

² Supplementary Information for

³ Dynamic Cluster Formation Determines Viscosity and Diffusion ⁴ in Dense Protein Solutions

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8 This PDF file includes:

- 9 Supplementary text
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¹⁴ Other supplementary materials for this manuscript include the following:

15 Movie S1

16 Supporting Information Text

17 Supplementary Methods

MD Simulations of Dense Protein Solutions Initial configurations for all systems were generated using Monte 18 Carlo simulations with a coarse-grained protein model (1) with purely repulsive interactions ($\epsilon = 0.1 k_{\rm B}T$). 19 For the coarse-grained and all-atom simulations we used cubic simulation boxes of equal size. For the 20 atomistic simulations, all proteins were protonated with the Maestro modeling package (Schroedinger 21 (2)) at pH 7.0. All Asp and Glu residues of UBQ, GB3, VIL were deprotonated, only Glu35 of LYZ was 22 protonated. Lys and Arg residues of all proteins were protonated. His68 of UBQ was neutral, protonated 23 at the δ -carbon atom. His15 of LYZ was neutral, protonated at the ϵ -carbon atom. N and C termini of all 24 proteins were unblocked and charged. The structure of VIL is destabilized by the water model and unfolds 25 within several nanoseconds simulation time. We therefore applied harmonic distance restraints (force 26 constant = $200 \,\text{kJmol}^{-1} \text{nm}^{-2}$) on atom pairs 51CE1-73CB, 51CE1-58CZ, 47CE1-51E2, 58CE1-69CB, 27 42CD1-51CE2, 47CZ-55CG, 58CD2-66CG and 69CB-73CG. 28 MD simulations were performed using GROMACS (v2016.3) (3) with the Amber99SB*-ILDN-Q (4-7)29

force field, TIP4P-D water (8), and NaCl ion concentrations (9) of 0.157 M for UBQ solutions, 0.200 M 30 for GB3 solutions, 0.120 M for LYZ solutions and 0.200 M for VIL solutions, respectively. Different ion 31 concentrations were used for the different proteins to be consistent with respective experiments. The 32 structures were energy-minimized and equilibrated at $300 \,\mathrm{K}$ (10) with temperature coupling time constant 33 $\tau_T = 0.1$ ps for 100 ps in an NVT ensemble and for 5 ns at 1 bar (11) with pressure coupling time constant 34 $\tau_p = 5 \text{ ps}$ and compressibility $4.5 \times 10^{-5} \text{ bar}^{-1}$ in an NPT ensemble. Production runs in an NPT ensemble 35 (12) $(\tau_T = 1.0 \text{ ps}, \tau_p = 5.0 \text{ ps})$ were carried out at each density for times as listed in Table S1. The leap-frog 36 integrator with timestep 2 fs was used for all simulations. Atomic bonds to hydrogens were converted to 37 constraints with LINCS (13). Short-range electrostatics and van der Waals cutoffs were set to 1.0 nm in all 38 simulations. Long-range electrostatic interactions were accounted for using the Particle Mesh Ewald (14) 39 method. Configurations were recorded every 100 ps. Every tenth snapshot (1 ns timestep) was used for all 40 analyses. 41

⁴² **Protein Structure Fluctuations.** To calculate root-mean-square deviations (RMSD) and root-mean-square ⁴³ fluctuations (RMSF), we superimposed the structures onto a reference structure using the qcprot RMSD ⁴⁴ alignment algorithm (15, 16) implemented in MDAnalysis (17, 18). As reference we used the average ⁴⁵ simulation structure, obtained by RMSD alignment of the α -carbon backbone atoms (UBQ: residues 1–70, ⁴⁶ GB3: residues 1–58, LYZ: 1–129, VIL: 41–76) and averaging the simulation structures iteratively until ⁴⁷ convergence (19). The crystal structure was used for the initial alignment. The RMSD was calculated as

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$$\operatorname{RMSD}(t) = \sqrt{\frac{1}{N} \sum_{i=1}^{N} \|\vec{x}_i(t) - \langle \vec{x}_i \rangle \|^2} , \qquad [S1]$$

⁴⁹ with N the number of α -carbon backbone atoms and $\langle \vec{x}_i \rangle$ the position of atom *i* of the averaged simulation ⁵⁰ structure. The RMSF were calculated as

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$$RMSF_i = \sqrt{\langle \|\vec{x}_i - \langle \vec{x}_i \rangle \|^2 \rangle} .$$
[S2]

