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Abstract

When experimental protein NMR data is too sparse to apply traditional structure determination techniques, *de novo* protein structure prediction methods can be leveraged. Here we describe the incorporation of NMR restraints into the protein structure prediction algorithm BCL::Fold. The method assembles discreet secondary structure elements using a Monte Carlo sampling algorithm with a consensus knowledge-based energy function. New components were introduced into the energy function to accommodate chemical shift, nuclear Overhauser effect, and residual dipolar coupling data. In particular, since side chains are not explicitly modeled during the minimization process, a knowledge based potential was created to relate experimental side chain proton-proton distances to C_{β} - C_{β} distances. In a benchmark test of 67 proteins of known structure with the incorporation of sparse NMR restraints, the correct topology was sampled in 65 cases, with an average best model RMSD100 of 3.4 ± 1.3 Å versus 6.0 ± 2.0 Å produced with the *de novo* method. Additionally, the correct topology is present in the best scoring 1% of models in 61 cases. The benchmark set includes both soluble and membrane proteins with up to 565 residues, indicating the method is robust and applicable to large and membrane proteins that are less likely to produce rich NMR datasets.

Introduction

Traditional structure determination via NMR spectroscopy requires a rich dataset with a preference for distance restraints between amino acids that are far apart in sequence which serve to define the protein topology. In cases of sparse or primarily local restraints, identification of the correct topology becomes more difficult as several incorrect topologies may also satisfy the restraints. Additionally, knowledge of the topology is often required to assign otherwise ambiguous nuclear Overhauser effect (NOE) cross peaks that can then be used as additional distance restraints to further refine the structure. Recently, spectroscopists have begun taking advantage of advances in protein NMR

such as perdeuteration, selective labeling, and TROSY to study large proteins that were previously considered outside the realm of protein NMR. Nonetheless, the data collected on these large proteins are often sparse and of reduced quality, making structure determination challenging. Thus computational tools designed to predict protein topology from sparse data could facilitate the structure determination process.

Incorporating sparse NMR data into computational protein structure prediction algorithms has been shown to be extremely successful ¹⁻⁴. Rosetta, for example, was able to correctly fold proteins up to 25 kDa using backbone-only NMR data ⁵. For larger proteins, the algorithm was unable to sample native-like topologies, which indicates that conformational sampling is still the computational bottleneck, even with the inclusion of experimental restraints. Incorporation of sparse side chain distance restraints from deuterated samples increased the feasible upper limit to 40 kDa ⁶.

Like many protein structure-prediction methods, Rosetta uses a simplified side chain approximation during the model building stages, so handling of any available side chain-side chain NOE restraints is not directly modeled. In these cases, an arbitrary amount is typically added to the distance restraint in order to represent the restraint as a backbone-backbone distance. This approach however reduces the information content of each restraint. The problem of relating experimentally determined distances to distances measurable during the minimization process is not unique to NMR data. In site-directed spin labeling electron paramagnetic resonance (SDSL-EPR) experiments, distances are reported between two spin labels covalently attached at specific sites on the protein model. A knowledge-based potential has been developed and successfully used to evaluate the probability of observing the C_{β} - C_{β} distance given the spin label-spin label distance ⁷. We take a similar approach with side chain-side chain proton distances from NOE data to evaluate C_{β} - C_{β} distances in the model with the hypothesis that this method will produce more native-like models.

A protein structure prediction method, BCL::Fold, was recently introduced with the goal of efficiently sampling larger and more complex topologies than those accessible to other *de novo* protein structure prediction algorithms ⁸. Like most algorithms, BCL::Fold begins with protein secondary structure prediction. The predicted secondary structure elements (SSEs) are then collected into a pool, with loops and side chains being discarded. A Monte Carlo algorithm assembles the SSE building blocks into a viable topology, guided by a consensus knowledge-based energy function. The final model is generated via subsequent loop building and side-chain replacement. Both the assembly and scoring stages are flexible, making the incorporation of experimental restraints possible. This has already been successfully demonstrated with cryo-electron microscopy data ⁹.

Here we describe the incorporation of three types of NMR restraints – chemical shifts (CSs), NOEs, and residual dipolar couplings (RDCs) – into the BCL::Fold algorithm. A novel NOE knowledge-based potential was developed in order to evaluate $C_{\beta} - C_{\beta}$ distances observed in the model based on experimental side chain-side chain restraints. The method was benchmarked using 23 structures with experimental restraints and an additional 44 proteins with simulated restraints. The incorporation of restraints enhanced native-like sampling and facilitated the selection of low RMSD models. BCL::Fold is therefore a viable method for rapid identification of protein topology from sparse NMR restraints.

Materials and Methods

INPUT FILES. Chemical shift data is read in indirectly as a TALOS+ ¹⁰ secondary structure prediction file (*SS.tab). Both RDC and NOE data are read in directly using the NMR-STAR 3.1 format ¹¹ as supported by the BMRB. RDC data can be normalized to N-H values or have signs adjusted to

account for the negative gyromagnetic ratio of nitrogen via command-line flags, but was not necessary for the selected benchmark proteins.

SELECTION OF BENCHMARK PROTEINS. 67 total proteins were selected from three groups: 1) 6 large proteins from the BCL::Fold benchmark, 2) 38 membrane proteins from the BCL::MP-Fold benchmark, and 3) 23 small, soluble proteins containing experimental NMR data. The experimental benchmark set contains proteins that have both NOE and RDC data available on the BMRB ¹², aside from 1CFE ¹³, 1ULO ¹⁴, and 2EE4, which have no RDC data. The benchmark proteins with experimental data contain no ligands, have less than 30% sequence similarity, range in length from 58 to 224 residues, and are soluble, single chains. Additionally, the proteins were selected to have a diverse set of alpha, beta, and alpha/beta topologies with > 50% SSE content.

MODIFICATION TO THE ALGORITHM. The NMR restraint scores are added to the BCL::Fold method as part of the restraint protocol. Refer to the supplementary information for required command line flags and modifications to the stage and score weight set files. Iterative folding rounds were also introduced to better leverage experimental restraint information. After generating 1000 models, the top 10 models were selected by restraint score and used as start models to generate a new set of 1000 models. For the six large, soluble proteins, this process was repeated once more. In the subsequent analysis, only the models produced by the last iteration are considered.

BENCHMARK. 1000 models were generated with and without the incorporation of NMR restraints for each protein in the benchmark set. All CS and RDC data for residues in SSEs were used when available. When CS data was not available for SSE pool generation, it was simulated using SPARTA+¹⁵. In order to simulate sparse NOE data, random subsets of the experimental restraints were selected where both atoms were in SSEs and at least five residues apart. Here we exclude short and

medium range distance restraints in order to focus on the long range distance restraints that serve to constrain the topology. Experimental selective labeling strategies also enrich for long range distance restraints since there is an increased chance neighboring atoms are not labeled; instead there is a predominance of side chain methyl groups that engage in long range van der Waals contacts in the protein core. For each protein, ten random subsets were selected, and the subset size was equal to the number of residues in SSEs. These datasets were further reduced (down to 0.1 restraints/residue) and expanded (up to 2.0 restraints/residue) in order to evaluate the effect of restraint density on topology prediction accuracy. To generate the complete 1000 models, 100 models were constructed for each NOE restraint subset. Example command lines for running BCL::Fold can be found in the Supporting Information.

AVAILABILITY. BCL::Fold is implemented as part of the BioChemical Library, a suite of software currently under development in the Meiler laboratory (www.meilerlab.org). BCL software, including BCL::Fold, is freely available for academic use.

Results and Discussion

RESTRAINT SCORE FUNCTIONS. Three scoring functions were introduced into BCL::Fold in order to accommodate evaluation of NMR restraints. RDCs are evaluated using the traditional Q-value measure ¹⁶. To evaluate NOE distance restraints, a knowledge-based score, NOE-KB, and an atom distance penalty score, NOE-pen, are used in conjunction. CS's are evaluated indirectly using the previously described secondary structure prediction agreement score ¹⁷ via the program TALOS+ ¹⁰.

To evaluate RDC restraints, the optimal tensor is determined using the Saupe order matrix approach ¹⁸⁻²⁰ after each minimization step. This gives a calculated theoretical RDC value for each

supplied experimental value. The Q-value is then calculated, $Q = \sqrt{\sum_{ij} (D_{exp}^{ij} - D_{theor}^{ij})^2 / \sum_{ij} (D_{exp}^{ij})^2}$, where D^{ij} is the dipolar coupling between nuclei *i* and *j*¹⁶. The unweighted score is given by, $RDC = Q^{-1}$, so that a perfect agreement gives a score of -1.

Since BCL::Fold assembles SSEs lacking side chain atoms, a method was needed to relate distance restraints between side chain protons to useable backbone-to-backbone distances. The PISCES databank ²¹ was used to cull a list of 4379 proteins with less than 25% sequence identity and better than 2.0 Å resolution. Proton atoms were added using the program Reduce ²². Statistics were then collected in order to relate each H-H distance to the corresponding C_{β} - C_{β} distance. A separate histogram was created for the total number of bonds the protons were away from the C_{β} . For example, a $H_{\beta3}$ - $H_{\delta2}$ pair totals four bonds away from C_{β} 's. Separate histograms were generated for restraints to H_{α} or amide H since the coordinates of these atoms can be determined directly from BCL::Fold models. The C_{β} - C_{β} distance minus the H-H distance was computed and placed in a corresponding 0.5 Å bin. This process was repeated for each H-H pair at least 5 residues apart in sequence but no more than 6.0 Å apart in space for each of the proteins in the dataset. Each histogram was then converted to a cubic spline such that distances in the most common bin receive a score near -1 and distances not observed receive a score of zero (Figure 1A-C). The unweighted NOE-KB score is set as the mean individual restraint scores.

The NOE-pen score is simply a trigonometric transition between the maximal score, zero, and the ideal score, -1. The width of the transition is set to 25 Å. The curve is generated such that it reaches a value of -1 at a distance of 2 Å greater than the smallest observed distance for the given atom types (Figure 1D). This score was introduced to evaluate moderately to severely violated distance restraints; the NOE-KB score has a rather narrow minimum, and thus cannot adequately discriminate these violations.

