

MONTE CARLO GEOMETRY PROCESSING A GRID-FREE APPROACH TO PDEs

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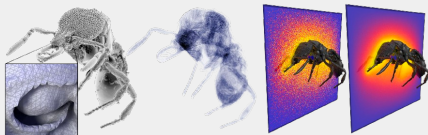
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MASTER MVA : GEOMETRIC DATA ANALYSIS

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MOTIVATION: WHY MESH-FREE?

- **Goal:** solve PDEs on complex domains **without volumetric meshing** (Monte Carlo).
- **Why avoid meshes?**
 - ▶ Meshing is costly and brittle (hours; holes / noisy scans).
 - ▶ A mesh **approximates** geometry \Rightarrow loss of detail + geometric error.
- **Takeaway:** work directly on raw geometry \Rightarrow **Walk-on-Spheres.**



FROM BROWNIAN MOTION TO WALK ON SPHERES

Problem

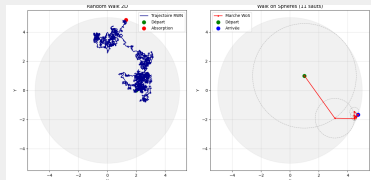
$$\begin{cases} \Delta u(x) = 0 & x \in \Omega \\ u(x) = g(x) & x \in \partial\Omega \end{cases} \quad (\text{Laplace equation})$$

Kakutani's principle

$$u(x) = \mathbb{E}[g(W_\tau) \mid W_0 = x]$$

Mean Value Property

$$u(x) = \frac{1}{|\partial B(x)|} \int_{\partial B(x)} u(y) dy$$



2D Random walk VS WoS

Idea

Brownian motion \rightarrow many small steps

Walk on Spheres \rightarrow direct jumps to sphere boundaries

MONTE CARLO ESTIMATOR

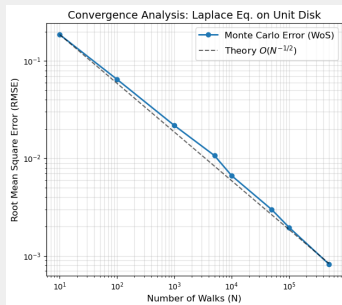
We simulate n WoS trajectory : $x_0, x_{1_i}, \dots, x_{s_i}$ for $1 \leq i \leq n$.

Our estimator is then:

$$\hat{u}_n(x) = \frac{1}{n} \sum_{i=1}^n g(x_{s_i}).$$

Monte Carlo convergence :

$$\begin{aligned} \text{RMSE} &= \sqrt{\mathbb{E}[(\hat{u} - u)^2]} \\ &= \mathcal{O}\left(\frac{1}{\sqrt{N}}\right) \end{aligned}$$



RMSE convergence of the Monte Carlo estimator

ALGORITHM

Require: Query point x_0 , Boundary $\partial\Omega$, Tolerance ϵ , Number of walks N

```
1:  $u_{sum} \leftarrow 0$ 
2: for  $i \leftarrow 1$  to  $N$  do
3:    $x \leftarrow x_0$  ▷ Start a new walk
4:   while  $d(x, \partial\Omega) > \epsilon$  do
5:      $R \leftarrow d(x, \partial\Omega)$ 
6:      $\vec{v} \leftarrow \text{UniformSampleUnitSphere}()$ 
7:      $x \leftarrow x + R \cdot \vec{v}$  ▷ Jump to sphere surface
8:   end while
9:    $x_b \leftarrow \text{ClosestPoint}(x, \partial\Omega)$ 
10:   $u_{sum} \leftarrow u_{sum} + g(x_b)$  ▷ Accumulate boundary value
11: end for
12: return  $u_{sum}/N$  ▷ Return average
```

EXTENDING TO POISSON: HANDLING SOURCE TERMS

Problem

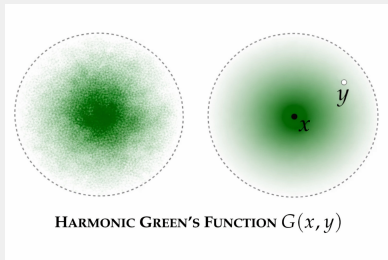
$$\begin{cases} \Delta u(x) = f(x) & x \in \Omega \\ u(x) = g(x) & x \in \partial\Omega \end{cases} \quad (\text{Poisson equation})$$

Stochastic representation (any domain)

$$\mathbb{E} \left[\int_0^T f(W_t) dt \mid W_0 = x \right]$$

Integral representation (source term on ball)

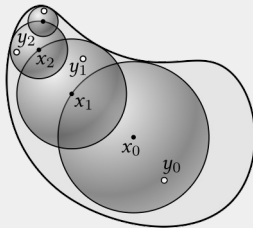
$$\int_{B(x)} f(y) G(x, y) dy$$



Monte Carlo estimator

$$\hat{u}(x_k) = \begin{cases} g(\bar{x}_k), & x_k \in \partial\Omega_\varepsilon, \\ \hat{u}(x_{k+1}) + |B(x_k)| f(y_k) G(x_k, y_k), & \end{cases}$$

