# Monte Carlo Simulation of Interacting Electron Models by a New Determinant Approach 

by

## Mucheng Zhang

(Under the direction of Robert W. Robinson and Heinz-Bernd Schüttler)


#### Abstract

This work discusses the calculation of determinants and Monte Carlo simulation of Hubbard models by a new determinant approach which is derived from a Feynman diagram expansion for the single particle Green's function of the Hubbard model. We developed a determinant formalism for the extended Hubbard model and a Monte Carlo summation algorithm to evaluate the relevant diagram determinant sums.

Index words: Monte Carlo Simulation, Hubbard Model, Feynman diagram, Determinant


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Dedicated To My Dear Wife Cao Lin

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## Chapter 1

## INTRODUCTION

Monte Carlo simulation of interacting electron models (in particular, the Hubbard models) has been an active topic of investigation in computational physics since the 1970s.

The Hubbard model, named after John Hubbard, is used to describe magnetism and superconductivity in strongly correlated electron systems. It was originally developed to explain the metal-insulator transition in strongly correlated electronic materials, and has subsequently been applied to the study of magnetism. Over the last 20 years, the twodimensional (2D) Hubbard model has been used as a "minimal" model to describe hightemperature superconductors and has been applied extensively in that context.

Mathematically, it is very difficult to solve the Hubbard model. There are some reliable numerical solution methods, including quantum Monte Carlo, exact diagonalization and density matrix renormalization (see [2]), but these methods are limited to only small 2D clusters with typically fewer than 16 lattice sites. Recently, cluster mean-field embedding approaches have been developed which allow small cluster calculations to be effectively extrapolated to larger and even infinite lattice sizes (see [4], [5], [7] and [1]). The infinite limit, also referred to as the thermodynamic limit, is the appropriate limit of the model to describe macroscopic crystalline materials.

In this dissertation, we introduce a new determinant approach to these studies. Our approach is derived from a Feynman diagram expansion for the so-called single particle Green's function of the Hubbard model. Green's functions are mathematical objects of particular interest in the quantum theory of many-electron systems, since they model predictions
which can be directly compared to the data obtained in real materials by the various experimental probes. For example, the single-particle Green's function can be used to predict the results of photo-emission spectroscopy experiments. A similar determinant formalism was recently derived by functional integral techniques (see [10]) and used for Monte Carlo simulations of small 2D Hubbard model clusters. In the present work, we have developed a determinant formalism for the extended Hubbard model and developed an alternative Monte Carlo summation algorithm to evaluate the relevant determinant diagram sums. We have tested it on small $2 \times 2$ Hubbard clusters.

This dissertation is organized as follows. In Chapter 2, we review methods for the calculation of determinants of general matrices. We describe Feynman diagram expansions in chapter 3 and the extended Hubbard model on a 2D rectangular lattice in Chapter 4. In Chapter 5 we detail our new method for Monte Carlo simulation of the extended Hubbard model. Finally, we present the results of our tests in Chapter 6.

## Chapter 2

## CALCULATION OF DETERMINANTS

In this chapter, we will review preliminaries for determinants in $\S 2.1$, then introduce several algorithms for calculating determinants of general matrices in $\S 2.2$ and compare these algorithms in §2.3.

Throughout, $n$ is a positive integer, $\vec{x}$ is a column vector with components $x_{1}, x_{2}, \ldots, x_{l}$, $\vec{e}_{k}$ is the $k$ th canonical vector

$$
(\overbrace{0, \ldots, 0}^{k-1}, 1, \overbrace{0, \ldots, 0}^{n-k})^{T}
$$

$0_{n}$ is the $n \times n$ zero matrix, $I_{n}$ is the identity matrix of order $n, A=\left(a_{i j}\right)$ is a real $n \times n$ matrix, $A^{T}$ is the transpose of $A$, and $A\left(i_{1}: i_{2}, j_{1}: j_{2}\right)$ is the submatrix

$$
\left(a_{i j}: i_{1} \leq i \leq i_{2}, j_{1} \leq j \leq j_{2}\right)
$$

of $A$. We will write $i_{1}$ for $i_{1}: i_{1}$ and : for $1: n$. For two subsets $I=\left\{i_{1}, \ldots, i_{s}\right\}$ and $J=\left\{j_{1}, \ldots, j_{t}\right\}$ of $\{1, \ldots, n\}, A_{I, J}$ denotes the submatrix

$$
\left(a_{i j}: i \in I, j \in J\right)
$$

### 2.1 Preliminaries

### 2.1.1 Signs of permutations

Let $S_{n}$ be the set of all permutations of the numbers $\{1,2, \ldots, n\}$. A permutation $\pi \in S_{n}$ can be produced by $k_{\pi}$ exchanges of two elements (these exchanges are called transpositions), and $\pi$ is called an even permutation (or odd permutation, respectively) if $k_{\pi}$ is an even number
(or odd number, respectively). The sign of a permutation $\pi$ is defined by

$$
\operatorname{sgn}(\pi)= \begin{cases}1 & \text { if } \pi \text { is an even permutation } \\ -1 & \text { otherwise }\end{cases}
$$

From algebra, we know that $\pi \in S_{n}$ can be uniquely written as a product of disjoint cycles. If $k$ is the number of these cycles (including 1 -cycles), then we have

$$
\begin{equation*}
\operatorname{sgn}(\pi)=(-1)^{n-k} \tag{2.1}
\end{equation*}
$$

### 2.1.2 Determinants

The determinant of a $n \times n$ matrix $A=\left(a_{i j}\right)$, denoted by $\operatorname{det} A$, is defined by

$$
\begin{equation*}
\operatorname{det} A=\sum_{\pi \in S_{n}}\left(\prod_{i=1}^{n} a_{i \pi(i)}\right) \tag{2.2}
\end{equation*}
$$

The determinant has the following properties.
(1) If matrix $B$ results from $A$ by exchanging two rows or columns, then

$$
\begin{equation*}
\operatorname{det} B=-\operatorname{det} A \tag{2.3}
\end{equation*}
$$

(2) If $B$ results from $A$ by multiplying one row or column with a constant $c$, then

$$
\begin{equation*}
\operatorname{det} B=c \operatorname{det} A . \tag{2.4}
\end{equation*}
$$

(3) If $B$ results from $A$ by adding a multiple of one row to another row, or a multiple of one column to another column, then

$$
\begin{equation*}
\operatorname{det} B=\operatorname{det} A \text {. } \tag{2.5}
\end{equation*}
$$

(4) For any $n \times n$ matrix $B$, we have

$$
\begin{equation*}
\operatorname{det}(A B)=\operatorname{det} A \cdot \operatorname{det} B \tag{2.6}
\end{equation*}
$$

### 2.1.3 The Laplace expansion theorem

The determinant of $A=\left(a_{i j}\right)$ can be expanded along a row i:

$$
\begin{equation*}
\operatorname{det} A=\sum_{j=1}^{n}(-1)^{i+j} a_{i j} B_{i, j}, \tag{2.7}
\end{equation*}
$$

where the $B_{i, j}$ is the determinant of the matrix that results from A by removing the $i-$ th row and the $j$-th column.

More generally, let $I$ be a $k$-subset of $\{1,2, \ldots, n\}, 1 \leq k<n$, then we have the Laplace expansion theorem:

$$
\begin{equation*}
\operatorname{det} A=\sum_{J}(-1)^{s(I, J)} \cdot \operatorname{det} A_{I, J} \cdot \operatorname{det} A_{I^{c}, J^{c}}, \tag{2.8}
\end{equation*}
$$

where $J$ goes through all $k$-subsets of $\{1,2, \ldots, n\}, s(I, J)$ is the sum of numbers in $I$ and $J$, and $I^{c}$ is the complement of $I$. In particular, if for $a_{i j}=0$ for all $i \in I$ and $j \notin I$, then

$$
\begin{equation*}
\operatorname{det} A=\operatorname{det} A_{I, I} \cdot \operatorname{det} A_{I^{c}, I^{c}} . \tag{2.9}
\end{equation*}
$$

Formula (2.9) is useful for our simulation.

### 2.1.4 Determinants of some special matrices

Now, we consider the determinants of some special matrices.
(1) Triangular matrix If $A$ is an upper triangular matrix (i.e., $a_{i j}=0$ for $1 \leq j<i \leq$ $n$ ) or lower triangular matrix (i.e., $a_{i j}=0$ for $1 \leq i<j \leq n$ ), then

$$
\begin{equation*}
\operatorname{det} A=\prod_{i=1}^{n} a_{i i} \tag{2.10}
\end{equation*}
$$

(2) Elementary matrices Let $i, j \in \mathbb{N}$ with $i \neq j$. An elementary transformation matrix $L(i, j, \alpha)=\left(l_{k l}\right)$ is the identity matrix with the correction

$$
l_{i j}=\alpha,
$$

and an elementary permutation matrix $E(i, j)$ is obtained by exchanging the $i$ th row and the $j$ th row of $I_{n}$. Using $L(i, j, \alpha)$ to premultiply a matrix $M$ will add $\alpha M(j,:)$ to the $i$ th
row of $M$, and using $E(i, j)$ to premultiply $M$ will exchange the $i$ th row and the $j$ th row of M. It is clear that we have

$$
\begin{equation*}
\operatorname{det}(L(i, j, \alpha))=1, \quad \operatorname{det}(E(i, j))=-1 \tag{2.11}
\end{equation*}
$$

(3) Orthogonal matrix $A$ is an orthogonal matrix if $A A^{T}=I_{n}$, where $A^{T}$ is the transpose of $A$. It is clear that if $A$ is orthogonal, then

$$
\begin{equation*}
\operatorname{det} A= \pm 1 \tag{2.12}
\end{equation*}
$$

(4) Vandermonde matrix If

$$
A=\left(\begin{array}{ccccc}
1 & 1 & 1 & \cdots & 1 \\
x_{1} & x_{2} & x_{3} & \cdots & x_{n} \\
x_{1}^{2} & x_{2}^{2} & x_{3}^{2} & \cdots & x_{n}^{2} \\
\cdots & \cdots & \cdots & \cdots & \cdots \\
x_{1}^{n-1} & x_{2}^{n-1} & x_{3}^{n-1} & \cdots & x_{n}^{n-1}
\end{array}\right)
$$

where $x_{1}, \ldots, x_{n}$ are real numbers, then $A$ is called a Vandermonde matrix, and

$$
\begin{equation*}
\operatorname{det} A=\prod_{i=2}^{j} \prod_{j=1}^{i-1}\left(x_{i}-x_{j}\right) \tag{2.13}
\end{equation*}
$$

(5) Cauchy matrix If

$$
A=\left(\begin{array}{cccc}
\frac{1}{x_{1}+y_{1}} & \frac{1}{x_{1}+y_{2}} & \cdots & \frac{1}{x_{1}+y_{n}} \\
\frac{1}{x_{2}+y_{1}} & \frac{1}{x_{2}+y_{2}} & \cdots & \frac{1}{x_{2}+y_{n}} \\
\cdots & \cdots & \cdots & \cdots \\
\frac{1}{x_{n}+y_{1}} & \frac{1}{x_{n}+y_{2}} & \cdots & \frac{1}{x_{n}+y_{n}}
\end{array}\right)
$$

where $x_{1}, \ldots, x_{n}$ and $y_{1}, y_{2}, \ldots, y_{n}$ are real numbers such that for each pair $(i, j), x_{i}+y_{j} \neq 0$, then $A$ is called a Cauchy matrix, and

$$
\begin{equation*}
\operatorname{det} A=\frac{\prod_{i=2}^{j} \prod_{j=1}^{i-1}\left(x_{i}-x_{j}\right)\left(y_{i}-y_{j}\right)}{\prod_{i=1}^{n} \prod_{j=1}^{n}\left(x_{i}+y_{j}\right)} \tag{2.14}
\end{equation*}
$$

### 2.2 Determinants of arbitrary matrices

In general, we can calculate $\operatorname{det} A$ in the following way: First, write $A$ in the form

$$
A=L B R,
$$

where $B$ is an upper triangular matrix, and $L$ and $R$ are products of triangular or orthogonal matrices. Then we have

$$
\begin{equation*}
\operatorname{det} A=\operatorname{det} L \cdot \operatorname{det} B \cdot \operatorname{det} R \tag{2.15}
\end{equation*}
$$

The following algorithms are adapted from the algorithms that find the $L U$ or $Q R$ factorizations. The running time for each of the algorithms is determined by the number of multiplications required by the algorithm.

### 2.2.1 Gaussian elimination with Partial Pivoting (GEP)

A Gaussian transformation is a matrix of the form

$$
M_{k}=I_{m}-\vec{\tau} \vec{e}_{k}^{T}=\prod_{j=k+1}^{m} L\left(j, k,-\tau_{j}\right),
$$

where the first $k$ components of $\vec{\tau}$ are zeros. It is clear that $M_{k}$ is lower triangular and det $M_{k}=1$. The vector $\vec{\tau}$ is called the Gauss vector and its nonzero components are called multipliers.

Suppose $\vec{x} \in \mathbb{R}^{m}$ with $x_{k} \neq 0$. Let

$$
\vec{\tau}^{T}=\left(0, \ldots, 0, \tau_{k+1}, \ldots, \tau_{m}\right), \quad \tau_{i}=\frac{x_{i}}{x_{k}}, i=k+1, \ldots, m
$$

Then we have

$$
\begin{equation*}
M_{k} \vec{x}=\left(x_{1}, \ldots, x_{k}, 0, \ldots, 0\right)^{T} \tag{2.16}
\end{equation*}
$$

Hence, we can upper-triangularize $A$ by applying a series of Gaussian transformations to $A$. This method is called Gaussian elimination.

