 \\ 1 & (kh)^2 - 2 & 1 & & & & . \\ . & . & . & . & & & . \\ . & . & 1 & (kh)^2 - 2 & 1 & & . \\ . & . & . & . & . & . & . \\ 0 & . & . & . & . & 1 & (kh)^2 - 2 \end{bmatrix} \bar{y} = \begin{Bmatrix} f(x_1)h^2 \\ . \\ . \\ f(x_i)h^2 \\ . \\ . \\ f(x_n)h^2 \end{Bmatrix}$$

Tridiagonal Matrix

Strict Diagonal Dominance?

$$kh > 2 \Rightarrow h > \frac{2}{k}$$

Considering Jacobi, a sufficient condition for convergence is:

With  $\mathbf{B} = -\mathbf{D}^{-1}(\mathbf{L} + \mathbf{U})$ : If  $|a_{ii}| > \sum_{j=1, j \neq i}^n |a_{ij}| \Rightarrow \|\mathbf{B}\|_\infty = \max_{i=1 \dots n} (\sum_{j=1}^n |b_{ij}|) = \max_{i=1 \dots n} (\sum_{j=1, j \neq i}^n \frac{|a_{ij}|}{|a_{ii}|}) < 1$



# vib\_string.m (Part I)

```
n=99;                                % Exact solution
L=1.0;                                 y=inv(a)*f;
h=L/(n+1);                            subplot(2,1,2); p=plot(x,y,'b');set(p,'LineWidth',2);
k=2*pi;                               p=legend(['Off-diag. = ' num2str(o)]);
kh=k*h                                set(p,'FontSize',14);
                                         p=title('String Displacement (Exact)');
                                         set(p,'FontSize',14);
                                         xlabel('x');
                                         set(p,'FontSize',14);

%Tri-Diagonal Linear System: Ax=b
x=[h:h:L-h]';
a=zeros(n,n);
f=zeros(n,1);
% Offdiagonal values
o=1.0

a(1,1) =kh^2 - 2;
a(1,2)=o;

for i=2:n-1
    a(i,i)=a(1,1);
    a(i,i-1) = o;
    a(i,i+1) = o;
end
a(n,n)=a(1,1);
a(n,n-1)=o;

% Hanning window load
nf=round((n+1)/3);
nw=round((n+1)/6);
nw=min(min(nw,nf-1),n-nf);
figure(1)
hold off

nw1=nf-nw;
nw2=nf+nw;
f(nw1:nw2) = h^2*hanning(nw2-nw1+1);
subplot(2,1,1); p=plot(x,f,'r');set(p,'LineWidth',2);
p=title('Force Distribution');
set(p,'FontSize',14)
```



# vib\_string.m (Part II)

```
%Iterative solution using Jacobi's and Gauss-Seidel's methods
b=-a;
c=zeros(n,1);
for i=1:n
    b(i,i)=0;
    for j=1:n
        b(i,j)=b(i,j)/a(i,i);
        c(i)=f(i)/a(i,i);
    end
end

nj=100;
xj=f;
xgs=f;

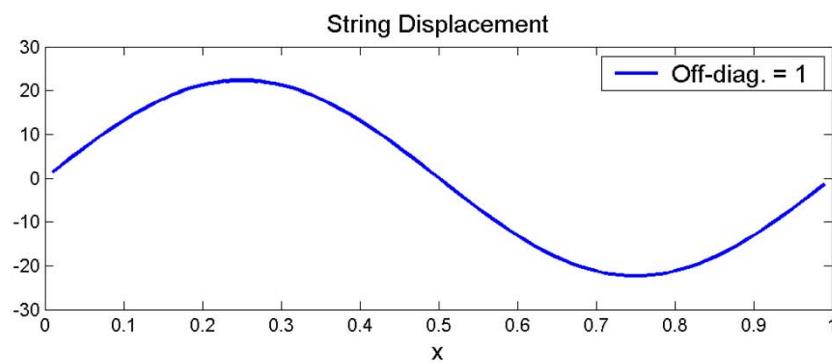
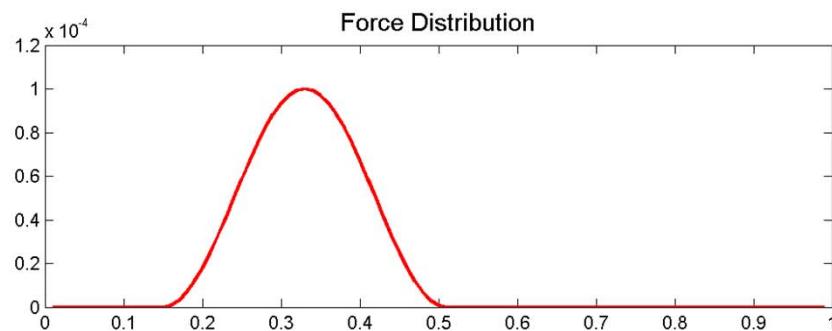
figure(2)
nc=6
col=['r' 'g' 'b' 'c' 'm' 'y']
hold off
for j=1:nj
    % jacobi
    xj=b*xj+c;
    % gauss-seidel
    xgs(1)=b(1,2:n)*xgs(2:n) + c(1);
    for i=2:n-1
        xgs(i)=b(i,1:i-1)*xgs(1:i-1) + b(i,i+1:n)*xgs(i+1:n) +c(i);
    end
    xgs(n)= b(n,1:n-1)*xgs(1:n-1) +c(n);
    cc=col(mod(j-1,nc)+1);
    subplot(2,1,1); plot(x,xj,cc); hold on;
    p=title('Jacobi');
    set(p,'FontSize',14);
    subplot(2,1,2); plot(x,xgs,cc); hold on;
    p=title('Gauss-Seidel');
    set(p,'FontSize',14);
    p=xlabel('x');
    set(p,'FontSize',14);
end
```