Protein Volume Fraction. To determine the protein volume fraction ϕ at different protein concentrations, 52 we used the NPT simulations of N = 15 (UBQ) and N = 20 (GB3, LYZ, VIL) proteins at different box 53 sizes and numbers of water molecules (Table S1). We found that the equilibrated volumes of the simulation 54 boxes depend linearly on the number of water molecules (Fig. S12). From the intercepts of linear fits 55 divided by N, we obtained the effective protein volumes, $v_p(\text{UBQ}) = 10.407 \,\text{nm}^3$, $v_p(\text{GB3}) = 7.222 \,\text{nm}^3$, 56 $v_p(\text{LYZ}) = 17.228 \,\text{nm}^3$ and $v_p(\text{VIL}) = 5.118 \,\text{nm}^3$, respectively. The protein volume fraction in simulations 57 with N proteins was then calculated as $\phi = N v_p / \langle V \rangle$, where $\langle V \rangle$ is the box volume averaged over an NPT 58 simulation. 59

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Viscosity Calculation. The low-frequency, low-shear viscosity η of dense protein solutions differs from the viscosity η_0 of the pure solvent consisting of only water and ions. We determined $\eta(\phi)$ and η_0 from MD simulations in an NVT ensemble by integration of the autocorrelation functions $C_{ij}(t) = \langle P_{ij}(t)P_{ij}(0)\rangle$ of the pressure tensor fluctuations (20),

 η_i

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$$_{ij} = \frac{V}{k_{\rm B}T} \int_0^\infty C_{ij}(t) \,\mathrm{d}t \;, \tag{S3}$$

where $C_{ij}(t)$ was determined for the three off-diagonal pressure tensor elements $(P_{ij} = P_{xy}, P_{xz}, \text{ and } P_{yz})$ and the three corresponding combinations of the diagonal pressure tensor elements $[P_{ij} = (P_{xx} - P_{yy})/2, (P_{xx} - P_{zz})/2, \text{ and } (P_{yy} - P_{zz})/2]$. V is the (fixed) volume of the simulation box, T is the absolute temperature, and $k_{\rm B}$ is the Boltzmann constant. Starting structures for the NVT runs were taken from the long NPT simulations (see below).

Numerical integration of the tails of $C_{ij}(t)$ is prone to large errors due to sampling noise. We therefore split the integration of $C_{ij}(t)$ into a direct integration up to a cutoff time τ_{cut} (see Table S2) and an analytical integration of a bi-exponential fit to the tail,

$$C_{ij}(t) = a_0 e^{-t/\tau_0} + a_1 e^{-t/\tau_1} \text{ for } t > \tau_{\text{cut}} , \qquad [S4]$$

where a_0, a_1, τ_0 , and τ_1 denote the fit parameters. The left (τ_{cut}) and right bounds of the fit are listed in Table S2. The fit function was integrated analytically from τ_{cut} to $\tau = \infty$.

The viscosity of TIP4P-D water (8) with different ion concentrations was calculated by evaluating $P_{ii}(t)$ 76 at 10 fs intervals from 100 ns simulations in the NVT ensemble. C_{ij} of P_{ij} was integrated to give η_{ij} . η was 77 then calculated by averaging η_{ij} for the six P_{ij} with the standard error of the mean used as error estimate. 78 To efficiently sample the viscosity of the dense protein solutions, we extracted fifty starting configurations 79 from the respective trajectories and conducted NVT simulations from each of the starting configurations. 80 Each extracted configuration was equilibrated for 1 ns (NPT) followed by 5 ns of simulation at constant 81 volume (NVT), evaluating P_{ij} every 10 fs. C_{ij} was averaged over the fifty simulations and integrated to 82 give η_{ij} . η_{ij} was then averaged as above to obtain the viscosity η . 83

Translational Diffusion. Mean squared displacements (MSD) were calculated for each density for time delays $\tau = 1$ ns to $\tau = 500$ ns. For each protein in the simulation box, long-time translational diffusion coefficients were obtained by fitting the Einstein relation

$$MSD(\tau) = c + 6D_t^{PBC}\tau, \quad \text{for } \tau \to \infty$$
[S5]

