Diderot: AA Parallel Domain-Specific Language for Image Analysis and Visualization

Charisee Chiw and Nick Seltzer

University of Chicago

Jan 28, 2012

Roadmap

- Image analysis
- Parallel DSLs
- Diderot design and examples
- Implementation issues
- Performance
- Conclusion

Joint work with Gordon Kindlmann and graduate students Charisee Chiw, Lamont Samuels, and Nick Seltzer.

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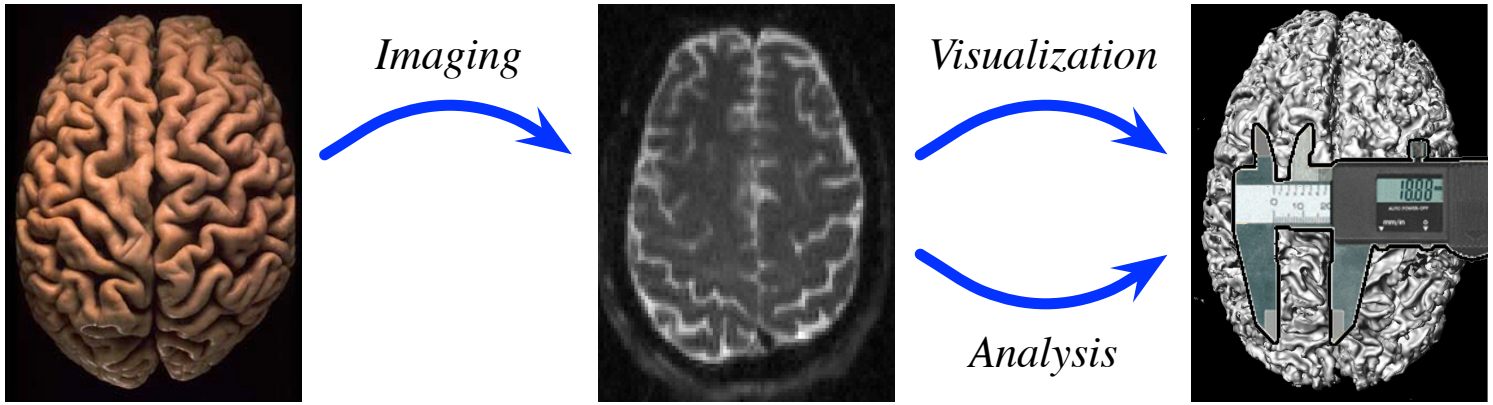

Physical object **Image data** **Computational representation**

- Scientists need software tools to extract structure from many kinds of image data.
- Creating new analysis/visualization programs is part of the experimental process.
- The challenge of getting knowledge from image data is getting harder.

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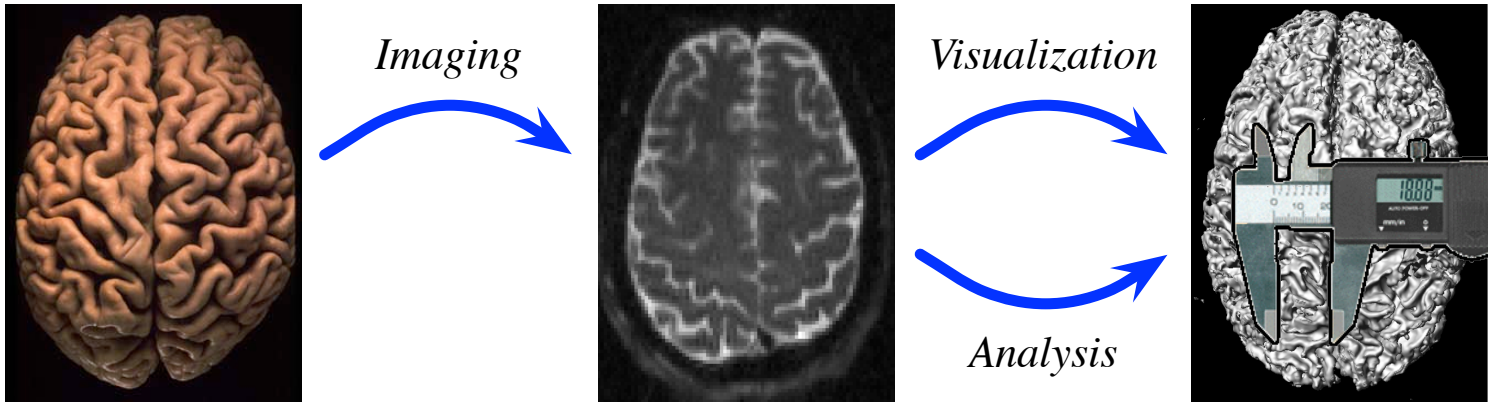

