

Studies of an off-lattice model for protein folding: Sequence dependence and improved sampling at finite temperature

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We study the thermodynamic behavior of a simple off-lattice model for protein folding. The model is two dimensional and has two different “amino acids.” Using numerical simulations of all chains containing eight or ten monomers, we examine the sequence dependence at a fixed temperature. It is shown that only a few of the chains exist in unique folded state at this temperature, and the energy level spectra of chains with different types of behavior are compared. Furthermore, we use this model as a testbed for two improved Monte Carlo algorithms. Both algorithms are based on letting some parameter of the model become a dynamical variable; one of the algorithms uses a fluctuating temperature and the other a fluctuating monomer sequence. We find that by these algorithms one gains large factors in efficiency in comparison with conventional methods. © 1995 American Institute of Physics.

I. INTRODUCTION

The protein molecule is a very complex system, and understanding the folding of natural proteins remains one of the most challenging problems in biophysics. In recent years there has been an increasing interest in understanding the relevant mechanisms of the folding process by studying simplified models. Several authors have used ideas from spin-glass theory to gain useful insights into the behavior of self-interacting random chains.¹⁻⁵ The picture emerging from these studies is that the phase diagram consists of coil, globule, and frozen phases. In the frozen phase the system exists in one of a number of different states, each corresponding to a fairly well-defined shape. This phase is interesting from the viewpoint of proteins, but for a generic random sequence it appears impossible to identify a state corresponding to the unique native state of a protein.

The sequence dependence of the folding properties has been studied numerically in various models.⁶⁻¹⁴ An extensive study was reported recently by Šali *et al.*,¹¹ who examined the behavior of 200 randomly selected sequences in a lattice model with contact interactions. It was found that 30 of these exhibited a folded state which was both thermodynamically dominant and kinetically accessible in a reasonable time. The existence of folding and nonfolding sequences has been observed also in off-lattice models,¹⁰ but much less is known about the behavior of such models. In this paper we study the thermodynamic behavior of different sequences in a very simple off-lattice model.

The model studied has been proposed by Stillinger *et al.*¹⁵ It is two dimensional and has only two kinds of “amino acids.” In Refs. 15 and 16 the energy and structure of the ground state was determined for all possible chains with seven or fewer monomers, and an interesting interpretation of the results was obtained by employing neural-network techniques. In this paper we study the behavior of the model at finite temperature. To study the sequence de-

pendence, we have carried out numerical simulations of all possible chains containing eight or ten monomers at a fixed temperature. We find that only a few of the chains exist in a unique folded state at this temperature. These chains have a relatively high folding temperature T_f . This property is important because the dynamics tends to be very slow at low temperature. Chains with a high T_f are therefore more likely to satisfy both the thermodynamic and kinetic requirements for folding. We have also determined the low-lying energy levels of a few different sequences. Sequences with good folding properties are expected to exhibit a large stability gap,¹⁴ which is defined as the energy gap between the native state and the lowest of all states with little structural similarity to the native state. The stability gaps of the sequences we have studied show a wide variation, and, as expected, it is large when T_f is high.

This first part of our study shows that the model displays interesting features for relatively short chains. It has been performed by using the well established hybrid Monte Carlo algorithm.¹⁷ In the second part of the paper, we use the model as a testbed for two algorithms that are meant to facilitate the study of longer chains.

Simulations of heteropolymeric chains at low temperature are notoriously difficult, due to the presence of high free-energy barriers separating different folded states. The problem is that any local algorithm requires the system to pass through these barriers, which leads to a suppression of transitions between different free-energy valleys. A method designed to overcome this difficulty is the multicanonical Monte Carlo algorithm,¹⁸ which is closely related to the umbrella-sampling method.¹⁹ The trick used here is to simulate a modified energy function which one tries to choose so as to eliminate the free-energy barriers. The canonical distribution is then extracted by means of the reweighting technique.²⁰

An alternative approach is provided by the method of simulated tempering.²¹ In this method the temperature becomes a dynamical variable which takes values ranging over a definite set. In this way one tries to utilize the fact that at higher temperature the free-energy barriers are lower. In Ref.

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21 this method was successfully applied to the random-field Ising model. The idea to let some parameter of the model become a dynamical variable has subsequently been used to accelerate simulations of other systems, too.^{22–25} It had earlier been shown by Lyubartsev *et al.*²⁶ that this is a useful method for calculating the free energy.

In this paper we investigate the use of the dynamical-parameter method in simulating heteropolymeric chains. We consider the simulated-tempering algorithm, and also another algorithm of the same type which we call the multisequence algorithm. In this algorithm the sequence degrees of freedom become a dynamical variable, which means that a number of different monomer sequences are simulated in parallel. We compare the performance of these two algorithms with that of hybrid Monte Carlo. Our results show that by the dynamical-parameter algorithms one greatly reduces the amount of computer time required for a representative sampling of the different folded states.

The plan of this paper is as follows. The model is described in Sec. II and the algorithms in Sec. III. Section IV deals with homopolymers, whereas general sequences are studied in Sec. V. In Sec. VI we present the results of our tests of the dynamical-parameter algorithms. Section VII is a summary.