to the MSD curves in the range 10 to 30 ns, where c is a fitted offset that accounts for short-time non-diffusive 84 behavior. The diffusion coefficients of all proteins in the simulation box were then averaged. The error of 85 D_t for proteins in the dense solutions was estimated from the standard error of the mean of all proteins in 86 the simulation box. The error of D_t in the dilute UBQ and GB3 system (N = 1) was estimated from 1000 87 one-dimensional random walks of lengths corresponding to the simulation trajectories (Table S1). From the 88 random walks, MSDs were calculated and fitted to the Einstein relation in the range 0 to 5 ns to obtain 89 D_t (in analogy to the calculation of the protein's D_t). The estimated error of D_t was then obtained from 90 $\sigma/\sqrt{3}-1$, with σ the standard deviation of the distribution of D_t from the random walks. The denominator 91 corrects for the three dimensions in the real system compared to the one-dimensional random walk. For 92 dilute LYZ and VIL solutions, two independent simulations were carried out, respectively, to determine 93 D_t^{PBC} . Finite-size corrected D_t was obtained from the y-intercept of fitting the finite-size correction formula 94 (Eq. 7) to $D_t^{\text{PBC}}(1/L)$. The error of dilute LYZ and VIL solutions was obtained from the curvature of the 95 likelihood in the fitting procedure, taking into account the individual errors of D_t^{PBC} , which were obtained 96 from one-dimensional random walks, as for the dilute UBQ and GB3 solutions. 97

We compared the reduced translational diffusion coefficients $D_t(\phi)/D_{t,\phi=0}$ to the approximate form for monodisperse non-interacting HS colloidal suspensions (21),

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$$D_{t,\text{coll}}(\phi)/D_{t,\phi=0} = \frac{(1-\phi)^3}{1+3/2\phi+2\phi^2+3\phi^3} , \qquad [S6]$$

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¹⁰¹ which was obtained as an extension of Batchelor's quadratic approximation (22). We also compared reduced

¹⁰² translational diffusion coefficients to an alternative approximation of the diffusive behavior of monodisperse

¹⁰³ non-interacting HS colloidal suspensions (including hydrodynamic interactions) (23),

$$D_{t,\text{coll}}(\phi)/D_{t,\phi=0} = \frac{1 - 9\phi/32}{1 + H(\phi) + (\phi/\phi_0)/(1 - \phi/\phi_0)^2} , \qquad [S7]$$

105 with $\phi_0 \approx 0.5718$ and

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$$H(\phi) = \frac{2b(\phi)^2}{1 - b(\phi)} - \frac{c(\phi)}{1 + 2c(\phi)} - \frac{b(\phi)c(\phi)(2 + c(\phi))}{(1 + c(\phi))(1 - b(\phi) + c(\phi))},$$
 [S8]

107 with $b(\phi) = (9\phi/8)^{1/2}$ and $c(\phi) = 11\phi/16$.

Rotational Diffusion Coefficient from the Orientational Correlation Function. The mean rotational diffusion coefficient \bar{D}_r^{PBC} was calculated as

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$$\bar{D}_r^{\text{PBC}} = \frac{1}{3}(D_1 + D_2 + D_3),$$
 [S9]

with D_1 , D_2 , and D_3 the rotational diffusion coefficients in the principal coordinate system of the rotation diffusion tensor. The finite size effect of the mean rotation diffusion coefficient was corrected using (24)

$$\bar{D}_r = \bar{D}_r^{\text{PBC}} + \frac{k_{\text{B}}T}{6\eta(\phi)V} , \qquad [S10]$$

114 with V the mean box volume.

Additionally, the effective rotational diffusion coefficient was obtained from fits to the orientational correlation function $\langle\!\langle P_1(\cos\theta(t))\rangle\!\rangle = \langle\!\langle\cos\theta(t)\rangle\!\rangle$ (25, 26), where $\theta(t)$ is the angle traveled during time t, with $\cos\theta(t) = \vec{v}(t) \cdot \vec{v}(0)$ and \vec{v} a unit vector associated with the protein (19). Here, $\langle\!\langle\ldots\rangle\!\rangle$ indicates averaging over starting times and isotropic orientations of \vec{v} . We approximate the rotational behavior of the system by assuming two isotropically tumbling species with distinct tumbling rates, one for fast-tumbling free proteins and the other for slower-tumbling proteins in clusters. Therefore, a bi-exponentially decaying function was fitted to the data

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$$\langle\!\langle P_1(\cos\theta(t))\rangle\!\rangle = a_1 e^{-t/\tau_1} + (1-a_1)e^{-t/\tau_2}$$
, [S11]

with fit parameters a_1 , τ_1 , and τ_2 . In the infinitely diluted system, Eq. S11 reduces to $\langle\!\langle P_1(\cos\theta(t))\rangle\!\rangle = e^{-t/\tau_1}$ with τ_1 the only fitting parameter. Integration of $\langle\!\langle P_1(\cos\theta(t))\rangle\!\rangle$ yields

$$\tau_c = a_1 \tau_1 + (1 - a_1) \tau_2 \tag{S12}$$

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and $\tau_c = \tau_1$ in the dilute system. An effective diffusion coefficient was obtained by averaging the contributions from slow and fast rotational diffusion, weighting the individual correlation times τ_1 and τ_2 by the exponential prefactors a_1 and $1 - a_1$

$$\tilde{D}_r^{\text{PBC}} = \frac{a_1}{2\tau_1} + \frac{1 - a_1}{2\tau_2}.$$
[S13]

130 \tilde{D}_r was obtained from \tilde{D}_r^{PBC} by correcting for finite-size effects using Eq. S10.

