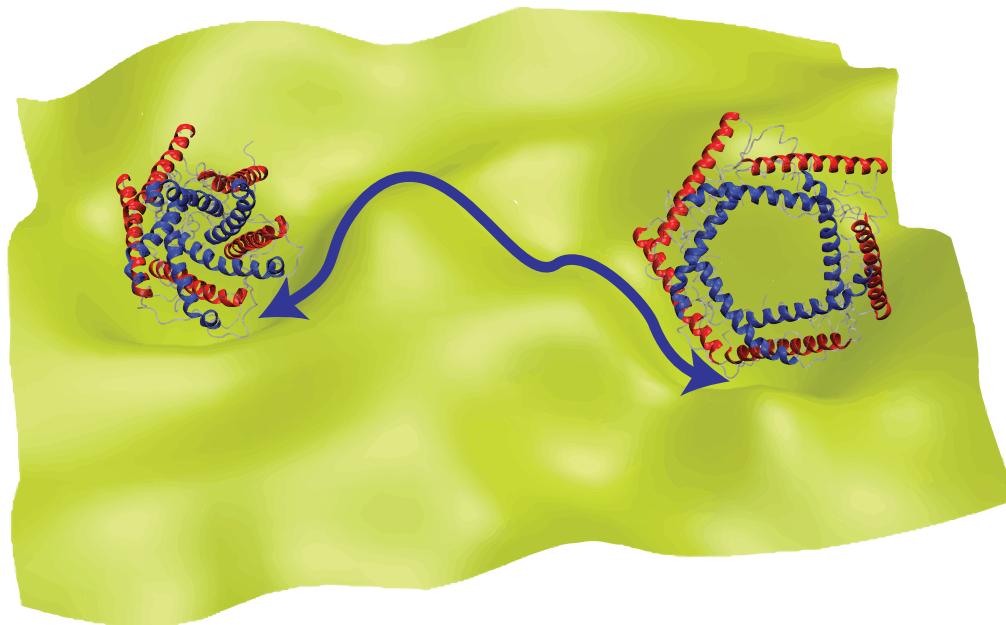


# Exploring Complex Reaction Pathways

Mahmoud Moradi

Department of Chemistry and Biochemistry  
University of Arkansas



"Hands-on" Workshop on Enhanced Sampling and  
Free-Energy Calculation at Urbana, IL

**September 29, 2017**

# Outline

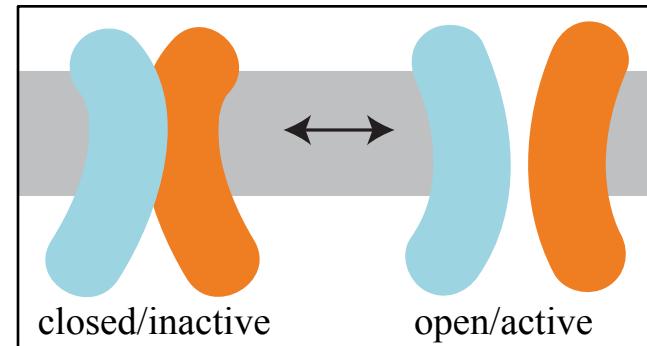
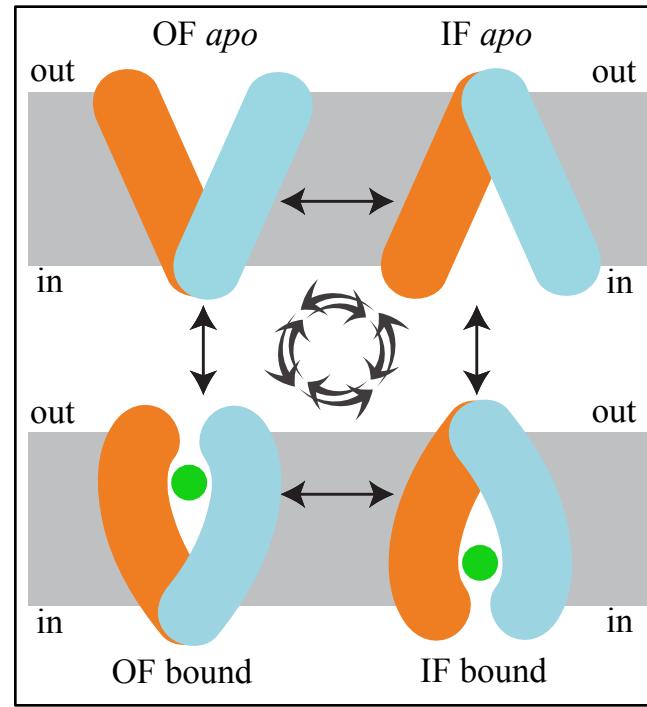
- **Introduction**
  - How to study large-scale conformational changes?
- **Methodology**
  - Empirical search for good pulling protocols
  - Iterative combination of free energy calculation methods and path-finding algorithms
- **Theoretical Framework**
  - Effective Riemannian diffusion model
- **Applications**
  - Membrane transport proteins

# Outline

- **Introduction**
  - How to study large-scale conformational changes

# Large-Scale Conformational Changes in Membrane Transport Proteins

- **Membrane transporters** rely on large-scale conformational changes between **inward-facing (IF)** and **outward-facing (OF)** states (**alternating access mechanism**)
- **Channels** may require large-scale conformational changes between their **open/active** and **closed/inactive** states.



# A Case Study: Proton-coupled Oligopeptide Transporters (POTs)

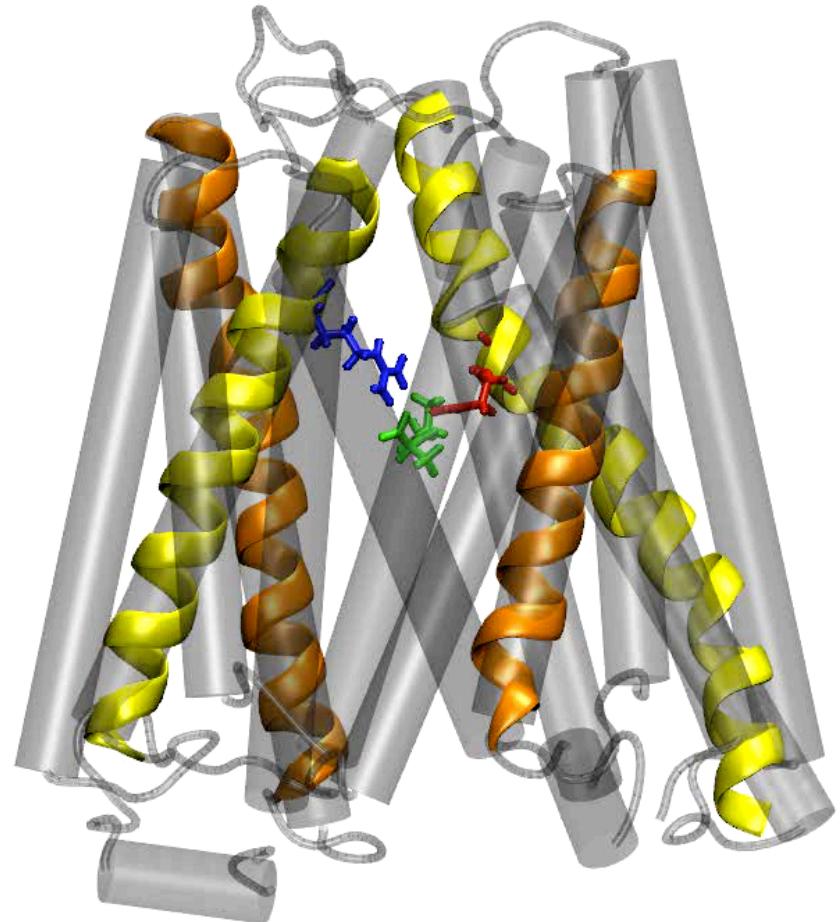
GkPOT (4IKV, 1.9 Å)

~100,000 atoms

Conventional unbiased  
simulations performed:

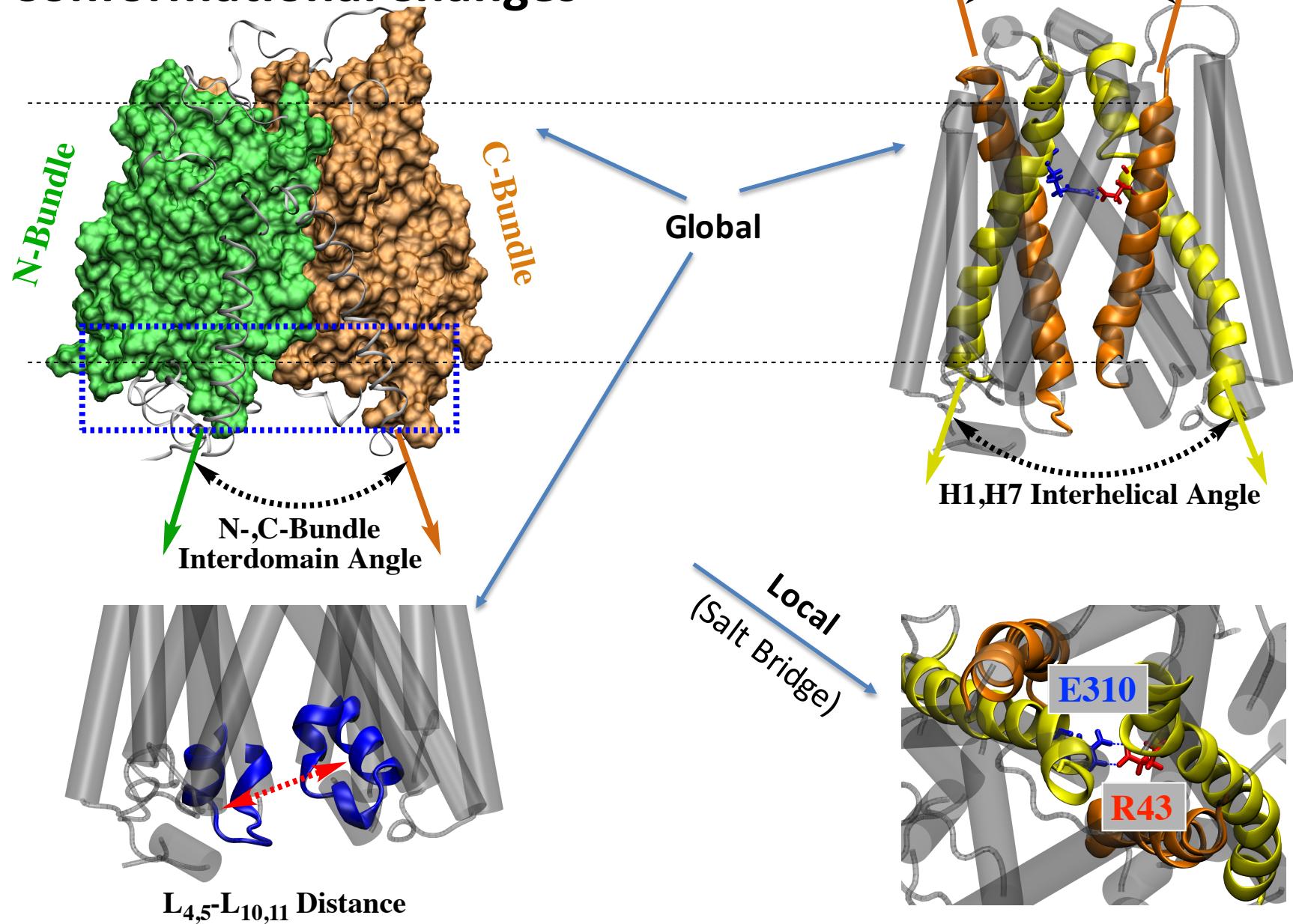
8 conditions × 400 ns

× 2 repeats = 6.4 μs

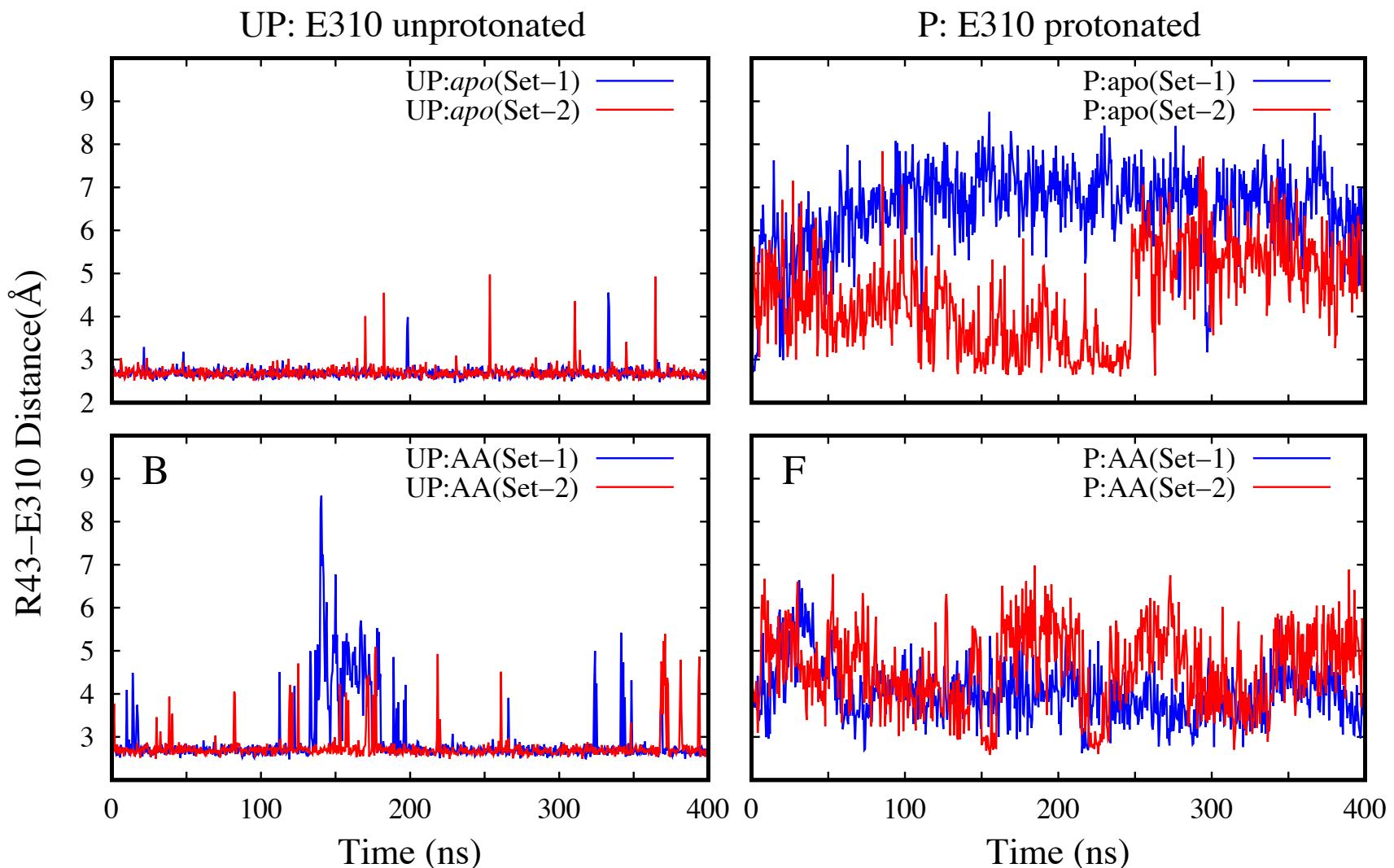


K Immadisetty, J Hettige, and M Moradi, *What Can and Cannot Be Learned from Molecular Dynamics Simulations of Bacterial Proton-Coupled Oligopeptide Transporter GkPOT?* *J. Phys. Chem. B*, **121**:3644-3656, 2017.

# Monitoring Global and Local Conformational Changes

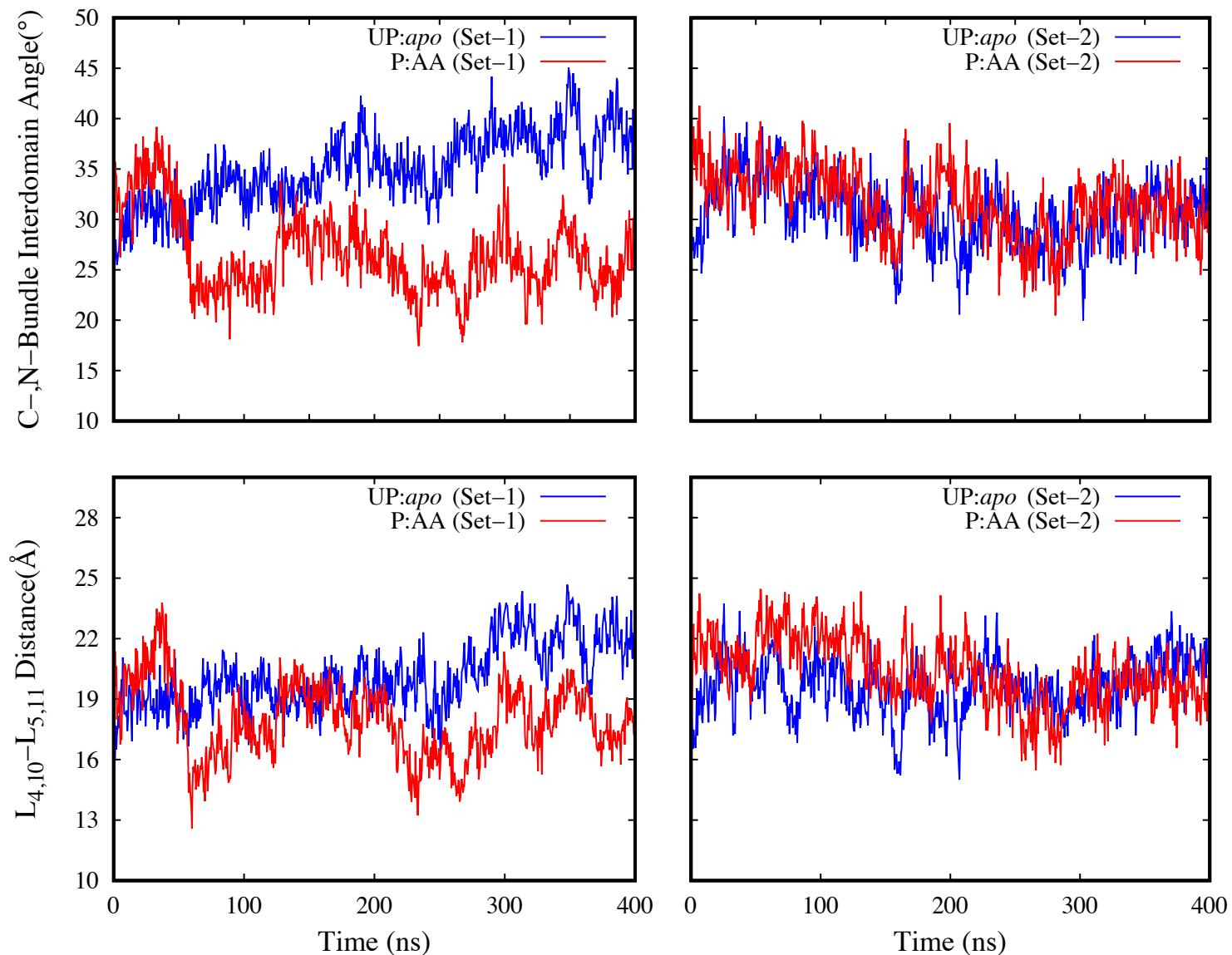


# Local Conformational Changes



There is a clear distinction between different conditions.

# Global Conformational Changes



There is no clear reproducible distinction between different conditions.

# Global Conformational Changes

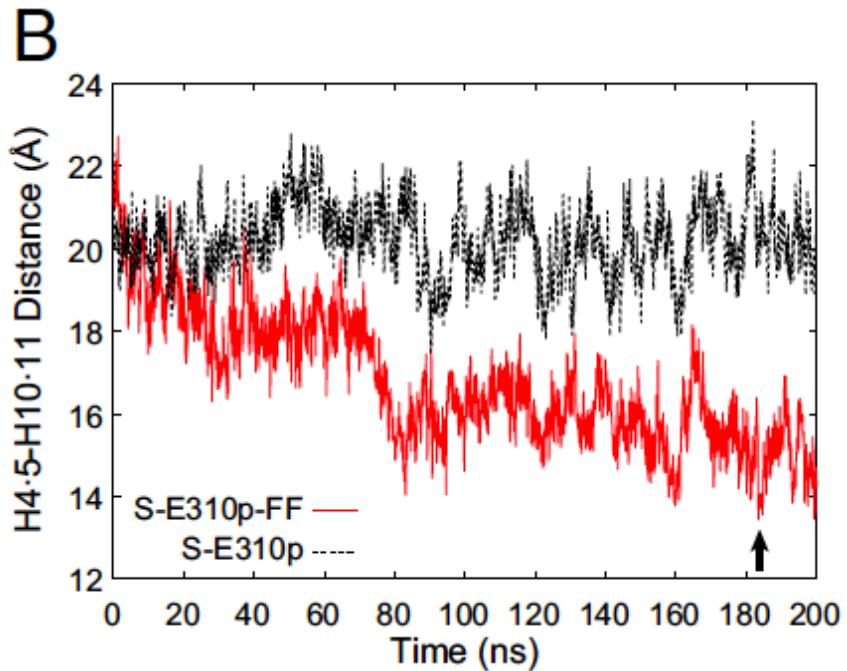
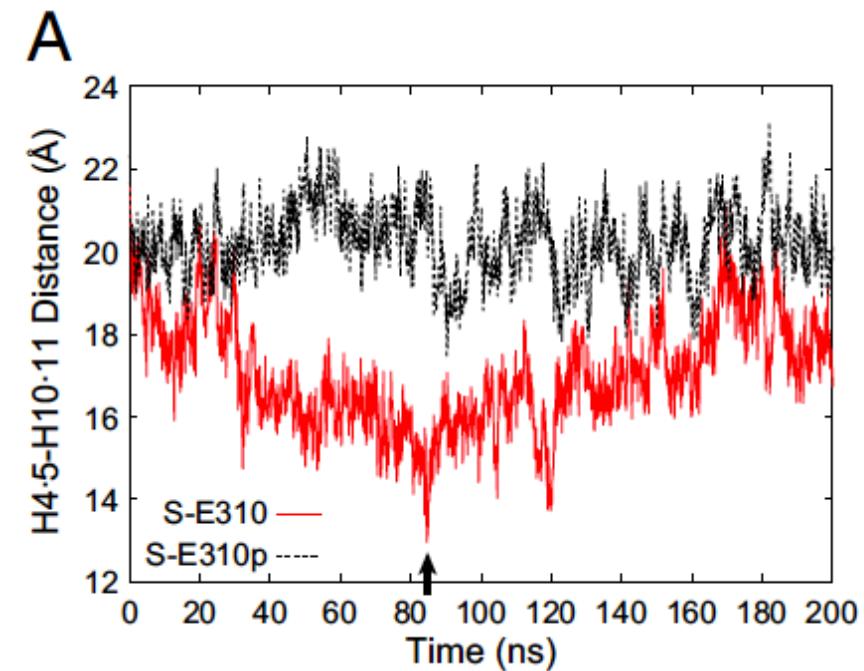
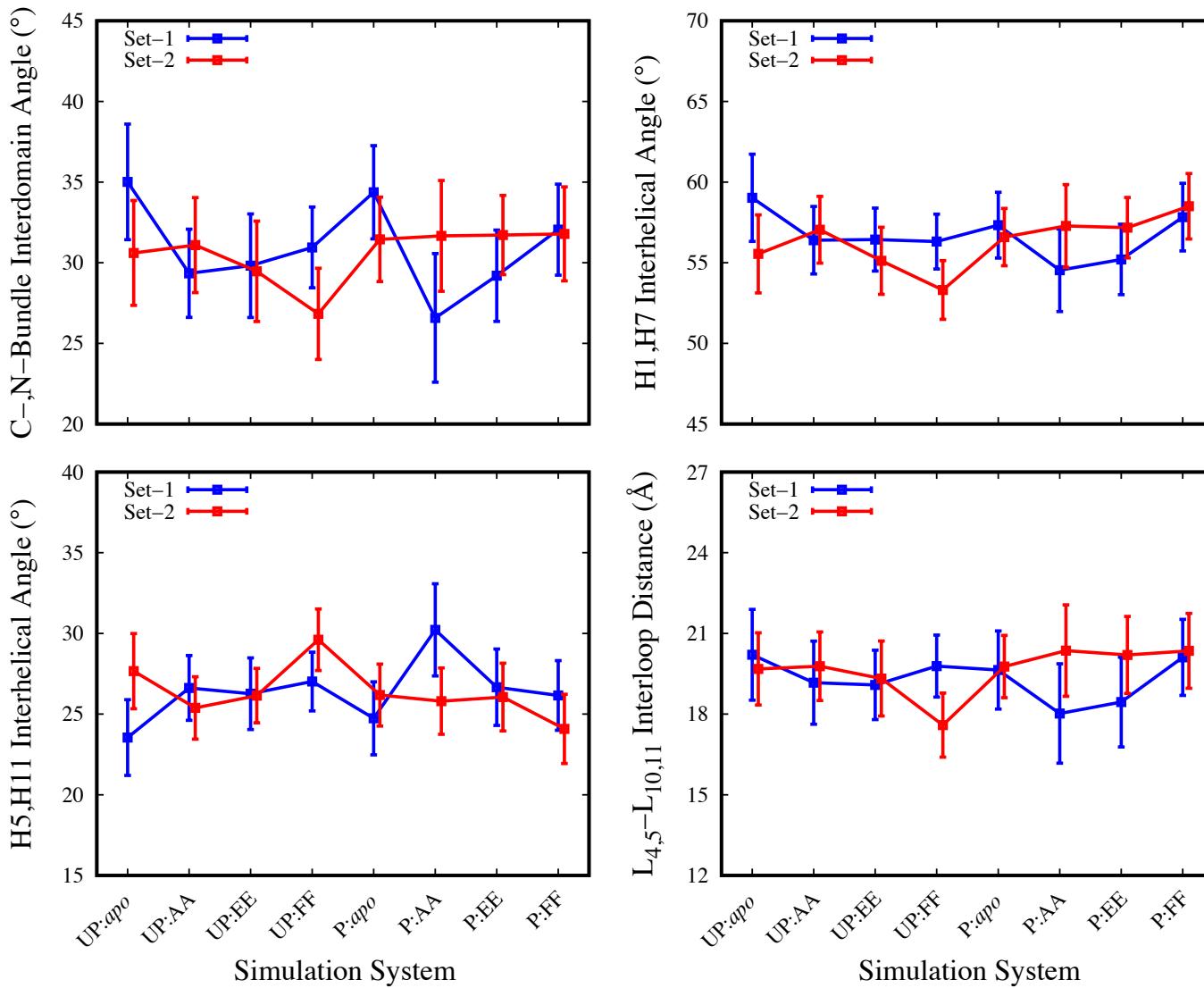


Fig. 4. Structural transitions revealed by MD simulations. Time series of the distances between the cytosolic-side helices of the N- and C-terminal bundles (residues 141–156 and 420–440, respectively) in the S-E310 and S-E310p-FF simulations.

