QM/MM methods

(Slides from Edina Rosta, Todd Martinez, Marc Vanderkamp)



Enzymes lower the activation energy for reaction



Enzyme catalytic cycles



- Difficult to dissect experimentally: *use computer simulation*
- To simulate chemical change, we need to go beyond molecular mechanics

Enzyme Catalysis



e.g. protease hydrolysis of peptide bonds

 $k_{\rm cat}/k_{\rm uncat}$ can reach 10¹⁶ e.g. uroporphyrinogen III decarboxylase



Finding more efficient enzymes for producing biofuels.







CHALLENGE

Finding more efficient enzymes for producing biofuels.

SOLUTION

JMP's design of experiment tools, multivariate analysis, the distribution platform, fit Y by X, fit model and the cluster platform.

RESULTS

Novozymes is improving the enzymes that render a more cost-effective and sustainable process for commercially viable biofuels.

MORE INFORMATION www.novozymes.com www.jmp.com

Novozymes

Reducing the cost of producing biofuels

Improving processes for its customers with enzyme products-that's the kernel of the issue-and that's Novozymes' business.

"Rethink Tomorrow" is Novozymes' slogan, and one of the areas where it's doing so is in looking for more efficient enzymes for producing biofuels. Novozymes is a Denmarkbased world leader in bio-innovation. In cooperation with its customers across a wide range of industries, Novozymes is helping create tomorrow's industrial bio-solutions for a greener planet.

Optimizing enzymes with JMP[®]

Here in the US-in Novozymes' North American subsidiary in Franklinton, North Carolina-Jesper Frickmann is tasked with supporting customers in implementing and optimizing Novozymes' enzymes for biofuel solutions within their businesses.

JMP statistical discovery software from SAS is an integral tool in Novozymes' research. Frickmann himself began using JMP more than 10 years ago. He's an engineer by training, but before working in customer support, he served as a statistician, providing statistical help to anyone at Novozymes. He used JMP then and still does.

Frickmann says: "Anytime we run an experiment in R&D to find new and better enzyme candidates or to optimize the reaction conditions, we use JMP to design an experiment and analyze the data.

"Or if a customer wants to try a different enzyme in our line, we'll run the two different enzymes in their application, collect the data-for example, the amount of alcohol produced-and determine if there's a significant difference in the two products."

One of the ongoing objectives of Novozymes' researchers is to consistently improve the enzymes that render a more cost-effective and sustainable process for commercially viable biofuels.

Also within the next-generation cellulosic ethanol are biofuels made from feedstocks such as cobs, stalks and leaves from corn, wood chips, paper, switchgrass, etc. "Today all that is mainly left in the field to rot," says Frickmann. "But it could be collected, and the cellulose from that could be converted. We're trying to make all this happen."



Kendall Houk, UCLA David Baker, University of Washington



nature

Vol 453 8 May 2008 doi:10.1038/nature06879



Figure 4 | **Comparison of the designed model of KE07 and the crystal structure.** The crystal structure (cyan) was solved in the unbound state and shows only modest rearrangement of active site side chains compared to the designed structure (grey) modelled in the presence of the transition state (yellow, transparent). (Backbone r.m.s.d. for the active site is 0.32 Å versus 0.95 Å for the active site including the side chains.) The observed electron

Kemp elimination catalysts by computational enzyme design

Daniela Röthlisberger¹*, Olga Khersonsky⁴*, Andrew M. Wollacott¹*, Lin Jiang^{1,2}, Jason DeChancie⁶, Jamie Betker³, Jasmine L. Gallaher³, Eric A. Althoff¹, Alexandre Zanghellini^{1,2}, Orly Dym⁵, Shira Albeck⁵, Kendall N. Houk⁶, Dan S. Tawfik⁴ & David Baker^{1,2,3}

The design of new enzymes for reactions not catalysed by naturally occurring biocatalysts is a challenge for protein engineering and is a critical test of our understanding of enzyme catalysis. Here we describe the computational design of eight enzymes that use two different catalytic motifs to catalyse the Kemp elimination—a model reaction for proton transfer from carbon—with measured rate enhancements of up to 10^5 and multiple turnovers. Mutational analysis confirms that catalysis depends on the computationally designed active sites, and a high-resolution crystal structure suggests that the designs have close to atomic accuracy. Application of *in vitro* evolution to enhance the computational designs produced a >200-fold increase in k_{cat}/K_m (k_{cat}/K_m of 2,600 M⁻¹s⁻¹ and k_{cat}/k_{uncat} of >10⁶). These results demonstrate the power of combining computational protein design with directed evolution for creating new enzymes, and we anticipate the creation of a wide range of useful new catalysts in the future.