The standard BCL::Fold KB energy potentials scale linearly with respect to protein size. For consistency, each restraint score is therefore multiplied by the number of residues in the protein model to achieve the same property. An additional consideration for restraint scores is how to handle scaling of the score with the number of restraints. We chose to have the score scale logarithmically with the number of restraints. This allows for the score to change with additional restraints, but not overwhelmingly so. Finally, each score was given a relative weight of 5.0. With this scaling the experimental data contribute approximately 50% to the total score of the model while the KB potentials contribute the remainder of the score. The final restraint energy is given by the following equation:

$$E_{rest} = N(w_{RDC}(Q-1)\log(M_{RDC}+1) + (w_{KB}\bar{s}_{KB} + w_{Pen}\bar{s}_{Pen})\log(M_{NOE}+1)),$$

where *M* is the number of restraints, *N* is the number of amino acids in the target, *w* is the weight (the default case being 5.0), and \overline{s} is the average NOE score.

SELECTION OF A DIVERSE BENCHMARK SET. A benchmark set of proteins of known structure was collected to test for the ability of the NMR scores to enhance native-like sampling during BCL::Fold minimizations. The set contains 67 total proteins, broken into three groups. 23 proteins are small, soluble proteins, with structures determined by NMR and with CS, NOE, and/or RDC data available on the BMRB. An additional six are large (> 220 residues) proteins from the original BCL::Fold method benchmark test ⁸. The final 38 proteins are membrane proteins from the BCL::MP-Fold benchmark test ²³. Membrane proteins are on the frontier of protein NMR, and are therefore more likely to produce sparse, rather than complete, datasets.

The small soluble proteins have complete datasets, so random subsets of NOE restraints were selected for a total of one long-range restraint per residue in SSEs to create sparse data. NMR restraints were simulated for the large soluble proteins and the membrane proteins. Again one restraint per residue

was selected as the initial restraint density. For the membrane proteins, side chain NOE restraints (1 restraint/residue) were limited to isoleucine, leucine, and valine residues to mimic the increasingly popular strategy of specific isotopic labeling of methyl groups ²⁴.

NOE KNOWLEDGE-BASED FUNCTION ENRICHES FOR NATIVE-LIKE MODELS. Each small, soluble native protein in the benchmark set was scored with the NOE-KB score and the NOE-pen score for agreement with all available long range experimental NOEs. With an ideal score of -1.00, the mean NOE-KB score was -0.84 \pm 0.07 BCL energy units (BCLEUs), and the mean NOE-pen score was -1.00 \pm 0.00 BCLEUs. The NOE-KB score is not exactly -1.00 BCLEUs due to experimental error and the fact that the score represents a rather wide distribution of observed distances, with only the most commonly occurring receiving scores near -1.00 BCLEUs.

In order to test the ability of NOE scores to select for native-like models, we created a set of decoy models. For each protein, 10,000 decoys were generated by de novo protein structure prediction without restraints using BCL::Fold. These decoys were then also scored with the two NOE scores. We define any model with less than 8.0 Å RMSD100²⁵ to the native as "native-like" or a "good" model. RMSD100 is the C_{α} RMSD normalized to a protein length of 100 residues. This measure is useful when evaluating proteins of varying sizes, such as those used in this benchmark. Using the 8.0 Å cutoff, the enrichment was calculated for those proteins which produced at least 0.1% "good" models¹⁷. Ranking the models by the sum of the NOE scores produces an average enrichment of 5.5 ± 1.6 out of a maximal 10.0. In contrast, using a quadratic energy function analogous to the bounded energy potential in Rosetta ¹ produces an average enrichment of 4.9 ± 1.4 (p = 0.02). This demonstrates that the NOE-KB and NOE-pen scoring functions improve the identification of native-like models when compared to the traditional score.

NATIVE-LIKE SAMPLING IS ENHANCED WITH NMR RESTRAINT SCORES. For each protein in the benchmark set, 1000 models were generated using the de novo BCL::Fold method. An additional 1000 models were also constructed using the available NMR restraints in combination with the implemented scoring functions. Over all proteins, the average C_{α} RMSD100 of the best model to the native structure was 3.4 ± 1.3 Å with restraints and 6.0 ± 2.0 Å without (Table I, Figures 2,3). When a structure with an RMSD100 of less than 8.0 Å is considered to be the correct topology, the inclusion of restraints allows for sampling of the correct topology in 65 of 67 cases (97%) compared to 54 of 67 cases (81%) when no restraints are incorporated. With a cutoff of 6.0 Å, the correct topology is sampled in 64 cases (96%) with restraints and in 41 cases (61%) without. With a cutoff of 4.0 Å, the correct topology is sampled in 54 cases (81%) with restraints and in 9 cases (13%) without. When looking at the top 5% of models produced from the first round, the best dataset contributes 18% of the top models on average (vs 10% expected with a random distribution), with the worst contributing 3% (Table S1). We conclude that while there is a dataset bias, even the 'worst' dataset is capable of producing highly accurate models – possible additional sampling is needed.

Of the small, soluble proteins, 2KYY showed the largest improvement upon the incorporation of restraints, with a best model RMSD100 decrease of 5.8 Å. The protein is a mixed α/β fold with 153 residues. The de novo method assembles a sheet, but the strand order is incorrect and the helices are not properly placed on either side of the major sheet. In contrast, the NMR method is able to build the sheet with the proper ordering and the helices are appropriately placed. Of the proteins with simulated NMR data, 1VIN ²⁶ showed the largest improvement upon the incorporation of restraints, with a best model RMSD100 decrease of 7.5 Å. This protein contains thirteen helices and 252 residues, placing it on the upper edge of de novo BCL::Fold's predictive capabilities; the native topology is sampled however, even without restraints ⁸. Here restraints serve to improve accuracy by promoting sampling of those

models with the correct topology. After the first round of iterative folding, the best model produced has an RMSD100 of 4.7 Å. The subsequent iterations then are typically starting their minimizations with the correct topology, making production of an accurate model much more likely.

BCL::FOLD COMPARES FAVORABLY WITH THE ROSETTA METHOD. Rosetta is a well established protein structure prediction method with a proven track record of producing quality models with limited experimental data. The structures of the soluble proteins in the benchmark were also predicted using the same sparse datasets using the AbinitioRelax application in Rosetta. Chemical shift data were used to generate fragments, and both NOE and RDC data were used during the minimizations. Side chain NOE restraints were converted to C_{β} restraints by adding 1.0 Å to the restraint distance per bond from the side chain proton to the C_{β} . 1000 models were generated per target, and the top 5% of models selected by RMSD100 to the native were retained for comparison with BCL models. The mean RMSD100 of the top Rosetta models was 4.9 ± 1.8 Å compared to 3.9 ± 1.4 Å for BCL::Fold (Table S2, p = 0.003). While BCL::Fold appears to sample topologies slightly better than Rosetta in our experiment, it should be noted that Rosetta is still the method of choice for loop building and side chain replacement once the topology has been constructed.

FEW NOE RESTRAINTS ARE REQUIRED FOR THE SAMPLING IMPROVEMENT. The previously described benchmark test used one NOE restraint per residue in SSEs. As a next step, additional restraint densities (0.1, 0.2, 0.5, and 2.0 restraints/residue) were tested for those proteins containing experimental data (Figure 4). After iterative folding, the top 5% of models by RMSD100 were analyzed from each group. The model quality improves up to 0.5 restraints/residue, but further increasing the number of restraints to 1.0 restraints/residue shows no effective additional improvement (the mean RMSD100 decrease is 0.2 ± 0.9 Å, p = 0.31). Analyzed separately, however, sampling for the larger proteins (> 125 residues) does improve overall from 0.5 to 1.0 restraints/residue. For proteins less 11

than 125 residues, the average improvement in the top 5% of models selected by RMSD100 sampled is 0.0 ± 0.6 Å. For proteins with more than 125 residues, the improvement is 0.6 ± 1.3 Å.

RESTRAINT SCORES FACILITATE MODEL SELECTION. The selection of the best model(s) out of the thousands generated is a difficult problem, especially when using low-resolution energy functions, as is the case with BCL::Fold. Table I highlights this problem by listing the RMSD100 of the lowest energy model. When no restraints are considered, the average RMSD100 is 10.6 ± 2.3 Å. However when NMR restraints are used, the average RMSD100 of the model with the lowest score is 5.4 ± 2.6 Å. Perhaps more strikingly, when the top 1% of models are selected by score, the native topology is contained within this subset in 27 out of 67 cases (40%) without restraints versus 61 out of 67 cases (91%) when using sparse NMR data.

BUILDING FULL ATOM MODELS. In order to explore the feasibility of constructing full atom models from BCL::Fold-generated topologies, we used the protein 1VIN as a test case. For this 252 residue helical protein, BCL::Fold produced models with an RMSD100 down to 1.8 Å compared to the native when sparse restraints were considered. The 50 lowest scoring models of the 1000 generated during the BCL::Fold benchmark test were retained for loop building using the Rosetta CCD loop building protocol. Side chains were then added using the Rosetta FastRelax protocol to generate 1000 complete, full atom models. Of the 20 best scoring final models, the mean backbone C_{α} RMSD100 was 2.4 ± 0.2 Å RMSD100 to the native SSE residues and 4.5 ± 0.4 Å over all residues.

POTENTIAL APPLICATIONS. One potential use of sparse restraints with BCL::Fold is to assist in the identification of ambiguous NOE assignments. For proteins that are suitable for traditional NMR structure determination methods, this would speed up the process by allowing for more confident NOE assignments during the structure determination process. Additionally, the BCL::Score program

can be used to identify any violated restraints in the given model, which can lead to subsequent NOE reassignments or model refinement.

Perhaps the most exciting application for BCL::Fold lies with membrane proteins. Membrane proteins constitute roughly 50% of all known drug targets, yet only 2% of the deposited PDB structures ²⁷. BCL::Fold can sample the native topology in all but 2 of the 38 membrane proteins in the benchmark when combined with sparse NMR data. This includes predicted models of less than 4.0 Å RMSD100 to the native for five proteins larger than 400 residues (with up to 15 transmembrane helices).

