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### Authors

Woldeyes, Rahel A

Sivak, David A

Fraser, James S

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## ***E pluribus unum, no more: From one crystal, many conformations***

Rahel A Woldeyes<sup>1</sup>, David A Sivak<sup>2</sup>, and James S Fraser<sup>3</sup>

<sup>1</sup>Chemistry and Chemical Biology Graduate Program, University of California San Francisco, San Francisco, CA 94158

<sup>2</sup>Center for Systems and Synthetic Biology, University of California San Francisco, San Francisco, CA 94158

<sup>3</sup>Department of Bioengineering and Therapeutic Sciences and California Institute for Quantitative Biosciences, University of California San Francisco, San Francisco, CA 94158

### **Abstract**

Several distinct computational approaches have recently been implemented to represent conformational heterogeneity from time- and space-averaged X-ray crystallography datasets. As these modeling methods mature, newly discovered alternative conformations are being used to derive functional protein mechanisms. Room temperature X-ray data collection is emerging as a key variable for sampling functionally relevant conformations also observed in solution studies. Although concerns about radiation damage are warranted with higher temperature data collection, “diffract and destroy” strategies on X-ray free electron lasers may permit radiation damage-free data collection. X-ray crystallography need not be confined to “static unique snapshots”; these experimental and computational advances are revealing how the many conformations populated within a single crystal are used in biological mechanisms.

### **Introduction**

Macromolecular X-ray crystallography measures averaged intensities diffracted from  $\sim 10^{13}$  molecules in the crystal lattice. The resulting electron density map, which is used to locate the positions of atoms in the unit cell, is therefore an ensemble-averaged probability distribution. Traditionally, structural models are built into the highest peaks of the electron density distribution. The lower electron density values that surround these high signals are fit by the B-factor (the temperature factor, thermal factor, Debye-Waller factor, or atomic displacement parameter) [1] (Figure 1a), which models the isotropic fall-off of the density from the mean position as a Gaussian. Although the electron density distribution around each atom is often anisotropic, the additional parameters needed for anisotropic B-factors

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Correspondence to: JSF - james.fraser@ucsf.edu, tel: 415-493-8421, fax: 415-514-0169.

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require a higher number of observations that is only afforded by very high resolution data [2].

Additionally, even in the crystal lattice, proteins can adopt multiple discrete conformations [3]. Both anharmonic motion and static disorder can result in multiple relatively weak peaks in electron density maps [4]. Even individual anisotropic or grouped Translation Libration Screw (TLS) B-factors are an insufficient description of these multiple minima in the probability distribution [5-7] (Figure 1b). This review focuses on the emerging strategies for modeling conformational heterogeneity from X-ray data and the potential for modeled alternative conformations to generate new mechanistic insights into the function of macromolecules.

## Electron density maps: More than meets the eye

Local maxima in electron density maps can be difficult to identify visually when electron density maps are rendered at a single threshold, as is common in the isosurface wire-frame representation used by Coot [8] and other graphics programs. Multiple contours or colour maps may be preferable for identifying conformations in weak, irregular electron density [9]. Maps modified by applying local feature enhancement [10], maximum entropy principles [11], and B-factor sharpening [12] may also aid in visually identifying important alternative conformations.

An alternative approach to visual inspection of electron density maps involves plotting electron density distributions as a function of dihedral angle (Figure 1c) [13]. Most side chain alternative conformations are confined to preferred rotameric torsion angles. The program Ringer identifies peaks originating from discrete alternative conformations sampled by protein side chains. Recent work demonstrates that these secondary peaks preferentially occur at low-energy rotameric positions [14]. Placing maps on an absolute electron-density scale and using new estimates of the noise throughout the map increases the power of Ringer to identify alternative conformations of protein and ligand atoms [15].

## Transforming electron density into models reflecting heterogeneity

Performing multiple independent refinements from a slightly perturbed starting model can reveal conformational heterogeneity (Figure 2a). The starting diversity can be generated by multiple simulated annealing trajectories [16-18], alternative parameter sets [19], Monte Carlo sampling [20], or randomly-seeded automated rebuilding (using ARP/wARP [21], RAPPER [22], or Phenix Autobuild [23]). Blundell and colleagues interpreted the variability across multiple RAPPER rebuilding runs as yielding a “potentially more accurate representation of the true underlying structure than does a single model” [23,24]. However, Terwilliger later showed, using synthetic data and Phenix Autobuild, that repetitive rebuilding often does not accurately sample known conformations, but rather gives an estimate of the imprecision of the coordinates of the main conformation [25].