“...”, PNAS 2013, ...

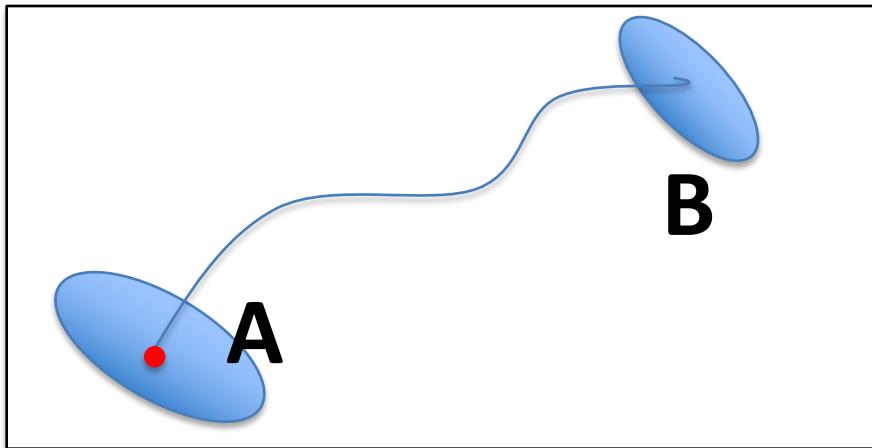
There is no clear reproducible distinction between different conditions even if it is claimed to be so in the literature!

# Global Conformational Changes

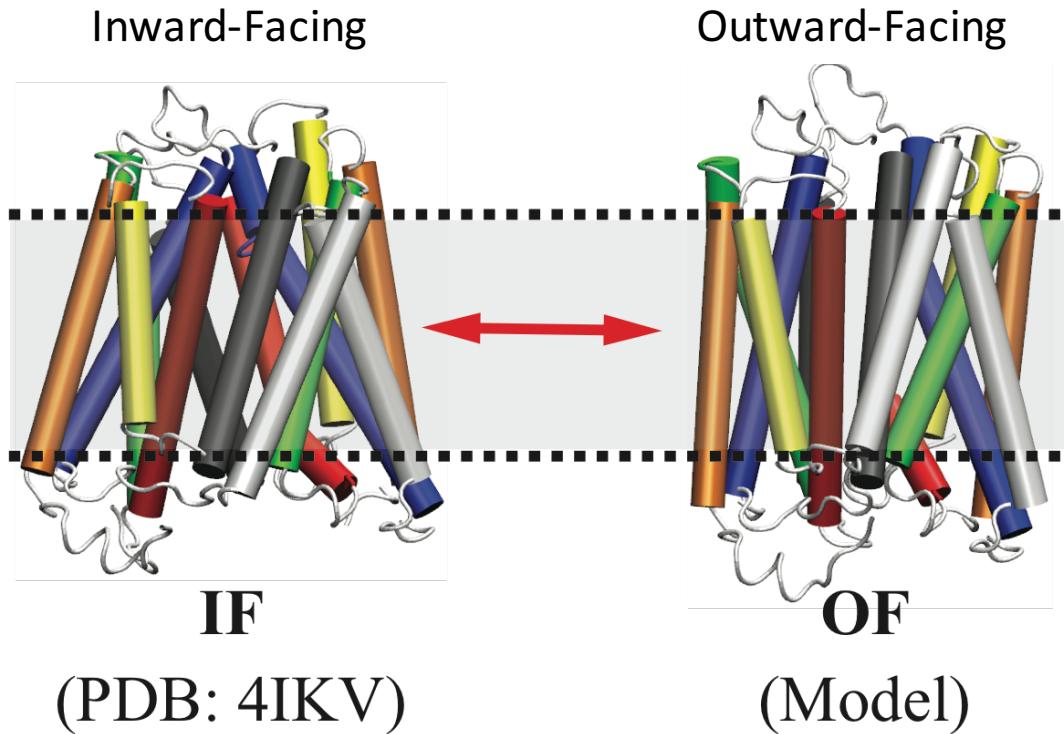


There is no statistically significant distinction between different conditions.

- **Introduction**
  - How to study large-scale conformational changes  
It is not reasonable to speculate about the conformational transition between two states based on fluctuations around one of the end points.



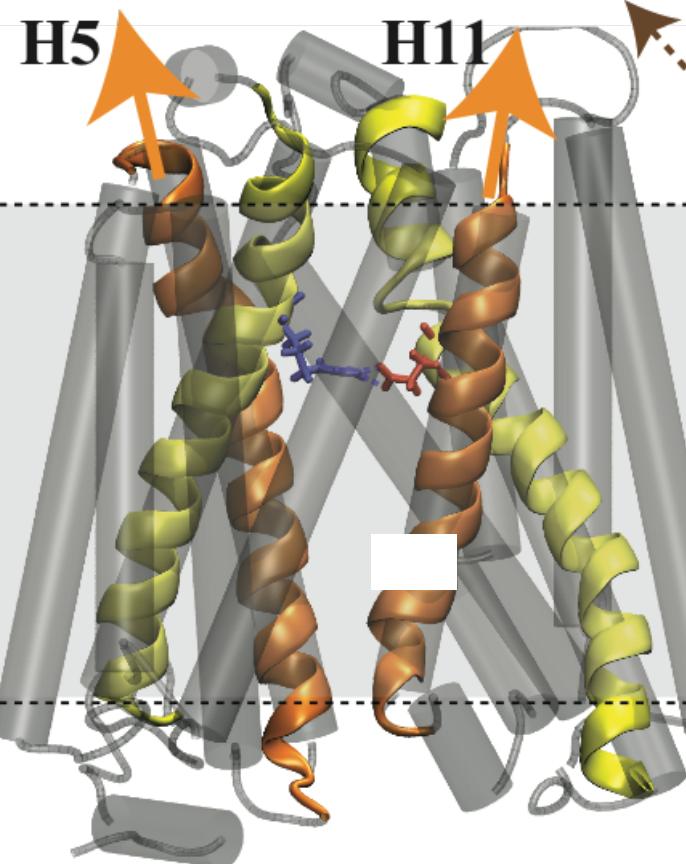
# How to study large-scale conformational changes?



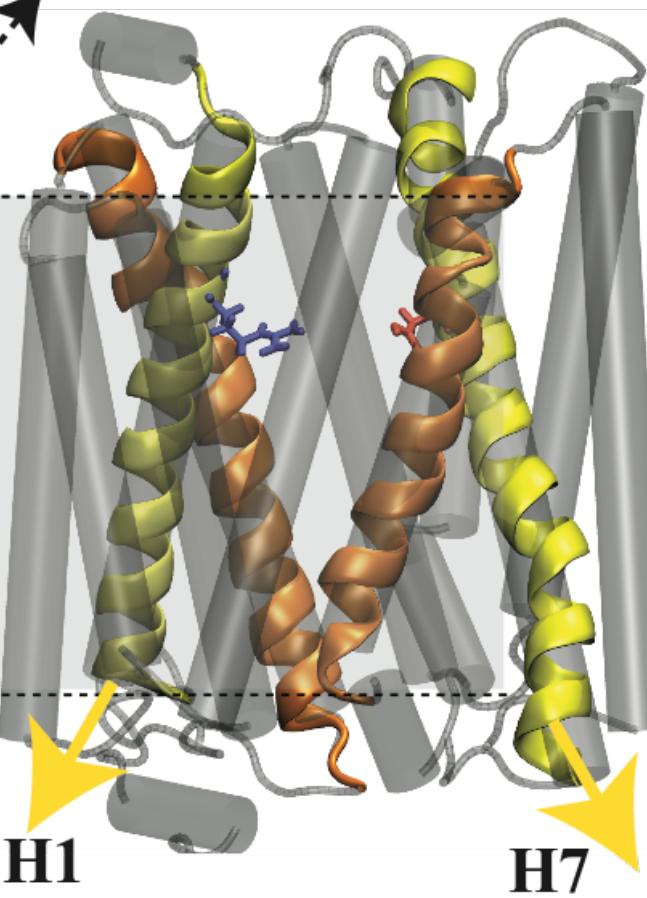
**GkPOT**

# How to study large-scale conformational changes?

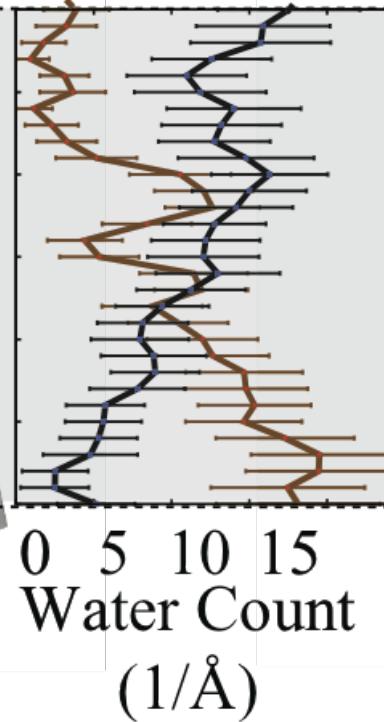
Inward-Facing (IF)



Outward-Facing (OF)



Periplasm



- **Introduction**
  - How to study large-scale conformational changes?
- **Methodology**
  - Empirical search for good pulling protocols
  - Iterative combination of free energy calculation methods and path-finding algorithms

# Sampling Ideas

- Free energy calculations require **dimensionality reduction**.
- Traditionally, this is done by designing intuitive, ad-hoc, knowledge-based **collective variables**.
- Another approach is to use **data-driven** collective variables using standard **dimensionality reduction techniques** (PCA, diffusion maps, etc).
- Alternatively (or in combination with the above approaches), one can calculate **free energy along a transition path** (a 1D curve).
- The path can be obtained from **path-finding algorithms**.
- Since sampling is never perfect the procedure could be **iterative** to reach higher accuracies.

# Sampling Ideas

- **Reaction coordinates**
  - System-specific collective variables
- **Searching for efficient pulling protocols**
  - An empirical approach to sampling
- **Along-the-curve free energy calculations**
  - Free energy calculations combined with path-finding algorithms
- **Iterative sampling**
  - A posteriori tests of self-consistency

Moradi et al., *Proc Natl Acad Sci* **106** 20746 (2009)

Moradi et al., *Chem Phys Lett* **518** 109 (2011)

Moradi et al., *J Chem Phys* **133** 125104 (2010)

Moradi et al., *Int J Quantum Chem* **110** 2865 (2010)

Moradi et al., *Biophys J* **100** 1083 (2011)

Moradi et al., *J Phys Chem B* **115** 8645 (2011)

Moradi et al., *PLoS Comput Biol* **8** e1002501 (2012)

Moradi et al., *Nucleic Acid Res* **41** 33 (2013)

Moradi et al., *Proc Natl Acad Sci* **110** 18916 (2013)

Moradi et al., *J Phys Chem Lett* **4** 1882 (2013)

Moradi et al., *Methods Mol Biol* **924** 313 (2013)

Moradi et al., *J Chem Phys* **140** 034114 (2014)

Moradi et al., *J Chem Phys* **140** 034115 (2014)

Moradi et al., *J Chem Theory Comput* **10** 2866 (2014)

Moradi et al., *J Phys Conf Ser* **640** 012014 (2015)

Moradi et al., *J Phys Conf Ser* **640** 012020 (2015)

Moradi et al., *Nat Commun* **6** 8393 (2015)

Fakharzadeh & Moradi, *J Phys Chem Lett* **7** 4980 (2016)

# Sampling Ideas

- **Reaction coordinates**
  - System-specific collective variables
- **Searching for efficient pulling protocols**
  - An empirical approach to sampling
- **Along-the-curve free energy calculations**
  - Free energy calculations combined with path-finding algorithms
- **Iterative sampling**
  - A posteriori tests of self-consistency

## I.1 Defining Practical Collective Variables

Empirical search for practical collective variables for inducing the conformational changes involved in the transition.

## I.2 Optimizing the Biasing Protocols

Systematic search for a practical biasing protocol by using different combinations of collective variables.

## II. Optimizing the Transition Pathway

Use all of the conformations available to generate the most reliable transition pathway:  
1. Bayesian approach for combining the data  
2. Post-hoc string method (analysis tool)  
3. String method with swarms of trajectories

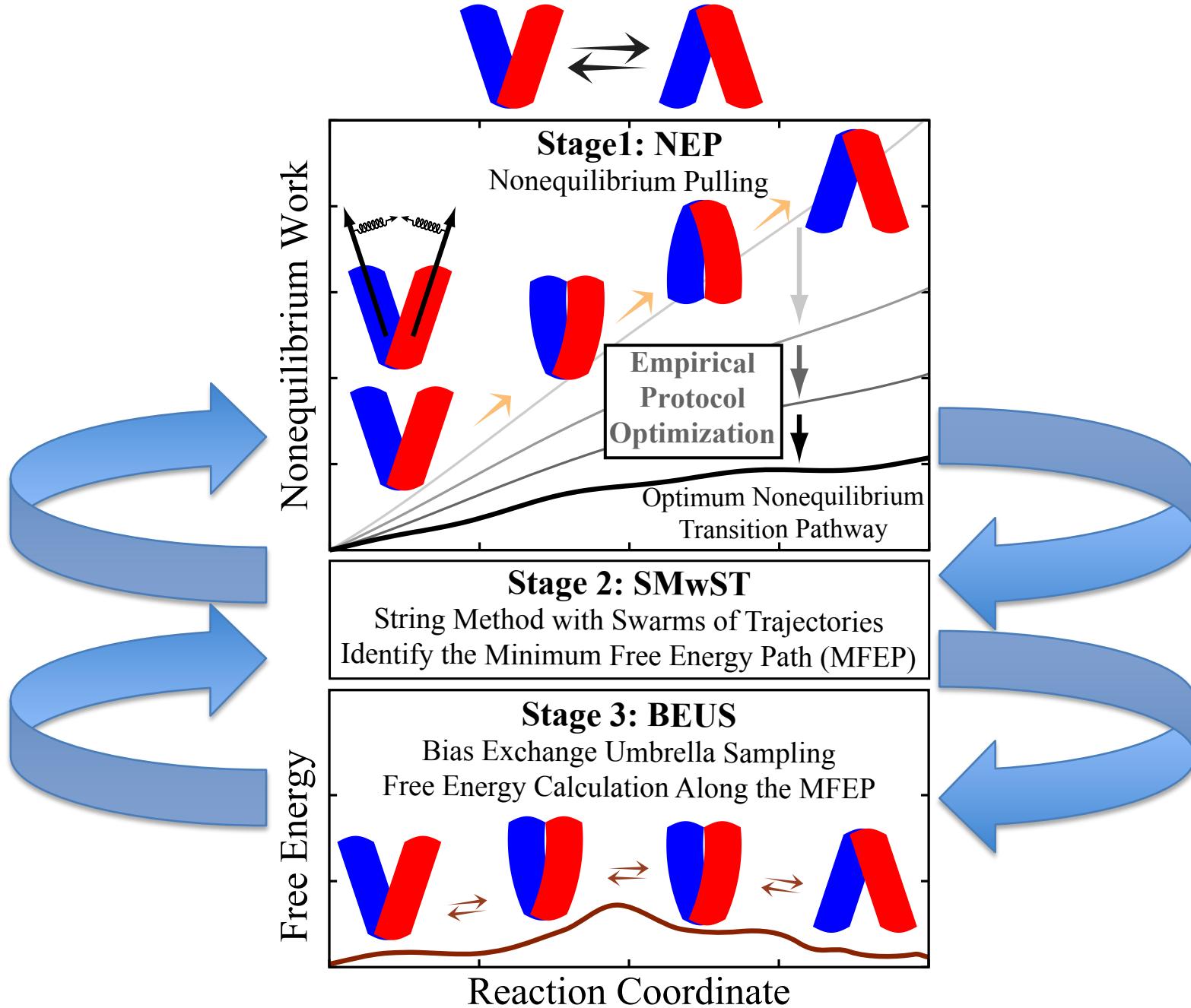
## III.1 Free Energy Calculations

Using the most relevant collective variables (from I.1), biasing protocol (from I.2), and initial conformations (from I.2).

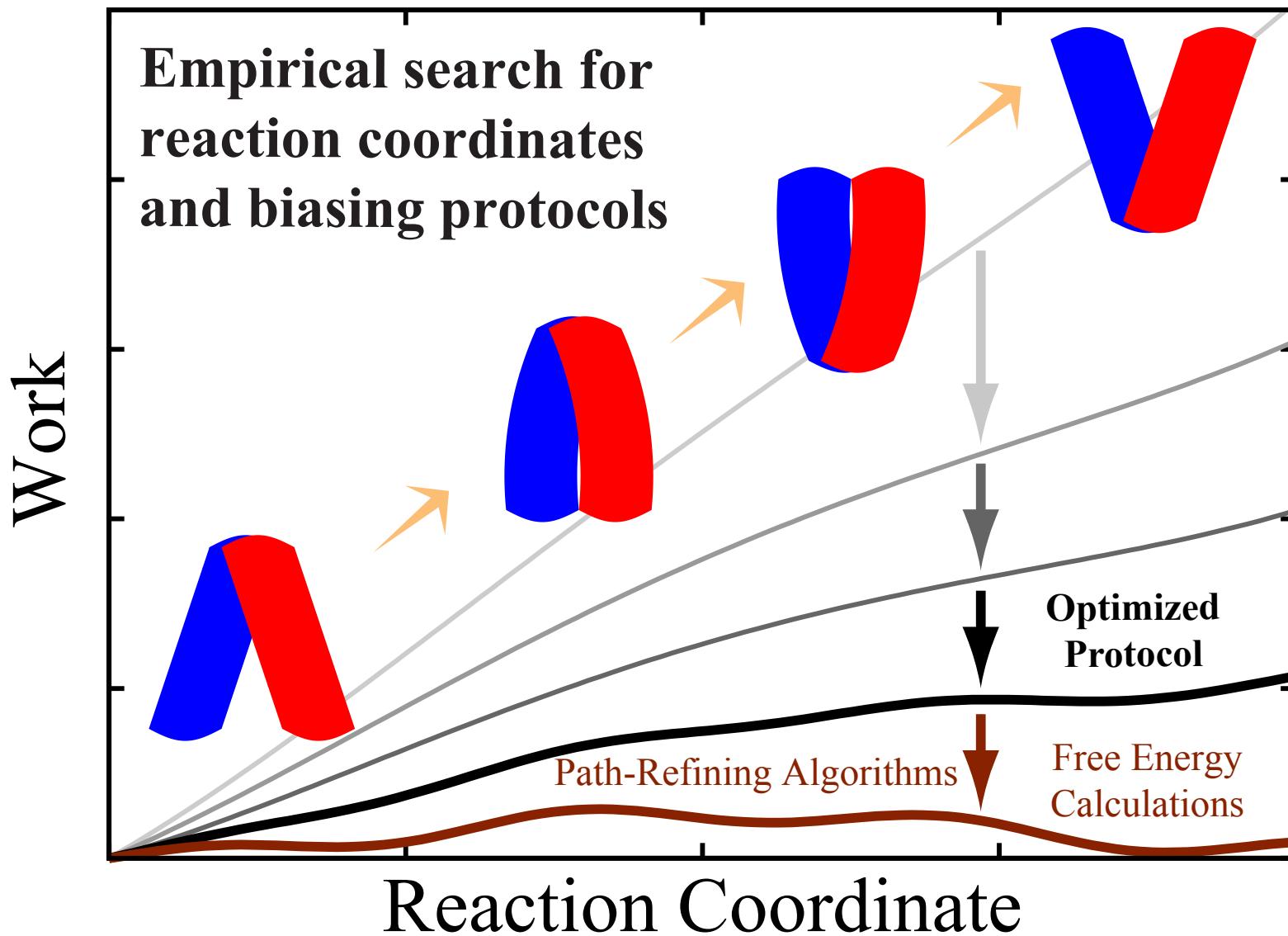
## III.2 Assessing the Sampling Efficiency

Detecting the poorly sampled, but potentially important regions, e.g., by using PCA.

# Conformational Transition



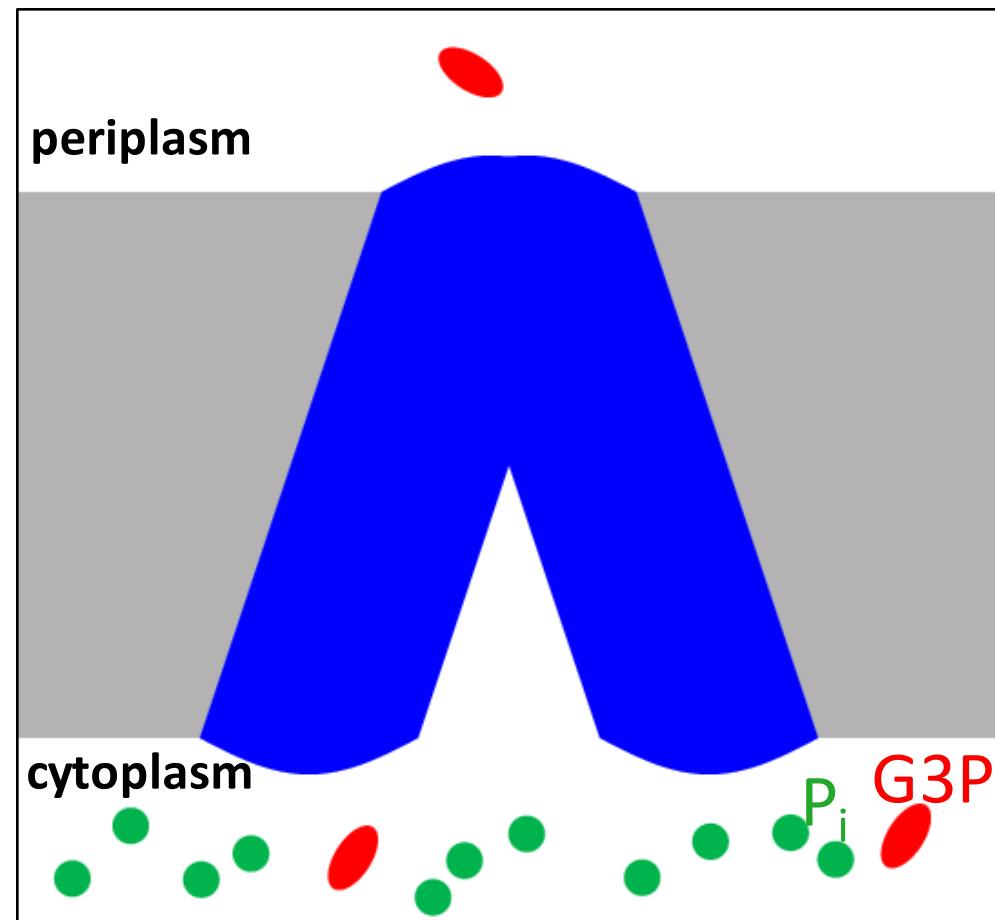
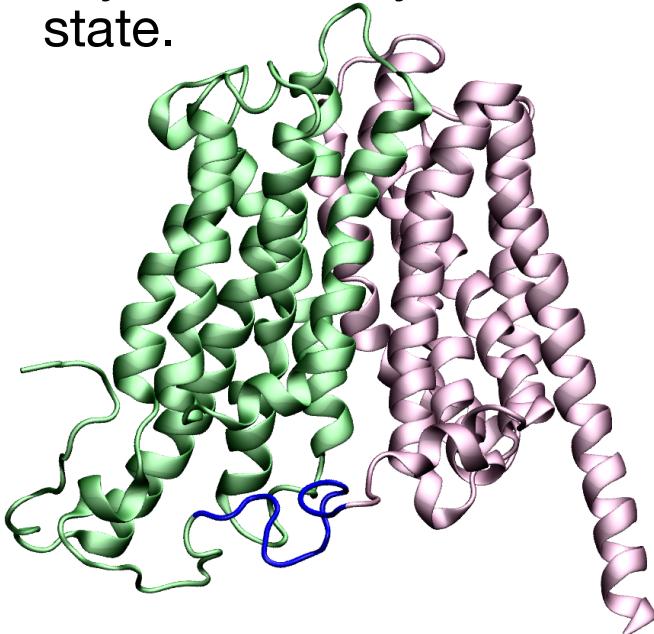
# Sampling Ideas



- **Introduction**
  - How to study large-scale conformational changes?
- **Methodology**
  - **Empirical search for good pulling protocols**
  - Iterative combination of free energy calculation methods and path-finding algorithms

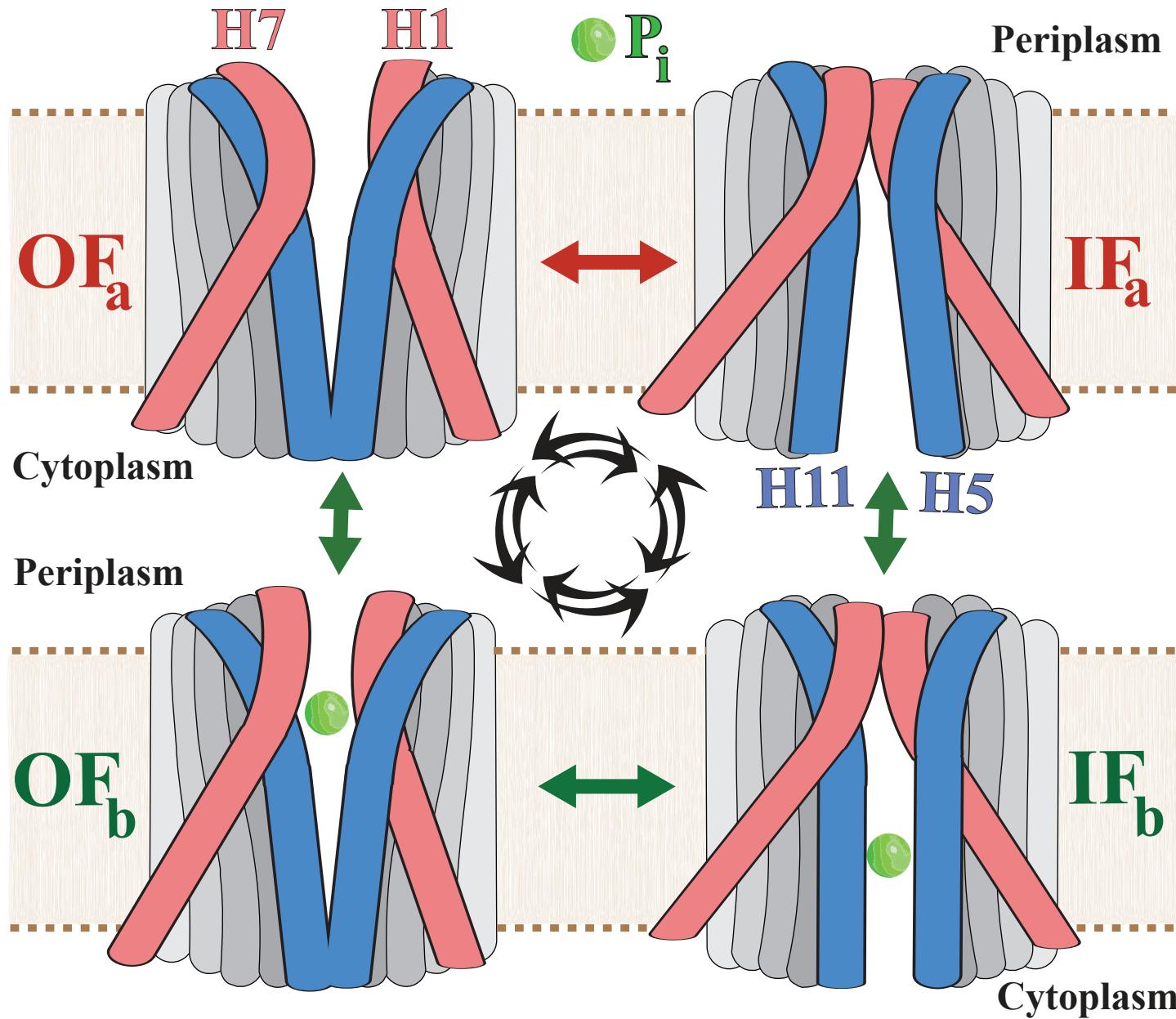
# Example: Glycerol-3-Phosphate Transporter (GlpT)

- Major facilitator superfamily (MFS)
- Secondary active transporter
- Crystalized only in the IF state.



