Gauss–Seidel Iteration for Linear Systems

Direct vs. Iterative Solvers

MMAE 350: Computational Mechanics

Motivation

We have already seen the *Thomas Algorithm*:

- Direct
- Exact
- $\mathcal{O}(n)$ for tridiagonal systems

What if:

- The matrix is not tridiagonal?
- The system is very large?
- We want an approximate solution that improves iteratively?

Problem Statement

We seek to solve the linear system

$$\boldsymbol{A}\boldsymbol{x} = \boldsymbol{b},$$

where:

- $\boldsymbol{A} \in \mathbb{R}^{n \times n}$
- $\boldsymbol{x}, \boldsymbol{b} \in \mathbb{R}^{n}$

The Gauss–Seidel method constructs a sequence

$$\boldsymbol{x}^{(0)}, \boldsymbol{x}^{(1)}, \boldsymbol{x}^{(2)}, \ldots$$

that converges to the solution.

Component-Wise Update Formula

For each equation $i = 1, \ldots, n$:

$$x_i^{(k+1)} = \frac{1}{a_{ii}} \left(b_i - \sum_{j<i} a_{ij} x_j^{(k+1)} - \sum_{j>i} a_{ij} x_j^{(k)} \right).$$

Key observation:

- New values are used immediately
- Old values are used where necessary

Algorithm Outline

1. Choose an initial guess $\boldsymbol{x}^{(0)}$
2. For $k = 0, 1, 2, \ldots$:
   - Loop through equations $i = 1$ to n
   - Update $x_i^{(k+1)}$ using latest values
3. Check convergence

One full sweep through the equations constitutes one iteration.

Convergence Behavior

Gauss–Seidel converges if:

- $\boldsymbol{A}$ is strictly diagonally dominant, or
- $\boldsymbol{A}$ is symmetric positive definite

Physical interpretation:

- Diagonal dominance means local effects outweigh coupling
- Common in diffusion and elasticity problems

Gauss–Seidel vs. Jacobi

Feature	**Jacobi**	**Gauss–Seidel**
Uses updated values	No	Yes
Convergence speed	Slower	Faster
Parallel friendly	Yes	Less so

Gauss–Seidel can be viewed as *Jacobi with memory*.

Gauss–Seidel vs. Thomas Algorithm

Feature	**Thomas**	**Gauss–Seidel**
Method type	Direct	Iterative
Accuracy	Exact	Approximate
Matrix type	Tridiagonal	General sparse
Cost	$\mathcal{O}(n)$	$\mathcal{O}(n\,k)$

Thomas is unbeatable when applicable; Gauss–Seidel works when Thomas cannot.

Role in Computational Mechanics

Gauss–Seidel is foundational to:

- Successive Over-Relaxation (SOR)
- Multigrid smoothers
- Nonlinear Newton solvers

Iterative thinking is essential for large-scale simulations.

Key Takeaways

- Gauss–Seidel is an *iterative* solver
- Updates occur *in-place*
- Convergence depends on matrix structure
- Complements direct methods like Thomas

Gauss–Seidel Sweep: What is "new" vs "old"?

already updated ($x^{(k+1)}$)

not yet updated ($x^{(k)}$)

diagonal / pivot

a_{11}	a_{12}	a_{13}	a_{14}
a_{21}	a_{22}	a_{23}	a_{24}
a_{31}	a_{32}	a_{33}	a_{34}
a_{41}	a_{42}	a_{43}	a_{44}

$$x_1^{(k+1)} = \frac{1}{a_{11}} \left(b_1 - a_{12} x_2^{(k)} - a_{13} x_3^{(k)} - a_{14} x_4^{(k)} \right)$$

Updating x_1: everything to the right uses old values.

Gauss–Seidel Sweep: What is "new" vs "old"?

already updated ($x^{(k+1)}$)

not yet updated ($x^{(k)}$)

diagonal / pivot

$$
\begin{matrix}
a_{11} & a_{12} & a_{13} & a_{14} \\
a_{21} & a_{22} & a_{23} & a_{24} \\
a_{31} & a_{32} & a_{33} & a_{34} \\
a_{41} & a_{42} & a_{43} & a_{44}
\end{matrix}
$$

$$x_2^{(k+1)} = \frac{1}{a_{22}} \left(b_2 - a_{21} x_1^{(k+1)} - a_{23} x_3^{(k)} - a_{24} x_4^{(k)} \right)$$

Updating x_2: left is new (green), right is old (orange).

Gauss–Seidel Sweep: What is “new” vs “old”?

already updated ($x^{(k+1)}$) not yet updated ($x^{(k)}$)

diagonal / pivot

$$\begin{matrix} a_{11} & a_{12} & a_{13} & a_{14} \\ a_{21} & a_{22} & a_{23} & a_{24} \\ a_{31} & a_{32} & a_{33} & a_{34} \\ a_{41} & a_{42} & a_{43} & a_{44} \end{matrix}$$

$$x_3^{(k+1)} = \frac{1}{a_{33}} \left(b_3 - a_{31} x_1^{(k+1)} - a_{32} x_2^{(k+1)} - a_{34} x_4^{(k)} \right)$$

Updating x_3: x_1, x_2 are new; x_4 is old.

Gauss–Seidel Sweep: What is “new” vs “old”?

already updated ($x^{(k+1)}$) not yet updated ($x^{(k)}$)

diagonal / pivot

a_{11}	a_{12}	a_{13}	a_{14}
a_{21}	a_{22}	a_{23}	a_{24}
a_{31}	a_{32}	a_{33}	a_{34}
a_{41}	a_{42}	a_{43}	a_{44}

$$x_4^{(k+1)} = \frac{1}{a_{44}}\left(b_4 - a_{41}x_1^{(k+1)} - a_{42}x_2^{(k+1)} - a_{43}x_3^{(k+1)}\right)$$

Updating x_4: all previous are new; diagonal is the pivot.

Convergence of Gauss–Seidel

Gauss–Seidel produces a sequence

$$\boldsymbol{x}^{(0)}, \boldsymbol{x}^{(1)}, \boldsymbol{x}^{(2)}, \dots$$

that (hopefully) converges to the solution of

$$\boldsymbol{A}\boldsymbol{x} = \boldsymbol{b}.$$

Residual-Based Convergence (Preferred)

Define the residual

$$\boldsymbol{r}^{(k)} = \boldsymbol{b} - \boldsymbol{A}\boldsymbol{x}^{(k)}.$$

Stop the iteration when

$$\frac{\|\boldsymbol{r}^{(k)}\|}{\|\boldsymbol{b}\|} < \varepsilon.$$

Update-Based Convergence (Common in Practice)

Alternatively, stop when the solution stops changing: