Bilinear Quantum Monte Carlo: Expectations and Energy Differences

Shiwei Zhang¹ and M. H. Kalos¹

Received April 24, 1992

We propose a bilinear sampling algorithm in the Green's function Monte Carlo for expectation values of operators that do not commute with the Hamiltonian and for differences between eigenvalues of different Hamiltonians. The integral representations of the Schrödinger equations are transformed into two equations whose solution has the form $\psi_a(x) t(x, y) \psi_b(y)$, where ψ_a and ψ_b are the wavefunctions for the two related systems and t(x, y) is a kernel chosen to couple x and y. The Monte Carlo process, with random walkers on the enlarged configuration space $x \otimes y$, solves these equations by generating densities whose asymptotic form is the above bilinear distribution. With such a distribution, exact Monte Carlo estimators can be obtained for the expectation values of quantum operators and for energy differences. We present results of these methods applied to several test problems, including a model integral equation, and the hydrogen atom.

KEY WORDS: Algorithm; bilinear sampling; energy difference; Green's function Monte Carlo; quantum expectations; random walk.

1. INTRODUCTION

Quantum Monte Carlo (QMC) methods have found their way into increasingly many applications in the study of many-body systems. Among them, the Green's function Monte Carlo $(GFMC)^{(1-4)}$ has proved a very powerful way to solve the Schrödinger equation in many dimensions. Based on an iterative stochastic process, asymptotically it yields a Monte Carlo (MC) representation of the ground-state wavefunction of the system. For quantum operators whose eigenfunctions are the wavefunctions, such as the Hamiltonian itself, only one MC sample is needed together with an

¹Laboratory of Atomic and Solid State Physics and Center for Theory and Simulation in Science and Engineering, Cornell University, Ithaca, New York 14853.

analytical trial wavefunction to evaluate exactly their expectation values. Therefore, the GFMC method is capable of calculating ground-state energies and related quantities in a relatively straightforward fashion. Indeed, numerous highly accurate and effective calculations have been performed along these lines for many very different systems.

Due to the random and discrete nature of MC, however, difficulties arise in calculating expectations which involve two wavefunctions. One obvious example is the calculation of expectation values of quantum operators that do not commute with the Hamiltonian. One way of calculating expectations with respect to ψ^2 is to generate enough independent samples from ψ so that, with substantial probability, two lie within range of a known Green's function.⁽⁵⁾ For a many-body system, this requires two very large samples. Another example is the computation of small energy differences between two systems, described by similar Hamiltonians whose ground-state eigenvalues differ slightly. The statistical variance associated with the mean in energies computed independently can be comparable to the energy difference, causing the signal in the calculation of the difference to be lost in noise.

Attempts have been made to overcome these difficulties, leading to success in specific cases. But the proposed approaches all present certain limitations, making such computations either inexact or much more complicated than the energy calculation. Among these, the "extrapolation" method^(1, 6) is the most straightforward and has been widely applied to obtain expectation values for quantum operators that do not commute with the Hamiltonian. It gives a biased estimate to the expectation value, and the bias is often hard to assess. A trial wavefunction is required which accurately describes the desired property of the system. Thus, for systems that are not well understood, this method will always be uncertain. Other approaches⁽⁷⁻¹¹⁾ for expectation values keep track of decedents of walkers or employ "side walks." These methods are in principle asymptotically exact and they have been successfully applied to certain problems to obtain very accurate results for expectation values. But they are often technically quite delicate and asymptotically unstable in the sense that increasing the length of the side walks so as to decrease the bias leads to a reduction of signal-to-noise ratio. In the limit of infinite side walks, the ratio is zero. Furthermore, their efficiency or even success largely depends also on the quality of the guiding wavefunction, i.e., a priori knowledge of the true wavefunction. For the problem of energy differences, it is sometimes possible to arrange carefully to correlate the two random walks such that the errors in energies would largely cancel.⁽¹²⁾ But unfortunately this is also limited in its applicability.

Underlying the difficulties of these calculations is the fact that they

require highly correlated configurations in the MC process representing two related functions. We propose in this paper a bilinear sampling algorithm in the GFMC framework that achieves such a correlation naturally within a single random walk. We show that it is possible to apply this to calculate expectation values of quantum operators that do not commute with the Hamiltonian as well as to compute energy differences. As a new and very different approach, it results from the integral representation of the Schrödinger equations used by standard GFMC calculations for energies. Instead of sampling a function linear in the unknown wavefunctions, we transform the Schrödinger equations into a pair of integral equations whose solutions are bilinear in the wavefunctions. The random walk based on the new pair of equations *directly* samples the ground state of such solutions, namely, $\psi_{a_0}(x) t(x, y) \psi_{b_0}(y)$, where a and b label the two related systems and ψ_{a_0} and ψ_{b_0} are correspondingly their ground-state wavefunctions. (The labels a and b can be the same, in which case the wavefunctions describe the same system.) The function t(x, y) is chosen to couple appropriately the configurations x and y. The object of the random walk is an ensemble of pairs of configurations (x, y) rather than individual configurations x.

As we shall show in Section 2, the bilinear sampling method yields asymptotic distributions of configurations (x, y) which can provide exact MC estimators for the function $\psi_{a_0}(x) \psi_{b_0}(x)$. When a = b, this is simply the square of the ground-state wavefunction for a system, and we thus have an exact way to compute ground-state expectation values of quantum operators. If a and b are different, it permits a direct calculation of the energy difference as $\Delta E = \langle \psi_{a_0} | \Delta H | \psi_{b_0} \rangle / \langle \psi_{a_0} | \psi_{b_0} \rangle$, where $\Delta H = H_a - H_b$ is the difference in the Hamiltonians for the two systems.

