Computational Design of Polymers and Macromolecular Biomaterials

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<u>Research Group Website: http://udel.edu/~arthij/</u>

Polymer Modeling and Simulation in Jayaraman Group

How molecular features affect macroscopic morphology





How molecular features impact macromolecular interactions



Polymer Nanocomposites: Polymer grafted nanoparticles in a polymer matrix

Using theory and molecular simulations we are able to link features of polymer functionalization to particle dispersion/aggregation in a polymer matrix





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Polymer Grafted Nanoparticles in a Polymer Matrix









Physics Governing Morphology when Graft and Matrix Polymers are Chemically Similar

Particle Aggregation

Matrix MW > Graft MW





Bates and coworkers, J. Polym. Sci. B: Polym. Phys., 45, 2284 (2007)

Particle Dispersion Matrix MW<< Graft MW

Grafted → Chain Matrix ↗ Chain



Bates and coworkers, J. Polym. Sci. B: Polym. Phys., 45, 2284 (2007)

Dry Brush

Wetting/dewetting of the grafted layer tunes the polymer grafted particle dispersion/aggregation in the polymer matrix

Wet Brush



Designing polymer functionalization to improve nanoparticle dispersion in polymer matrix



Polydispersity in graft polymer increases wetting of grafted layer by matrix chains, and thus improves particle dispersion in monodisperse polymer matrix.

Tyler Martin, P. Dodd, and A. Jayaraman Phys Rev Lett 110, 018301 (2013)

 \Rightarrow Our predictions were confirmed by experiments by Krishnamoorti and coworkers

Experiments showing agreement with our predictions



Results from laboratory of Prof. Ramanan Krishnamoorti at University of Houston

Polydisperse polymer grafted nanoparticles exhibit

a) *Higher swelling (or wetting*) of grafted particles by matrix chains than monodisperse grafts

b) Reduced macrophase separation (or particle aggregation)

So far, experiments in agreement with our predictions.

Tailoring Entropic Driving Forces to Tune Morphology



Increasing *graft length polydispersity* can *stabilize dispersions* of polymer grafted nanoparticles in a *monodisperse* polymer matrix.

> Martin T.B., Dodd P.M., Jayaraman A., *Phys Rev Lett* 2013, 110 (1), 018301



Interparticle Distance (d)

Decreasing *graft and matrix flexibility* can *stabilize dispersions* of polymer grafted nanoparticles in a *monodisperse* polymer matrix.

> Lin B.⁺, Martin T.B.⁺, Jayaraman A., *ACS Macro Lett* 2014, 3 (7) 628-632

Chemically Dissimilar Graft and Matrix Homopolymers



With attractive interactions between graft and matrix monomers, at low temperatures the enthalpically driven graft-matrix mixing should lead to particle dispersion even when N_{matrix} >> N_{graft}



Dispersion-Aggregation & Wetting Dewetting Transition

- Simulations and experiments show that wetting-dewetting transition is gradual and distinct from the sharp dispersion-aggregation.
 - Critical wetting that marks onset of dispersion->aggregation is equal to the wetting found in corresponding athermal system.

Tyler B. Martin, K. Mongcopa, P. Butler, R. Krishnamoorti, A. Jayaraman JACS (2015) 137 (33), pp 10624–10631

Tailoring Thermodynamic Driving Forces to Tune Polymer Nanocomposite Morphology

Tuning Entropic Driving Forces

Increasing Graft MW Dispersity



Martin T.B., Dodd P.M., Jayaraman A., *Phys Rev Lett* 2013, 110 (1), 018301

Tuning *mostly* **Enthalpic Driving Forces**

Chemically dissimilar graft and matrix polymers

T. B. Martin, K. Mongcopa, P. Butler, R. Krishnamoorti, A. Jayaraman *JACS* (2015)

137 (33), pp 10624–10631



Decreasing Polymer Flexibility



Lin B.⁺, Martin T.B.⁺, Jayaraman A., ACS Macro Lett 2014, 3 (7) 628-632 Copolymer grafted nanoparticles compatibilizing interfaces in homopolymer blends

