

MATH 676

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**Finite element methods in
scientific computing**

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Lecture 33.5:

Which quadrature formula to use

The need for quadrature

Recall from lecture 4 and many example programs:

We compute

$$A_{ij} = (\nabla \phi_i, \nabla \phi_j) \quad F_i = (\phi_i, f)$$

by **mapping** back to the reference cell...

$$\begin{aligned} A_{ij} &= (\nabla \phi_i, \nabla \phi_j) \\ &= \sum_K \int_K \nabla \phi_i(x) \cdot \nabla \phi_j(x) \\ &= \sum_K \int_{\hat{K}} J_K^{-1}(\hat{x}) \hat{\nabla} \hat{\phi}_i(\hat{x}) \cdot J_K^{-1}(\hat{x}) \hat{\nabla} \hat{\phi}_j(\hat{x}) |\det J_K(\hat{x})| \end{aligned}$$

...and **quadrature**:

$$A_{ij} \approx \sum_K \sum_{q=1}^Q J_K^{-1}(\hat{x}_q) \hat{\nabla} \hat{\phi}_i(\hat{x}_q) \cdot J_K^{-1}(\hat{x}_q) \hat{\nabla} \hat{\phi}_j(\hat{x}_q) \underbrace{|\det J_K(\hat{x}_q)| w_q}_{=: JxW}$$

Similarly for the right hand side F .

The need for quadrature

Question:

When approximating

$$A_{ij} = (\nabla \phi_i, \nabla \phi_j)$$

by

$$A_{ij} \approx \sum_K \sum_{q=1}^Q J_K^{-1}(\hat{x}_q) \hat{\nabla} \hat{\phi}_i(\hat{x}_q) \cdot J_K^{-1}(\hat{x}_q) \hat{\nabla} \hat{\phi}_j(\hat{x}_q) |\det J(\hat{x}_q)| w_q$$

how should we choose the points \hat{x}_q and weights w_q ?

In other words:

Which quadrature rule should we choose?

Considerations

Question: Which quadrature rule should we choose?

$$A_{ij} \approx \sum_K \sum_{q=1}^Q J_K^{-1}(\hat{x}_q) \hat{\nabla} \hat{\phi}_i(\hat{x}_q) \cdot J_K^{-1}(\hat{x}_q) \hat{\nabla} \hat{\phi}_j(\hat{x}_q) |\det J(\hat{x}_q)| w_q$$

Goals:

- Efficient: Make Q as small as possible
- Accurate: Do not introduce unnecessary errors

About accuracy:

In particular, do nothing that affects the convergence *order*!

1d: The matrix

Question: Which quadrature rule should we choose?

$$A_{ij} \approx \sum_K \sum_{q=1}^Q J_K^{-1}(\hat{x}_q) \hat{\nabla} \hat{\phi}_i(\hat{x}_q) \cdot J_K^{-1}(\hat{x}_q) \hat{\nabla} \hat{\phi}_j(\hat{x}_q) |\det J_K(\hat{x}_q)| w_q$$

Consider the 1d case:

- We use an element of polynomial degree k
- We use a linear mapping

Then:

- $J_K, J_K^{-1}, \det J_K$ are constant
- $\hat{\nabla} \hat{\phi}_j(\hat{x}_q)$ is a polynomial of degree $k-1$
- The integrand has polynomial degree $2(k-1)$

1d: The matrix

Question: Which quadrature rule should we choose?

$$A_{ij} = (\nabla \phi_i, \nabla \phi_j) \\ \approx \sum_K \sum_{q=1}^Q J_K^{-1}(\hat{x}_q) \hat{\nabla} \hat{\phi}_i(\hat{x}_q) \cdot J_K^{-1}(\hat{x}_q) \hat{\nabla} \hat{\phi}_j(\hat{x}_q) |\det J_K(\hat{x}_q)| w_q$$

Consider the 1d case:

- The integrand has polynomial degree $2(k-1)$
- Gauss quadrature with n points is exact for polynomials up to degree $2n-1$

Consequence:

We can compute the integral $A_{ij} = (\nabla \phi_i, \nabla \phi_j)$ *exactly* via Gauss quadrature with $n=k$ points!