Nature vol 453, pages190-195 (08 May 2008)

Kendall Houk, UCLA David Baker, University of Washington Science 07 Mar 2008: Vol. 319, Issue 5868, pp. 1387-1391 DOI: 10.1126/science.1152692

De Novo Computational Design of Retro-Aldol Enzymes

Lin Jiang, ^{1,2}* Eric A. Althoff, ¹* Fernando R. Clemente, ⁴ Lindsey Doyle, ⁵ Daniela Röthlisberger, ¹ Alexandre Zanghellini, ^{1,2} Jasmine L. Gallaher, ¹ Jamie L. Betker, ¹ Fujie Tanaka, ⁶ Carlos F. Barbas III, ⁶ Donald Hilvert, ⁷ Kendall N. Houk, ⁴ Barry L. Stoddard, ⁵ David Baker^{1,2,3}†

The creation of enzymes capable of catalyzing any desired chemical reaction is a grand challenge for computational protein design. Using new algorithms that rely on hashing techniques to construct active sites for multistep reactions, we designed retro-aldolases that use four different catalytic motifs to catalyze the breaking of a carbon-carbon bond in a nonnatural substrate. Of the 72 designs that were experimentally characterized, 32, spanning a range of protein folds, had detectable retro-aldolase activity. Designs that used an explicit water molecule to mediate proton shuffling were significantly more successful, with rate accelerations of up to four orders of magnitude and multiple turnovers, than those involving charged side-chain networks. The atomic accuracy of the design process was confirmed by the x-ray crystal structure of active designs embedded in two protein scaffolds, both of which were nearly superimposable on the design model.



Kendall Houk, UCLA David Baker, University of Washington *Science* 16 Jul 2010: Vol. 329, Issue 5989, pp. 309-313 DOI: 10.1126/science.1190239

Computational Design of an Enzyme Catalyst for a Stereoselective Bimolecular Diels-Alder Reaction

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The Diels-Alder reaction is a cornerstone in organic synthesis, forming two carbon-carbon bonds and up to four new stereogenic centers in one step. No naturally occurring enzymes have been shown to catalyze bimolecular Diels-Alder reactions. We describe the de novo computational design and experimental characterization of enzymes catalyzing a bimolecular Diels-Alder reaction with high stereoselectivity and substrate specificity. X-ray crystallography confirms that the structure matches the design for the most active of the enzymes, and binding site substitutions reprogram the substrate specificity. Designed stereoselective catalysts for carbon-carbon bond-forming reactions should be broadly useful in synthetic chemistry.



Fig. 1. The Diels-Alder reaction. Diene (1) and dienophile (2) undergo a pericyclic [4 + 2] cycloaddition (3) to form a chiral cyclohexene ring (4). Also shown in (3) is a schematic of the design target active site, with hydrogen bond acceptor and donor groups activating the diene and dienophile and a complementary binding pocket holding the two substrates in an orientation optimal for catalysis.



Nobel Prize in Chemistry 1998



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The recipients

Walter Kohn

Developed the Density Functional Theory (DFT), which became the most widely used quantum chemistry method due to its efficiency and accuracy.

• John Pople

Developed numerous algorithms for quantum chemistry methods. Main founder behind the currently most widely used quantum chemistry software, Gaussian.



Walter Kohn



John A. Pople

Their work enables us to

- Obtain the solution of the Schrödinger equation using approximate methods $H\Psi = E\Psi$
- Find energies and wave functions of small to medium sized molecules
- Provide accurate models of chemical structure and reactivity



Nobel Prize in Chemistry 2013



Their work enables us to

- Find the structures of complex biomolecules by calculating their Newtonian dynamics
- Find reaction mechanisms of enzymes
- Model and predict structure and function of biological systems





A Hybrid QM/MM Approach

The development of hybrid QM/MM approaches is guided by the general idea that large chemical systems may be partitioned into an electronically important region which requires a quantum chemical treatment and a remainder which only acts in a perturbative fashion and thus admits a classical description.