- GlpT transports **G3P** using  $P_i$  gradient.
- $P_i:P_i$  exchanger (in the absence of organic phosphate)

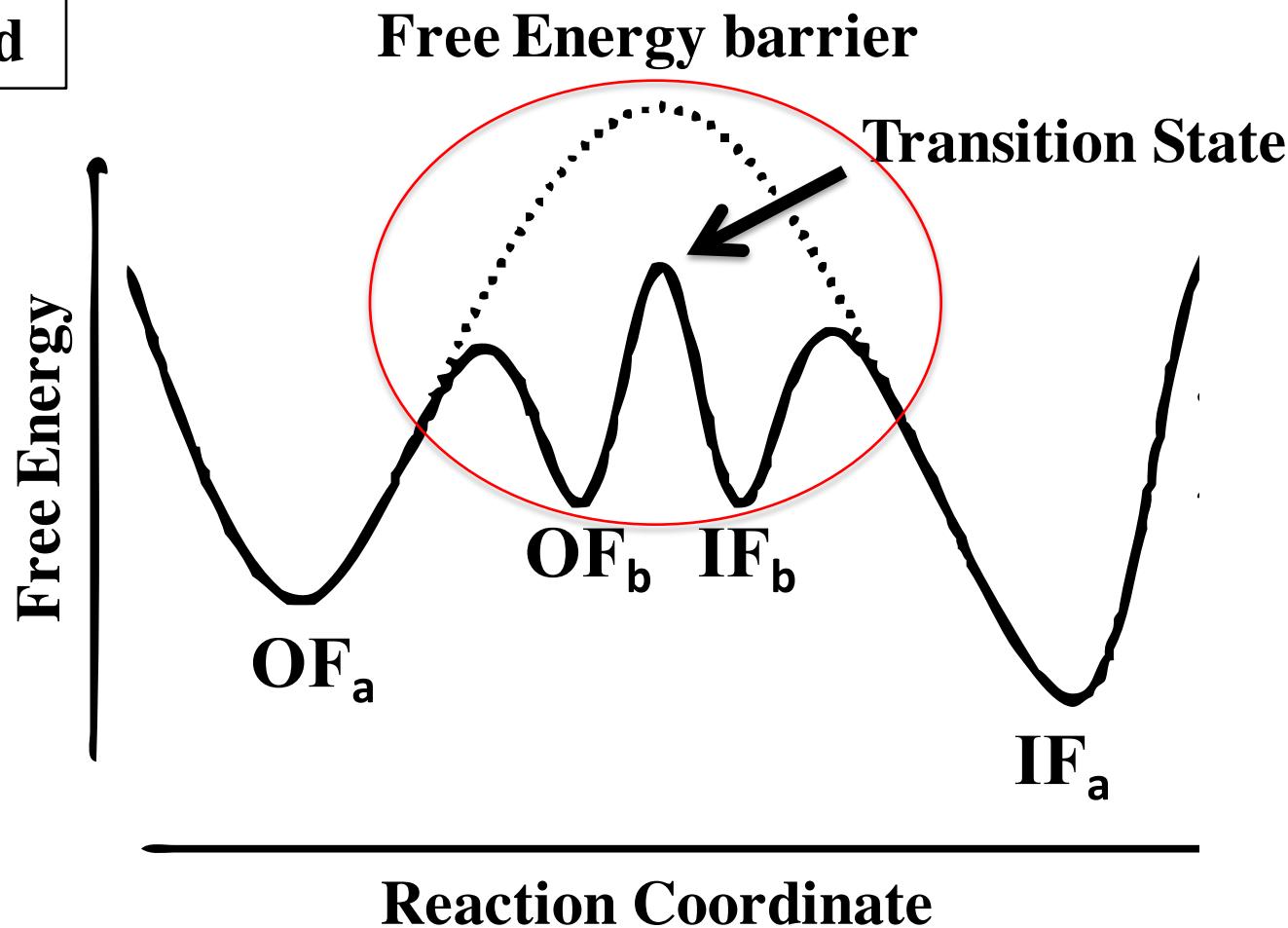
# Transport Thermodynamics



# Transport Thermodynamics

a: *apo*

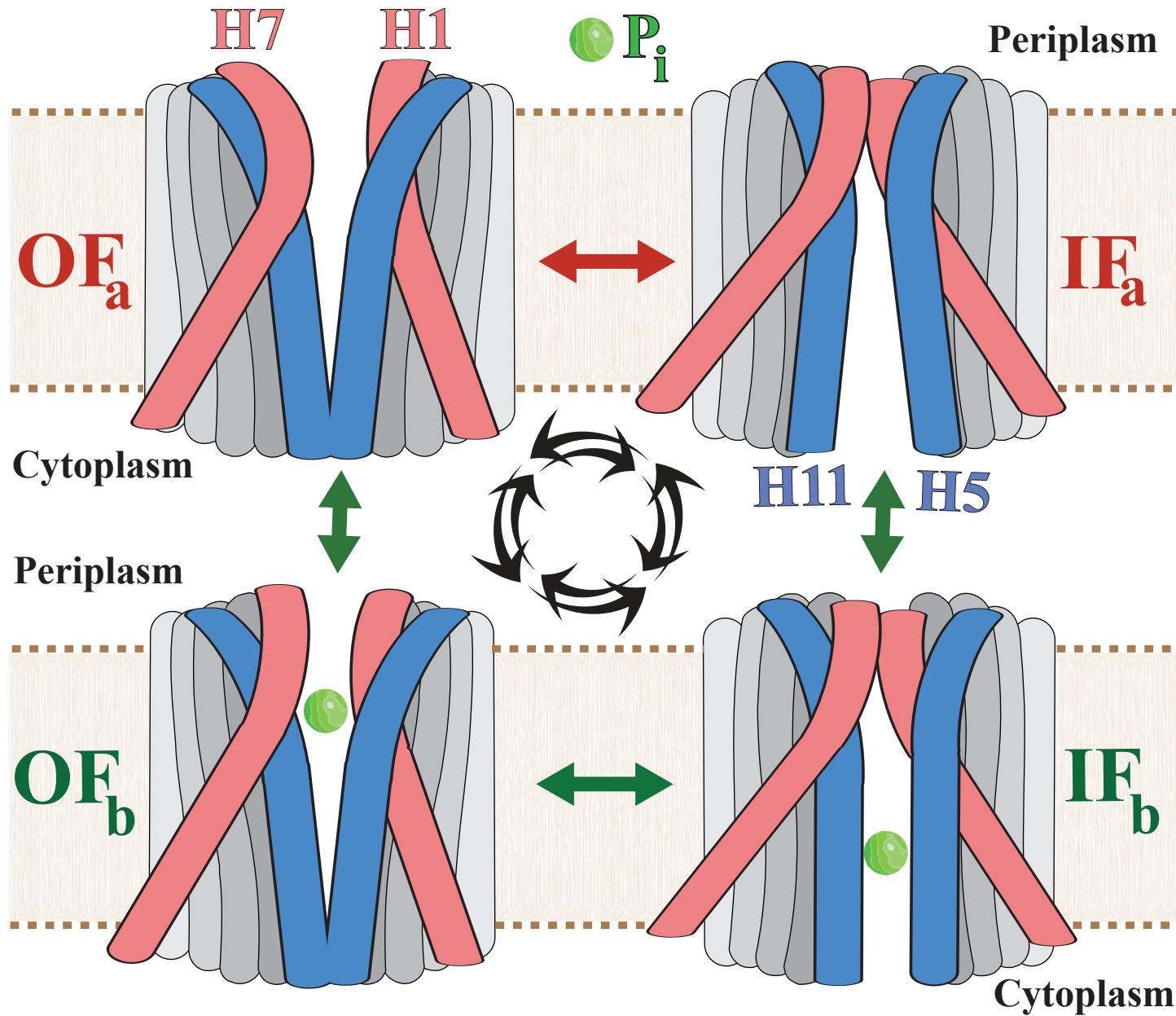
b: bound



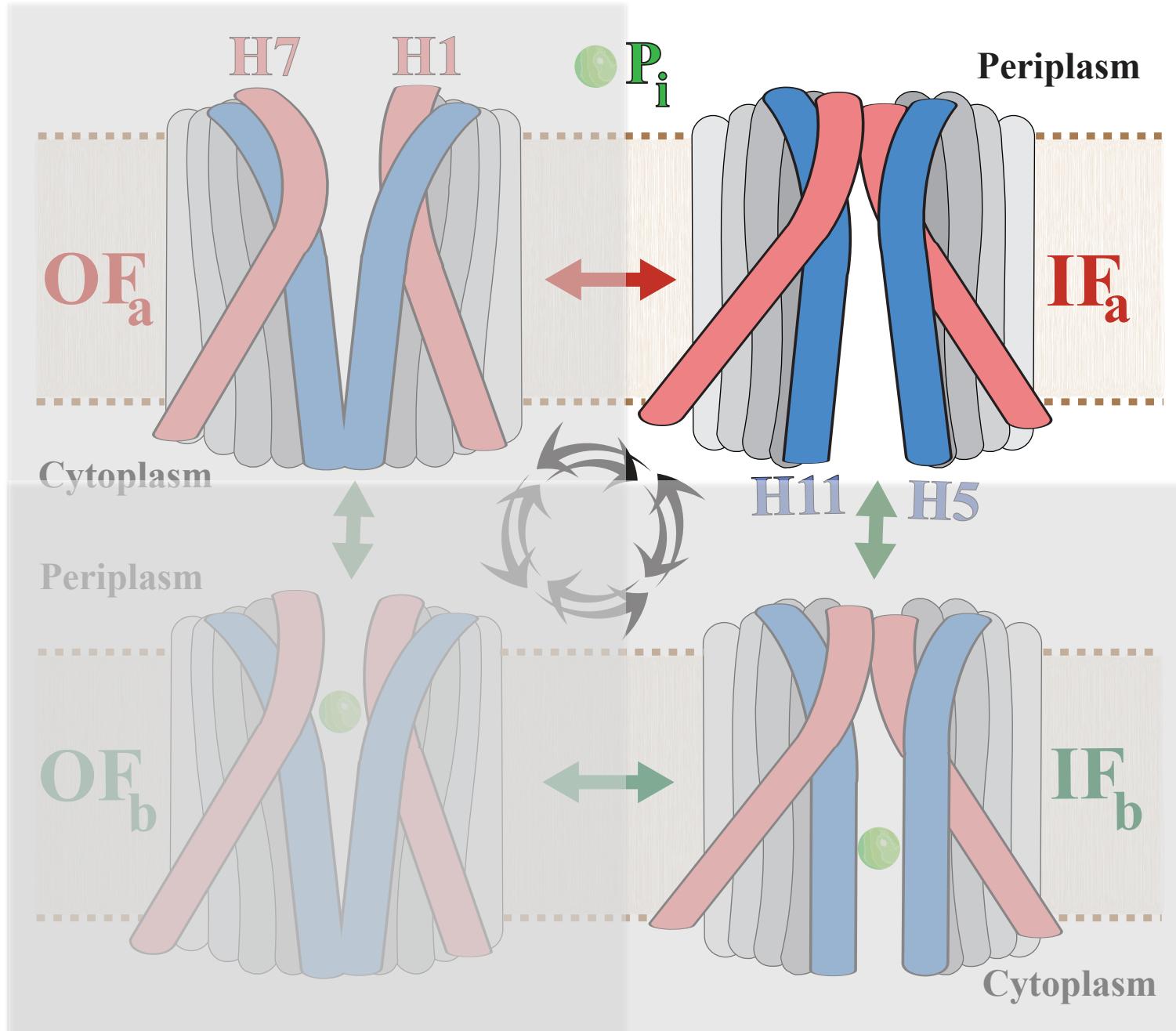
Lemieux, et al., *Curr. Opin. Struct. Biol.* **14**, 405 (2004).

Law, et al., *Biochemistry* **46**, 12190 (2007).

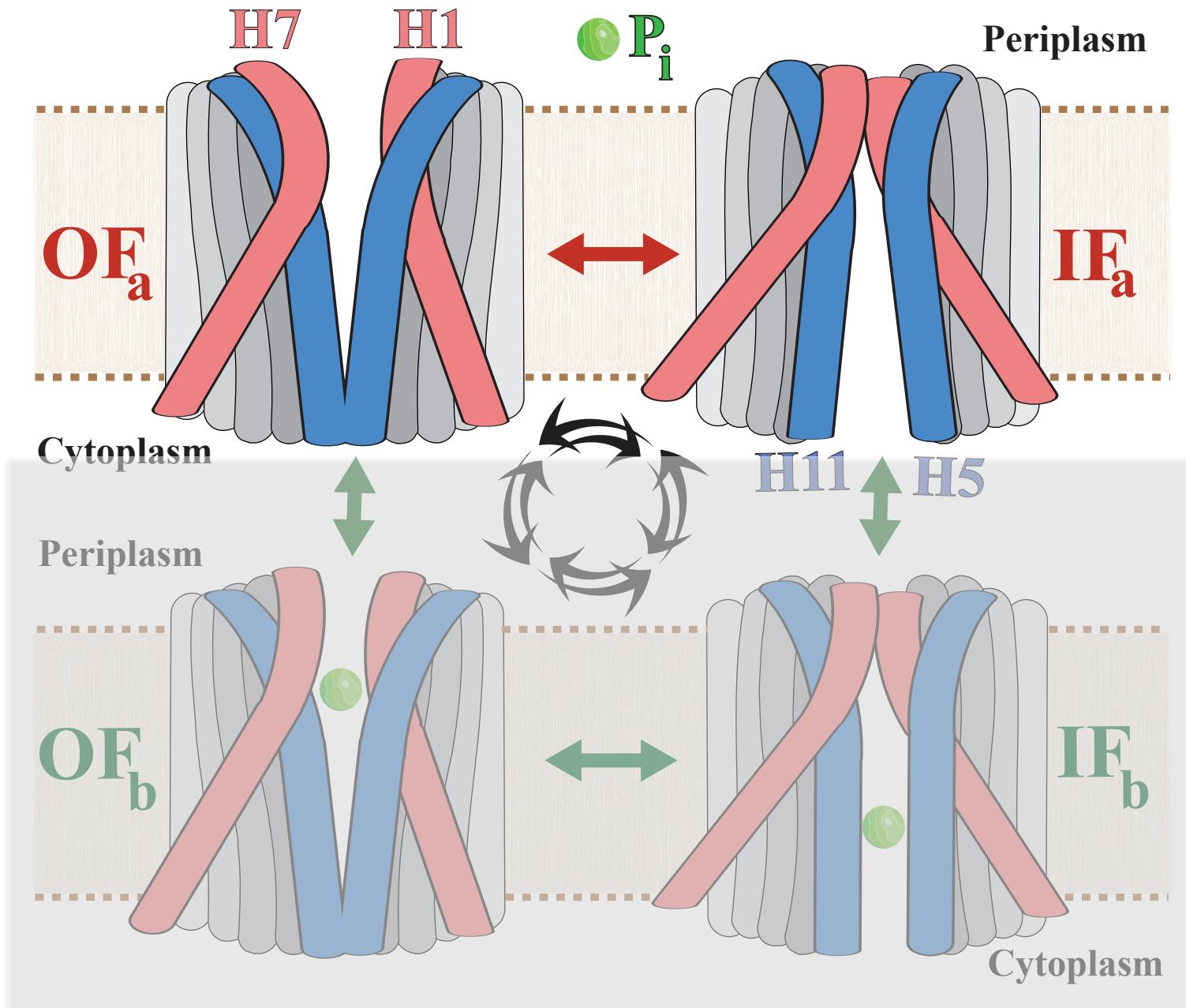
# Full Thermodynamic Cycle



# the only available crystal structure

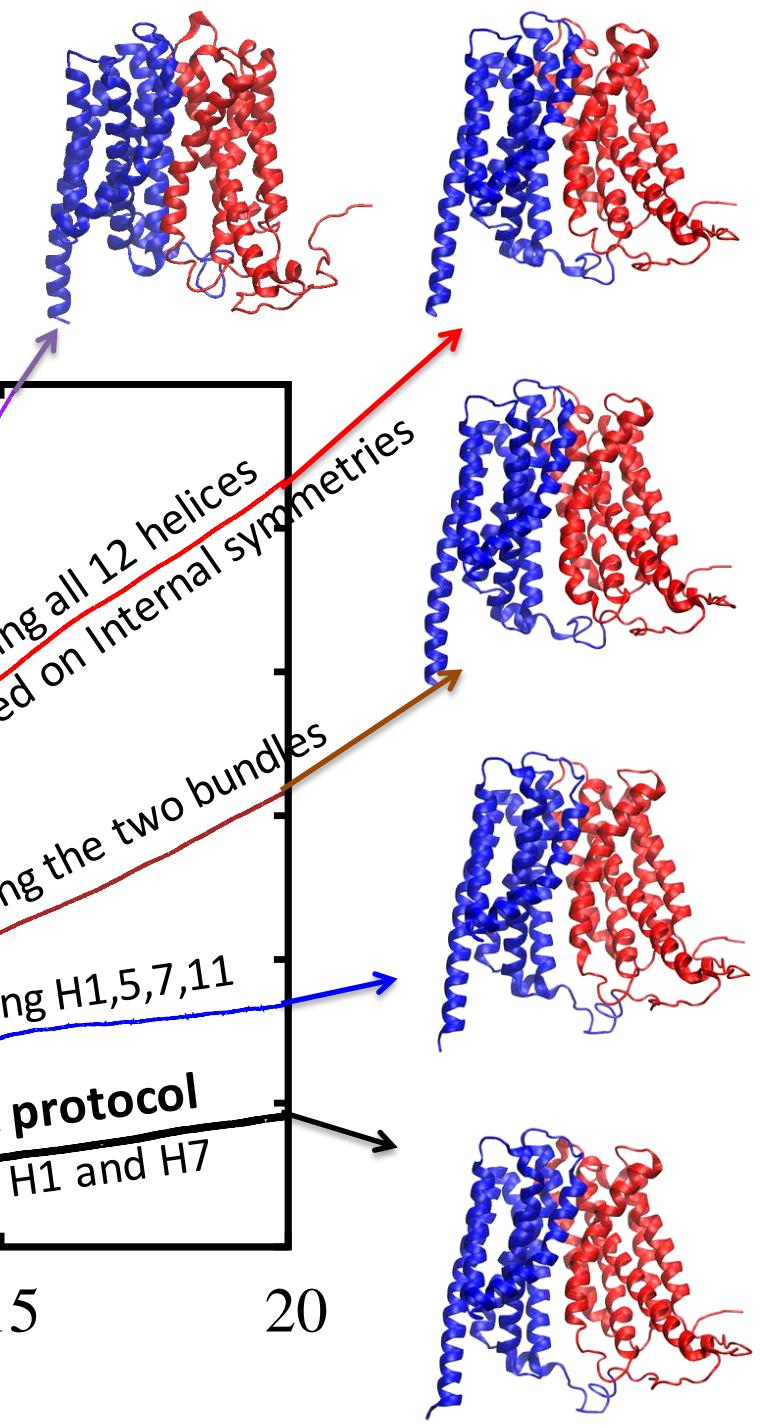
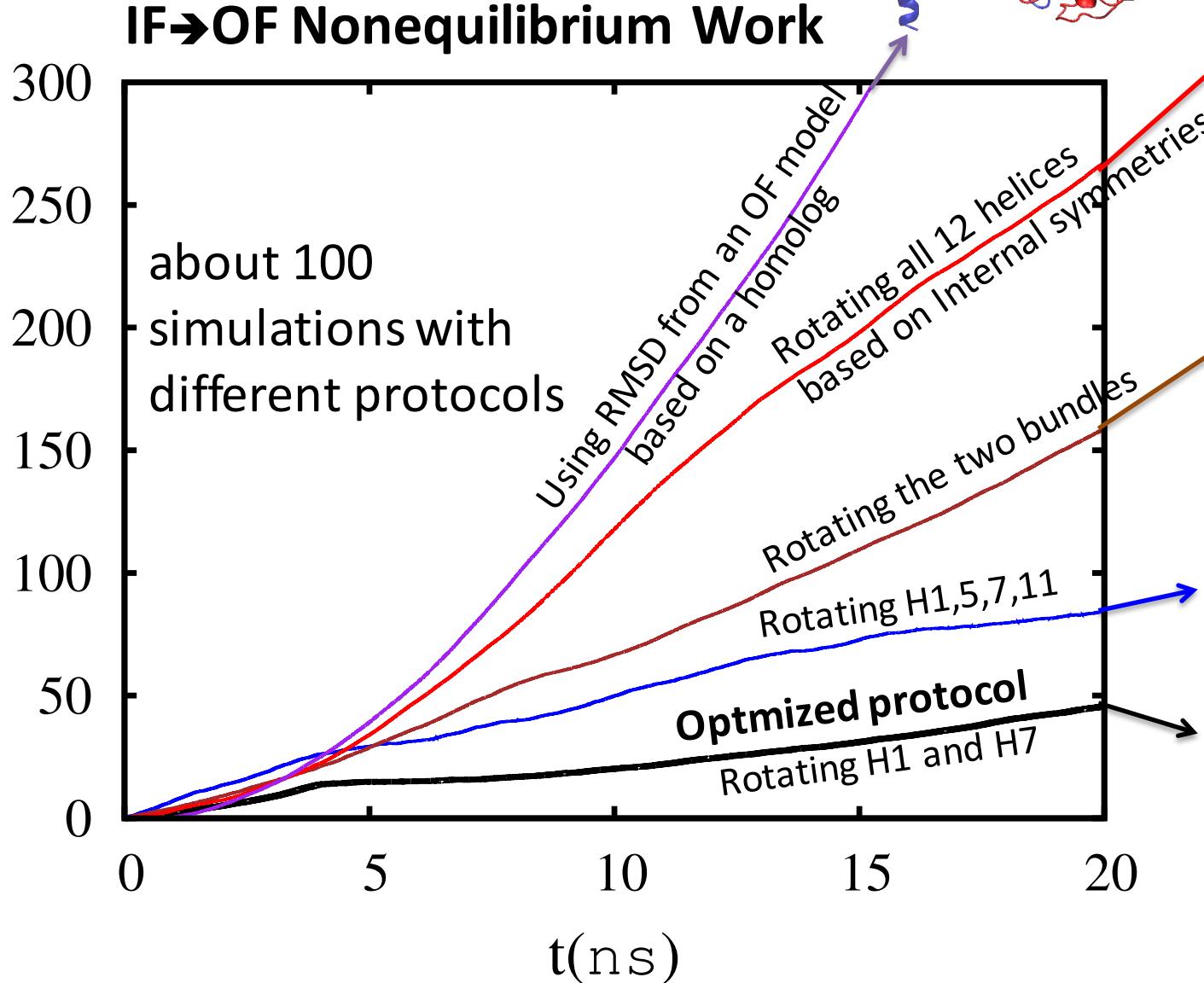