As tests, we have applied this new algorithm to a model problem to compute various moments and also to the ground states of the hydrogen atom and related systems. The former is based on an integral equation composed entirely of Gaussians. Because of its simplicity and flexibility, it provides a very transparent picture of various aspects of the problem and enables us to study the algorithm from many different angles. In the latter, we calculate expectation values of various operators for the ground state of H and also energy differences between the ground states of H and similar systems with different potentials. This provides tests of the necessary ingredients for the application of the new algorithm to larger systems of the same class.

In Section 2 we outline the formalism of the bilinear sampling method and its numerical implementation. Then the application to two model systems is described in Section 3. In Section 4 we give a discussion of the method and its further possibilities. Finally, in the Appendix the sampling techniques involved in the hydrogen calculation are developed. These are in fact general techniques necessary for a class of such calculations for atoms and molecules.

2. FORMALISM AND THE RANDOM WALK

As we shall discuss in Section 4, the bilinear sampling approach is by no means limited to a certain type of Green's function. But for simplicity in presentation, we use the original form of GFMC.⁽²⁾ In atomic units, the Schrödinger equation for a many-electron system can be written as

$$\left[-\frac{1}{2}\nabla^2 + V(x)\right]\psi(x) = E\psi(x) \tag{1}$$

where x is a 3*M*-dimensional vector denoting the coordinates of all *M* electrons in 3D space, and the energy is negative for any bound state. We will use the Green's function g(x, z) for the operator $(-\frac{1}{2}\nabla^2 - E)$ in 3*M* dimensions. The energy *E* is unknown, but it can be either scaled away for Coulomb systems⁽¹³⁾ or obtained iteratively, which usually converges very fast (see Section 3.2.2). We can then transform the Schrödinger equation (1) into the following integral equation:

$$\psi(x) = \lambda \int g(x, z) w(z) \psi(z) dz$$
(2)

The Green's function g here has an analytically known form and w = -V. Equation (2) has a set of solutions ψ with different eigenvalues λ , the lowest of which is 1. With an arbitrary initial function having nonzero overlap with the ground-state wavefunction, this equation can be iterated to yield asymptotically the solution corresponding to the lowest λ , or the ground state ψ_0 . This forms the basis of the GFMC method. In practice, the process is carried out with the wavefunction in each iteration represented by a generation of individual configurations, or random walkers. The walkers live in configuration space and they move from one point z in this space to another x according to the probability distribution function g(x, z). The function w in Eq. (2) is treated as a multiplicative weight or as a source of branching of walkers.

We consider two related systems described by Eq. (2):

$$\psi_a(x) = \lambda_a \int g_a(x, u) w_a(u) \psi_a(u) du$$
 (3a)

$$\psi_b(y) = \lambda_b \int g_b(y, v) w_b(v) \psi_b(v) dv$$
(3b)

where again the subscripts a and b denote the two systems, respectively. In order to obtain an asymptotic solution bilinear (rather than linear) in the wavefunctions, we use a coupling function t(x, y) and multiply each equation in Eqs. (3) by t(x, y) and the wavefunction for the other system to arrive at the following pair of equations:

$$\psi_{a}(x) t(x, y) \psi_{b}(y) = \lambda_{a} \int \frac{t(x, y) g_{a}(x, u)}{t(u, y)} w_{a}(u) \psi_{a}(u) t(u, y) \psi_{b}(y) du$$
(4a)

and

$$\psi_{a}(x) t(x, y) \psi_{b}(y) = \lambda_{b} \int \frac{t(x, y) g_{b}(y, v)}{t(x, v)} w_{b}(v) \psi_{a}(x) t(x, v) \psi_{b}(v) dv$$
(4b)

These hold for any positive coupling function t in principle and their solution now has the form $\psi_a(x) t(x, y) \psi_b(y)$. Equations (4) are completely defined once the kernel t is chosen. In this paper, we assume that t is symmetric in x and y solely for simplicity. Equations (4) can be rewritten so that they are more transparent for a random walk interpretation:

$$\Phi(x, y) = \lambda_a \int \Gamma_a(x, y | u, v) N_a(u, v) \Phi(u, v) du dv$$
 (5a)

and

$$\Phi(x, y) = \lambda_b \int \Gamma_b(y, x | v, u) N_b(v, u) \Phi(u, v) du dv$$
 (5b)

where $\Phi(x, y) = \psi_a(x) t(x, y) \psi_b(y)$ is the bilinear solution we seek. The kernel Γ_s is a normalized probability distribution function of x and y conditional on u and v defined as

$$\Gamma_s(x, y | u, v) \propto [g_s(x, u) t(x, v)] \delta(y - v)$$
(6)

where s is either a or b. The multiplicative factor N_s is

$$N_{s}(u, v) = w_{s}(u) \int g_{s}(x, u) t(x, v) dx/t(u, v)$$
(7)

We note that neither Γ_s nor N_s is symmetric in its variables.