Quantum Mechanics

- In theory, a very accurate treatment of the system
- Largely *ab initio*, i.e. parameter-free
- Very expensive typically scales as O(N⁴) or worse
- Limited to very small systems at high accuracy (e.g. DFT)
- Can be used for larger systems at lower accuracy (e.g. semi-empirical)
- Entire proteins cannot be simulated without enormous supercomputer power



aussian.com



Software Packages

- QM software packages:
 - ORCA
 - Q-Chem
 - Gaussian
 - Turbomole
 - MOPAC
- MM software packages with QM/MM:
 - NAMD (NEW!)
 - CHARMM
 - ChemShell
 - AMBER
 - GROMACS
 - Q Site Schrodinger







The Simplest Hybrid QM/MM Model

Hamiltonian for the molecular system in the Born-Oppenheimer approximation:

$$H = -\frac{1}{2} \sum_{i}^{electrons} \nabla^2 - \sum_{i}^{electrons} \sum_{j}^{nuclei} \frac{Z_j}{R_{ij}} + \sum_{i}^{electrons} \sum_{j < i}^{electrons} \frac{1}{r_{ij}} + \sum_{i}^{nuclei} \sum_{j < i}^{nuclei} \frac{Z_i Z_j}{R_{ij}} \quad \leftarrow \text{`Standard'' QM hamiltonian}$$

$$H = -\frac{1}{2} \sum_{i}^{electrons} \nabla^2 - \sum_{i}^{electrons} \sum_{j}^{nuclei} \frac{Z_j}{R_{ij}} + \sum_{i}^{electrons} \sum_{j < i}^{electrons} \frac{1}{r_{ij}} + \sum_{i}^{nuclei} \sum_{j < i}^{nuclei} \frac{Z_i Z_j}{R_{ij}} - \sum_{i}^{electrons} \sum_{k}^{ch} \frac{Q_k}{R_{ik}} + \sum_{i}^{nuclei} \sum_{k}^{ch} \frac{Z_i Q_k}{R_{ik}}$$

Effect of External Ch arg es

The main drawbacks of this simple QM/MM model are:

 \Rightarrow it is impossible to optimize the position of the QM part relative to the external charges because QM nuclei will collapse on the negatively charged external charges.

 \Rightarrow some MM atoms possess no charge and so would be invisible to the QM atoms

 \Rightarrow the van der Waals terms on the MM atoms often provide the only difference in the interactions of one atom type versus another, i.e. chloride and bromide ions both have unit negative charge and only differ in their van der Waals terms.



So, it is quite reasonable to attribute the van der Waals parameters (as it is in the MM method) to every QM atom and the Hamiltonian describing the interaction between the QM and MM atoms can have a form:

$$\hat{H}_{QM/MM} = -\sum_{i}^{electrons} \sum_{j}^{MM \ atoms} \frac{Q_{j}}{r_{ij}} + \sum_{i}^{nuclei} \sum_{j}^{MM \ atoms} \frac{Z_{i}Q_{j}}{R_{ij}} + \sum_{i}^{nuclei} \sum_{j}^{MM \ atoms} \left\{ \frac{A_{ij}}{R_{ij}^{12}} - \frac{B_{ij}}{R_{ij}^{6}} \right\}$$

The van der Waals term models also electronic repulsion and dispersion interactions, which do not exist between QM and MM atoms because MM atoms possess no explicit electrons.

A. Warshel, M. Levitt // Theoretical Studies of Enzymic Reactions: Dielectric, Electrostatic and steric stabilization of the carbonium ion in the reaction of lysozyme. // *J.Mol.Biol.* 103(1976), 227-49

Mechanical Embedding

Crudest level of QM/MM Include only Van der Waals in E_{OM/MM} Useful to impose only steric constraints

Can take advantage of this to isolate effects...

