

S9277 - OpenACC-Based GPU Acceleration of Chemical Shift Prediction

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Xu, et al. Nature (2018)







motor ... and much more

Only 20 unique amino acids...

Function arises from **structure**



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Hierarchy of protein structure

Primary structure: sequence of amino acids

Sequence is organized into secondary structure



Secondary structure causes chain to fold into tertiary structure

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Quaternary structure complexes multiple, folded chains



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Structure is essential to function

Determining a protein's *native* structure is critical

Tools of structure determination:

- X-Ray crystallography
- Electron microscopy
- Nuclear Magnetic Resonance (NMR)







NMR studies proteins with minimal tampering (i.e., freezing or crystallization)



https://pdb101.rcsb org/motm/72 Medical Research Council: Mitochondrial Biology Unit (Creative commons attribution license)

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Semi-empirical chemical shift prediction: PPM_One

Treats chemical shift as a sum of differentiable functions which depend on internal coordinates

$$\delta_{CSpredicted} = \delta_{HBond} + \delta_{Dihedral} + \delta_{Ring\ Current} + \delta_{Magn\ Anisotropy} + \delta_{Electric}$$

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Higher dimensional data (3D cartesian) maps to lower dimensional **internal coordinates** e.g., dihedral angle:



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Takeaway: theoretical biophysics is compute and data intensive

Large systems necessitate highperformance codes and systems



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Perilla, et al. Nature (2016)

64 million atomistic simulation of HIV-1 virion

Project Motivation

- Nuclear Magnetic Resonance (NMR) is a vital tool in structural biology and biochemistry
- Chemical shift gives insight into the physical structure of the protein
- Predicting chemical shift has important uses in scientific areas such as drug discovery

Our goal:

- To enable execution of multiple chemical shift predictions repeatedly
- To allow chemical shift predictions for larger scale structures





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Introduction to the PPM_One code

- Parametrize a new empirical knowledge-based chemical shift predictor of protein backbone atoms
- Accepts a single static 3D protein structure (PDB format) as input
- Emulates local protein dynamics
- Outputs chemical shift prediction with high accuracy

ATTN		N.	NET		244	16 210	8 266	2 223	1 00	2 33	<u>_</u> M
ATOM		CA.	MET	2	144	16 996	5 807	2 883	1.00	8.00	2
ATOM		e.	MET	2	244	19 074	5 964	9 /00	1 00	9.99	
ATTIN	-		MET	2	144	13.970	4 194	9.999	2.00	0.00	2
TON	2	0	NET	2	144	10.009	0.220	3.220	1.66	8.00	
ATUM.		CB	MET	ĉ	144	15.052	4.0//	4.002	1.00	0.00	
ATOM	•	CE	MET	4	144	15.859	2.822	4.885	2.66	8.88	C
ATUM	7	SD	MET	A	244	10.942	2.778	0.085	1.00	8.99	5
MUTA	8	CE	MET	A	144	16.943	1.212	6.703	1.00	8.99	C
ATOM	9	H1	MET	A	144	16.141	4.979	1.468	1.00	8.00	H
ATOM	1.8	H2	MET	A	144	16.523	3.361	1.816	1.00	8.88	н
MUTA	11	на	MET	A	144	16.917	4,580	2.924	1.00	8.00	H
ATOM	12	HA.	MET	A	144	14.453	3.164	2.565	1.00	8.00	H
ATOM	13	HB2	MET	A	144	15.632	4.955	6.788	1.00	8.88	H
ATOM	14	883	MET	A	144	14.116	4,878	4.880	1.66	8.00	н
ATOM	15	H62	MET	A	144	15.321	1.945	4.476	1.00	8.00	н
ATOM	16	HC3	MET	A	144	16.835	2.848	4.344	1.00	8.88	н
ATOM	17	HE1	MET	٨	144	10.382	8,441	6.202	1.00	8.00	н
ATOM	18	HE2	MET	A	144	17.078	8.941	7.741	1.00	8.99	H
ATOM	19	HES	MET	A	144	17.987	1.322	6.226	1.00	8.88	H
ATOM	28	N	TYR	A	145	13.350	5.138	1.321	1.00	8.00	N
ATOM	21	CA	TYR	A	145	12.445	6,172	0.838	1.00	8.00	C
ATOM	22	C	TYR	A	145	11.480	6.592	1.948	1.00	8.99	C
ATOM	23	0	TYR	A	145	11.464	7.751	2.353	1.00	8.88	0
ATOM	24	CB	TYR		145	11.672	5.657	-8.383	1.88	8.00	C