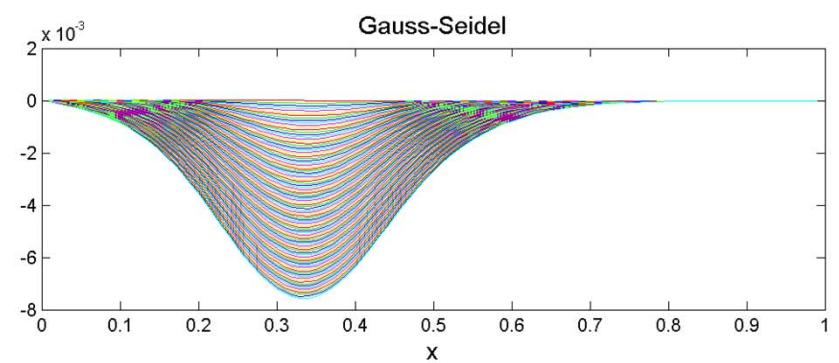
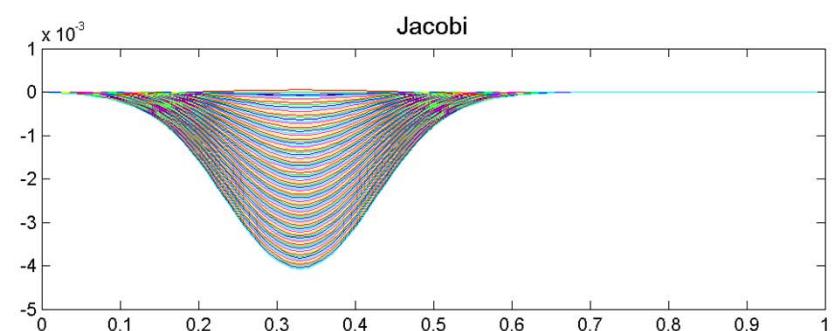
# vib\_string.m