# Step 1: $\text{OF}_a \leftrightarrow \text{IF}_a$

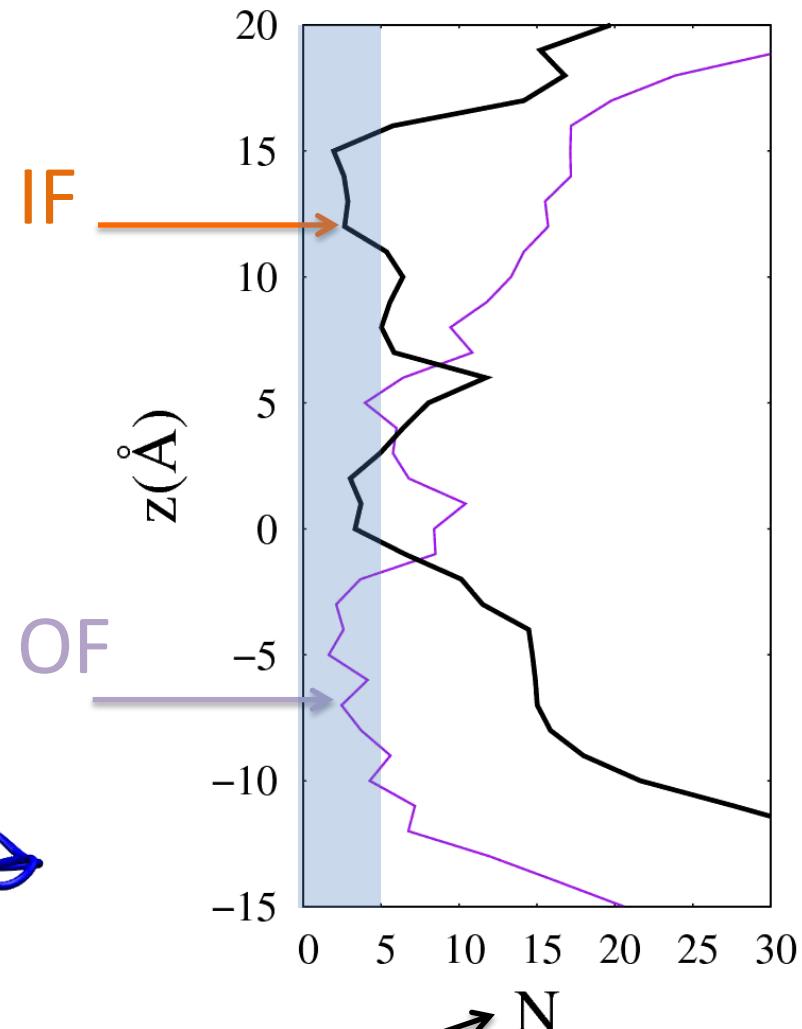
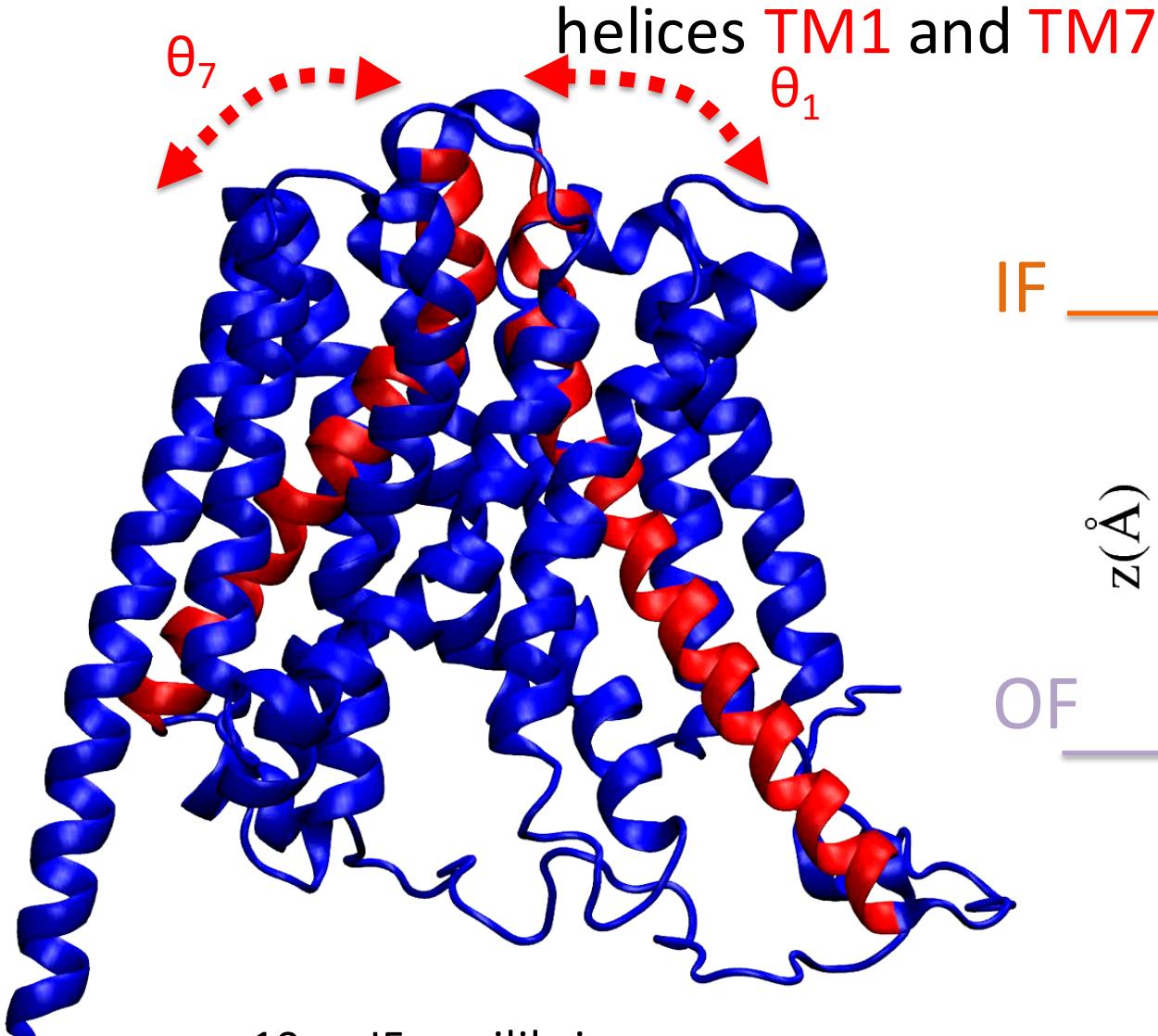


# Empirical search for reaction coordinates and biasing protocols:

work(kcal/mol)



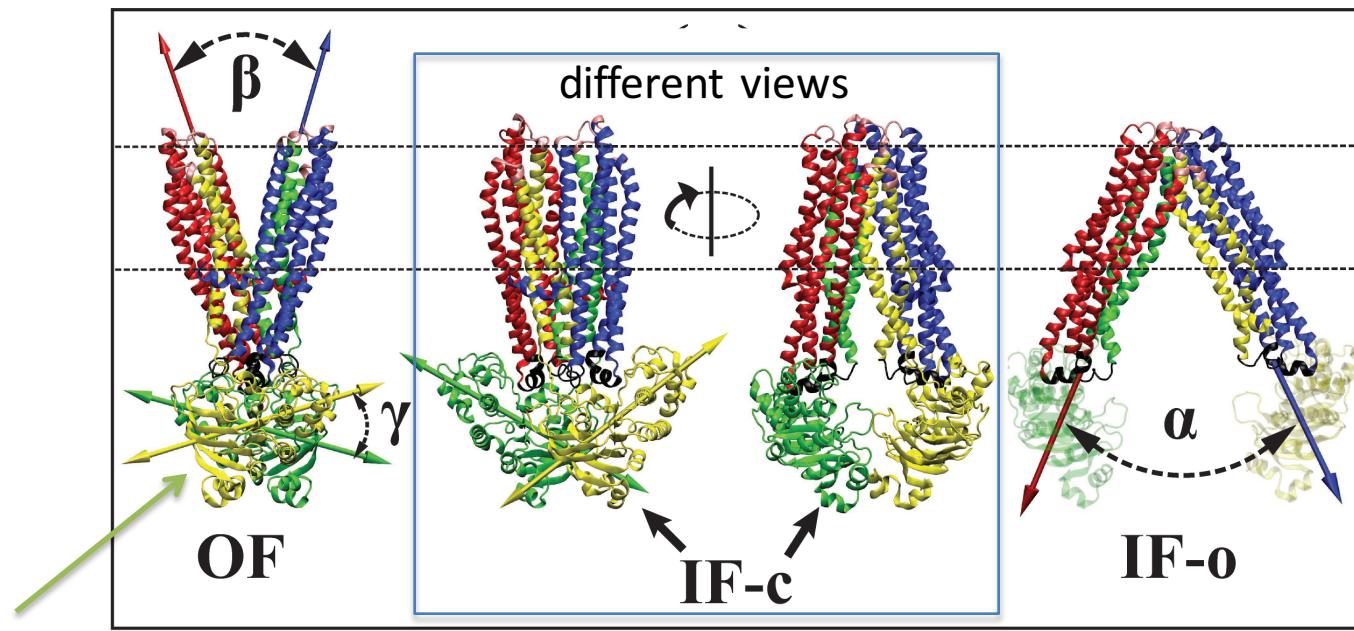
# IF↔OF transition induced by imposing rotational change on



Number of water molecules per  $\text{\AA}$   
(averaged over a 1 ns window)

# Example: MsbA Transporter

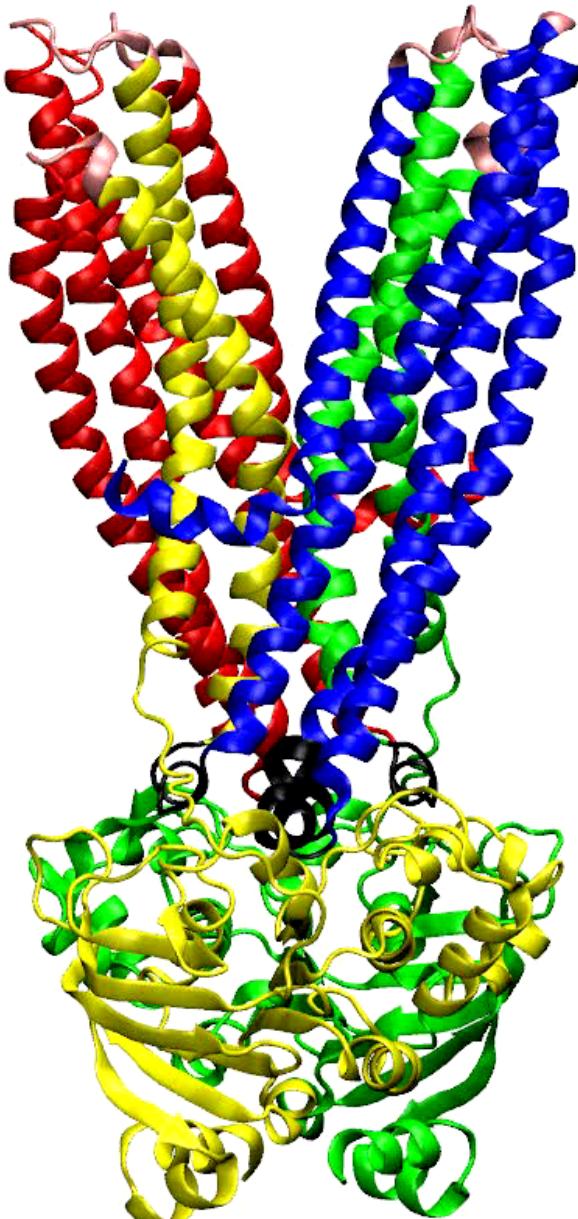
- ATP-binding cassette (**ABC**) exporter with three crystal structures. Ward A., Reyes C. L., Yu J., Roth C. B., Chang G.. PNAS **104** 19005 (2007)
- **Reaction coordinates:**  
 $\alpha$ ,  $\beta$ ,  $\gamma$  (relative orientation of different domains)



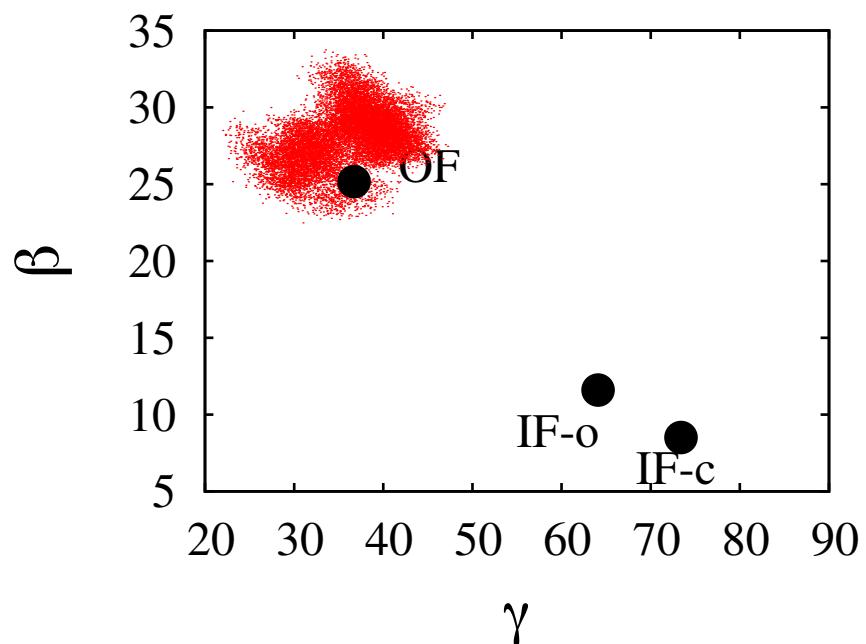
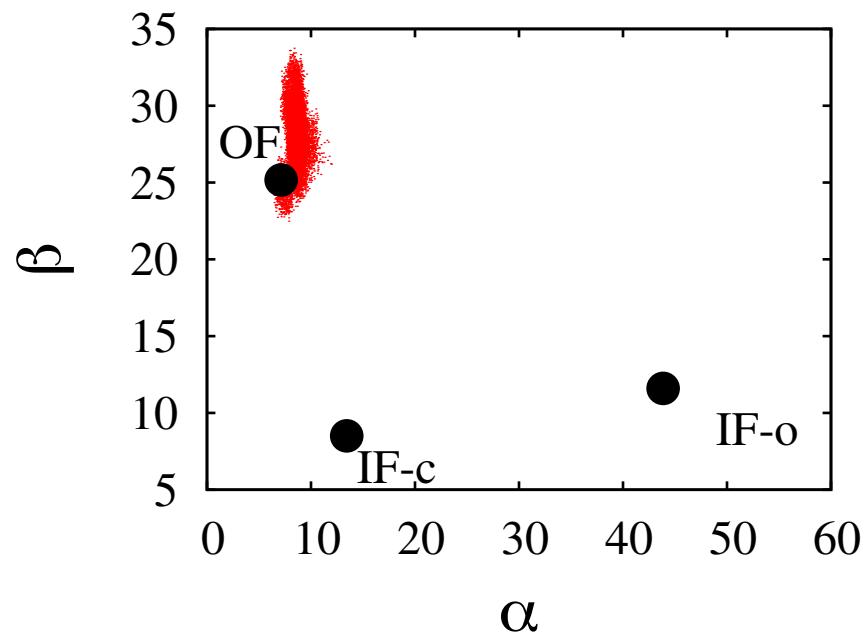
Nucleotide-binding  
domains (NBD)

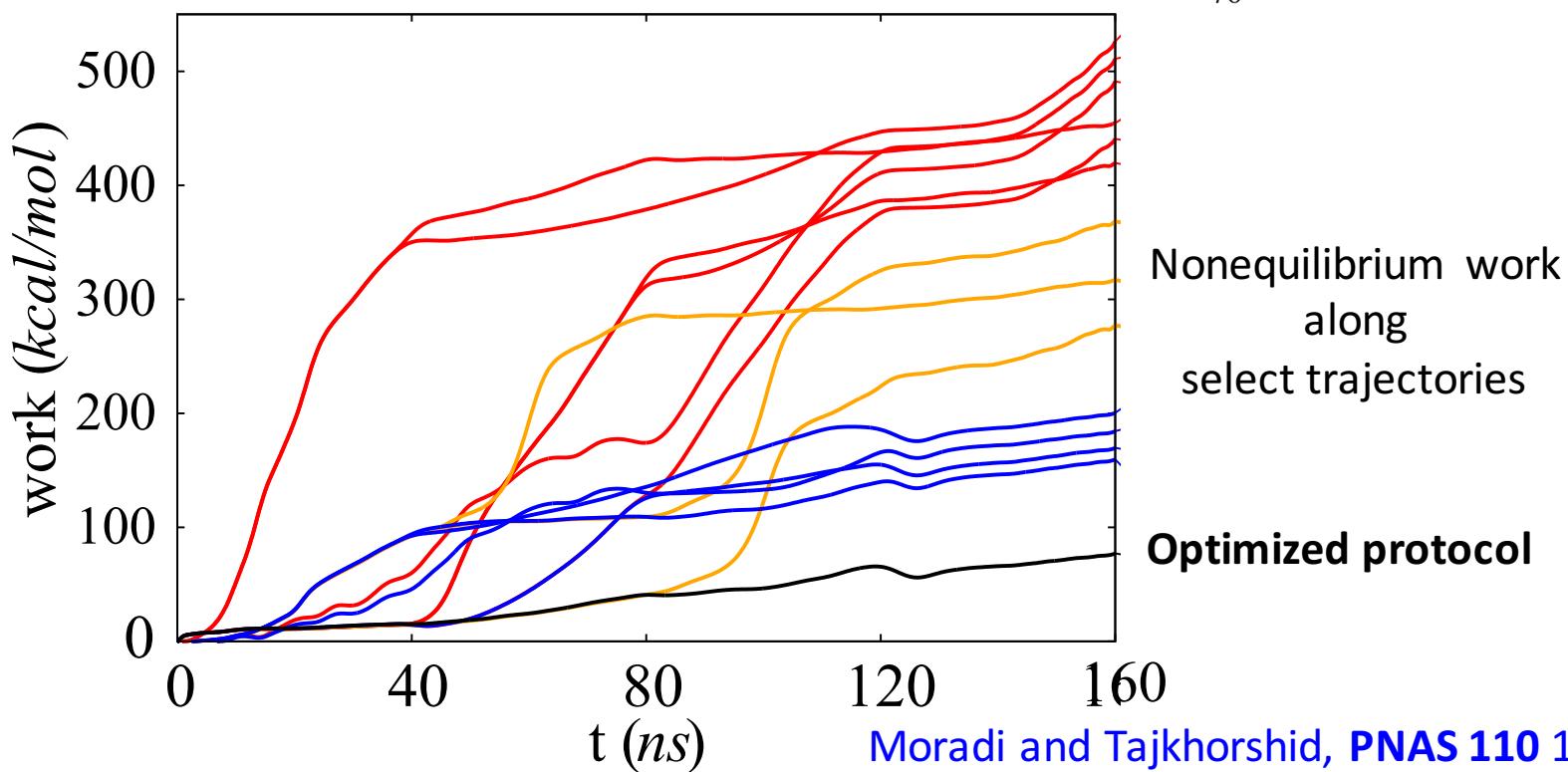
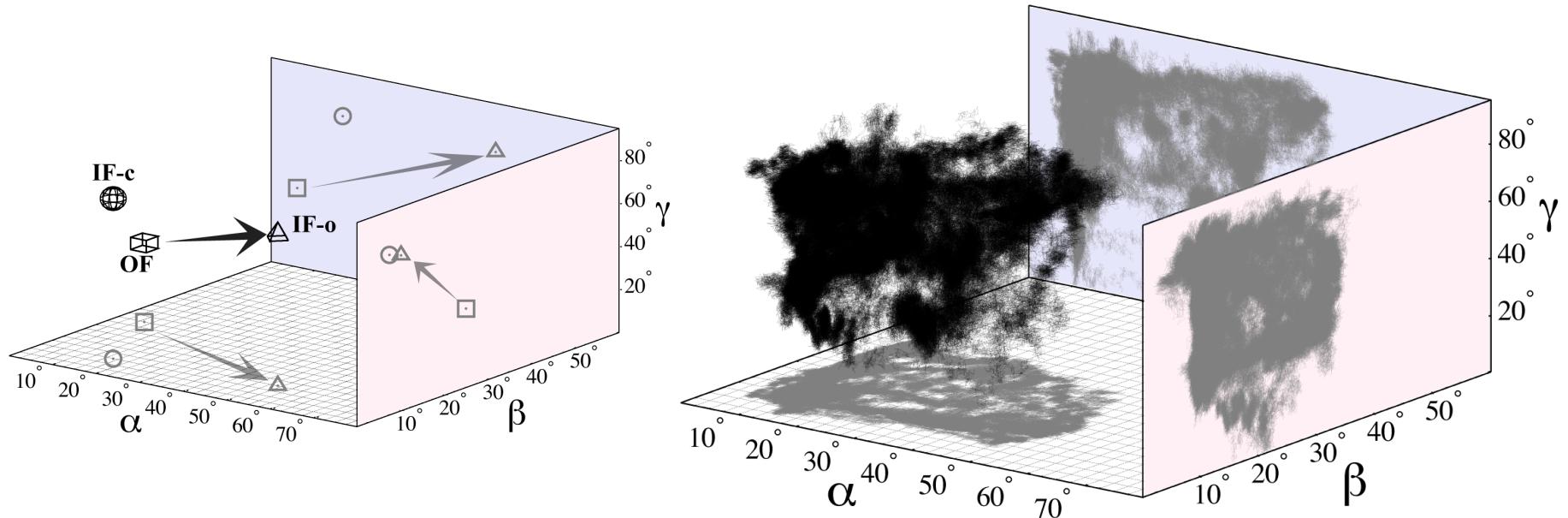
Two IF conformations:  
IF-closed (IF-c) and IF-open (IF-o)

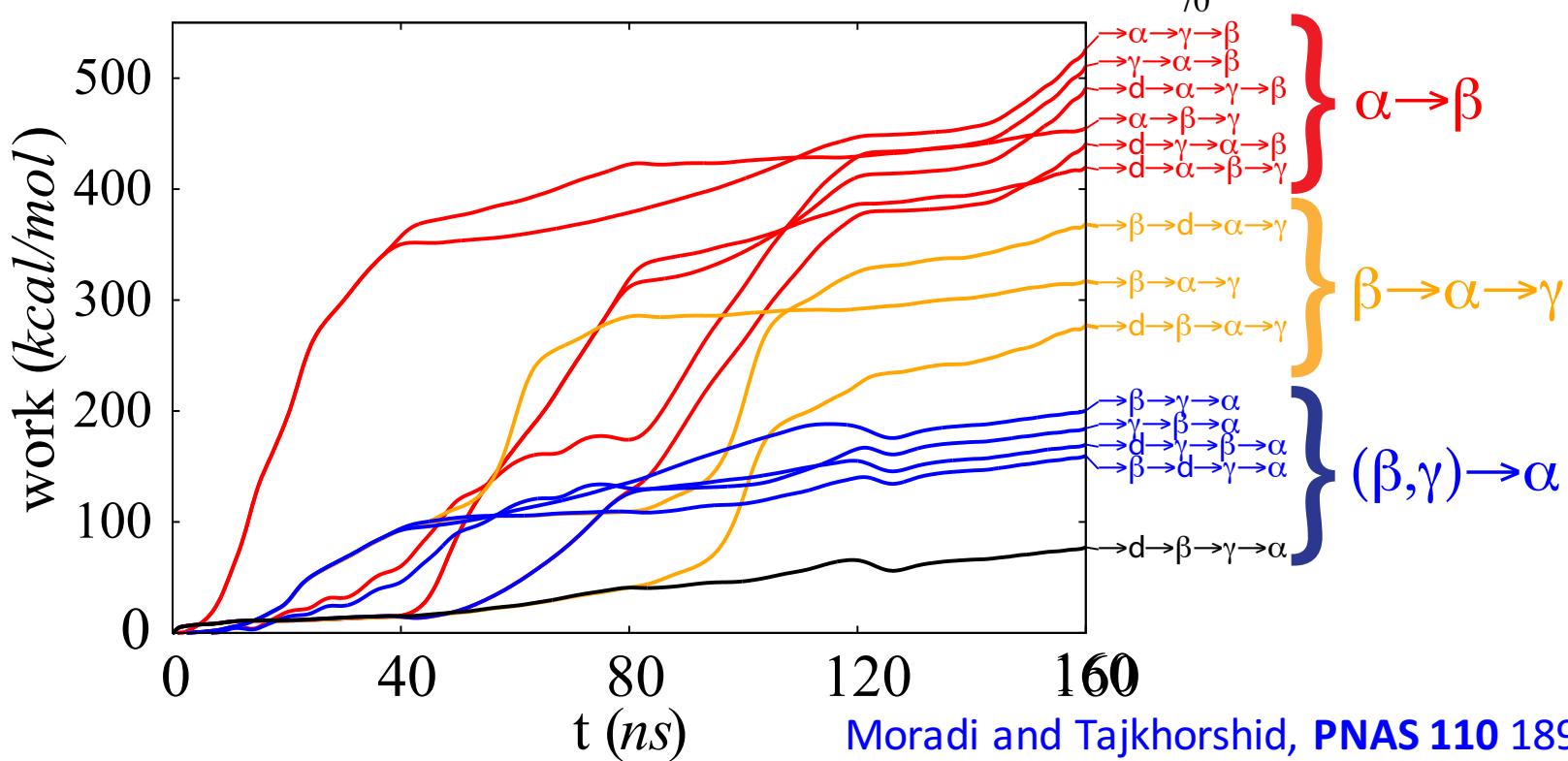
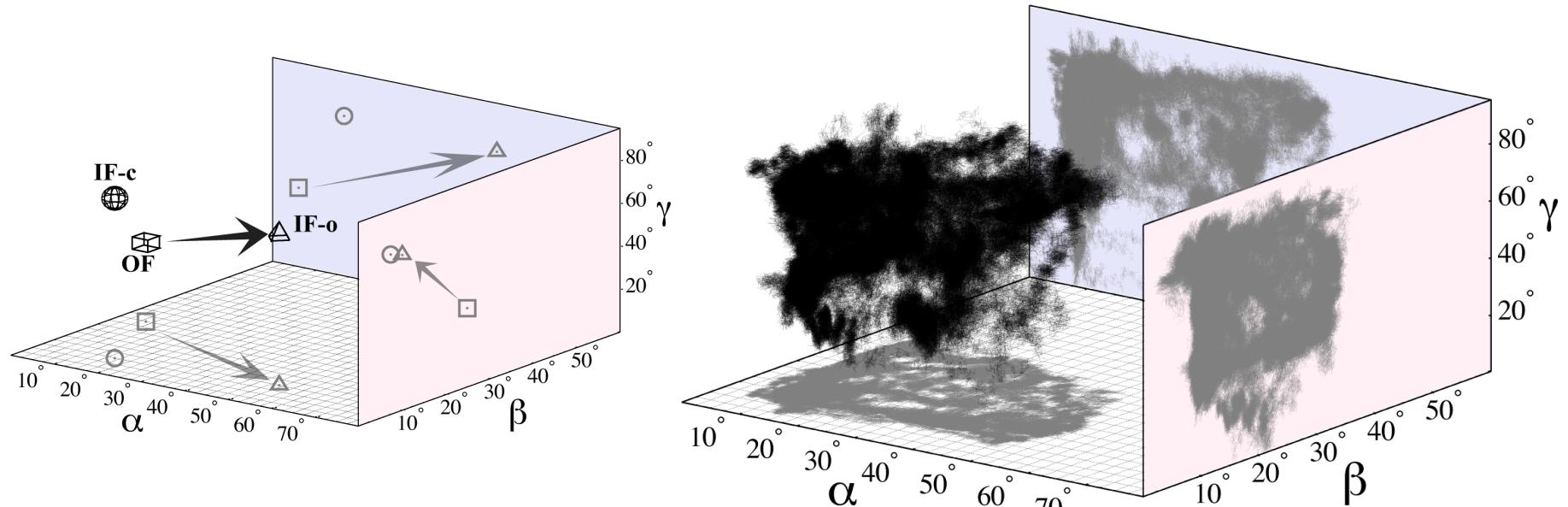
# Conventional Equilibrium Molecular Dynamics