We compared the reduced rotational diffusion coefficients $D_r(\phi)/D_{r,\phi=0}$ to predictions from colloidal models of non-interacting HS (27):

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$$D_{r,\text{coll}}(\phi)/D_{r,\phi=0} = (1-\phi)\frac{\eta_0}{\eta(\phi)}$$
 [S14]

Hydropro Calculations. Translational and rotational diffusion coefficients D_t and D_r were also calculated using the hydrodynamics program Hydropro (28) for T = 300 K, the "atom" model, and viscosities $\eta = 0.937$ mPa s, corresponding to the average pure-solvent values with ions (TIP4P-D water (8) with 0.120 M, 0.157 M and 0.200 M NaCl).

Protein Cluster Formation. Protein clusters with size m were defined based on a distance criterion. A 138 cluster encompasses all proteins with minimal α -carbon distance <0.65 nm to at least one other protein 139 in the cluster. Only pairs staying in contact for at least 1 ns were considered, which is the time interval 140 between consecutive structures in the analyzed trajectories. To assess the influence of slight changes in 141 the distance cutoff criterion, the cutoff distance was varied from 0.6 to 0.75 nm (Fig. S11), finding that a 142 cutoff of 0.65 nm leads to the good agreement of our cluster model with diffusion data also at the highest 143 concentration (200 mg/ml). At this concentration, the mean cluster size \overline{m} depends significantly on the 144 distance cutoff. Therefore, the calculation of cluster sizes based on a simple α -carbon distance criterion 145 employed here is not reliable above 100 mg/ml. 146

The lifetime of protein pairs was analyzed to determine if cluster formation is transient, dynamic, or permanent (following Liu's definition (29)). We analyzed the distributions of protein pair lifetimes, which we defined as the mean time in which the minimal distance between at least one pair of α -carbon atoms of two proteins does not exceed 0.65 nm.

We calculated the preferred contact interfaces of proteins by counting the number of heavy atom contacts. A three-tiered approach was employed to reduce the computational time needed for the analysis. First, the distances of the protein centers of mass (COM) were calculated. If the proteins were close (as identified by a COM distance ≤ 6 nm), then the α -carbon distances were computed. If at least one α -carbon distance was below the cutoff 0.65 nm, then all heavy-atom distances in the protein pair were calculated. The heavy-atoms involved in intermolecular heavy-atom pairs with distance ≤ 0.5 nm were counted per residue. Figs. 4 and S17 show the proteins color-coded by the counts.

Relation Between Cluster Size and Protein Binding Affinity. Consider a system of identical proteins at a number concentration ρ (i.e., proteins per unit volume). We assume that the protein clusters C_m of size mare in equilibrium with each other,

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$$C_{m'} + C_{m''} \rightleftharpoons C_{m'+m''} , \qquad [S15]$$

with concentrations $c_m = [C_m]$ that satisfy binding equilibria

$$\frac{c_{m'}c_{m''}}{c_{m'+m''}} = K_d \tag{S16}$$

for all $m', m'' \ge 1$ with K_d an effective dissociation constant. For simplicity, we assume K_d to be independent of m' and m''. In effect, this model assumes that a cluster of size m is held together by m-1 energetically equivalent interactions as, e.g., in a Cayley tree (Bethe lattice). We show that in our simulations of concentrated protein solutions the number of protein-protein connections (a connection between two proteins is established if at least one α -carbon distance is <0.65 nm) indeed increases as m-1 with cluster size m up to intermediate (100 mg/ml) protein concentration (Fig. S21). The concentrations c_m of the different cluster sizes then satisfy

$$c_m = c_1^m / K_d^{m-1}$$
 . [S17]

It is easily verified that for these c_m , with an as yet unknown monomer concentration c_1 , Eq. **S16** is satisfied. Using this expression for c_m , we obtain a relation between the total concentration of proteins ρ and the concentration of monomers c_1 ,

 $\sum_{m=1}^{\infty} mc_m = \frac{c_1}{(1 - c_1/K_d)^2} = \rho , \qquad [S18]$

which can be solved to express the monomer concentration c_1 in terms of ρ and K_d . The mean cluster size is

$$\overline{m} = \frac{\sum_{m=1}^{\infty} mc_m}{\sum_{m=1}^{\infty} c_m} = \frac{1}{1 - c_1/K_d} \; .$$

