

Singular quadrature for layer and volume potentials

Ludvig af Klinteberg (Chair)¹

Computational Tools for PDEs with Complicated Geometries and Interfaces
Day 3, 12 June 2024

¹Mälardalen University (MDU), Västerås, Sweden

Session plan

Start: 10.00

- Introduction talk (30–40 min), Ludvig af Klinteberg
- Quick break
- Short talks (5–10 min each)
 - Thomas G. Anderson, Rice
 - David Krantz, KTH
 - Zydrunas Gimbutas, NIST
 - Bowei Wu, UMass Lowell
- Group discussion

End: 12.30

Layer Potentials

We represent solutions to BVPs as layer potentials

$$u(\mathbf{x}) = \int_{\Gamma} k(\mathbf{x}, \mathbf{y}) \sigma(\mathbf{y}) d\mathbf{s}_{\mathbf{y}}$$

with k some weakly singular kernel e.g. Laplace 2D SLP $k(\mathbf{x}, \mathbf{y}) = \frac{1}{2\pi} \log \|\mathbf{x} - \mathbf{y}\|$

Density σ is solution to integral equation such as $(I + K)\sigma = f$ on Γ

Layer Potentials

We represent solutions to BVPs as layer potentials

$$u(\mathbf{x}) = \int_{\Gamma} k(\mathbf{x}, \mathbf{y}) \sigma(\mathbf{y}) d\mathbf{s}_{\mathbf{y}}$$

with k some weakly singular kernel e.g. Laplace 2D SLP $k(\mathbf{x}, \mathbf{y}) = \frac{1}{2\pi} \log \|\mathbf{x} - \mathbf{y}\|$

Density σ is solution to integral equation such as $(I + K)\sigma = f$ on Γ

We will need to evaluate $u(\mathbf{x})$ in three different regimes:

- **Smooth:** \mathbf{x} far away from Γ everything is easy here
- **Singular:** \mathbf{x} on Γ typically occurs when solving the integral equation
- **Nearly singular:** \mathbf{x} arbitrarily close to Γ surprisingly difficult

Input geometry

Our input is a geometry parametrization $\Gamma = \{\mathbf{y}(t) : t \in D\}$ line or surface

$$u(\mathbf{x}) = \int_{\Gamma} k(\mathbf{x}, \mathbf{y}) \sigma(\mathbf{y}) d\mathbf{s}_{\mathbf{y}} = \int_D k(\mathbf{x}, \mathbf{y}(t)) \sigma(t) |J_{\mathbf{y}}(t)| dt$$

note $\sigma(t) = \sigma(\mathbf{y}(t))$

Input geometry

Our input is a geometry parametrization $\Gamma = \{\mathbf{y}(t) : t \in D\}$ line or surface

$$u(\mathbf{x}) = \int_{\Gamma} k(\mathbf{x}, \mathbf{y}) \sigma(\mathbf{y}) d\mathbf{s}_{\mathbf{y}} = \int_D k(\mathbf{x}, \mathbf{y}(t)) \sigma(t) |J_{\mathbf{y}}(t)| dt$$

note $\sigma(t) = \sigma(\mathbf{y}(t))$

Parametrization can be:

- Analytical
- In terms of basis functions (polynomials, spherical harmonics, ...)
- (Just points will do, because we can interpolate to basis functions)

Layer Potential Discretization

We discretize with a quadrature rule $\{t_j, w_j\}$ for the *smooth* regime,

$$u(\mathbf{x}) = \int_{\Gamma} k(\mathbf{x}, \mathbf{y}) \sigma(\mathbf{y}) d\mathbf{s}_{\mathbf{y}} \approx \sum_{j=1}^N k(\mathbf{x}, \mathbf{y}(t_j)) \sigma(t_j) |J_{\mathbf{y}}(t_j)| w_j,$$

Layer Potential Discretization

We discretize with a quadrature rule $\{t_j, w_j\}$ for the *smooth* regime,

$$u(\mathbf{x}) = \int_{\Gamma} k(\mathbf{x}, \mathbf{y}) \sigma(\mathbf{y}) d\mathbf{s}_{\mathbf{y}} \approx \sum_{j=1}^N k(\mathbf{x}, \mathbf{y}(t_j)) \sigma(t_j) |J_{\mathbf{y}}(t_j)| w_j,$$

- Underlying/smooth quadrature is our base discretization
- Can *interpolate* surface quant. $(\sigma, \mathbf{y}, \partial_t \mathbf{y})$ from node data

Layer Potential Discretization

We discretize with a quadrature rule $\{t_j, w_j\}$ for the *smooth* regime,

$$u(\mathbf{x}) = \int_{\Gamma} k(\mathbf{x}, \mathbf{y}) \sigma(\mathbf{y}) d\mathbf{s}_{\mathbf{y}} \approx \sum_{j=1}^N k(\mathbf{x}, \mathbf{y}(t_j)) \sigma(t_j) |J_{\mathbf{y}}(t_j)| w_j,$$

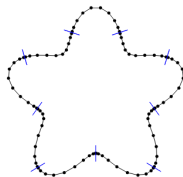
- Underlying/smooth quadrature is our base discretization
- Can *interpolate* surface quant. $(\sigma, \mathbf{y}, \partial_t \mathbf{y})$ from node data
- Quadrature either *global* or *local* (composite / panel-based)