The following algorithm uses Gaussian elimination to upper-triangularize the $n \times n$ matrix A.

## $\operatorname{GEP}(A, n)$

```
sign }\leftarrow1
for }i=1\mathrm{ to }n-1\mathrm{ do
```

    Determine \(t\) so that \(a_{i t}=\max \left\{a_{i i}, \ldots, a_{n i}\right\}\);
    if \(t \neq i\) then
            Exchange the \(t\) th row and the \(i\) th row of \(A, \operatorname{sign} \leftarrow-\operatorname{sign}\);
    for \(j=i+1\) to \(n\) do
        \(a_{j i} \leftarrow \frac{a_{j i}}{a_{i i}} ;\)
        \(A(j, i+1: n)=A(j, i+1: n)-a_{j i} A(i, i+1: n) ;\)
    The Lines 3-5 are doing partial pivoting that guarantees that no multiplier is greater than one in absolute value (large multipliers may cause large errors).

This algorithm requires at most $\frac{2}{3} n^{3}$ multiplications, and can be used to compute the $L U$ factorization of a row permuted version of $A([3], \mathrm{pp} .113-114)$.

### 2.2.2 Givens Rotation (GR)

A Givens rotation is a matrix $G=G(i, k, \theta)$ that is the identity matrix with corrections

$$
g_{i i}=g_{k k}=c, g_{i k}=s, g_{k i}=-s, c=\cos (\theta), s=\sin (\theta) .
$$

It is orthogonal with $\operatorname{det} G=1$. Premultipling a matrix $A$ by $G$ is equivalent to a counterclockwise rotation of $\theta$ radians in the $(i, k)$ coordinate plane that affects just two rows of $A$. By choosing the values of $i, k$ and $\theta$, we can zero selected elements in A, so we can upper triangularize $A$ by a series of Givens rotations.

Given scalars $a$ and $b$, the following function computes a unit vector $\vec{v}=(c, s)$ such that

$$
\left(\begin{array}{cc}
c & s  \tag{2.17}\\
-s & c
\end{array}\right)^{T}\binom{a}{b}=\binom{r}{0}
$$

$$
\vec{v}=\operatorname{givens}(a, b)
$$

$$
1 \text { if } b=0 \text { then }
$$

$2 \quad \vec{v} \leftarrow(1,0) ;$
3 else
$4 \quad t \leftarrow \frac{1}{\sqrt{a^{2}+b^{2}}} ;$
$5 \quad$ if $|a|<|b|$ then $\vec{v} \leftarrow(-a t, b t)$;
$6 \quad$ else $\vec{v} \leftarrow(a t,-b t)$.
Now, the following algorithm uses Givens rotations to upper-triangularize the $n \times n$ matrix $A$.

```
\(\boldsymbol{G R}(A, n)\)
1 for \(j=1\) to \(n-1\) do
2 for \(i=j+1\) to \(n\) do
\(3 \quad\) if \(a_{i j} \neq 0\) then
\(4 \quad \vec{v} \leftarrow \operatorname{givens}\left(a_{j j}, a_{i j}\right)\)
\(5 \quad \vec{x} \leftarrow v_{1} A(j, j: n)-v_{2} A(i, j: n) ;\)
\(6 \quad A(i, j: n) \leftarrow v_{1} A(i, j: n)+v_{2} A(j, j: n) ;\)
\(7 \quad A(j, j: n) \leftarrow \vec{x}\).
```

This algorithm requires at most $2 n^{3}$ multiplications, and can be used to compute the $Q R$ factorization of $A([3], \mathrm{pp} .226-227)$.

### 2.2.3 Householder Reflections (HR)

Let $\vec{v} \in \mathbb{R}^{m}$. An $m \times m$ matrix $P$ of the form

$$
P=I_{m}-\beta \vec{v}^{T} \vec{v}, \quad \beta=\frac{2}{\vec{v}^{T} \vec{v}}
$$

is called a Householder reflection. The vector $\vec{v}$ is called a Householder vector. If a vector $\vec{x}$ is multiplied by $P$, then it is reflected in the hyperplane span $\{\vec{v}\}^{\perp}$, and if we set

$$
\vec{v}=\vec{x}-\|\vec{x}\| \overrightarrow{e_{1}}
$$

where $\|\vec{x}\|=\sqrt{x_{1}^{2}+\cdots+x_{m}^{2}}$, then

$$
\begin{equation*}
P \vec{x}=\|\vec{x}\| \overrightarrow{e_{1}} . \tag{2.18}
\end{equation*}
$$

It is readily checked that $P$ is orthogonal, so $\operatorname{det} P= \pm 1$, and we have

$$
\begin{equation*}
\operatorname{det} P=-1 \Longleftrightarrow \beta\|\vec{v}\|>1 . \tag{2.19}
\end{equation*}
$$

Hence, we can compute $\operatorname{det} A$ by upper triangularizing $A$ using a series of Householder reflections.

The following function computes the normalized Householder vector $\vec{v}\left(i . e ., v_{1}=1\right)$ and $\beta$ for given $\vec{x} \in \mathbb{R}^{m}$.

$$
\begin{array}{ll}
{[\vec{v}, \beta]=\operatorname{house}(\vec{x})} \\
1 & m \leftarrow \operatorname{length}(\vec{x}) ; \\
2 & \sigma \leftarrow x(2: m) \cdot x(2: m) ; \\
3 & \vec{v} \leftarrow x, v_{1} \leftarrow 1 ; \\
4 & \text { if } \sigma=0 \text { then } \\
5 & \beta \leftarrow 0 ; \\
6 & \text { else } \\
7 & \mu \leftarrow \sqrt{x_{1}^{2}+\sigma} ; \\
8 & \text { if } x_{1} \leq 0 \text { then } v_{1} \leftarrow x_{1}-\mu ; \\
9 & \text { else } v_{1} \leftarrow-\frac{\sigma}{x_{1}+\mu} ; \\
10 & \beta \leftarrow \frac{2 v_{1}^{2}}{\sigma+v_{1}^{2}} ; \vec{v} \leftarrow \frac{\vec{v}}{v_{1}} ;
\end{array}
$$

Now, the following algorithm uses Householder reflections to compute $\operatorname{det} A$.

$$
\begin{aligned}
& \operatorname{HR}(A, n) \\
& 1 \quad k \leftarrow n, \operatorname{sign} \leftarrow 1 ; \\
& 2 \text { for } i=1 \text { to } n \text { do } \\
& 3 \quad[\vec{v}, \beta] \leftarrow \operatorname{house}(A(i: n, i)) \text {; } \\
& 4 \quad W \leftarrow I_{k}-\beta \vec{v} \vec{v}^{T} ; \\
& 5 \quad A(i: n, i: n) \leftarrow W A(i: n, i: n) \text {; } \\
& 6 \text { if } \beta \vec{v} \cdot \vec{v}>1 \text { then } \operatorname{sign} \leftarrow-\operatorname{sign} \text {; } \\
& 7 \quad k \leftarrow k-1 ; \\
& 8 \quad \operatorname{det} A \leftarrow \operatorname{sign} \cdot \prod_{i=1}^{n} a_{i i} .
\end{aligned}
$$

The algorithm HR requires at most $\frac{4}{3} n^{3}$ multiplications, and can be also used to compute the $Q R$ factorization of $A([3], \mathrm{pp} .224-226)$.