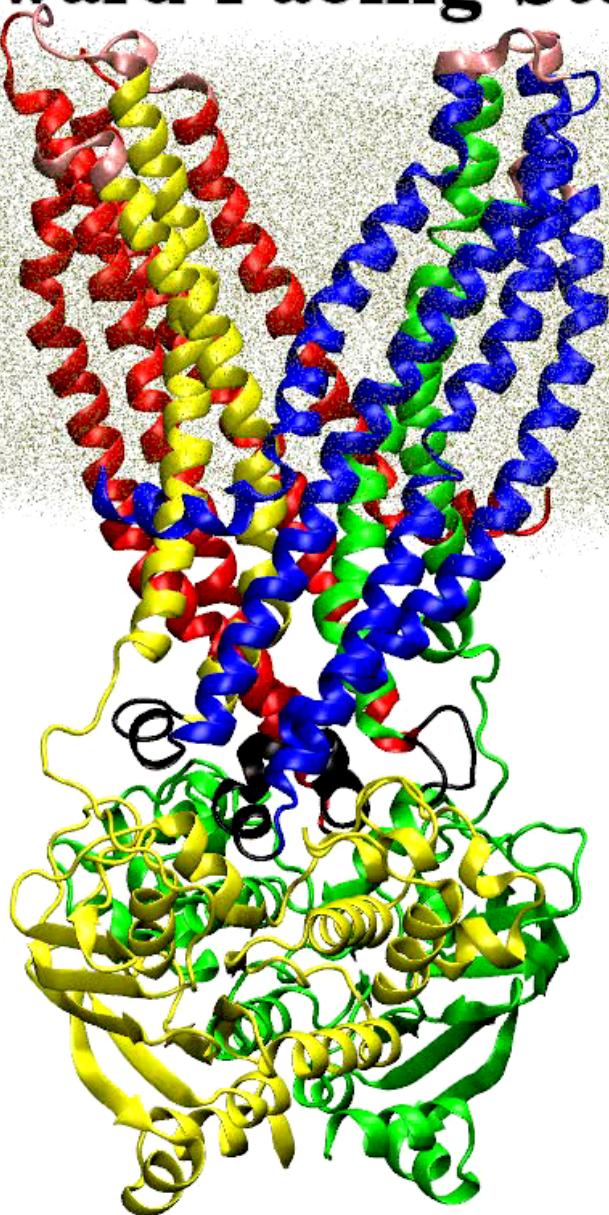
apo MsbA in explicit water/membrane (300 ns)







# Outward-Facing State



**OF → IF**

NBD Dissociation



Periplasmic Closure



NBD Twist



Cytoplasmic Opening



**IF → OF**

Cytoplasmic Closure



NBD Twist



Periplasmic Opening



NBD Dimerization



R      T      R      T      R      T      R      T      R

T Transition

R Relaxation

# Steering along orientation quaternion

To find the best rigid body rotation for  $\{x_k\} \rightarrow \{y_k\}$ ,  
find a unit quaternion  $q$  to minimize:

$$\left\langle \|\hat{q}x_k\hat{q}^* - y_k\|^2 \right\rangle$$

It turns out  $q = (\cos \frac{\theta}{2}, \sin \frac{\theta}{2} \hat{\mathbf{u}})$

$\theta$  and  $\hat{\mathbf{u}}$  are the angle and axis of rotation

target quaternion  
at time t

Biasing Potential:

$$U_B(q_{ref}(\{\mathbf{x}_k\}), t) = \frac{1}{2} k \Omega^2(q_{ref}(\{\mathbf{x}_k\}), Q(t))$$

$$\cos(\Omega(\hat{p}, \hat{q})) = \hat{p} \cdot \hat{q}$$

# Interpolation of orientation quaternion in *colvars*

At each time  $t + \Delta t$ :

(1) Linear interpolation:

$$(Q'(t + \Delta t) = Q(t) + \frac{Q(T) - Q(t)}{T - t} \Delta t)$$

(2) Normalization:

$$(Q(t + \Delta t) = \frac{Q'(t + \Delta t)}{\|Q'(t + \Delta t)\|})$$

# Interpolation of orientation quaternion in NAMD

It turns out:

$$\begin{aligned}\frac{\partial}{\partial t} U_B(q_{ref}, t) &= k \Omega(q_{ref}, Q(t)) \frac{\partial}{\partial t} \Omega(q_{ref}, Q(t)), \\ &= -\frac{\Omega}{\sin(\Omega)} (q - Q(t) \cos(\Omega)) \cdot \frac{Q(T) - Q(t)}{T - t}\end{aligned}$$

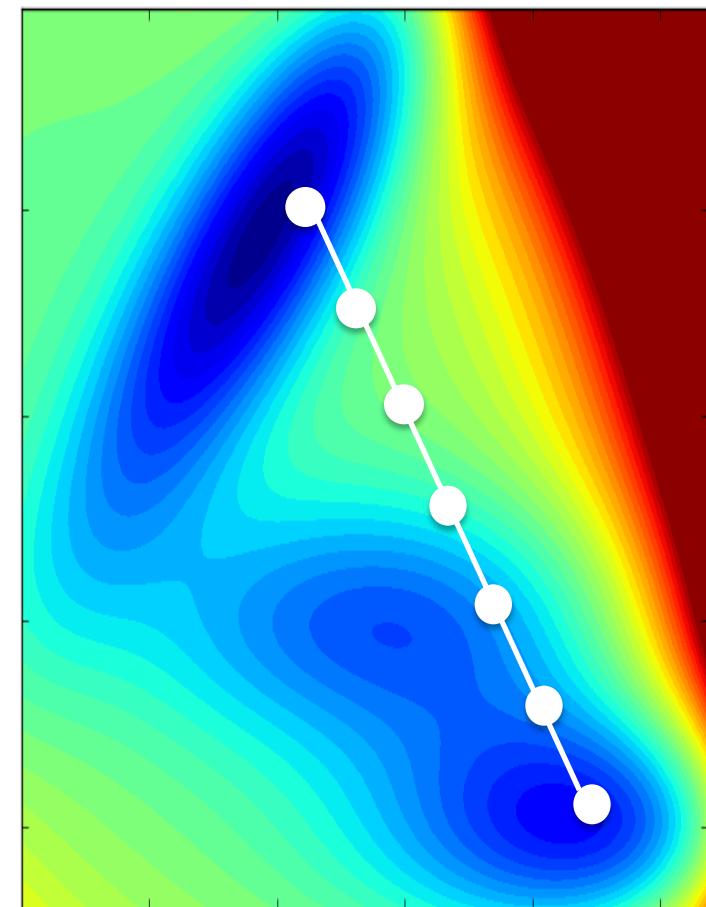
that can be used for work measurements using:

$$w^t = \int_0^t \frac{\partial}{\partial t'} U_B(q_{ref}(\{\mathbf{x}_k\}), t') dt'$$

- **Introduction**
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# Path-Refining Algorithms

- String method (finding approximate minimum free energy pathways on high-dimensional spaces)
  - A pathway is represented by a “string”, i.e., an ordered series of images  $\{\xi_i\}$  connecting reactant and product regions.
  - The string is iteratively updated according to some “rule” until converges to a stationary solution.



# Path-Refining Algorithms

- String method with swarms of trajectories (SMwST):
  - Start from an initial string of N images ( $\zeta_i$ )
  - Restrain M copies of each image for time  $\Delta t$

$$U_i(\xi) = \frac{1}{2}k(\xi - \zeta_i)^2$$

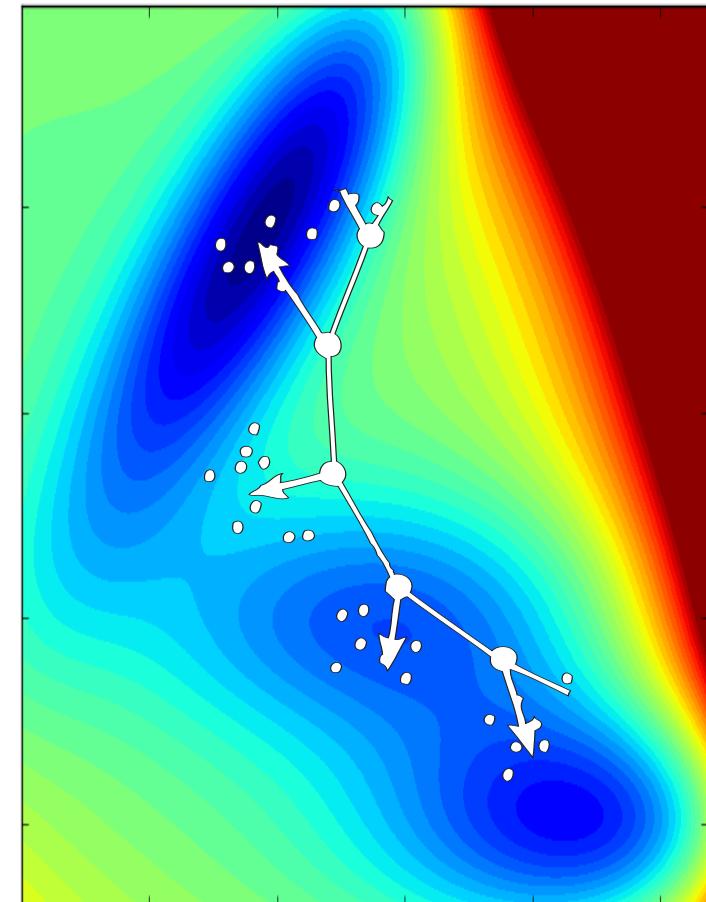
- Release the restraints and run for time  $\Delta t'$
- New string ( $\zeta_i$ ) is determined from  $\langle \xi \rangle_i$ 's
- Iterate until converged

---

Drift term:  $-\beta \mathbf{D} \cdot (\nabla G) + \nabla \cdot \mathbf{D}$

$$\xi(s) \parallel -\beta \mathbf{D} \cdot (\nabla G) + \nabla \cdot \mathbf{D}$$

SMwST gives the zero-drift path not the MFEP.



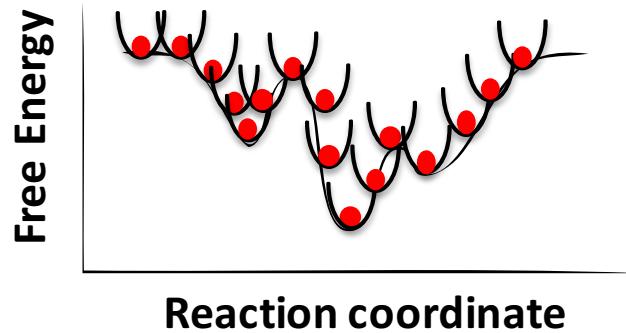
# Free Energy Calculations

## (Bias-Exchange Umbrella Sampling)

- Umbrella sampling

$$U_i(\xi_i^t) = \frac{1}{2}k(\xi_i^t - \xi_i)^2$$

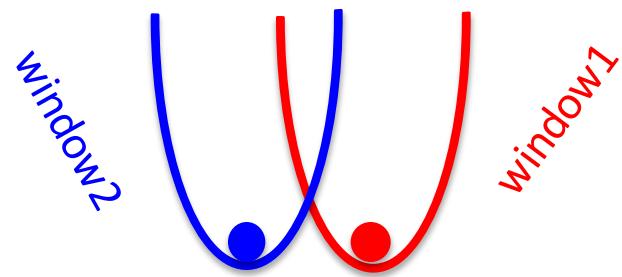
$$e^{-\beta F_i} = \left\langle \frac{e^{-\beta U_i(\xi^t)}}{\sum_j n_j e^{-\beta(U_j(\xi^t) - F_j)}} \right\rangle_{\text{all samples}}$$



- Replica exchange (Monte Carlo)

$$p(x_1x_2 \rightarrow x_2x_1) = \min \left( 1, \frac{\pi_1(x_2)\pi_2(x_1)}{\pi_1(x_1)\pi_2(x_2)} \right)$$
$$\min \left( 1, \frac{e^{-\beta U_1(\xi_2)} e^{-\beta U_2(\xi_1)}}{e^{-\beta U_1(\xi_1)} e^{-\beta U_2(\xi_2)}} \right)$$

Replica2 Replica1



# Non-Parametric Reweighting

$$V_l(x) = V(x) + U_l(x)$$

Biased potential  
Unknown

Unbiased potential  
Unknown

Biasing potential  
Known

$$g_l(x) \propto g(x) q_l(x)$$

Biased density  
Known

Unbiased density  
Unknown

Biasing factor  
Known

$$Z_l^{-1} = e^{f_l}$$

Partition function  
Unknown

$$Z_l = \int dx g(x) q_l(x)$$

$$q_l(x) = e^{-U_l(x)}$$

# Conventional WHAM

If the  $\mathbf{x}$  space is discrete or “binable” such that  
 $U_l(\mathbf{x}) \approx U_l(\mathbf{x}^k)$

e.g.,  $U_l$  is a smooth function of  
a 1D coordinate

$$U_l(\mathbf{x}) \approx U_l(\zeta),$$

$$k \equiv \left[ \frac{\zeta - \zeta_0}{\Delta \zeta} \right]$$

$$q_l^k \equiv q_l(\mathbf{x}^k)$$

$$\left. \begin{aligned} g^k &= \frac{H^k}{\sum_l N_l Z_l^{-1} q_l^k} \\ H^k &\equiv \sum_l n_l^k, N_l \equiv \sum_k n_l^k \\ Z_l &= \sum_k g^k q_l^k \end{aligned} \right\}$$

S. Kumar, J. M. Rosenberg, D. Bouzida, R. H. Swendsen, P. A. Kollman, “The weighted histogram analysis method for free-energy calculations on biomolecules.”  
*J. Comput. Chem.* **13**, 1011 (1992)

# Generalizations

$$\sum_{k=1}^K F^k \equiv \sum_l \sum_{t=1}^{N_l} F(\mathbf{x}_l(t))$$

Every conformation sampled is a state.

$$Z_l = \sum_k g^k q_l^k$$

Solved iteratively.

$$g^k = \frac{1}{\sum_l N_l Z_l^{-1}} q_l^k$$

C. Bartels, "Analyzing biased Monte Carlo and molecular dynamics simulations."  
*Chem. Phys. Letters* **331**, 446 (2000)

# Generalizations

$$Z_l = \sum_k g^k q_l^k$$

$$g^k = 1 / \sum_l N_l Z_l^{-1} q_l^k$$



$$Z_l = \sum_k \frac{q_l^k}{\sum_m N_m Z_m^{-1} q_m^k}$$

$$Z_l = e^{-f_l}$$

$$f_l = -\log \sum_k \frac{q_l^k}{\sum_m N_m e^{f_m} q_m^k}$$

Multi-state BAR (MBAR) equation

M. R. Shirts, J. D. Chodera, "Statistically optimal analysis of samples from multiple equilibrium states."

J. Chem. Phys., 129, 124105 (2008)

# Combining path-finding and free energy methods

- Potential of Mean Force:

$$G(\zeta) = -\beta^{-1} \log \langle \delta(\xi(x) - \zeta) \rangle$$

$$\langle \delta(\xi(x) - \zeta) \rangle = \int \delta(\xi(x) - \zeta) \rho(x, p) d^{3N}x d^{3N}p$$

- Perturbed Free Energy:

$$F_i = F(\zeta_i) = -\beta^{-1} \log Z_i$$

$$Z_i = \int e^{-\beta U_i(\xi)} \rho(x, p) d^{3N}x d^{3N}p = \int e^{-\beta(G(\xi) + U_i(\xi))} d^n\xi$$

- Non-parametric MLE estimates:

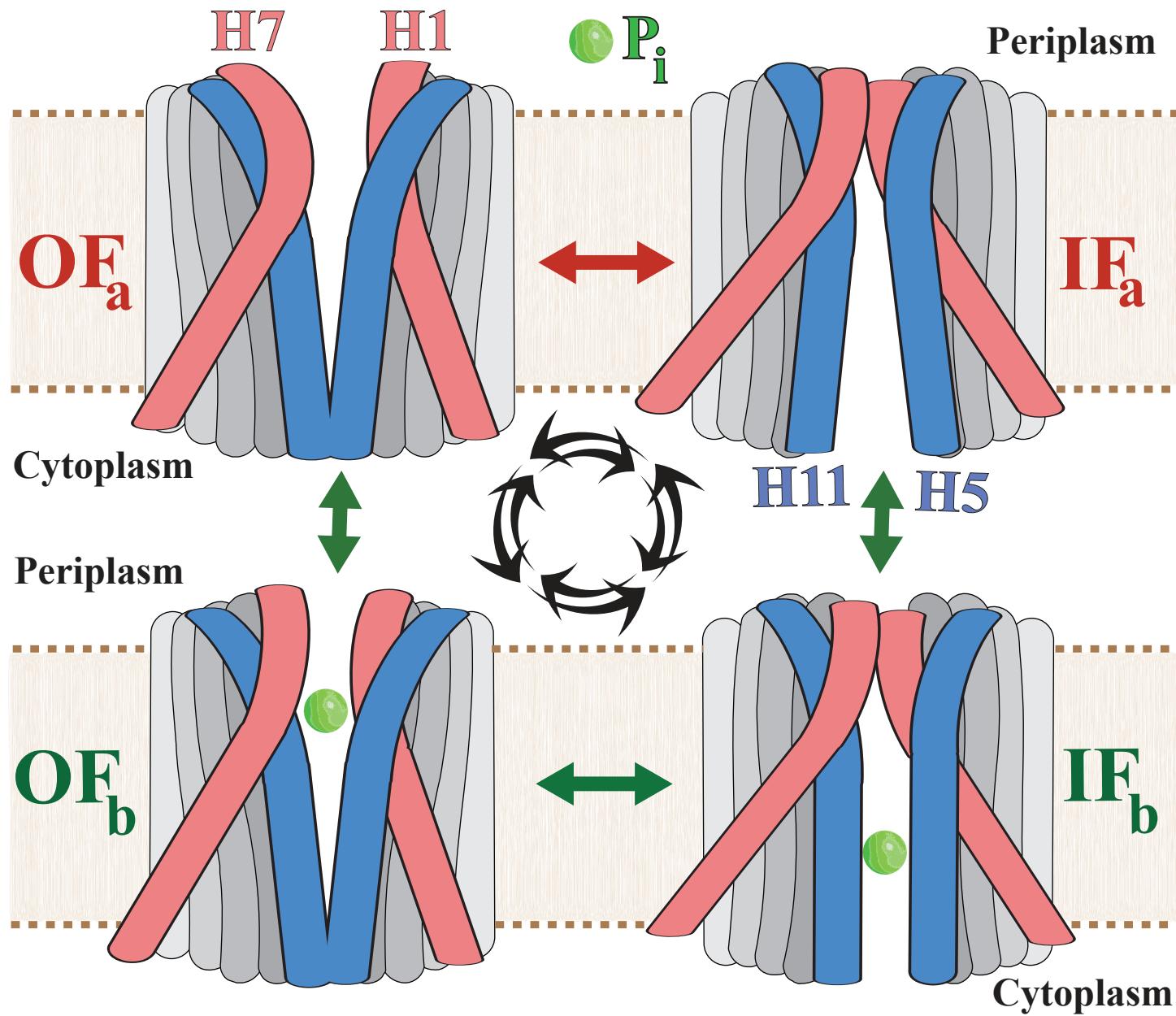
Shirts, Chodera, JCP, **129**, 124105 (2008)

$$e^{-\beta F_i} = \left\langle \frac{e^{-\beta U_i(\xi^t)}}{\sum_j n_j e^{-\beta(U_j(\xi^t) - F_j)}} \right\rangle_{\text{all samples}}$$

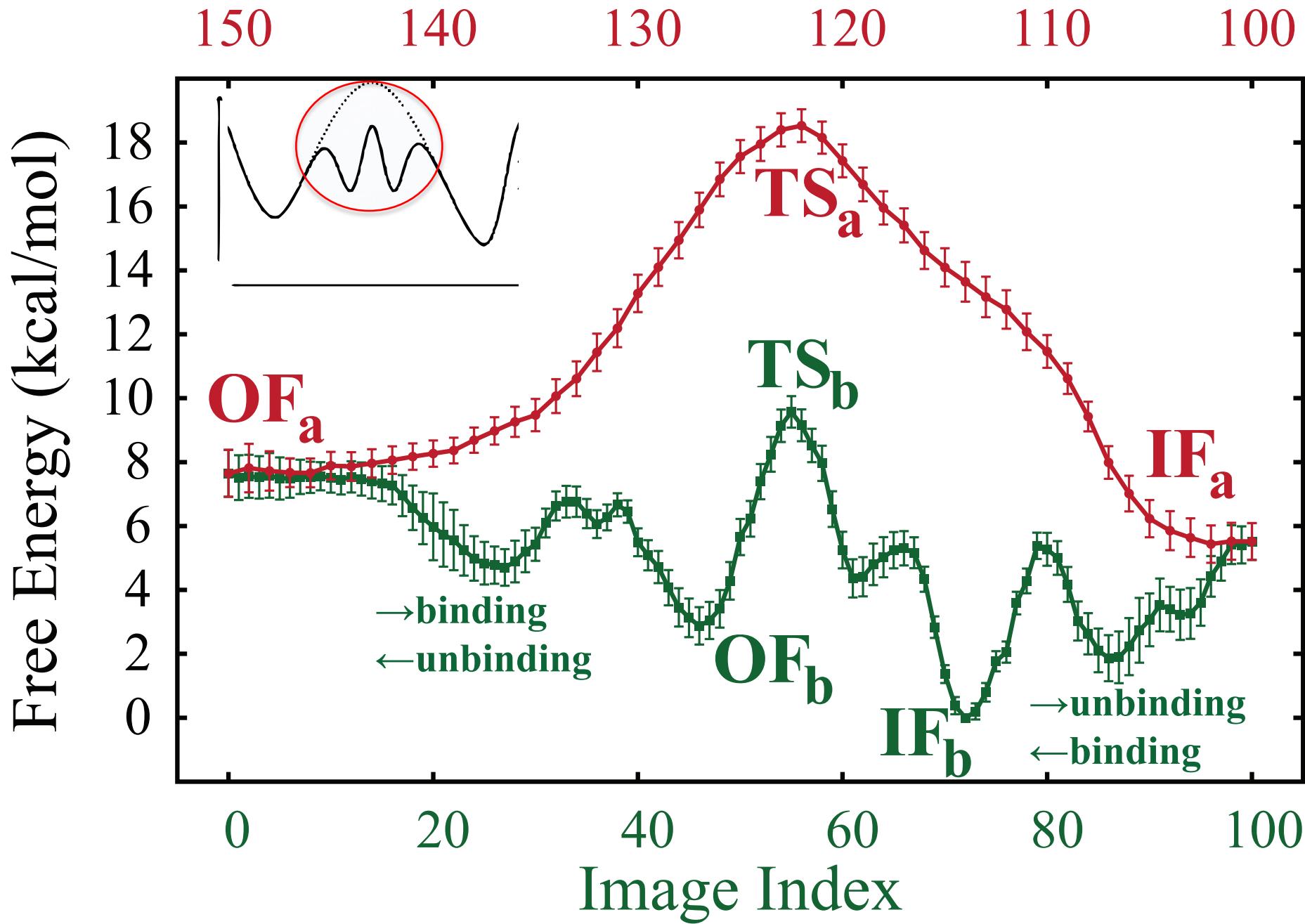
Bartels, CPL, **331**, 446 (2000)

$$e^{\beta F_i} = \frac{n_i}{\sum_t w^t e^{-\beta U_i(\xi^t)}}$$

$$w^t = \frac{1}{\sum_i e^{-\beta(U_i(\xi^t) - F_i)}}$$

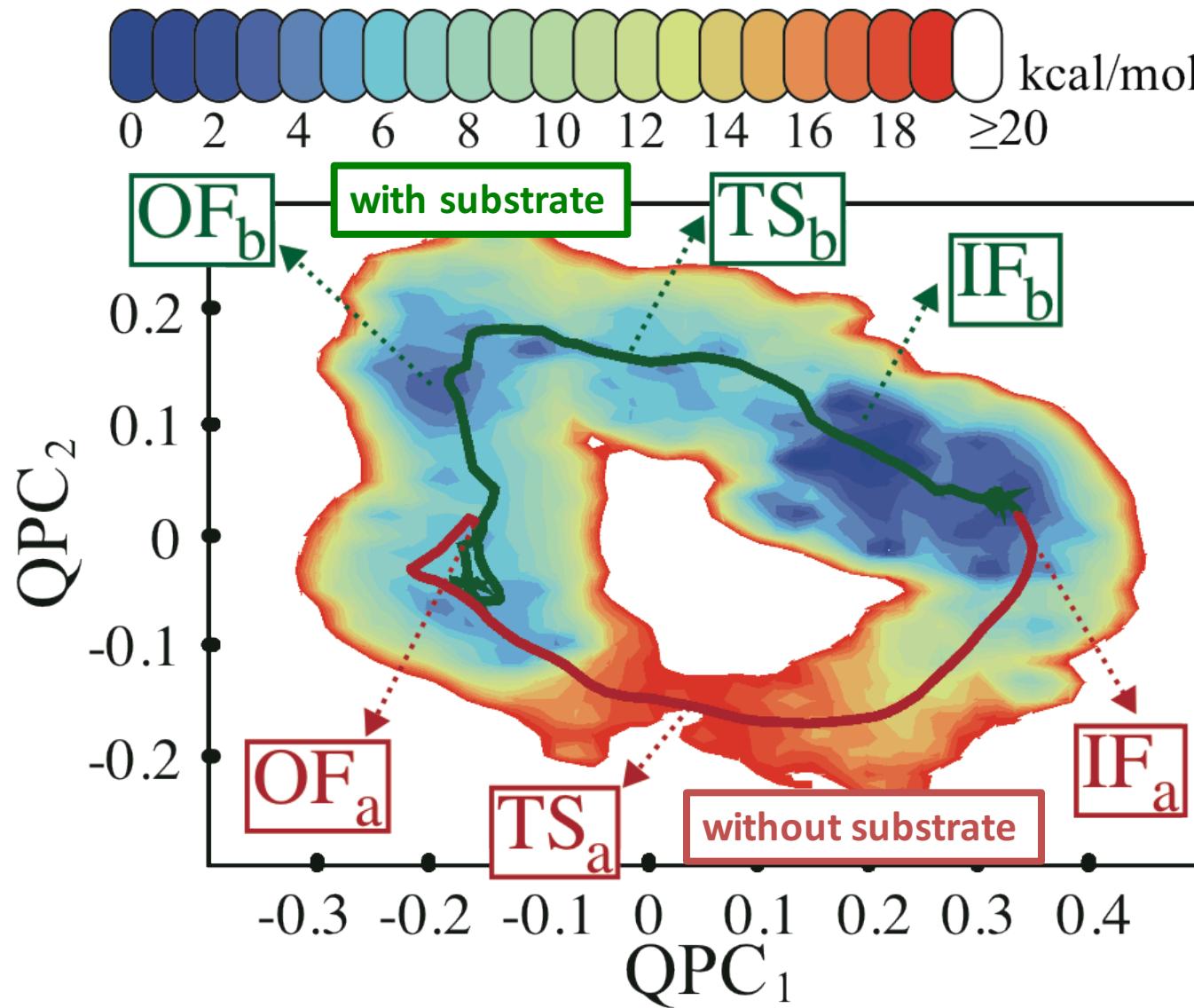


# Image Index



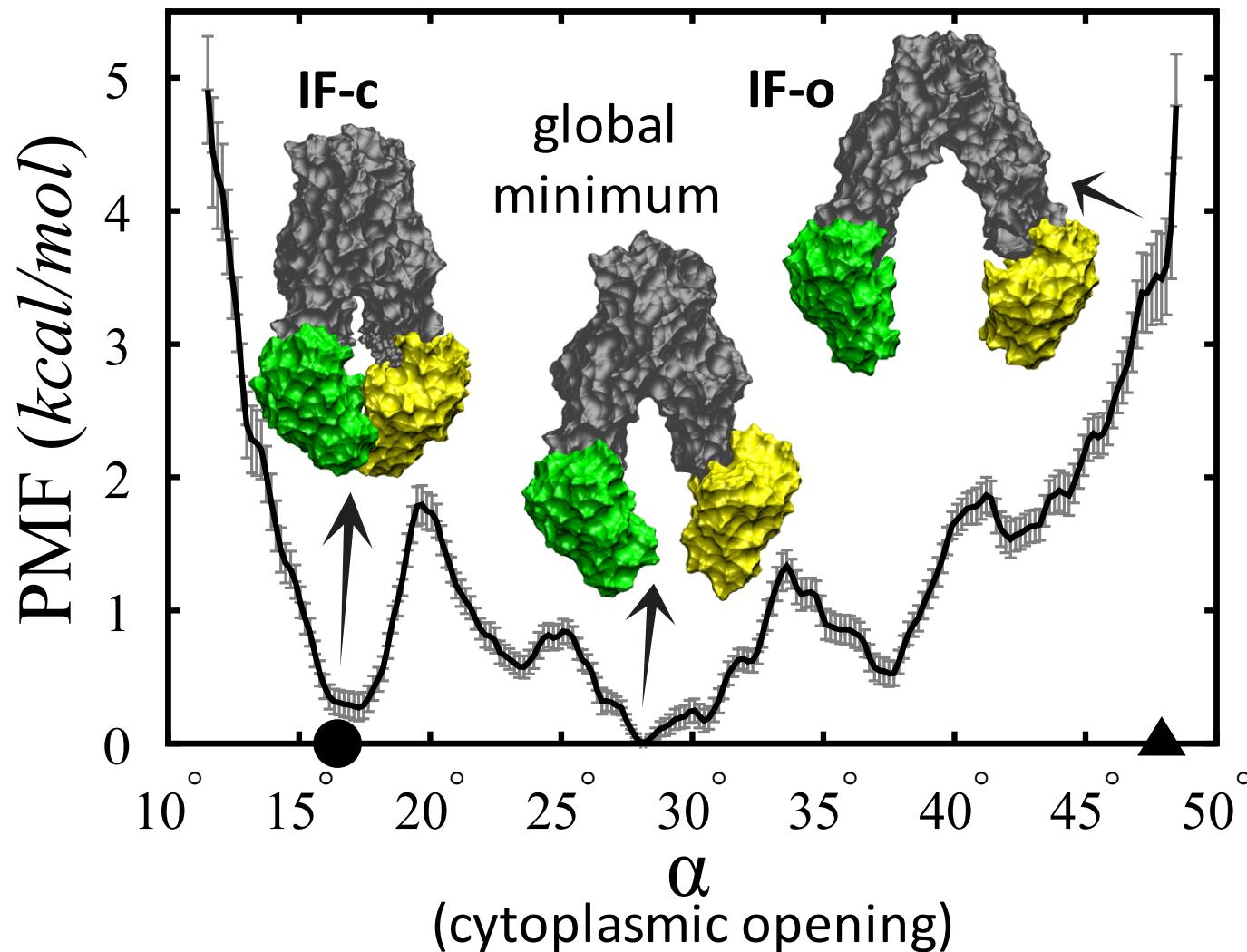
# Distinct conformational transition pathways

Quaternion-based principal components (QPCs) represent different modes of concerted motions of transmembrane helices.

