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Intra-chain organisation of hydrophobic residues controls inter-chain aggregation rates of amphiphilic polymers

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Aggregation of amphiphiles through the action of hydrophobic interactions is a common feature in soft condensed matter systems and is of particular importance in the context of biophysics as it underlies both the generation of functional biological machinery as well as the formation of pathological misassembled states of proteins. Here we explore the aggregation behaviour of amphiphilic polymers using lattice Monte-Carlo calculations and show that the distribution of hydrophobic residues within the polymer sequence determines the facility with which dry/wet interfaces can be created and that such interfaces drive the aggregation process.

Keywords: Hydrophobic effect — Protein aggregation — Polypeptide sequence

Due to their importance in governing self-assembly of biological components, hydrophobic interactions and the mechanism of hydrophobic collapse leading to the aggregation of hydrophobic species in an aqueous environment have been studied in detail using approaches ranging from spectroscopy to atomistic and coarse-grained simulations¹⁻¹⁶. The phenomenon of hydrophobic collapse by its very nature involves the removal of water molecules between adjacent hydrophobic entities in order to allow for them to come together, and therefore the creation of an interface with unsatisfied hydrogen-bonding separating "wet" solvent from "dry" aggregated hydrophobes in a manner reminiscent of a liquid-vapour phase transition. The picture that has emerged from computational studies of the collapse of hydrophobic chains is that it is the creation of such interfaces which controls the transition between solvated hydrophobes and their compact aggregated state^{17–19}. In biological systems, hydrophobic units rarely occur in isolation and are most commonly part of a macromolecular system. In the present work, we investigate using lattice Monte-Carlo calculations the nature of the hydrophobic collapse for polymers with a varying distribution of hydrophobic and hydrophilic elements and demonstrate that the clustering of hydrophobic entities is crucial for nucleating the formation of dry interfaces driving the eventual aggregation process.

I. OFF-LATTICE SOLUTES IN A LATTICE GAS SOLVENT MODEL

Hydrophobic assembly is characterised by the expulsion of water molecules from aggregates of hydrophobic entities. This effect can be captured by considering the evolution of the local water density field. The short length scale density fluctuations contributing to the local density are characterised by rapid relaxation and follow to a very good approximation Gaussian statistics²⁰. These short scale fluctuations can therefore be integrated analytically^{17,21,22}, resulting in a coarse grained density field $\rho(\vec{r})$ which is readily simulated with a discretized binary field n_i which tracks the density fluctuations resulting in the appearance of cells *i* with a lower density, "vapour" cells $n_i = 0$, and "wet" cells within the bulk solvent with $n_i = 1$. This description is particularly well suited for numerical evaluation as the computationally costly short length scale fluctuations characteristic of atomistic models have been treated analytically. Within this picture, there is a cost to create a wet/dry interface, given by nearest neighbour interactions of the form $n_i n_{i\pm 1}$ and an energy associated with the solvation of chemical species $n_i \mu_{ex}$. This description is therefore equivalent to a 3D lattice gas system with the Hamiltonian:

$$\mathcal{H}[\{n_i\}, \{h_i\}] = \sum_i [-\mu + \mu_{\text{ex}} h_i] n_i + \epsilon \sum_{\langle i,j \rangle} n_i n_j \qquad (1)$$

where μ is the solvent chemical potential and $\langle \dots \rangle$ indicates summation over nearest neighbours on the lattice. The presence of hydrophobic solutes at lattice sites *i* with $h_i = 1$ results in an excess chemical potential μ_{ex} .

The values of the parameters governing the coarse grained water degrees of freedom, $\mu = 3\epsilon - 2.25 \cdot 10^4 k_B T$ and $\epsilon = 1.51 k_B T$, can be determined for a lattice size of l = 0.21nm through comparisons with the experimental bulk values for the isothermal compressibility and the surface tension $\gamma = \epsilon/(2l^2) = 0.07 \mathrm{N \, m^{-1}}$ of water at room temperature and 1 atm pressure. The value of $\mu_{\rm coex} = 3\epsilon$ represents the chemical potential of the solvent at phase coexistence with the vapour phase, and the small difference $\mu - \mu_{\rm coex} \ll k_B T$ highlights the fact that water is close to phase coexistence under standard conditions. It has been shown that this description of water reproduces faithfully the key properties associated with hydrophobic interactions, in particular the characteristic solvation free energy changes with increasing solute sizes. This coarse-grained water description has previously been used to study the collapse of a single hydrophobic chain¹⁷, and we extend this approach here to cover the aggregation of amphiphilic chains.

