Parallel-tempering cluster algorithm for computer simulations of critical phenomena

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In finite-size scaling analyses of Monte Carlo simulations of second-order phase transitions one often needs an extended temperature range around the critical point. By combining the parallel-tempering algorithm with cluster updates and an adaptive routine to find the temperature window of interest, we introduce a flexible and powerful method for systematic investigations of critical phenomena. As a result, we gain one to two orders of magnitude in the performance for two- and three-dimensional Ising models in comparison with the recently proposed Wang-Landau recursion for cluster algorithms based on the multibondic algorithm, which is already a great improvement over the standard multicanonical variant.

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I. INTRODUCTION

While much attention has been paid in the past to simulations of first-order phase transitions and systems with rugged free-energy landscapes in generalized ensembles (umbrella, multicanonical, Wang-Landau, parallel or simulated tempering) [1], the merits of this non-Boltzmann sampling approach also for simulation studies of critical phenomena have been pointed out only recently. In Ref. [2], Berg and one of the authors combined multibondic sampling [3] with the Wang-Landau recursion [4] to cover the complete “desired” critical temperature window in a single simulation for each lattice size, where the “desired” range derives from a careful finite-size scaling (FSS) analysis of all relevant observables.

Recent developments in the field of graphic processing units make it possible to have access to a massively parallel computing solution at a low cost. To use these devices in a most efficient way new parallelized algorithms are needed. Our parallel-tempering cluster algorithm is a combination of replica-exchange methods [5] with the Swendsen-Wang cluster algorithm [6] and is therefore ideal for use in such devices.

II. PARALLEL-TEMPERING CLUSTER ALGORITHM

For the parallel-tempering procedure of the combined algorithm we use a set of $N_{rep}$ replicas, where the number of replicas depends on the “desired” range that is needed for the FSS analysis [7]. To determine this range we perform at the beginning of our simulations a short run in a reasonable temperature interval. We choose the number of replicas $N_{rep}$ such that the acceptance rate $A(1 \rightarrow 2)$ between adjacent replicas is about 50%, which can be calculated from

$$A(1 \rightarrow 2) = \sum_{E_1, E_2} P_{\beta_1}(E_1) P_{\beta_2}(E_2) P_{PT}(E_1, \beta_1 \rightarrow E_2, \beta_2),$$

where $P_{\beta_i}(E_i)$ is the probability for replica $i$ at inverse temperature $\beta_i$ to have energy $E_i$ and

$$P_{PT}(E_1, \beta_1 \rightarrow E_2, \beta_2) = \min[1, \exp(\Delta \beta \Delta E)]$$

with $\Delta \beta = \beta_2 - \beta_1$, and $\Delta E = E_2 - E_1$ is the probability to accept a proposed exchange of different, usually adjacent, replicas. This choice of $A(1 \rightarrow 2)$ ensures that the multihistogram reweighting [8] works properly and the flow in (inverse) temperature space, that is, the rate of round trips between low and high temperatures, is optimal [7]. This is the main difference from our preliminary note [9], where we used histogram overlaps instead. Using the data of this short run as input for the multihistogram reweighting routine, we determine the pseudocritical points $C_{\text{max}} = C(\beta_{\text{max}})$ of the specific heat $C(\beta) = \beta^2 V ((e^2) - (e)^2)$ and $\chi_{\text{max}}$ of the susceptibility $\chi(\beta) = \beta V (m^2) - (\langle |m| \rangle)^2$, where $e = E / V$ is the energy density, $m = M / V$ the magnetization density, and $V = L^d$ the size of the system. Furthermore, we measured the maxima of the slopes of the magnetic cumulants, $U_{2k}(\beta) = 1 - \langle |m^{2k}| \rangle / 3 \langle |m| \rangle^2$, and of the derivatives of the magnetization, $d \langle |m| \rangle / d \beta$, $d \langle \ln |m| \rangle / d \beta$, respectively. We also include the first structure factor $S_k(\beta)$, see, e.g., Ref. [10]) in our measurement scheme to allow a direct comparison with the results of Ref. [2].