$\omega=1.0, , k=2\pi, h=.01, kh<2$

Exact Solution



Iterative Solutions



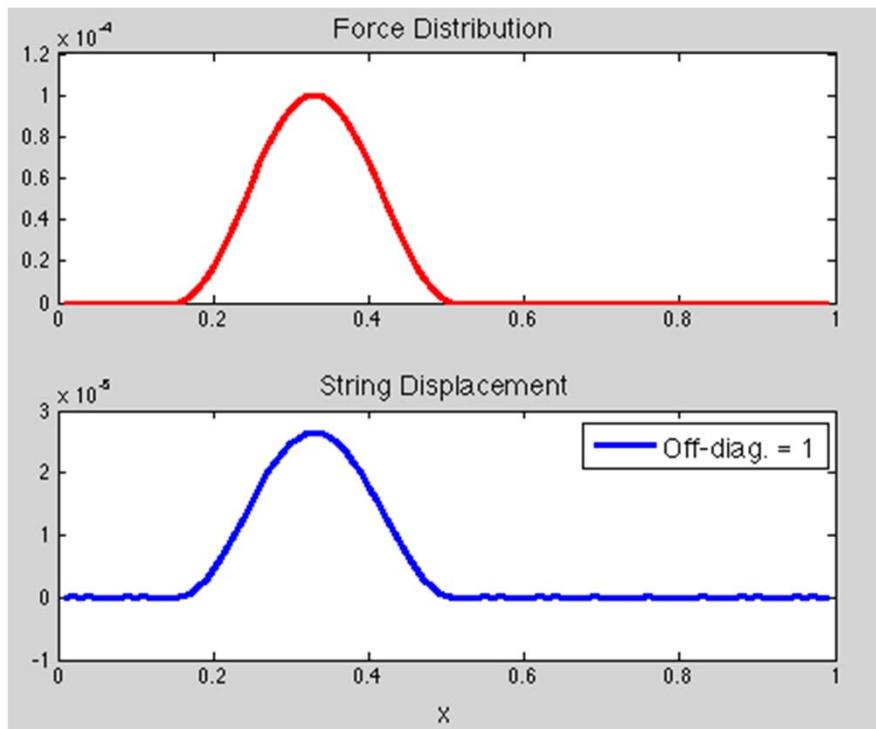
Coefficient Matrix Not Strictly Diagonally Dominant