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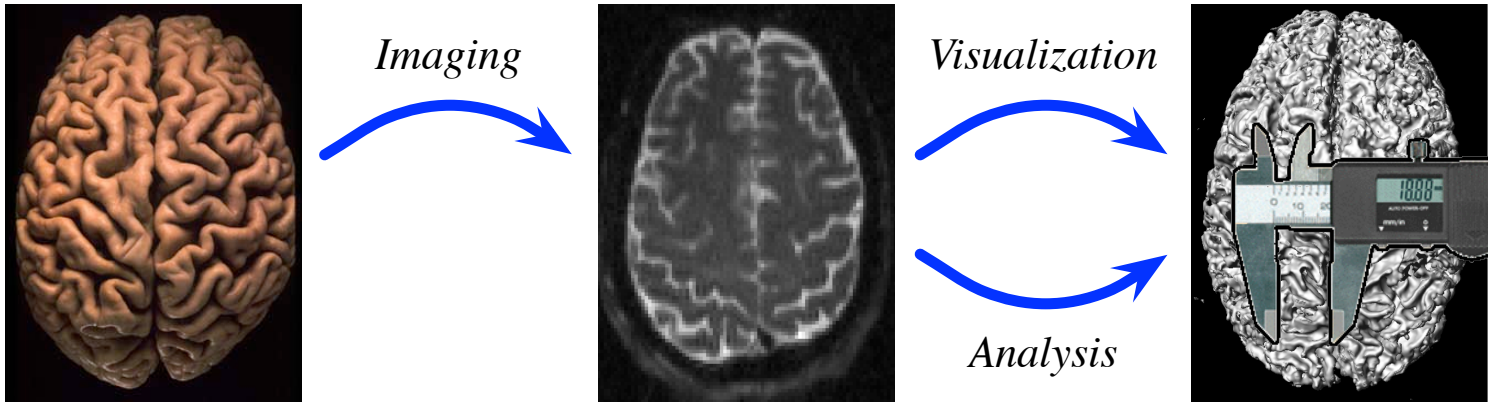

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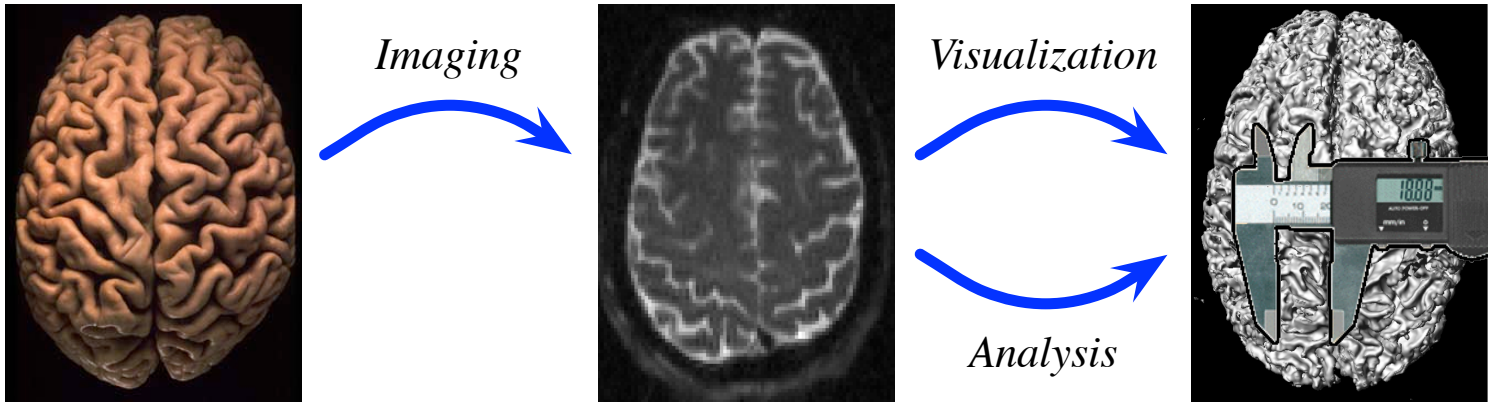

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- We are interested in a class of algorithms that compute geometric properties of objects from imaging data.
- These algorithms compute over a continuous tensor field F (and its derivatives), which are reconstructed from discrete data using a separable convolution kernel h:

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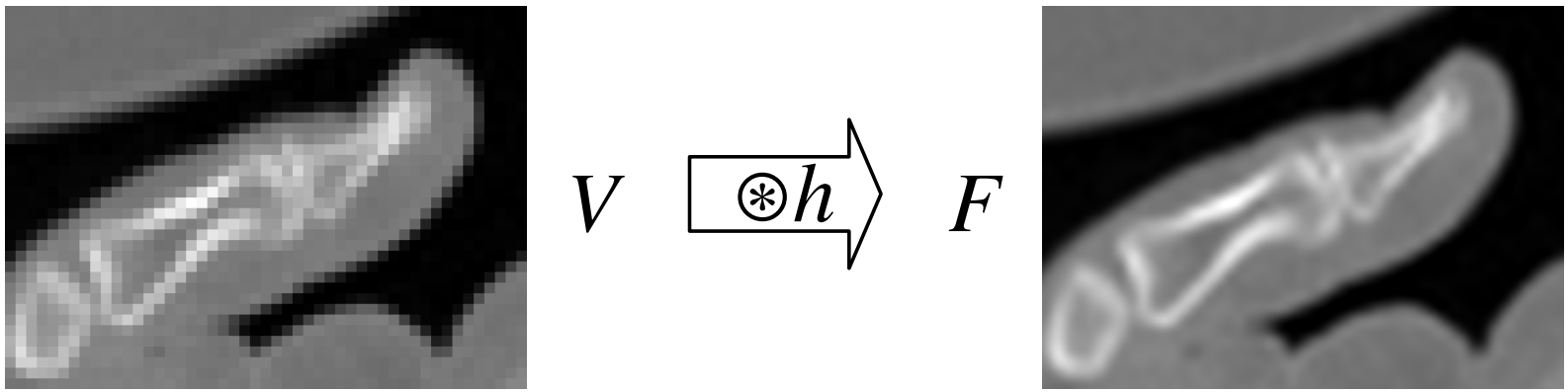