1d: The right hand side

Question: How about the right hand side?

$$F_i = (\phi_i, f) \approx \sum_K \sum_{q=1}^Q \hat{\phi}_i(\hat{x}_q) f(x_q) |\det J_K(\hat{x}_q)| w_q$$

Consider the 1d case:

- We use an element of polynomial degree k
- We use a linear mapping

Then:

- $\det J_K$ is constant
- $\nabla \hat{\phi}_j(\hat{x}_q)$ is a polynomial of degree k
- $f(x)$ is not in general a polynomial
- The integrand is not polynomial

1d: The right hand side

Question: What to do here?

$$F_i = (\phi_i, f) \approx \sum_K \sum_{q=1}^Q \hat{\phi}_i(\hat{x}_q) f(x_q) |\det J_K(\hat{x}_q)| w_q$$

Consider Gauss integration with n points:

- Integrates polynomials of degree $2n-1$ exactly
- For general $f(x)$ essentially integrates

$$\begin{aligned} F_i = (\phi_i, f) &\approx \sum_K \sum_{q=1}^Q \hat{\phi}_i(\hat{x}_q) f(x_q) |\det J_K(\hat{x}_q)| w_q \\ &\approx (\phi_i, I_{2n-k} f) \end{aligned}$$

where $I_{2n-k} f = f$ at the n quadrature points + $n-k$ others

1d: The right hand side

Consider Gauss integration with n points:

- Integrates polynomials of degree $2n-1$ exactly
- For general $f(x)$ essentially integrates

$$\begin{aligned} F_i &= (\phi_i, f) \approx \sum_K \sum_{q=1}^Q \hat{\phi}_i(\hat{x}_q) f(x_q) |\det J_K(\hat{x}_q)| w_q \\ &= \sum_K \int_K I_{2n}(\phi_i f) \approx (\phi_i, I_{2n-k} f) \end{aligned}$$

where $I_{2n-k} f = f$ at the n quadrature points + $n-k$ others on every cell

Consequence:

Inexact integration is equivalent to approximating the solution of a slightly perturbed problem!

1d: The right hand side

Consider the original and perturbed problems:

$$\begin{array}{ll} -\Delta u = f & \text{in } \Omega \\ u = 0 & \text{on } \partial\Omega \end{array} \qquad \begin{array}{ll} -\Delta \tilde{u} = \tilde{f} & \text{in } \Omega \\ u = 0 & \text{on } \partial\Omega \end{array}$$

Consequence:

$$\|u - \tilde{u}_h\|_{H^1} \leq \underbrace{\|u - \tilde{u}\|_{H^1}}_{\leq C_1 \|f - \tilde{f}\|_{H^{-1}} \leq C_2 h^{2n-k+1} \|f\|_{H^{2n-k}}} + \underbrace{\|\tilde{u} - \tilde{u}_h\|_{H^1}}_{\leq C_3 h^k \|\tilde{u}\|_{H^k}}$$

We want the first term to be at least as good as the second. We need to choose $n=k$.

Higher dimensions: The matrix

Question: Which quadrature rule should we choose?

$$A_{ij} \approx \sum_K \sum_{q=1}^Q J_K^{-1}(\hat{x}_q) \hat{\nabla} \hat{\phi}_i(\hat{x}_q) \cdot J_K^{-1}(\hat{x}_q) \hat{\nabla} \hat{\phi}_j(\hat{x}_q) |\det J_K(\hat{x}_q)| w_q$$

Consider the higher dimensional case:

- Use an element of polynomial degree k in each direction
- Use a d -linear mapping

Then:

- $J_K, \det J_K$ are polynomials of degree k, k^d
- J_K^{-1} is a rational function
- $\nabla \hat{\phi}_j(\hat{x}_q)$ is a polynomial of degree $dk-1$
- The integrand is rational
- For linear mappings, it is of degree $2(dk-1)$

Higher dimensions: The matrix

Question: Which quadrature rule should we choose?

$$A_{ij} \approx \sum_K \sum_{q=1}^Q J_K^{-1}(\hat{x}_q) \hat{\nabla} \hat{\phi}_i(\hat{x}_q) \cdot J_K^{-1}(\hat{x}_q) \hat{\nabla} \hat{\phi}_j(\hat{x}_q) |\det J_K(\hat{x}_q)| w_q$$

Consider the higher dimensional case:

- The integrand is rational
- For linear mappings, it is of degree $2(dk-1)$
- Gauss quadrature with n points per direction is exact for degree $2n-1$ in each variable

Nevertheless, using the tensor product structure:

We need to use Gauss quadrature with $n=k+1$ points per direction.

Higher dimensions: The right hand side

Question: Which quadrature rule should we choose?

$$F_i = (\phi_i, f) \approx \sum_K \sum_{q=1}^Q \hat{\phi}_i(\hat{x}_q) f(x_q) |\det J_K(\hat{x}_q)| w_q$$

Similar considerations can be applied:

We need to use Gauss quadrature with $n=k+1$ points per direction.

Summary

As a general rule of thumb:

- Gauss quadrature with $n=k+1$ points per direction is sufficient

- for the Laplace matrix $A_{ij} = (\nabla \phi_i, \nabla \phi_j)$

- for the mass matrix $M_{ij} = (\phi_i, \phi_j)$

- for the right hand side $F_i = (\phi_i, f)$

- It is generally also sufficient with variable coefficients:

$$A_{ij} = (a(x) \nabla \phi_i, \nabla \phi_j)$$

With $n=k+1$, the quadrature error does not dominate the overall error (if $a(x)$ is smooth).