Periodic trapezoidal rule (PTR)

trigonometric interpolation

error $\mathcal{O}(e^{-cp})$, $N \sim p^{d-1}$



Gauss-Legendre (G-L) panels

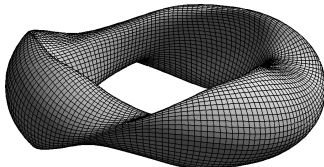
polynomial interpolation

error $\mathcal{O}(h^p)$, $N \sim \left(\frac{p}{h}\right)^{d-1}$

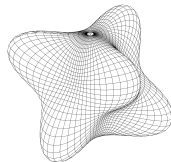
Global and local quadratures



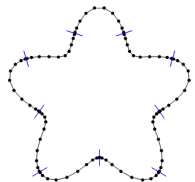
PTR



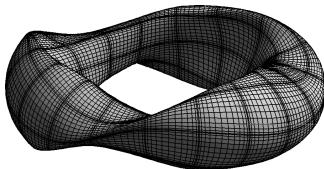
Double PTR



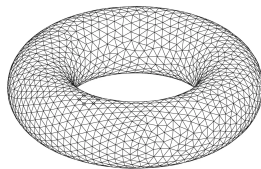
PTR + G-L



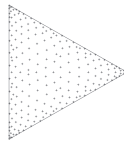
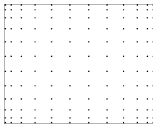
G-L panels



G-L (or Cheb.) quads



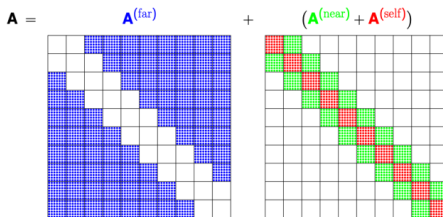
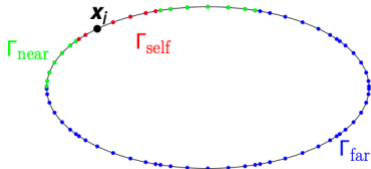
Vioreanu-Rokhlin triangles



What we need

The linear map that evaluates u from σ at a set of target points $\{\mathbf{x}_i\}$,
 $\mathbf{u} = \mathbf{A}\sigma$:

$$u(\mathbf{x}_i) = \sum_j a_{ij} \sigma_j,$$



What we need

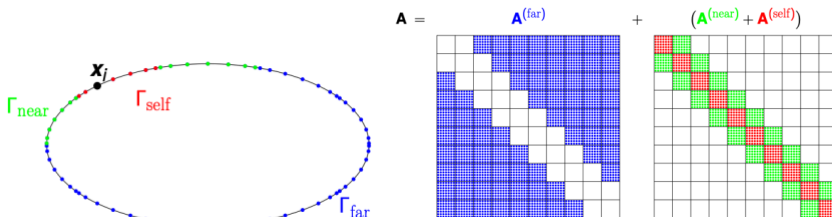
The linear map that evaluates u from σ at a set of target points $\{\mathbf{x}_i\}$,
 $\mathbf{u} = \mathbf{A}\sigma$:

$$u(\mathbf{x}_i) = \sum_j a_{ij} \sigma_j,$$

- For targets where smooth quadrature applies,

$$a_{ij} = k(\mathbf{x}_i, \mathbf{y}(t_j)) |J_{\mathbf{y}}(t_j)| w_j$$

This we can compute $\forall \mathbf{x}_i$ using fast methods (FMM)



What we need

The linear map that evaluates u from σ at a set of target points $\{\mathbf{x}_i\}$,
 $\mathbf{u} = \mathbf{A}\sigma$:

$$u(\mathbf{x}_i) = \sum_j a_{ij} \sigma_j,$$

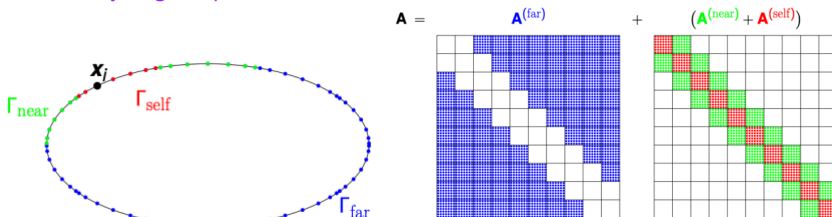
- For targets where smooth quadrature applies,

$$a_{ij} = k(\mathbf{x}_i, \mathbf{y}(t_j)) |J_{\mathbf{y}}(t_j)| w_j$$

This we can compute $\forall \mathbf{x}_i$ using fast methods (FMM)

- For other targets, we need something clever

Usually target-dependent: not FMM'able.



The problem

The kernel is composed of singularities and smooth parts, e.g.

$$\text{2D: } k(\mathbf{x}, \mathbf{y}) = k_0(\mathbf{x}, \mathbf{y}) + \log \|\mathbf{x} - \mathbf{y}\| k_L(\mathbf{x}, \mathbf{y}) + \frac{(\mathbf{x} - \mathbf{y}) \cdot \mathbf{n}}{\|\mathbf{x} - \mathbf{y}\|^2} k_2(\mathbf{x}, \mathbf{y}) + \dots$$

$$\text{3D: } k(\mathbf{x}, \mathbf{y}) = k_0(\mathbf{x}, \mathbf{y}) + \frac{k_1(\mathbf{x}, \mathbf{y})}{\|\mathbf{x} - \mathbf{y}\|} + \frac{(\mathbf{x} - \mathbf{y}) \cdot \mathbf{n}}{\|\mathbf{x} - \mathbf{y}\|^3} k_3(\mathbf{x}, \mathbf{y}) + \dots$$

with $k_{(\cdot)}(\mathbf{x}, \mathbf{y})$ smooth functions in \mathbf{y} . We can usually write down this split.