Estridge, C.E.; Jayaraman A. ACS Macro Letters 4(2) 155-159, 2015





Diblock copolymer functionalization to stabilize interfaces



Science B: Polymer Physics 2015,53,76-88

Designing polymer functionalization to direct nanoparticle assembly

Copolymer functionalization on the nanoparticles tuned to achieve

desired particle assembly and order



T. Martin, A. Seifpour and A. Jayaraman Soft Matter (2011) 7,5952-5964 (2011)
T. Martin, C. McKinney and A. Jayaraman Soft Matter (2013) 9, 155-169 2013

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Efficiency of organic photovoltaics depends upon active layer morphology



Donor: Conjugated **Acceptor**: Fullerene derivative



e.g. P3HT



e.g. PCBM

- 1) Excitons generated in donor material
- 2) Exciton dissociation at donor/acceptor interface
- 3) Charge transport to electrodes

Morphology (e.g. polymer crystallinity, domain connectivity, interfacial area) is important for device efficiency

Challenge: Various Length Scales in Donor-Acceptor Morphology

0.1nm- 5nm



>1nm < 100nm

Yin and Dadmun, ACS Nano 2011

Molecular-level detail, e.g. fullerene intercalation

Phase separation of donor and acceptor into domains (disorder→ order) Active layer film in solar cell

>100nm

Comparison of Molecular Simulation Approaches

	Atomistic models	Intermediate resolution CG models	Highly Coarse-Grained models Carrillo et: al., Physical Chemistry Chemical Physics, 2013
Length scale & Time scale	<10 nm << 100 ns	Up to 10-20nm 100s of ns	Up to 100nm > 1µs
Disorder to Order Transition	Computationally not feasible to capture Disorder to Order	Captures Disorder to Order	Captures Disorder to Order
Molecular packing, e.g. Crystallization, intercalation	Captures atomistic level packing (initial configuration has to be ordered)	Captures backbone orientational order Captures intercalation	Cannot capture most of the molecular level packing at the side chain- backbone level.

Simulation Results with our Donor Polymer -Acceptor Model & Experimental Comparison



Macromolecules 46 (14) 5775-5785 (2013).

Experiment



Observation of Intercalation



E. Jankowski^{*}, H. Marsh^{*}, A. Jayaraman, *Macromolecules* 46 (14) 5775-5785 (2013)



Miller et al. Adv. Energy Materials (2012)



Zhang, Briseno, Marsh, Jayaraman JACS 136 (52), 18120 (2014)

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Polymers for Non-viral DNA Delivery

- Simulations linking cationic polymers architecture and chemistry to DNA-polymer complexation
- Polymer synthesis and in-vitro DNA transfection in
 T. Emrick's lab at UMass

Effect of Varying Polymer Architecture On Polymer DNA Binding Thermodynamics



R. Elder, T. Emrick, and A. Jayaraman, *Biomacromolecules* 12 (11), 3870 (2011)





R. M. Elder and A. Jayaraman, *J. Phys. Chem. B.* (2013) 117 (40), pp 11988–11999

Zwitterion containing polymers for DNA delivery



Ahmad Ghobadi, R. Letteri, T.Emrick, A.Jayaraman, *Biomacromolecules* (2016) Article ASAP

We first developed appropriate models to simulate relevant length and time scales



Then, established the effect of sulfobetaine content on polymer-DNA complexation- thermodynamics & structure



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Peptide-Polymer Based Biomaterials



Computational Design of Oligopeptide Containing Poly(ethylene glycol) Brushes for Stimuli-Responsive Materials

Francesca Stanzione and Arthi Jayaraman Journal of Physical Chemistry B 119 (42), 13309-13320 2015

Computational Approach Scan of a Large Design Space



F Stanzione and A Jayaraman, J. Phys Chem B 119 (42), 13309-13320 2015

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http://udel.edu/~arthij/

Jayaraman Research Group

Theory and Simulations of Polymers and Biomaterials

Home Research Publications Members News Talks

Welcome!