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¹⁷⁹ Substituting the solution of Eq. **S18**, we obtain for the mean cluster size

$$\overline{m} = \frac{1 + \sqrt{1 + 4\rho/K_d}}{2} \approx 1 + \rho/K_d , \qquad [S20]$$

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[S19]

- where the last expression is the approximation for low protein concentrations ρ . We thus find that the mean
- cluster size grows approximately as $\overline{m} \approx 1 + \rho/K_d = 1 + \phi/(v_p K_d) = 1 + \zeta \phi$ at low protein concentrations,
- with v_p the protein volume, ϕ the protein volume fraction, and $\zeta = 1/(v_p K_d)$ the clustering propensity.

¹⁸⁴ **Colloidal Suspension Model.** Colloidal particles with attractive interactions are often modeled as sticky ¹⁸⁵ hard spheres (30) of radius *a* and diameter $\sigma = 2a$ with interaction potentials that depend on the pair ¹⁸⁶ distance *r* as

$$\beta u(r) = \begin{cases} \infty, & \text{for } r < \sigma \\ \ln \left[12\tau (d/\sigma - 1) \right], & \text{for } \sigma < r < d \\ 0, & \text{for } r > d \end{cases}$$
[S21]

in the limit of $d \to \sigma$. In the Monte Carlo simulations of the mean cluster size reported in the main text, we used a finite $d = 1.05\sigma$. At low concentrations, the radial distribution function can be approximated as $(31) \ g(r) = \theta(r-\sigma) + \delta(r-\sigma) \sigma/12\tau$ where $\theta(x)$ is the Heaviside step function and $\delta(x)$ is Dirac's delta function. In this limit, the fraction of bound particles is obtained by integration over the spherical shell, $f_{\text{bound}} = \lim_{\epsilon \to 0} 2\pi\rho \int_{2a-\epsilon}^{2a+\epsilon} r^2 dr \ g(r) = \rho v_{\text{HS}}/\tau$ with $v_{\text{HS}} = 4\pi a^3/3$ the hard-sphere volume and $\phi = v_{\text{HS}}\rho$. In an equilibrium binding model, this fraction is $K_a\rho$. We thus arrive at a relation between the association constant and Baxter parameter $\tau = v_{\text{HS}}/K_a = v_{\text{HS}}K_d$.

¹⁹⁵ **Displacement Pair Correlation Function.** We calculated the displacement pair correlation function H_{ij} for ¹⁹⁶ the motion of proteins *i* and *j* following the method of Ando and Skolnick (32),

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$$H_{ij}(\tau) = \frac{\sum \Delta \vec{r}_i(\tau) \cdot \Delta \vec{r}_j(\tau)}{\sqrt{\sum \|\Delta \vec{r}_i(\tau)\|^2} \sqrt{\sum \|\Delta \vec{r}_j(\tau)\|^2}},$$
[S22]

with $\Delta \vec{r}_i(\tau)$ the vector traveled by protein *i* in time delay τ . We evaluated H_{ij} for varying delays $\tau = 2, 4..., 40$ ns and 0.1 nm-wide minimum α -carbon distance windows from 0.6–3.0 nm. Here, only proteins are considered if their minimum α -carbon distance falls in the respective distance window both at time *t* and $t + \tau$.

202 Supplementary Results

Effect of Concentration on Protein Stability. Proteins in commonly employed protein force fields are too sticky, causing fast and irreversible aggregation in crowded solutions (33). In our atomistic MD simulations of dense and dilute protein solutions, we therefore used the TIP4P-D water model (8). An increase in the water-protein dispersion interaction attenuates the aggregation propensity. However, the TIP4P-D water model slightly destabilizes native protein structures (8).

²⁰⁸ UBQ α -carbon atoms show a mean RMSD of 1.2–1.5 Å to the average simulation structure throughout ²⁰⁹ all simulations (Fig. S1, left panels). The RMSD of the average simulation structure to the crystal structure ²¹⁰ is likewise in the range 1.3–1.5 Å. RMSF confirm a very similar flexibility of dilute and dense UBQ solutions ²¹¹ (Fig. S4), showing that the major contribution to the RMSD is from the C-terminal flexible tail (residues ²¹² 71-76). In the simulations, the internal structure and dynamics of UBQ is unperturbed by protein crowding ²¹³ and UBQ remains folded.