With the specific parameterization given above, the lattice solvent used here is below the roughening transition for the three-dimensional Ising model. As a result, there can be lattice artifacts due to a tendency of an interface to align with the orientation of the underlying lattice vectors²³. A true liquidvapor interface would not exhibit this behavior. Vaikuntanathan and Geissler have recently demonstrated that this tendency can give rise to inaccurate solvation free energies for hydrophobic solutes that are nanometer sized or larger²⁴. This inaccuracy is most significant for aspherical or irregularly shaped solutes, but grows less pronounced as the roughening transition is approached from below. In the case presented here the model is only slightly below the roughening transition, which is located at $\epsilon \approx 1.64 k_{\rm B}T$, and so lattice artifacts are only expected to manifest on length scales of about $1-2\ell$. Since the critical nucleus size for hydrophobic peptide aggregation is about 1nm, or $\approx 5\ell$, we expect any lattice artifacts associated with being below the roughening transition to be negligible for the results presented here. Indeed, the mechanism for collapse found for a hydrophobic chain with the lattice solvent model we employ¹⁷ is consistent with that found for same hydrophobic chain with an atomistic solvent model.¹⁸ For more generally shaped solutes, effects of lattice artifacts may best be avoided by adopting Vaikuntanathan and Geisslers related lattice model,^{24,25} which is slightly more complicated than that of Ref. (17).

For the hydrophobic segments, the excess chemical potential is given by $\mu_{ex} = c_{phob}v$, where $c_{phob} = 60 k_B T \, \mathrm{nm}^{-3}$ is taken to be the reversible work required to accommodate a hydrophobe of volume v. Idealised hydrophilic segments are water like and as such the excess chemical potential due to the presence of hydrophobic solutes vanishes $\mu_{ex} = 0$. Furthermore, weak depletion forces act between two hydrophobic particles and originate from the reduction of volume from which the solute excludes solvent molecules.

The solvent degrees of freedom in the model, $\{n_i\}$, can be efficiently sampled using a Metropolis Monte Carlo algorithm. By contrast, sampling the solute degrees of freedom is more complex. The principal problem is to calculate the overlap volume v_a between the excluded volume vand a given fine cell a. The volume v is typically a union of overlapping spheres, one for each excluded volume associated with a solute particle, here a polymer segment. Previously in Refs. (17) and (10), an interpolation scheme was used that only works if no point in space is within the solventexcluding radius of more than two spheres simultaneously, and a solute geometry was chosen that avoids this situation. In the present paper we focus on aggregation of multiple chains where densely packed structures are expected and thus multiple overlaps will occur - thus the existing interpolation scheme is not suitable.

Here, we discuss a partial solution to the above problem. Specifically, we present an approximate method of calculating v_a when v is, as above, a union of possibly overlapping spheres of a few different sizes. The gradient of v_a with respect to the centers of these spheres is also easy to calculate. In principle, propagating these gradients to obtain gradients



FIG. 1. Shown in A, the fine grid on which the overlap volume is calculated. This is mapped onto the lattice on which the field n_i is defined as shown in B. In C, the total volume excluded by two spheres of radius R = 4.20 Å when a distance d apart, as calculated exactly (Equation (4)) and by the numerical approximation scheme with spacing 1Å.

of $\mathcal{H}_{\text{eff}}[\{n_i\}]$ is then simply a (non-trivial) bookkeeping exercise. In describing our scheme, we treat cell indices a as vectors that can be added and subtracted. We denote by \mathbf{x}_a the coordinates of the corner of cell a with lowest Cartesian components. For a solvent-excluding sphere of radius R centered at \mathbf{x}_0 , we can pre-calculate the overlap volumes \hat{v}_s of all cells s by any method, such as Monte Carlo integration. We do this once at the beginning of a simulation.