To solve Eqs. (5) by Monte Carlo for the ground states in the bilinear form $\Phi_0 = \psi_{a_0}(x) t(x, y) \psi_{b_0}(y)$, we introduce random walks on the enlarged configuration space $x \otimes y$. In other words, each walker now consists of two configurations, namely x and y, which sample a joint distribution function $\Phi(x, y)$. The iteration, or the random walk, is carried out by

moving walkers according to either one of the two equations in each step. The initial distribution of walkers can be arbitrary or generated from a Metroplis sampling of Φ with the ψ 's replaced by trial wavefunctions for the ground states. The bilinear sampling technique enables us to treat explicitly functions bilinear in the wavefunctions and maintain highly correlated configurations. But since Eqs. (5) are a direct transformation of Eqs. (3), the convergence property of the original linear integral equations to the corresponding ground states simply carries through. In the random walk process, both equations need to be applied about equally often in order to ensure convergence and assure efficiency. In practice, this can be accomplished by using the two equations alternately, or randomly with equal probability. Once an equation has been selected in a step, the multiplicative factor [either $N_a(u, v)$ or $N_b(v, u)$ as determined by the equation] is constructed for each walker. New walkers for the next generation are then produced by: (1) choosing a walker (u, v) from the old population either with probability proportional to their multiplicative factors or by branching (depending on whether the size of the population is fixed or not); and (2) sampling a new walker from the parent walker according to the kernel Γ_s for that equation. We note from the form of Γ_s that in fact in step 2 only one new configuration (x or y) is selected and the complementary configuration in the old walker is simply carried along.

Much freedom still remains about the choice of the coupling function t. If we set t to a constant, bilinear sampling would reduce to generating two independent sets of configurations from two standard GFMC runs, from which the overlap would be difficult to extract in high-dimensional systems. The kernel t must generate configurations that are close together. The requirement of this is very clear in the current problem. When t is the same as one of the Green's functions, say, g_a , the bilinear sampling method yields a density $\psi_{a_0}(x) g_a(x, y) \psi_{b_0}(y)$. From the original integral equation, Eq. (3a), we have

$$\psi_{a_0}(y)\,\psi_{b_0}(y) = \lambda_{a_0} \int \psi_{a_0}(x)\,g_a(x,\,y)\,\psi_{b_0}(y)\,w_a(x)\,dx \tag{8}$$

As mentioned in Section 1, the product on the left-hand side of Eq. (8) is essential to the expressions for the expectation values we seek. In the asymptotic regime of the MC process, the distribution of pairs of configurations represents $\Phi_0(x, y)$ as a sum of delta functions in x and y:

$$\psi_{a_0}(x) g_a(x, y) \psi_{b_0}(y) = \sum_k \delta(x - x_k) \,\delta(y - y_k) \tag{9}$$

where $\{x_k, y_k\}$ is the collection of these pairs (random walkers) labeled by k. This combined with Eq. (8) gives

$$\psi_{a_0}(y)\,\psi_{b_0}(y)\propto\sum_k w_a(x_k)\,\delta(y-y_k) \tag{10}$$

In other words, $w_a(x_k)$ is an MC estimator for $\psi_{a_0}(y_k) \psi_{b_0}(y_k)$.

With the direct sampling of the product of two wavefunctions given by Eq. (10), we can easily obtain the desired expectation values of quantum operators exactly. If a = b, the ground-state expectation value of any multiplicative quantum operator O is

$$\langle O \rangle \equiv \frac{\int \psi_{a_0}(y) O(y) \psi_{a_0}(y) dy}{\int \psi_{a_0}(y) \psi_{a_0}(y) dy} = \frac{\sum_k O(y_k) w_a(x_k)}{\sum_k w_a(x_k)}$$
(11)

When $a \neq b$, we wish to calculate the ground-state energy difference between two systems a and b described by different but related Hamiltonians H_a and H_b . Their ground-state wavefunctions are given by ψ_{a0} and ψ_{b0} , which are assumed to be nonorthogonal to each other. If $H_a - H_b = V_a - V_b$, since

$$\Delta E = \frac{\int \psi_{a_0}(y) H_a \psi_{b_0}(y) dy}{\int \psi_{a_0}(y) \psi_{b_0}(y) dy} - \frac{\int \psi_{a_0}(y) H_b \psi_{b_0}(y) dy}{\int \psi_{a_0}(y) \psi_{b_0}(y) dy}$$
$$= \frac{\int \psi_{a_0}(y) [H_a - H_b] \psi_{b_0}(y)}{\int \psi_{a_0}(y) \psi_{b_0}(y) dy}$$
(12)

we have

$$\Delta E = \frac{\sum_{k} w_{a}(x_{k}) [V_{a}(y_{k}) - V_{b}(y_{k})]}{\sum_{k} w_{a}(x_{k})}$$
(13)

Of course, in both cases we can use Eq. (3b) in Eq. (8) to obtain $w_b(y_k) g_b(x_k, y_k)/g_a(x_k, y_k)$ as an estimator for $\psi_{a_0}(x_k) \psi_{b_0}(x_k)$, which can provide expressions similar to Eqs. (11) and (13). They can be combined with the equations shown here for better statistics.

Implicit above is the assumption that it is possible to evaluate N as well as to sample Γ . This is, of course, not universally valid. Fortunately, in the current GFMC approach, the Green's function for $(-\frac{1}{2}\nabla^2 - E)$ for any system can be written as a superposition of Gaussians and it is straightforward to sample the product of two such functions. The integrals in N can also be easily obtained. The assumption is also true for other classes of Green's functions for various systems of interest. For discrete systems such as certain quantum spin systems, it will be even less challenging in principle.