Discrete image data *Continuous field*

Image analysis and visualization

Example applications include

- Direct volume rendering (requires reconstruction, derivatives).
- Fiber tractography (requires tensor fields).
- Particle systems (requires dynamic numbers of computational elements).

These applications have a common algorithmic structure: large number of (mostly) independent computations.

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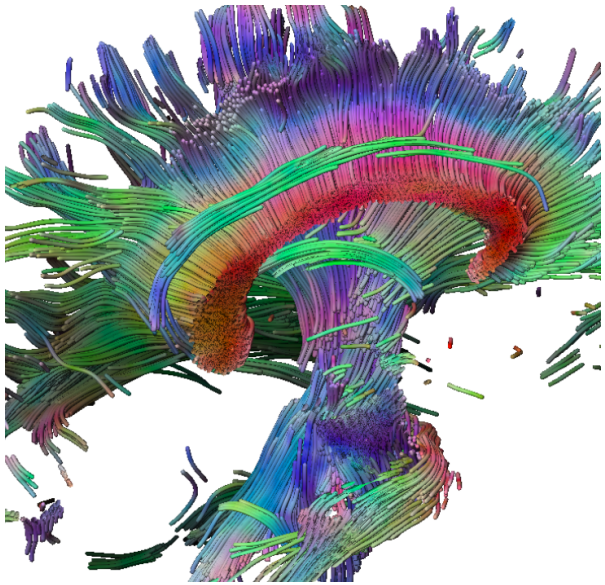

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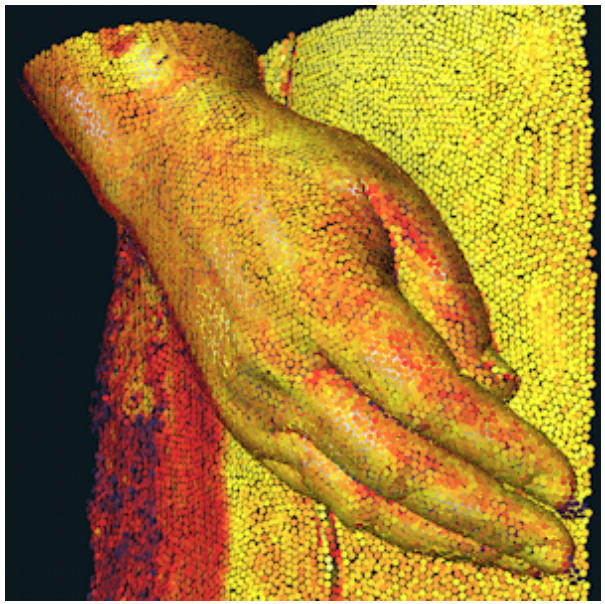

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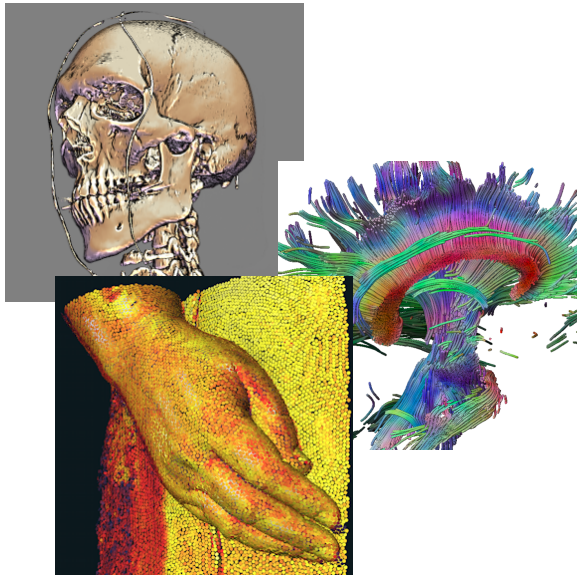

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Parallel DSLs

Domain-specific languages provide a number of advantages:

- High-level notation supports rapid prototyping and pedagogical presentation.
- Opportunities for domain-specific optimizations.

Parallel DSLs provide additional advantages

- High-level, abstract, parallelism models.
- Portable parallelism.

Parallel DSLs meet the Diderot design goals of improving programmability and performance.

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Related work

Some other examples of parallel DSLs:

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- Shadie: DSL for volume rendering applications.
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Diderot

Diderot is a parallel DSL for image analysis and visualization algorithms.

Its design models the algorithmic structure of its application domain: independent strands computing over continuous tensor fields.