GB3 is slightly destabilized in the dilute solution and its α -helix begins to unfold at ca. 2 μ s simulation 214 time. The mean RMSD values of GB3 α -carbon atoms to the average simulation structure in the dense 215 solutions are in the range 1.0–1.2 Å and thus consistently smaller than the RMSD values of the dilute 216 protein $(0-2\,\mu s)$ at 1.4 Å (Fig. S2, right panels), suggesting a stabilizing effect of macromolecular crowding 217 on the native state of GB3. The RMSD values of the mean simulation structures to the crystal structure are 218 0.9-1.1 Å for the dense solutions and 1.6 Å for the dilute solution $(0-2\,\mu s)$. RMSF calculations confirm that 219 the residues 28-42 of the α -helix fluctuate more in dilute solution than in the dense GB3 solutions (Fig. S4). 220 This finding, although in accordance with the theory of entropic stabilization of the native state due to 221 excluded volume, contrasts with a previous study (34), in which non-specific, shape-driven interactions led 222

to native state destabilization in crowded conditions. Although partial unfolding of the α -helix has only a minor effect on the translational and rotational diffusional behavior of the protein (not shown), we only considered the first 2 μ s of the dilute GB3 simulation for further analysis.

LYZ is stable throughout the simulation, with mean RMSD values to the average simulation structure of 1.0–1.1 Å in all simulations. The RMSD values of the mean simulation structures to the crystal structure are 1.5–1.9 Å and RMSF values of the dilute systems indicate high flexibility in the loop of residues 100–105, which is reduced in the dense solutions (Fig. S4).

VIL is the least stable protein model of the proteins studied. The unrestrained model readily unfolds in TIP4P-D water. When applying restraints to key residues in the hydrophobic core of the protein, the model remains stable throughout the simulation with mean RMSD values to the average simulation structure of 1.2–1.7 Å in all simulations. The RMSD values of the mean simulation structures to the crystal structure are 1.6–1.8 Å. One of the two simulations of the dilute VIL systems shows somewhat higher flexibility than all other simulations (Fig. S4). Nevertheless, the restrained protein remains folded in all cases.

Protein	Ν	Concentration	ϕ	Atoms	L	$t_{\rm total}$
		[mg/ml]			[nm]	[ns]
UBQ	1	pprox 0	pprox 0	36,000	6.464	5000
	15	30	0.0221	933,000	19.178	2000
	15	50	0.0370	556,000	16.152	2000
	15	100	0.0745	276,000	12.797	2000
	15	200	0.1503	135,000	10.127	2000
	120	200	0.1509	1,079,000	20.227	1000
	405	200	0.1503	3,657,000	30.382	1000
GB3	1	pprox 0	pprox 0	23,000	5.552	3000
	20	39	0.0277	690,000	17.345	2000
	20	100	0.0714	266,000	12.643	2000
	20	200	0.1447	130,000	9.994	2000
	160	200	0.1447	1,043,216	19.986	1000
	540	200	0.1447	3,520,854	29.979	1000
LYZ	1	≈ 0	pprox 0	46,990	7.092	1105
	1	pprox 0	pprox 0	69,688	8.082	1825
	20	100	0.0733	617,202	16.753	1001
	20	200	0.1459	306,738	13.315	1083
VIL	1	pprox 0	pprox 0	18,346	5.180	906
	1	pprox 0	pprox 0	49,106	7.186	1328
	20	100	0.0754	178,266	11.070	1042
	20	200	0.1517	87,830	8.770	1251

Table S1. Specifications of simulated dense protein solutions.^a

^{*a*} The concentration of proteins is approximate. N: Number of proteins in the simulation box. ϕ : Mean protein volume fraction. Atoms: Total number of atoms in the simulation box. *L*: Edge length of cubic simulation box. *t*_{total}: Total simulation time.

System		Left bound τ_{out}	Right bound	
TIP4P-D	0 mM NaCl	1.0 ps	4.0 ps	
	157 mM NaCl	1.0 ps	4.0 ps	
	200 mM NaCl	1.0 ps	4.0 ps	
UBQ	30 mg/ml	1.5 ps	7.0 ps	
	50 mg/ml	1.5 ps	6.5 ps	
	100 mg/ml	1.5 ps	8.0 ps	
	200 mg/ml	1.5 ps	10.0 ps	
GB3	39 mg/ml	1.5 ps	5.5 ps	
	100 mg/ml	1.5 ps	6.0 ps	
	200 mg/ml	1.5 ps	12.0 ps	
LYZ	100 mg/ml	1.5 ps	6.0 ps	
	200 mg/ml	1.5 ps	9.0 ps	
VIL	100 mg/ml	1.5 ps	7.0 ps	
	200 mg/ml	1.5 ps	15.0 ps	

Table S2. Time windows used to fit $C_{ij}(t)$.