The Jayaraman research group is lead by Prof. Arthi Jayaraman, Associate Professor, Chemical and Biomolecular Engineering and Materials Science and Engineering at University of Delaware. Our research interests lie in understanding molecular-level phenomena governing complex biological processes and material science problems using theoretical and simulation techniques.

Current Research Focus



Recent News

Our collaborative paper with Todd Emrick and coworkers (at UMass) on accepted in Biomacromolecules!

Tyler has been selected as a finalist for the Padden symposium at APS March meeting 2016!

Research highlight on our JACS paper!<u>Link</u> US Department of Energy also tweets about this work <u>Link</u>

Arthi has been selected as Princeton University's Saville Lecturer for 2015-16!

Current members of Jayaraman group

Tyler Martin - PhD student, Polymer Nanocomposites Joshua Condon - PhD student, Peptide-Polymer Biomaterials Thomas Gartner - PhD student, Polymer Nanocomposites Dr. Francesca Stanzione- Peptide based biomaterials Dr. Ahmad Ghobadi - Nucleic acid based biomaterials Christopher Knieste - undergrad

Some of the group alumni and their current positions

- Arezou Seifpour PhD 2013 Intel (May 2013-)
- Robert Elder PhD Dec 2013 Army Research Lab (Jan 2014)
- Carla Esteridge PhD May 2015 Boeing Research (July 2015-)
- Hilary Marsh PhD May 2015 NREL
- Charles Starbird MS 2012 Eastman (June 2012-)
- Eric Jankowski Postdoc 2012-13 Asst. Prof. at Boise State (2015-)
- Nitish Nair Postdoc 2009-11 **Shell** (2011-)
- D. Zhang Postdoc 2011-12 **UT Dallas** (2012-)

Overview of Using GPUs for Molecular Dynamics Simulations

Tyler B. Martin Advisor: Prof. Arthi Jayaraman

January 27, 2016

Polymer Nanocomposite Morphology



Aggregated Morphology



Polymer nanocomposite morphology dictates macroscopic properties

Mechanical Reinforcement



Contamination Barriers



placon.com

Aircraft Coatings



wikimedia.org

Microelectronics



Chlorineremoval.com

How do we simulate polymer nanocomposites?



The force calculation in MD scales $O(N^2)$ where N is the number of atoms.

This is the dominant bottleneck in these simulations

Molecular Dynamics Simulation



MD Simulation Steps

For each bead in simulation...

- 1. Calculate force on bead i
- 2. Calculate acceleration of bead
- 3. Update bead velocity
- 4. Update bead position

How do we simulate polymer nanocomposites?



1. Polymer nanocomposites have very long relaxation times (must integrate Newton's Equations millions of times for each bead)

2. Most interesting polymer phenomena only occurs for large polymer lengths and system sizes (N becomes very large i.e. force calculation is expensive)

The force calculation in MD scales $O(N^2)$ where N is the number of atoms.

This is the dominant bottleneck in these simulations For each bead in simulation...

- 1. Calculate force on bead i
- 2. Calculate acceleration of bead
- 3. Update bead velocity
- 4. Update bead position

How do we achieve the large system sizes and long time scales needed for polymer nanocomposite study?

Software Improvements

Neighbor Lists Neighbor List Sorting Memory Chunking Domain Decomposition

Hardware Improvements

CPU Clock Speed Memory Bandwidth CPU Parallelization GPU Parallelization

No Neighbor List



Verlet Lists



Cell List



How do GPUs improve MD simulations?

CPU



A few high-speed processors

CPU's are designed to handle complex rapidly-varying tasks quickly

GPU's are designed to handle simple, highly-repetitive tasks very quickly

GPU



many low-speed streaming-multiprocessors

MD Simulation Steps

For each bead in simulation...

- 1. Calculate force on bead i
- 2. Calculate acceleration of bead
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- 4. Update bead position

HOOMD-Blue: A General Purpose GPU-Based MD Simulator

https://codeblue.umich.edu/hoomd-blue/





Reasons to consider HOOMD-blue over other MD packages. HOOMD-blue...