Conclusions

The *de novo* protein structure prediction method, BCL::Fold, has been updated to incorporate sparse experimental NMR data. Scoring functions were introduced to evaluate CS, NOE, and RDC data. In particular, a NOE knowledge-based potential was developed to relate experimental side chain protonproton distance restraints to $C_{\beta}-C_{\beta}$ distances that are measurable during the BCL::Fold minimization.

The benchmark test using a robust dataset demonstrated that sparse NMR data can be combined with BCL::Fold to produce native topologies in 97% of the cases. Using 1.0 NOE distance restraint per residue produces a mean improvement of 2.6 Å RMSD100 versus the *de novo* method. Reducing the number of restraints to 0.1 per residue still produces a mean improvement of 1.1 Å RMSD100 versus the de novo method. BCL::Fold, therefore, has the potential to provide experimentalists with feasible models that satisfy available NMR data to be used to generate further structure-based hypotheses.

Acknowledgments

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References

- 1. Rohl CA. Protein structure estimation from minimal restraints using Rosetta. Methods Enzymol 2005;394:244-260.
- 2. Li W, Zhang Y, Kihara D, Huang YJ, Zheng D, Montelione GT, Kolinski A, Skolnick J. TOUCHSTONEX: protein structure prediction with sparse NMR data. Proteins 2003;53(2):290-306.
- 3. Latek D, Kolinski A. CABS-NMR--De novo tool for rapid global fold determination from chemical shifts, residual dipolar couplings and sparse methyl-methyl NOEs. J Comput Chem 2011;32(3):536-544.
- 4. Zheng D, Huang YJ, Moseley HN, Xiao R, Aramini J, Swapna GV, Montelione GT. Automated protein fold determination using a minimal NMR constraint strategy. Protein Sci 2003;12(6):1232-1246.
- 5. Raman S, Lange OF, Rossi P, Tyka M, Wang X, Aramini J, Liu G, Ramelot TA, Eletsky A, Szyperski T, Kennedy MA, Prestegard J, Montelione GT, Baker D. NMR structure determination for larger proteins using backbone-only data. Science 2010;327(5968):1014-1018.
- Lange OF, Rossi P, Sgourakis NG, Song Y, Lee HW, Aramini JM, Ertekin A, Xiao R, Acton TB, Montelione GT, Baker D. Determination of solution structures of proteins up to 40 kDa using CS-Rosetta with sparse NMR data from deuterated samples. Proc Natl Acad Sci U S A 2012;109(27):10873-10878.
- 7. Hirst SJ, Alexander N, McHaourab HS, Meiler J. RosettaEPR: an integrated tool for protein structure determination from sparse EPR data. J Struct Biol 2011;173(3):506-514.
- 8. Karakas M, Woetzel N, Staritzbichler R, Alexander N, Weiner BE, Meiler J. BCL::Fold--de novo prediction of complex and large protein topologies by assembly of secondary structure elements. PLoS One 2012;7(11):e49240.
- 9. Lindert S, Staritzbichler R, Wotzel N, Karakas M, Stewart PL, Meiler J. EM-fold: De novo folding of alphahelical proteins guided by intermediate-resolution electron microscopy density maps. Structure 2009;17(7):990-1003.
- 10. Shen Y, Delaglio F, Cornilescu G, Bax A. TALOS+: a hybrid method for predicting protein backbone torsion angles from NMR chemical shifts. J Biomol NMR 2009;44(4):213-223.
- 11. Hall SR, Cook APF. Star Dictionary Definition Language Initial Specification. Journal of Chemical Information and Computer Sciences 1995;35(5):819-825.
- 12. Ulrich EL, Akutsu H, Doreleijers JF, Harano Y, Ioannidis YE, Lin J, Livny M, Mading S, Maziuk D, Miller Z, Nakatani E, Schulte CF, Tolmie DE, Kent Wenger R, Yao H, Markley JL. BioMagResBank. Nucleic Acids Res 2008;36(Database issue):D402-408.
- 13. Fernandez C, Szyperski T, Bruyere T, Ramage P, Mosinger E, Wuthrich K. NMR solution structure of the pathogenesis-related protein P14a. J Mol Biol 1997;266(3):576-593.
- 14. Johnson PE, Joshi MD, Tomme P, Kilburn DG, McIntosh LP. Structure of the N-terminal cellulose-binding domain of Cellulomonas fimi CenC determined by nuclear magnetic resonance spectroscopy. Biochemistry 1996;35(45):14381-14394.

- 15. Shen Y, Bax A. Protein backbone chemical shifts predicted from searching a database for torsion angle and sequence homology. J Biomol NMR 2007;38(4):289-302.
- 16. Cornilescu G, Marquardt JL, Ottiger M, Bax A. Validation of protein structure from anisotropic carbonyl chemical shifts in a dilute liquid crystalline phase. Journal of the American Chemical Society 1998;120(27):6836-6837.
- 17. Woetzel N, Karakas M, Staritzbichler R, Muller R, Weiner BE, Meiler J. BCL::Score--knowledge based energy potentials for ranking protein models represented by idealized secondary structure elements. PLoS One 2012;7(11):e49242.
- 18. Losonczi JA, Andrec M, Fischer MW, Prestegard JH. Order matrix analysis of residual dipolar couplings using singular value decomposition. J Magn Reson 1999;138(2):334-342.
- 19. Saupe A. Recent Results in Field of Liquid Crystals. Angewandte Chemie-International Edition 1968;7(2):97-&.
- 20. Meiler J, Peti W, Griesinger C. DipoCoup: A versatile program for 3D-structure homology comparison based on residual dipolar couplings and pseudocontact shifts. J Biomol NMR 2000;17(4):283-294.
- 21. Wang G, Dunbrack RL, Jr. PISCES: recent improvements to a PDB sequence culling server. Nucleic Acids Res 2005;33(Web Server issue):W94-98.
- 22. Word JM, Lovell SC, Richardson JS, Richardson DC. Asparagine and glutamine: using hydrogen atom contacts in the choice of side-chain amide orientation. J Mol Biol 1999;285(4):1735-1747.
- 23. Weiner BE, Woetzel N, Karakas M, Alexander N, Meiler J. BCL::MP-Fold: Folding Membrane Proteins through Assembly of Transmembrane Helices. Structure 2013.
- 24. Rosen MK, Gardner KH, Willis RC, Parris WE, Pawson T, Kay LE. Selective methyl group protonation of perdeuterated proteins. J Mol Biol 1996;263(5):627-636.
- 25. Carugo O, Pongor S. A normalized root-mean-square distance for comparing protein three-dimensional structures. Protein Sci 2001;10(7):1470-1473.
- 26. Brown NR, Noble ME, Endicott JA, Garman EF, Wakatsuki S, Mitchell E, Rasmussen B, Hunt T, Johnson LN. The crystal structure of cyclin A. Structure 1995;3(11):1235-1247.
- 27. Bakheet TM, Doig AJ. Properties and identification of human protein drug targets. Bioinformatics 2009;25(4):451-457.

Figure Legends

Figure 1. NOE knowledge based potentials. The energy potential for each cumulative bond distance is plotted versus the measured C_{β} - C_{β} distance subtracted from the experimental H-H distance. The bond distance is the number of bonds between the measured proton and the C_{β} atom of the same residue. For example, an NOE between $H_{\beta3}$ and $H_{\delta2}$ would have a cumulative bond distance of four. (A) Potentials for side chain-side chain NOEs. (B) Potentials H_{α} -side chain NOEs. (C) Potentials for backbone amide H-side chain NOEs. (D) The NOE-KB and NOE-pen potentials are plotted for a cumulative bond distance of 5.

Figure 2. NMR restraints improve native-like sampling. (A) The mean RMSD100 values of the best 10 models sampled with and without restraints are plotted. Soluble proteins are represented by circles and membrane proteins by squares. Proteins are colored according to size: < 150 residues (green), \geq 150 and < 250 residues (yellow), \geq 250 and < 400 residues (orange), and \geq 400 residues (red). The dashed line at 8.0 Å indicates the cutoff for the correct topology, and the dashed line at 4.0 Å indicates a feasible target for continuing with full atom refinement. The error bars are ± 1 S.D. (B) Of the top 10 models by score, the RMSD100 value of the best model is plotted for folding with and without restraints. Marker shapes and colors are the same as in panel A.

Figure 3. Gallery of select benchmark results. Left column – Distribution of RMSD100 to native SSE values for models produced by the de novo method (red) and the restraint-based method (green). Right column – Superimposition of the best model produced by the restraint method (rainbow) with the native protein (gray). Refer to the supporting information for the complete gallery of benchmark results.

Figure 4. Sampling efficiency depends upon restraint density. The size of the random subset of NOEs selected for folding was adjusted relative to the total number of residues in native SSEs. Each of the 23 proteins with experimental data was folded at varying restraint densities (0.0, 0.1, 0.2, 0.5, 1.0, and 2.0 restraints/residue). The distribution of the mean RMSD100 for the top 5% (selected by RMSD100) of models for each benchmark protein are shown. The boxes contain values within one standard deviation of the mean (of mean RMSD100 values) and the lines represent the minimum and maximum values observed from the 23 proteins for that restraint density. *Improvement over previous restraint density (p

< 0.01).

Figure 5. Core side chain conformations can be accurately predicted. Native protein model 1VIN is shown in gray, with side chain atoms displayed for His63, Leu64, Tyr68, and Phe97. The corresponding side chains from the best scoring Rosetta model after full-atom refinement are shown in black.

Figure S1. Gallery of benchmark results with experimental data. Left column – Distribution of RMSD100 to native SSE values for models produced by the de novo method (red) and the restraint-based method (green). Right column – Superimposition of the best model produced by the restraint method (rainbow) with the native protein (gray). Refer to the supplementary information for the complete gallery of benchmark results.

Figure S2. Gallery of soluble protein benchmark results with simulated data. Left column – Distribution of RMSD100 to native SSE values for models produced by the de novo method (red) and the restraint-based method (green). Right column – Superimposition of the best model produced by the restraint method (rainbow) with the native protein (gray). Refer to the supplementary information for the complete gallery of benchmark results.