System		Ν	D_{t}^{PBC}	D_r^{PBC}
			$10^{-7} {\rm cm}^2 {\rm s}^{-1}$	$10^{7} {\rm s}^{-1}$
UBQ	0 mg/ml	1	4.56	3.70
	30 mg/ml	15	8.81	2.69
	50 mg/ml	15	7.32	2.27
	100 mg/ml	15	4.55	1.49
	200 mg/ml	15	1.58	0.56
	200 mg/ml	120	2.30	0.58
	200 mg/ml	405	2.19	0.42
GB3	0 mg/ml	1	4.60	4.30
	39 mg/ml	20	9.70	3.28
	100 mg/ml	20	5.27	1.90
	200 mg/ml	20	2.05	0.88
	200 mg/ml	160	2.59	1.06
	200 mg/ml	540	2.92	0.94
LYZ	0 mg/ml	1	3.66	1.76
	0 mg/ml	1	4.39	2.30
	100 mg/ml	20	5.47	1.67
	200 mg/ml	20	2.21	0.61
VIL	0 mg/ml	1	6.13	6.25
	0 mg/ml	1	8.84	6.59
	100 mg/ml	20	5.78	2.60
	200 mg/ml	20	1.92	1.05

Table S3. Translational and rotational diffusion coefficients before finite-size correction.



Fig. S1. RMSD of UBQ α -carbon atoms to the average simulation structure in simulations of dilute and dense solutions. Colored curves show mean RMSD values, averaged for all proteins N in the simulation box. Shades indicate the standard deviation of the distribution of RMSD values of individual proteins.



Fig. S2. RMSD of GB3 α -carbon atoms to the average simulation structure in simulations of dilute and dense solutions. Colored curves show mean RMSD values, averaged for all proteins N in the simulation box. Shades indicate the standard deviation of the distribution of RMSD values of individual proteins.



Fig. S3. RMSD of LYZ and VIL α -carbon atoms to the average simulation structure in simulations of dilute and dense solutions. Colored curves show mean RMSD values, averaged for all proteins N in the simulation box. Shades indicate the standard deviation of the distribution of RMSD values of individual proteins.



Fig. S4. RMSF of α -carbon atoms to the average simulation structure in simulations of dilute and dense solutions. Darker colors indicate higher protein concentration.



Fig. S5. Autocorrelation functions C_{ij} of the three off-diagonal pressure tensor elements P_{xy} , P_{xz} , P_{yz} and three combinations of the diagonal pressure tensor elements $\frac{1}{2}(P_{xx} - P_{yy})$, $\frac{1}{2}(P_{xx} - P_{zz})$ and $\frac{1}{2}(P_{yy} - P_{zz})$ of TIP4P-D water, dense UBQ solutions and dense GB3 solutions. Darker colors indicate higher ion concentration (top) or protein concentration (bottom). The insets shows C_{ij} at short times.



Fig. S6. MSD of UBQ, GB3, LYZ and VIL in dense protein solutions. Lines show the MSD averaged over all proteins in the solution. Respective standard errors of the mean are indicated as transparent surfaces. Black dashed lines indicate the linear fits in the region 10–30 ns (0–5 ns for dilute systems) used to extract the translational diffusion coefficients via Eq. S5. Darker colors indicate higher protein concentration.



Fig. S7. Fits to the time-dependence of the six distinct quaternion covariances $u_1u_1-u_2u_3$ of UBQ, GB3, LYZ and VIL in dense protein solutions. Solid lines are the results of the MD simulations. Dashed lines are the fits corresponding to rigid-body rotational diffusion. Darker colors indicate higher protein concentration. Numbers *i*-*j* above the panels indicate the quaternion-covariance u_iu_j .



Fig. S8. Rotational diffusion coefficients D_1 , D_2 , and D_3 of dense protein solutions before correction for finite-size effects. Rotational diffusion coefficients of individual proteins are shown in gray. Mean rotational diffusion coefficients are shown in colors. Darker colors indicate higher protein concentration.



Fig. S9. Orientational correlation functions of UBQ, GB3, LYZ and VIL in concentrated solutions. Solid lines: $\langle\langle P_1(\cos\theta(t))\rangle\rangle$ calculated from u_0u_0 . Dashed lines: Bi-exponential fit to $\langle\langle P_1(\cos\theta(t))\rangle\rangle$ (single exponential fit for dilute system). Darker colors indicate higher protein concentration.



