

Digital humans, virtual surgery and fast fluids; do they have more in common than their hunger for performance? Eftychios Sifakis **Department of Computer Sciences**

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Fast forward to lessons learned ...



Digital anatomy research yields **intrinsic benefits**, but is also a **catalyst for innovation** on synergistic disciplines.

Fast forward to lessons learned ...



Openness to **cross-layer interventions** maximizes the opportunity for breakthrough achievements ...

Fast forward to lessons learned ...



... and the impact of such design philosophy can be have **benefits beyond modeling** (or visual computing).

How did this journey start ... ?



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... and how it got into fracture and destruction ...



... or cutting and virtual surgery





Performance : Incremental benefit or critical feature?





Target performance?

Storage

- Explicit-assembly : 243 coefficients per vertex (give or take ...)
- Essential meta-data for matrix-free : 36 floats per vertex

Implicit mat-vec multiply cost:

- About I.8-2.5x of data access (read/write) cost
- Via SIMD + MultiThread optimizations.
- A developer's nightmare?
 - Sometimes ... see SVD for Disney's PhysGrid.
 - But there's a way to find a method to the madness.



Software engineering, programming models, computation delivery ...



Developments: Soft tissue surgery sim



Bringing hand-optimized code under control?



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Semantics : Execution of the 3x3 matrix operation $C=A^*B^T$ Arguments : **Streams** of 3x3 matrices $A^{(k)}$, $B^{(k)}$, $C^{(k)}$ Operation :

 $for(k=0;k<W;k++) C^{(k)} := A^{(k)} * [B^{(k)}]^T$

Guided Vectorization

template<class T_RAW,class T_DATA,int multiplicity>
void Matrix_Times_Transpose(const T_DATA (&A)[9], const T_DATA (&B)[9], T_DATA (&C)[9]);



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void Matrix_Times_Transpose(const T_DATA (&A)[9], const T_DATA (&B)[9], T_DATA (&C)[9]);

- template void Matrix_Times_Transpose<float,float>(const float (&A)[3][3], const float (&B)[3][3], float (&C)[3][3]);

Guided Vectorization

Findings:

- Matches or exceeds performance of hand-vectorized kernels
- ICC extremely efficient in eliminating temporaries (even <u>auto</u>'s)
- No problem with scaling to kernels in the 10,000s of instructions
- Promising performance on automatic fine-grain loop unrolling

Self collisions : Can we use level sets?



Production Rig

Our Method

Self collisions : Can we use level sets?



Production Rig

Our Method





Implicit Surface $\mathcal{C} = \{(x,y) | \phi(x,y) = 0\}$

Signed Distance Field

$$\phi(x,y) = \sqrt{x^2 + y^2} - 1$$















Signed distances on embedding mesh





Signed distances on embedding mesh














Current challenges?

Materials are inaccurate

- Way too permissive
 - Can't answer "will it reach?"
- Stress patterns don't always match our collaborators' experience





Well-intended evaluation practices ...

"My serial implementation of algorithm X on machine Y ran in Z seconds." When I parallelized my code, I got a speedup of 15x on 16 cores ..."

... are sometimes abused like this:

"... when I ported my implementation to CUDA, this numerical solver ran 200 times faster than my original MATLAB code ..."

So, what is wrong with that premise?

Are we pursuing the right efficiency?



Watch for warning signs:

- Speedup across platforms grossly exceeding specification ratios
 - e.g. NVIDIA GTX Titan X vs. Intel Xeon E5-2650v4 (Q1/16)
 - Relative (peak) specifications :
 - GPU has about 6x higher (peak) compute capacity
 - GPU has about 4x higher (peak) memory bandwidth
 - Significantly higher speedups likely indicate:
 - Different implementations on the 2 platforms
 - Baseline code was not optimal/parallel enough
- "Standard" parallelization yields linear speedups on many cores
 - [Reasonable scenario] Implementation is CPU-bound
 - [Problematic scenario] Implementation is CPU-wasteful

Are we pursuing the right efficiency?



A different perspective ...

"... after optimizing my code, the runtime is about 5x slower than **the best possible performance** that I could expect from this machine ..."

... i.e. 20% of maximum theoretical efficiency!