### 2.2.4 Fast Givens Transformation(FGT)

There are two types of fast Givens transformations. The "type 1" transformation is a matrix $F_{1}=F_{1}(i, k, \alpha, \beta)$ that is the identity matrix with corrections

$$
f_{i k}=f_{j k}=1, f_{i i}=\beta, f_{k k}=\alpha
$$

and the 'type 2" transformation is a matrix $F_{2}=F_{2}(i, k, \alpha, \beta)$ that is the identity matrix with corrections

$$
f_{i k}=\alpha, f_{j k}=\beta, f_{i i}=f_{k k}=1
$$

where $\alpha, \beta$ satisfy $-1 \leq \alpha \beta \leq 0$. It is clear that

$$
\operatorname{det} F_{1}<0, \quad \text { and } \quad \operatorname{det} F_{2}>0
$$

From linear algebra (see [3], pp.219-221), applying a series of fast Givens transformations to the matrix $A$, we can get a diagonal matrix

$$
D=\operatorname{diag}\left(d_{1}, d_{2}, \ldots, d_{n}\right)
$$

with all $d_{i}>0$, and an upper triangular matrix $T=M^{T} A=\left(T_{i j}\right)$ where $M$ is the product of the fast Givens transformations, such that

$$
Q=M D^{-1 / 2}
$$

is orthogonal, where

$$
D^{-1 / 2}=\operatorname{diag}\left(\frac{1}{\sqrt{d_{1}}}, \frac{1}{\sqrt{d_{2}}}, \ldots, \frac{1}{\sqrt{d_{n}}}\right)
$$

and if $R=D^{1 / 2} T$ where

$$
D^{1 / 2}=\operatorname{diag}\left(\sqrt{d_{1}}, \sqrt{d_{2}}, \ldots, \sqrt{d_{n}}\right)
$$

then $A=Q R$ is the $Q R$ factorization of $A$. Note that

$$
\operatorname{det} Q= \begin{cases}1 & \text { if } t \text { is even } \\ -1 & \text { otherwise }\end{cases}
$$

where $t$ is the number of fast Givens transformations used, so we have

$$
\begin{equation*}
\operatorname{det} A=(-1)^{t} \frac{\prod_{i=1}^{n} T_{i i}}{\prod_{i=1}^{n} d_{i}} \tag{2.20}
\end{equation*}
$$

Given $\vec{x} \in \mathbb{R}^{2}$ and positive $\vec{d} \in \mathbb{R}^{2}$, the following function computes a $2 \times 2$ fast Givens transformation $M$ and its type, such that $M^{T} \overrightarrow{d M}=\operatorname{diag}\left(d_{1}, d_{2}\right)$.

$$
[M, \text { type }]=\operatorname{fastgivens}(\vec{x}, \vec{d})
$$

1 if $x_{2}=0$ then
$2 \quad M \leftarrow I_{2}$, type $\leftarrow 1$;
3 else
$4 \quad \alpha \leftarrow-\frac{x_{1}}{x_{2}} ; \beta \leftarrow-\frac{\alpha d_{2}}{d_{1}} ; \gamma \leftarrow-\alpha \beta ;$
5 if $\gamma>1$ then
$6 \quad$ type $\leftarrow 1 ; \vec{d} \leftarrow\left(1+\frac{1}{\gamma}\right) \vec{d}$;
$7 \quad M \leftarrow I_{2} ; t_{12} \leftarrow \frac{1}{\alpha} ; t_{21} \leftarrow \frac{1}{\beta} ;$
8 else
$9 \quad$ type $\leftarrow-1 ; y \leftarrow d_{1} ;$
$10 \quad t_{11} \leftarrow \beta ; t_{22} \leftarrow \alpha ; t_{12} \leftarrow 1 ; t_{21} \leftarrow 1 ;$
$11 \quad d_{1} \leftarrow(1+\gamma) d_{2} ; d_{2} \leftarrow(1+\gamma) y$.
Now, the following algorithm computes $\operatorname{det} A$ by using fast Givens transformations ( $A$ is overwritten by $T$ ).
$\boldsymbol{\operatorname { F G T }}(A, n)$
$1 \operatorname{sign} \leftarrow 1 ; \vec{d} \leftarrow(1, \ldots, 1) ;$
2 for $j=1$ to $n-1$ do
$3 \quad$ for $i=n$ downto $j+1$ do
$4 \quad$ if $a_{i j} \neq 0$ then
5

$$
[M, \text { type }] \leftarrow \text { fastgivens }(A(i-1: i, j), d(i-1: i))
$$

$$
\begin{array}{lc}
6 & \text { if } \text { type }=-1 \text { then } \operatorname{sign}=-\operatorname{sign} ; \\
7 & A(i-1: i, j: n) \leftarrow M A(i-1: i, j: n) ; \\
8 & \operatorname{det} A \leftarrow \operatorname{sign} \cdot \frac{\prod_{i=1}^{n} A(i, i)}{\sqrt{\prod_{i=1}^{n} d(i)}}
\end{array}
$$

The algorithm requires at most $\frac{4}{3} n^{3}$ multiplications.

Each of the four algorithms requires $0\left(n^{3}\right)$ multiplications. However, the running times of these algorithms differ systematically and significantly from each other. This is discussed in the next section.

### 2.3 Comparisons of the algorithms

To determine the most efficient and accurate of the algorithms in $\S 1.2$, we have performed several experiments. The programs were written in FORTRAN90 based on these algorithms, and were run on the machine origin.rcr.uga.edu. In the experiments, we used Vandermonde matrices and Cauchy matrices since the true values of determinants of these matrices can be easily computed by (2.13) and (2.14).

Throughout this section, $T_{1}, T_{2}, T_{3}, T_{4}$ and $E_{1}, E_{2}, E_{3}, E_{4}$ denote the CPU times and relative errors of GEP, GR, HR and FGT, respectively.

### 2.3.1 Experiment 1

In Experiment 1, we compute determinants of Vandermonde matrices with $\left\{x_{1}, \ldots, x_{n}\right\}$ taken to be the first $n$ numbers of the randomly generated sequence

$$
\begin{aligned}
& \{2.87076397,2.62174494,0.46096613,1.79393912,1.73782442,2.40223898 \\
& 3.06015478,0.96327602,2.09695352,1.16681509,0.52530896,0.38936178 \\
& 3.89913013,1.72542264,0.00551535,2.09386799,0.27771812,0.00571990\}
\end{aligned}
$$

The results are in Table 2.1 and 2.2.