Non-smooth coefficients

What to do with non-smooth terms?

For example

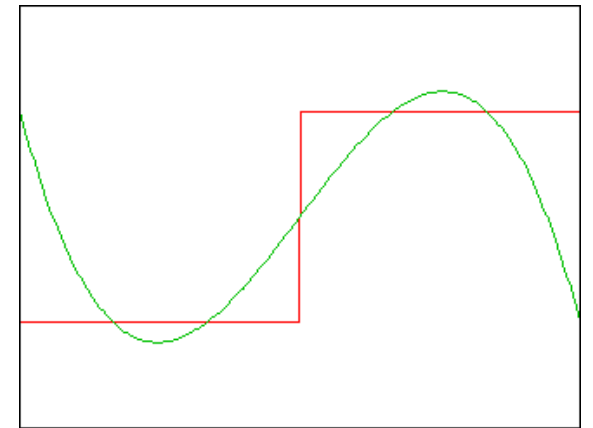
$$A_{ij} = (a(x) \nabla \phi_i, \nabla \phi_j)$$

$$F_i = (\phi_i, f)$$

where $a(x)$ or $f(x)$ are discontinuous.

Recall: Quadrature is equivalent to exact integration with an interpolated coefficient.

For discontinuous functions, interpolation does not help very much: Quadrature produces large errors.



Non-smooth coefficients

What to do with non-smooth terms?

For example

$$A_{ij} = (a(x) \nabla \phi_i, \nabla \phi_j)$$

$$F_i = (\phi_i, f)$$

where $a(x)$ or $f(x)$ are discontinuous.

Before:

$$\|u - \tilde{u}_h\|_{H^1} \leq \underbrace{\|u - \tilde{u}\|_{H^1}}_{\leq C_1 \|f - \tilde{f}\|_{H^{-1}} \leq C_2 h^{2n-k+1} \|f\|_{H^{2n-k}}} + \underbrace{\|\tilde{u} - \tilde{u}_h\|_{H^1}}_{\leq C_3 h^k \|\tilde{u}\|_{H^k}}$$

Now: The interpolation step fails! We may only get

$$\|u - \tilde{u}_h\|_{H^1} \leq \underbrace{\|u - \tilde{u}\|_{H^1}}_{\leq C_1 \|f - \tilde{f}\|_{H^{-1}} \leq C_2 h^{s+1} \|f\|_{H^s}} + \underbrace{\|\tilde{u} - \tilde{u}_h\|_{H^1}}_{\leq C_3 h^k \|\tilde{u}\|_{H^k}}$$

Non-smooth coefficients

What to do with non-smooth terms?

For example

$$A_{ij} = (a(x) \nabla \phi_i, \nabla \phi_j)$$

$$F_i = (\phi_i, f)$$

where $a(x)$ or $f(x)$ are discontinuous.

Now:

$$\|u - \tilde{u}_h\|_{H^1} \leq \underbrace{\|u - \tilde{u}\|_{H^1}}_{\leq C_1 \|f - \tilde{f}\|_{H^{-1}} \leq C_2 h^{s+1} \|f\|_{H^s}} + \underbrace{\|\tilde{u} - \tilde{u}_h\|_{H^1}}_{\leq C_3 h^k \|\tilde{u}\|_{H^k}}$$

Solution: Subdivide the cell into L pieces so that

$$C_2 \left(\frac{h}{L}\right)^{s+1} \|f\|_{H^s} \approx C_3 h^k \|\tilde{u}\|_{H^k}$$

This is what the *QIterated* class does.

Special purpose quadratures

There are situations where we want quadrature rules other than Gauss:

- To affect stability properties of a discretization
 - Underintegration for nearly incompressible elasticity
 - Special purpose quadrature for mixed problems
- To improve sparsity of matrices
 - Make some terms zero
 - Make a matrix diagonal

Sparsifying matrices

Using the trapezoidal rule for the Laplace matrix:

Assume:

- Uniform mesh with square cells
- Q_1 element with shape functions

$$\begin{aligned}\phi_1 &= (1 - \hat{x})(1 - \hat{y}), & \phi_2 &= \hat{x}(1 - \hat{y}), \\ \phi_3 &= (1 - \hat{x})\hat{y}, & \phi_4 &= \hat{x}\hat{y}\end{aligned}$$

and gradients

$$\begin{aligned}\hat{\nabla} \phi_1 &= \begin{pmatrix} -(1 - \hat{y}) \\ -(1 - \hat{x}) \end{pmatrix}, & \hat{\nabla} \phi_2 &= \begin{pmatrix} (1 - \hat{y}) \\ -\hat{x} \end{pmatrix} \\ \hat{\nabla} \phi_3 &= \begin{pmatrix} -\hat{y} \\ 1 - \hat{x} \end{pmatrix}, & \hat{\nabla} \phi_4 &= \begin{pmatrix} \hat{y} \\ \hat{x} \end{pmatrix}\end{aligned}$$