A DSL approach provides

- Improve programmability by supporting a high-level mathematical programming notation and a simple model of parallelism.
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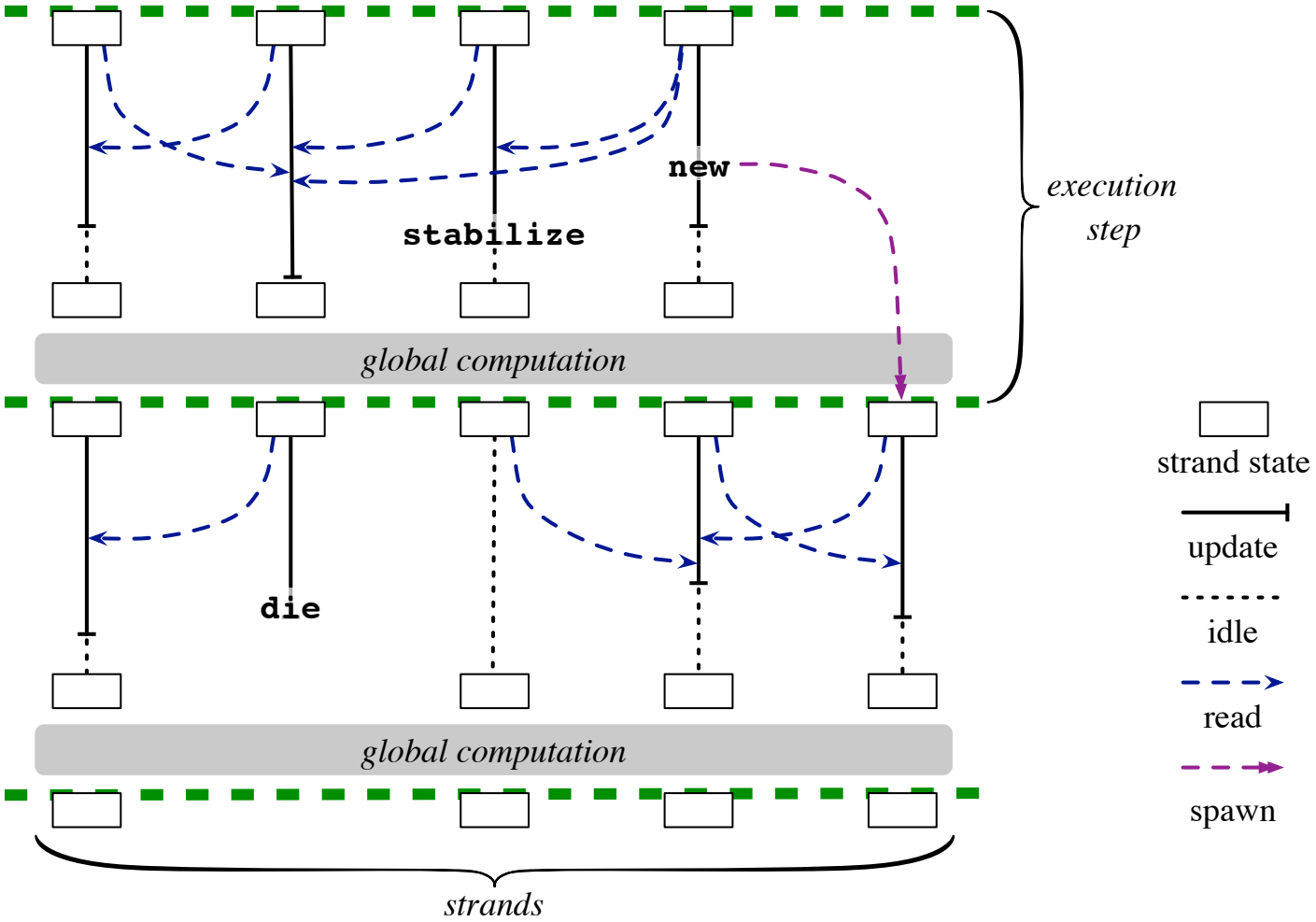
Diderot parallelism model

Bulk-synchronous parallel with "deterministic" semantics.