Next we determine $\beta$ values where the observables $S = \{C, \chi, \ldots \}$ reach the value $S(S_{\text{max}})$ with $r \leq 1$. This leads to a sequence of $\beta^{\pm 1}_{\text{max}}$ values satisfying $\beta^{+}_{\text{max}} \leq \beta^{+}_{\text{max}}$, and $\beta^{-}_{\text{max}} \geq \beta^{-}_{\text{max}}$ as illustrated for the two-dimensional (2D) Ising model in Fig. 1. The actual simulation range is then given by the largest interval covered by these $\beta^{\pm 1}_{\text{max}}$ values; i.e., for the example in Fig. 1 the “desired” simulation window would be $[\beta^{+}_{\text{min}}, \beta^{-}_{\text{max}}]$. In practice we start by estimating for a very small system a reasonable (inverse) temperature interval $[\beta^{-}, \beta^{+}]$ and the number of replicas $N_{rep}$ by trial and error. For successively larger systems we use the measured temperature interval and $N_{rep}$ of the next smaller system as input parameters. The work flow of our method is then given by the following general recipe:

(1) Compute the simulation temperatures of the replicas equidistant in $\beta$.
(2) Perform several hundred thermalization sweeps and a short measurement run.
(3) Check the histogram overlap between adjacent replicas: If the overlap is too small ($<10\%$), add a further replica and go back to step 1, else go on.

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(4) Use multihistogram reweighting to determine $\beta^-_c$ and $\beta^+_c$ for all observables $S$, leading to the temperature interval $[\beta^-_{\min}, \beta^+_{\max}] = \{\min S(\beta^-_c) \text{ and } \max S(\beta^+_c)\}$.

(5) Start with $\beta^- = \beta^-_{\min}$ and compute a sequence of temperatures $\beta_i$ with fixed acceptance rate $A(1 \rightarrow 2)$ until $\beta_i = \beta^+_C \geq \beta^+_{\max}$.

(6) Perform several thousand thermalization sweeps and a long measurement run.

III. RESULTS

A. 2D Ising model

Applying this recipe to the 2D Ising model, our computer program simulated system sizes from $L = 8$ up to $L = 1024$ fully automatically. This shows how robust our new method is. Table I gives an overview of the resulting temperature intervals and the numbers of replicas needed when for comparison with Ref. [2] $r = 2/3$ is used. Due to the acceptance rate criterion in step 5 of our iterative procedure, the upper bounds $\beta^+_C$ of the temperature intervals slightly overshoot $\beta^+_{\max}$ and show relatively large fluctuations. With increasing system sizes this discretization effect becomes less pronounced; see Fig. 2, where we compare the automatically determined interval of our algorithm with the exact temperature interval $[\beta^-_{C}, \beta^+_{C}]$ using the specific-heat formula of Ferdinand and Fisher [11].

To assess the performance of the method, we measured the integrated autocorrelation times $\tau_{\text{int}}(\beta_i, L)$ and determined the maximum over all replicas, $\tau_{\text{int}}(L) = \max_{i, \text{rep}} \tau_{\text{int}}(\beta_i, L)$, for each lattice size. By fitting the critical slowing down ansatz $\tau_{\text{int}}(L) \propto L^z$ to the data, we find for $e$, $m^2$, and $S_h$ rather small dynamical critical exponents $z = 0.19(1)$, $z = 0.11(1)$, and $z = 0.01(1)$, respectively. As an example, we compare in Fig. 2 our data for $\tau_{\text{int}}(L)$ of the energy with the results of Ref. [2]. Of course, in our case the computational effort depends linearly on the number of replicas needed. We therefore also show the effective autocorrelation time $\tau_{\text{eff}} = N_{\text{rep}} \tau_{\text{int}}$, which enables a fair comparison in units of lattice sweeps. We see that for $L > 100$, our $\tau_{\text{eff}}$ is more than one order of magnitude smaller than using the recently proposed multibondic Wang-Landau method [2]. For $r = 2/3$, $N_{\text{rep}}$ grows with increasing lattice size as $L^{z'}$ with $z' \approx 0.18$ (cf. Table I). Consequently, $\tau_{\text{eff}} \propto L^{z_{\text{eff}}}$ with $z_{\text{eff}} = z + z'$. For the energy this gives $z_{\text{eff}} \approx 0.37$, which is still much smaller than the exponent $z \approx 1.04$ found in Ref. [2], so that the gain in efficiency becomes more and more pronounced with increasing lattice size.