The problem

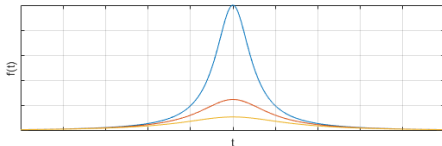
The kernel is composed of singularities and smooth parts, e.g.

$$\text{2D: } k(\mathbf{x}, \mathbf{y}) = k_0(\mathbf{x}, \mathbf{y}) + \log \|\mathbf{x} - \mathbf{y}\| k_L(\mathbf{x}, \mathbf{y}) + \frac{(\mathbf{x} - \mathbf{y}) \cdot \mathbf{n}}{\|\mathbf{x} - \mathbf{y}\|^2} k_2(\mathbf{x}, \mathbf{y}) + \dots$$

$$\text{3D: } k(\mathbf{x}, \mathbf{y}) = k_0(\mathbf{x}, \mathbf{y}) + \frac{k_1(\mathbf{x}, \mathbf{y})}{\|\mathbf{x} - \mathbf{y}\|} + \frac{(\mathbf{x} - \mathbf{y}) \cdot \mathbf{n}}{\|\mathbf{x} - \mathbf{y}\|^3} k_3(\mathbf{x}, \mathbf{y}) + \dots$$

with $k_{(\cdot)}(\mathbf{x}, \mathbf{y})$ smooth functions in \mathbf{y} . We can usually write down this split.

- **Smooth regime:** $\|\mathbf{x} - \mathbf{y}\|$ varies slowly when \mathbf{x} far from Γ
- **Singular regime:** Weak (integrable) singularities as $\mathbf{y} \rightarrow \mathbf{x}$
- **Nearly singular regime:** $k(\mathbf{x}, \mathbf{y})$ "sharply peaked" when \mathbf{x} close to Γ



TODO: Fix better plot

Kernels on Complex Form

Things get simpler in 2D if we use complex variables.

Let (ζ, τ) correspond to (\mathbf{x}, \mathbf{y}) in \mathbb{C} , then the Laplace DLP is

$$\int_{\Gamma} \frac{(\mathbf{x} - \mathbf{y}) \cdot \mathbf{n}}{\|\mathbf{x} - \mathbf{y}\|^2} \sigma(\mathbf{y}) d\mathbf{s}_{\mathbf{y}} = \text{Im} \int_{\Gamma} \frac{\sigma(\tau)}{\tau - \zeta} d\tau$$

Kernels on Complex Form

Things get simpler in 2D if we use complex variables.

Let (ζ, τ) correspond to (\mathbf{x}, \mathbf{y}) in \mathbb{C} , then the Laplace DLP is

$$\int_{\Gamma} \frac{(\mathbf{x} - \mathbf{y}) \cdot \mathbf{n}}{\|\mathbf{x} - \mathbf{y}\|^2} \sigma(\mathbf{y}) d\mathbf{s}_{\mathbf{y}} = \text{Im} \int_{\Gamma} \frac{\sigma(\tau)}{\tau - \zeta} d\tau$$

Other kernels leave us with integrals on the form

$$\int_{\Gamma} g(\tau) \log(\tau - \zeta) d\tau \quad \text{and} \quad \int_{\Gamma} \frac{g(\tau)}{(\tau - \zeta)^q} d\tau, \quad q = 1, 2, \dots$$

with $g(\tau)$ smooth and implicitly dependent on ζ .

Kernels on Complex Form

Things get simpler in 2D if we use complex variables.

Let (ζ, τ) correspond to (\mathbf{x}, \mathbf{y}) in \mathbb{C} , then the Laplace DLP is

$$\int_{\Gamma} \frac{(\mathbf{x} - \mathbf{y}) \cdot \mathbf{n}}{\|\mathbf{x} - \mathbf{y}\|^2} \sigma(\mathbf{y}) d\mathbf{s}_{\mathbf{y}} = \text{Im} \int_{\Gamma} \frac{\sigma(\tau)}{\tau - \zeta} d\tau$$

Other kernels leave us with integrals on the form

$$\int_{\Gamma} g(\tau) \log(\tau - \zeta) d\tau \quad \text{and} \quad \int_{\Gamma} \frac{g(\tau)}{(\tau - \zeta)^q} d\tau, \quad q = 1, 2, \dots$$

with $g(\tau)$ smooth and implicitly dependent on ζ .

With parametrization $\Gamma = \{\gamma(t) : t \in [0, 2\pi)\}$

$$\int_{\Gamma} \frac{g(\tau)}{(\tau - \zeta)^q} d\tau = \int_0^{2\pi} \frac{g(\gamma(t))}{(\gamma(t) - \zeta)^q} |\gamma'(t)| dt = \int_0^{2\pi} \frac{f(t)}{(\gamma(t) - \zeta)^q} dt$$

$f(t) = g(\gamma(t))|\gamma'(t)|$ is also assumed smooth

Singular quadrature: 2D

- Smooth quadrature has fixed (t_j, w_j) for all smooth integrands,

$$\int_a^b f(t)dt = \sum_{j=1}^n f(t_j)w_j$$

Singular quadrature: 2D

- Smooth quadrature has fixed (t_j, w_j) for all smooth integrands,

$$\int_a^b f(t)dt = \sum_{j=1}^n f(t_j)w_j$$

- Singular quadrature is tailored on type of quadrature and location t_0 .
E.g. $f(t) = k_0(t) + \log|t - t_0|k_L(t)$