Table 2.1: CPU time in Experiment 1.

| $\boldsymbol{n}$ | $\boldsymbol{T}_{\mathbf{1}}(\mathrm{ms})$ | $\boldsymbol{T}_{\mathbf{2}} / \boldsymbol{T}_{\mathbf{1}}$ | $\boldsymbol{T}_{\mathbf{3}} / \boldsymbol{T}_{\mathbf{1}}$ | $\boldsymbol{T}_{\mathbf{4}} / \boldsymbol{T}_{\mathbf{1}}$ |
| :---: | :---: | :---: | :---: | :---: |
| 10 | 0.018 | 2.22 | 9.33 | 11.5 |
| 12 | 0.026 | 2.31 | 8.96 | 12.2 |
| 14 | 0.038 | 2.26 | 8.21 | 12.0 |
| 16 | 0.053 | 2.25 | 7.60 | 11.8 |
| 18 | 0.072 | 2.22 | 7.10 | 11.8 |

Table 2.2: Relative errors in Experiment 1.

| $\boldsymbol{n}$ | $\boldsymbol{E}_{\mathbf{1}}$ | $\boldsymbol{E}_{\mathbf{2}} / \boldsymbol{E}_{\mathbf{1}}$ | $\boldsymbol{E}_{\mathbf{3}} / \boldsymbol{E}_{\mathbf{1}}$ | $\boldsymbol{E}_{\mathbf{4}} / \boldsymbol{E}_{\mathbf{1}}$ |
| :---: | :---: | :---: | :---: | :---: |
| 10 | $5.0 \times 10^{-10}$ | 1.15 | 1.37 | 0.83 |
| 12 | $1.1 \times 10^{-9}$ | 1.29 | 2.90 | 1.36 |
| 14 | $2.31 \times 10^{-7}$ | 3.87 | 0.72 | 5.22 |
| 16 | $1.16 \times 10^{-5}$ | 1.56 | 4.47 | 13.7 |
| 18 | $1.16 \times 10^{-5}$ | 3.98 | 6.98 | 13.5 |

### 2.3.2 Experiment 2

In Experiment 2, we compute determinants of Vandermonde matrices with with $x_{i}=\frac{i}{5}$. The results are in Table 2.3 and 2.4.

### 2.3.3 Experiment 3

In Experiment 3, we compute determinants of Cauchy matrices with $\left\{x_{1}, \ldots, x_{n}\right\}$ taken to be the first $n$ numbers of the randomly generated sequence

$$
\begin{aligned}
\{ & 0.07176910,0.06554362,0.01152415,0.04484848,0.04344561 \\
& 0.06005598,0.07650387,0.02408190,0.05242384,0.02917038\}
\end{aligned}
$$

and $\left\{y_{1}, \ldots, y_{n}\right\}$ be the first $n$ numbers of the randomly generated sequence
$\{\quad 0.09747825,0.04313557,0.00013788,0.05234670,0.00694295$

$$
0.00014300,0.07939814,0.08336780,0.07268485,0.06766319\}
$$

The results are in Table 2.5 and 2.6.

Table 2.3: CPU time in Experiment 2.

| $\boldsymbol{n}$ | $\boldsymbol{T}_{\mathbf{1}}(\mathrm{ms})$ | $\boldsymbol{T}_{\mathbf{2}} / \boldsymbol{T}_{\mathbf{1}}$ | $\boldsymbol{T}_{\mathbf{3}} / \boldsymbol{T}_{\mathbf{1}}$ | $\boldsymbol{T}_{\mathbf{4}} / \boldsymbol{T}_{\mathbf{1}}$ |
| :---: | :---: | :---: | :---: | :---: |
| 10 | 0.018 | 2.17 | 9.22 | 11.7 |
| 12 | 0.026 | 2.35 | 8.73 | 12.3 |
| 14 | 0.037 | 2.35 | 8.19 | 12.5 |
| 16 | 0.053 | 2.31 | 7.58 | 12.2 |
| 18 | 0.071 | 2.25 | 7.14 | 11.8 |

Table 2.4: Relative errors in Experiment 2.

| $\boldsymbol{n}$ | $\boldsymbol{E}_{\mathbf{1}}$ | $\boldsymbol{E}_{\mathbf{2}} / \boldsymbol{E}_{\mathbf{1}}$ | $\boldsymbol{E}_{\mathbf{3}} / \boldsymbol{E}_{\mathbf{1}}$ | $\boldsymbol{E}_{\mathbf{4}} / \boldsymbol{E}_{\mathbf{1}}$ |
| :---: | :---: | :---: | :---: | :---: |
| 10 | $2.37 \times 10^{-11}$ | 2.96 | 11.5 | 14.3 |
| 12 | $6.94 \times 10^{-10}$ | 2.62 | 4.61 | 14.4 |
| 14 | $1.59 \times 10^{-6}$ | 0.08 | 0.08 | 2.50 |
| 16 | $1.42 \times 10^{-4}$ | 0.61 | 0.67 | 2.25 |
| 18 | $6.25 \times 10^{-2}$ | 0.01 | 0.11 | 0.02 |

### 2.3.4 Experiment 4

In this Experiment, we compute determinants of Cauchy matrices with $x_{i}=\frac{i}{10}$ and $y_{i}=\frac{i}{5}$, and the results are in Table 2.7 and 2.8.

### 2.3.5 Conclusion

The data in Tables 2.1 to 2.8 show that among the algorithms given in $\S 2.2$, GEP is the most efficient, and, in most cases, the most accurate. So in terms of efficiency and accuracy, GEP is a good algorithm for evaluating determinants. However, when GEP produced large errors, GR may be a good alternative method. HR and FGT have their advantages when finding $Q R$ factorizations, but they are not as good for evaluating determinants.

We used GEP to calculate determinants in our simulations.

Table 2.5: CPU time in Experiment 3.

| $\boldsymbol{n}$ | $\boldsymbol{T}_{\mathbf{1}}(\mathrm{ms})$ | $\boldsymbol{T}_{\mathbf{2}} / \boldsymbol{T}_{\mathbf{1}}$ | $\boldsymbol{T}_{\mathbf{3}} / \boldsymbol{T}_{\mathbf{1}}$ | $\boldsymbol{T}_{\mathbf{4}} / \boldsymbol{T}_{\mathbf{1}}$ |
| :---: | :---: | :---: | :---: | :---: |
| 6 | 0.008 | 1.75 | 10.6 | 8.5 |
| 7 | 0.008 | 2.38 | 13.1 | 11.8 |
| 8 | 0.012 | 2.00 | 10.5 | 10.3 |
| 9 | 0.014 | 2.29 | 10.8 | 11.6 |
| 10 | 0.016 | 2.50 | 10.9 | 13.0 |

Table 2.6: Relative errors in Experiment 3.