The choice $r = 2/3$ of Ref. [2] is quite conservative as even for $r = 1$ the peaks determining the left and right boundaries of the “desired” simulation window are usually sufficiently well sampled. This amounts to a somewhat smaller temperature range, and repeating the above procedure with $r = 1$, we arrive at a smaller $z_{\text{eff}} = z = 0.27$; see Fig. 3. Here $z_{\text{eff}} = z$ because the integer-valued $N_{\text{rep}}$ turn out to be so small (3 for $L = 8$, 16 and 4 for $32 \leq L \leq 1024$) that they practically stay constant over a wide range of system sizes. For large $L$, this leads to a significant gain, and also for the moderate system sizes of Fig. 3, $\tau_{\text{eff}}$ is already reduced by a factor of about 3 compared with the case of $r = 2/3$ and a factor of about 100 compared with Ref. [2].
energy of the 2D Ising model, where

\[
\beta_e - \beta_{S_{10}} \propto L^{-\alpha_{10}} \quad \text{and} \quad \beta_e - \beta_{S_{20}} \propto L^{-\alpha_{20}}
\]

for the 2D Ising model with \( a/b = 10 \), for which we expect that our routine will use the same number of replicas needed, \( \tau_{\text{eff}} = N_{\text{rep}} \tau_{\text{int}} \) is slightly smaller than in the case including \( C \). If one again simply fits a power law to both \( \tau_{\text{int}} \) and \( \tau_{\text{eff}} \) (i.e., ignores the logarithmic behavior of \( N_{\text{rep}} \)), one finds excellent fits with \( z = 0.20(1) \) and \( \varepsilon_{\text{eff}} = 0.31(1) = \varepsilon + 0.11 \) for the energy \( [\varepsilon = 0.11(1), \varepsilon_{\text{eff}} = 0.22(1) \text{ for } m^2 \text{ and } z = 0.03(1), \varepsilon_{\text{eff}} = 0.13(1) \text{ for } S_k] \), confirming that effectively \( \sqrt{\ln L} \approx L^{0.11} \) for moderately large \( L \gtrsim 1000 \).

B. 3D Ising model

In the three-dimensional (3D) Ising model where \( \alpha \approx 0.11 > 0 \), both the reweighting range and the “desired” temperature window should scale with \( L^{-1/\nu} \), so that one would expect that our routine will use the same number of replicas for all system sizes. This is indeed the case for the simplest choice \( r = 1 \), where our routine determines for all

\[
\beta_e - \beta_{S_{10}} \propto L^{-\alpha_{10}} \quad \text{and} \quad \beta_e - \beta_{S_{20}} \propto L^{-\alpha_{20}}
\]
TABLE II. Simulation windows and numbers of replicas for the 3D Ising model simulations with \( r = 2/3 \) on \( L^3 \) lattices.