Challenge : How can we tell how fast the <u>best</u> implementation could have been? (without implementing it ...)





Example : Solving the quadratic equation

 $ax^2 + bx + c = 0$

What is the *minimum* amount of time needed to solve this?

Data access cost bound

"We cannot solve this faster than the time needed to read **a,b,c** and write **x**"

"We cannot solve this faster than the time needed evaluate the polynomial, for given values of a,b,c and x" (i.e. 2 ADDs, 2 MULTs plus data access)

Solution verification bound

 $ax^2 + bx + c =$

(ax + b)x +

Equivalent operation bound

"We cannot solve this faster than the time it takes to compute a square root"

Are we pursuing the right efficiency?



What about linear systems of equations?

Ax = b

"Textbook Efficiency" (for elliptic systems)

... or ...

It is **theoretically possible** to compute the solution to a linear system (with certain properties) with a cost comparable to **10x the cost of verifying** that a given value **x** is an actual solution

It is theoretically possible to compute the solution to a linear system (with certain properties) with a cost comparable to 10x the cost of computing the expression **r=b-Ax** and verifying that **r=0** (i.e. slightly over 10x of the cost of a matrix-vector multiplication)

But what algorithm gets there?

Prime Candidates

- Multigrid
- Domain decomposition

In more specialized (unrealistic?) contexts ...

- Fourier Analysis
- Cyclic Reduction
- etc

What can spoil this potential?

Systemic (?) Challenges

- Irregular domains
- Adaptive discretizations
- Heterogeneous/nonuniform compute platforms
- Anisotropy
- Inhomogeneous operators

Not-so-systemic (hopefully?) challenges

- Nonlinearity
- Contact (????)

- At core of elastic body simulators
 - Newton iteration for force balance
 - Need to solve **sparse** linearized system
 - Approximate solution good enough

- Direct or iterative solvers?
 - Direct methods need little tuning ...
 - ... but are memory-bound and tough to parallelize
 - Iterative schemes get approximate solution fast ...
 - ... but require many iterations for large models

- Best of both worlds?
 - Split work into local problems (elastic blocks)
 - Use direct algebra within blocks (and ensure local problem fits in cache)
 - Use iterative solver across block





- But wait, there's more ...
 - Direct solver **could** fit in a single core's cache
 - But we need to use SIMD for parallelism
 - ... and be extremely frugal with storage



- Challenges
 - Forward/Backward substitution are inherently serial (at least, textbooks say they are)
 - Uses matrix-vector multiplication (and any of this sort is doomed to be memory bound)
 - No clear opportunity for SIMD (although we are underutilizing computation capability by at least a factor of 100x)

• Remedies

- VPU optimization is <1%.
- Can easily afford to do 10x more computations, if in return we get :
 - I 0x reduction in bandwidth requirements, and
 - SIMD opportunities exposed

• Invert using divide-and-conquer

$$\begin{pmatrix} \mathbf{K}_{11} & \mathbf{K}_{1c} \\ \mathbf{K}_{22} & \mathbf{K}_{2c} \\ \mathbf{K}_{c1} & \mathbf{K}_{c2} & \mathbf{K}_{cc} \end{pmatrix}^{-1} = \begin{pmatrix} \mathbf{I} & -\mathbf{K}_{11}^{-1}\mathbf{K}_{1c} \\ \mathbf{I} & -\mathbf{K}_{22}^{-1}\mathbf{K}_{2c} \\ \mathbf{I} & \mathbf{I} \end{pmatrix} \begin{pmatrix} \mathbf{K}_{11}^{-1} \\ \mathbf{K}_{22}^{-1} \\ \mathbf{C}^{-1} \end{pmatrix} \begin{pmatrix} \mathbf{I} & \mathbf{I} \\ -\mathbf{K}_{c1}\mathbf{K}_{11}^{-1} & -\mathbf{K}_{c2}\mathbf{K}_{22}^{-1} & \mathbf{I} \end{pmatrix}$$















SPGrid - Virtual memory tricks sparse/adaptive grid data



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Adaptive I 35M cells Uniform 113M cells