| $\boldsymbol{n}$ | $\boldsymbol{E}_{\mathbf{1}}$ | $\boldsymbol{E}_{\mathbf{2}} / \boldsymbol{E}_{\mathbf{1}}$ | $\boldsymbol{E}_{\mathbf{3}} / \boldsymbol{E}_{\mathbf{1}}$ | $\boldsymbol{E}_{\mathbf{4}} / \boldsymbol{E}_{\mathbf{1}}$ |
| :---: | :---: | :---: | :---: | :---: |
| 6 | $2.40 \times 10^{-8}$ | 1.50 | 2.87 | 1.06 |
| 7 | $7.82 \times 10^{-8}$ | 2.68 | 11.9 | 3.76 |
| 8 | $8.37 \times 10^{-7}$ | 1.00 | 0.02 | 1.11 |
| 9 | $7.09 \times 10-5$ | 2.84 | 1.27 | 1.56 |
| 10 | $1.55 \times 10^{-3}$ | 5.31 | 2.54 | 2.87 |

Table 2.7: CPU time in Experiment 4.

| $\boldsymbol{n}$ | $\boldsymbol{T}_{\mathbf{1}}(\mathrm{ms})$ | $\boldsymbol{T}_{\mathbf{2}} / \boldsymbol{T}_{\mathbf{1}}$ | $\boldsymbol{T}_{\mathbf{3}} / \boldsymbol{T}_{\mathbf{1}}$ | $\boldsymbol{T}_{\mathbf{4}} / \boldsymbol{T}_{\mathbf{1}}$ |
| :---: | :---: | :---: | :---: | :---: |
| 6 | 0.007 | 2.00 | 11.7 | 9.7 |
| 7 | 0.009 | 2.11 | 11.4 | 10.6 |
| 8 | 0.011 | 2.27 | 12.2 | 11.5 |
| 9 | 0.014 | 2.21 | 10.7 | 11.6 |
| 10 | 0.018 | 2.22 | 9.78 | 11.6 |

Table 2.8: Relative errors in Experiment 4.

| $\boldsymbol{n}$ | $\boldsymbol{E}_{\mathbf{1}}$ | $\boldsymbol{E}_{\mathbf{2}} / \boldsymbol{E}_{\mathbf{1}}$ | $\boldsymbol{E}_{\mathbf{3}} / \boldsymbol{E}_{\mathbf{1}}$ | $\boldsymbol{E}_{\mathbf{4}} / \boldsymbol{E}_{\mathbf{1}}$ |
| :---: | :---: | :---: | :---: | :---: |
| 6 | $8.70 \times 10^{-11}$ | 0.08 | 6.54 | 12.5 |
| 7 | $9.50 \times 10^{-9}$ | 2.33 | 2.07 | 2.72 |
| 8 | $2.98 \times 10^{-7}$ | 2.37 | 0.56 | 3.69 |
| 9 | $8.53 \times 10-7$ | 7.32 | 17.9 | 14.0 |
| 10 | $1.51 \times 10^{-6}$ | 1.99 | 3.86 | 2.52 |

## Chapter 3

## FEYNMAN DIAGRAM EXPANSIONS

A Feynman diagram is a tool invented by Richard Feynman for performing scattering calculations in quantum field theory. To simulate an electron system, we need to expand it to a series of Feynman diagrams. In this chapter, we describe the elements of Feynman diagrams for general 1-electron spaces in $\S 3.1$, then introduce the Feynman diagram series $\S 3.2$ and calculation of them in $\S 3.3$. Finally, we discuss the $m$-electron Green's function in $\S 3.4$ and the integral padding functions in $\S 3.5$.

Throughout, $\mathscr{E}$ denotes the (general) 1-electron space, $T \in(0, \infty)$ is the temperature, $\beta_{T}=\frac{1}{T}$ is the inverse temperature, and the interval $\left[0, \beta_{T}\right]$ is called the imaginary-time interval.

### 3.1 Elements of Feynman diagrams for 1-Electron spaces

There are two kinds of elements of Feynman diagrams for $\mathscr{E}$ : fermions and bosons. The order of a Feynman diagram is the number of bosons in it. A vertex that incidents with a boson is called an internal vertex and denoted by $\bullet$. A diagram of order $n$ has exactly $2 n$ internal vertices that labeled by $1,2, \ldots, 2 n$, and we will identify a vertex with its label.

### 3.1.1 Fermions

A fermion (or $g$-line) is a directed edge denoted by

or

$$
g(\alpha, \tau \mid \bar{\alpha}, \bar{\tau})
$$

Where $\alpha, \bar{\alpha} \in \mathscr{E}$ and $\tau, \bar{\tau} \in\left[0, \beta_{T}\right]$.

### 3.1.2 Bosons

A boson (or interaction, or $V$-line) stands for an instantaneous interaction. and is denoted by

or

$$
V\left(\bar{\alpha}_{j}, \bar{\alpha}_{i} \mid \alpha_{i}, \alpha_{j}\right) \delta\left(\tau_{j}-\tau_{i}\right) \delta\left(\bar{\tau}_{j}-\bar{\tau}_{i}\right) \delta\left(\tau_{j}-\bar{\tau}_{i}\right)
$$

where $i, j$ are two vertices, $\left.\alpha_{i}, \alpha_{j}, \bar{\alpha}_{i}, \bar{\alpha}_{j} \in \mathscr{E}, \tau_{i}, \tau_{j}, \overline{\tau_{i}}, \overline{\tau_{i}} \in\left[0, \beta_{T}\right]\right)$, and $\delta$ is the Dirac $\delta-$ function defined by

$$
\delta(x)= \begin{cases}0 & \text { if } x \neq 0 \\ \infty & \text { if } x=0\end{cases}
$$

### 3.2 The Feynman diagram series

In this section, we will describe the Feynman diagrams and the Feynman diagram series for $m$-electron systems.

### 3.2.1 The Feynman diagrams

Each internal vertex in a diagram has exactly 1 incident boson, 1 incoming fermion and 1 outgoing fermion. We will assume that the $k$-th boson connects vertices $2 k-1$ and $2 k$.