Generically, the center \mathbf{r} of a solvent-excluding sphere will not coincide with a cell corner. We denote the indices of the eight corners of the cell containing \mathbf{r} by a_1, \ldots, a_8 , and their positions by $\mathbf{x}_1, \ldots, \mathbf{x}_8$. We construct eight non-negative weights $c_1(\mathbf{r}), \ldots, c_8(\mathbf{r})$, the sum of which is 1 and whose value depends continuously on \mathbf{r} , such that $\mathbf{r} = \sum_{k=1}^{8} c_k(\mathbf{r})\mathbf{x}_k$. Any scheme with these characteristics, such as trilinear interpolation, can be used. The overlap volumes for cells *a* near \mathbf{x} are then estimated by

$$\tilde{v}_a(\mathbf{r}) \approx \sum_{k=1}^8 c_k(\mathbf{r}) \hat{v}_{a-a_k}.$$
(2)

This interpolation scheme has the desirable property that the total volume of a sphere, given by $\sum_{a} \tilde{v}_{a}(\mathbf{r})$, is independent



FIG. 2. Hydrophobic collapse of an amphiphilic chains. In A is shown the system before collapse and in B the state of the system after 20,000 MC moves have been performed. Vapour lattice sites are shown as grey, transparent cubes, hydrophobic residues in red, and hydrophilic residues in blue.

of **r**.



FIG. 3. Map of the free energy landscape for the aggregation of a solution of diblock polymer chains composed of six hydrophilic residues followed by six hydrophilic residues computed using umbrella sampling (colour scale: energy in k_BT). Superimposed in black is shown an unbiased trajectory displaying aggregation.

When a solute is composed of multiple spheres, centered at \mathbf{r}^N , we simply add together the overlap volumes given by Equation (2) for each solute, but we cap the sum at the total volume of each fine cell, λ_f^3 . In summary, we have

$$v_a \approx \min\left[\lambda_f^3, \sum_{n=1}^N \tilde{v}_a(\mathbf{r}_n)\right]$$
 (3)

This scheme is exact whenever one or more spheres overlaps cell a completely, as well as when two spheres both overlap cell a but not each other. When two or more spheres both partially overlap cell a and each other, our scheme mildly

overestimates the overlap volume. We have evaluated the precision of our scheme by calculating the total volume V_{tot} of two spheres of radius R whose position is varied, and the two spheres are placed at arbitrary positions with respect to the fine grid. The total volume can be calculated analytically when the two sphere centers are a distance d apart,

$$V_{\text{tot}}(d) = \begin{cases} 2 \times \frac{4}{3}\pi R^3, & d > 2R, \\ 2 \times \frac{4}{3}\pi R^3 & (4) \\ -\frac{\pi}{12}(4R+d)(2R-d)^2, & \text{otherwise.} \end{cases}$$

The results of this comparison are shown in Figure 1C when R = 4.20 Å and the fine grid resolution is 1 Å. As expected, the exact and numerical results agree closely. Of equal importance, the spread in the numerical estimate of the total volume is small, which suggests that the lattice artifacts of our overlap-volume scheme are quite modest while offering a robust and computationally advantageous solution to the problem of computing overlap integrals for off-lattice solutes.

We note that if the solute needed to be propagated through some variant of molecular dynamics, such as Langevin dynamics¹⁷, the gradient of $\mathcal{H}_{\text{eff}}[\{n_i\}]$ with respect to solute positions would also be needed, and this is easy to calculate to the present approximation scheme.

II. RESULTS

The framework presented in this paper allows the study of solutes that can move freely in space in combination with an effective and computationally tractable explicit solvent model that exploits the statistical mechanics of lattice gas models. Using this approach, we have probed the aggregation behaviour of amphiphilic polymers with differing sequences of hydrophilic and hydrophobic residues. We model the dimensions of our chains on that of polypeptide chains; the excluded volume of the residues $V = 310.3 \text{ Å}^3$ with a core volume $V = 92.0 \text{ Å}^3$, is chosen to match that determined experimentally for amino acids²⁶. Furthermore, the excess chemical potentials of solvation possess values which cover the range measured for hydrophilic and hydrophobic amino acids²⁷. The polymer is modeled as a Gaussian chain, and the simulation box with periodic boundary conditions has a volume of 216.0 nm^3 . We used a polymer mass concentration of 79.6 mg/ml, a value comparable to the total protein concentration in many organisms.

First, a solution of polymer chains composed of six hydrophobic residues followed by six hydrophilic residues spontaneously aggregates during unbiased simulations to form a cluster as shown in Fig. 2 where the hydrophobic sections form a dry core and the hydrophilic segments are solvated on the outside of this core. We follow the mechanism of aggregation of the chains by focusing on two coordinates: a solvent coordinate measuring the size of largest bubble of vapour sites, and a polymer coordinate which describes the number of hydrophobic residues that are in contact, defined as their centres lying within a distance less than $2R + 1\text{\AA}$, where R is the residue radius. In this manner we have a reporter for both the



FIG. 4. The free energy landscape in the solvent coordinate for polymers which all have as half of their residues hydrophobes and as the other half hydrophilic residues, but where the distribution of hydrophobes within the sequence has been varied.

changes in the conformations of the polymer chains as well as on the behaviour of the solvent. Unbiased trajectories show that during the aggregation process initially rapid fluctuations in the number of hydrophobic contacts are observed; this process in itself does not, however, lead to aggregation of the chains since any contacts formed are able to dissociate readily during the simulation. However, the system may undergo a critical fluctuation in the water coordinate leading to the drying of a hydrophobic contact. This fluctuation then drives the complete aggregation as other residues are subsequently recruited into this hydrophobic core. This mechanism is analogous to that observed for the formation of intra-molecular contacts in purely hydrophobic chains studied previously¹⁷.