Diderot program structure

Square roots of integers using Heron's method.

```
// global definitions
input int N = 1000;
input real eps = 0.000001;

// strand definition
strand SqRoot (real val)
{
    output real root = val;

    update {
        root = (root + val/root) / 2.0;
        if (|root^2 - val|/val < eps)
            stabilize;
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// initialization
initially [ SqRoot(real(i)) | i in 1..N ]
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Globals are *immutable*, and are used for *program inputs* and other shared globals.

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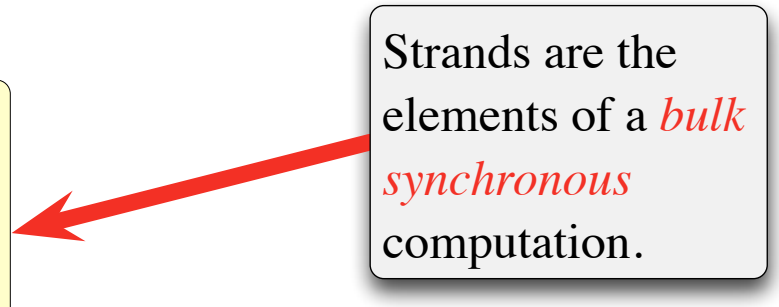

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Strands have *parameters* that are used to initialize them.

Strands have *state*, which includes *outputs*.

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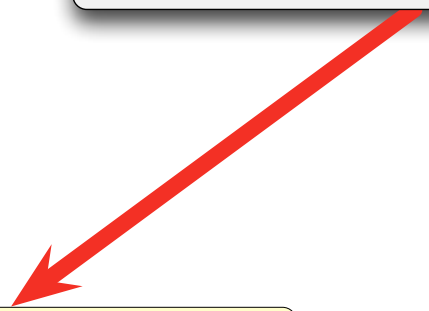
Strands have an *update method* that is invoked each *super step*.



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Strands have an *update method* that is invoked each *super step*.

Strands can *stabilize* or *die* during the computation.

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The initial collection of strands is created using *comprehension notation*.

Fields

- Fields are functions from $\Re^d$ to tensors.
- Field types describe the domain, range, and continuity of the function:

where $k \geq 0$, $d > 0$, and the $d_i > 1$.

- Diderot provides higher-order operations on fields: ∇, $\nabla\otimes$, .
- Diderot also lifts tensor operations to work on fields (, $+$).

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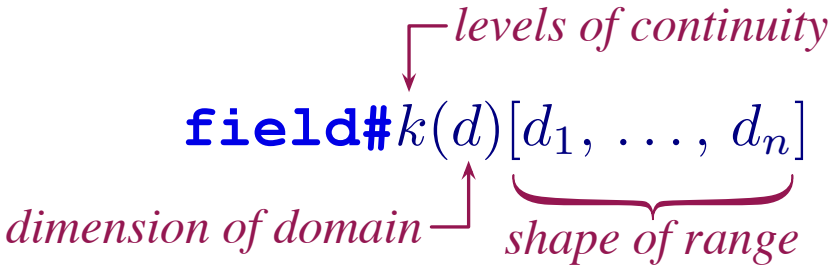

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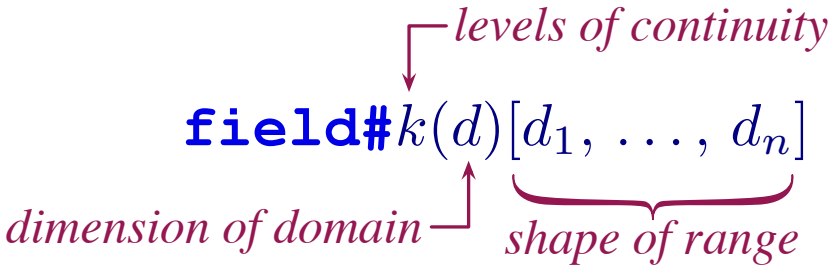

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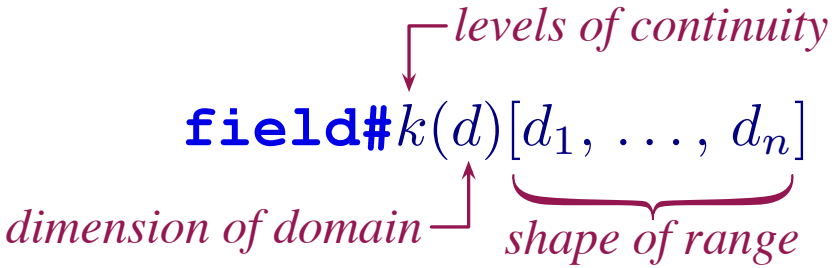

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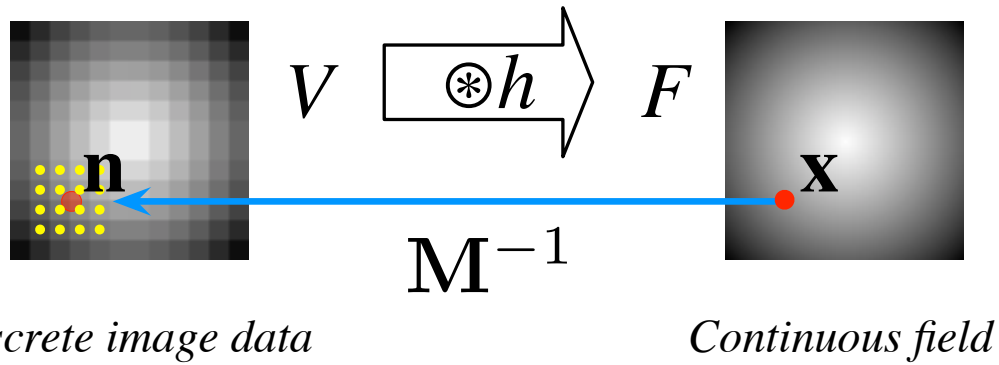
Applying tensor fields

A field application $F(\mathbf{x})$ gets compiled down into code that maps the world-space coordinates to image space and then convolves the image values in the neighborhood of the position.



In 2D, the reconstruction is

$$F(\mathbf{x}) = \sum_{i=1-s}^{s} \sum_{j=1-s}^{s} V[\mathbf{n} + \langle i, j \rangle] h(\mathbf{f}_x - i) h(\mathbf{f}_y - j)$$