Singular quadrature: 2D

- Smooth quadrature has fixed (t_j, w_j) for all smooth integrands,

$$\int_a^b f(t) dt = \sum_{j=1}^n f(t_j) w_j$$

- Singular quadrature is tailored on type of quadrature and location t_0 .
E.g. $f(t) = k_0(t) + \log|t - t_0| k_L(t)$
 - **Product quadrature** integrates the singularity explicitly, $\tilde{w}_i = \tilde{w}_i(t_0)$

$$\int_a^b \log|t - t_0| k_L(t) dt = \sum_{j=1}^n f_L(t_j) \tilde{w}_j$$

Singular quadrature: 2D

- Smooth quadrature has fixed (t_j, w_j) for all smooth integrands,

$$\int_a^b f(t)dt = \sum_{j=1}^n f(t_j)w_j$$

- Singular quadrature is tailored on type of quadrature and location t_0 .
E.g. $f(t) = k_0(t) + \log|t - t_0|k_L(t)$
 - Product quadrature** integrates the singularity explicitly, $\tilde{w}_i = \tilde{w}_i(t_0)$

$$\int_a^b \log|t - t_0|k_L(t)dt = \sum_{j=1}^n f_L(t_j)\tilde{w}_i$$

- Implicit rules** integrate the complete expression, $\tilde{t}_i, \tilde{w}_i = \tilde{t}_i(t_0), \tilde{w}_i(t_0)$

$$\text{Modified weights: } \int_a^b f(t)dt = \sum_{j=1}^n f(t_j)\tilde{w}_i$$

$$\text{Auxiliary nodes: } \int_a^b f(t)dt = \sum_{j=1}^{\tilde{n}} f(\tilde{t}_i)\tilde{w}_i$$

Singular quadrature: 2D Global (PTR)

(Review by Hao et al. 2013)

- **Spectral accuracy:**

Kress product quadrature $\oint_{\Gamma} \log \|\mathbf{x} - \mathbf{y}\| f(\mathbf{y}) d\mathbf{s}_{\mathbf{y}} = \sum_{j=1}^N f(\mathbf{y}_j) w_j$

Requires split $k_0(\mathbf{x}, \mathbf{y}) + \log \|\mathbf{x} - \mathbf{y}\| k_L(\mathbf{x}, \mathbf{y})$

Singular quadrature: 2D Global (PTR)

(Review by Hao et al. 2013)

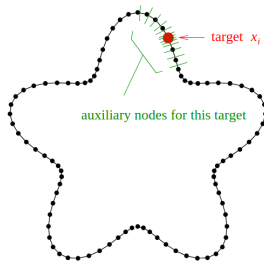
- **Spectral accuracy:**

Kress product quadrature $\oint_{\Gamma} \log \|\mathbf{x} - \mathbf{y}\| f(\mathbf{y}) d\mathbf{s}_{\mathbf{y}} = \sum_{j=1}^N f(\mathbf{y}_j) w_j$

Requires split $k_0(\mathbf{x}, \mathbf{y}) + \log \|\mathbf{x} - \mathbf{y}\| k_L(\mathbf{x}, \mathbf{y})$

- ***p*th order accuracy:**

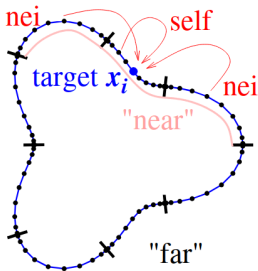
- *Kapur–Rokhlin* modifies fixed number of weights near sing.
- *Alpert* introduces fixed number of nodes and weights near sing.



Singular quadrature: 2D Local (G-L panels)

Maintains p th order accuracy of panels.

- *Helsing* product quadrature
 - For $\int_{\tau_a}^{\tau_b} g(\tau) \log(\tau - \zeta) d\tau$ and $\int_{\tau_a}^{\tau_b} \frac{g(\tau)}{(\tau - \zeta)^q} d\tau$
 - Requires explicit kernel split

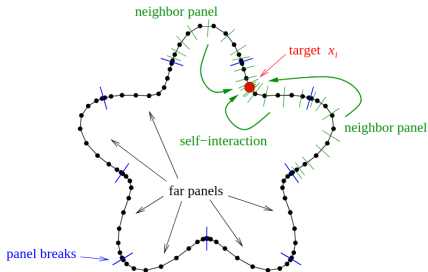
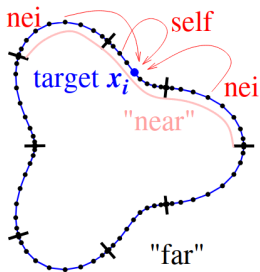


Neighboring panels must be involved.

Singular quadrature: 2D Local (G-L panels)

Maintains p th order accuracy of panels.

- *Helsing* product quadrature
 - For $\int_{\tau_a}^{\tau_b} g(\tau) \log(\tau - \zeta) d\tau$ and $\int_{\tau_a}^{\tau_b} \frac{g(\tau)}{(\tau - \zeta)^q} d\tau$
 - Requires explicit kernel split
- *Generalized Gaussian* quadrature
 - Forms nodes and weights through nonlinear optimization
 - Needs singularity type and location, but not explicit split



Neighboring panels must be involved.

Near singularity?

Can understand near singularity through analytic continuation of $\gamma(t)$:

- Find preimage t_0 such that $\gamma(t_0) = \zeta$ Done using poly. approx.

$$\int_D \frac{f(t)dt}{(\gamma(t) - \zeta)^p} = \int_D \frac{f(t)dt}{(\gamma(t) - \gamma(t_0))^p}$$

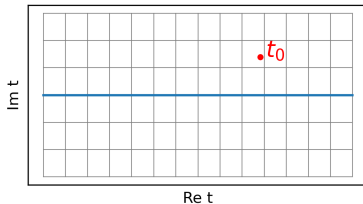
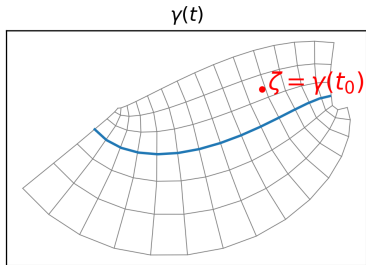
Near singularity?