Profile Driven Development





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Profile Driven Development

- Tackling a large and unfamiliar code is daunting
- Advantages of profiling:
 - High-level view of the code
 - Baseline performance metrics
 - Sanity check during the development process







Serial Code Profile (Main Function)

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Main Function	% Runtime
main()	100%
predict_bb_static_ann(void)	81.226%
predict_proton_static_new(void)	16.276%
load(string)	1.921%



Serial Profile Visual

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- Profiled code using PGPROF
 - Without any optimizations
- Gave a baseline snapshot of the code
 - Identified hotspots within the code
 - Identified functions that are potential bottlenecks
- Obtained large overview without needing to read thousands of lines of code



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Optimization in steps

- getselect()
- Looking into optimizing the serial code prior to parallelizing it







Serial Optimization (getselect)

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Serial Optimization (getselect)

```
getselect originally
// Pseudocode for getselect function
                                                         accounted for 25% of
                                                         the codes runtime.
                                                         After optimization, it
for( ... ) // Large loop
                                                         takes less than 1%.
    c2=pdb->getselect(":1-%@allheavy");
    traj->get contact(c1,c2,&result);
                                // Pseudocode for getselect function
                                c2=pdb->getselect(":1-%@allheavy");
                                for( ... ) // Large loop
                                    traj->get contact(c1,c2,&result);
```

Serial Optimizations (other smaller optimizations)

- Filtering functions:
 - Filter objects from a large list
 - Written in an inefficient C++ style way
 - Runtime for filtering functions went from 5+min to 1 second for some datasets
- Replace C++ stl vectors:
 - All data is stored within stl vectors
 - There are a few ways to work around this for GPUs
 - We chose to just replace them with pointers when possible





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Serial Profile After Optimization

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Porting PPM to GPUs







Our Weapon of Choice









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Introduction to OpenACC

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- OpenACC is a directive based parallel programming model used to accelerate code on heterogenous systems.
- Implemented by PGI, GCC, and Cray (until 2.0)
- PGI community editions are freely available:

https://www.pgroup.com/products/community.htm











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Introduction to OpenACC

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Benefits:

- Portable without sacrificing performance
- Simple, based on directives
- Ease of code porting (no large code rewrites)



#pragma acc parallel loop
for(int i = 0; i < N; ++i)
 a[i] = a[i]*b[i] + c[i];</pre>



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Most compute intensive







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Accelerating get_contact

- get_contact is called many times in the code
- The "pos" vector actually only contains 3 values; x, y, z coordinates
- The **"used"** vector contains all of the atoms in the structure
- GPU focused, we collapsed the outer loop
 - Now we compute 3 contacts simultaneously
- We also combined all calls to get_contact into one large function called get_all_contacts

```
for(i=1;i<index_size-1;i++)
{
    ...
    traj->get_contact(c1,c2,&result);
    ...
}
```





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Accelerating get_contact

- get_contact is called many times in the code
- The "pos" vector actually only contains 3 values; x, y, z coordinates
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- GPU focused, we collapsed the outer loop
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Inside of the get_contact function

```
// For x,y,z coordinate
for(i=0;i<(int)pos.size();i++)</pre>
    // For every atom
    for(j=0;j<(int)used.size();j++)</pre>
         // Calculate contact
    result->push back(contact);
```





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Accelerating get_contact

```
#pragma acc parallel loop private(...) \
 present(..., results[0:results size]) copyin(...)
for(i=1;i<index size-1;i++)</pre>
    #pragma acc loop reduction(+:contact1, +:contact2, \
     +:contact3) private(...)
    for(j=0;j<c2 size;j++)</pre>
        // Calculate contact1, contact2, contact3
    results[((i-1)*3)+0]=contact1;
    results[((i-1)*3)+1]=contact2;
    results[((i-1)*3)+2]=contact3;
```

- Large outer-loop covers all individual get_contact calls
- Inner-loop still iterates over all atoms
- Now calculating 3 different contacts simultaneously
- Writing contacts to one large results array to be used later