where s is the support of h, $\mathbf{n} = \lfloor \mathbf{M}^{-1}\mathbf{x} \rfloor$ and $\mathbf{f} = \mathbf{M}^{-1}\mathbf{x} - \mathbf{n}$.

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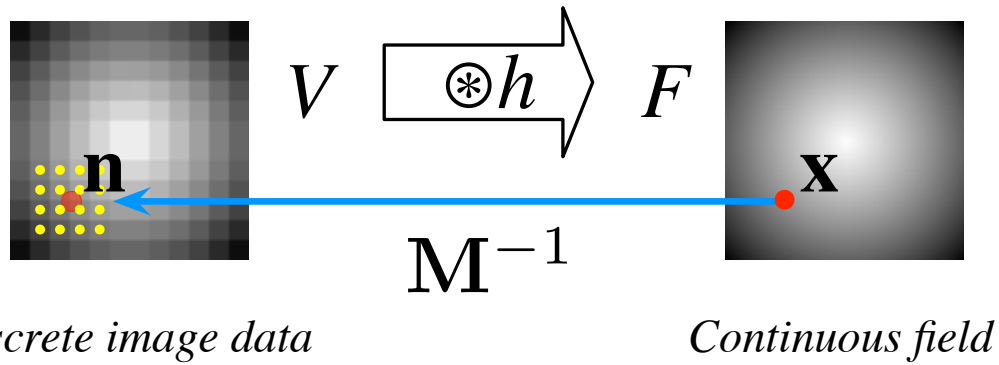

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Applying tensor fields *(continued ...)*

In general, compiling the field applications is more challenging.

For example, we might have

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field#2(2)[] F = h ⊛ V;
... ∇(s * F)(x) ...
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The first step is to normalize the field expressions.

$$\begin{aligned}\nabla(s * (V \circledast h))(x) &\Rightarrow (s * (\nabla(V \circledast h)))(x) \\ &\Rightarrow s * ((\nabla(V \circledast h))(x)) \\ &\Rightarrow s * (V \circledast (\nabla h))(x)\end{aligned}$$

In the implementation, we view ∇ as a "tensor" of partial-derivative operators

$$\nabla = \begin{bmatrix} \frac{\partial}{\partial x} \\ \frac{\partial}{\partial y} \end{bmatrix} \qquad \nabla \otimes \nabla = \begin{bmatrix} \frac{\partial^2}{\partial x^2} & \frac{\partial^2}{\partial xy} \\ \frac{\partial^2}{\partial xy} & \frac{\partial^2}{\partial y^2} \end{bmatrix}$$

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Applying tensor fields *(continued ...)*

Each component in the partial-derivative tensor corresponds to a component in the result of the application.

$$
\begin{aligned}
\nabla(s * F)(x) &= s * (V \circledast (\nabla h))(x) \\
&= s * (V \circledast \begin{bmatrix} \frac{\partial}{\partial x} \\ \frac{\partial}{\partial y} \end{bmatrix} h)(x) \\
&= s * \begin{bmatrix} \sum_{i=1-s}^{s} \sum_{j=1-s}^{s} V[\mathbf{n} + \langle i, j \rangle]\, h'\,(\mathbf{f}_x - i)\, h(\mathbf{f}_y - j) \\ \sum_{i=1-s}^{s} \sum_{j=1-s}^{s} V[\mathbf{n} + \langle i, j \rangle]\, h(\mathbf{f}_x - i)\, h'\,(\mathbf{f}_y - j) \end{bmatrix}
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A later stage of the compiler expands out the evaluations of h and h'.

Probing code has high arithmetic intensity and is trivial to vectorize.

Applying tensor fields *(continued ...)*

Each component in the partial-derivative tensor corresponds to a component in the result of the application.

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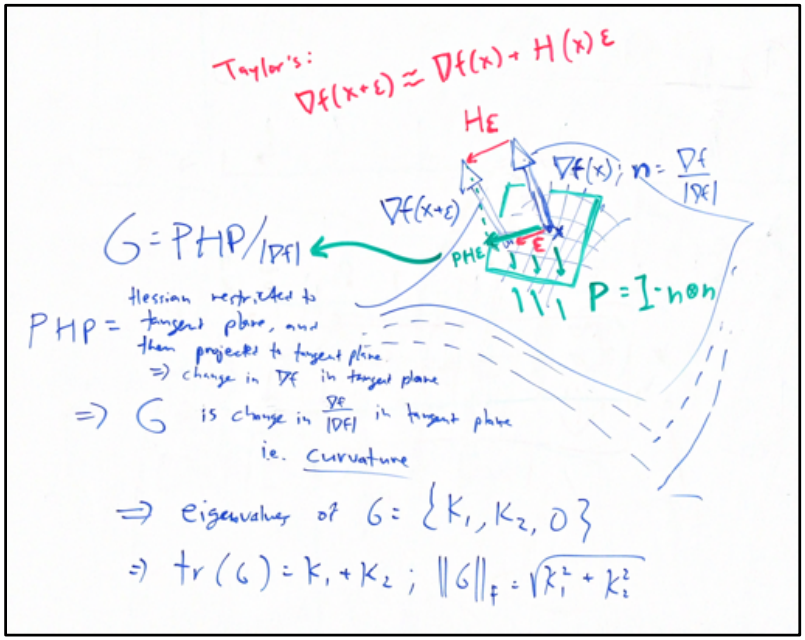

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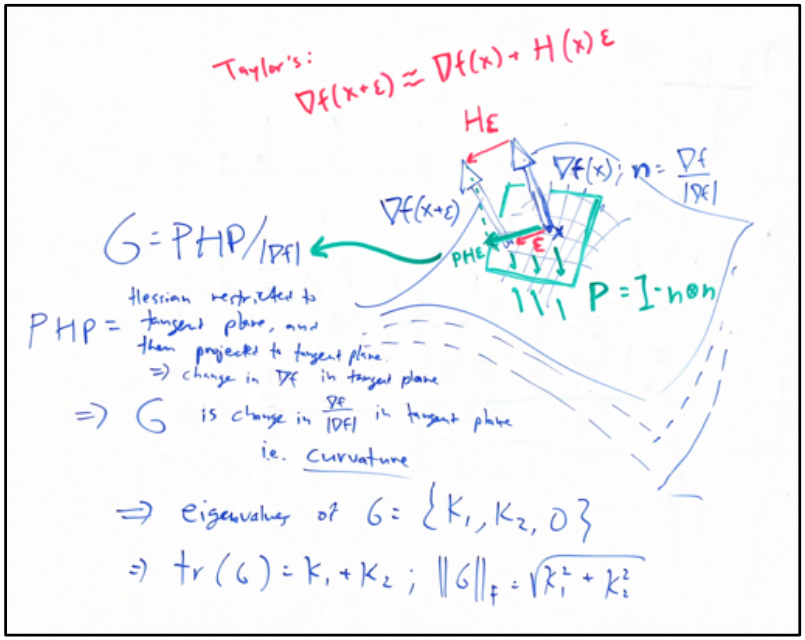