Can understand near singularity through analytic continuation of $\gamma(t)$:

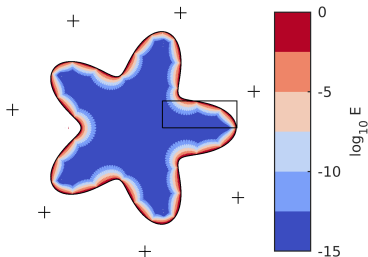
- Find preimage t_0 such that $\gamma(t_0) = \zeta$ Done using poly. approx.

$$\int_D \frac{f(t)dt}{(\gamma(t) - \zeta)^p} = \int_D \frac{f(t)dt}{(\gamma(t) - \gamma(t_0))^p}$$

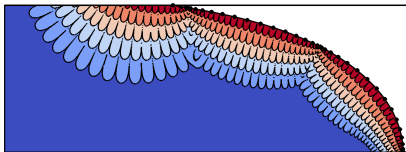
- Clear where singularity is *in parametrization* t
- t_0 bounds region of analyticity of integrand



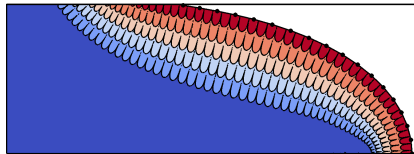
Close evaluation errors



Gauss-Legendre panels



Trapezoidal

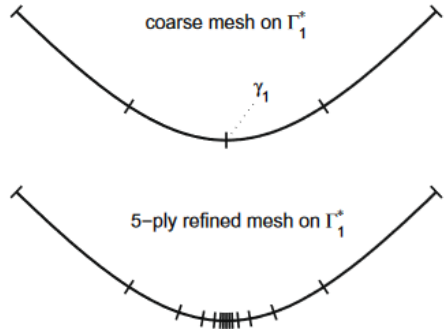
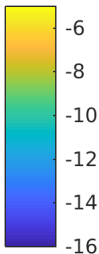
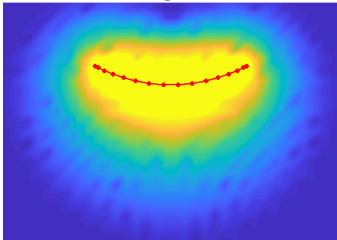


Black contours are estimates based on having found t_0

2D: Nearly singular quadrature

- Many different ideas and methods.
- Easiest: Upsampling to more points
- More efficient: Adaptive refinement near target
- Very effective in 2D: Helsing quadrature (or variant SSQ based on t_0)

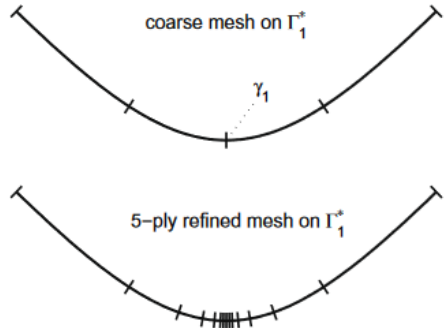
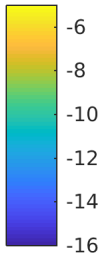
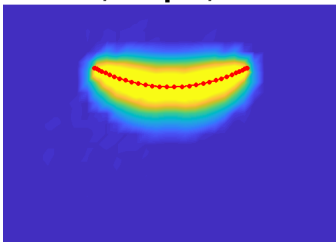
Direct, 16 pts, $k=0.25$



2D: Nearly singular quadrature

- Many different ideas and methods.
- Easiest: Upsampling to more points
- More efficient: Adaptive refinement near target
- Very effective in 2D: Helsing quadrature (or variant SSQ based on t_0)

Direct, 32 pts, $k=0.25$



Interlude: Helsing product quadrature

Want to compute nearly singular

$$I = \int_{\Gamma} \frac{g(\tau)}{(\tau - \zeta)^q} d\tau = \int_{\tau_a}^{\tau_b} \frac{g(\tau)}{(\tau - \zeta)^q} d\tau = \{\text{var. change}\} = \int_{-1}^1 \frac{g(\tau)}{(\tau - \zeta)^q} d\tau$$

Interlude: Helsing product quadrature

Want to compute nearly singular

$$I = \int_{\Gamma} \frac{g(\tau)}{(\tau - \zeta)^q} d\tau = \int_{\tau_a}^{\tau_b} \frac{g(\tau)}{(\tau - \zeta)^q} d\tau = \{\text{var. change}\} = \int_{-1}^1 \frac{g(\tau)}{(\tau - \zeta)^q} d\tau$$

- Form monomial expansion $g(\tau) = \sum_{j=0}^{n-1} c_k \tau^k$ by solving Vandermonde system $V\mathbf{c} = \mathbf{g}$ Not a problem for $n < 40$

Interlude: Helsing product quadrature

Want to compute nearly singular

$$I = \int_{\Gamma} \frac{g(\tau)}{(\tau - \zeta)^q} d\tau = \int_{\tau_a}^{\tau_b} \frac{g(\tau)}{(\tau - \zeta)^q} d\tau = \{\text{var. change}\} = \int_{-1}^1 \frac{g(\tau)}{(\tau - \zeta)^q} d\tau$$