In the case $m=0$, all vertices are internal vertices, the fermions of a diagram $F$ of order $n$ determine a permutation $\pi_{F} \in S_{2 n}$ on its vertices, and the closed fermion loops form a cycle decomposition of $\pi_{F}$. Then

$$
\begin{equation*}
\operatorname{sgn}\left(\pi_{F}\right)=(-1)^{k} \tag{3.1}
\end{equation*}
$$

by (2.1), where $k$ is the number of closed fermion loops in $F$.
More generally, let $m \geq 0$; for each electron in the $m$-electron system, an exterior vertex (denoted by a pair of $\otimes s$ ) with an outgoing fermion and an incoming fermion is included in
the diagram. The fermions in a diagram $F$ of order $n$ determine a permutation $\pi_{F} \in S_{2 n+m}$ on the vertices, and the closed fermion loops form a cycle decomposition of $\pi_{F}$. Then by (2.1), we have

$$
\begin{equation*}
\operatorname{sgn}\left(\pi_{F}\right)=(-1)^{k+m} \tag{3.2}
\end{equation*}
$$

where $k$ is the number of closed fermion loops in $F$
The Feynman diagram series for $m$-electron systems

$$
R_{m}\left(\beta_{1}, \ldots, \beta_{m}\left|\bar{\beta}_{1}, \ldots, \overline{\beta_{m}}, \theta_{1}, \ldots, \theta_{m}\right| \bar{\theta}_{1}, \ldots, \overline{\theta_{m}}\right)
$$

is the sum of all Feynman diagrams for $m$-electron systems, where $\beta_{i}, \bar{\beta}_{i} \in \mathscr{E}$ and $\theta_{i}, \bar{\theta}_{i} \in$ $\left[0, \beta_{T}\right]$. As examples, we give more details for $m=0$ and $m=1$.

### 3.2.2 The series $R_{0}$

Let $R_{0}^{n}$ be the series of Feynman diagrams of order $n$ for 0 -electron system, $\alpha_{i}, \overline{\alpha_{i}} \in \mathscr{E}$ and $\tau_{i}, \bar{\tau}_{i} \in\left[0, \beta_{T}\right]$. Then we have

$$
R_{0}=\sum_{n=1}^{\infty} R_{0}^{n}
$$

where $R_{0}^{0}=1$, and


### 3.2.3 The series $R_{1}(\beta|\bar{\beta}, \theta| \bar{\theta})$

Let $R_{1}^{n}$ be the series of Feynman diagrams of order $n$ for 1 -electron systems, $\alpha_{i}, \overline{\alpha_{i}} \in \mathscr{E}$ and $\tau_{i}, \bar{\tau}_{i} \in\left[0, \beta_{T}\right]$. Then we have

$$
R_{1}(\beta|\bar{\beta}, \theta| \bar{\theta})=\sum_{n=1}^{\infty} R_{1}^{n}
$$

where

$$
R_{1}^{0}=\otimes{\underset{\beta, \theta}{ }<\overline{\bar{\beta}, \bar{\theta}}}^{\otimes}
$$

and

### 3.3 Calculation of Feynman diagram series

In this section, we will discuss the calculation of Feynman diagram series for $m$-electron systems.

### 3.3.1 Compact notation

In the remainder of this dissertation, we will use the following compact notation.
Given $\hat{\alpha}=\left(\alpha_{1}, \ldots, \alpha_{2 n}, \bar{\alpha}_{1}, \ldots, \bar{\alpha}_{2 n}\right) \in \mathscr{E}^{4 n}$ and $\hat{\beta}=\left(\beta_{1}, \ldots, \beta_{m}, \bar{\beta}_{1}, \ldots, \bar{\beta}_{m}\right) \in \mathscr{E}^{2 m}$, let

$$
V(n, \hat{\alpha}):= \begin{cases}\prod_{k=1}^{n} V\left(\bar{\alpha}_{k}, \bar{\alpha}_{k+n} \mid \alpha_{k+n}, \alpha_{k}\right) & \text { if } n>0 \\ 1 & \text { if } n=0\end{cases}
$$

and

$$
\hat{\gamma}:=\hat{\alpha} \oplus \hat{\beta}:=\left(\alpha_{1}, \ldots, \alpha_{2 n}, \beta_{1}, \ldots, \beta_{m}, \bar{\alpha}_{1}, \ldots, \bar{\alpha}_{2 n}, \bar{\beta}_{1}, \ldots, \bar{\beta}_{m}\right) \in \mathscr{E}^{2(2 n+m)}
$$

Given $\hat{\tau}=\left(\tau_{1}, \ldots, \tau_{n}, \bar{\tau}_{1}, \ldots, \bar{\tau}_{n}\right) \in\left[0, \beta_{T}\right]^{4 n}$ with

$$
\tau_{k+n}=\tau_{k}, \bar{\tau}_{j}=\tau_{j}, \quad 1 \leq k \leq n, 1 \leq j \leq 2 n,
$$

and given $\left.\hat{\theta}=\left(\theta_{1}, \ldots, \theta_{m}, \bar{\theta}_{1}, \ldots, \bar{\theta}_{m}\right) \in\left[0, \beta_{T}\right]^{2 m}\right)$, let

$$
\hat{\varphi}:=\hat{\tau} \oplus \hat{\theta}:=\left(\tau_{1}, \ldots, \tau_{2 n}, \theta_{1}, \ldots, \theta_{m}, \bar{\tau}_{1}, \ldots, \bar{\tau}_{2 n}, \bar{\theta}_{1}, \ldots, \bar{\theta}_{m}\right) \in\left[0, \beta_{T}\right]^{2(2 n+m)}
$$

Let $\hat{\alpha}, \hat{\tau}, \hat{\gamma}$ and $\hat{\varphi}$ as above. For $i, j \in\{1, \ldots, 2 n\}$, let

$$
g_{\hat{\alpha} \hat{\tau}}(i, j)=g\left(\alpha_{i}, \tau_{j} \mid \bar{\alpha}_{i}, \bar{\tau}_{j}\right)
$$

and for $i, j \in\{1, \ldots, 2 n+m\}$, let

$$
g_{\hat{\gamma} \hat{\varphi}}(i, j)=g\left(\gamma_{i}, \varphi_{j} \mid \bar{\gamma}_{i}, \bar{\varphi}_{j}\right) .
$$

Then we define matrices

$$
\hat{g}_{\hat{\alpha} \hat{\tau}}:=\left(g_{\hat{\alpha} \hat{\tau}}(i, j)\right)_{1 \leq i, j \leq 2 n}
$$

and

$$
\hat{g}_{\hat{\gamma} \hat{\varphi}}:=\left(g_{\hat{\gamma} \hat{\varphi}}(i, j)\right)_{1 \leq i, j \leq 2 n+m} .
$$

### 3.3.2 FEYNMAN RULES FOR $\mathscr{E}$

To calculate diagrams for $\mathscr{E}$, we have the following rules that are called Feynman rules.
(1) Each fermion gives a factor $g$.
(2) Each boson gives a factor $V$.
(3) At each internal vertex

sum over $\alpha, \bar{\alpha}$ :

$$
\sum_{\alpha \in \mathcal{E}} \sum_{\alpha \in \mathcal{E}} \cdots
$$

and integrate over $\tau, \bar{\tau}$ :

$$
\int_{0}^{\beta_{T}} d \tau \int_{0}^{\beta_{T}} d \bar{\tau} \cdots
$$

(4) For each diagram $F$ for $m$-electron system, multiply by the prefactor

$$
\frac{(-1)^{n}}{2^{n} n!}(-1)^{m+N_{L}}=\frac{(-1)^{n}}{2^{n} n!} \operatorname{sgn}\left(\pi_{F}\right),
$$

where $N_{L}$ is the number of closed fermion loops in $F, n$ is the order of $F$ and $\pi_{F} \in S_{2 n+m}$ is the permutation determined by $F$.