- is purpose-built for the GPU
- is flexible enough to simulate simple bead-systems to complex bio-macromolecules
- leverages the full power of Python scripting



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Fast analysis of molecular dynamics trajectories with graphics processing units—Radial distribution function histogramming

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ABSTRACT

The calculation of radial distribution functions (RDFs) from molecular dynamics trajectory data is a common and computationally expensive analysis task. The rate limiting step in the calculation of the RDF is building a histogram of the distance between atom pairs in each trajectory frame. Here we present an implementation of this histogramming scheme for multiple graphics processing units (GPUs). The algorithm features a tiling scheme to maximize the reuse of data at the fastest levels of the GPU's memory hierarchy and dynamic load balancing to allow high performance on heterogeneous configurations of GPUs. Several versions of the RDF algorithm are presented, utilizing the specific hardware features found on different generations of GPUs. We take advantage of larger shared memory and atomic memory operations available on state-of-the-art GPUs to accelerate the code significantly. The use of atomic memory operations allows the fast, limited-capacity on-chip memory to be used much more efficiently, resulting in a fivefold increase in performance compared to the version of the algorithm without atomic operations. The ultimate version of the algorithm running in parallel on four NVIDIA GeForce GTX 480 (Fermi) GPUs was found to be 92 times faster than a multithreaded implementation running on an Intel Xeon 5550 CPU. On this multi-GPU hardware, the RDF between two selections of 1,000,000 atoms each can be calculated in 26.9 s per frame. The multi-GPU RDF algorithms described here are implemented in VMD, a widely used and freely available software package for molecular dynamics visualization and analysis.

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Arthi Jayaraman's Research Group Dep. of Chemical and Biomolecular Engineering & Dep. of Material Science and Engineering 1/27/2016



What do I do with Farber?



Generate Data (using Lammps)

Project definition:

- Relatively small system of interacting molecules
- Two different temperature (T1 & T2)
- Three simulation trials
- Each simulation needs 24 hrs on 10 cpu cores (no GPU)



A.F. Ghobadi and A. Jayaraman, Soft Matter (2016, advance article), DOI: 10.1039/C5SM02868J

File preparation:

- Simulation input files (data file, etc)
- Simulation submission file (qs file)
- Scripts to submit multiple simulations at once

Generate Data (using Lammps) – Input files



Simulation input file (inp_eq):

Read initConf.dat

T = temp #*Temperature*

Random number = XXX

•••

•••

Write restart*

Simulation restart file (inp_res):

```
Read restart*
T = temp
Random number = XXX
...
dump output to temp-runY-prodZ.dat
Write restart*
```

Generate Data (using Lammps) – Submission file

<u>"submit.qs" file:</u>

```
#$ -pe threads 10
                              # export OMP NUM THREADS=$NSLOTS
\# -1 m mem free=2G
                              # Memory that must be available
#$ -1 standby=1
# -1 exclusive=1
#$ -1 h rt=8:00:00
# -m eas
# -M ahmadg@udel.edu
#$ -o dummy.o
#$ -e dummy.e
                              # This is generally ignored
#$ -V
#$ -N dummy
                              # Names the job to dummy
export VALET_PATH=$VALET_PATH: ...some path...
vpkg require jlab-lammps/ahmad
lmprun_FLAGS = "input file "
#WANT CPU AFFINITY=YES
MY EXE = 1 \text{mp}
mpirun ${OPENMPI FLAGS} $MY_EXE < $1mprun_FLAGS</pre>
```

Generate Data (using Lammps) – Bash script

"runs.sh" file:

```
Log into Farber
#!/bin/bash
                                       Navigate to your workgroup
for T in T1 T2
                                       Navigate to $Lustre/scratch/...
    for run in 1 2 3
                                       [Parent directory] $ bash runs.sh
        ··· some lines ···
                                       [Parent directory] $ qstat
        RND1=$RANDOM
        sed -i "s/temp/$T/g" inp eq
                                                        some jobs ..... r
        sed -i "s/XXX/$RND1/g" inp eq
                                                        some jobs ..... hqw
        ··· some lines ···
        job = job name $T $run
        sed -i "s/dummy/$job/g" submit.qs
                                                                       eq
        sed -i "s/input file/inp eq/g" submit.qs
        ··· some lines ···
        jid = `qsub -terse submit.qs`
                                                                      prod1
         ··· some lines ···
        for next in 1 2 3
                                                                      prod2
            ••• replace ZZ in inp prod file with $next •••
            jid = `qsub -terse -hold_jid $jid submit.qs
                                                                      prod3
        done
    done
done
```