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Next most compute intensive









Acceleration of gethbond





Acceleration of gethbond

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```
#pragma acc parallel loop gang
for(i=0;i< hbond size;i++)</pre>
    #pragma acc loop vector
    for(j=0;j<hbond_size;j++)</pre>
         #pragma acc loop seq
         for(k=0;k<nframe;k++)</pre>
```



#pragma acc atomic update

#pragma acc atomic update effect arr[nid].n phi+=phi;

#pragma acc atomic update

#pragma acc atomic update

effect arr[cid].c lengh+=d; #pragma acc atomic update effect arr[cid].c phi+=phi; #pragma acc atomic update effect arr[cid].c psi+=psi;

effect arr[nid].n psi+=psi

effect arr[nid].n length+=d;



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Acceleration of gethbond

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```
if(hbond[i].type==1){
#pragma acc parallel loop gang
for(i=0;i< hbond size;i++)</pre>
    #pragma acc loop vector
    for(j=0;j<hbond_size;j++)</pre>
                                                       if(hbond[j].type==1){
        #pragma acc loop seq
        for(k=0;k<nframe;k++)</pre>
```





And the next most...and so on





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Data Movement

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- CPU and GPU memory is separate in a heterogenous system
- Connected via an IO Bus (PCI-E or NVLink)
- Programmer must explicitly manage two separate memory pools







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Data Movement

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// Initialize X, Y, Z on host

• • •

- Allocate memory on host first (main memory)
- Create copy of our data on the device (GPU memory)
- Ensure that the correct data is on the GPU when we need it
 - And vice versa







Parallel Profile









Parallel Profile

	21.8 s	21.9 s	22 s	22.1 s	22.2 s	22.3 s	22.4 s	22.5 s	22.6
Process "ppm_stable -pdb tub									
Thread 313460992									
- OpenACC			acc_c acc_e		acc_compute_ acc_w	_construct@tra ait@traj.cpp:34	j.cpp:3410 110		
L Driver API			cuMe		cuStr	eamSynchroniz	ze		
Profiling Overhead									
[0] GeForce GTX TITAN X									
Context 1 (CUDA)									
🗆 🍸 MemCpy (HtoD)									
L 🍸 MemCpy (DtoH)									
Compute			_ZN5	_ZN5C	Traj16get_all_co	ontactsEPSt6ve	ctorI8bb_grou	pS	
- 🍸 41.4% _ZN5CTraj16				_ZN5C	Traj16get_all_co	ontactsEPSt6ve	ctorI8bb_grou	pS	
- 🍸 30.2% _ZN5CTraj6g			_ZN5						
└ 🍸 22.7% _ZN5CTraj7g									
– 🍸 3.2% _ZN5CTraj6ge									
- 🍸 2.5% _ZN5CTraj7ge									
– 🍸 0.0% _ZN5CTraj7ge									
└ 🍸 0.0% _ZN5CTraj6ge									
- 🝸 0.0% _ZN5CTraj7ge									
└ 🍸 0.0% _ZN5CTraj6ge									





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Parallel Profile

	s 25.6 s	25.7 s	25.8 s	25.9 s	26 s	26.1 s	26.2 s	26.3 s
Process "ppm_stable -pdb tub								
Thread 313460992								
└ OpenACC			acc_compute_c acc_enqueue_c	onstruct@traj.o lownload@traj.	c acc_compu acc_wait@	ute_construc ptraj.cpp:1613		
Driver API			cuMemcp	yDtoHAsync	cuStream	Synchronize		
Profiling Overhead								
[0] GeForce GTX TITAN X								
Context 1 (CUDA)								
🗆 🍸 MemCpy (HtoD)								
- 🍸 MemCpy (DtoH)								
Compute			_ZN5CTraj6get	aniEP9ani_grou	ZN5CTraj	7getringEP1		
└ 🍸 41.4% _ZN5CTraj16								
L 🍸 30.2% _ZN5CTraj6g			_ZN5CTraj6get	aniEP9ani_grou				
└ 🍸 22.7% _ZN5CTraj7g					_ZN5CTraj	7getringEP1		
L 🍸 3.2% _ZN5CTraj6ge								
└ 🍸 2.5% _ZN5CTraj7ge								
└ 🍸 0.0% _ZN5CTraj7ge								
└ 🍸 0.0% _ZN5CTraj6ge								
└ 🍸 0.0% _ZN5CTraj7ge								
⊢ 🍸 0.0% _ZN5CTraj6ge								



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44

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Results

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Was it worth it?