3. APPLICATIONS

3.1. A Model Problem

In this part, we apply the bilinear sampling method to a model problem⁽¹⁴⁾ described by an integral equation of exactly the same form as the general many-dimensional equation given by Eq. (2). We shall test the capability of the algorithm in calculating expectation values by evaluating various moments of the "ground-state" distribution. The labels a and b (thus s) may be omitted in this section. Without altering the notation, we simply redefine as follows:

$$g(x, z) = \frac{1}{(\alpha \pi)^{1/2}} \exp\left[-\alpha (x-z)^2\right]$$

and

$$w(z) = \left(\frac{2\alpha}{(2\alpha - 1)}\right)^{1/2} \exp\left(-\frac{1}{4\alpha - 2}z^2\right)$$

where α can be any real number greater than 0.5. It can be easily verified that under this new definition, Eq. (2) has a set of solutions which are products of Gaussians and polynomials. Among them the ground state, the solution corresponding to the lowest eigenvalue $\lambda = 1$, is

$$\psi_0(x) = \exp(-\frac{1}{2}x^2)$$

We choose the coupling function t to be also a Gaussian,

$$t(x, y) = \exp[-\beta(x-y)^2]$$

and we shall solve Eqs. (5) by MC for the joint distribution Φ_{θ} of the ground state.

With every term in Gaussian form, this problem is easy to study analytically from every aspect. The parameters α and β are completely at our disposal and they can be varied to provide insight into the behavior of the algorithm under very different conditions of the Green's function and coupling. Furthermore, if necessary, the iteration can also be carried out directly without doing MC. That is, assuming a general solution $\exp(-a_nx^2 + b_nxy - c_ny^2)$ for the *n*th iterate of Eqs. (5), we can determine a_{n+1} , b_{n+1} , and c_{n+1} at every stage. This can be used to generate numerical trajectories so as to observe the convergence. The product g(x, u) t(x, v)in the kernel $\Gamma(x, y | u, v)$ can be easily transformed into a single Gaussian in the unknown x by completing the square in the exponents. Not surprisingly, then, sampling Γ amounts to sampling a Gaussian.

The MC process generates random walkers $\{x_k, y_k\}$ representing the distribution $\psi_0(x) t(x, y) \psi_0(y)$ for the ground state. Since

$$\int \psi_0(x) t(x, y) \psi_0(y) \exp\left(-\frac{1}{4\beta - 2} y^2\right) dy \propto \psi_0^2(x) = \exp(-x^2)$$

the MC result is adequate to determine completely the function $\exp(-x^2)$. For example, various moments can be computed in a similar fashion as in Eq. (11) and compared with the exact results. Also, a histogram can be easily made for this function in one or two dimensions. The second moment $\langle x^2 \rangle$ is always computed in our tests. We have carried out calculations in nine dimensions and the result is satisfactory. For the present study, however, one dimension suffices in revealing the characteristics of the algorithm. Wide ranges of values have been used for both α and β . Table I presents our results for the second moment in one dimension. We see that all the computed answers agree well with the exact result, namely 0.5.

One important issue is how the algorithm performs when α and β are large, since that is the case when both kernels are very sharply peaked. That the Green's function is sharp implies that the step size of the random walk is small in configuration space, which more closely resembles the situation in higher dimensions resulting from actual many-dimensional problems and also the situation in which a QMC is generated by a diffusion process. The coupling is consequently also very sharp, as indicated in Section 2. In fact, in many cases, such as that of the hydrogen atom treated below, the coupling is simply the Green's function. Under this circumstance, the probability becomes extremely small to have two independent and random configurations appear close in configuration space. Therefore the bilinear sampling method must effectively couple two sets of configura-

α	β : Result					
0.6	0.6:	0.5005(5)	1.0:	0.5001(4)	3.0:	0.501(6)
1.0	0.6:	0.5001(2)	1.0:	0.4998(2)	3.0:	0.503(5)
3.0	1.0:	0.4999(7)	3.0:	0.501(3)	5.0:	0.501(2)
5.5	1.0:	0.5003(9)	3.0:	0.500(4)	5.5:	0.502(3)
10.5	0.6:	0.500(1)	3.0:	0.501(3)	10.0:	0.504(5)

 Table I. Results of the Bilinear Sampling Method Applied to the 1D Model Problem^a

^a Shown is the second moment $\langle x^2 \rangle$ from the sampled distribution for $\psi^2(x)$. The exact answer is 0.5. The parameters α and β give the sharpness of the Gaussian kernels g (the Green's function) and t (the coupling), respectively. The statistical errors in the results are in the last digits and are indicated in prentheses.

tions without distorting the distribution. It is reasonable to expect less efficiency as α and β increase, but the sampled distribution must nevertheless be correct. From Table I, we see that this is indeed the case.