Averaging the structure factors from independently refined structures often results in a lower  $R_{\text{free}}$  than that from any individual refinement [25]. This result suggests a logical extension of the multiple independent copies approach: multiple conformations that are simultaneously

refined together as an ensemble (Figure 2b). In an early application, Kuriyan showed that “twin” conformations, moving independently while contributing equally to the refinement, could improve R-factors relative to a single model [26]. But why stop at “twin” refinement? Many subsequent ensemble-modeling efforts scanned 2-20 copies of the protein [27-30]. In a recent, more comprehensive evaluation of ensemble refinement, Phillips and colleagues scanned ensembles of 2, 4, 8, and 16 copies across 50 structural genomics targets and selected a final ensemble based on the lowest  $R_{\text{free}}$  [31]. Their ensembles averaged 10.6 copies and improved  $R_{\text{free}}$  by 1.9%, suggesting that the conformations sampled across the ensemble agree well with the X-ray data. Although the most obvious improvements generally occurred in going from 1 to 2 or from 2 to 4 copies, the diminishing returns do not preclude moving beyond 16 copies. Could having even more structures further improve  $R_{\text{free}}$ ?

Time-averaging can slow the increase in effective free parameters as the number of copies increases: the samples in the ensemble are not truly independent as they are generated by a single molecular dynamics simulation restrained by (time-averaged) agreement with X-ray structure factors (Figure 2c) [32]. Although any individual snapshot is generally a poor fit to the observed X-ray data, the agreement improves when averaged over many simulation snapshots. In practice, this creates attraction towards relatively undersampled regions (those with positive  $F_{\text{obs}}-F_{\text{calc}}$  difference density) and repulsion away from relatively oversampled local energy minima (those with negative  $F_{\text{obs}}-F_{\text{calc}}$  difference density). Although the original implementation, which did not include any B-factors, was susceptible to overfitting [33], including a reasonable B-factor model allowed for parallel reductions in R and  $R_{\text{free}}$  during the simulation [34-36].

Burnley and Gros have recently contributed a dramatically improved time-averaged ensemble refinement method [37], which is incorporated into the Phenix software suite [38]. To account for lattice disorder, an underlying TLS [39] B-factor model is first fit to the core of the molecule and then applied to the entire modeled structure. In addition to a bulk solvent model, explicitly-modeled solvent atoms are added and deleted throughout the simulation based on conventional real-space map criteria. In principle the restrained simulation could be extended to produce an arbitrarily large number of snapshots. Burnley and Gros keep only those simulation blocks of 250 consecutive snapshots with low  $R_{\text{work}}$  values. The still ungainly number of structures is further reduced to the final output ensemble, the smallest evenly-distributed set of structures that reproduces the time-averaged  $R_{\text{free}}$  to within 0.1%. This procedure resulted in ensembles containing between 50-800 structures across a wide variety of proteins [37]. In addition, the Gros group has recently applied this exciting method for an in-depth study of conformational heterogeneity of proteases [41].

A distinct model type, the multiconformer model, represents conformational diversity without creating multiple copies of the entire protein (Figure 2d). In multiconformer models, if the electron density distribution for a continuous segment is well fit by a single conformation with an appropriate B-factor model, then only a single conformation is used. However, if the electron density distribution suggests discrete conformations, the heterogeneous atoms are copied and given an “ALTLOC” identifier in the PDB record. This

second (or third or fourth) conformation is allowed to diverge and a new parameter “q” is refined reflecting the occupancies of the primary and secondary conformations. This tedious manual process can be subject to the whim and thoroughness of the model builder. Despite the small gains in  $R_{\text{free}}$ , modeling alternative conformations can reduce geometric distortions and rotamer-outlier side chain conformations. Fortunately, van den Bedem developed an automated approach to identify, build, and refine multiple conformations: qFit [42]. qFit enumerates many potential main and side chain conformations for each residue. Next, the program selects the optimal combination of conformations and associated initial occupancies based on combined fit to the density; often, only one conformation is selected. Fragments of neighboring residues are assembled using computational approaches borrowed from robotics to build the final model. Although correlated movement along directly adjacent residues sharing the same number of conformations is assumed, global correlated movements through tertiary contacts cannot be inferred directly from experimental data without reference to diffuse scattering features [43,44]. To address this problem, a companion approach, CONTACT, identifies networks of residues that can move between experimentally observed alternative conformations in a coupled manner [45]. In DHFR, residues with functionally relevant concerted motion (originally revealed using solution NMR experiments) were independently identified using the combined qFit - CONTACT approach. Both multiconformer and ensemble models present additional complications for validation. In particular, the use of  $R_{\text{free}}$  in the parameter optimization and validation steps highlights a potential need for a new generation of model selection criteria [40].