- Trapezoidal rule with integration points at the vertices

Sparsifying matrices

Using the trapezoidal rule for the Laplace matrix:

- Q_1 element with shape gradients

$$\hat{\nabla} \phi_1 = \begin{pmatrix} -(1-\hat{y}) \\ -(1-\hat{x}) \end{pmatrix}, \quad \hat{\nabla} \phi_2 = \begin{pmatrix} (1-\hat{y}) \\ -\hat{x} \end{pmatrix}$$
$$\hat{\nabla} \phi_3 = \begin{pmatrix} -\hat{y} \\ 1-\hat{x} \end{pmatrix}, \quad \hat{\nabla} \phi_4 = \begin{pmatrix} \hat{y} \\ \hat{x} \end{pmatrix}$$

- Trapezoidal rule with integration points at the vertices:

$$A_{ij} \approx \sum_K \sum_{q=1}^Q J_K^{-1}(\hat{x}_q) \hat{\nabla} \hat{\phi}_i(\hat{x}_q) \cdot J_K^{-1}(\hat{x}_q) \hat{\nabla} \hat{\phi}_j(\hat{x}_q) |\det J_K(\hat{x}_q)| w_q$$

- At all *vertices*, we have

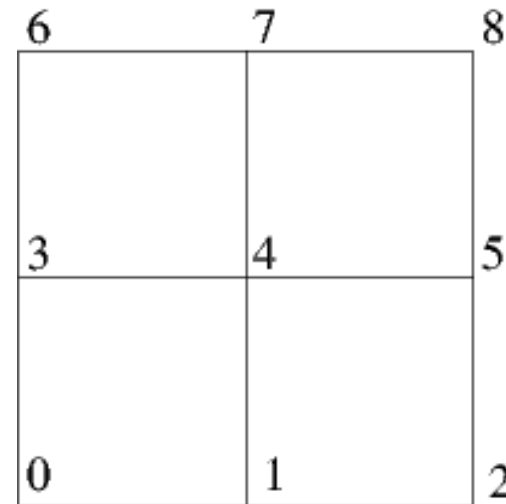
$$\nabla \phi_1 \cdot \nabla \phi_3 = 0, \quad \nabla \phi_2 \cdot \nabla \phi_4 = 0,$$

- Degrees of freedom diagonal across cells do not couple

Sparsifying matrices

Using the trapezoidal rule for the Laplace matrix:

- Degrees of freedom diagonal across cells do not couple:



- $A_{40} = A_{42} = A_{46} = A_{48} = 0$
- We can also show: $A_{41} = A_{43} = A_{45} = A_{47} = -A_{44}/4$
- This is exactly the 5-point stencil (\rightarrow finite differences)!
- In 3d, this leads to the usual 7-point stencil
- This matrix is sparser than normal

Diagonal mass matrices

Using the trapezoidal rule for the mass matrix:

- Q_1 element with shape values

$$\begin{aligned}\phi_1 &= (1 - \hat{x})(1 - \hat{y}), & \phi_2 &= \hat{x}(1 - \hat{y}), \\ \phi_3 &= (1 - \hat{x})\hat{y}, & \phi_4 &= \hat{x}\hat{y}\end{aligned}$$

- Trapezoidal rule with integration points at the vertices:

$$M_{ij} \approx \sum_K \sum_{q=1}^Q \hat{\phi}_i(\hat{x}_q) \hat{\phi}_j(\hat{x}_q) |\det J_K(\hat{x}_q)| w_q$$

- At all *vertices*, we have $\hat{\phi}_i(\hat{x}_q) \hat{\phi}_j(\hat{x}_q) = \delta_{ij} \delta_{iq}$ and thus

$$M_{ij} \approx \sum_K \left(\sum_{q=1}^Q |\det J_K(\hat{x}_q)| w_q \right) \delta_{ij} = \sum_K |K \cap \text{supp } \phi_i| \delta_{ij}$$

- This mass matrix is diagonal!

Diagonal mass matrices

Using the trapezoidal rule for the mass matrix:

- This results in a diagonal mass matrix
- This is useful in explicit time stepping schemes

- Generalized to arbitrary elements by choosing quadrature points at nodal interpolation points

Summary

General rule:

- Use Gaussian quadrature with $n=k+1$ per coordinate direction where k is the highest polynomial degree in your finite element
- Think about the implications if you have non-smooth coefficients
- Only use quadrature rules other than Gaussian if you know why.

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