We keep a constant number of walkers in our simulations. This results in a bias, since generations with high multiplicity contribute less than they should and conversely. Branching can be introduced instead of strict population control to avoid this. It is also possible to correct for such a bias by carrying weights.⁽¹⁵⁾ The sum of multiplicative factors over all walkers in a generation labeled by n, \mathcal{N}_n , indicates the total number of walkers the next generation should include. Thus, with the number of walkers fixed at L for every generation, each generation can be assigned a weight formed by a product of \mathcal{N}/L from a certain number of previous generations, i.e., $\mathcal{W}_n = \prod_{l=1}^m \mathcal{N}_{n-l}/L$. The number of previous generations to be included, m, can be tuned so that it is large enough to remove the bias and yet not introduce excessive fluctuation. For this model problem, with a fairly small number of walkers (usually 1000), it requires less than ten generations to correct for the bias. It is observed that, without the correction, the bias effect is often quite significant. As the kernels become sharper, the bias becomes more and more serious. Moreover, it does not seem to always exhibit a clear 1/L behavior as in many GFMC calculations. The population control bias can be attributed to fluctuation of the multiplicative function N. In bilinear sampling, due to the extra function t inserted to couple two points, it is not implausible to have relative large variation in N. For instance, in this model problem, $N(u, v) \propto \exp[\beta^2(u-v)^2/(\alpha+\beta)] w(u)$. In these calculations caution must be exercised to ensure that the result is unbiased, in other words, robust against population size.

We also mention in passing that even though Eqs. (4) and therefore Eqs. (5) are true for any nonzero t, they are not necessarily always well behaved in an MC calculation. To illustrate this, recall that the variance⁽¹⁶⁾ of the total weights for a generation in the random walk is given by $(N(u, v)^2 \Phi(u, v) du dv)$. But when the coupling function t is much sharper than the Green's function g, this expression diverges, which implies that the MC sampling would not actually converge to a definite answer. For the model problem, it is possible to determine the range of β for each α where infinite variance can be expected. We have verified that when the parameters are given in this range, the MC answer can disagree with the exact one significantly. The above analysis has employed no knowledge of the specific form of the kernels and thus is general to bilinear sampling. For the purpose of computing the expectation values of quantum operators, however, it is always possible to avoid a kernel t in that regime. So this should not pose any problem. As an additional probe of the diverging weights, we can monitor the fluctuation of population sizes in a calculation.

3.2. The Hydrogen Atom

As another test case, we use the algorithm to study the ground state of the hydrogen atom. In the first part, expectation values of operators with respect to the ground state are computed. In the second, we study similar systems with different potentials and evaluate the energy difference between the ground states of the new and original systems. It is assumed the systems are nonrelativistic with the nucleus fixed. Except for technical details, implementation of the new algorithm to address these problems directly follows the formalism developed in Section 2. Based on Eq. (8), the natural choice of t is $t = g_a$, where g_a is the Green's function for the hydrogen atom.

In general, the Green's function g for an M-electron system as defined in Section 2 can be written in an integral representation which is a superposition of Gaussians with different widths. There also exists an analytical expression for g in terms of polynomials and modified Bessel functions of the second kind, so that it can be conveniently evaluated. Using these expressions, the integral in N can be easily computed for any M and there exists an efficient way to sample x from the product of functions in the same class, $g_a(x, u) g_b(x, v)$ (cf. Appendix).

3.2.1. Ground-State Expectation Values. Similarly to Section 3.1, we can sample the square of the ground-state wavefunction and compute *directly* within a single run expectation values of multiplicative operators. The sampling techniques are only a special case of that discussed in the Appendix. In Table II, we show computed expectation values of the potential energy V, the radial distance |x|, x^2 , and the square of the third component of the electron coordinate x_3^2 , together with the exact answers. The number of walkers is typically 3000 and the bias is not noticeable. Because of the simplicity of the sampling process and the direct sampling

Item	$\langle V \rangle$	$\langle (x^2)^{1/2} \rangle$	$\langle x^2 \rangle$	$\langle x_3^2 \rangle$
Bilinear		1.500(3)	3.000(9)	1.002(3)
Exact		1.5	3.0	1.0

 Table II. Results of the New Algorithm Applied to the Ground State of the Hydrogen Atom Together with the Exact answers^a

^a The items are the expectation values of the potential, the radial distance, the second moment, and the z component of the second moment. All quantities are in atomic units. The statistical errors in the MC results are in the last digits and are indicated in parentheses.

of the product of wavefunctions, the code is fast and the algorithm quite efficient. We see that the agreement between the bilinear sampling and the exact results is again excellent.

3.2.2. Energy Difference Calculations. In this part, we describe tests of the capability of the bilinear sampling method to calculate energy differences by considering systems similar to the hydrogen atom but with different potentials. We will employ bilinear sampling to compute the energy differences between the ground states of such systems and the hydrogen atom. The Green's functions corresponding to the two Hamiltonians belong to the same class discussed in the Appendix, only with a possible difference between multiplicative factors in their arguments that is a function of the energy. The difference in the potential terms causes w_a to differ from w_b in Eqs. (4).

The simplest way to obtain such a system is to add a perturbation term to the original hydrogen Hamiltonian, i.e., $H_b = H_a - \gamma H'$, where H'is a multiplicative operator and γ is a small coefficient. From Eq. (13), we can compute $\Delta E/\gamma$ as a function of γ , where ΔE is the energy difference between the ground states of the two systems. When $\gamma = 0$, this in fact is exactly the bilinear approach of calculating the expectation value of H' in the ground state of H_a . Therefore, in a sense, all results in Section 3.2.1 can be viewed as special cases of these calculations. As γ is increased, the result should deviate from the ground-state expectation of H' and should always give the exact energy difference divided by γ . From the MC point of view, it implies the ability to compute the exact energy difference for all ranges of the parameter γ . Moreover, the effect of the small perturbation is generated with a small fluctuation. In fact, the statistical error may decrease with γ .