ALGORITHM



Require: Query point x_0 , Boundary $\partial\Omega$, Tolerance ϵ , Number of walks N

```
1:  $u_{sum} \leftarrow 0$ 
2: for  $i \leftarrow 1$  to  $N$  do
3:    $x \leftarrow x_0$  ▷ Start a new walk
4:   while  $d(x, \partial\Omega) > \epsilon$  do
5:      $R \leftarrow d(x, \partial\Omega)$ 
6:      $y \leftarrow \text{UniformSampleBall}(x, R)$  ▷ Random point inside ball
7:      $u_{sum} \leftarrow u_{sum} + \pi R^2 G(x, y, R) f(y)$  ▷ Source contribution
8:      $\vec{v} \leftarrow \text{UniformSampleUnitSphere}()$ 
9:      $x \leftarrow x + R \cdot \vec{v}$  ▷ Jump to sphere surface
10:  end while
11:   $x_b \leftarrow \text{ClosestPoint}(x, \partial\Omega)$ 
12:   $u_{sum} \leftarrow u_{sum} + g(x_b)$  ▷ Accumulate boundary value
13: end for
14: return  $u_{sum}/N$  ▷ Return average
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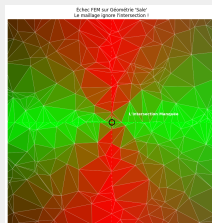
ADVANTAGES

Problem

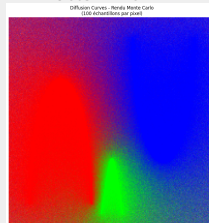
- Challenge: Impossible to mesh cleanly for FEM.
- If we extend this diffusion problem in 3D, the computational time and memory take by pre-processing will explode.

Result

- infinite zoom
- parameter ϵ
- mesh.



Problem with FEM

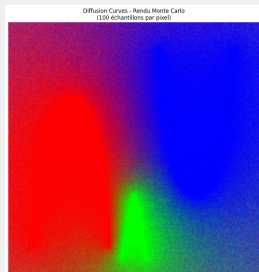


diffusion with Bézier curves

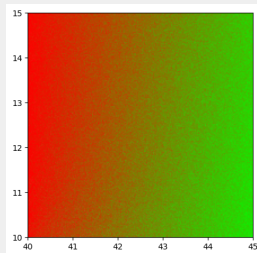
THE "INFINITE ZOOM"

Local Evaluation Property

Unlike FEM, we can compute the solution at a specific window without solving the global system.



Global View



Zoom $\times 10$

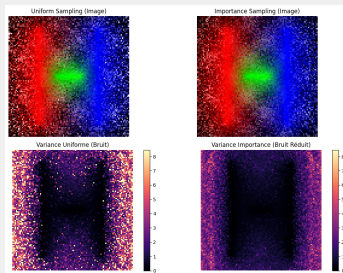
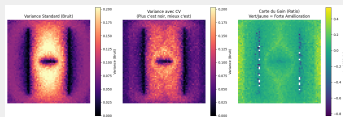
VARIANCE REDUCTION

Problem: Monte Carlo noise is high for complex sources. We have to reduce variance.

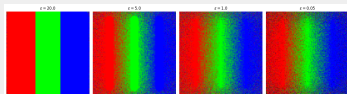
Techniques Implemented:

- Control Variates
- Importance Sampling

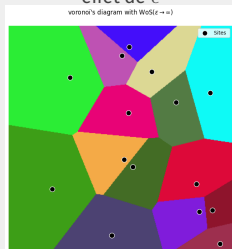
→ Significant reduction in RMSE for the same computational budget.



PARAMETER ϵ



effet de ϵ



Effect when ϵ tends to infinity

- **Problem:** Will ϵ change our final figure?
- Computational cost = $O(\log(1/\epsilon))$
- A large tolerance can be useful in other applications like Voronoi diagram.

CRITICAL LIMITATIONS

We identified two major bottlenecks in our stress tests:

1. The "Blindness" Problem

- *Scenario:* Narrow tunnels (dumbbell shape).
- *Issue:* Random walkers get trapped, bouncing inside the tunnel.
- *Result:* Convergence takes minutes vs seconds for FEM.

2. Gradient Explosion

- *Scenario:* Evaluation near boundaries.
- *Issue:* Estimator contains a $1/R$ term. As $R \rightarrow 0$, variance $\rightarrow \infty$.
- *Result:* Extreme noise at the edges.

CONCLUSION

Summary

- **WoS is a powerful alternative** for geometry processing, specifically for "dirty" or non-manifold geometry.
- **Key strengths:** Implementation simplicity, infinite resolution, memory efficiency.

Future Work

- **Walk on Stars:** To solve the "tunnel" issue by allowing larger steps in star-shaped domains.