Figure S3. Gallery of membrane protein benchmark results with simulated data. Left column – Distribution of RMSD100 to native SSE values for models produced by the de novo method (red) and the restraint-based method (green). Right column – Superimposition of the best model produced by the restraint method (rainbow) with the native protein (gray). Refer to the supplementary information for the complete gallery of benchmark results.

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Table I. Benchmark statistics and results.

		-		<u> </u>					100 (8)	$00(\hat{\lambda})$ Score $(\hat{\lambda})$					
1				Statistics		1			RMSD	100 (A)			Scor	e (A)	
	PDB	AA	Type	Helices	Strands	rco	Restraints	Bes	st	Тор	5%	Be	st	Тор	5%
			51					NMR	dn	NMR	dn	NMR	dn	NMR	dn
	1Q2N	58	А	3	0	0.41	exp	4.0	2.8	4.7	4.0	5.2	8.4	5.5	10.4
	2KIQ	62	А	4	0	0.37	exp	3.0	4.9	4.3	6.7	5.1	13.8	5.3	12.5
	2L9R	69	А	3	0	0.27	exp	3.0	4.1	3.5	5.2	9.5	13.3	5.2	10.8
	1WCL	76	А	5	0	0.27	exp	2.9	5.5	3.2	7.1	3.9	10.7	4.4	11.0
	2L7K	76	А	4	0	0.45	exp	3.3	5.9	3.9	7.3	7.4	10.4	7.2	11.0
	10P1	82	А	3	0	0.31	exp	2.8	3.4	3.2	4.2	5.1	12.9	6.9	10.7
	2AMW	83	А	3	0	0.38	exp	4.1	4.2	4.5	6.2	6.7	7.1	7.0	10.2
	2KYW	87	В	0	7	0.37	exp	4.8	7.0	5.3	8.5	5.4	10.7	6.7	11.7
	2BG9	91	A (MP)	3	0	0.41	sim	2.3	2.8	2.5	3.4	2.8	9.9	2.8	6.7
	1W09	92	А	3	0	0.44	exp	1.9	3.5	2.0	4.5	4.4	10.1	2.8	11.3
	1NKZ	93	A (MP)	3	0		sim	5.8	4.3	6.8	4.6	16.2	11.2	12.0	8.3
	2KCT	94	В	0	6	0.27	exp	4.0	8.6	4.6	9.3	10.0	12.0	9.1	12.3
	2H45	95	В	0	6	0.32	exp	4.1	4.1	6.1	5.7	10.2	13.3	8.2	9.7
ſ	2L35	-95	A (MP)	3	0		sim	2.6	3.1	2.8	3.7	3.5	17.2	3.5	9.7
	2KLC	101	A/B	1	5	0.28	exp	3.6	4.6	4.4	7.2	7.2	11.8	5.4	11.6
	2KSF	107	A (MP)	4	0	0.34	sim	2.9	3.9	3.1	4.5	3.6	5.1	3.3	5.6
	2JV3	110	А	6	0	0.28	exp	2.5	5.1	3.2	7.1	5.7	8.9	4.9	10.0
	2A70	112	А	3	0	0.34	exp	1.7	2.3	2.1	4.2	4.1	11.6	3.7	11.0
	2KCK	112	А	6	0	0.18	exp	3.0	5.7	3.8	7.8	6.3	12.6	5.3	10.0
	1J4N	116	A (MP)	4	0	0.40	sim	2.6	4.9	3.2	5.9	4.6	9.6	4.9	9.0
	2KD1	118	А	5	0	0.25	exp	2.6	4.5	2.8	5.5	5.0	9.8	4.6	9.2
	3SYO	122	A (MP)	4	0	0.33	sim	4.9	5.2	5.4	6.3	7.6	9.7	8.6	10.0
	1PY7	123	A (MP)	4	0	0.28	sim	2.4	3.9	2.7	4.7	3.1	5.4	3.2	6.4
	2PNO	130	A (MP)	4	0	0.29	sim	1.8	5.0	2.3	6.7	2.8	5.4	3.1	8.6
	1CFE	135	A/B	4	4	0.35	exp	2.8	5.7	3.2	8.3	3.9	12.2	4.3	10.8
	2L3W	143	А	7	0	0.32	exp	2.8	6.2	3.3	8.1	3.4	9.6	5.3	10.3
	2BL2	145	A (MP)	6	0	0.37	sim	2.2	2.9	2.5	3.8	3.2	6.7	3.6	7.3
	1CMZ	152	А	9	0	0.26	exp	4.4	7.7	5.0	9.6	5.7	12.2	5.8	12.6
	1ULO	152	В	0	10	0.34	exp	4.1	6.9	4.6	8.7	5.4	12.4	6.1	11.3
	2KYY	153	A/B	3	6	0.31	exp	3.2	9.0	3.6	9.8	4.8	11.5	4.3	12.0
	2K73	164	A (MP)	6	2	0.33	sim	3.3	4.7	4.1	5.9	9.0	10.1	6.8	9.1
	1RHZ	166	A (MP)	6	0	0.33	sim	3.8	6.7	4.3	8.0	5.7	9.9	5.4	10.4
	1IWG	168	A (MP)	7	0	0.31	sim	2.4	4.3	2.9	5.6	3.2	8.5	3.6	8.3
-	3P5N	179	A (MP)	8	0	0.24	sim	2.6	5.8	3.3	7.4	4.4	8.3	4.5	9.8
	2IC8	182	A (MP)	8	0	0.25	sim	2.9	6.0	3.8	7.2	4.3	9.5	5.2	9.3
	2YVX	188	A (MP)	5	0	0.34	sim	3.3	5.1	4.1	6.9	5.5	9.2	5.5	9.4
	1PV6	189	A (MP)	11	0	0.42	sim	2.6	5.7	2.8	6.8	3.4	10.6	4.1	9.4

	10CC	191	A (MP)	5	0	0.33	sim	2.2	4.6	2.5	5.9	3.2	8.5	3.7	8.0
	2NR9	192	A (MP)	8	0	0.24	sim	3.5	5.7	4.1	7.2	4.7	8.7	5.0	9.5
	4A2N	192	A (MP)	6	2	0.31	sim	3.7	4.3	4.0	6.2	4.0	8.1	4.7	8.8
	1RW5	199	А	5	0	0.38	exp	1.6	4.7	1.8	7.9	2.3	11.5	3.0	11.1
	1KPL	203	A (MP)	8	0	0.31	sim	3.0	8.7	3.4	10.5	6.6	14.4	4.9	12.5
	2EE4	209	А	12	0	0.23	exp	2.8	7.5	3.5	9.4	3.6	12.8	4.6	11.4
	2ZW3	216	A (MP)	8	3	0.35	sim	2.6	4.0	3.2	5.1	5.3	9.2	5.8	8.1
	2BS2	217	A (MP)	8	0	0.27	sim	3.4	5.4	3.9	6.9	5.1	11.0	4.8	9.2
	1L0V	221	A (MP)	9	0		sim	3.3	5.2	3.9	7.2	8.2	9.0	7.5	9.4
	1UAI	223	В	0	16	0.25	sim	5.8	7.9	6.7	9.1	8.2	11.0	8.2	10.8
	2KSY	223	A (MP)	9	2	0.26	sim	2.1	5.1	2.6	6.3	3.4	9.3	3.2	8.6
	1PY6	227	A (MP)	7	2	0.27	sim	2.1	4.8	2.5	5.9	2.4	6.1	3.3	8.4
	1VIN	252	А	13	0	0.12	sim	1.8	9.3	2.3	10.1	2.9	12.3	2.7	11.9
	3KCU	252	A (MP)	14	0	0.29	sim	3.5	7.3	4.0	8.5	3.8	11.2	4.8	10.5
	1XQO	253	А	14	0	0.23	sim	6.6	8.8	7.6	10.1	9.7	12.6	9.3	12.2
	1FX8	254	A (MP)	12	0	0.28	sim	4.0	6.4	4.7	7.6	5.5	9.3	5.7	9.8
	20F3	266	А	15	0	0.13	sim	3.4	9.6	3.9	11.2	4.7	13.5	4.8	13.6
	1U19	278	A (MP)	10	2	0.24	sim	3.0	5.3	3.9	6.6	3.8	8.9	4.2	8.8
	2ZCO	284	А	15	0	0.17	sim	2.3	8.9	2.7	10.2	2.7	13.0	3.1	12.3
1	2R0S	285	А	14	0	0.20	sim	3.1	9.1	3.4	10.0	4.8	11.2	4.0	11.9
	10KC	292	A (MP)	11	0	0.25	sim	4.4	7.1	4.9	8.2	5.6	9.9	8.1	10.3
	3KJ6	311	A (MP)	15	0	0.28	sim	3.5	5.9	4.8	7.4	3.5	10.5	5.5	10.0
	3B60	319	A (MP)	11	0	0.27	sim	4.7	9.5	5.6	10.8	7.3	12.4	7.4	13.2
	3HD6	403	A (MP)	15	2	0.23	sim	3.5	7.2	4.1	8.2	4.5	11.0	4.6	10.3
	3GIA	433	A (MP)	18	0	0.34	sim	3.0	9.6	3.6	10.7	6.6	13.4	7.3	12.6
	300R	449	A (MP)	18	0	0.15	sim	2.9	6.9	3.6	8.2	2.9	10.2	4.1	10.3
	2XUT	488	A (MP)	24	0	0.22	sim	8.8	7.7	9.6	9.0	12.1	10.2	11.6	11.4
	3HFX	493	A (MP)	18	0	0.36	sim	3.2	8.9	3.7	9.7	4.1	13.1	4.6	11.4
	1YEW	528	A (MP)	20	3		sim	8.2	9.7	9.6	11.5	10.4	14.1	11.8	13.3
	2XQ2	565	A (MP)	28	0	0.29	sim	3.5	8.2	4.0	10.1	5.4	12.2	5.7	12.1
	Mean	199		8	1	0.30		3.4	6.0	4.0	7.3	5.4	10.6	5.5	10.3
	SD	119		6	3	0.07		1.3	2.0	1.5	2.1	2.6	2.3	2.1	1.7
Ī	Protein t	ypes	are "A"	for alpha	-helical	and	"B" for be	ta-stra	ands.	"MP"	deno	tes a 1	memb	rane	

protein. The NMR restraints used were from published experimental data ("exp") or simulated computationally ("sim"). The best models were selected by either RMSD100 ("RMSD100" columns) or score ("Score" columns). RMSD100 values are displayed for both the best model and the mean of top 5% of models.