We consider a perturbation H' = 1/|x|. This is just the original Coulomb potential and the energy difference is trivially obtained analytically. In Fig. 1, we plot the computed $\Delta E/\gamma$ for some values of γ from bilinear sampling and compare them with the exact result. The groundstate energy of H is -0.5 in atomic units. We see that the agreement is excellent. For instance, in the case of $\gamma = 0.003$ the bilinear sampling method easily yields an energy difference of 0.0030036(12), which would be extremely challenging, if possible at all, for an approach by independent MC calculations.

We next study a system described by the Hamiltonian H_b for the so-called Hulthén potential

$$V_{\text{Hul}}(|x|) = -V_0 \frac{\exp(-\rho |x|)}{1 - \exp(-\rho |x|)}$$



Fig. 1. The "effective" energy difference $\Delta E/\gamma$ between the original and perturbed systems for a perturbation $\gamma V(x)$ to the ground state of the hydrogen atom. Results of the bilinear sampling method are shown with statistical fluctuations and are compared with the exact result. V(x) is the potential energy operator. The bilinear calculations were done with the arbitrarily chosen values $\gamma = 0.003$, 0.005, 0.01, 0.05, 0.1. The first-order perturbation result is 1. Atomic units are used.

where V_0 and ρ are parameters. This system can be solved exactly⁽¹⁷⁾ and its ground-state energy is given by $E_{b_0} = -(2V_0/\rho - \rho)^2/8$ ($\rho^2 < 2V_0$). Let $V_0 = \rho$. Then this potential behaves like the Coulomb potential at small values of |x| and approaches zero exponentially at large distances. By varying the parameter ρ , we can control how similar this system is to the hydrogen atom and the energy difference between their ground states can be calculated from the bilinear sampling method and compared with the exact results. In Table III, we show the computed and analytical results for ΔE for some values of ρ . Again extremely accurate values are easily obtained with bilinear sampling for small as well as large energy differences. (Each number corresponds to roughly 1 h on an IBM RS6000 workstation.)

As mentioned above, the argument of the Green's functions scales with the ground-state energies and has the form $g(k_s |x - y|)$, where g is the Green's function for the operator $(-\nabla^2 + 1)$ and $k_s = (2 |E_{s_0}|)^{1/2}$ (s = a, b). This does not pose any difficulty because we can obtain iteratively and very quickly the correct values for the two energies. In fact, it is observed that, quite generally, the final result of a standard GFMC calculation in this approach is rather insensitive to the initial input of the energy. We have tested the effect of iterations from a very poor starting value of the energy

ρ	Exact	Bilinear-exact
0.001	0.00049987500	0.0000000004(8)
0.0125	0.00623047	0.00000000(1)
0.03333	0.01652778	0.0000007(6)
0.08333	0.0407986	-0.0000001(4)
0.4	0.180000	0.000004(4)

Table III. Energy Differences $\Delta E = E_{b_0} - E_{s_0}$ from Bilinear Sampling Between the Ground States of the Hydrogen Atom and a Similar System Described by the Hulthén Potential, Compared with Exact Results^a

^a The Hulthén potential is given by $V_{\text{Hul}}(|x|) = -\rho \exp(-\rho |x|)/$ [1-exp(- $\rho |x|$)], whereas the Coulomb potential in H is V(|x|) = -1/|x|. Atomic units are used. The ground-state energy of H is $E_{a_0} = -0.5$ and E_{b_0} is higher. The second column is the exact result for ΔE , while the last column gives the error (bilinear-exact) in the bilinear result. The statistical errors from MC are again in the last digits and are shown in parentheses in the last column.



Fig. 2. Convergence of iterations with the input of the energy E_{b_0} of the perturbed system in the energy difference calculations for *H*. The perturbation is again $-\gamma/|x|$ and large perturbations ($\gamma = 0.1$ and 0.5) are chosen in order to show a visible convergence process. Values of $\Delta E/\gamma$ are plotted as a function of the number of iterations. The exact results are given as straight lines. In both calculations an initial value 0 is assumed for the energy difference. In one iteration, they both give $\Delta E/\gamma = 0.9995(9)$, equivalent to the first-order perturbation result. The calculation with $\gamma = 0.1$ (lower curve) requires only one more iterations to the correct answer $\Delta E/\gamma = 1.25$.

 E_{b_0} in our calculations with the 1/|x| perturbation, and, indeed, the convergence is very fast. For example, if we use E_{a_0} as initial value for both Green's functions, then within one run, we can obtain the first-order correction to E_{b_0} . Even for large γ the effect of the uncertainty of an initial energy guess becomes unnoticeable in the final answer in one to a few more iterations. In Fig. 2, we illustrate this by plotting $\Delta E/\gamma$ as a function of iterations for two large values of the coefficient γ (0.1 and 0.5).

The number of walkers in these calculations is typically 2000 and we correct for the bias with several previous generations as described in Section 3.1. We alternate the two equations in (5). In the bias correction, we calculate the averages of N_l separately for even and odd l and normalize each accordingly such that these multiplicity factors are kept around unity.

4. DISCUSSION

It is interesting to note that the manipulation of the original integral equation (3a) to arrive at Eq. (4a) is very similar to an importance sampling transformation.^(1,4) In fact, if the coupling kernel t(x, z) is the same as $g_a(x, z)$, we can use as importance function the correct form, namely, the unknown wavefunction ψ_{a_0} in its integral representation as given by Eq. (3a). Since the MC process in effect does the integral in this importance function, we only use the integrand and also drop the potential term w_a and Eq. (4a) ensues. This also suggests that the algorithm should be rather efficient and explains to some degree why no trial wavefunction is needed in the method.