## Warming up to different data collection strategies

As these modeling methods mature (Table 1), the major question is changing from “is there conformational heterogeneity?” to “what functions can conformational heterogeneity mediate?” Several recent studies, building on classic work by Petsko and others on the protein “glass transition” [46,47], highlight that the common practice of cryo-cooling can complicate the process of relating heterogeneity to function: cryo-cooling has obvious advantages in reducing radiation damage [48], but elegant theoretical studies by Halle suggest that the annealing that occurs during cryo-cooling may redistribute conformational heterogeneity [49]. The idea that conformational heterogeneity within the crystal can connect to biological function is dramatically exemplified by CypA [50]: data collection at room temperature allowed sampling of higher-energy conformations essential for catalysis also observed in solution by NMR experiments; in contrast, high-resolution cryogenic data revealed only a single conformational state. Similar changes to conformational ensembles were also observed across a larger sample of 30 proteins [51].

However, concerns about radiation damage have historically reduced the widespread use of higher temperatures during data collection. Cryo-cooling makes complete datasets obtainable from a single crystal for many systems that otherwise could not have structures determined. Several strategies have been applied to outrun or reduce the damage at “room temperature,” where the temperature is generally maintained at 0-15°C. While it is always best to evenly expose the entire diffracting volume, the beam size is often limited by the physical setup of the beam line. In these cases, strategic translation can enable crystals to be exposed for longer and yield higher-quality data [52]. The ability to use higher dose rates

and free-radical scavengers to outrun damage remains controversial, and there are many aspects of room temperature diffraction still available to optimize [53].

X-ray free electron lasers (XFELs), which can deliver short pulses of extremely large doses of X-rays [54], decouple the relationship between diffraction, radiation damage, and temperature. In “diffract and destroy” data collection strategies, diffraction occurs on a faster timescale than the radiation damage, affording an approximately radiation damage-free view of the molecule at any temperature. Indeed, differences are already being observed between the same molecules imaged at cryogenic temperatures at synchrotrons and room temperature at XFELs [55]. While XFELs provide obvious applications for viewing conformational dynamics of proteins within a crystal, there remain several roadblocks before “molecular movies” can be routinely recorded [56]. In particular, improved crystal delivery methods [57], synchronized triggering of conformational changes [58], and data processing schemes [59] are on the horizon.

## Conclusions

What do the next 5-10 years hold? As the focus of our modeling efforts shift to representing the conformational ensemble, opportunities for integrative refinement and cross validation with solution experiments [60,61] will undoubtedly play a larger role. The major challenges will shift from describing conformational ensembles to understanding which of the populated conformations are important for biochemical functions. Time-resolved studies will likely be critical in this endeavor, but synchrotron-based Laue diffraction studies have previously been applied only to a limited set of systems [62-64]. The large changes in conformational ensembles often observed in the same crystal form [65,66] (Figure 3) coupled with the capabilities of XFELs for circumventing radiation damage at ambient temperatures suggest that the future will be dominated by teasing apart not only how the many conformations populated in a crystal relate to each other in space, but also how they relate to each other in time.

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### Highlights

- X-ray crystallography contains information about multiple conformations
- Multiple strategies are being tested to model conformational heterogeneity
- Free electron lasers present new room temperature data collection opportunities
- The dream of routinely creating molecular movies of proteins now seems attainable

### Highlighted References

#### \*\* - of outstanding interest

*Fenwick 2014* – Order parameters, calculated from X-ray data that integrate displacements from B-factors and alternative conformations, agree with NMR solution measurement. The combination of room temperature data collection and qFit multiconformer modeling is key to integrative studies by NMR and X-ray crystallography.