II. THE MODEL

The model studied has two kinds of monomers, to be called *A* and *B*. The monomers are linked by rigid bonds of unit length to form linear chains living in two dimensions. For an *N*-mer we specify the sequence of monomers by the binary variables ξ_1, \dots, ξ_N and the configuration by the angles $\theta_2, \dots, \theta_{N-1}$, where θ_i denotes the bend angle at site *i* and is taken to satisfy $|\theta_i| \leq \pi$. The energy function is

$$E(\theta, \xi) = \sum_{i=2}^{N-1} E_1(\theta_i) + \sum_{i=1}^{N-2} \sum_{j=i+2}^N E_2(r_{i,j}, \xi_i, \xi_j), \quad (1)$$

where

$$E_1(\theta_i) = \frac{1}{4}(1 - \cos \theta_i),$$

$$E_2(r_{ij}, \xi_i, \xi_j) = 4(r_{ij}^{-12} - C(\xi_i, \xi_j)r_{ij}^{-6}) \quad (2)$$

and $r_{ij} = r_{ij}(\theta_{i+1}, \dots, \theta_{j-1})$ denotes the distance between sites *i* and *j* of the chain. The term $E_1(\theta_i)$ favors alignment of the three successive sites *i*−1, *i* and *i*+1. The nonbonded interactions E_2 are Lennard-Jones potentials with a species-dependent coefficient $C(\xi_i, \xi_j)$, which is taken to be 1 for an *AA* pair (strong attraction), 1/2 for a *BB* pair (weak attraction), and −1/2 for an *AB* pair (repulsion). Consequently, there is an energetic preference for separation between the two kinds of monomers. In fact, it was demonstrated in Ref. 15 that ground-state configurations tend to have a core consisting mainly of *A* monomers, which shows that *A* and *B* monomers behave respectively as hydrophobic and polar residues.

The energy is, for fixed sequence, a function only of the angles θ_i , and is therefore translationally and rotationally invariant. In addition, it is invariant under reflection ($\theta_i \rightarrow -\theta_i$ for all *i*) and change of the orientation ($\theta_i \rightarrow \theta_{N-i+1}$ and $\xi_i \rightarrow \xi_{N-i+1}$ for all *i*). This implies that a

generic energy level is fourfold degenerate for symmetric sequences, and twofold degenerate for asymmetric sequences. In numerical simulations these symmetries provide useful checks on effective ergodicity breaking.

The behavior of the model at finite temperature *T* is defined by the partition function

$$Z(T, \xi) = \int \left[\prod_{i=2}^{N-1} d\theta_i \right] \exp(-E(\theta, \xi)/T). \quad (3)$$

That the *T* dependence of this simple model exhibits an interesting phase structure will become clear in Secs. IV and V.

III. THE ALGORITHMS

A. Hybrid Monte Carlo

We give a brief description of the hybrid Monte Carlo algorithm,¹⁷ which is a general method for simulating systems with continuous degrees of freedom at constant temperature. More about the use of this method in simulating polymers and proteins can be found in Refs. 27–30.

The algorithm is based on the evolution arising from a fictitious Hamiltonian, which in our calculations was taken as

$$H_{MC}(\pi, \theta) = \frac{1}{2} \sum_{i=2}^{N-1} \pi_i^2 + E(\theta, \xi)/T, \quad (4)$$

where π_i is an auxiliary momentum variable conjugate to θ_i . The first step in the algorithm is to generate a new set of momenta π_i from the equilibrium distribution $P(\pi_i) \propto \exp(-\pi_i^2/2)$. Starting from these momenta and the old configuration, the system is evolved through a finite-step approximation of the equations of motion. The configuration generated in such a trajectory is finally subject to an accept-or-reject question. The probability of acceptance in this global Metropolis step is $\min(1, \exp(-\Delta H_{MC}))$, where ΔH_{MC} is the energy change in the trajectory. This accept-or-reject step removes errors due to the discretization of the equations of motion.

When integrating the discretized equations of motion, two sites of the chain can come so close to each other that the hard r^{-12} repulsion causes numerical instabilities. To avoid this problem, we have used a modified, linear potential for very small monomer—monomer separations. The effect of this on the sampling distribution was negligible, as the original and modified Boltzmann weights were both extremely small in this part of configuration space. In our simulations none of the accepted configurations belonged to the region with modified potential.

The algorithm described above has two tunable parameters, namely the step size, ϵ , and the number of steps in each trajectory, *n*. In our calculations we have used trajectories of length $n\epsilon = 1$ and values of *n* between 50 and 125.

It has been shown how hybrid Monte Carlo can be used to simulate efficiently various homopolymers with self-repulsion.²⁹ However, in the application considered here, we expect the efficiency of hybrid Monte Carlo to be similar to that of conventional methods.

B. The dynamical-parameter method

A simulation method meant for systems with a rough free-energy landscape is the dynamical-parameter method. The basic step in this approach is to create an enlarged configuration space by introducing a new variable k . This variable can take K different values, $k=1, \dots, K$, which correspond to different values of the parameters of the model. In this way one tries to circumvent the barriers in the original free-energy landscape.

We use the dynamical-parameter method to simulate the Boltzmann distribution $P_{\xi, T}(\theta) \propto \exp(-E(\theta, \xi)/T)$ for fixed sequence ξ and temperature T . To do that, we assign one sequence, $\xi^{(k)}$, and one temperature, $T^{(k)}$, to each k , taking $\xi^{(k)} = \xi$ and $T^{(k)} = T$ for some k . Using standard methods, we then simulate the joint probability distribution $P(\theta, k) \propto \exp(-g_k - E(\theta, \xi^{(k)})/T^{(k)})$, where the g_k 's are constants that will be discussed below. Finally, knowing $P(\theta, k)$, one can obtain the distribution $P_{\xi^{(k_0)}, T^{(k_0)}}(\theta)$, for any k_0 , by simply restricting $P(\theta, k)$ to the subspace of fixed $k=k_0$.

We study two different algorithms of this type, simulated tempering²¹ and the multisequence algorithm. The difference between these algorithms lies in the choice of the sets $\{\xi^{(k)}\}$ and $\{T^{(k)}\}$. In simulated tempering the temperature fluctuates, while the sequence is held fixed, i.e., $\xi^{(1)} = \dots = \xi^{(K)}$. The multisequence algorithm, on the other hand, uses a set of different sequences and a fixed temperature, i.e., $T^{(1)} = \dots = T^{(K)}$.

The g_k 's are free parameters that determine the weights p_k of the different k values, which are given by

$$p_k = \frac{\exp(-g_k)Z_k}{\sum_{k'}^K \exp(-g_{k'})Z_{k'}},$$

where $Z_k = Z(T^{(k)}, \xi^{(k)})$. The method is free from systematic errors for any choice of the g_k 's, but the efficiency depends strongly on these parameters. In fact, if they are not chosen carefully, it can easily happen that the system gets trapped at a fixed value of k . In our calculations the g_k 's have been chosen so as to obtain a roughly uniform k distribution. To that end, we used a number of trial runs, as will be described in Sec. VI. If the p_k 's corresponding to some choice of the g_k 's are known, the uniform distribution is obtained by replacing g_k by $g_k + \ln p_k$.

Next we turn to our simulations of the joint distribution $P(\theta, k)$. For the θ update we have employed the hybrid Monte Carlo method described above. To facilitate comparisons, we used the same values of n and ϵ as in our hybrid Monte Carlo runs. Our updates of k were ordinary Metropolis steps.³¹ In our simulated-tempering runs we used an ordered set of allowed temperature values and changed k in steps of ± 1 . Each hybrid Monte Carlo trajectory was followed by one Metropolis step in k , and the average acceptance rate was 79% for the k update. In our multisequence runs we chose to work with all possible sequences with a fixed composition, i.e., with fixed numbers of A and B monomers, and the updates of k corresponded to interchanges of the monomers at two randomly chosen sites. Here, one update cycle consisted of one hybrid Monte Carlo

trajectory followed by 100 Metropolis steps in k . In the final run, after adjusting the g_k 's, about 4% of the cycles led to a change of k .

The acceptance rate for the θ update depends on k and was typically around 90%. The fraction of the total computer time spent on k updates was about 12% in our multisequence calculations and much less than 1% in our simulated-tempering calculations. Notice that the k update leave the energy unchanged in simulated tempering.

In simulated tempering it is possible to avoid a low acceptance rate for the k update by choosing a sufficiently dense (and large) set of $T^{(k)}$'s. The situation is different for the multisequence algorithm, since the sequences $\xi^{(k)}$ are picked from a discrete set. If the acceptance rate is low in a multisequence simulation, it may be useful to introduce auxiliary sequences that interpolate between those of the model studied.

IV. HOMOPOLYMERS

We begin our study of the model defined in Sec. II by investigating the behavior of homopolymers and how that depends on the temperature. The numerical simulations discussed in this and the next section have been performed by using the hybrid Monte Carlo method.

It is well known that the importance of the r^{-6} terms in the potential varies with the temperature. At high temperature the influence of these terms is weak and the chains are expected to behave essentially as self-avoiding walks. At low temperature, on the other hand, they give rise to a strong effective attraction between monomers of the same type, which leads to globular chains.

To study how the extent of the homopolymers varies with the temperature, we carried out numerical simulations for $N=8$ and 12. In Fig. 1(a) we show the results for the ratio $R = \langle r_{ee}^2 \rangle / \langle r_{gyr}^2 \rangle$, where r_{ee} denotes the end-to-end distance and r_{gyr} the radius of gyration. At high temperature the results are fairly close to $R \approx 7.13$, which is the value expected for two-dimensional self-avoiding walks in the limit $N \rightarrow \infty$.^{32,33} The corresponding value for ideal and quasi-ideal chains is $R=6$. Values of R less than six indicate that the system is in the globule phase. From the figure we estimate that both the homopolymers are in the globule phase if $T < 0.3$. Our study of general sequences, which will be discussed in the next section, has been carried out using $T=0.2$.