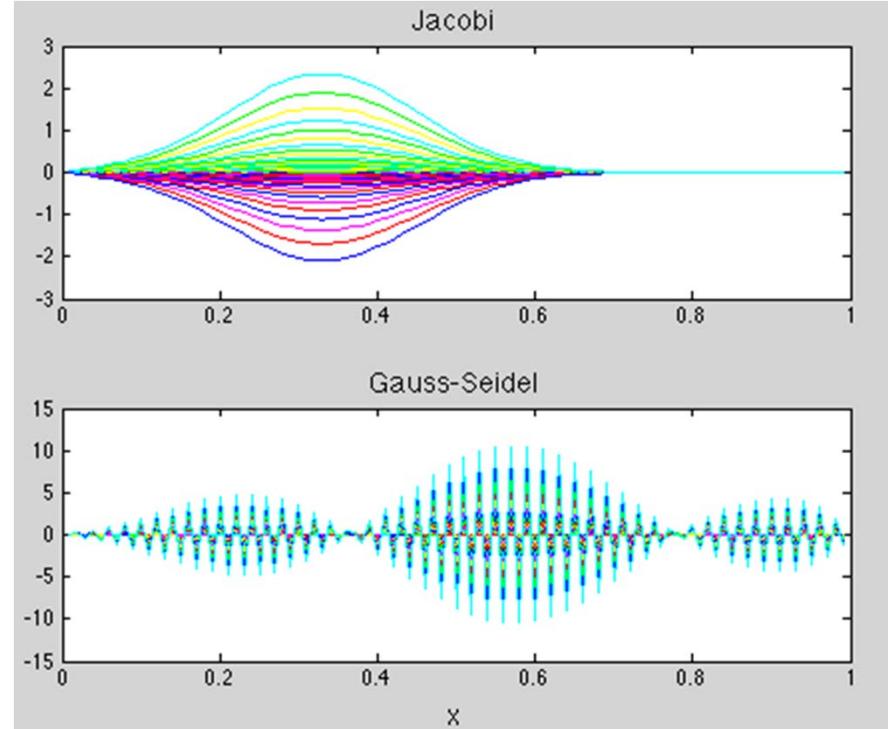
# vib\_string.m

$\omega=1.0, , k=2\pi/31, h=.01, kh < 2$

Exact Solution



Iterative Solutions



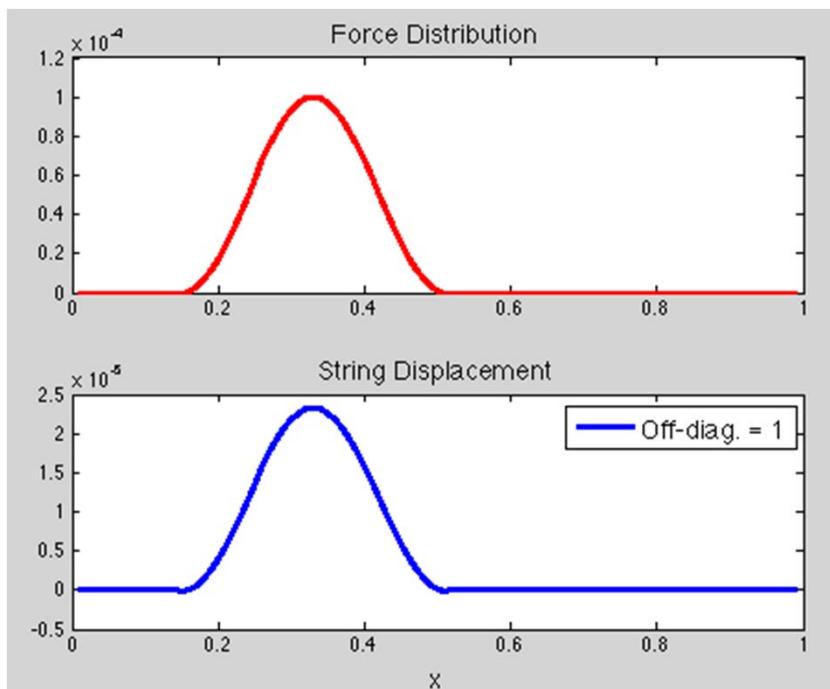
Coefficient Matrix Not Strictly Diagonally Dominant