*Burnley 2012* – The updated time-averaged ensemble refinement method has been integrated into Phenix. A TLS model to capture lattice disorder and a dual bulk/discrete solvent model are key new features that lead to improved  $R_{\text{free}}$  values.

*Liu 2013* – Serial femtosecond crystallography of GPCR microcrystals reveals conformational differences compared to a previously determined cryogenic structure. Although flexibility increases overall, functionally important regions are even more flexible than expected. Additionally, several key enthalpic interactions are strengthened by cryo-cooling.

*Zhu 2013* – This work is a striking example of the large conformational changes that can occur in the context of a crystal lattice. Soaking RGD ligand peptides into integrin headpiece crystals reveals, across 8 independent datasets, how allosteric changes propagate over 40 Å.

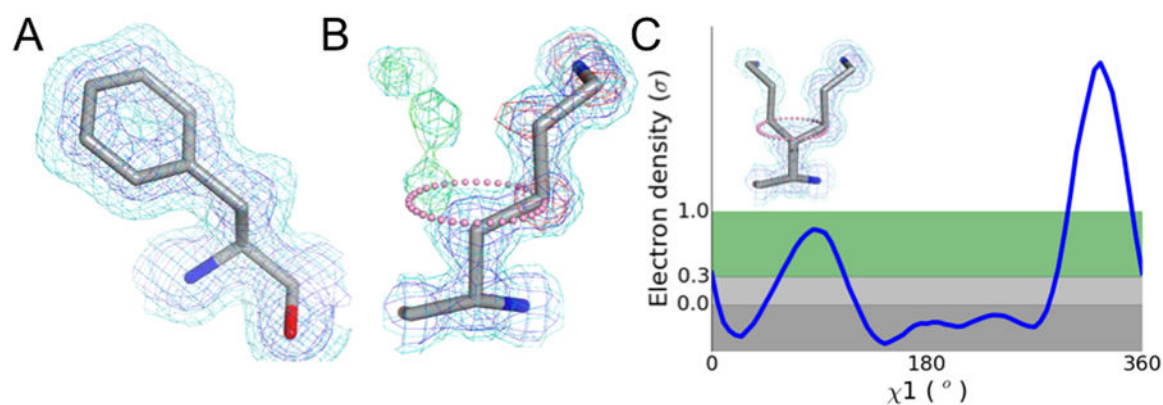
#### \* - of interest

*Kuzmanic 2014* – Molecular dynamics simulations in the context of the crystal lattice provide a control dataset for showing that the RMSDs calculated from harmonic B-factors are a poor model for heterogeneity calculated over snapshots of the MD simulation. Outlier snapshot conformations significantly influence the RMSD without greatly increasing electron density spread.

*Terwilliger 2008* – This work is a masterful control experiment using synthetic datasets to examine how well multiple independent refinements represent conformational heterogeneity.

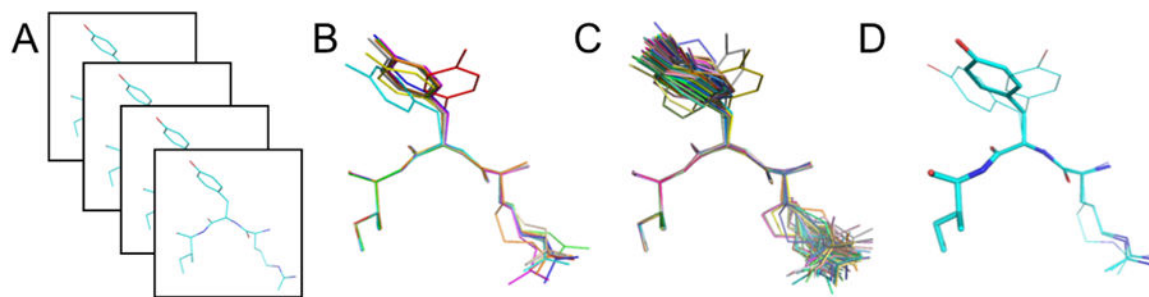
*van den Bedem 2013* – This paper introduces a new approach for identifying networks of residues that collectively sample alternative conformations from multiconformer refinement of experimental X-ray data (CONTACT: COntact Networks Through Alternate Conformation Transitions).

*Zeldin 2013* – The authors contribute software to optimize data collection strategies to avoid radiation damage. This advance is especially important for experimental phasing and room temperature data collection.