As a straightforward method that depends little on *a priori* knowledge, bilinear sampling should be useful to different quantum problems as the GFMC approach is employed more and more to understand various many-body systems. For example, it seems possible to study with this method ground-state properties of certain quantum spin systems.⁽¹¹⁾ A generalized version of the ideas developed here with quadrilinear sampling provides the possibility of calculating transition moments between two quantum states, as opposed to a method using side walks.⁽¹⁰⁾

By sampling the product of wavefunctions, the bilinear approach is more promising than dealing with two independent sets of configurations^(5, 10) from two GFMC calculations. We need to study more the behavior of the method as g and t become very sharp so as to give a general prescription for avoiding the large biases or fluctuations we have seen in that limit. In many-electron systems, we inevitably will encounter the "sign" problem in quantum MC.^(3, 13) We have not yet formulated a bilinear sampling algorithm mechanism that also addresses that problem in an exact way. But it is possible to use bilinear sampling within the fixednode^(3, 18) approximation. With this, the method is clearly generalizable to many-electron systems in which the random walk is either generated by a diffusion approximation or by domain Green's function methods. In either case, there are three possible choices for t(x, y). We can use g(x, y) as in the present work, ignoring the fact that a small number of estimates will be negative [because w(x) = -V(x) is negative]. We can couple the two configurations x and y using the kernel by which new points are generated (itself a Green's function either in a short-time approximation or over some finite domain). Finally, it is possible, in principle, to couple the walkers by the full Green's function (unknown in advance, but generated by walks that would go from x to y) and modify the coupling recursively using local Green's functions. Investigation of these alternatives will be the subject of future research.

The bilinear sampling algorithm derives directly from the integral representation of the many-body Schrödinger equation of the system. It appears to be quite natural for the problems involving functions quadratic in ground-state wavefunctions, and for the calculation of energy differences.

APPENDIX. SAMPLING THE PRODUCT OF TWO GREEN'S FUNCTIONS

In this Appendix, we complete the technical part associated with the sampling of the kernel Γ_s in Eq. (6) and the evaluation of the multiplicative factor N in Eq. (7). These are general to Green's functions for the operator $(-\frac{1}{2}\nabla^2 + |E|)$ with any number of particles. As discussed in Section 3.2.2, we can assume the energy is known.

Again let M be the number of particles in the system we treat. Then the Green's function^{(2), 2} as defined above is given by

$$g(x, z) = \left(\frac{k^2}{4\pi}\right)^{3M/2} \int_0^\infty t^{-3M/2} \exp\left(-t - \frac{k^2 |x - z|^2}{4t}\right) dt$$
(A1)

where $k = (2 |E|)^{1/2}$. As already mentioned, g also has a form which can be used to evaluate the Green's function:

$$g(x, z) = \left(\frac{k^2}{2\pi}\right)^{3M/2} K_{3M/2-1}(k |x-z|)/(k |x-z|)^{3M/2-1}$$
(A2)

where K_m is the modified Bessel function of the second kind. In the bilinear sampling process we need to evaluate N_s and sample Γ_s . With $t(x, y) = g_a(x, y)$, both N_s and Γ_s involve the product of two Green's functions of

² See also ref. 19, where the basic idea of bilinear sampling is discussed briefly.

the same class. It is necessary to sample such products as well as evaluate integrals based on them.

We consider the product of two Green's functions with k_a and k_b . Let $\xi = (k_b^2 - k_a^2)/2$ (≥ 0) and $\sigma = (k_b^2 + k_a^2)/2$. From Eq. (A1), by completing squares and changing variables, it is straightforward to obtain the following expression:

$$g_{b}(x, y) g_{a}(x, z) \propto \int_{0}^{\infty} \int_{-p}^{p} T(x | y, z, \tau_{1}, \tau_{2}) \exp(-\xi q)$$
$$\times p^{-3M/2} \exp\left(-\sigma p - \frac{(y-z)^{2}}{4p}\right) dq \, dp \qquad (A3)$$

The new pair of variables p and q are

$$p = \tau_1 + \tau_2$$
$$q = \tau_1 - \tau_2$$

and $T(x | y, z, \tau_1, \tau_2)$ is a normalized probability distribution function of x conditional on $\tau_{1,2}$ (or p and q), y, and z:

$$T(x \mid y, z, \tau_1, \tau_2) = \left(\frac{\tau_1 + \tau_2}{4\pi\tau_1\tau_2}\right)^{3M/2} \exp\left[-\frac{\tau_1 + \tau_2}{4\tau_1\tau_2} \left(x - \frac{y\tau_2 + z\tau_1}{\tau_2 + \tau_1}\right)^2\right]$$
(A4)

Now we describe the actual sampling and integrating of this product of Green's functions $g_b(x, y) g_a(x, z)$ given the positions of the parent walkers y and z. Since integration over x in Eq. (A3) simply removes T, we have

$$\int g_b(x, y) g_a(x, z) dx \propto \frac{1}{\xi} \left[k_a^{3M-2} g_a(y, z) - k_b^{3M-2} g_b(y, z) \right]$$
(A5)