Even though A and B homopolymers are both compact at $T=0.2$, they behave slightly differently. This can be seen from the probability distributions of the total bend angle $\theta = \sum_{i=2}^{N-1} \theta_i$ which are shown in Fig. 1(b). The distribution for the A chain has many narrow peaks, while that for the B chain is dominated by a single, broad peak. The origin of this difference becomes clear when studying the low-lying energy minima. To determine local energy minima we have employed a quenching procedure; during a Monte Carlo simulation at fixed temperature, the system was quenched to zero temperature at regular intervals by using a conjugate gradient method. In Fig. 2 we show the minimum energy configurations for $N=12$. After checking the results by re-

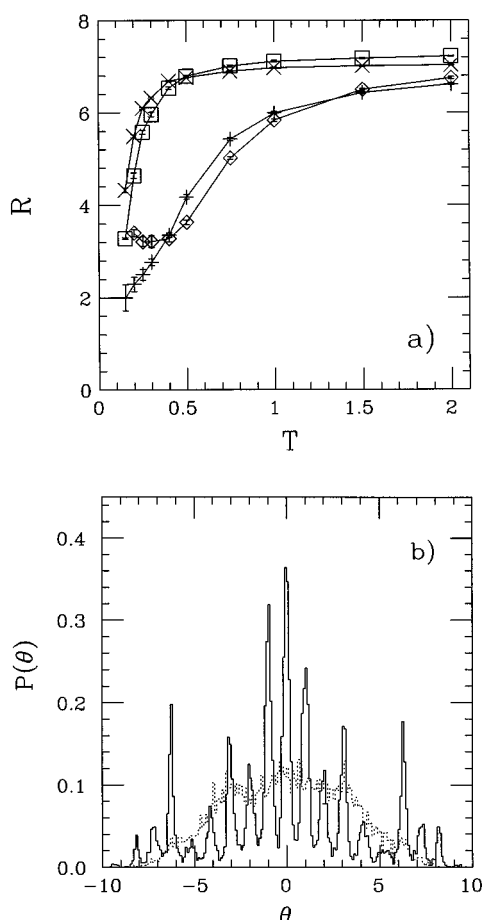


FIG. 1. (a) The temperature dependence of the ratio $R = \langle r_{cc}^2 \rangle / \langle r_{gyr}^2 \rangle$ for A (pluses $N=8$, diamonds $N=12$) and B (crosses $N=8$, squares $N=12$) homopolymers. (b) Histogram of the total bend angle θ for A (solid line) and B (dotted line) homopolymers with $N=12$ at $T=0.2$.

peated use of simulated annealing, we feel confident that indeed these are ground-state configurations. Also, we checked that all the four symmetry related copies of these states were visited in the simulations.

The structure of the ground state is the result of an interplay between the bend energy and the Lennard-Jones terms. In Fig. 2 the sites of the A chain approximately reside on a regular triangular lattice, which is not true for the B chain. This reflects the fact that the bend energy plays a more important role for the B than for the A chain, which has deeper Lennard-Jones potentials. The lattice structure can also be seen in other low-lying states of the A homopolymer, and is responsible for the many distinct peaks in the θ distribution [see Fig. 1(b)].

V. GENERAL SEQUENCES

Our study of general sequences has been carried out using $N=8$ and 10 and a fixed temperature $T=0.2$. At this temperature the homopolymers have a compact form, but large fluctuations take place in the positions of the individual monomers. As will be shown in this section, there are mixed sequences which, by contrast, exist in a unique state of fairly well-defined shape.

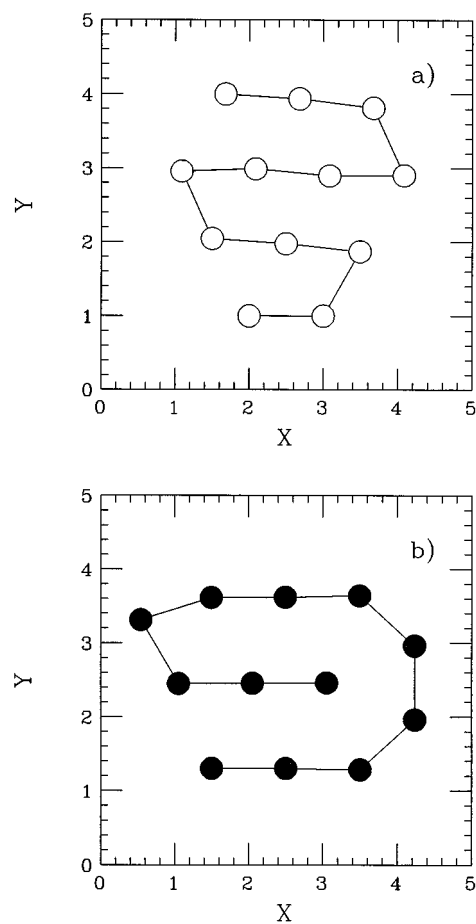


FIG. 2. Ground-state configurations for the (a) A and (b) B homopolymers with $N=12$.