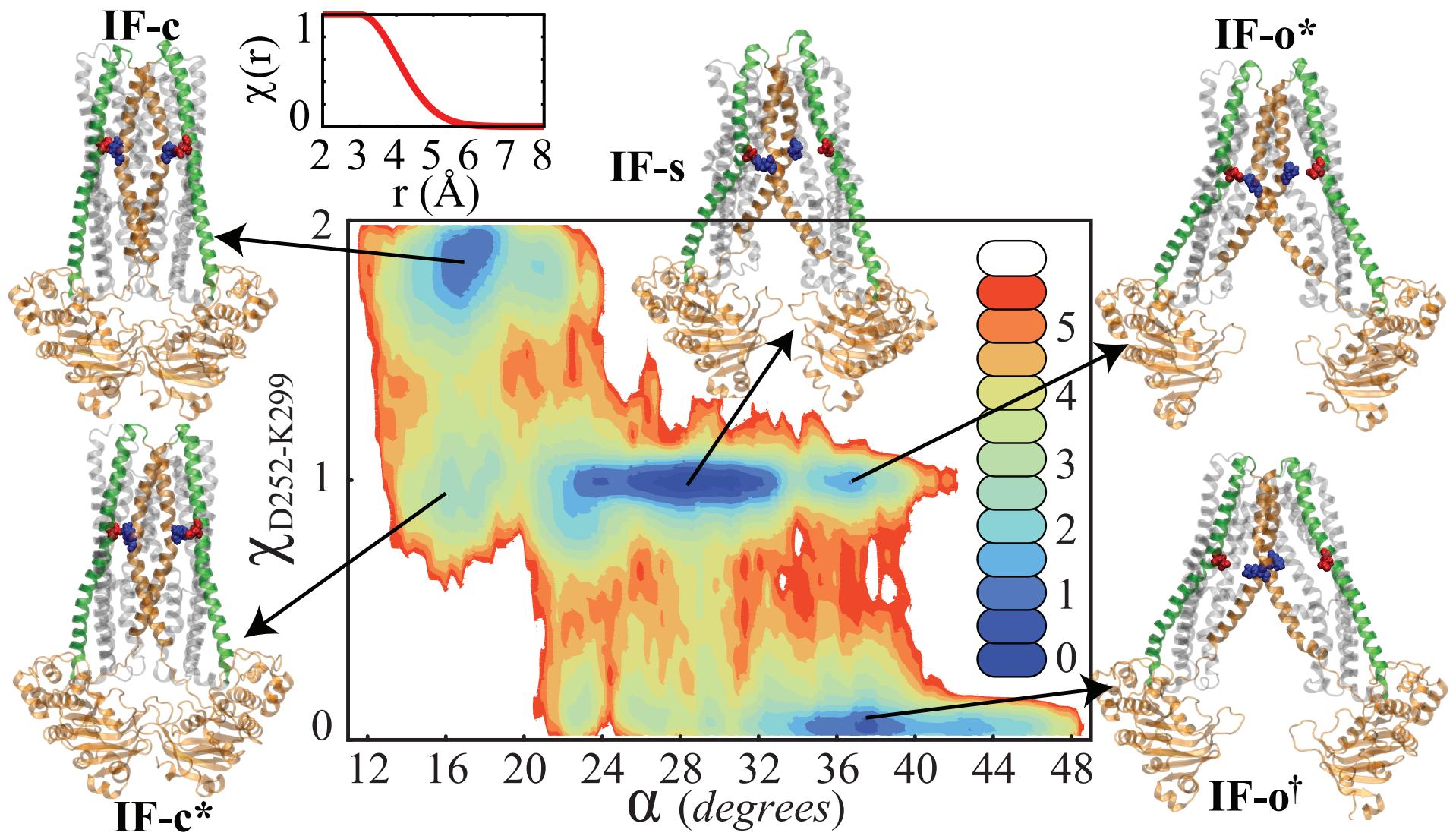


# Free Energy Profile

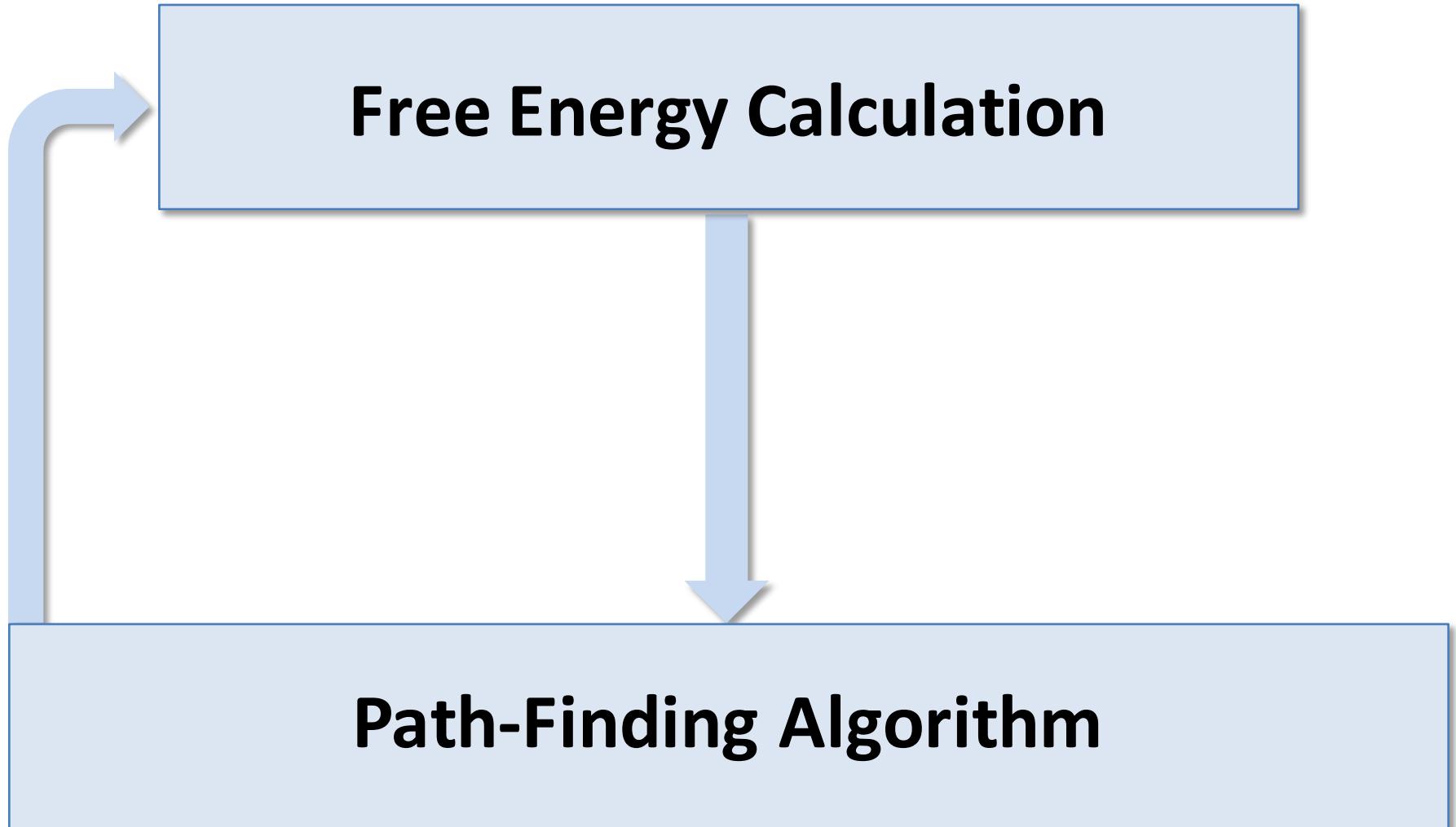
(along one of the four stages of IF-OF transition)



# Asymmetric behavior of a homodimer?



# Iterative path-finding algorithms and free energy calculations



# Iterative path-refining algorithms and free energy calculations

**Bias-Exchange Umbrella Sampling  
(Free Energy Calculation)**



**String Method with Swarms of Trajectories  
(Path-Refining Algorithm)**

# Iterative path-refining algorithms and free energy calculations

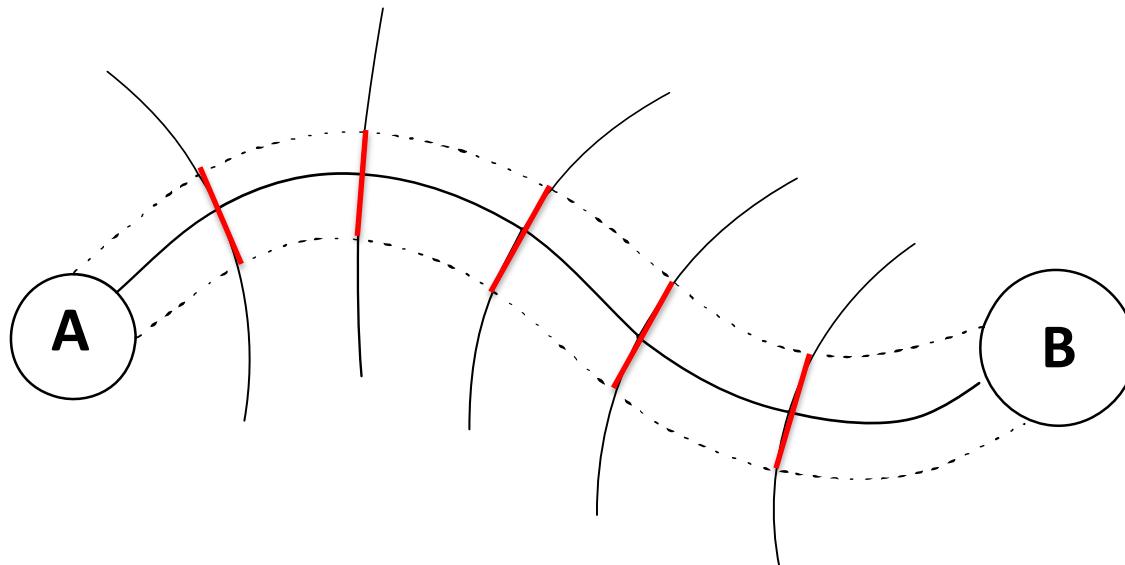
**Bias-Exchange Umbrella Sampling  
(Free Energy Calculation)**

**Post-Hoc String Method  
(Analysis)**

**String Method with Swarms of Trajectories  
(Path-Refining Algorithm)**

# Post-hoc string method (PHSM)

- Suppose we have already sampled a particular “**continuous**” region of configuration space (or some multi-dimensional collective variable space  $\{\xi_i\}$ ) and estimated the **weight** of each sample  $\{w^t\}$ .
  - PHSM finds the **principal curve** in the  $\xi$  space using available samples as an **approximate minimum free energy pathway**.
- 



# Post-hoc string method (PHSM)

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- PHSM finds the **principal curve** in the  $\xi$  space using available samples as an **approximate minimum free energy pathway**.

- 
- For each image  $i$  with center  $\xi_i$ , find all samples that are closer to  $\{\xi_i\}$  than any other image center (Voronoi tessellation):

$$B_i = \left\{ \xi^t \mid |\xi^t - \xi_i| < |\xi^t - \xi_j| \quad \forall j \neq i \quad \& \quad |\xi^t - \xi_i| < \varepsilon \right\}$$

- Find the new image center by weighted averaging over all the samples in the Voronoi cell:

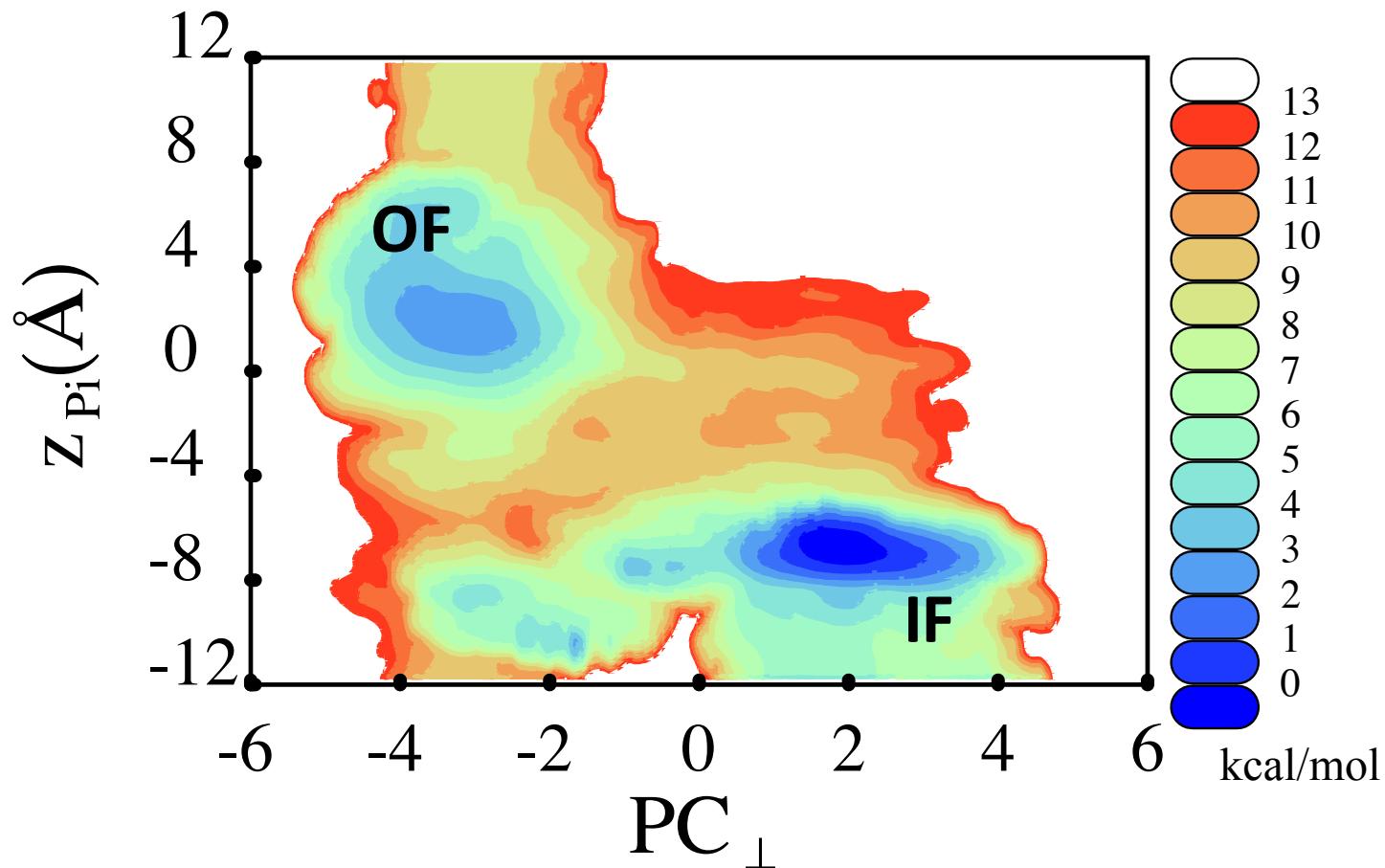
- Smooth and reparametrize.

$$\xi_i = \frac{\langle w^t \xi^t \chi_i^t \rangle}{\langle w^t \chi_i^t \rangle}$$

indicator  
function

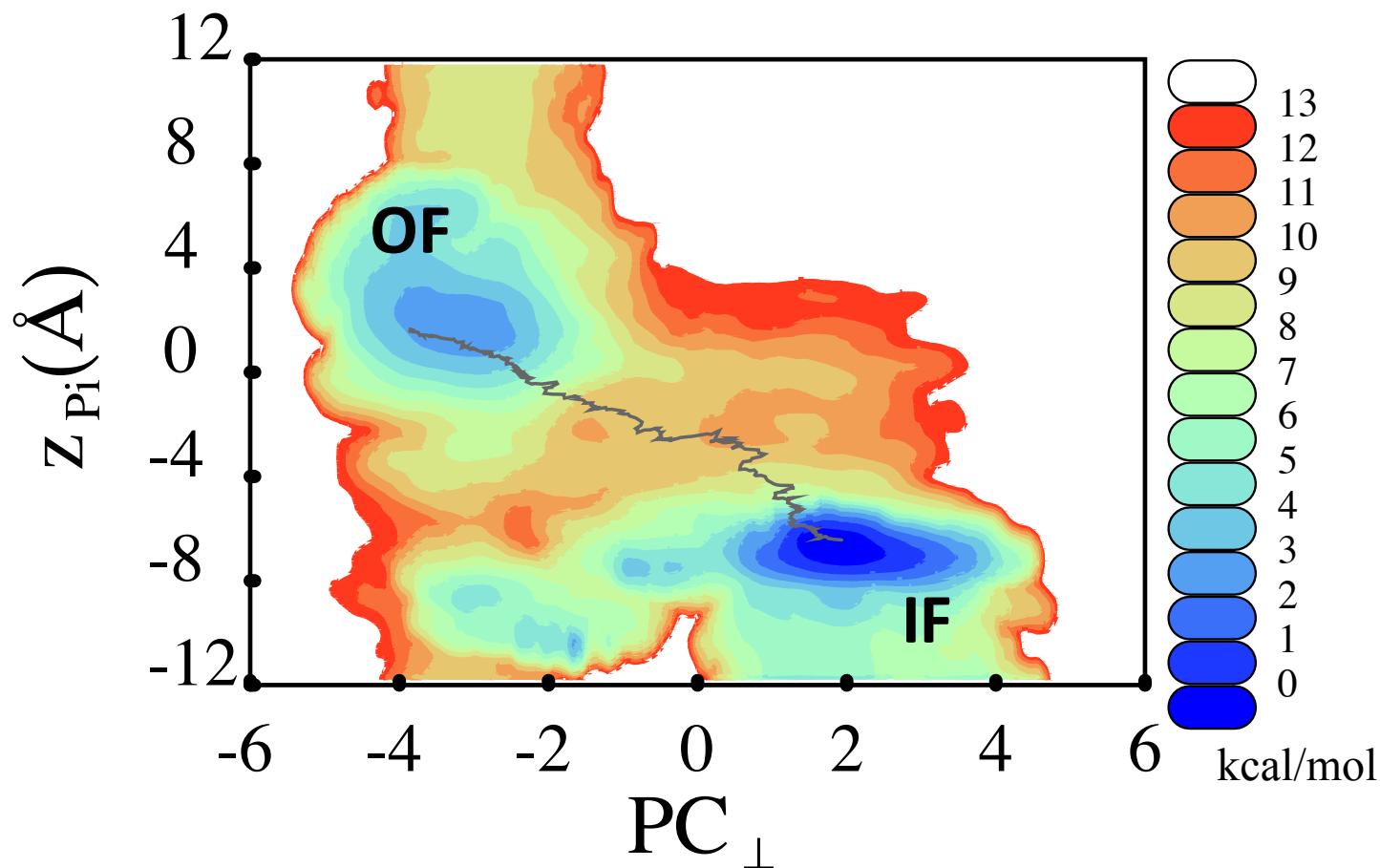
# Post-hoc string method (PHSM)

- Free energy landscape in a given 2D collective variable space
- Note: The algorithm is non-parametric, i.e., the pathway is not optimized in a particular low-dimensional space.