As a special case, in the limit $k_a = k_b$, i.e., when the two Green's functions correspond to the same system, the above expression reduces to

$$\int g_a(x, y) g_a(x, z) dx \propto \frac{1}{2\pi} k_a^{3M-4} g_a^{3M/2-1}(y, z)$$
(A6)

where the superscript on g indicates that the Green's function is for 3M/2-1 dimensions rather than 3M/2 for the original functions. To sample an x from a probability distribution function proportional to $g_b(x, y) g_a(x, z)$, we note that for any known pair of y and z, Eq. (A3) can be written as

$$g_b(x, y) g_a(x, z) \propto \iint T(x \mid p, q) Q(q \mid p) P(p) dp dq$$
(A7)

where T is the same as in Eq. (A4) with the variables changed from τ_1 , τ_2 to p and q. Here Q is a normalized probability distribution function of q conditional on p as follows:

$$Q(q \mid p) = \begin{cases} \xi \exp(-\xi q) / [\exp(\xi p) - \exp(-\xi p)] & \text{if } |q| \le p \\ 0 & \text{otherwise} \end{cases}$$
(A8)

P is a positive function of *p* on $(0, \infty)$ which therefore can be viewed as a probability density function

$$P(p) \propto \frac{1 - \exp(-2\xi p)}{2\xi p} p^{-3M/2 + 1} \exp\left[-k_a^2 p - \frac{(y-z)^2}{4p}\right]$$
(A9)

Thus, to obtain x according to the probability density given by Eq. (A3) or Eq. (A7), we need to sample a p from Eq. (A9), then a q on [-p, p] according to (A8), and finally sample the Gaussian in Eq. (A4). Sampling of (A9) is elementary⁽¹⁶⁾ and can be accomplished by, e.g., sampling the exponential distribution in p in the last term and then doing rejections. The case $k_a = k_b$ is once again straightforward, since Q becomes uniform on [-p, p] and the first term in P(p) is simply 1. We also mention that analogous (though possibly less elegant) methods will apply for any coupling kernel that can be written in the form

$$t(x, y) = \int_0^\infty h(t) \exp\left[-\frac{(x-y)^2}{4t}\right] dt$$

for $h(t) \ge 0$.

ACKNOWLEDGMENTS

We thank G. V. Chester, C. J. Umrigar, T. MacFarland, and S. A. Vitiello for helpful discussions. The Cornell Theory Center is funded by the U.S. National Science Foundation, the state of New York, IBM, and Cornell University.

REFERENCES

- 1. D. M. Ceperley and M. H. Kalos, in Monte Carlo Methods in Statistical Physics, K. Binder, ed. (Springer-Verlag, Berlin, 1979).
- 2. M. H. Kalos, Phys. Rev. 128:1791 (1962).
- 3. K. E. Schmidt and M. H. Kalos, in *Applications of the Monte Carlo Method in Statistical Physics*, K. Binder, ed. (Springer-Verlag, Berlin, 1984).
- 4. M. H. Kalos, D. Levesque, and L. Verlet, Phys. Rev. A 9:2178 (1974).
- 5. M. H. Kalos, J. Comput. Phys. 2:257 (1967).

- 6. P. A. Whitlock, D. M. Ceperley, G. V. Chester, and M. H. Kalos, *Phys. Rev. B* 19:5598 (1979).
- M. H. Kalos, Phys. Rev. A 2:250 (1970); K. S. Liu, M. H. Kalos, and G. V. Chester, Phys. Rev. A 10:303 (1974).
- P. J. Reynolds, R. N. Barnett, B. L. Hammond, R. M. Grimes, and W. A. Lester, Jr., Int. J. Quant. Chem. 29:589 (1986); P. J. Reynolds, R. N. Barnett, B. L. Hammond, and W. A. Lester, Jr., J. Stat. Phys. 43:1017 (1986).
- 9. R. N. Barnett, P. J. Reynolds, and W. A. Lester, Jr., J. Comput. Phys. 96:258 (1991).
- R. N. Barnett, P. J. Reynolds, and W. A. Lester, Jr., J. Chem. Phys. 96:2141 (1992);
 R. N. Barnett, P. J. Reynolds, and W. A. Lester, Jr., unpublished.
- K. J. Runge and R. J. Runge, in *Quantum Simulations of Condensed Matter Phenomena*, J. D. Doll and J. E. Gubernatis, eds. (World Scientific, Singapore, 1990); K. J. Runge, *Phys. Rev. B* (to be published).
- B. H. Wells, Chem. Phys. Lett. 115:89 (1985); C. A. Traynor and J. B. Anderson, Chem. Phys. Lett. 147:389 (1988).
- 13. S. Zhang and M. H. Kalos, Phys. Rev. Lett. 67:3074 (1991).
- M. H. Kalos, in *Computational Atomic and Nuclear Physics*, C. Bottcher, M. R. Strayer, and J. B. McGrory (World Scientific, Singapore, 1989).
- M. P. Nightingale, in *Finite Size Scaling and Numerical Simulation of Statistical Systems*, V. Privman, ed. (World Scientific, Singapore, 1990).
- 16. M. H. Kalos and P. A. Whitlock, Monte Carlo Methods. (Wiley, New York, 1986).
- 17. S. Flügge, Practical Quantum Mechanics I (Springer-Verlag, Berlin, 1971), p. 175.
- 18. J. B. Anderson, J. Chem. Phys. 63:1499 (1975); 65:4121 (1976); 73:3897 (1980).
- M. H. Kalos and S. Zhang, in *Recent Progress in Mang-Body Theories*, Vol. 3, C. E. Campbell and E. Krotscheck, eds. (Plenum Press, New York, in press).