The models generated with NMR restraints ("NMR") and without ("dn").



Figure 1. NOE knowledge based potentials. The energy potential for each cumulative bond distance is plotted versus the measured C β -C β distance subtracted from the experimental H-H distance. The bond distance is the number of bonds between the measured proton and the C β atom of the same residue. For example, an NOE between H β 3 and H δ 2 would have a cumulative bond distance of four. (A) Potentials for side chain-side chain NOEs. (B) Potentials Ha-side chain NOEs. (C) Potentials for backbone amide H-side chain NOEs. (D) The NOE-KB and NOE-pen potentials are plotted for a cumulative bond distance of 5. 82x115mm (300 x 300 DPI)



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Figure 2. NMR restraints improve native-like sampling. (A) The mean RMSD100 values of the best 10 models sampled with and without restraints are plotted. Soluble proteins are represented by circles and membrane proteins by squares. Proteins are colored according to size: < 150 residues (green), \geq 150 and < 250 residues (yellow), \geq 250 and < 400 residues (orange), and \geq 400 residues (red). The dashed line at 8.0 Å indicates the cutoff for the correct topology, and the dashed line at 4.0 Å indicates a feasible target for continuing with full atom refinement. The error bars are ± 1 S.D. (B) Of the top 10 models by score, the RMSD100 value of the best model is plotted for folding with and without restraints. Marker shapes and colors are the same as in panel A. 84x168mm (300 x 300 DPI)

1RW5 0.4 0.35 0.3 0.25 Fraction 0.2 0.15 0.1 0.05 10 RMSD100 2A70 0.3 0.25 0.2 raction 0.15 0.1 0.05 10 RMSD100 1VIN 0.6 0.5 0.4 Fraction 0.3 0.2 0.1 0 10 RMSD100 2ZCO 0.8 0.7 0.6 0.5 raction 0.4 0.3 0.2 0.1 10 15 RMSD100 10CC 0.45 0.4 0.35 0.3 Fraction 0.25 0.2 0.15 0.1 0.05 10 SD100 2PN0 0.6 0.5 0.4 raction 0.3 0.2 0.1 10 RMSD100 15

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Figure 3. Gallery of select benchmark results. Left column – Distribution of RMSD100 to native SSE values for models produced by the de novo method (red) and the restraint-based method (green). Right column – Superimposition of the best model produced by the restraint method (rainbow) with the native protein (gray). Refer to the supporting information for the complete gallery of benchmark results. 127x240mm (300 x 300 DPI)

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Figure 4. Sampling efficiency depends upon restraint density. The size of the random subset of NOEs selected for folding was adjusted relative to the total number of residues in native SSEs. Each of the 23 proteins with experimental data was folded at varying restraint densities (0.0, 0.1, 0.2, 0.5, 1.0, and 2.0 restraints/residue). The distribution of the mean RMSD100 for the top 5% (selected by RMSD100) of models
for each benchmark protein are shown. The boxes contain values within one standard deviation of the mean (of mean RMSD100 values) and the lines represent the minimum and maximum values observed from the 23 proteins for that restraint density. *Improvement over previous restraint density (p < 0.01). 84x61mm (300 x 300 DPI)

Accel



Figure 5. Core side chain conformations can be accurately predicted. Native protein model 1VIN is shown in gray, with side chain atoms displayed for His63, Leu64, Tyr68, and Phe97. The corresponding side chains from the best scoring Rosetta model after full-atom refinement are shown in black. 101x76mm (300 x 300 DPI)

BCL::Fold – Protein topology determination from limited NMR restraints

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Supporting Materials and Methods

Creating an SSE pool

The BCL application, "CreateSSEPool" is used to create pools from TALOS+ predictions. A sample command line is:

./bcl.exe CreateSSEPool -ssmethods TALOS -pool_min_sse_lengths 5 3 -sse_threshold 0.0 0.0 0.0 -chain_id -prefix input/1CMZA -join_separate -factory SSPredMC

This will create a pool for protein 1CMZ using the TALOS+ predictions. The "input" folder must contain 1CMZA.fasta and 1CMZASS.tab.

Folding with NMR restraints

Below is a sample command line for using BCL::Fold in combination with sparse NMR data to predict protein structure:

/bcl.exe Fold -nmodels 100 -native input/1CMZ.pdb -pool_separate 1 -pool input/1CMZA_TALOS.pool -sspred TALOS JUFO PSIPRED -sspred_path_prefix input 1CMZ -pool_min_sse_lengths 5 3 -mc_temperature_fraction 0.5 0.2 500 10 -quality RMSD GDT_TS -superimpose RMSD -stages_read stages.txt -function_cache message_level Critical -protein_storage output/ Overwrite -restraint_types NOE RDC -restraint_prefix input/1CMZ -prefix 1CMZA -random_seed 1

Input files are placed in the "input" folder. This command will generate 100 models in the "output" folder. The "input" folder should contain:

- 1CMZ.pdb Native PDB file for quality measurements. Use "-fasta" with a FASTA formatted file if no native model is available.
- 1CMZ_OCT.pool Pool generated from TALOS+ predictions, which for this example, contains:

```
bcl::assemble::SSEPool
HELIX 1 1 PRO A 14 TRP A 20 1
                                              7
HELIX 2 2 PRO A 31 THR A 43 1
                                              13
HELIX 3 3 GLU A 47 LYS A 60 1
                                             14
HELIX 4 4 GLN A 65 TYR A 79 1
                                             15
HELIX 5 5 SER A 92 LYS A 101 1
                                             10
HELIX 6 6 PHE A 110 LEU A 130 1
                                              21
HELIX 7 7 PRO A 133 LEU A 138 1
                                              6
END
```

- 1CMZA.jufo JUFO secondary structure predictions
- 1CMZA.psipred PSIPRED secondary structure predictions
- 1CMZASS.tab TALOS+ secondary structure predictions
- stages.txt Stage file, which contains:

```
NUMBER_CYCLES 1
```

STAGE Stage_assembly_1

SCORE_PROTOCOLS Default Restraint

SCORE_WEIGHTSET_FILE input/assembly_01.scoreweights

MUTATE_PROTOCOLS Default Assembly

NUMBER_ITERATIONS 2000 400

STAGE_END

STAGE Stage_assembly_1

SCORE_PROTOCOLS Default Restraint

SCORE_WEIGHTSET_FILE input/assembly_02.scoreweights

MUTATE_PROTOCOLS Default Assembly

NUMBER_ITERATIONS 2000 400

STAGE_END

STAGE Stage_assembly_3 SCORE_PROTOCOLS Default Restraint SCORE_WEIGHTSET_FILE input/assembly_03.scoreweights MUTATE_PROTOCOLS Default Assembly NUMBER_ITERATIONS 2000 400 STAGE_END STAGE Stage_assembly_4 SCORE_PROTOCOLS Default Restraint SCORE_WEIGHTSET_FILE input/assembly_04.scoreweights MUTATE_PROTOCOLS Default Assembly NUMBER_ITERATIONS 2000 400 STAGE_END STAGE Stage_assembly_5 SCORE_PROTOCOLS Default Restraint SCORE_WEIGHTSET_FILE input/assembly_05.scoreweights MUTATE_PROTOCOLS Default Assembly NUMBER_ITERATIONS 2000 400 STAGE_END STAGE Stage_refinement SCORE_PROTOCOLS Default Restraint SCORE_WEIGHTSET_FILE input/refine.scoreweights MUTATE_PROTOCOLS Default Refinement NUMBER_ITERATIONS 4000 400 STAGE_END



NOE-KB histograms

Displayed below is the histogram file used by BCL::Fold for the NOE-KB score. The following histograms first list the BCL atom type corresponding the observed distance. "CB" is a side chain-side chain distance. "H" is a backbone amide proton-side chain distance. "HA" is an H_{α}-side chain distance. The following line is the sum of bonds from the side chain atoms to the corresponding C_{β}. Then the bin centers are listed followed by the observed counts for the given atom types and bond distance. The bin refers to the H-H distance - C_{β}-C_{β} distance. This raw data is converted to an energy potential using the inverse Boltzmann relation.