To get a measure of the fluctuations in shape, we introduce the usual mean-square distance between configurations. For two configurations a and b we define

$$\delta_{ab}^2 = \min \frac{1}{N} \sum_{i=1}^N |\bar{x}_i^{(a)} - \bar{x}_i^{(b)}|^2, \quad (6)$$

where $|\bar{x}_i^{(a)} - \bar{x}_i^{(b)}|$ denotes the distance between the sites $\bar{x}_i^{(a)}$ and $\bar{x}_i^{(b)}$ ($\bar{x}_i^{(a)}, \bar{x}_i^{(b)} \in \mathbb{R}^2$), and where the minimum is taken over translations, rotations and the discrete symmetries discussed in Sec. II. The probability distribution of δ^2 for fixed temperature and sequence, $P(\delta^2)$, can be obtained numerically and is very informative,³⁴ as it describes the magnitude of the thermodynamically relevant fluctuations. To determine $P(\delta^2)$, we computed δ^2 for every possible pair in a set of 2000 configurations, recorded at intervals of 100 trajectories or more.

We have calculated $P(\delta^2)$ for all the 136 distinguishable chains with $N=8$ (the number of distinguishable $2n$ -mers is $2^{n-1}(2^n + 1)$). In Fig. 3(a) we show the average values $\langle \delta^2 \rangle$ of these distributions, plotted against the number of B monomers. This figure shows that $\langle \delta^2 \rangle$ varies considerably, and that values occur which are much smaller than those for the homopolymers. In Fig. 3(b) we show $P(\delta^2)$ for the sequences S1–4 in Table I. S1 and S2 are the two homopolymers. S3 has the smallest average value $\langle \delta^2 \rangle$ of all

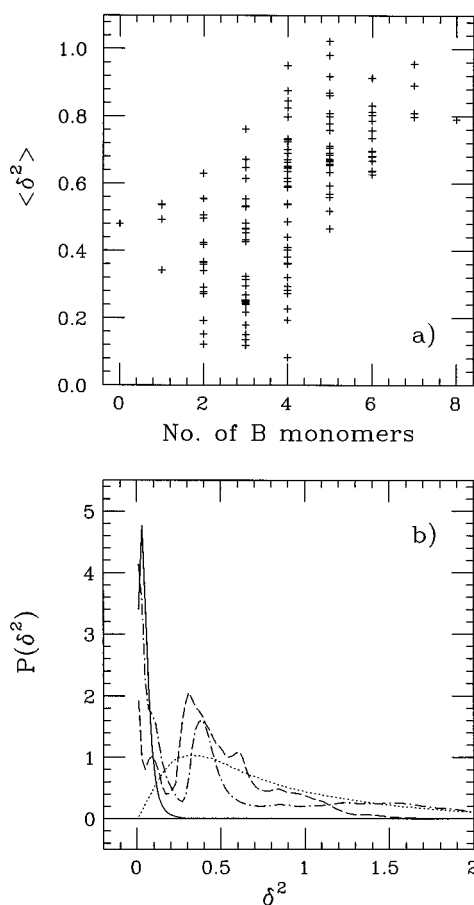


FIG. 3. (a) Average values $\langle \delta^2 \rangle$ for the 136 chains with $N=8$, plotted against the number of B monomers. The statistical errors are roughly of the size of the plot symbols. (b) Histograms of δ^2 for the sequences S1 (dashes), S2 (dots), S3 (solid), and S4 (dot-dash) (see Table I). The distribution for S3 has been normalized to 1/3.

the 136 sequences. S4 has the same composition as S3 but a more typical $\langle \delta^2 \rangle$. That the shape of $P(\delta^2)$ is irregular for the A homopolymer is due to the lattice structure discussed above. It should become smoother with increasing N . For S3 the distribution is dominated by a single, narrow peak located at low δ^2 , which shows that this chain exists in a state of fairly precise shape. There are other $N=8$ chains which exhibit the same type of behavior. However, the number of such sequences is small, as can be seen from the average values in Fig. 3(a).

TABLE I. Sequences referred to in the text. The average values were obtained at $T=0.2$.

N	Sequence	$\langle \delta^2 \rangle$	$\langle r_{\text{gyr}}^2 \rangle$	
S1	8	AAAAAAA	0.48(2)	1.262(3)
S2	8	BBBBBBB	0.79(2)	2.31(2)
S3	8	AABBBAA	0.081(6)	1.555(5)
S4	8	ABAABBA	0.57(2)	1.919(2)
S5	10	AAAAAAAAA	0.778(6)	1.633(2)
S6	10	BBBBBBBBB	1.164(12)	2.941(11)
S7	10	AABAABA	0.090(8)	1.707(2)
S8	10	ABAAAABA	0.510(12)	1.827(2)