 $H_{QM/MM} = \sum V_{ij}^{VdW}(r_i, r_j)$

i∈MM $j \in OM$

Simple QM/QM implementation

ONIOM a divides the system into the 'real' (full) system and the 'model' (subset) and treats the model at high level, and the real at low level, giving the total energy as

 $E(high, real) \simeq E(low, real) + E(high, model) - E(low, model)$

which relies on the approximation

 $E(high, model) - E(low, model) \simeq E(high, real) - E(low, real)$

- The 'model' system still has to be properly terminated
- Extension to three level systems is relatively straightforward (e.g. *ab initio* core, semi-empirical boundary, MM surroundings)

^aSvensson, M. et. al. J. Phys. Chem. **1996**, 100, 19357

Electrostatic Embedding

Include electrostatic interaction in H_{QM/MM}

 Many possible implementations – best is to evaluate integrals over continuous QM charge density and discrete MM charge density

$$H_{QM/MM} = H_{QM/MM}^{mechanical} + \sum_{i \in MM} q_i \int \frac{\rho_{QM}(r)}{|r - r_i|} dr$$

Oft-used approximation (questionable):

 $H_{QM/MM} = H_{QM/MM}^{mechanical} + \sum q_i q_j (\rho_{QM}) / f_{\hat{U}}$ $i \in MM$ $j \in OM$

Atomic Charge Schemes

- * "Atoms" are not well-defined in molecules there is no quantum mechanical operator corresponding to an atom.
- This leads to ambiguity in the definition of an atomic charge
- Population Analysis Schemes
 - Basically, sum over all electrons using the basis functions of a given atom
 - Depends on the atom-centered nature of the basis set
 - Breaks down as the basis functions become more delocalized – results do not usually converge with increasing basis set!



Charge Schemes 2

ESP-Fitting

- Determine charges which reproduce the electrostatic potential generated by the molecule
- If using charges in an MM potential, this appears to be the right way
- But, equations have many solutions, especially when molecule has an "interior"



Charge for solvated ion will be essentially undetermined

The Hybrid QM/MM Model

Now we can construct a "real" hybrid QM/MM Hamiltonian:

$$\begin{split} \hat{H} &= \hat{H}_{QM} + \hat{H}_{QM/MM} + \hat{H}_{MM} \\ \hat{H}_{QM/MM} &= -\sum_{i}^{electrons} \sum_{j}^{MM \text{ atoms}} \frac{Q_{j}}{r_{ij}} + \sum_{i}^{nuclei} \sum_{j}^{MM \text{ atoms}} \frac{Z_{i}Q_{j}}{R_{ij}} + \sum_{i}^{nuclei} \sum_{j}^{MM \text{ atoms}} \left\{ \frac{A_{ij}}{R_{ij}^{12}} - \frac{B_{ij}}{R_{ij}^{6}} \right\} \\ \hat{H}_{QM/MM}^{el} &= -\sum_{i}^{electrons} \sum_{j}^{MM \text{ atoms}} \frac{Q_{j}}{r_{ij}} + \sum_{i}^{nuclei} \sum_{j}^{MM \text{ atoms}} \frac{Z_{i}Q_{j}}{R_{ij}} \\ \hline \mathbf{E} &= \left\langle \Psi \left| \hat{H}_{QM} + \hat{H}_{QM/MM}^{el} \right| \Psi \right\rangle + \mathbf{E}_{QM/MM}^{vdw} + \mathbf{E}_{MM} \end{split}$$

A "standard" MM force field can be used to determine the MM energy. For example, CHARMM force field has a form:

$$E_{MM} = \sum_{nonbonded} \left[\frac{A_{ij}}{R_{ij}^{12}} - \frac{B_{ij}}{R_{ij}^{6}} + \frac{q_i q_j}{R_{ij}} \right] + \sum_{bonds} \frac{K_b}{2} (R - R_0)^2 + \sum_{angles} \frac{K_\theta}{2} (\theta - \theta_0)^2 + \sum_{dihedrals} V_\phi \left(1 + \cos(n\phi + \delta) \right)$$



A "standard" MM force field can be used to determine the MM energy. For example, CHARMM force field has a form:

$$E_{MM} = \sum_{nonbonded} \left| \frac{A_{ij}}{R_{ij}^{12}} - \frac{B_{ij}}{R_{ij}^{6}} + \frac{q_i q_j}{R_{ij}} \right| + \sum_{bonds} \frac{K_b}{2} (R - R_0)^2 + \sum_{angles} \frac{K_\theta}{2} (\theta - \theta_0)^2 + \sum_{dihedrals} V_\phi \left(1 + \cos(n\phi + \delta)\right)$$

What does the QM program provide?

We need the QM/MM gradients corresponding to the total energy.