bcl::biol "CB"	::AtomTypes	::Enum											
2													
bcl::math	::Histogram	ı											
		<	<>	<>	<>	<>	<>	<>	<>	<>	<>	<>	<>
	<>	<>	<>	<>	<>	<>	<>	>					
center		-2.500	-2.375	-2.125	-1.875	-1.625	-1.375	-1.125	-0.875	-0.625	-0.375	-0.125	0.125
	0.375	0.625	0.875	1.125	1.375	1.625	1.875	2.000					
counts		0.000	0.000	31146.000	50547.000	85134.000	116487.00	C	133230.00	0	140441.00	0	
	156505.000)	147030.00	0	125014.00	0	90527.000	45714.000	22612.000	8622.000	1821.000	169.000	6.000
	0.000	0.000											
bcl::biol	::AtomTypes	::Enum											
"CB"													
3													
bcl::math	::Histogram	1											
		<	<>	<>	<>	<>	<>	<>	<>	<>	<>	<>	<>
	<>	<>	<>	<>	<>	<>	<>	<>	<>	<>	<>	<>	<>
	<>	>											

center	-1.125	-4.000	-3.875 -0.625	-3.625 -0.375	-3.375 -0.125	-3.125 0.125	-2.875 0.375	-2.625 0.625	-2.375 0.875	-2.125 1.125	-1.875 1.375	-1.625 1.625	-1.375 1.875
counts	244783.000 181385.000 0.000	0.000	0.000 253551.000 146896.000	55.000 0	540.000 258450.000 103488.000	29726.000 D D	87533.000 255853.000 72117.000	148012.000 0 50464.000	0 235557.000 27561.000	197587.00 D 9698.000	0 209837.000 1543.000	226916.000 79.000	2.000
bcl::biol "CB"	::AtomTypes	s∶∶Enum											
4 bcl::math	::Histogram	n	~ `			~ `						~ `	
	<>	<> <>	<> <>	<> <>	<> <>	<> <>	<> >	<>	<>	<>	<>	<>	<>
center	-2.375	-5.250	-5.125	-4.875	-4.625	-4.375	-4.125	-3.875 -0.625	-3.625 -0.375	-3.375 -0.125	-3.125 0.125	-2.875 0.375	-2.625 0.625
counts	255676.000	0.000	1.375 0.000 299176.00	1.625 2.000 0	1.875 464.000 325759.00	2.125 8263.000 0	2.250 35122.000 338233.00	75956.000 0	133996.00))	196068.00))	
	345106.000 142763.000))	323100.00 107127.00	0 0	290098.00 73637.000	0 46783.000	251653.00 25055.000	0 9501.000	215081.00 1725.000) 109.000	179098.00 4.000	0.000	0.000
bcl::biol "CB"	::AtomTypes	s∶∶Enum											
5 bcl::math	::Histogram	n											
	<>	····< <> <>	<> <>	<> <>	<> <> <>	<> <>	<> <>	<> <> <>	<> <> <>	<> <> <>	<> <> >	<>	<>
center	-3.625	-6.500 -3.375	-6.375 -3.125	-6.125 -2.875	-5.875	-5.625	-5.375 -2.125	-5.125	-4.875 -1.625	-4.625 -1.375	-4.375 -1.125	-4.125 -0.875	-3.875 -0.625
counts	-0.375	-0.125	0.125 0.000 199082.00	0.375 4.000 0	0.625 145.000 225422.00	0.875 4103.000	1.125 17312.000 242961.00	1.375 33612.000 0	1.625 56121.000 257142.000	1.875 94303.000 0	2.000 131996.00 268348.00))	
	274669.000 198752.000)	275610.00 173014.00	0	272801.00 144763.00	о С	261601.00 114644.00	0 0	242884.00 86050.000	0 61461.000	222270.00 42523.000	0 27344.000	14109.000
bcl::biol	4843.000	780.000 s::Enum	62.000	0.000	0.000								
"CB" 6													
bcl::math	<>	n < <>	<>	<>	<>	<>	<>	<>	<>	<>	<>	<>	<>
	<> <>	<> <>	<> >	<>	<>	<>	<>	<>	<>	<>	<>	<>	<>
center	-4.625	-7.500 -4.375 -1.125	-7.375 -4.125 -0.875	-7.125 -3.875 -0.625	-6.875 -3.625 -0.375	-6.625 -3.375 -0.125	-6.375 -3.125 0.125	-6.125 -2.875 0.375	-5.875 -2.625 0.625	-5.625 -2.375 0.875	-5.375 -2.125 1.125	-5.125 -1.875 1.375	-4.875 -1.625 1.625
counts	1.875	2.125 0.000	2.250 0.000	22.000	788.000	4556.000	10562.000	20444.000	33862.000	47886.000	65755.000	85477.000	
	164682.000))	166578.00	0 0	167418.00	2 2	165436.00	0 0	161498.000	J D 76787.000	154666.00	J D 45997.000	32823.000
	22259.000	14145.000	7149.000	2162.000	308.000	17.000	5.000	0.000	0.000				
CB"	::AtomTypes	s::Enum											
bcl::math	.::Histogram	n <	<>	<>	<>	<>	<>	<>	<>	<>	<>	<>	<>
	<> <>	<> <> <>	<> <> <>	<> <> <>	<> <> <>	<> <> <>	<> <> >	<> <>	<> <>	<> <>	<> <>	<> <>	<> <>
center	-5.875	-8.750 -5.625	-8.625 -5.375	-8.375 -5.125	-8.125 -4.875	-7.875 -4.625	-7.625 -4.375	-7.375 -4.125	-7.125 -3.875	-6.875 -3.625	-6.625 -3.375	-6.375 -3.125	-6.125 -2.875
counts	-2.625 0.625	-2.375 0.875 0.000	-2.125 1.125 0.000	-1.875 1.375 9.000	-1.625 1.625 119.000	-1.375 1.875 915 000	-1.125 2.000 2003 000	-0.875	-0.625	-0.375	-0.125	0.125	0.375
counce	44194.000 71395.000	51180.000 70136.000	58012.000 67122.000	64300.000 64066.000	68566.000 61562.000	71321.000 57073.000	73116.000 51214.000	74210.000 44617.000	75133.000 37091.000	74976.000 29148.000	74787.000 22484.000	74035.000	73525.000
bcl::biol	7280.000	3683.000	1242.000	202.000	19.000	0.000	0.000						
"CB" 8	incourt per												
bcl::math	::Histogram	n <	<>	<>	<>	<>	<>	<>	<>	<>	<>	<>	<>
	<>	<>	<>	<>	<>	<>	<>	<>	<>	<>	<>	<>	<>
center	-6.875	-9.750 -6.625	-9.625 -6.375 -3.125	-9.375 -6.125 -2.875	-9.125 -5.875 -2.625	-8.875 -5.625 -2.375	-8.625 -5.375 -2.125	-8.375 -5.125 -1.875	-8.125 -4.875 -1.625	-7.875 -4.625 -1.375	-7.625 -4.375 -1.125	-7.375 -4.125	-7.125 -3.875
counts	-0.375	-0.125	0.125	0.375	0.625	0.875	1.125	1.375 1848.000	1.625 3348.000	1.875 5632.000	2.125	2.250 11034.000	13673.000
	16486.000 35807.000	19357.000 35074.000	22559.000 34668.000	25453.000 33779.000	27733.000 33147.000	30133.000 31847.000	31753.000 30761.000	33363.000 29241.000	34376.000 27652.000	35276.000	35770.000	35847.000 20008.000	36123.000 16623.000
bcl::biol	::AtomTypes	5005.000 s::Enum	5270.000	1,37.000	2007.000	1102.000	JJZ.UUU	00.000	0.000	1.000	0.000	0.000	
"CB" 9	. Di ata m												
JCI · · IIId LII	<>	" < <>	<> <>	<> <>	<> <>	<> <>	<> <>	<> <>	<> <>	<> <>	<> <>	<> <>	<> <>
	<>	<>	<>	<>	<>	<>	<>	<>	<>	<>	<>	<>	<>