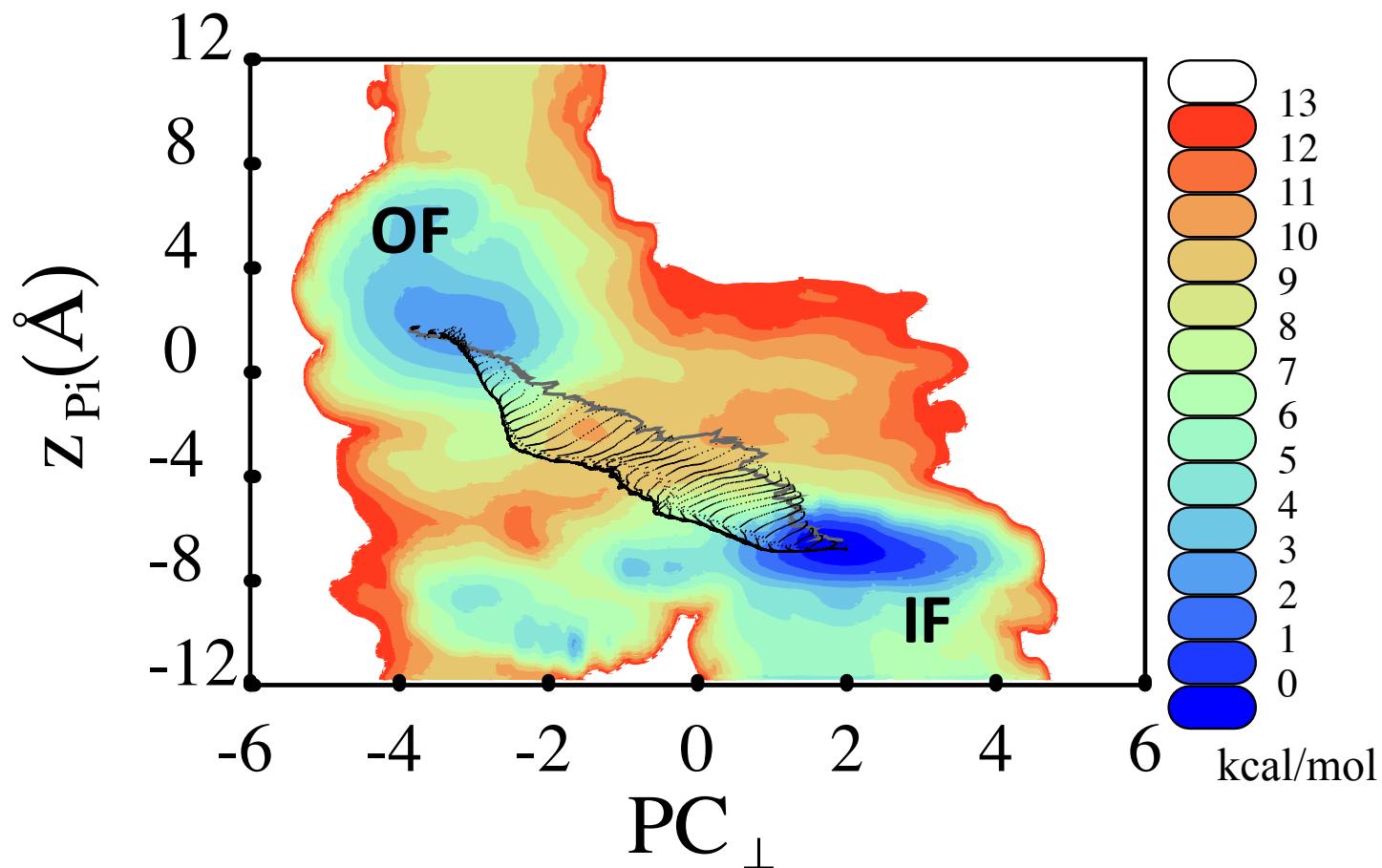
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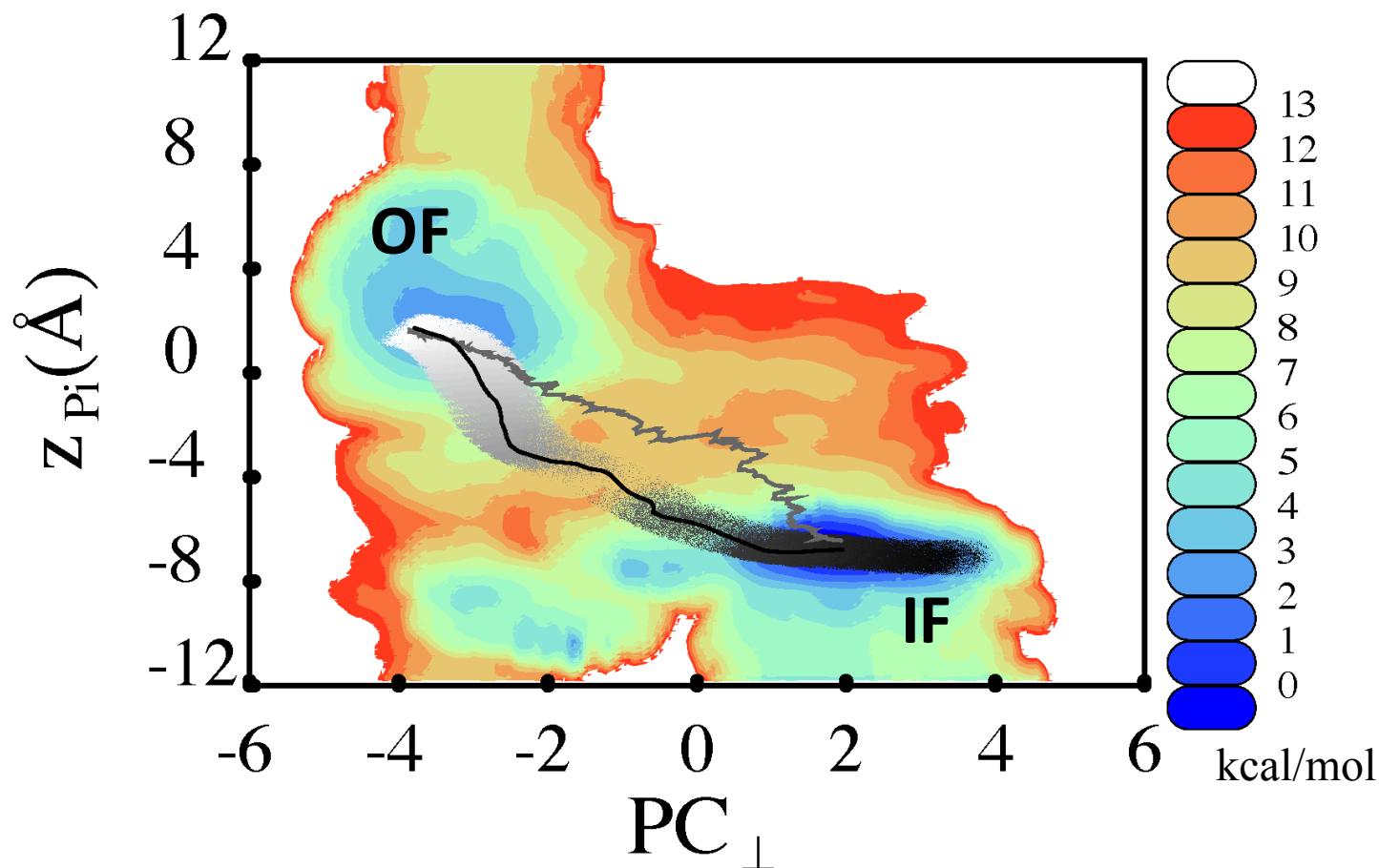
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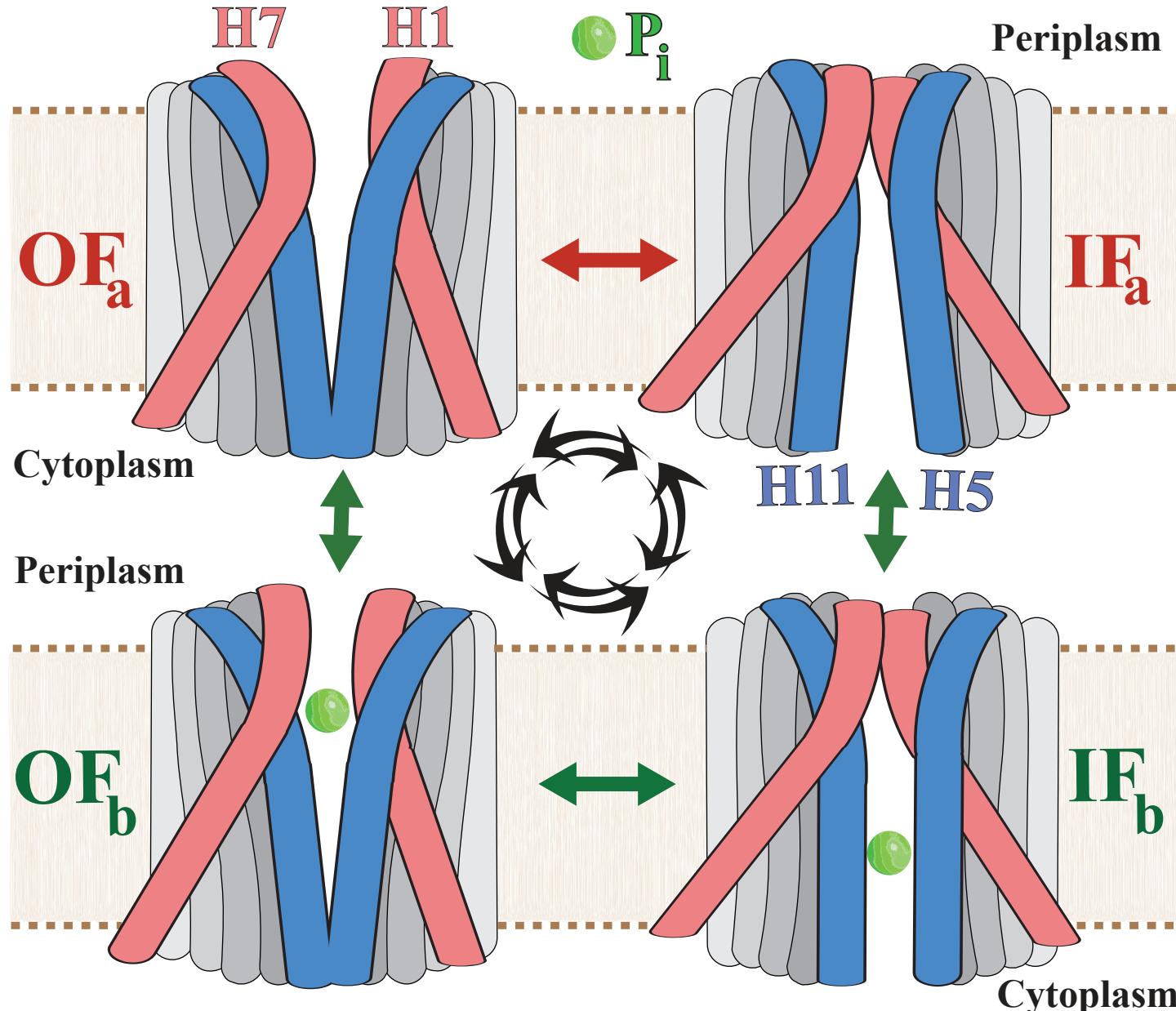


# Post-hoc string method (PHSM)

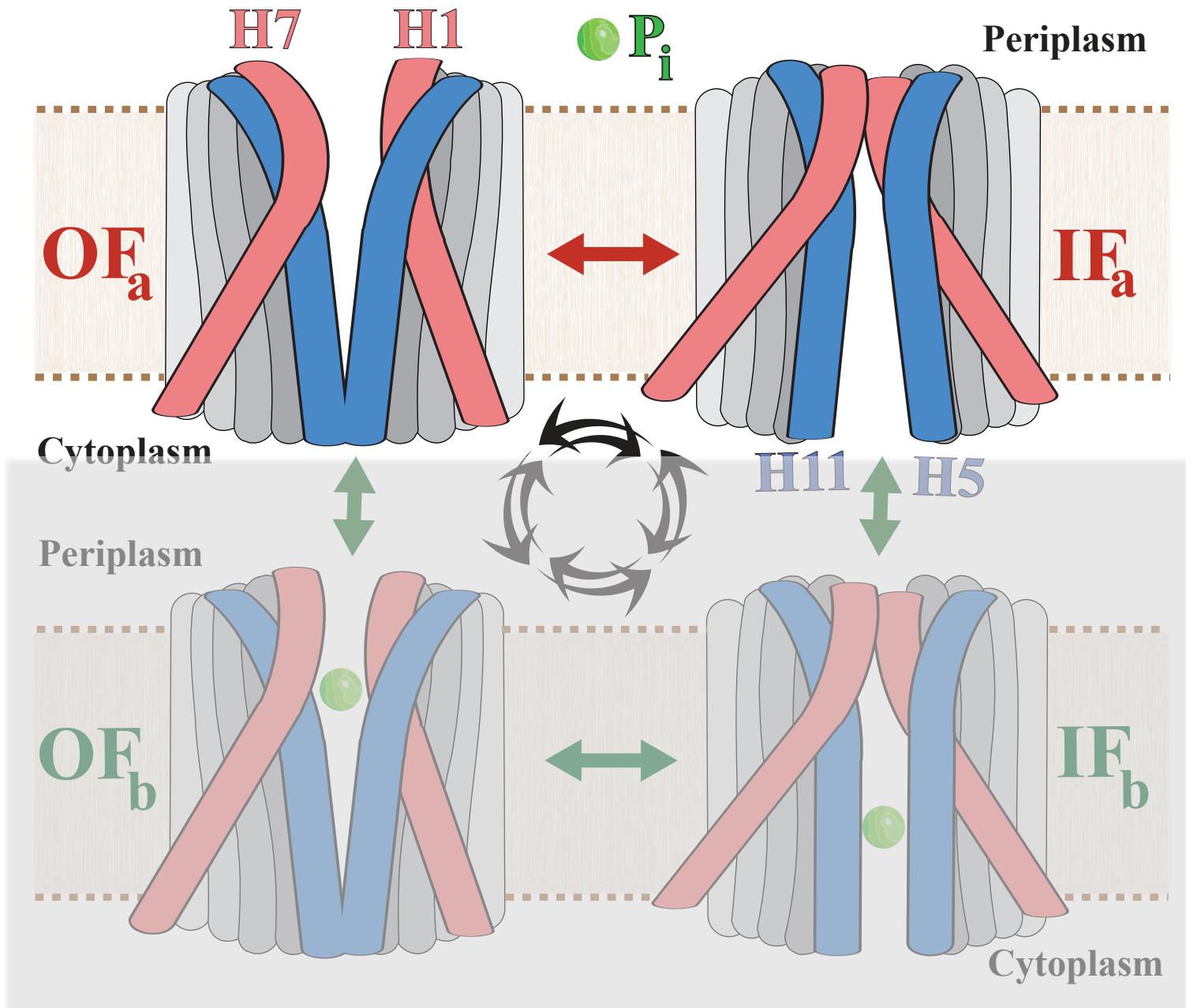
- Free energy landscape in a given 2D collective variable space
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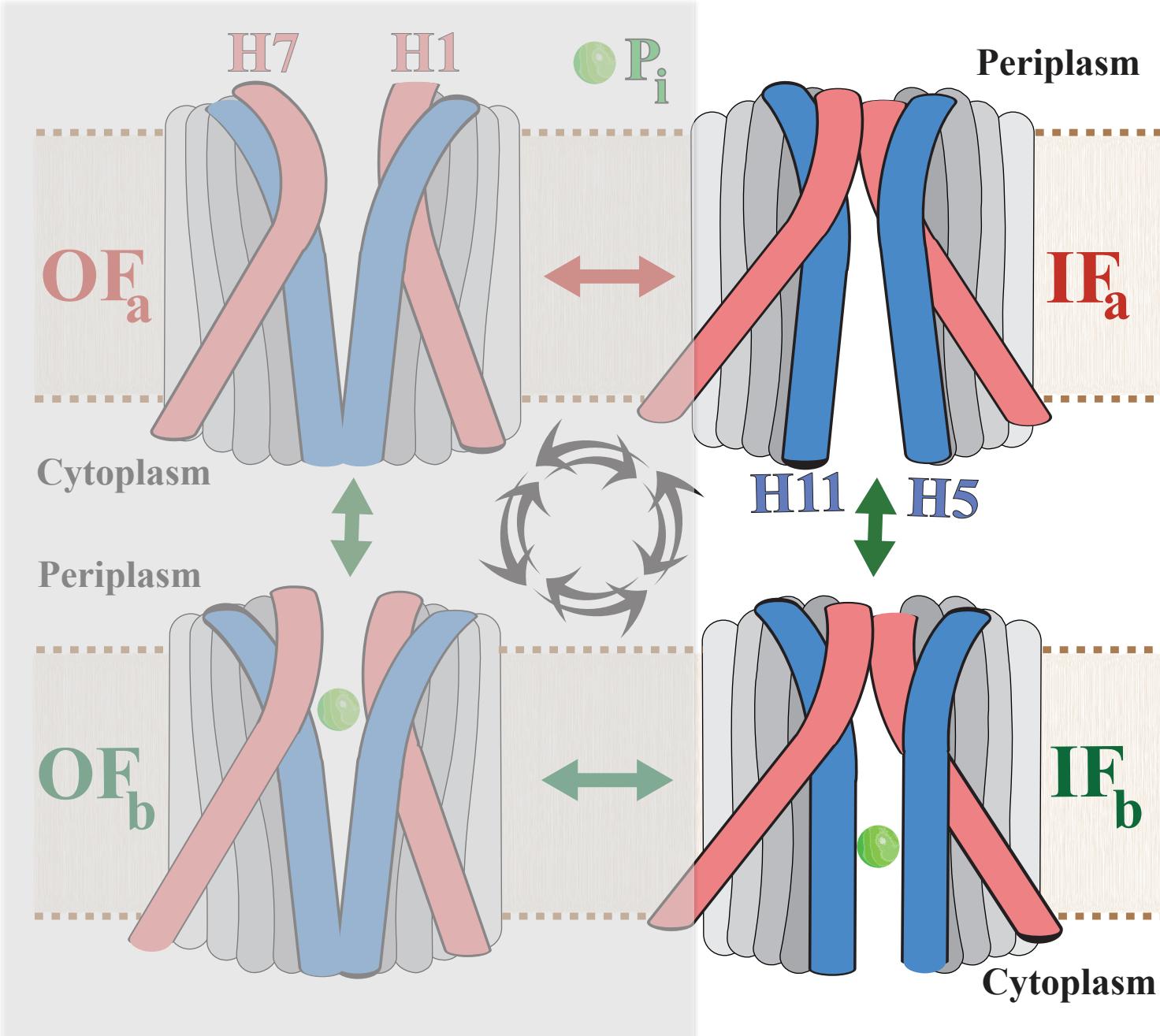
# Example: Transport Cycle of GlpT



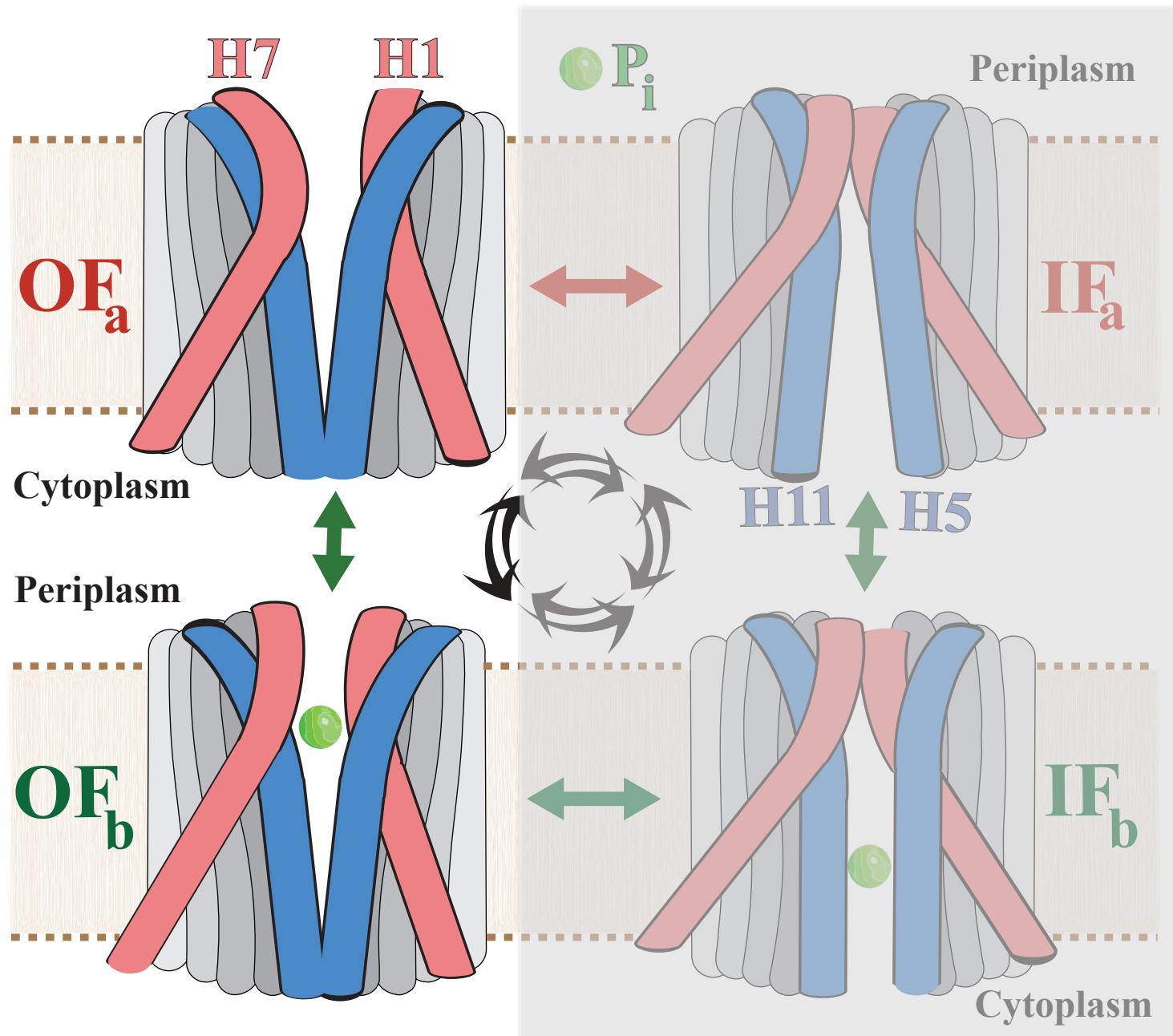
# Step 1: $\text{OF}_a \leftrightarrow \text{IF}_a$



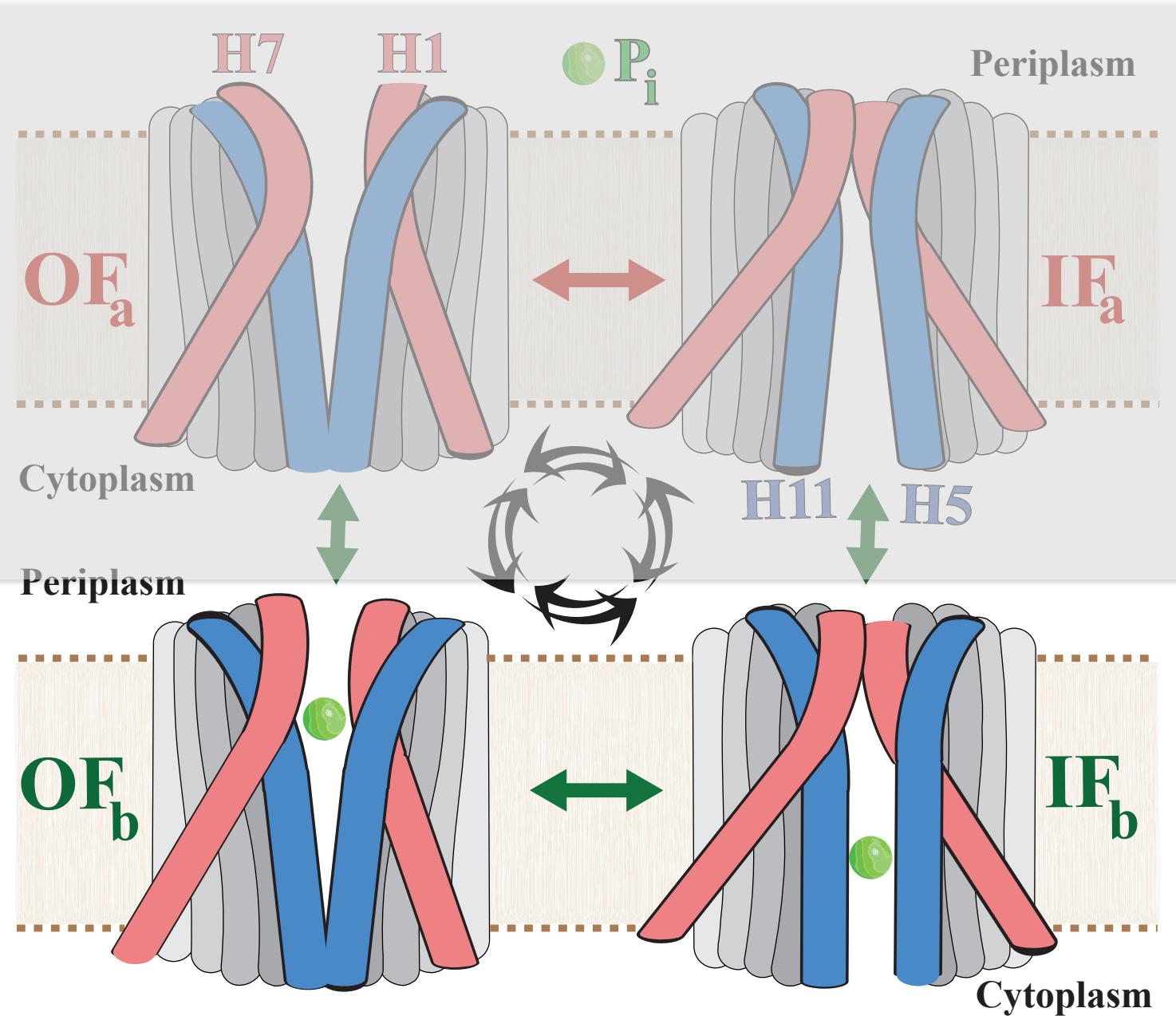
## Step 2: $\text{IF}_a \leftrightarrow \text{IF}_b$

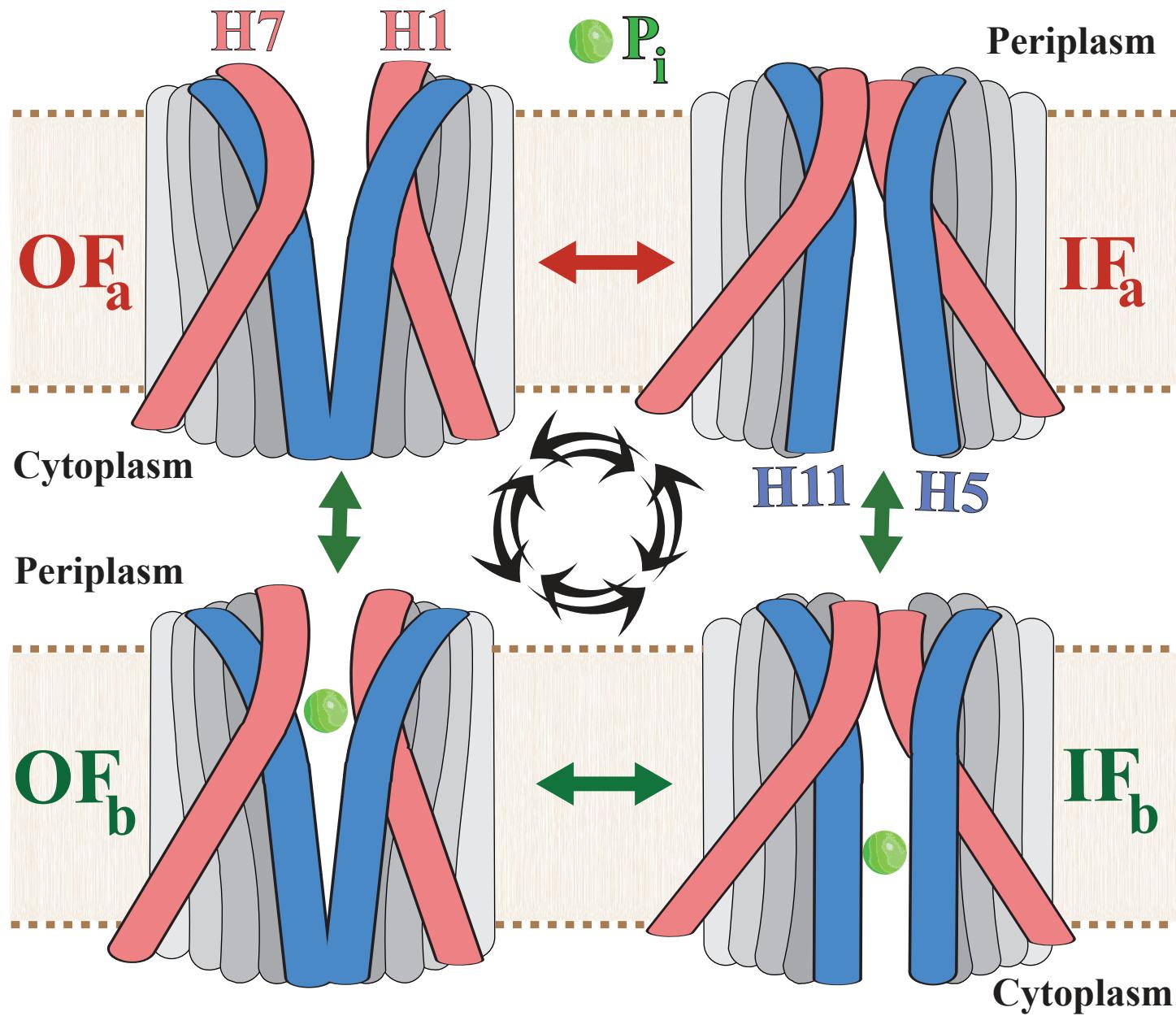


### Step 3: $\text{OF}_a \leftrightarrow \text{OF}_b$



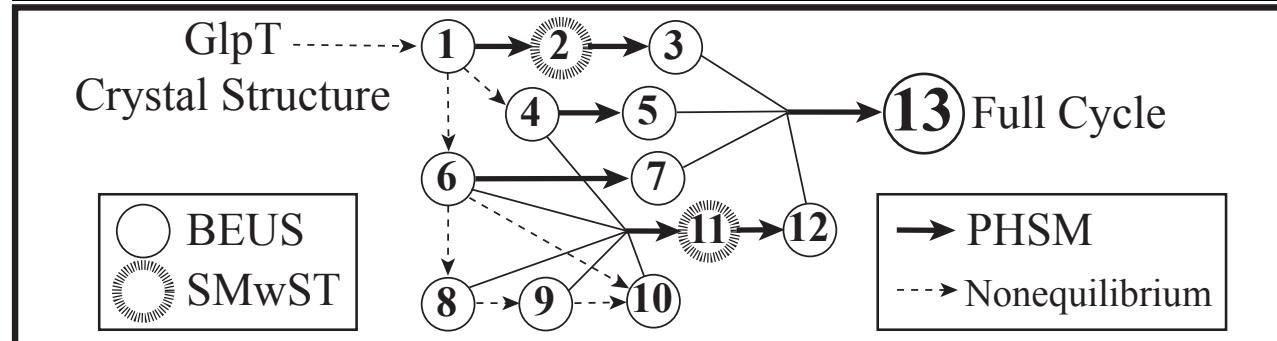
## Step 4: $\text{OF}_b \leftrightarrow \text{IF}_b$