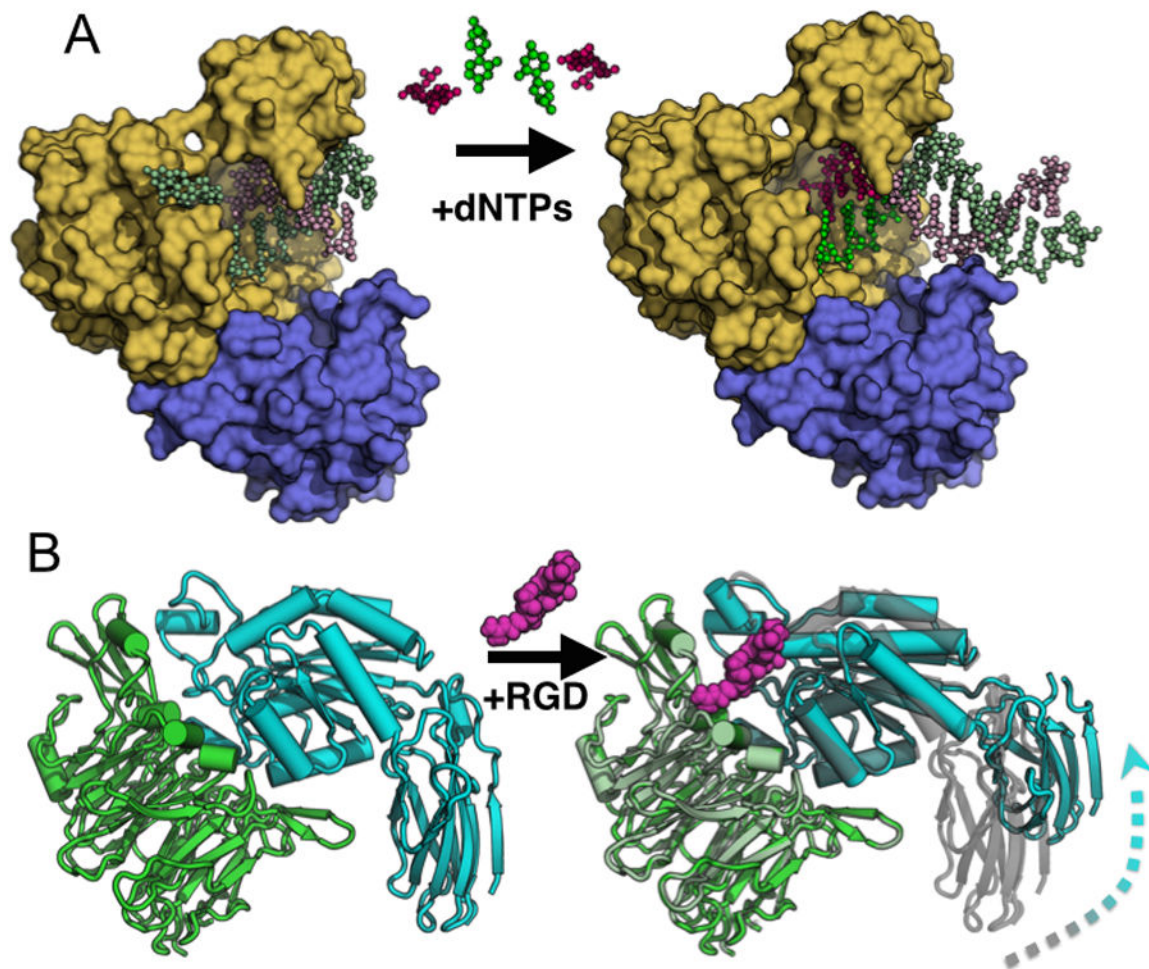


**Figure 1. Electron density maps contain ensemble-averaged information about multiple protein conformations**

**a)** The spread in electron density (blue mesh,  $1\sigma$  high contour; cyan mesh,  $0.5\sigma$  low contour) around each atom is approximated by a B-factor, which models the thermal motion as a Gaussian displacement about the mean position. **b)** An electron density map with multiple maxima (blue mesh, high contour; cyan mesh, low contour) is inadequately modeled by B-factors, resulting in difference map peaks (red mesh,  $-1.5\sigma$  Fo-Fc peak underlying the model; green mesh,  $+1.5\sigma$  Fo-Fc peak indicating potential placement of alternative conformations). Because the alternative conformation partially overlaps with the primary conformation and is at lower occupancy, it is not visible at high contour. **c)** Sampling the electron density around the  $\chi_1$  dihedral angle of the map shown in (b) (pink dots) reveals the presence of a distinct peak at the rotameric angle of  $-60^\circ$ , providing an anchor point for manual model building of an alternative conformation. Automated model building is further complicated by the potential for backbone motions that can shift these peaks out of rotameric angles.