Gradient of the potential (field) at the position of the MM atoms (x q_i)

To evaluate the gradient (and energy) of the QM/MM potential at given nuclei positions, the following practical information is required from the QM calculations:

- Gradient of the wave function in the position of the QM atoms
- Derivative of the electrostatic potential arising from the QM wave function at the position of the MM atoms (Field)
- (Energy of polarized QM system)

Dividing Covalent Bonds across the QM and MM Regions



In many simulations it is necessary to have the QM/MM boundary cut covalent bonds, and a number of additional approximations have to be made.

Covalent Embedding

Most difficult embedding – cutting across covalent bonds

Almost always required in biological context

Many strategies; still not clear which is best or whether any of them "work"

Singh & <u>Kollman</u> (1986)



Covalent Embedding 2

Potential Problems with Link Atom Idea

- Extra degrees of freedom which somehow need to be removed; i.e. the link atom somehow needs to be connected to the MM part of the simulation
- Electronic structure at boundary will be very different if H and the atom it replaces do not have similar electronegativities

Implementation of "link" atom approach



The link atom is placed along the bond vector joining the QM and MM atom

The default link atom type is hydrogen

It interacts with MM region only electrostatically (no VDW term).

VdW interaction between QM and MM atoms which form 1-2 and 1-3 "bonded" pairs *is not calculated*.

Bond stretching, angle bending, and torsion interactions between QM and MM regions are calculated as those in MM if 1-2, 1-2-3, or 1-2-3-4 terms contain at least one MM atom

Hints for running QM/MM calculations Choosing the QM region





Rivail & co-workers (1994)

E_{QM}: AM1

E_{MM}: AMBER

 $E_{QM/MM}\!\!:$ Hybrid MO



Effective Fragment Potential ^b adds 'fragments' to a standard QM treatment, which are fully polarizable and are 'parameterized' from separate *ab initio* calculations

 Treatment of bonds between the 'true' QM region and the fragments is still problematic



^bWebb, P. and Gordon, M. *J. Phys. Chem.* **1999**, *103*, 1265

Cautions

- Most force fields do not include polarizability, but QM region will
- This can lead to imbalance and amplification of errors

All covalent embedding schemes should be treated with caution – it is surely possible to break almost every implemented scheme

One needs to test carefully the dependence of the results on the QM/MM partitioning

Classical alternative: EVB



- Electrostatic & Mechanical embedding
- Possible switching function to cut off long range electrostatics



- NAMD uses partial charges for the QM atoms to calculate the electrostatic interaction with classical point charges.
- There are two possibilities for the origin of the QM partial charges:
 - the original partial charges found in the force field parameter files can be used
 - updated partial charges can be gathered at each step form the QM software output (controllable through the "qmChargeMode" keyword).

The continuous update in charge distribution allows for a partial reparameterization of the targeted molecule at each time step.



- Link atom treatment
- keywords
 "qmBondDist"
 to scale the bond
 length
- "qmLinkElement" to change the terminating atom type



- Several charge redistribution scheme to remove partial charges from nearby QM atoms
- "qmBondScheme" keyword
- No charge or Redistributed Charge and Dipole (RCD) methods



- ORCA and MOPAC natively supported
- python wrapper scripts for <u>GAUSSIAN</u>, <u>TeraChem</u> and <u>Q-Chem</u>







TURBOMOLE

- Multiple QM regions are supported
- More on keywords, etc:
- http://www.ks.uiuc.edu /Research/qmmm/



QM/MM reaction modelling

 To overcome activation energy, need to 'force' a reaction happening: apply 'bias' along a 'reaction coordinate'



Free Energy Surface

QM/MM MD + *statistics*



Dynamics on QM/MM potential

Minimizations corresponding to 0K is often problematic for larger systems:

- Missing entropy effects are important in e.g., protein folding, ligand binding, etc.
- Even is enthalpic contributions dominate, only local minima are found

There are several methods to model the thermostatted movements of the atoms on a given potential. These should provide a proper thermodynamic ensemble at long time scales.

A popular one is Langevin dynamics to obtain canonical ensemble:

$$M\ddot{X} = -\nabla U(X) - \gamma M\dot{X} + \sqrt{2\gamma k_B T M} R(t),$$

R(t) is a delta-correlated stationary Gaussian process with zero-mean and a constant variance.

γ: damping constant

Others: Andersen, Nose-Hoover, etc...