Fig. S10. Cumulative cluster size distributions of dense protein solutions of small simulation systems $N \le 20$ (circles) and large simulation systems $N \ge 120$ (diamonds). The insets show the significant contribution of large cluster sizes to the cluster distribution of the large systems. Darker colors indicate higher protein concentration.



Fig. S11. Dependence of cluster size m on protein volume fraction ϕ for α -carbon distance cutoffs from 0.6 to 0.75 nm. Circles show results for small systems $N \leq 20$, diamonds show results for large systems $N \geq 120$



Fig. S12. Dependence of the mean volume of the simulation box on the number of water molecules n_{wat} . (Individual lower panels) Zoom-ins showing intersections of fit with axes.



Fig. S13. Times spent unbound. Simulation times in which the protein has not been part of a cluster for at least 5 ns are indicated by colored lines.



Fig. S14. MSD curves of unbound proteins in concentrated protein solutions. For each protein, MSDs were recorded for the times spent unbound (i.e. not in a cluster). Darker colors indicate higher protein concentration.



Fig. S15. Dependence of the product of viscosity and diffusion coefficient D_t^{free} of 'free' (unbound) protein (stars) and the product of viscosity and diffusion coefficient D_t of all proteins (circles) on protein volume fraction ϕ . Dotted lines show the values of the dilute solutions.



Fig. S16. Dependence of the displacement pair correlation on the minimum α-carbon distance of the protein pairs (y-axis) and on the time delay (x-axis).



Fig. S17. Contributions to protein-protein interaction. The proteins are colored from no contribution (blue), intermediate contribution (white) to strong contribution (red). Residues that contribute most to interactions are labeled. The experimental dimer interface for UBQ is derived from (35).



Fig. S18. Radial distribution functions g(r) of protein centers of mass of UBQ (30 mg/ml) and GB3 (39 mg/ml) solutions, which are, respectively, the lowest finite concentrations simulated. For the calculation of B_2 , g(r) - 1 was integrated from r = 0 to r = 4 nm.



Fig. S19. Distribution of protein pair lifetimes. Darker colors indicate higher protein concentration.



Fig. S20. Concentration-dependent protein diffusion. (A) Dependence of the normalized translational diffusion coefficient D_t^{red} on protein volume fraction ϕ . Filled circles show MD data from this study. Open circles show data from simulation studies (36–39). Other open symbols denote data from experimental studies (29, 38, 40–52). Mb: Myoglobin, Hb: Hemoglobin, Ova: Ovalbumin, "Mixed": Cl2 in different dense protein solutions. All data refer to the long-time translational diffusion coefficient, with the exception of (49, 50), which refer to the short-time diffusion coefficient, indicated by D^{*} . The solid curves show the prediction of the dynamic cluster model $D_{t, \text{clust}}(\phi)$ for UBQ, GB3, LYZ and VIL solutions, indicated by corresponding colors. The dashed and dotted curves show the slowdown of D_t^{red} predicted from colloid theory on non-interacting HS by van Blaaderen (21) and Tokuyama (23), respectively. The dash-dotted line shows a linear fit to D_t^{red} of UBQ and GB3 at $\phi \leq 0.04$. (B) Dependence of the normalized rotational diffusion subclices D_r^{red} on protein volume fraction ϕ . Open circles show the prediction of the dynamic cluster model $D_{r,\text{clust}}(\phi)$ and VIL solutions, indicated by corresponding colors. The dashed and dotted curves show the slowdown of D_t^{red} of UBQ and GB3 at $\phi \leq 0.04$. (B) Dependence of the normalized rotational diffusion coefficient D_r^{red} on protein volume fraction ϕ . Open circles show data from simulation studies (37, 39). Other open symbols denote data from experimental studies (48, 51, 53). "Cell": Hb or Mb in different cell types. The solid curves show the prediction of the dynamic cluster model $D_{r,\text{clust}}(\phi)$ for UBQ, GB3, LYZ and VIL solutions, indicated by corresponding colors. The dashed curve shows the slowdown of D_r^{red} predicted from colloid theory on non-interacting HS (27).



Fig. S21. Dependence of the number of protein-protein connections (1 if C_{α} -distance ≤ 0.65 nm, 0 otherwise) and number of heavy-atom pairs (distance ≤ 0.50 nm) on the cluster size. The grey line in the upper panels shows y = m - 1.

Movie S1. MovieS1.avi: Atomistic MD simulation of 540 GB3 proteins in concentrated solution (200 mg/ml) at simulation time 0-500 ns. The fully flexible proteins are shown in surface representation and differentiated by color. For clarity, water and ions are omitted. Proteins that seem to appear and disappear traverse the periodic boundary in the direction of sight.

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