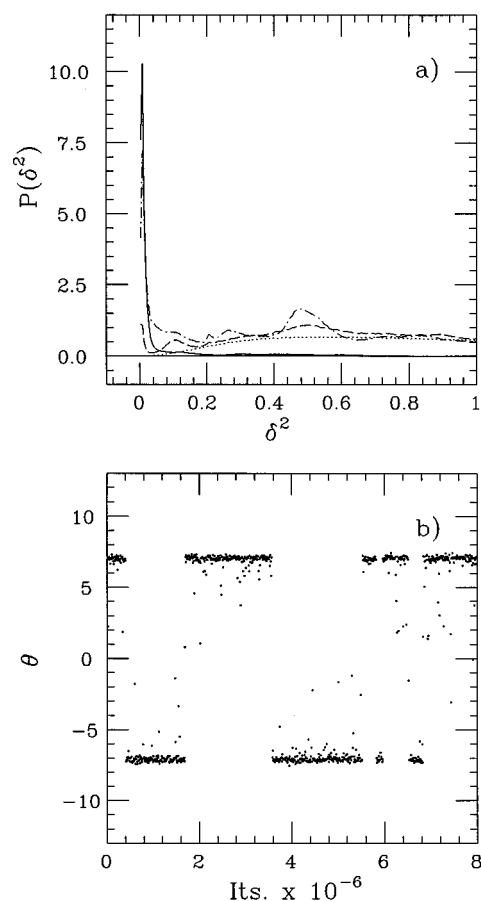


FIG. 4. (a) Histogram for δ^2 for the sequences S5 (dashes), S6 (dots), S7 (solid), and S8 (dot-dash) (see Table I). The distribution for S7 has been normalized to 1/5. (b) Monte Carlo evolution of the total bend angle θ for the chain S7. Data have been taken every 10 000 trajectories.

The folding temperature T_f may be defined as the lowest temperature at which $\langle \delta^2 \rangle$ takes some suitably chosen value c . For reasonable choices of c , it is clear from Fig. 3(a) that the number of $N=8$ sequences with $T_f > 0.2$ is small.

To test the size dependence of these results, we have also studied the chains containing ten monomers. First we performed short simulations of all the 528 chains of this length. Even though some of these simulations were too short, the results clearly showed that most of the chains do not exhibit a well-defined shape at this temperature. Notice that too short runs tend to give underestimates of $\langle \delta^2 \rangle$. After these preliminary runs, we picked out the four sequences S5–8 in Table I and performed longer simulations of these. S7 is the $N=10$ sequence with smallest $\langle \delta^2 \rangle$, according to the preliminary runs, and S8 is a sequence with the same composition as S7. In Fig. 4(a) we show $P(\delta^2)$ for S5–8. The result of the longer run confirms that S7 exists in a unique folded state. Since the sequence is asymmetric, there are two copies of this state. From Fig. 4(b) it can be seen that these symmetry related states were both visited in the simulation, but transitions from one state to the other are rare.

The results presented so far in this section were obtained at a fixed temperature. Let us also briefly discuss the transition to the folded low-temperature phase for the sequence

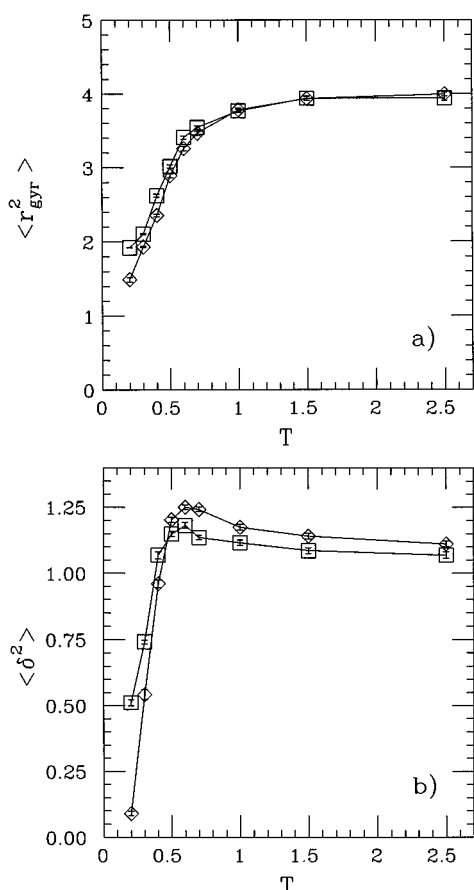


FIG. 5. Temperature dependence of (a) $\langle r_{\text{gyr}}^2 \rangle$ and (b) $\langle \delta^2 \rangle$ for the sequences S7 (diamonds) and S8 (squares) (see Table I).

S7. We compare the behavior of S7 with that of S8, which has a folding temperature lower than 0.2. In Fig. 5(a) we show the temperature dependence of $\langle r_{\text{gyr}}^2 \rangle$ and $\langle \delta^2 \rangle$. The radius of gyration is similar for the two sequences, which is expected since they have the same composition, and it decreases gradually as the temperature is decreased. The temperature dependence of $\langle \delta^2 \rangle$ is more dramatic. We see that the transition from a high-temperature state with large fluctuations in shape to a frozen shape is fairly abrupt for S7.

Finally, let us compare the energy level spectra of the sequences S3 and S5–8. We have seen that S3 and S7, unlike the other three sequences, have a folding temperature higher than 0.2. In Fig. 6 we show how the low-lying local energy minima are distributed in the $(\delta_0^2, \Delta E)$ plane, where δ_0^2 is the mean-square distance to the lowest minimum found [cf. Eq. (6)] and ΔE is the energy difference to this minimum. The minima were determined by using the quenching procedure mentioned in Sec. IV, and the figure shows all the minima found with $\Delta E < 0.9$. From the figure it can be seen that for S7 there is only one minimum with $\Delta E < 0.9$. For S3 there are two such minima which are structurally very similar. The stability gap defined in Sec. I is therefore large for both the sequences with high T_f , as expected. The behavior of S3 illustrates that it is important to distinguish between this gap and the energy gap between the two lowest of all minima.