Analyze Data – Serial Jobs

<u>"analyze.sh" file:</u>

```
#!/bin/bash
for T in T1 T2
    for run in 1 2 3
        ··· some lines ···
        Read temp-runY-prod3. dat
        g++ analyze
        ··· some lines ···
    done
```

<u>"analyze.py" file:</u>

```
Import os ??
for T in T1 T2
    for run in 1 2 3
        ··· some lines ···
        Read temp-runY-prod3. dat
        python myscript.py (T1*a)/2
        ··· some lines ···
    done
```

done

```
done
```

[Parent directory] \$ qlogin (to ask 1 core from Jayaraman_lab.q) [Parent directory] \$ vpkg require some packages [Parent directory]@some node \$ bash analyze.sh Or

[Parent directory] \$ vpkg_require *python-numpy* [Parent directory]@some_node \$ python analyze.py

Using GROMACS and Open MPI to perform Parallel Atomistic Molecular Dynamic (MD) Simulations on Farber

Francesca Stanzione Prof. Arthi Jayaraman's group

> HPC Symposium 2016 January 27th 2016

Atomistic Molecular Dynamics



Several software for Atomistic Molecular Dynamics: GROMACS, Amber, NAMD, CHARMM...

GROMACS one of the fastest molecular dynamics packages and it is implemented on Farber

Atomistic MD Simulation on Farber

GROMACS available on Farber: Version 4.6.7 and version 5.0



Parallel simulations on multiple nodes: Open MPI

Open MPI: the dominant multi-node parallelization-scheme



Open MPI Specifics

```
OPENMPI FLAGS="--display-map --mca btl ^tcp"
if [ "x$WANT CPU AFFINITY" = "xYES" ]; then
  OPENMPI FLAGS="${OPENMPI FLAGS} --bind-to core"
fi
if [ "${WANT NPROC:-0}" -gt 0 ]; then
  OPENMPI FLAGS="${OPENMPI FLAGS} --np ${WANT NPROC} --map-by node"
fi
if [ "x$SHOW MPI DEBUGGING" = "xYES" ]; then
  OPENMPI FLAGS="${OPENMPI FLAGS} --debug-devel --debug-daemons --
display-devel-map --display-devel-allocation --mca mca verbose 1 --
mca coll base verbose 1
--mca ras base verbose 1 --mca ras gridengine debug 1 --mca
ras gridengine verbose 1 --mca btl base verbose 1 --mca
mtl base verbose 1 --mca plm base verbose
1 --mca pls rsh debug 1"
  if [ "x$WANT_CPU_AFFINITY" = "xYES" -o "x$WANT_HALF_CORES_ONLY" =
"xYES" ]; then
    OPENMPI FLAGS="${OPENMPI FLAGS} --report-bindings"
  fi
fi
```

Benchmarking

to evaluate how many resources are required by a single simulation



Optimizing the Performance with GROMACS

A crucial calculation to be optimized is the long range interactions which consist of dispersion-type particle-particle (PP) interactions and the electrostatic forces obtained from the Particle Mesh Ewald (PME) method.



Optimizing the Performance with Grid-Engine flags

my_gromacs.qs

#\$ -pe mpi 128
#\$ -l m_mem_free=2G
#\$ -q jayaraman_lab.q
#\$ -l h_rt=04:00:00
-l exclusive=1
#\$ -R y
vpkg_require gromacs/double
\$ WANT CPU AFFINITY=YES

Disable the exclusive flag Reserve the minimum number of nodes to satisfy my CPUs request

MDRUN_FLAGS="-s run.tpr -deffnm run -npme -1"