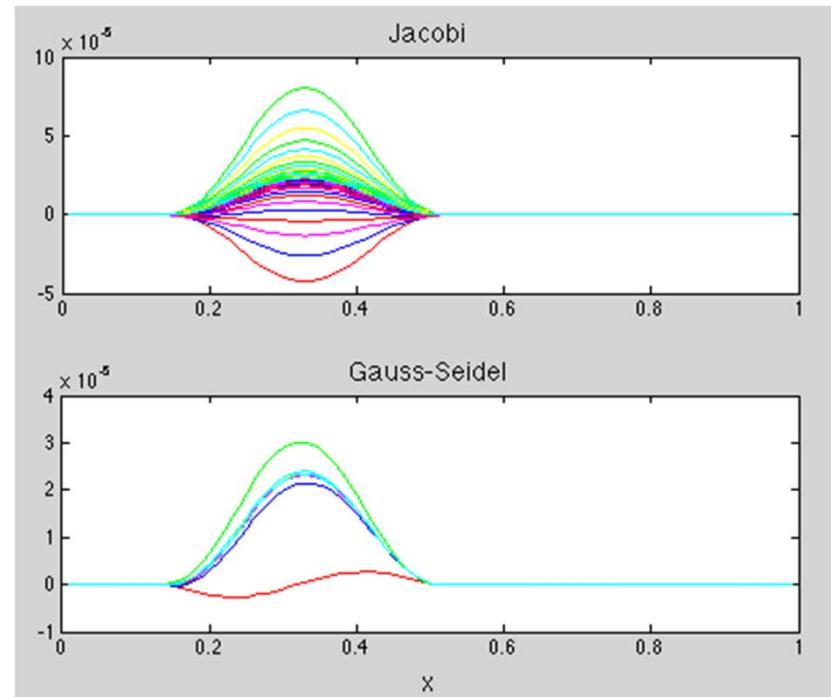
# vib\_string.m

$\omega=1.0$ ,  $k=2\pi\sqrt{33}$ ,  $h=.01$ ,  $kh>2$

Exact Solution



Iterative Solutions



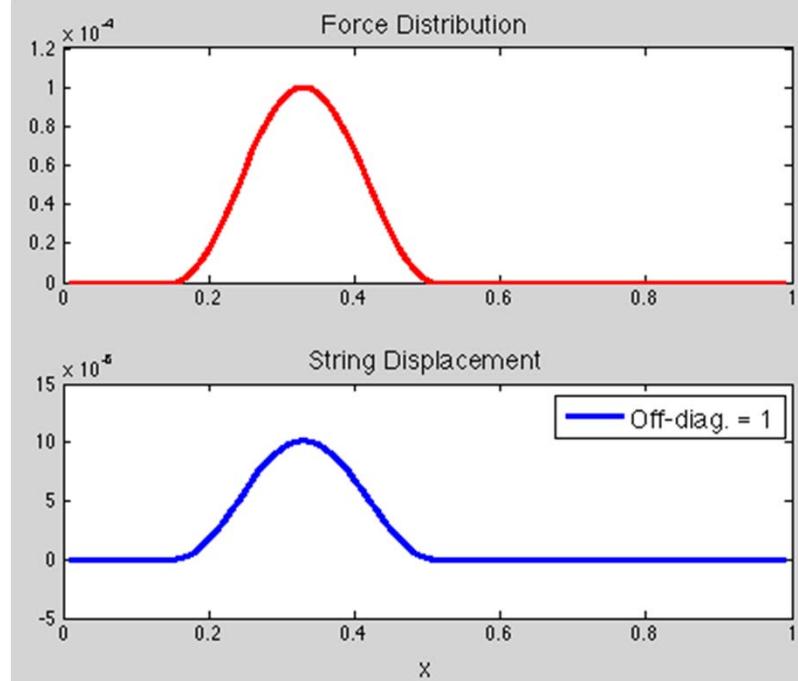
Coefficient Matrix Strictly Diagonally Dominant



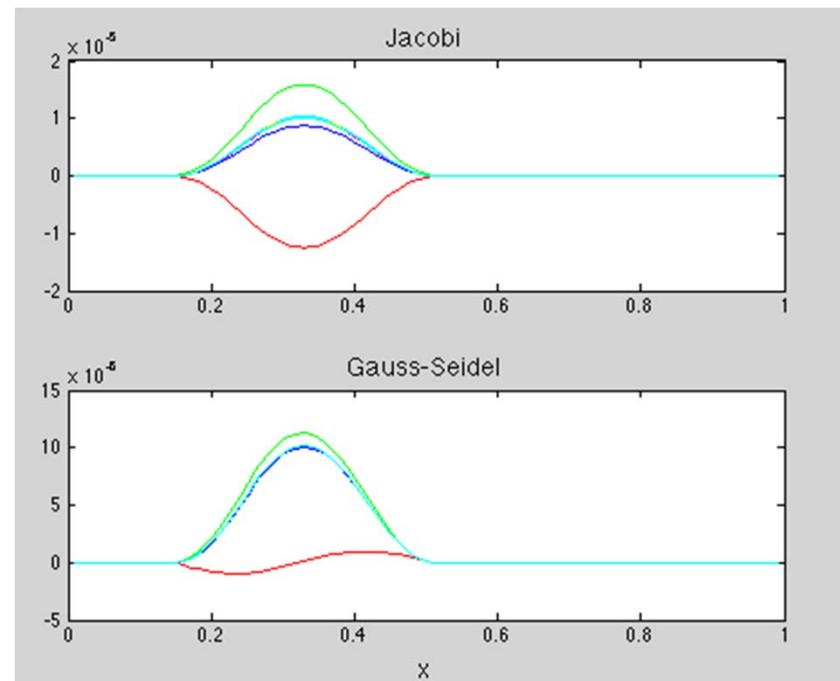
# vib\_string.m

$\omega=1.0$ ,  $k=2\pi\cdot 50$ ,  $h=.01$ ,  $kh>2$

Exact Solution



Iterative Solutions



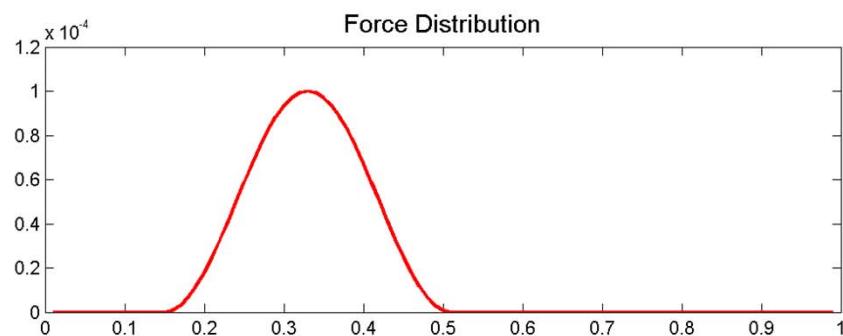
Coefficient Matrix Strictly Diagonally Dominant