- Form monomial expansion $g(\tau) = \sum_{j=0}^{n-1} c_j \tau^j$ by solving Vandermonde system $V\mathbf{c} = \mathbf{g}$ Not a problem for $n < 40$
- Recursively compute $p_k = \int_{-1}^1 \frac{\tau^k}{(\tau - \zeta)^q} d\tau$

Interlude: Helsing product quadrature

Want to compute nearly singular

$$I = \int_{\Gamma} \frac{g(\tau)}{(\tau - \zeta)^q} d\tau = \int_{\tau_a}^{\tau_b} \frac{g(\tau)}{(\tau - \zeta)^q} d\tau = \{\text{var. change}\} = \int_{-1}^1 \frac{g(\tau)}{(\tau - \zeta)^q} d\tau$$

- Form monomial expansion $g(\tau) = \sum_{j=0}^{n-1} c_j \tau^j$ by solving Vandermonde system $V\mathbf{c} = \mathbf{g}$ Not a problem for $n < 40$
- Recursively compute $p_k = \int_{-1}^1 \frac{\tau^k}{(\tau - \zeta)^q} d\tau$
- Quadrature is now product

$$\int_{-1}^1 \frac{g(\tau)}{(\tau - \zeta)^q} d\tau \approx \sum_{j=0}^{n-1} c_j p_j = \mathbf{c}^T \mathbf{p}$$

Interlude: Helsing product quadrature

Want to compute nearly singular

$$I = \int_{\Gamma} \frac{g(\tau)}{(\tau - \zeta)^q} d\tau = \int_{\tau_a}^{\tau_b} \frac{g(\tau)}{(\tau - \zeta)^q} d\tau = \{\text{var. change}\} = \int_{-1}^1 \frac{g(\tau)}{(\tau - \zeta)^q} d\tau$$

- Form monomial expansion $g(\tau) = \sum_{j=0}^{n-1} c_j \tau^j$ by solving Vandermonde system $V\mathbf{c} = \mathbf{g}$ Not a problem for $n < 40$
- Recursively compute $p_k = \int_{-1}^1 \frac{\tau^k}{(\tau - \zeta)^q} d\tau$
- Quadrature is now product

$$\int_{-1}^1 \frac{g(\tau)}{(\tau - \zeta)^q} d\tau \approx \sum_{j=0}^{n-1} c_j p_j = \mathbf{c}^T \mathbf{p}$$

- We actually want weights w_j s.t. $I \approx \sum g(t_j) w_j = \mathbf{g}^T \mathbf{w}$
- These we get by solving adjoint Vandermonde $V^T \mathbf{w} = \mathbf{p}$

Interpolation and precomputation

- Quadrature often ends up needing σ at new nodes (upsampling, adaptive refinement, auxiliary nodes, ...)

$$\int_{\Gamma} k(\mathbf{x}, \mathbf{y}) \sigma(\mathbf{y}) d\mathbf{s}_{\mathbf{y}} \approx \sum_{j=1}^{\tilde{n}} k(\mathbf{x}, \mathbf{y}(\tilde{t}_j)) \sigma(\tilde{t}_j) |J_{\mathbf{y}}(\tilde{t}_j)| \tilde{w}_j = \tilde{\mathbf{a}}^T \tilde{\boldsymbol{\sigma}},$$

Interpolation and precomputation

- Quadrature often ends up needing σ at new nodes (upsampling, adaptive refinement, auxiliary nodes, ...)

$$\int_{\Gamma} k(\mathbf{x}, \mathbf{y}) \sigma(\mathbf{y}) d\mathbf{s}_{\mathbf{y}} \approx \sum_{j=1}^{\tilde{n}} k(\mathbf{x}, \mathbf{y}(\tilde{\mathbf{t}}_j)) \sigma(\tilde{\mathbf{t}}_j) |J_{\mathbf{y}}(\tilde{\mathbf{t}}_j)| \tilde{w}_j = \tilde{\mathbf{a}}^T \tilde{\boldsymbol{\sigma}},$$

- Density at new nodes we get through interpolation

$$\tilde{\boldsymbol{\sigma}} = \underbrace{P}_{\tilde{n} \times n} \boldsymbol{\sigma}, \quad \tilde{n} > n$$

Interpolation and precomputation

- Quadrature often ends up needing σ at new nodes (upsampling, adaptive refinement, auxiliary nodes, ...)

$$\int_{\Gamma} k(\mathbf{x}, \mathbf{y}) \sigma(\mathbf{y}) d\mathbf{s}_{\mathbf{y}} \approx \sum_{j=1}^{\tilde{n}} k(\mathbf{x}, \mathbf{y}(\tilde{t}_j)) \sigma(\tilde{t}_j) |J_{\mathbf{y}}(\tilde{t}_j)| \tilde{w}_j = \tilde{\mathbf{a}}^T \tilde{\boldsymbol{\sigma}},$$

- Density at new nodes we get through interpolation

$$\tilde{\boldsymbol{\sigma}} = \underbrace{P}_{\tilde{n} \times n} \boldsymbol{\sigma}, \quad \tilde{n} > n$$

- If reusable, we can compress this into $\mathbf{a} = P^T \tilde{\mathbf{a}}$ such that

$$\mathbf{a}^T \boldsymbol{\sigma} = \tilde{\mathbf{a}}^T \tilde{\boldsymbol{\sigma}}$$