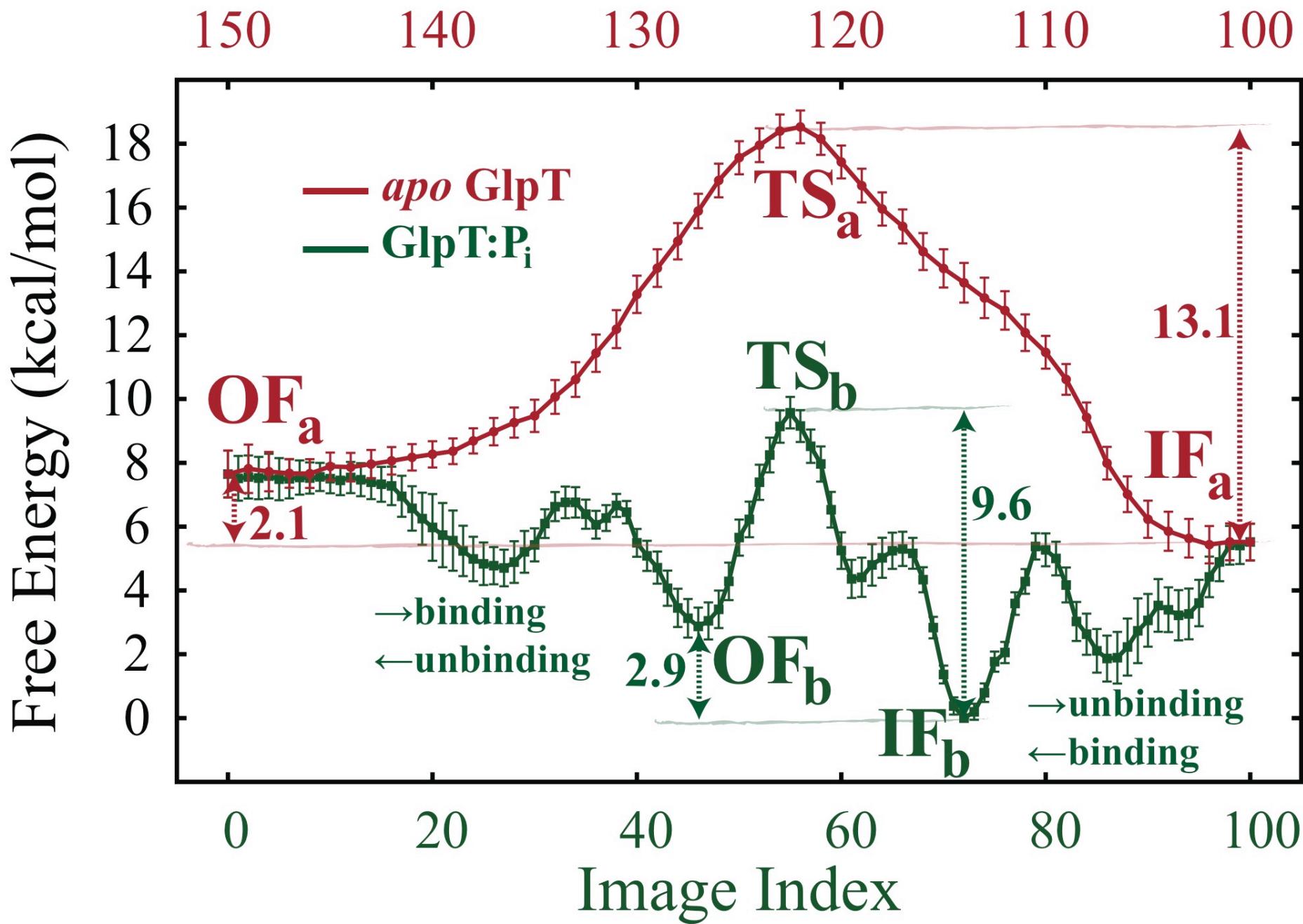


# Simulation Protocols

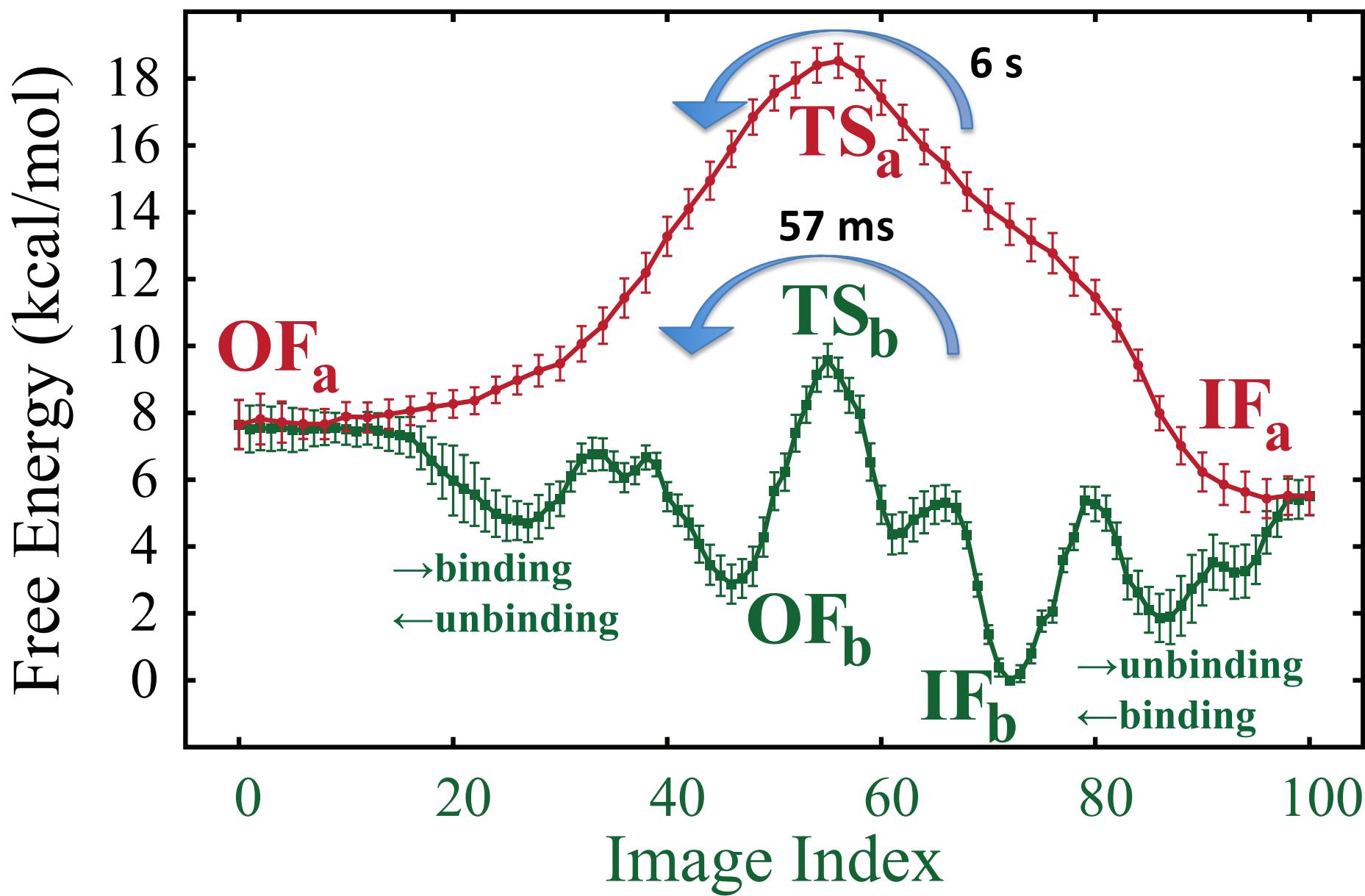
Transition	Technique	Collective Variables	# of Replicas × Runtime	=	Runtime
1	$\text{IF}_a \leftrightarrow \text{OF}_a$	BEUS	( $Q_1, Q_7$ )	$12 \times 40$ ns	$= 0.5 \mu\text{s}$
2		SMwST	{ $Q$ }	$1000 \times 1$ ns	$= 1 \mu\text{s}$
3		BEUS	{ $Q$ }	$50 \times 20$ ns	$= 1 \mu\text{s}$
4	$\text{IF}_a \leftrightarrow \text{IF}_b$	BEUS	$Z_{P_i}$	$30 \times 40$ ns	$= 1.2 \mu\text{s}$
5		BEUS	( $\{Q\}, Z_{P_i}$ )	$30 \times 40$ ns	$= 1.2 \mu\text{s}$
6	$\text{OF}_a \leftrightarrow \text{OF}_b$	BEUS	$Z_{P_i}$	$30 \times 40$ ns	$= 1.2 \mu\text{s}$
7		BEUS	( $\{Q\}, Z_{P_i}$ )	$30 \times 40$ ns	$= 1.2 \mu\text{s}$
8	$\text{IF}_b \leftrightarrow \text{OF}_b$	BEUS	( $Q_1, Q_7$ )	$24 \times 20$ ns	$= 0.5 \mu\text{s}$
9		BEUS	$Z_{P_i}$	$15 \times 30$ ns	$= 0.5 \mu\text{s}$
10		2D BEUS	( $\Delta\text{RMSD}, Z_{P_i}$ )	$200 \times 5$ ns	$= 1 \mu\text{s}$
11	IF <sub>b</sub> ↔ OF <sub>b</sub>	SMwST	( $\{Q\}, Z_{P_i}$ )	$1000 \times 1$ ns	$= 1 \mu\text{s}$
12		BEUS	( $\{Q\}, Z_{P_i}$ )	$50 \times 20$ ns	$= 1 \mu\text{s}$
13	Full Cycle	BEUS	( $\{Q\}, Z_{P_i}$ )	$150 \times 50$ ns	$= 7.5 \mu\text{s}$
Total Simulation Time					$18.7 \mu\text{s}$



# Image Index



# Image Index



- **Introduction**
  - How to study large-scale conformational changes?
- **Methodology**
  - Empirical search for good pulling protocols
  - Iterative combination of free energy calculation methods and path-finding algorithms
- **Theoretical Framework**
  - Effective Riemannian diffusion model

# Dynamics of the Atomic System

- Langevin equation:

$$dp_i = \left( -\frac{\partial}{\partial x_i} V(x) + \gamma_i m_i^{-1} p_i \right) dt + \sqrt{2\gamma_i \beta^{-1}} dB_i$$

$x \in \mathbb{R}^{3N}$        $\gamma_i = \gamma m_i$

$p = m\dot{x}$        $V(x)$

Wiener process

- Overdamped Langevin equation:

$$dx_i = -\gamma_i^{-1} \frac{\partial}{\partial x_i} V(x) dt + \sqrt{2\gamma_i^{-1} \beta^{-1}} dB_i$$

$\beta D_i$        $D_i$

$$\langle B_i(t) \rangle = 0$$
$$\langle B_i(t) B_j(t) \rangle = \delta_{ij} t$$

# Effective Dynamics (Euclidean Geometry)

$$x \mapsto \xi(x) \ (3N \rightarrow n)$$

- Overdamped Langevin equation:

$$d\xi = (-\beta \mathbf{D} \cdot \nabla A(\xi) + \nabla \cdot \mathbf{D}) dt + \sqrt{2}\sigma dB$$

generally

a position-dependent  
anisotropic tensor

$$d\xi_i = \sum_j \left( -\beta D_{ij} \frac{\partial}{\partial \xi_j} A(\xi) + \frac{\partial}{\partial \xi_j} D_{ij} \right) dt + \sqrt{2} \sum_j \sigma_{ij} dB_j$$

Note: zero drift path is not the same as MFEP.

$$\sum_j \sigma_{ij} \sigma_{jk} = D_{ik}$$

Johnson & Hummer JPCB 2012, 116, 8573.

- $A(\xi(x))$ : the potential of mean force of the atomic system

$$A(\zeta) = -\beta^{-1} \log \langle \delta(\xi(x) - \zeta) \rangle$$

- $A(\xi)$ : the “effective” potential energy of the reduced system

$$A(\zeta) = -\beta^{-1} \log \langle \delta(\xi - \zeta) \rangle$$

# Effective Dynamics (Euclidean Geometry)

$$x \mapsto \xi(x) (x:3N-d, \xi: n-d)$$

- Fokker-Planck/Smoluchowski equation:

$$\frac{\partial}{\partial t} \mu(\xi, t) = \sum_{ij} \left( \beta \frac{\partial}{\partial \xi_i} \left( \mu(\xi, t) D_{ij} \frac{\partial}{\partial \xi_j} A(\xi) \right) + \frac{\partial}{\partial \xi_i} \left( D_{ij} \frac{\partial}{\partial \xi_j} \mu(\xi, t) \right) \right)$$

$\downarrow$   
 $p(\xi, t | \xi_0, 0)$

$$\boxed{\begin{aligned} \frac{\partial}{\partial t} p(\xi, t | \xi_0, 0) &= \mathcal{L} p(\xi, t | \xi_0, 0) \\ \mathcal{L} &\equiv \nabla \cdot \mathbf{D} \cdot (\beta \nabla A + \nabla) \end{aligned}}$$

- In this formalism, neither the PMF (which is the “effective” potential energy), nor the MFEP (which is the minimum-“effective”-potential-energy path) is invariant under coordinate transformations.

# Riemannian Reformulation

$\xi : \mathbb{R}^{3N} \rightarrow M$      $(M, g)$ : Riemannian manifold (n-d)

- Overdamped Langevin equation:

$$d\xi = (-\beta D \nabla G(\xi) + b) dt + \sqrt{2D} dW$$
$$d\xi^i = (-\beta D g^{ij} \partial_j G(\xi) + b^i) dt + \sqrt{2D} dW^i$$

drift rate ← geometric drift  $-Dg^{jk} \Gamma_{jk}^i$  Christoffel symbols

Riemannian Wiener process

$\langle W^i(t) \rangle = 0$  $\langle W^i(t) W^j(t) \rangle = g^{ij} t$

D: a position-independent scalar

$g$ : Riemannian metric tensor    $G(\xi)$ : Riemannian PMF

Fakharzadeh & Moradi Effective Riemannian diffusion model for conformational dynamics of biomolecular systems. *J Phys Chem Lett.* 2016;7(24):4980-4987.

# Riemannian Reformulation

Riemannian PMF or “effective” potential:

$$G(\zeta) = -\beta^{-1} \log \langle \delta_\zeta(\xi(x)) \rangle \text{ atomic system}$$

$$G(\zeta) = -\beta^{-1} \log \langle \delta_\zeta(\xi) \rangle \text{ reduced system}$$

$$\begin{aligned} G(\zeta) &= -\beta^{-1} \log \langle \delta_\zeta(\xi) \rangle \\ A(\zeta) &= -\beta^{-1} \log \langle \delta(\xi - \zeta) \rangle \\ G(\zeta) &= A(\zeta) + \frac{1}{2} \beta^{-1} \log g \end{aligned}$$

Gibbs measure:

$$e^{-\beta G(\xi)} d\Omega_\xi = e^{-\beta A(\xi)} d^n \xi$$

invariant

Riemannian  
Dirac delta function

$$\mathcal{F}(\zeta) = \int d\Omega_\xi \delta_\zeta(\xi) \mathcal{F}(\xi)$$

$$d\Omega_\xi = \sqrt{g} d^n \xi$$

Conventional  
Dirac delta function

$$\mathcal{F}(\zeta) = \int d^n \xi \delta(\xi - \zeta) \mathcal{F}(\xi)$$

# Riemannian Reformulation

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Potential/FE  
gradient  
(invariant)

$-Dg^{jk} \Gamma_{jk}^i$   
Geometric drift  
(non-invariant)

In a geodesic normal coordinate system,  $b^i$  disappears.

$$d\xi = (-\beta D \cdot \nabla A(\xi) + \nabla \cdot D)dt + \sqrt{2\sigma}dB$$

non-invariant

non-invariant

# Riemannian Reformulation

- Fokker-Planck/Smoluchowski equation:

$$\frac{\partial}{\partial t} u(\xi, t) = \beta D \frac{1}{\sqrt{g}} \partial_i \left( u(\xi, t) \sqrt{g} g^{ij} \partial_j G(\xi) \right) + D \frac{1}{\sqrt{g}} \partial_i \left( \sqrt{g} g^{ij} \partial_j u(\xi, t) \right)$$
$$\frac{\partial}{\partial t} u(\xi, t) = \beta D \nabla \cdot (u(\xi, t) \nabla G) + D \Delta u(\xi, t)$$

$$\frac{\partial}{\partial t} p(\xi, t | \xi_0, 0) = \mathcal{L} p(\xi, t | \xi_0, 0)$$

$$\mathcal{L} \equiv D \nabla \cdot (\beta \nabla G + \nabla)$$

It can be shown the conventional diffusion with potential  $A(\xi)$  and diffusion tensor  $D$  and the Riemannian diffusion with potential  $G(\xi)$  and metric  $g$  are equivalent if:

$$D = D g^{-1} \text{ and } G = A + \frac{1}{2} \beta^{-1} \log g$$

# Riemannian Reformulation

- The Riemannian formulation allows for developing more **robust** free energy calculation methods and path-finding algorithms (due to the “**invariance**”).
- Methods such as (BE)US and SM(wST) can be modified by using **geodesic distance** instead of **Euclidean distance** (and modifying the definitions of differential operators, etc)
- For certain collective variables, the geodesic distance can be approximated by analytic expressions, e.g., for **orientation quaternions**:

$$d(\mathbf{q}_1, \mathbf{q}_2) \approx \cos^{-1}(\mathbf{q}_1 \cdot \mathbf{q}_2)$$

- For other collective variables, on-the-fly metric calculations maybe necessary.

# Free Energy Calculation Methods Revisited

- Biasing potential:  $U_c(\xi) = \frac{1}{2} k d(\xi, \xi_c)$
- Perturbed free energy:  $e^{-\beta f(\xi_c)} = \int e^{-\beta(G(\xi) + U_c(\xi))} d\Omega_\xi$
- Connecting perturbed free energy to PMF:

$$e^{-\beta G(\xi)} = \left(\frac{2\pi}{\beta k}\right)^{-\frac{n}{2}} e^{-\frac{1}{2\beta k} \Delta} e^{-\beta f(\xi)}$$

Fakharzadeh & Moradi *J Phys Chem Lett.* 2016;7(24):4980-4987.

- This relation was first proven for a 1D case.

Hummer, G.; Szabo, A. *PNAS.* 2010, 107, 21441.

- Stiff-spring approximation (large  $k$ ):

$$G(\xi) = f(\xi) + \frac{1}{2\beta k} (\beta \nabla f(\xi) \cdot \nabla F(\xi) - \Delta f(\xi)) + O\left(\left(\frac{1}{\beta k}\right)^2\right) + \text{constant}$$

# Free Energy on a Curve

- A curve  $\xi(s)$  parameterized by its arc-length  $s$ :  $ds^2 = g_{\mu\nu} d\xi^\mu d\xi^\nu$
- Free energy on the curve:  $F(s) = f(\xi(s))$
- Stiff-spring correction term ( $\times 2\beta k$ ):

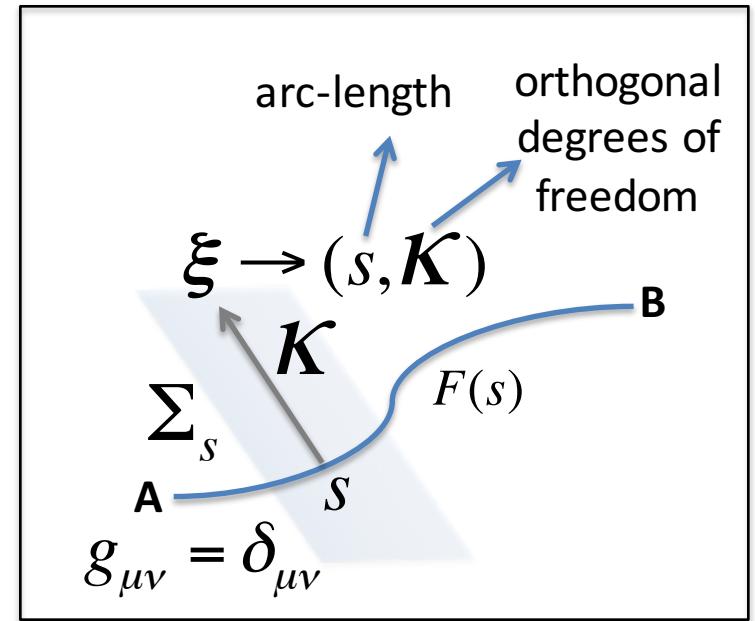
$$\begin{aligned} & \beta \nabla f(\xi) \cdot \nabla F(\xi) - \Delta f(\xi) \\ &= \beta \left( \frac{d}{ds} F(s) \right)^2 - \frac{d^2}{ds^2} F(s) \\ &+ \beta \nabla_\perp f(\xi) \cdot \nabla_\perp F(\xi) - \Delta_\perp f(\xi) \end{aligned}$$

- Minimum free energy path:

$$\xi(s) \parallel \nabla f(\xi(s)) \quad (\nabla : g^{\mu\nu} \partial_\nu)$$

$$G(s) = F(s) + \frac{1}{2\beta k} \left( \beta \left( \frac{d}{ds} F(s) \right)^2 - \frac{d^2}{ds^2} F(s) \right) + O\left(\left(\frac{1}{\beta k}\right)^2\right) + \text{constant}$$

**Frenet frame**



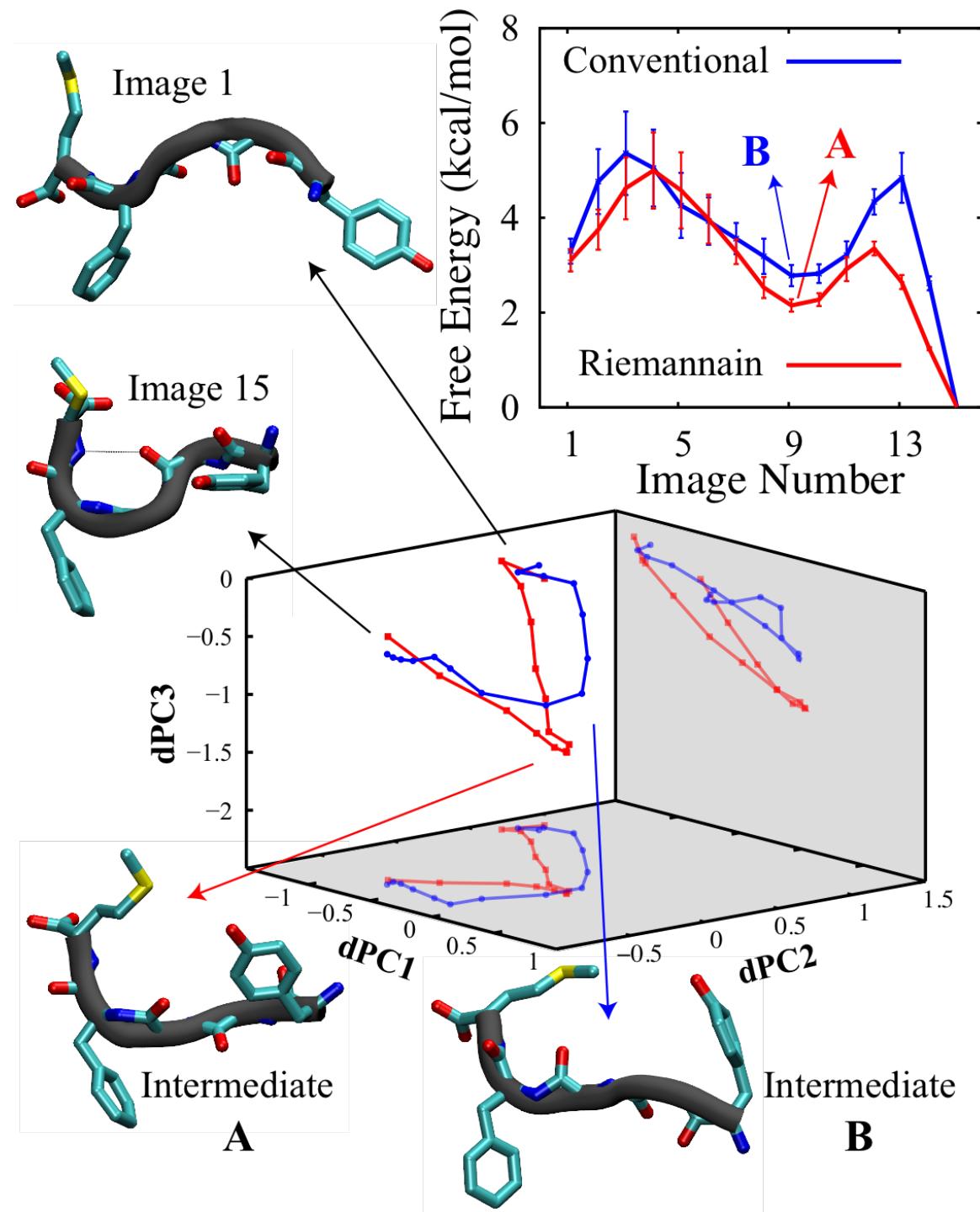
**Metric estimation**

$$\begin{aligned} \langle \delta \xi^i \delta \xi^j \rangle_{s, \delta t} &= 2D \langle \delta W^i \delta W^j \rangle \delta t + O(\delta t^2) = 2D g^{ij} \delta t + O(\delta t^2) \\ \langle \delta \xi^i \delta \xi^j \rangle_{s, \delta t} &\approx 2 \sum_l D_l \left\langle \frac{\partial}{\partial x^l} \xi^i \frac{\partial}{\partial x^l} \xi^j \right\rangle_s \delta t + O(\delta t^2) \end{aligned} \quad \boxed{\sum_l \frac{m}{m_l} \left\langle \frac{\partial}{\partial x_l} \xi^i \frac{\partial}{\partial x_l} \xi^j \right\rangle}$$

$g^{ij} \approx$

# Conformational transition between two configurations of Met-enkephalin peptide

- All backbone dihedral angles were used as collective variables
- The trajectories are projected onto the first three dPCs (dihedral principal components)



Coordinate transformation changes the results of conventional SMwST/BEUS substantially.

Riemannian SMwST/BEUS results in an invariant PMF and MFEP.

$$dPC_i = \sum_j a_{ij} \cos \theta_j + a_{ij} \sin \theta_j$$

$\theta_j$ 's are the dihedral angles