Umbrella Sampling 1.

Run parallel simulations with harmonic constraints moving along the reaction coordinate

Torrie and Valleau; J. Comp. Phys. 1977 Cited: ~ 3200 times

Recover the unbiased free energy surface from combined data using e.g., WHAM





Ferrenberg, Swendsen; Phys. Rev. Lett. 1989 - Cited: ~ 2800 times Kumar, Rosenberg, Bouzida, Swendsen, Kollman; J. Comput. Chem. 1992 (WHAM) - Cited: ~ 3600 times

1. WHAM

$$\begin{split} & \Pr^{(k)} \propto \prod_{i=1}^{Nbin} \left(p_i^{(k)}\right)^{n_i^{(k)}} & Probability of observing a trajectory in the k-th simulation. \\ & \tilde{L} = \ln \prod_{k=1}^{NSim} \prod_{i=1}^{Nbin} \left(p_i^{(k)}\right)^{n_i^{(k)}} & P_i^{(k)} & Equilibrium probability for bin i \\ & n_i^{(k)} & Histogram count in bin i \\ & p_i^{(k)} = f^{(k)} e^{-\beta U_i^{(k)}} p_i = \frac{e^{-\beta U_i^{(k)}} p_i}{\sum_{j=1}^{N_{bin}} e^{-\beta U_j^{(k)}} p_j} & e^{\frac{-U_i^{(k)}}{k_B T}} & Boltzmann factor \\ & e^{\frac{-U_i^{(k)}}{k_B T}} & Boltzmann factor for biasing energy \\ & f^{(k)} = \frac{1}{\sum_{j=1}^{N_{bin}} e^{-\beta U_j^{(k)}} p_j} & f^{(k)} = \frac{1}{\sum_{j=1}^{N_{bin}} e^{-\beta U_i^{(k)}} p_j} & Normalizing factor for \\ & L = \ln \prod_{k=1}^{NSim} \sum_{i=1}^{Nbin} \left(f^{(k)} e^{-\beta U_i^{(k)}} p_i\right)^{n_i^{(k)}} + \sum_{k=1}^{NSim} \lambda^{(k)} \left(1 - \sum_{i=1}^{N_{bin}} f^{(k)} e^{-\beta U_i^{(k)}} p_i\right) \end{split}$$

1. WHAM

 $n_i^{(k)}$

$$\operatorname{Pr}^{(k)} \propto \prod_{i=1}^{Nbin} \left(p_i^{(k)} \right)^{n_i^{(k)}}$$



Probability of observing a trajectory in the *k*-th simulation.

 $p_i^{(k)}$ Equilibrium probability for bin *i*

Histogram count in bin i







 $L = \ln \prod_{i=1}^{NSim} \prod_{i=1}^{Nbin} \left(f^{(k)} e^{-\beta U_i^{(k)}} p_i \right)^{n_i^{(k)}} + \sum_{i=1}^{NSim} \lambda^{(k)} \left(1 - \sum_{i=1}^{Nbin} f^{(k)} e^{-\beta U_i^{(k)}} p_i \right)$ k=1 i=1

 String-type methods have become highly successful in recent years

Henkelman, Jonsson, W. Yang, Brooks, ...

 Optimized a 1D string in the multidimensional space of the internal reaction coordinates to obtain minimum free energy path

E, Ren, Vanden-Eijnden, Phys. Rev. B, 2002

 Hamiltonian replica exchange between string images

Rosta, Nowotny, Yang, Hummer, J. Am. Chem. Soc., 2011



- Start with a guess for the string
- Run Umbrella Sampling simulations
- Determine forces for the images along the string
- Fit new string



- Start with a guess for the string
- Run Umbrella Sampling simulations
- Determine forces acting on the images along the string
- Fit new string
- Redistribute images
- Run next iteration



• Converged string:

- Forces are parallel to string

 We use all data from all string simulations with Histogram Free implementation of WHAM: works with very high dimensionality





Rosta, Nowotny, Yang, Hummer, J. Am. Chem. Soc., 2011



Hamiltonian Replica Exchange



K. Hukushima and K. Nemotto, *J. Phys. Soc. Japan*, 1996 Fukunishi, Watanabe & Takada, *J. Chem. Phys.*, 2002

- Running MD at different temperatures in parallel
- Couple the runs in order to speed up lowest temperature's dynamics
 - Preserve P_{eq} at each temperature
- Detailed balance condition has to be satisfied