**Figure 2. Different model types are being used to interrogate conformational heterogeneity**  
**a)** In multiple independent refinements, each copy contributes to a distinct set of model structure factors. The distinct structures, separated here by boxes, yield an estimate of the relative precision of the refinement method. **b)** In multi-copy ensemble refinement, a set number of copies of the protein, represented here by different colors, are refined together. **c)** Similarly, in time-averaged ensemble refinement, multiple copies of the protein are selected from an MD simulation where the structure factors are averaged over a defined time window. **d)** In multiconformer approaches, an optimal combination of between 1 and 4 conformations with associated occupancies (represented here by the thickness of the sticks) is constrained to sum to unit occupancy for each residue.



**Figure 3. Examples of functional conformational changes within a single crystal lattice**  
**a)** *Bacillus* DNA polymerase I can catalyze DNA synthesis in the crystal lattice. The initial complex (PDB: 1L3S) containing the polymerase domain (yellow) and exonuclease domain (blue) is soaked with dNTPs. During catalysis the nascent strands are extended (brighter colors) and the pre-existing strands are extruded towards the solvent channels (PDB: 1L3V).  
**b)** The head domain of  $\alpha_{IIb}\beta_3$  integrin (PDB: 3ZDX) undergoes a large allosteric conformational change when the ligand RGD peptide (magenta) is soaked into the crystal lattice (PDB: 3ZE2). Aligning the  $\beta$ -propeller domains (green) reveals how the  $\beta_3$  inserted and hybrid domains extend and swing away (cyan) from the initial position (grey) upon peptide binding.

**Table 1**  
**Comparison of approaches to address the challenge of modeling conformational heterogeneity**

	<b>Independent</b>	<b>Multi-copy Ensemble</b>	<b>Time-averaged Ensemble</b>	<b>Multiconformer</b>
<b>Overall goal</b>	Many independent models that each independently explain the data	Fixed number of models that collectively explain the data	Ensemble of models related by dynamical simulation and fit to the data	Single model with locally-fit 1-4 conformations per segment
<b>Diversity generation</b>	Multi-start simulated annealing or automated rebuilding	Simulated annealing	Molecular dynamics simulation augmented with an X-ray energy term	Rotamer library extended from backbone atoms sampled along extent of anisotropic ellipsoids
<b>Output</b>	User-specified number of completely independent models	2-16 copies of the protein with equal occupancies, collectively contributing to $F_{calc}$	50-800 related models with equal occupancies, selected from the simulation	Single model with each residue having 0-3 alternative conformations, each with a partial occupancy
<b>User-defined parameters</b>	Rebuild fragment size, degree of cross-over between parallel models, and others depending on program	Ensemble size, B-factor model	TLS B-factor group selection, simulation relaxation time (default value determined by data resolution), X-ray:MD energy weight	Extent of sampling of backbone conformations from which to build rotamer library
<b>Output structure selection</b>	Retain all models within an $R_{free}$ threshold	Vary ensemble size to minimize $R_{free}$	Minimize sampling frequency subject to maintaining $R_{free}$ within 0.1% of final rolling average	Optimal combination of conformations for each residue that best explains local density features
<b>Potential weaknesses</b>	Biased to local energy minima; yields only an estimated precision of the refinement procedure	Low observation-to-parameter ratio for larger ensembles; occupancies fixed to number of models	Validation and interpretation of ensemble models requires new tools; coupling information may be limited	Limited backbone conformational sampling
<b>Potential advantages</b>	Extensive sampling of starting conformations	Sampling of anharmonic distributions	Time averaging may limit number of free parameters	Refinement of intermediate occupancies; limited number of free parameters
<b>Implementation</b>	RAPPER[22], phenix.autobuild[23], ExCoR[19]	CNS[31], custom scripts in other refinement protocols	phenix.ensemble-refinement[37]	qFit[42]