	<>	<>	<>	<>	<>	<>	<>	<>	<>	<>	<>	<>	<>
center	-8.125 -4.875 -1.625	-11.000 -7.875 -4.625 -1.375	> -10.875 -7.625 -4.375 -1.125	-10.625 -7.375 -4.125 -0.875	-10.375 -7.125 -3.875 -0.625	-10.125 -6.875 -3.625 -0.375	-9.875 -6.625 -3.375 -0.125	-9.625 -6.375 -3.125 0.125	-9.375 -6.125 -2.875 0.375	-9.125 -5.875 -2.625 0.625	-8.875 -5.625 -2.375 0.875	-8.625 -5.375 -2.125 1.125	-8.375 -5.125 -1.875 1.375
counts	1.625 4127.000 16919.000 13770.000 1.000	1.875 0.000 4878.000 17303.000 12727.000 0.000	2.000 0.000 5985.000 17656.000 11263.000 0.000	1.000 6939.000 18055.000 9634.000	12.000 8015.000 18230.000 7916.000	50.000 9313.000 18181.000 6126.000	150.000 10262.000 18176.000 4583.000	361.000 11384.000 18133.000 3405.000	621.000 12451.000 17564.000 2361.000	1136.000 13608.000 17253.000 1530.000	1525.000 14516.000 16572.000 748.000	2259.000 15018.000 16070.000 289.000	3085.000 15752.000 15209.000 41.000
bcl::biol "CB"	::AtomType:	s::Enum											
10 bcl::math	::Histogram	m											
	<> <> <>	· < < > < > < >	<> <> <> <>	<> <> <> <>	<> <> <> <>	<> <> <> <>	<> <> <> <>	<> <> <>	<> <> <>	<> <> <>	<> <> <>	<> <> <>	<> <> <>
center	-9.125 -5.875 -2.625	-12.000 -8.875 -5.625 -2.375 0.875	-11.875 -8.625 -5.375 -2.125 1 125	-11.625 -8.375 -5.125 -1.875 1.375	-11.375 -8.125 -4.875 -1.625	-11.125 -7.875 -4.625 -1.375 1.875	-10.875 -7.625 -4.375 -1.125 2.000	-10.625 -7.375 -4.125 -0.875	-10.375 -7.125 -3.875 -0.625	-10.125 -6.875 -3.625 -0.375	-9.875 -6.625 -3.375 -0.125	-9.625 -6.375 -3.125 0.125	-9.375 -6.125 -2.875 0.375
counts	1208.000 4797.000 4738.000 598.000	0.000 1556.000 5020.000 4539.000 282.000	0.000 1864.000 5103.000 4320.000 98.000	1.000 2129.000 5167.000 4178.000 25.000	7.000 2426.000 5244.000 3953.000 1.000	23.000 2729.000 5377.000 3557.000 0.000	60.000 2943.000 5364.000 3376.000 0.000	128.000 3249.000 5519.000 3025.000	265.000 3475.000 5295.000 2653.000	432.000 3776.000 5246.000 2153.000	514.000 4023.000 5018.000 1629.000	782.000 4257.000 5075.000 1289.000	1058.000 4373.000 4685.000 971.000
bcl::biol "CB"	::AtomType:	s::Enum											
11 bcl::math	1::Histogram	n < > >	<> <> <>	<> <> <>	<> <> <>	<> <> <>	<> <> <>	<> <> <>	<> <> <>	<> <> <>	<> <> <>	<> <> <>	<> <> <>
center	<> -9.625 -6.375 -3.125	<> -12.500 -9.375 -6.125 -2.875	<> -12.375 -9.125 -5.875 -2.625	<> -12.125 -8.875 -5.625 -2.375	<> -11.875 -8.625 -5.375 -2.125	<> -11.625 -8.375 -5.125 -1.875	<> -11.375 -8.125 -4.875 -1.625	> -11.125 -7.875 -4.625 -1.375	-10.875 -7.625 -4.375 -1.125	-10.625 -7.375 -4.125 -0.875	-10.375 -7.125 -3.875 -0.625	-10.125 -6.875 -3.625 -0.375	-9.875 -6.625 -3.375 -0.125
counts	0.125 453.000 1426.000 1334.000 367.000	0.375 0.000 520.000 1404.000 1287.000 326.000	0.625 0.000 614.000 1460.000 1225.000 153.000	0.875 3.000 673.000 1593.000 1234.000 98.000	1.125 11.000 818.000 1530.000 1162.000 37.000	1.375 24.000 839.000 1556.000 1122.000 3.000	1.625 61.000 886.000 1554.000 1165.000 0.000	1.750 85.000 1042.000 1592.000 1104.000 0.000	130.000 1059.000 1623.000 1039.000	179.000 1188.000 1504.000 926.000	226.000 1130.000 1464.000 841.000	320.000 1342.000 1470.000 678.000	382.000 1353.000 1407.000 472.000
bcl::biol	::AtomTypes	s::Enum											
12 bcl::math	1::Histogram	m											
	<>	< <>	<> <>	<> <>	<> <>	<> <>	<> <>	<> <>	<> <>	<> <>	<> <>	<> <>	<> <>
center	<> <> <> -10.375 -7.125 -3.875 -0.625	<> <> <> <> -13.250 -10.125 -6.875 -3.625 -0.375 0.000	<> <> <> -13.125 -9.875 -6.625 -3.375 -0.125 0.000	<> <> <> <> -12.875 -9.625 -6.375 -3.125 0.125 7.000	<> <> <> -12.625 -9.375 -6.125 -2.875 0.375 2.000	<> <> <> -12.375 -9.125 -5.875 -2.625 0.625 8.000	<> <> <> <> -12.125 -8.875 -5.625 -2.375 0.875 28.000	<> <> <> <> -11.875 -8.625 -5.375 -2.125 1.125 39.000	<> <> <> -11.625 -8.375 -5.125 -1.875 1.375 66.000	<> <> <> -11.375 -8.125 -4.875 -1.625 1.625 76.000	<> <> <> -11.125 -7.875 -4.625 -1.375 1.750 117.000	<> <> -10.875 -7.625 -4.375 -1.125 136.000	<> <> -10.625 -7.375 -4.125 -0.875 192.000
	226.000 949.000 1094.000 495.000	285.000 1009.000 1056.000 423.000	360.000 1087.000 1045.000 326.000	372.000 1047.000 923.000 237.000	421.000 1156.000 925.000 163.000	523.000 1184.000 882.000 108.000	553.000 1139.000 926.000 45.000	662.000 1139.000 855.000 15.000	671.000 1170.000 891.000 5.000	758.000 1227.000 754.000 0.000	825.000 1138.000 740.000 0.000	857.000 1120.000 655.000	897.000 1106.000 599.000
bcl::biol "H"	::AtomTypes	s::Enum											
bcl::math center counts	::Histogram	m -0.250 0.000	<> -0.125 0.000	<> 0.125 306240.000	<> 0.375	> 0.500 0.000	0.000						
bcl::biol	::AtomTypes	s::Enum											
1 bcl::math	::Histogram	n											
	<>	· < >	<>	<>	<>	<>	<>	<>	<>	<>	<>	<>	<>
center	1.375	-1.500 1.500 0.000	-1.375 0.000	-1.125 87595.000	-0.875	-U.625	-0.375	-U.125	U.125	0.375 0	U.625 66249.000	U.875	1.125 57924.000
halini	50599.000	28106.000	3222.000	0.000	0.000								
UCI::DIOL "H" 2	Atom Types	s.:Enum											
bcl::math	::Histogram	m < <>	<> <>	<> <>	<> <>	<> <>	<> <>	<> <>	<> <>	<> <>	<> <>	<> >	<>

S6

center	-0.125	-3.000	-2.875	-2.625	-2.375	-2.125	-1.875	-1.625 1.625	-1.375	-1.125 2.125	-0.875	-0.625 2.500	-0.375
counts	100467.000 511.000	75.000	86022.000 0.000	69498.000 0.000	58035.000	52464.000	39955.000	29820.000	23063.000	16589.000	11434.000	5949.000	2088.000
bcl::biol: "H"	:AtomTypes	::Enum											
3 bcl::math:	:Histogram												
	<>	< <> <>	<> <> <>	<> <> <>	<> <> <>	<> <> >	<> <>	<> <>	<> <>	<> <>	<> <>	<> <>	<> <>
center	-1.625	-4.500 -1.375	-4.375 -1.125 2.125	-4.125 -0.875 2.375	-3.875 -0.625 2.625	-3.625 -0.375 2.750	-3.375 -0.125	-3.125 0.125	-2.875 0.375	-2.625 0.625	-2.375 0.875	-2.125 1.125	-1.875 1.375
counts	62965.000	0.000	0.000 42534.000	1.000 37637.000	1.000 34103.000	422.000 28569.000	27472.000 23535.000	30483.000 17574.000	35312.000 13305.000	93681.000 10881.000	92521.000 8316.000	81600.000 5116.000	72879.000 2068.000
bcl::biol:	:AtomTypes	::Enum	20.000	5.000	0.000	0.000							
"H" 4 bcl::math:	:Histogram												
	<>	< <>	<> <>	<> <>	<> <>	<> <>	<> <>	<> <>	<> <>	<> <>	<> <>	<> <>	<> <>
center	-2.625	-5.500 -2.375	-5.375	-5.125 -1.875	-4.875 -1.625	-4.625 -1.375	-4.375 -1.125	-4.125 -0.875	-3.875 -0.625	-3.625 -0.375	-3.375 -0.125	-3.125 0.125	-2.875 0.375
counts	0.625 18951.000 2127.000	0.875 0.000 17984.000 1391.000	1.125 0.000 16584.000 755.000	1.375 28.000 14760.000 366.000	1.625 282.000 13331.000 198.000	1.875 10606.000 11242.000 60.000	2.125 17419.000 9434.000 18.000	2.375 18949.000 8032.000 2.000	2.625 19380.000 6799.000 0.000	2.750 19728.000 5519.000 0.000	19092.000 4776.000	19347.000 4252.000	19800.000 2993.000
bcl::biol:	:AtomTypes	::Enum											
5 bcl::math:	:Histogram												
	<>	< <>	<> <>	<> <>	<> <>	<> <>	<> <>	<> <>	<> <>	<> <>	<> <>	<> <>	<> <>
center	-3.375	-6.250	-6.125	-5.875	-5.625	-5.375	-5.125	-4.875	-4.625	-4.375	-4.125	-3.875	-3.625
counts	-0.125	0.125 0.000 5787.000	0.375 0.000 5595.000	0.625 1064.000 5041.000	0.875 1587.000 4720.000	1.125 5445.000 4072.000	1.375 7613.000 3657.000	1.625 7822.000 3065.000	1.875 7534.000 2588.000	2.125 7330.000 2273.000	2.375 7160.000 1905.000	2.625 6900.000 1470.000	2.750 6551.000 1111.000
bal: biol:	863.000	737.000	554.000	317.000	172.000	97.000	41.000	15.000	8.000	4.000	1.000	0.000	0.000
"H" 6	·Acourypes	··Ende											
bcl::math:	:Histogram	· < < >	<>	<> <>	<> <>	<> <>	<>	<> <>	<> <>	<> <>	<> <>	<> <>	<>
center	<>	<> <> -7 500	<> <> -7 375	<> <> -7 125	<> > -6.875	<>	<>	<>	<>	<>	<>	<>	<>
	-4.625 -1.375	-4.375	-4.125	-3.875	-3.625	-3.375 -0.125	-3.125 0.125	-2.875	-2.625	-2.375	-2.125	-1.875 1.375	-1.625 1.625
counts	1.875	2.125 0.000 8590.000	2.375 0.000 8418.000	2.625 7.000 8129.000	2.750 286.000 7558.000	711.000 6977.000	2293.000 6444.000	4416.000 6028.000	6846.000 5459.000	7415.000 4900.000	7814.000 4545.000	8031.000 3957.000	8362.000 3596.000
	3036.000 7.000	2332.000 3.000	1893.000 1.000	1496.000 0.000	1076.000 0.000	813.000	646.000	517.000	418.000	317.000	183.000	95.000	51.000
bcl::biol: "HA"	:AtomTypes	::Enum											
0 bcl::math:	:Histogram	<	<>	<>	<>	>							
center counts		-0.250 0.000	-0.125 0.000	0.125 1125600.0	0.375 00	0.500 0.000	0.000						
bcl::biol: "HA"	:AtomTypes	::Enum											
1 bcl::math:	:Histogram	<	<>	<>	<>	<>	<>	<>	<>	<>	<>	<>	<>
center	<>	>	-1.375	-1.125	-0.875	-0.625	-0.375	-0.125	0.125	0.375	0.625	0.875	1.125
counts	1.375	1.500	0.000 78461.000	138735.00	0 39990.000	252203.00	0	213171.00	0	175214.00	0	134758.00	C
bcl::biol:	:AtomTypes	::Enum											
2 bcl::math:	:Histogram												
center	<>	<< <> -3 000	<> <> -2.875	<> <> -2 625	<> <> -2 375	<> <> -2 125	<> <> _1 875	<> <> -1 625	<> <> _1 375	<> <> -1 125	<> <> -0.875	<> <> -0.625	<> > -0 375
counts	-0.125 136466.000 7575.000	0.125 0.000 3528.000	0.375 0.000 109328.000 532.000	0.625 320.000 1.000	0.875 1390.000 95665.000 0.000	1.125 109270.00 92318.000 0.000	1.375 0 77404.000	1.625 193935.000 62613.000	1.875 0 55519.000	2.125 170375.00 50589.000	2.375 0 40548.000	2.625 152456.00 28678.000	2.750 2 15987.000
bcl::biol: "HA"	:AtomTypes	::Enum											
3													