The importance of fluctuations in the solvent degrees of freedom, which allow hydrophobic contacts to be stabilised, raises the question of how the ease of generating such fluctuations depends on the sequence in which hydrophobic and hydrophilic residues are distributed within the polymer chain. This question is also motivated by the empirical observation that there is evidence from studies of protein sequences that significant evolutionary pressures govern the distributions of hydrophilic and hydrophobic residues in order to avoid unwanted aggregation²⁹, in addition to the more conventional role of sequence in determining the final fold of the chain³⁰.

We investigated this question by generating different sequences of polymers which all share the same average composition of 50% hydrophilic residues and 50% hydrophobic residues. The evaluation of the free energy barriers in Fig. 4 against aggregation reveals that the sequence of the polymer, even for a constant average composition, has a major role in determining its propensity to aggregate. The free energy barriers are significantly larger for polymers which have only small hydrophobic clusters and where the residues are evenly distributed throughout the chain. By contrast, for polypeptide chains where the hydrophobic residues are segregated to one end of the chain, we observe a significantly reduced barrier



FIG. 5. Analysis of the aggregation propensity horse heart apomyoglobin and a scrambled sequence²⁸ (top). The local Kyte-Doolittle hydrophobicity is shown as a bar chart as a function of residue number for both the wild type and scrambled sequence; a sliding window average of size 4 over the sequence length of wild type horse heart apomyoglobin (solid lines) compared to scrambled sequence resulting in an aggregation prone mutant (red line), highlighting the role of clusters of hydrophobic residues in favouring aggregation even in the absence of an overall increase of the hydrophobicity of the sequence, in agreement with the simulation results in Fig.4. The sequences are from²⁸.

and increased propensity to aggregate. The entropic penalty of bringing together a critical number of hydrophobic residues, that are required to observe a drying transition leading a stable hydrophobic contact, is significantly greater when these residues are not at adjacent positions in the chain but distributed throughout the sequence. In this manner, the interplay between polymer degrees of freedom and solvent degrees of freedom generates a very significant and sensitive dependency of the aggregation potential of the chain on the precise placement of the hydrophobic residues.

Interestingly, experiments designed to probe the aggregation propensity of sequence scrambled variants of the first 29 residues of horse heart apomyoglobin have been reported²⁸. This system consists of a short peptide where the amino acid composition has been kept constant, but several mutants were generated where the position of the amino acids within the sequence was varied. It was observed that such mutants possessed markedly different aggregation propensities despite their common amino acid composition, with aggregation prone clusters of hydrophobic residues being particularly associated with a high propensity to aggregate. To facilitate a quantitative comparison between these different peptides we map their sequences onto a quantitative measure of hydrophobicity. The Kyte-Doolittle scale³¹ is one such measure that associates a scalar hydrophobicity score with each amino acid. If we consider the local Kyte-Doolittle hydrophobicity³¹

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of the most aggregation prone mutant reported in the study relative to the aggregation resistant wild type, as shown in Fig. 5, a marked difference in the distribution pattern of the hydrophobic residues is apparent, with the aggregation-prone mutant possessing a cluster of hydrophobic residues which are distributed more evenly throughout the sequence for the wild type. This type of observation is in close agreement with the importance of clusters of hydrophobic residues determined from simulations in the present work.

III. CONCLUSIONS

In this paper we have developed and described an approach to use off-lattice solutes within a statistical mechanical model of lattice solvents. Our system is computationally tractable, yet includes the relevant solvent degrees of freedom. We have used this system to probe the role of the distribution within the sequence of amphiphilic polymers of the positions of hydrophobes. Our simulations show that highly aggregation prone chains result when the hydrophobes are not distributed evenly within the chain but cluster in close proximity along the chain. This clustering favours the nucleation of a dry hydrophobic core when two or more such chains come together, leading to an inter-molecular hydrophobic collapse stabilising the aggregated state.