Experimental Datasets









Experimental Datasets



5 nm









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Experimental Datasets

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Experimental Setup

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Machine	СРИ	GPU	Machine	CPU
NVIDIA PSG (V100)	Intel Xeon E5-2698 (16 cores)	NVIDIA Tesla V100 (16GB HBM2)	NVIDIA PSG (V100)	Intel Xeon E5-2698 (16 cores)
NVIDIA PSG (P100)	Intel Xeon E5-2698 (16 cores)	NVIDIA Tesla P100 (16GB HBM2)	NVIDIA PSG (P100)	Intel Xeon E5-2698 (16 cores)
University of Delaware Vader	Intel i7 990x (12 cores)	NVIDIA Volta Titan V (12GB HBM2)	University of Delaware Vader	Intel i7 990x (12 cores)
University of Delaware Savina	Intel Xeon E5-2603 (8 cores)	NVIDIA Maxwell Titan X (12GB GDDR5)	University of Delaware Savina	Intel Xeon E5-2603 (8 cores)





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Performance Results

	Very Small	Medium	Large	Very Large
	(100K) Atoms	(2.1M) Atoms	(6.8M) Atoms	(13.3M) Atoms
Serial	167.11s	3547.07	7 hours	14 hours
(Unoptimized)		(1 hour)	approx.	approx.





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Performance Results

	Very Small	Medium	Large	Very Large
	(100K) Atoms	(2.1M) Atoms	(6.8M) Atoms	(13.3M) Atoms
Serial	167.11s	3547.07	7 hours	14 hours
(Unoptimized)		(1 hour)	approx.	approx.
Serial	32s	2209.64s	2939s	9035s
(Optimized)		(37 min)	(48 min)	(2.5 hours)





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Performance Results

	Very Small	Medium	Large	Very Large
	(100K) Atoms	(2.1M) Atoms	(6.8M) Atoms	(13.3M) Atoms
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(Unoptimized)		(1 hour)	approx.	approx.
Serial	32s	2209.64s	2939s	9035s
(Optimized)		(37 min)	(48 min)	(2.5 hours)
Multicore (32 cores)	2.93s	109s	172s	427s





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Performance Results

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	(100K) Atoms	(2.1M) Atoms	(6.8M) Atoms	(13.3M) Atoms
Serial	167.11s	3547.07	7 hours	14 hours
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Serial	32s	2209.64s	2939s	9035s
(Optimized)		(37 min)	(48 min)	(2.5 hours)
Multicore (32 cores)	2.93s	109s	172s	427s
NVIDIA PASCAL P100 GPU	1.72s	36s	69s	170s







Performance Results

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	Very Small (100K) Atoms	Medium (2.1M) Atoms	Large (6.8M) Atoms	Very Large (13.3M) Atoms	
Serial (Unoptimized)	167.11s	3547.07 (1 hour)	7 hours approx.	14 hours approx.	
Serial (Optimized)	32s	2209.64s (37 min)	2939s (48 min)	9035s (2.5 hours)	21x
Multicore (32 cores)	2.93s	109s	172s	427s	
NVIDIA PASCAL P100 GPU	1.72s	36s	69s	170s	~3.4x
NVIDIA VOLTA V100 GPU	1.68s	29s	56s	134s	TT



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Performance Results









Performance Results (per function)

Function Name	Serial
get_contact	2505s
gethbond	337s
getani	29s
getring	19s





Performance Results (per function)

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Function Name	Serial	Multicore	Speedup (Multicore vs Serial)
get_contact	2505s	100s	25x
gethbond	337s	19s	17x
getani	29s	1.5s	19x
getring	19s	0.84s	22x





Performance Results (per function)

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Function Name	Serial	Multicore	Speedup (Multicore vs Serial)	V100 GPU	Speedup (V100 vs Serial)
get_contact	2505s	100s	25x	15s	167x
gethbond	337s	19s	17x	1.24s	271x
getani	29s	1.5s	19x	0.09s	322x
getring	19s	0.84s	22x	0.09s	211x





Performance Results (per function)

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Function Name	Serial	Multicore	Speedup (Multicore vs Serial)	V100 GPU	Speedup (V100 vs Serial)	Speedup (V100 vs Multicore)
get_contact	2505s	100s	25x	15s	167x	7x
gethbond	337s	19s	17x	1.24s	271x	15x
getani	29s	1.5s	19x	0.09s	322x	17x
getring	19s	0.84s	22x	0.09s	211x	9x



3D printed





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Conclusions

- Achieved ~67x performance (in our best case) using a directive based programming model on GPUs
- Created a portable code that can run on single core, multicore, and GPU
- Allowed chemical shift to be estimated for large structures in a much more realistic amount of time
- Maintain the same accuracy (10e-3) as the base code