- \mathbf{a} corresponds to modified row entries in A matrix

QBX

Very different idea: Quadrature By eXpansion. For 2D Laplace DLP

$$u(\zeta) = \int_{\Gamma} \frac{g(\tau)}{(\tau - \zeta)} d\tau = \sum_{m=0}^{\infty} (\zeta - \zeta_0)^m \underbrace{\int_{\Gamma} \frac{g(\tau)}{(\tau - \zeta_0)^{m+1}} d\tau}_{c_m(\zeta_0)}$$

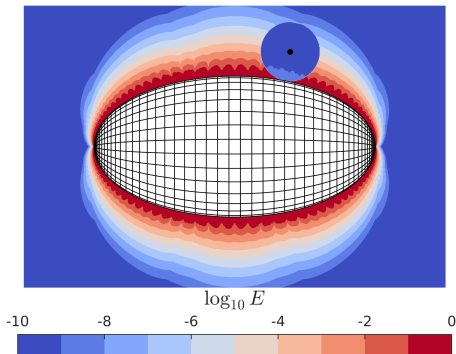
for $|\zeta - \zeta_0| \leq \sup_{\tau \in \Gamma} |\tau - \zeta_0|$.

QBX

Very different idea: Quadrature By eXpansion. For 2D Laplace DLP

$$u(\zeta) = \int_{\Gamma} \frac{g(\tau)}{(\tau - \zeta)} d\tau = \sum_{m=0}^{\infty} (\zeta - \zeta_0)^m \underbrace{\int_{\Gamma} \frac{g(\tau)}{(\tau - \zeta_0)^{m+1}} d\tau}_{c_m(\zeta_0)}$$

for $|\zeta - \zeta_0| \leq \sup_{\tau \in \Gamma} |\tau - \zeta_0|$. Same idea extends to 3D.

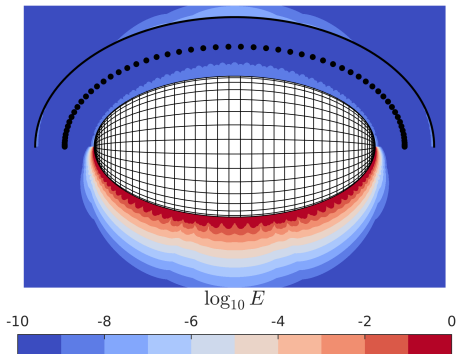


QBX

Very different idea: Quadrature By eXpansion. For 2D Laplace DLP

$$u(\zeta) = \int_{\Gamma} \frac{g(\tau)}{(\tau - \zeta)} d\tau = \sum_{m=0}^{\infty} (\zeta - \zeta_0)^m \underbrace{\int_{\Gamma} \frac{g(\tau)}{(\tau - \zeta_0)^{m+1}} d\tau}_{c_m(\zeta_0)}$$

for $|\zeta - \zeta_0| \leq \sup_{\tau \in \Gamma} |\tau - \zeta_0|$. Same idea extends to 3D.

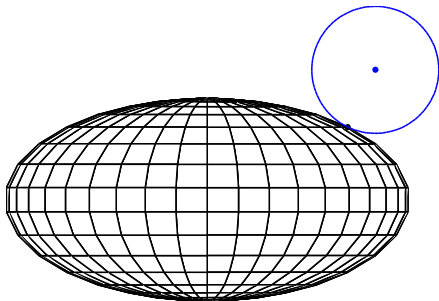
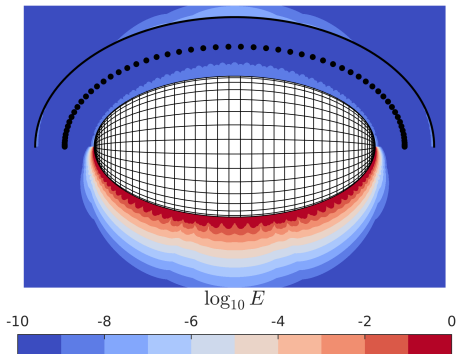


QBX

Very different idea: Quadrature By eXpansion. For 2D Laplace DLP

$$u(\zeta) = \int_{\Gamma} \frac{g(\tau)}{(\tau - \zeta)} d\tau = \sum_{m=0}^{\infty} (\zeta - \zeta_0)^m \underbrace{\int_{\Gamma} \frac{g(\tau)}{(\tau - \zeta_0)^{m+1}} d\tau}_{c_m(\zeta_0)}$$

for $|\zeta - \zeta_0| \leq \sup_{\tau \in \Gamma} |\tau - \zeta_0|$. Same idea extends to 3D.

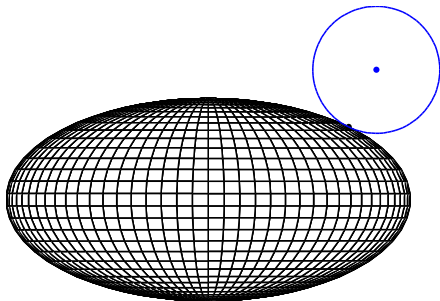
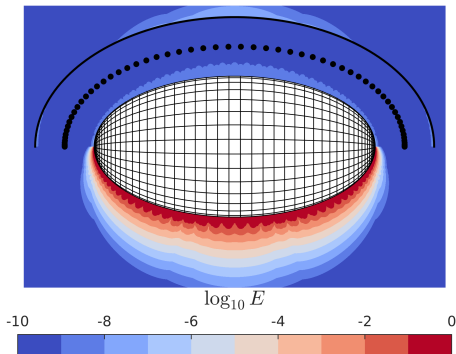


QBX

Very different idea: Quadrature By eXpansion. For 2D Laplace DLP

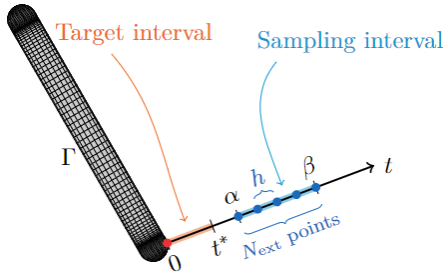
$$u(\zeta) = \int_{\Gamma} \frac{g(\tau)}{(\tau - \zeta)} d\tau = \sum_{m=0}^{\infty} (\zeta - \zeta_0)^m \underbrace{\int_{\Gamma} \frac{g(\tau)}{(\tau - \zeta_0)^{m+1}} d\tau}_{c_m(\zeta_0)}$$

for $|\zeta - \zeta_0| \leq \sup_{\tau \in \Gamma} |\tau - \zeta_0|$. Same idea extends to 3D.