Virtual memory tricks for adaptive simulation



Geometric Octree

SPGrid Hierarchy












Lexicographical





Morton Ordering



Blocked Grid

Lexicographical traversal **within** block



Z-curve traversal **across** blocks



132	133	134	135	148	149	150	151	196	197
128	129	130	131	144	145	146	147	192	19 3
44	45	46	47	60	61	62	63	108	109
40	41	42	43	56	57	58	59	104	10 5
36	37	38	39	52	53	54	55	100	101
32	33	34	35	48	49	50	51	9 6	97
12	13	14	15	28	29	30	31	76	77
8	9	10	11	24	25	26	27	72	73
4	5	6	7	20	21	22	23	68	69
0	1	2	3	16	17	18	19	64	65

	196 197	151	150	149	148	135	134	133	132	1001	
	192 19 3	147	146	145	144	131	130	129	128	1000	
	108 10 9	63	62	61	60	47	46	45	44	0111	(
	104 10 5	59	58	57	56	43	42	41	40	0110	binary →
	100 1 01	55	54	53	52	39	38	37	36	0101	nate (l
	96 97	51	50	49	48	35	34	33	32	0100	oordii
	7 6 77	31	30	29	28	15	14	13	12	0011	лу Ү-с
	72 73	27	26	25	24	11	10	9	8	0010	Arre
	68 69	23	22	21	20	7	6	5	4	0001	
Array X-coordinate	64 65	19	18	17	16	3	2	1	0	0000	
(binary)	1000 1 001	0111	0110	0101	0100	0011	0010	0001	0000		

		132	133	134	135	148	149	150	151	196	197	
Array Y-coordinate (binary)	1000	128	129	130	131	144	145	146	147	192	19 3	
	0111	44	45	(46)	47	60	61	62	63	108	109	0 1 11
	0110	40	41	42	43	56	57	58	59	104	105	0 0 10
	0101	36	37	38	39	52	53	54	55	100	101	
	0100	32	33	34	35	48	49	50	51	96	97	
	0011	12	13	14	15	28	29	30	31	76	77	
	0010	8	9	10	11	24	25	26	27	72	73	
	0001	4	5	6	7	20	21	22	23	68	69	
	0000	0	1	2	3	16	17	18	19	64	65	Array X-coordinate
	I	0000	0001	0010	0011	0100	0101	0110	0111	1000	1001	(binary)





Remaining details ...

- Solver : Multigrid-Preconditioned CG
- MG adapted to grid hierarchy, too
- Can do dynamically changing adaptation pattern
- Originally designed for CPU (+Xeon Phi trivially), but GPU analogues implemented to follow-up work

- Heterogeneous platforms
 - Multi-GPU equipped SMP servers ...
 - Small "fast" memory + Large "slow" memory hybrids (e.g.Knights Landing) ...
 - Or any reasonably deep memory hierarchy ...
 - Best ratio of \$\$ to Raw Computational Capacity

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(110+TFlops, 768GB RAM, 4.5+GB/s bandwidth : \$20k)

- Challenges
 - GFlops/Gload ratio approaching 100:1 today (closer to 12-15:1 in "good old pre-GPU/SIMD days")
 - Access to non-local memory at least one order of magnitude slower (PCle/Infiniband vs DDD4, or KNL fast/slow memory)
 - Even worse scenario :

Workload **too slow** for CPU, **too large** for GPU

• Offload overhead often a non-starter for traditional distributed parallelization

• A crisis or an opportunity?

• Dream scenario :

Making an algorithm work on a heterogeneous platform as fast as a homogeneous one with the **aggregate** specs

- Certainly not possible *in general* (via automated means)
- ... but doable for many problems in computational dynamics!



Challenges:

- Expensive to assemble
- Yields dense system
- •Must run on CPU



• Performance restored by:

- Making any offloaded tasks are large enough to absorb communication cost (and get something in return)
- Tweaking the math (adaptivity) to reduce complexity
- Use an "approximate" divide and conquer design



1.2B Active Cells, 1024x1024x2048 Grid





In retrospect ...

Should we be open to cross-layer interventions? Why?

- Might be a necessity for competitiveness ...
- Other disciplines appreciate this, too! (and graphics researchers have experience doing it)
- A more fundable vision?
- Historical precedent ...



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