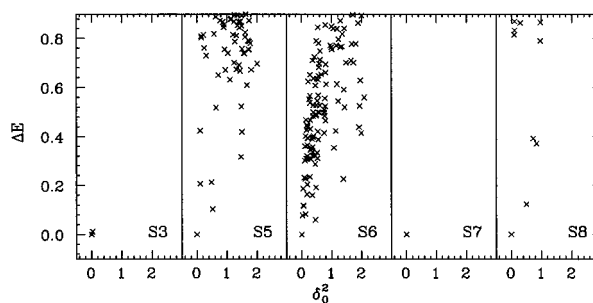


FIG. 6. Local energy minima for the sequences S3 and S5–8 (see Table I).

VI. TESTS OF THE DYNAMICAL-PARAMETER ALGORITHMS

We have tested the performance of the two dynamical-parameter algorithms described in Sec. III using several different sequences. The results obtained for the different sequences were qualitatively very similar. For clarity we focus here on the results for a specific sequence, namely AA-BAAABBA, at $T=0.17$.

In Fig. 7(a) we show the probability distribution of the total bend angle $\theta = \sum_{i=2}^{N-1} \theta_i$, which is dominated by three narrow and well separated peaks. By measuring mean-square deviations [cf. Eq. (6)], we checked that the central peak represents small fluctuations around the minimum energy configuration, which is shown in Fig. 7(b). The next-lowest energy minimum is shown in Fig. 7(c), and is very similar to the lowest minimum if one neglects the chain structure. However, for the next-lowest minimum we have $\theta \approx 6.1$, which coincides with the position of the rightmost peak in $P(\theta)$. The third peak, at $\theta \approx -6.1$, is related by symmetry to the one at $\theta \approx 6.1$.

When simulating this system by standard methods, the major difficulty is that transitions between the three different regions corresponding to these peaks are strongly suppressed. By the dynamical-parameter method one can greatly improve the frequency of these transitions, as will be seen below. Frequent transitions between the two symmetry re-

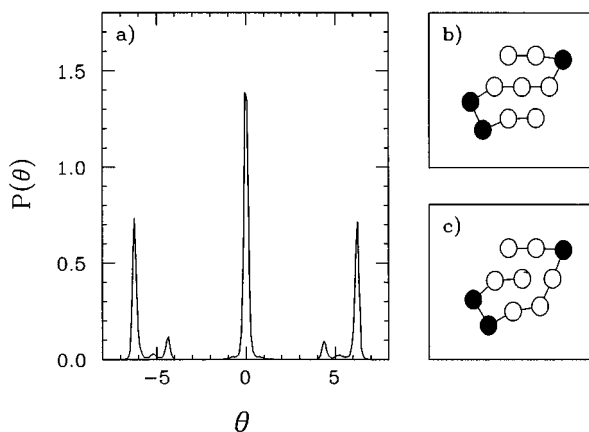


FIG. 7. (a) Histogram of the total bend angle θ . (b) Ground-state configuration. (c) The next-lowest local energy minimum. Open and filled circles represent A and B monomers, respectively.

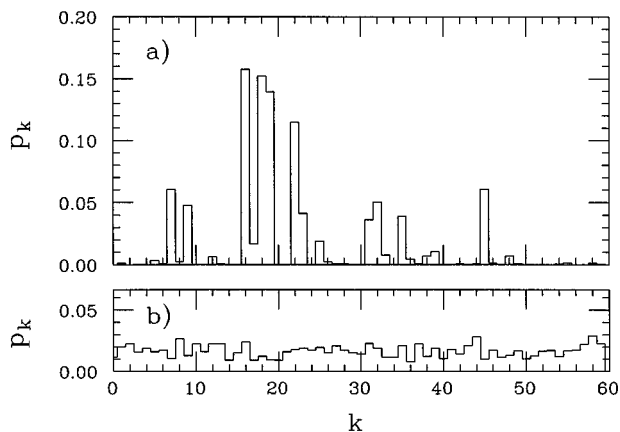


FIG. 8. The weights p_k in the multisequence calculation: (a) for all $g_k=0$ and (b) for our final choice the g_k 's.

lated regions can, of course, also be obtained by incorporating global, random flips of the signs of the θ_i 's into the update scheme. The important and nontrivial problem is to obtain transitions that connect these two regions with the $\theta \approx 0$ region.

Before running the dynamical-parameter algorithms, one has to determine the parameters g_k . We have done that in slightly different ways for the two algorithms. In our multisequence runs the set of sequences $\xi^{(k)}$ consisted of all the 60 sequences containing seven *A* and three *B* monomers. To determine the corresponding g_k 's, we carried out four trial runs, covering a total of 6×10^5 update cycles. After each of these runs the g_k 's were adjusted, using the measured weights p_k as described in Sec. III. In Fig. 8 we show the 60 different weights before and after the tuning procedure. None of the final p_k 's is smaller than $1/2 \times 1/60 \approx 0.008$.