```
vec3 grad = -∇F(pos);
vec3 norm = normalize(grad);
tensor[3,3] H = ∇⊗∇F(pos);
tensor[3,3] P = identity[3] - norm⊗norm;
tensor[3,3] G = -(P•H•P)/|grad|;
real disc = sqrt(2.0*|G|^2 - trace(G)^2);
real k1 = (trace(G) + disc)/2.0;
real k2 = (trace(G) - disc)/2.0;
```

Example — Curvature

```
field#2(3)[] F = bspln3 ⊛ image("quad-patches.nrrd");
field#0(2)[3] RGB = tent ⊛ image("2d-bow.nrrd");
...
strand RayCast (int ui, int vi) {
  ...
  update {
    ...
    vec3 grad = -∇F(pos);
    vec3 norm = normalize(grad);
    tensor[3,3] H = ∇⊗∇F(pos);
    tensor[3,3] P = identity[3] - norm⊗norm;
    tensor[3,3] G = -(P•H•P)/|grad|;
    real disc = sqrt(2.0*|G|^2 - trace(G)^2);
    real k1 = (trace(G) + disc)/2.0;
    real k2 = (trace(G) - disc)/2.0;
    vec3 matRGB = // material RGBA
        RGB([max(-1.0, min(1.0, 6.0*k1)),
             max(-1.0, min(1.0, 6.0*k2))]);
    ...
  }
...
}
```

k2

Example — 2D Isosurface