1. RNase H: Free Energy Surface



 $Q_p = r_3 - r_4 + r_5 - r_6 + r_7 - r_8$

Rosta, Nowotny, Yang, Hummer, J. Am. Chem. Soc., 2011



Ganguly, Thaplyal, Rosta, Bevilacqua, Hammes-Schiffer, JACS 2014







- A: **concerted** mechanism with phosphorane intermediate
- B: sequential pathway with a protontransferred intermediate
- C: **sequential** pathway with a phosphorane intermediate

Ganguly, Thaplyal, Rosta, Bevilacqua, Hammes-Schiffer, JACS 2014

С

HDV ribozyme

U23

H₂O

C22

U-1





Ganguly, Thaplyal, Rosta, Bevilacqua, Hammes-Schiffer, JACS 2014

1. Umbrella Sampling Simulations & WHAM



- MC simulations
- 7 Umbrellas with 50 kcal/mol biasing force each

Rosta, Hummer, JCTC, 2015

1. Systematic error when using WHAM in conjunction with small biasing force



- 6 Umbrellas with 50 kcal/mol biasing force each
- 1 Umbrella with 1 kcal/mol biasing force each

Rosta, Hummer, JCTC, 2015

1. Markov-state models of conformational transitions



DHAM: Dynamic Histogram Analysis Method

Our approach:

- Discretized reaction coordinates
- Short lagtimes

• Markov property: $P_{1|n-1}(x_n, t_n | x_{n-1}, t_{n-1}; ...; x_1, t_1) = \overbrace{P_{1|1}(x_n, t_n | x_{n-1}, t_{n-1})}^{\text{transition probability}}, \quad t_1 < ... < t_n$

Most molecular dynamics integrators are Markovian!

1. DHAM: Dynamic Histogram Analysis Method

$$\operatorname{Pr}^{(k)} \propto \prod_{i=1}^{Nbin} \prod_{j=1}^{Nbin} \left(M_{ji}^{(k)} \right)^{T_{ji}^{(k)}}$$

$$\tilde{L} = \ln \bigotimes_{k=1}^{NSim} \bigotimes_{i=1}^{Nbin} \bigotimes_{j=1}^{Nbin} \left(M_{ji}^{(k)} \right)^{T_{ji}^{(k)}}$$

$$M_{ji}^{(k)} = f_i^{(k)} c_{ji}^{(k)} M_{ji} = \frac{c_{ji}^{(k)} M_{ji}}{\sum_{l=1}^{N_{bin}} c_{li}^{(k)} M_{li}}$$
$$\frac{M_{ji}^{(k)}}{M_{ji}^{(0)}} = f_i^{(k)} c_{ji}^{(k)} \approx \exp\left(-\left(u_j^{(k)} - u_i^{(k)}\right)/2k_BT\right)$$



Biased Dynamical Trajectories Histogram of Transitions Markov Model **Free Energy** & Kinetics $t_2 = -\tau_{lag} / \ln \lambda_2$

Rosta, Hummer, JCTC, 2015

Applications using Umbrella Sampling



1. Applications for "downhill" unbiased nonequilibrium trajectories

MC trajectories initiated from around x=0.63



1. Applications for "downhill" unbiased nonequilibrium trajectories



1. Umbrella sampling QM/MM simulations of catalytic reactions



 $H_{H} = H_{2} C_{H} + H_{2} C_{H} + H_{2} C_{H} + H_{2} + H_$

Hydrogen abstraction from arachidonic acid in the catalytic reaction of human 15-LOX-2 lipoxygenase.

1. Umbrella sampling QM/MM simulations of catalytic reactions



Lag time	Rate
1 fs	0.24 s ⁻¹
10 fs	0.17 s ⁻¹
50 fs	0.29 s ⁻¹

Experimental $k_{cat} = 0.7 \text{ s}^{-1}$

$$k = A e^{-\Delta G^{\ddagger}/k_B T}$$

k=0.22 s⁻¹ @T=300K Calculated prefactor using a barrier of 18.7 kcal/mol:

A = 8.6x10¹² s⁻¹

2

 $k_{\rm B}T/h = 6.3 \times 10^{12} \, {\rm s}^{-1}$