In our simulated-tempering runs there were 12 allowed values of the temperature, $0.17 = T^{(1)} < \dots < T^{(12)} = 0.47$, which were equidistant in $1/T$. Here, we first performed short hybrid Monte Carlo simulations, each consisting of 1000 trajectories, to get rough estimates of the average energy at these temperature values, $\langle E \rangle_k$. We then put $g_{12} = 0$ and $g_{k-1} = g_k - \langle E \rangle_k (1/T^{(k-1)} - 1/T^{(k)})$ for $k < 12$. This relation between g_{k-1} and g_k is obtained by requiring that $p_{k-1} = p_k$ and neglecting terms that are of order 2 or higher in $1/T^{(k-1)} - 1/T^{(k)}$. One of the g_c 's can be chosen freely, since only the differences between them are relevant. To fine-tune the g_c 's, we finally carried out two simulated-tempering runs, each consisting of 2×10^4 update cycles.

Having chosen the g_k 's, we performed one long production run for each of the two algorithms. In Fig. 9 we show the evolution of θ in these simulations. Only data corresponding to $T=0.17$ and sequence *AABAAABBAA* are shown, and they are plotted against the total number of update cycles. Also shown in Fig. 9 is the result of a hybrid Monte Carlo run. The same values of the simulation parameters n and ϵ have been used in the three different runs. The CPU time per iteration is therefore very similar for the hybrid Monte Carlo and simulated-tempering runs, and 12% higher for the multisequence run.

From Fig. 9 it is evident that transitions between the

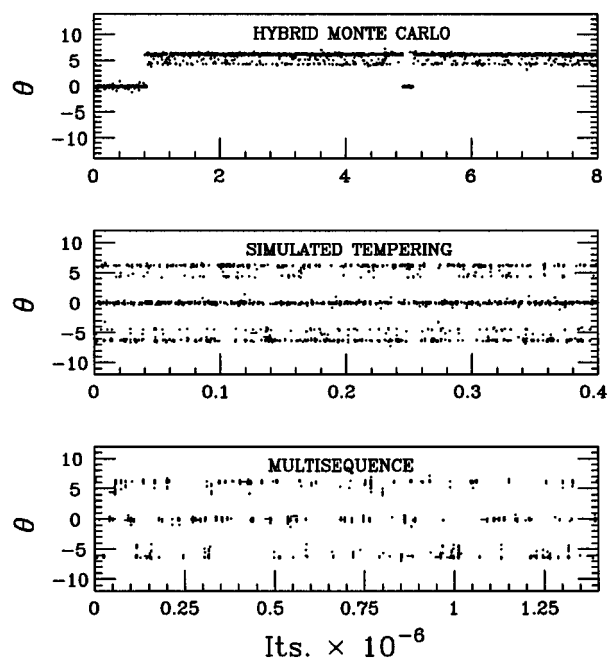


FIG. 9. Evolution of the total bend angle θ in three different simulations.

three different regions mentioned above are indeed much more frequent in the dynamical-parameter simulations than in the hybrid Monte Carlo simulation. In the hybrid Monte Carlo run there are only six transitions (three of which are difficult to see in the figure) in 8×10^6 trajectories, and one of the three regions is, in fact, never visited. By contrast, every region is visited many times in the two other runs, even though these are shorter. The frequency of transitions to and from the region with $\theta \approx 0$ is respectively 9.4×10^{-4} and 5.7×10^{-5} per update cycle in the simulated-tempering and multisequence runs.

The improved transition frequency is the major advantage of the dynamical-parameter simulations. In addition, these simulations can be used to study several different temperature values or sequences. The disadvantage of the method is that a number of trial runs are needed in order to determine the g_k 's. In our simulated-tempering and multisequence calculations we have spent, respectively, 12% and 30% of the total computer time on trial runs. Let us stress that the total cost of each of these two calculations is still considerably lower than that of our hybrid Monte Carlo run (cf. Fig. 9).

VII. SUMMARY

We have studied numerically the finite-temperature behavior of a simple off-lattice model for protein folding. All possible chains containing eight or ten monomers were studied at a fixed temperature, which was chosen low enough for all the chains to be fairly compact. We showed that most of the chains undergo large fluctuations in shape at this temperature, while a few exist in a unique state of well-defined shape. We determined the low-lying local energy minima for a few different sequences, and found that the stability gaps

vary considerably. This suggests that there are important differences in folding temperature, and, therefore, in the ability to fold fast, between different sequences.

Although the relatively short chains studied here exhibit interesting properties, it would, of course, be desirable to extend the study to considerably longer chains. To be able to do that, it is of great interest to find improved Monte Carlo methods. We have in this paper studied two dynamical-parameter algorithms, simulated tempering and the multisequence algorithm, which were found to be much more efficient than conventional simulation methods. The two algorithms are also useful for energy minimization, if combined with a suitable local optimization method.

It would be interesting to compare the performance of these algorithms with that of the multicanonical Monte Carlo algorithm which was mentioned in Sec. I. Multicanonical heteropolymer simulations have recently been reported.^{35–37}

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