```
int stepsMax = 10;
...
strand sample (int ui, int vi) {
  output vec2 pos = ...;
// set isovalue to closest of 50, 30, or 10
  real isoval = 50.0 if F(pos) >= 40.0
              else 30.0 if F(pos) >= 20.0
              else 10.0;
  int steps = 0;
  update {
    if (inside(pos, F) && steps <= stepsMax)
    // delta = Newton-Raphson step
      vec2 delta = normalize(∇F(pos)) * (F(pos) - isoval)/|∇F(pos)|;
      if (|delta| < epsilon)
        stabilize;
      pos = pos - delta;
      steps = steps + 1;
    }
    else die;
  }
}
```

Normalization

- The current compiler uses "direct-style" notation when normalizing tensor and field expressions.
- This approach does not extend to some interesting operations, such as $\nabla\times$.
- Expanding tensor operations to their scalar subcomputations is unwieldy.
- Einstein Index Notation (EIN) provides a compact representation of tensor expressions.
- New IR operator,

$$\lambda\bar{T}.\langle e\rangle_{\alpha}$$

whose semantics are specified by the EIN expression e, where $\bar{T}$ are tensor parameters and α is a multi-index that determines the shape of the result.

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Einstein Index Notation *(continued ...)*

- Concise specification of families of operators. For example, $\lambda(u, v).\langle u_{\alpha i} v_{i\beta} \rangle_{\alpha\beta}$ covers dot product, matrix-vector multiplication, matrix-matrix multiplication, etc.
- Code and data-representation synthesis (need cache-friendly and SSE-friendly mappings).
- Automatic discovery of linear-algebra identities.

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Optimizing tensor operations

Consider the expression `trace(a⊗b)`.

This Diderot expression is represented in the compiler as

$$\begin{array}{l} \mathit{let}\ M = (\lambda(u, v).\langle u_i v_j \rangle_{ij})(a, b) \\ \mathit{let}\ t = (\lambda X.\langle X_{kk} \rangle)(M) \\ \mathit{in}\ t \end{array}$$

substitution of the definition of M for X yields

$$\begin{array}{l} \mathit{let}\ t = (\lambda(u, v).\langle u_k v_k \rangle)(a, b) \\ \mathit{in}\ t \end{array}$$

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Experimental framework

- SMP machine: 16-core Linux machine with two 3.10 GHz Xeon E5-2687W processors
- Four typical benchmark programs
  - **vr-lite** — simple volume-renderer with Phong shading running on CT scan of hand
  - **illust-vr** — fancy volume-renderer with cartoon shading running on CT scan of hand
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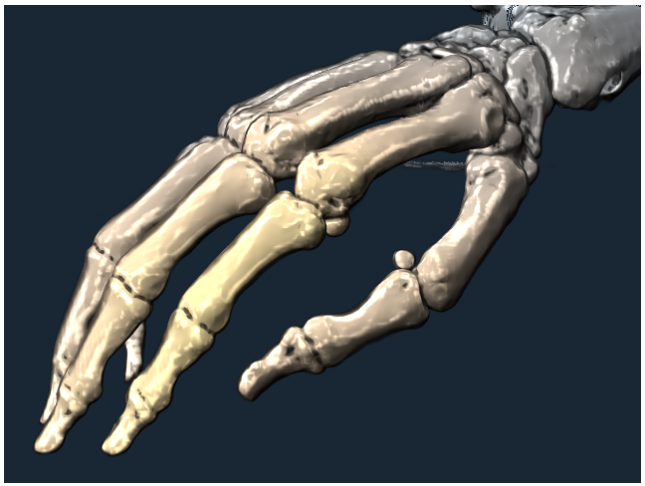

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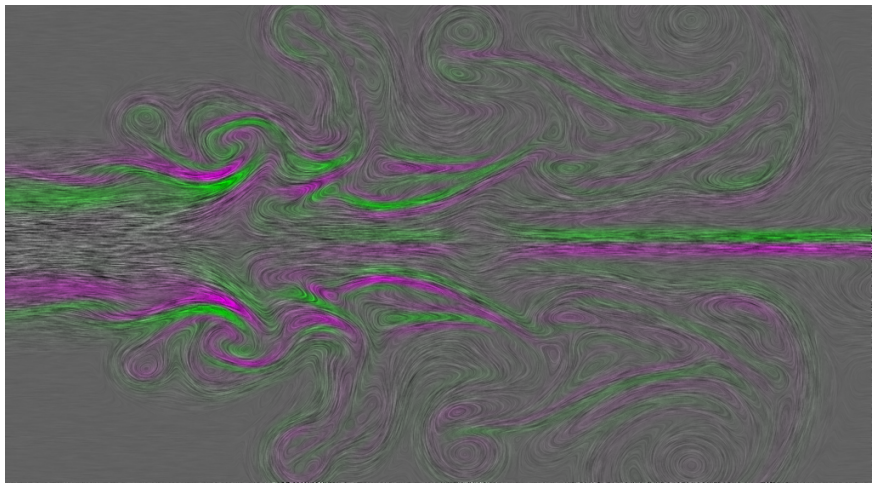

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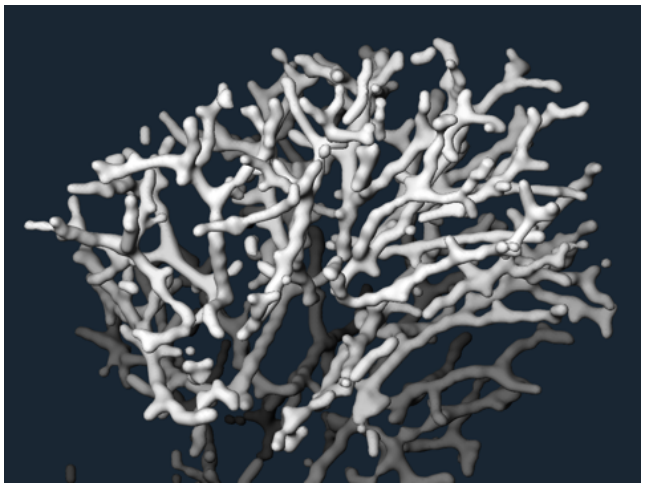

SMP scaling

Parallel performance scaling with respect to sequential Diderot.

Comparison across platforms

Compare performance on four platforms: sequential, 8-way parallel, 16-way parallel, and NVIDIA Tesla C2070.

Baseline is Teem/C implementation on 3.10 GHz Xeon.

Conclusion

Diderot provides:

- High-level programming notation.
- Domain-specific optimizations.
- Portable parallel performance.

These advantages apply to Parallel DSLs in general!

Thanks to NVIDIA and AMD for their support.

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Questions?

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