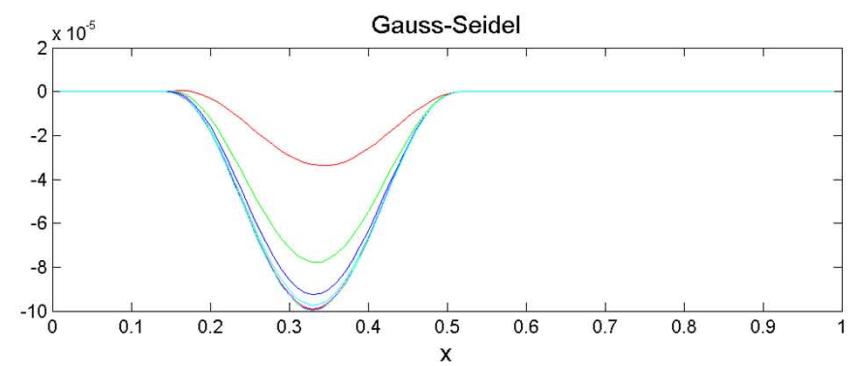
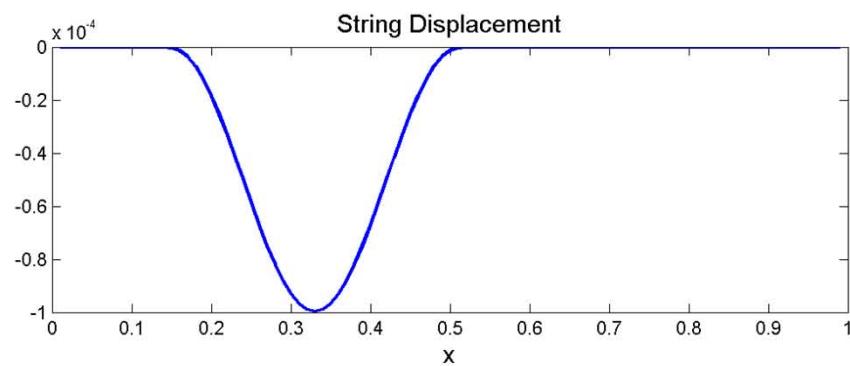
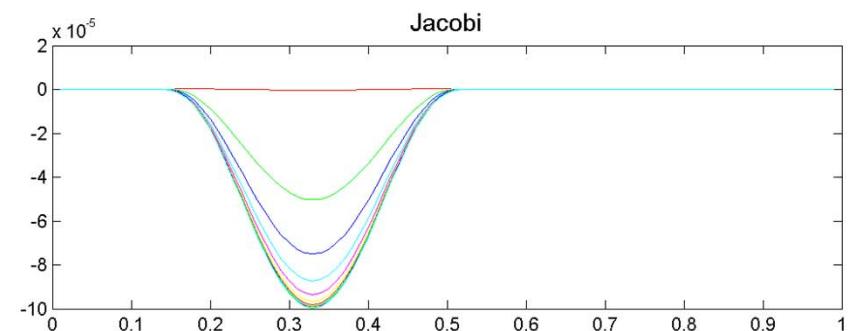
# vib\_string.m

$\omega = 0.5, k=2\pi, h=.01$

Exact Solution



Iterative Solutions



Coefficient Matrix Strictly Diagonally Dominant



# Successive Over-relaxation (SOR) Method

- Aims to reduce the spectral radius of  $B$  to increase rate of convergence
- Add an extrapolation to each step of Gauss-Seidel

$$\mathbf{x}_i^{k+1} = \omega \bar{\mathbf{x}}_i^{k+1} + (1 - \omega) \mathbf{x}_i^k, \text{ where } \bar{\mathbf{x}}_i^{k+1} \text{ computed by Gauss - Seidel}$$

$\omega = 1 \Rightarrow SOR \equiv \text{Gauss-Seidel}$

$1 < \omega < 2 \Rightarrow \text{Over-relaxation (weight new values more)}$

$0 < \omega < 1 \Rightarrow \text{Under-relaxation}$

- If “A” symmetric and positive definite  $\Rightarrow$  converges for  $0 < \omega < 2$
- Matrix format:

$$\mathbf{x}^{k+1} = (\mathbf{D} + \omega \mathbf{L})^{-1} [-\omega \mathbf{U} + (1 - \omega) \mathbf{D}] \mathbf{x}^k + \omega (\mathbf{D} + \omega \mathbf{L})^{-1} \mathbf{b}$$

- Hard to find optimal value of over-relaxation parameter for fast convergence (aim to minimize spectral radius of  $B$ ) due to BCs, etc.

$$\omega = \omega_{opt} = ?$$

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