<table>
<thead>
<tr>
<th>( L )</th>
<th>( \beta^- = \beta_{S_{k1}}^- )</th>
<th>( \beta^+_C )</th>
<th>( \beta^+ )</th>
<th>( N_{\text{rep}} )</th>
</tr>
</thead>
<tbody>
<tr>
<td>4</td>
<td>0.061 955</td>
<td>0.284 066</td>
<td>0.311 321</td>
<td>7</td>
</tr>
<tr>
<td>6</td>
<td>0.142 959</td>
<td>0.259 876</td>
<td>0.272 522</td>
<td>8</td>
</tr>
<tr>
<td>8</td>
<td>0.173 712</td>
<td>0.252 866</td>
<td>0.259 229</td>
<td>9</td>
</tr>
<tr>
<td>10</td>
<td>0.188 447</td>
<td>0.246 916</td>
<td>0.252 136</td>
<td>10</td>
</tr>
<tr>
<td>12</td>
<td>0.197 404</td>
<td>0.241 159</td>
<td>0.243 106</td>
<td>10</td>
</tr>
<tr>
<td>16</td>
<td>0.206 422</td>
<td>0.236 610</td>
<td>0.236 773</td>
<td>11</td>
</tr>
<tr>
<td>20</td>
<td>0.211 183</td>
<td>0.233 407</td>
<td>0.233 621</td>
<td>12</td>
</tr>
<tr>
<td>24</td>
<td>0.213 807</td>
<td>0.232 462</td>
<td>0.233 016</td>
<td>14</td>
</tr>
<tr>
<td>28</td>
<td>0.215 553</td>
<td>0.229 853</td>
<td>0.230 301</td>
<td>14</td>
</tr>
<tr>
<td>32</td>
<td>0.216 670</td>
<td>0.229 221</td>
<td>0.229 293</td>
<td>15</td>
</tr>
<tr>
<td>36</td>
<td>0.217 572</td>
<td>0.228 026</td>
<td>0.228 613</td>
<td>16</td>
</tr>
<tr>
<td>40</td>
<td>0.218 172</td>
<td>0.227 703</td>
<td>0.228 025</td>
<td>17</td>
</tr>
<tr>
<td>48</td>
<td>0.219 082</td>
<td>0.226 669</td>
<td>0.226 754</td>
<td>18</td>
</tr>
<tr>
<td>56</td>
<td>0.219 621</td>
<td>0.225 353</td>
<td>0.225 555</td>
<td>18</td>
</tr>
<tr>
<td>64</td>
<td>0.220 031</td>
<td>0.224 758</td>
<td>0.224 775</td>
<td>18</td>
</tr>
<tr>
<td>72</td>
<td>0.220 309</td>
<td>0.224 359</td>
<td>0.224 435</td>
<td>19</td>
</tr>
<tr>
<td>80</td>
<td>0.220 505</td>
<td>0.224 331</td>
<td>0.224 347</td>
<td>21</td>
</tr>
</tbody>
</table>

Lattice sizes \( N_{\text{rep}} = 4 \). The autocorrelation analysis along the same lines as in two dimensions gives \( z = z_{\text{eff}} = 0.62(2) \) for the energy \( [z = z_{\text{eff}} = 0.59(2) \) for \( m^2 \) and \( z = z_{\text{eff}} = 0.37(2) \) for \( S_{k1} \). This exponent is thus again much smaller than \( z \approx 1.05 \) obtained in Ref. [2], and already for moderate system sizes \( L \approx 40 \) – 80 the values of \( \tau_{\text{eff}} \) are about 20 – 30 times smaller; cf. Fig. 5.

If we choose \( r = 2/3 \) as in Ref. [2], however, we find here as well a weak system-size dependence \( N_{\text{rep}} \propto L^{1.36} \), cf. Table II, where the automatically determined temperature intervals also are given. Here we obtain \( z = 0.44(1) \) and thus \( z_{\text{eff}} = 0.80(1) \) for the energy; cf. Fig. 5 \( [z = 0.41(1), z_{\text{eff}} = 0.78(1) \) for \( m^2 \) and \( z = 0.18(2), z_{\text{eff}} = 0.55(2) \) for \( S_{k1} \]. The reason for this unexpected result can be traced back to the fact that the upper boundary \( \beta_{S_{k1}}^- \) of the “desired” simulation window, determined by the low-temperature tail of \( C \), lies for \( r = 2/3 \) clearly outside the FSS region. In fact, omitting \( C \) as a criterion for the FSS window, \( N_{\text{rep}} = 7 \) – 9 stays almost constant. The choice \( r < 1 \) is thus less favorable, but even for \( r = 2/3 \) one gains about one order of magnitude in computing time compared with Ref. [2].

IV. CONCLUSIONS

To summarize, we have introduced a very flexible and simple approach for a systematic determination and simulation of the critical temperature window of interest for second-order phase transitions, which one needs for an accurate estimation of critical exponents and other quantities characterizing critical phenomena. The efficiency of the method depends, of course, on the chosen or available update scheme in the particular case, with nonlocal cluster flips being the favorable choice. Since the setup of our method is completely general and can be combined also with any other update scheme (multigrid, worms, Metropolis, heat bath, Glauber, ...), it could be employed for all simulations in statistical physics, chemistry and biology, high-energy physics, and quantum field theory where one is interested in critical phenomena.

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