bcl::math	::Histogra	n											
		<	<>	<>	<>	<>	<>	<>	<>	<>	<>	<>	<>
	<>	<>	<>	<>	<>	<>	<>	<>	<>	<>	<>	<>	<>
center		-4.250	-4.125	-3.875	-3.625	-3.375	-3.125	-2.875	-2.625	-2.375	-2.125	-1.875	-1.625
	-1.375	-1.125	-0.875	-0.625	-0.375	-0.125	0.125	0.375	0.625	0.875	1.125	1.375	1.625
	1.875	2.125	2.375	2.625	2.750								
counts		0.000	0.000	1.000	486.000	34917.000	42496.000	51350.000	133932.00)	132579.00	0	
	122487.00	10002 000	12728 000	0	96/63.000	84433.000	/5031.000	66669.000 E6 000	58072.000	49619.000	41456.000	34143.000	28/69.000
_	21111.000	19995.000	13/20.000	0557.000	5250.000	2322.000	575.000	50.000	0.000	0.000			
bcl::biol	::AtomType	s::Enum											
"HA"													
4													
bcl::math	::Histogra	n	~ `	~ `	~ `	~ `	~ `	~ ~	~ ~	~ `		~ `	~ ~
	<>	<>	<>	<>	<>	<>	<>	<>	<>	<>	<>	<>	<>
	<>	<>	<>	<>	<>	<>	<>	<>	<>	<>	>		
center		-5.500	-5.375	-5.125	-4.875	-4.625	-4.375	-4.125	-3.875	-3.625	-3.375	-3.125	-2.875
	-2.625	-2.375	-2.125	-1.875	-1.625	-1.375	-1.125	-0.875	-0.625	-0.375	-0.125	0.125	0.375
	0.625	0.875	1.125	1.375	1.625	1.875	2.125	2.375	2.625	2.875	3.000		
counts	07550 000	0.000	0.000	25.000	364.000	15193.000	23937.000	26183.000	27989.000	27746.000	27410.000	27613.000	28842.000
	27559.000	26106.000	24365.000	22644.000	211/6.000	19595.000	1/645.000	21 000	14351.000	12685.000	11583.000	10164.000	83/5.000
	0734.000	5074.000	3074.000	2319.000	1033.000	/21.000	227.000	21.000	1.000	0.000	0.000		
bcl::biol	::AtomType	s::Enum											
"HA "													
5													
bcl::math	: Histogra	n											
	< >		<>	<>	<>	<>	<>	<>	<>	<>	<>	<>	<>
	<>	<>	<>	<>	<>	<>	<>	<>	<>	<>	<>	<>	<>
	>												
center		-6.500	-6.375	-6.125	-5.875	-5.625	-5.375	-5.125	-4.875	-4.625	-4.375	-4.125	-3.875
	-3.625	-3.375	-3.125	-2.875	-2.625	-2.375	-2.125	-1.875	-1.625	-1.375	-1.125	-0.875	-0.625
	-0.375	-0.125	0.125	0.375	0.625	0.875	1.125	1.375	1.625	1.875	2.125	2.375	2.625
counte	2.750	0 000	0 000	2 000	1310 000	2208 000	6858 000	10135 000	10737 000	11104 000	11146 000	10851 000	10252 000
countes	9905.000	9443.000	8978.000	8437.000	8014.000	7460.000	6934.000	6301.000	5732.000	5306.000	4932.000	4359.000	4130.000
	3645.000	3291.000	2878.000	2398.000	1896.000	1501.000	1072.000	733.000	374.000	173.000	31.000	2.000	0.000
	0.000												
bcl::blol	::Atomlype	s::Enum											
6													
bcl::math	::Histogram	n											
		<	<>	<>	<>	<>	<>	<>	<>	<>	<>	<>	<>
	<>	<>	<>	<>	<>	<>	<>	<>	<>	<>	<>	<>	<>
	<>	<>	<>	<>	<>	<>	<>	<>	<>	<>	<>	<>	<>
contor	<>	<>	<>	<>	>	6 625	6 275	6 105	E 07E	E 60E	E 27E	E 10E	4 975
Center	-4 625	-4 375	-4 125	-3 875	-3 625	-3 375	-3 125	-2 875	-2 625	-2 375	-2 125	-1 875	-1 625
	-1.375	-1.125	-0.875	-0.625	-0.375	-0.125	0.125	0.375	0.625	0.875	1.125	1.375	1.625
	1.875	2.125	2.375	2.625	2.750								
counts		0.000	0.000	6.000	426.000	874.000	2785.000	5849.000	9015.000	9696.000	10303.000	11002.000	11683.000
	12583.000	12954.000	12562.000	12407.000	11893.000	11233.000	10582.000	9920.000	9155.000	8493.000	7817.000	7097.000	6438.000
	5899.000	5269.000	4/32.000	4064.000	3389.000	∠940.000	2620.000	2201.000	1862.000	1457.000	T038.000	667.000	344.000
_	120.000	33.000	5.000	0.000	0.000								
h = 1 + + h + = 1													

bcl::biol::AtomTypes::Enum "Undefined"

Rosetta Folding

The soluble proteins in the benchmark set were folded using Rosetta with the available NMR data. Fragments were generated using any available CS data with homologs excluded. 1000 models were generated for each target using the AbinitioRelax application. RMSD100 was calculated (using the BCL application, ScoreProtein) to native SSEs to allow for a direct comparison to BCL::Fold-produced topologies. An example command line is:

^{./}AbinitioRelax.linuxgccrelease -out:nstruct 100 -out:output -out:overwrite -in:file:fasta input/1CMZA.fasta -in:file:frag3 input/cs_aa1CMZA03_06.200_v1_3 -in:file:frag9 input/cs_aa1CMZA09_06.200_v1_3 -in:file:native input/1CMZA.pdb -stage2_patch input/weights.wts -stage3a_patch input/weights.wts -stage3b_patch input/weights.wts

residues:patch_selectors CENTROID_HA -in:file:rdc input/ICMZA.dpl -score:weights score12_full -score:patch input/weights.wts -in:path:database ./rosetta_database - constraints:cst_file input/1CMZA_0.cst -out:user_tag cst_1000_0 -out:file:silent output/1CMZA_cst_1000_0.silent -out:sf output/1CMZA_cst_1000_0.score - run:constant_seed -run:jran 1

Input files are placed in the "input" folder. This command will generate 100 models in the "output" folder. The "input" folder should contain:

- 1CMZA.fasta FASTA file
- cs_aa1CMZA0[3,9]_06.200_v1_3 Fragement files generated from make_fragments.pl
- weights.wts Weights file:
- rdc = 1.0

atom_pair_constraint = 1.0

- 1CMZA.dpl –Rosetta formated RDC restraints
- 1CMZA_0.cst Rosetta formated NOE constraints. Side chain NOE restraints were converted to C_{β} restraints by adding 1.0 Å to the restraint distance per bond from the side chain proton to the

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Supporting Results

 Table S1. Contribution of random data sets to best first round models.

Protein	Best	Worst
1CFE	22%	4%
1CMZ	14%	6%
10P1	14%	6%
1Q2N	22%	2%
1RW5	18%	4%
1ULO	18%	4%
1W09	22%	2%
1WCL	18%	2%
2A70	18%	2%
2AMW	16%	6%
2EE4	14%	4%
2H45	16%	4%
2JV3	16%	0%
2KCK	22%	4%
2KCT	20%	2%
2KD1	18%	2%
2KIQ	20%	0%
2KLC	16%	6%
2KYW	26%	4%
2КҮҮ	20%	4%
2L3W	16%	0%
2L7K	16%	2%
2L9R	26%	2%
Mean	19%	3%
SD	3%	2%

Of the top 5% of models (by RMSD100) produced in the first round of folding, the contribution of the

data set contributing the most ("Best") and least ("Worst") are shown.

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Protein	BCL::Fold (Å)	Rosetta (Å)
1CFE	3.2	5.8
1CMZ	5.0	4.6
10P1	3.2	3.5
1Q2N	4.7	4.0
1RW5	1.8	5.3
1ULO	4.6	5.9
1W09	2.0	2.2
1WCL	3.2	1.9
2A70	2.1	3.4
2AMW	4.5	4.6
2EE4	3.5	4.6
2H45	6.1	7.6
2JV3	3.2	4.6
2КСК	3.8	3.7
2КСТ	4.6	8.4
2KD1	2.8	4.7
2KIQ	4.3	2.6
2KLC	4.4	3.9
2KYW	5.3	6.8
2ΚΥΥ	3.6	8.2
2L3W	3.3	4.9
2L7K	3.9	3.9
2L9R	3.5	4.7
1UAI	6.7	8.8
1VIN	2.3	4.8
1XQO	7.6	5.6
20F3	3.9	3.5
2R0S	3.4	6.9
2ZCO	2.7	3.4
Mean	3.9	4.9
SD	1.4	1.8

The mean RSMD100 of the top 5% of models (selected by RMSD100) are shown for BCL::Fold and

Rosetta with sparse NMR restraints.



























Figure S1. Gallery of benchmark results with experimental data. Left column – Distribution of RMSD100 to native SSE values for models produced by the de novo method (red) and the restraint-based method (green). Right column – Superimposition of the best model produced by the restraint method (rainbow) with the native protein (gray). Refer to the supplementary information for the complete gallery of benchmark results.

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Figure S2. Gallery of soluble protein benchmark results with simulated data. Left column – Distribution of RMSD100 to native SSE values for models produced by the de novo method (red) and the restraint-based method (green). Right column – Superimposition of the best model produced by the restraint method (rainbow) with the native protein (gray). Refer to the supplementary information for the complete gallery of benchmark results.

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Figure S3. Gallery of membrane protein benchmark results with simulated data. Left column – Distribution of RMSD100 to native SSE values for models produced by the de novo method (red) and the restraint-based method (green). Right column – Superimposition of the best model produced by the restraint method (rainbow) with the native protein (gray). Refer to the supplementary information for the complete gallery of benchmark results.

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