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- ¹Wallqvist, A.; Berne, B. J. Chem. Phys. 1995, 99(9), 2893-2899.
- ²Lum, K.; Chandler, D.; Weeks, J. D. J. Phys. Chem. B **1999**, 103(22), 4570– 4577.
- ³Huang, D. M.; Geissler, P. L.; Chandler, D. J. Phys. Chem. B **2001**, 105(28), 6704–6709.
- ⁴Raschke, T. M.; Tsai, J.; Levitt, M. Proc. Natl. Acad. Sci **2001**, 98(11), 5965–5969.
- ⁵Huang, D. M.; Chandler, D. J. Phys. Chem. B 2002, 106(8), 2047–2053.
- ⁶Dixit, S.; Crain, J.; Poon, W.; Finney, J.; Soper, A. *Nature* **2002**, *416*(6883), 829–832.
- ⁷Chandler, D. *Nature* **2005**, *437*(7059), 640–647.
- ⁸Granick, S.; Bae, S. C. Science (New York, NY) **2008**, 322(5907), 1477–1478.
- ⁹Rasaiah, J. C.; Garde, S.; Hummer, G. Annu. Rev. Phys. Chem. 2008, 59, 713–740.
- ¹⁰Willard, A. P.; Chandler, D. J. Phys. Chem. B 2008, 112(19), 6187–6192.
- ¹¹Berne, B. J.; Weeks, J. D.; Zhou, R. Annu. Rev. Phys. Chem. **2009**, 60, 85.
- ¹²Patel, A. J.; Varilly, P.; Chandler, D. J. Phys.Chem. B 2010, 114(4), 1632– 1637.
- ¹³Hummer, G. Nature chemistry **2010**, 2(11), 906–907.
- ¹⁴Garde, S.; Patel, A. J. Proc. Natl. Acad. Sci 2011, 108(40), 16491–16492.
- ¹⁵Patel, A. J.; Varilly, P.; Jamadagni, S. N.; Hagan, M. F.; Chandler, D.; Garde, S. J. Phys.Chem. B 2012, 116(8), 2498–2503.
- ¹⁶Ben-Amotz, D. J. Phys. Chem. Lett 2015.
- ¹⁷ten Wolde, P. R.; Chandler, D. Proc. Natl. Acad. Sci **2002**, 99(10), 6539– 6543.
- ¹⁸Miller, T. F.; Vanden-Eijnden, E.; Chandler, D. Proc. Natl. Acad. Sci 2007, 104(37), 14559–14564.
- ¹⁹Jamadagni, S. N.; Godawat, R.; Dordick, J. S.; Garde, S. J. Phys.Chem. B 2008, 113(13), 4093–4101.
- ²⁰Hummer, G.; Garde, S.; Garcia, A. E.; Pohorille, A.; Pratt, L. R. *Proc. Natl. Acad. Sci* **1996**, *93*(17), 8951–8955.
- ²¹Chandler, D. Phys. Rev. E 1993, 48(4), 2898.
- ²²Varilly, P.; Patel, A. J.; Chandler, D. J. Chem. Phys. 2011, 134(7), 074109.
- ²³Weeks, J. D. J. Chem. Phys 1977, 67, 3106.
- ²⁴Vaikuntanathan, S.; Geissler, P. L. Phys. Rev. Lett. 2014, 112(2), 020603.
- ²⁵Vaikuntanathan, S.; Rotskoff, G.; Hudson, A.; Geissler, P. L. Proc. Natl. Acad. Sci **2016**, *113*(16), E2224–E2230.
- ²⁶Levitt, M. J. Mol. Biol. 1976, 104(1), 59-107.
- ²⁷Roseman, M. A. J. Mol. Biol **1988**, 201(3), 621–623.
- ²⁸Monsellier, E.; Ramazzotti, M.; de Laureto, P. P.; Tartaglia, G.-G.; Taddei, N.; Fontana, A.; Vendruscolo, M.; Chiti, F. *Biophys. J.* **2007**, *93*(12), 4382 – 4391.
- ²⁹DuBay, K. F.; Pawar, A. P.; Chiti, F.; Zurdo, J.; Dobson, C. M.; Vendruscolo, M. J. Mol. Biol **2004**, 341(5), 1317–1326.
- ³⁰Anfinsen, C. B. Science **1973**, 181(96), 223–230.
- ³¹Kyte, J.; Doolittle, R. F. J. Mol. Biol 1982, 157(1), 105–132.