Hedgehog

- Same underlying idea as QBX: Expand solution in domain
- Here: Along a line
- Simple, but hard to optimize



3D: Everything harder

Weak sing. integrable if at center of polar coord. system on surface

$$\int_D k(\mathbf{x}, \mathbf{y}(r, \theta)) \sigma(r, \theta) |J_{\mathbf{y}}(r, \theta)| r dr d\theta$$

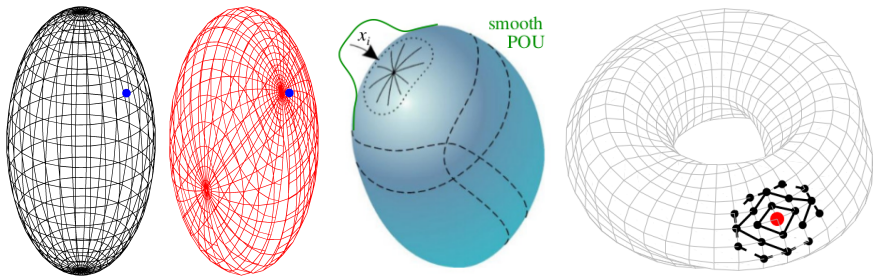
3D: Everything harder

Weak sing. integrable if at center of polar coord. system on surface

$$\int_D k(\mathbf{x}, \mathbf{y}(r, \theta)) \sigma(r, \theta) |J_{\mathbf{y}}(r, \theta)| r dr d\theta$$

Global discretization:

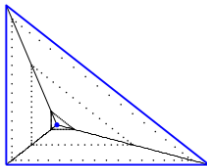
Grid rotations / Local patch / High-order correction



Other approaches: Regularization, singularity subtraction (limited order)

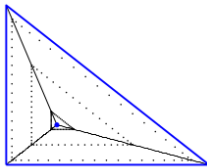
Local discretization: As used in FMM3DBIE

Singular: Auxiliary nodes from generalized Gaussian quadrature

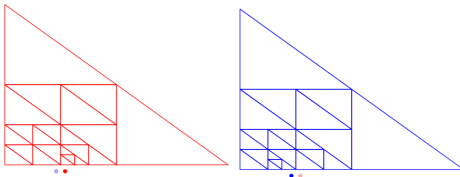


Local discretization: As used in FMM3DBIE

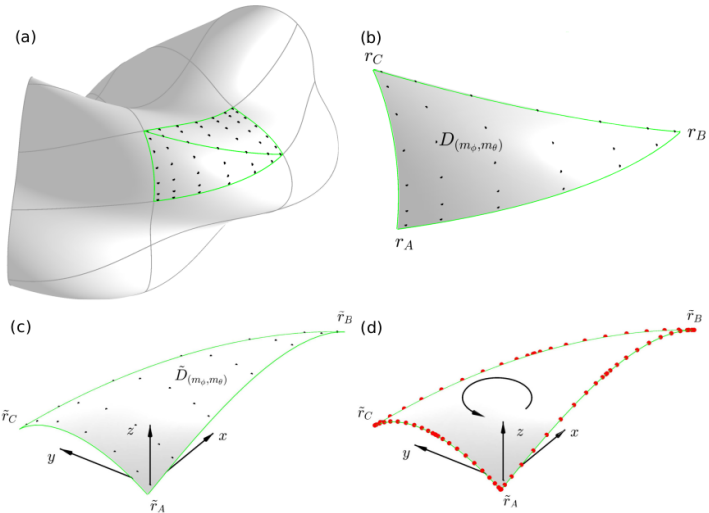
Singular: Auxiliary nodes from generalized Gaussian quadrature



Close eval: Adaptive refinement



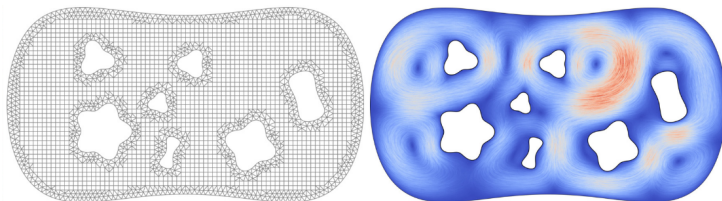
New alternative: Product quadrature using Stokes theorem



Volume potentials

Did not mention these much.

$$V[\sigma](\mathbf{x}) = \int_{\Omega} k(\mathbf{x}, \mathbf{y}) \sigma(\mathbf{y}) d\mathbf{y}$$



(Anderson et al.)

Looking forward

- 2D can be considered solved, focus on 3D!
- Wishlist:
 - Close eval & On-surface & Volume
 - High order
 - Fast, parallelizable (moving / deforming geometries)
 - Robust w.r.t. geometry
 - Generalizable to the full zoo of kernels

(Apologies for figures stolen and credit not given.)