### 3.3.3 Calculation of Feynman diagram series

For each $n \geq 0$, let

$$
\alpha_{1}, \ldots, \alpha_{2 n}, \bar{\alpha}_{1}, \ldots, \bar{\alpha}_{2 n} \in \mathscr{E}
$$

and

$$
\tau_{1}, \ldots, \tau_{2 n}, \bar{\tau}_{1}, \ldots, \bar{\tau}_{2 n} \in\left[0, \beta_{T}\right]
$$

with

$$
\bar{\tau}_{j}=\tau_{j}, \tau_{k+n}=\tau_{k}, 1 \leq j \leq 2 n, 1 \leq k \leq n
$$

Then, applying Feynman rules to the series $R_{0}$, we have

$$
\begin{aligned}
& R_{0} \quad \sum_{n=0}^{\infty} \frac{(-1)^{n}}{2^{n}!} \sum_{\alpha_{1} \ldots \alpha_{2 n}} \sum_{\bar{\alpha}_{1} \ldots \bar{\alpha}_{2 n}} \prod_{k=1}^{n} V\left(\bar{\alpha}_{k}, \bar{\alpha}_{k+n} \mid \alpha_{k+n}, \alpha_{k}\right) \\
& \times \int_{0}^{\beta_{T}} d \tau_{1} \cdots \int_{0}^{\beta_{T}} d \tau_{n} \sum_{\pi \in S_{2 n}} \operatorname{sgn}(\pi) \prod_{j=1}^{2 n} g\left(\alpha_{\pi(j)}, \tau_{\pi(j)} \mid \bar{\alpha}_{j}, \bar{\tau}_{j}\right)
\end{aligned}
$$

Rewriting in the compact notation, we have

$$
\begin{equation*}
R_{0}=\sum_{n=0}^{\infty} \sum_{\hat{\alpha} \in \mathscr{E}^{4 n}} \int_{0}^{\beta_{T}} d \tau_{1} \cdots \int_{0}^{\beta_{T}} d \tau_{n} \frac{(-1)^{n}}{2^{n} n!} V(n, \hat{\alpha}) \operatorname{det}\left(\hat{g}_{\hat{\alpha} \hat{\tau}}\right) . \tag{3.3}
\end{equation*}
$$

Note that $\operatorname{det}\left(\hat{g}_{\hat{\alpha} \hat{\tau}}\right)=1$ for $n=0$.
Similarly, given $\hat{\beta}=(\beta, \bar{\beta}) \in \mathscr{E}^{2}$ and $\hat{\theta}=(\theta, \bar{\theta}) \in\left[0, \beta_{T}\right]^{2}$, then we have

$$
\begin{equation*}
R_{1}(\hat{\beta}, \hat{\theta})=\sum_{n=0}^{\infty} \sum_{\hat{\alpha} \in \mathscr{E}^{4 n}} \int_{0}^{\beta_{T}} d \tau_{1} \cdots \int_{0}^{\beta_{T}} d \tau_{n} \frac{(-1)^{n}}{2^{n} n!} V(n, \hat{\alpha}) \operatorname{det}\left(\hat{g}_{\hat{\alpha} \oplus \hat{\beta}, \hat{\tau} \oplus \hat{\theta}}\right) . \tag{3.4}
\end{equation*}
$$

More generally, given

$$
\hat{\beta}=\left(\beta_{1}, \ldots, \beta_{m}, \bar{\beta}_{1}, \ldots, \bar{\beta}_{m}\right) \in \mathscr{E}^{m}, \hat{\theta}=\left(\theta_{1}, \ldots, \theta_{m}, \bar{\theta}_{1}, \ldots, \bar{\theta}_{m}\right) \in\left[0, \beta_{T}\right]^{m}
$$

we have

$$
\begin{equation*}
R_{m}(\hat{\beta}, \hat{\theta})=\sum_{n=0}^{\infty} \sum_{\hat{\alpha} \in \mathscr{E}^{4 n}} \int_{0}^{\beta_{T}} d \tau_{1} \cdots \int_{0}^{\beta_{T}} d \tau_{n} \frac{(-1)^{n}}{2^{n} n!} V(n, \hat{\alpha}) \operatorname{det}\left(\hat{g}_{\hat{\alpha} \oplus \hat{\beta}, \hat{\tau} \oplus \hat{\theta}}\right) . \tag{3.5}
\end{equation*}
$$

### 3.4 The $m$-Electron Green's function

The $m$-electron Green's Function $G_{m}$ on $\mathscr{E}^{2 m} \times\left[0, \beta_{T}\right]^{2 m}$ is defined by

$$
G_{m}(\hat{\beta}, \hat{\theta})=\frac{1}{R_{0}} R_{m}(\hat{\beta}, \hat{\theta})
$$

This function is what we want to calculate by Monte Carlo simulation.
Note that the fermion $g$ can be viewed as a function on $\mathscr{E}^{2} \times\left[0, \beta_{T}\right]^{2}$, and is called 1-electron Green's function. We will give some important properties of $g$ below, and these properties also hold for the function $G_{m}$.
(1) Anti-periodicity: for an integer $l$, we have

$$
g\left(\alpha, \tau \mid \bar{\alpha}, \bar{\tau}+l \beta_{T}\right)=(-1)^{l} g(\alpha, \tau \mid \bar{\alpha}, \bar{\tau})
$$

and

$$
g\left(\alpha, \tau+l \beta_{T} \mid \bar{\alpha} \bar{\tau}\right)=(-1)^{l} g(\alpha, \tau \mid \bar{\alpha}, \bar{\tau}) .
$$

(2) Time translation invariance: for a real number $\delta$, we have

$$
g(\alpha, \tau+\delta \mid \bar{\alpha}, \bar{\tau}+\delta)=g(\alpha, \tau \mid \bar{\alpha}, \bar{\tau})
$$

In particular, setting $\delta=-\bar{\tau}$, we have

$$
g(\alpha, \tau-\bar{\tau} \mid \bar{\alpha}, 0)=g(\alpha, \tau \mid \bar{\alpha}, \bar{\tau})
$$

Hence we can write

$$
g(\alpha, \tau \mid \bar{\alpha}, \bar{\tau}) \equiv g(\alpha \mid \bar{\alpha}, \tau-\bar{\tau})
$$

(3) Jump discontinuity: Let $\tau_{g}=\tau-\bar{\tau}$. Then the function $g\left(\alpha \mid \bar{\alpha}, \tau_{g}\right)$ is continuous (actually, holomorphic) for $\tau_{g} \in\left(0, \beta_{T}\right)$, but it has jump discontinuities (assume orthonormal 1 -electron basis states " $\mid \alpha$ ") at $\tau_{g}=l \beta_{T}$, where $l$ is an integer. In particular, at $\tau_{g}=0$, we have

$$
\lim _{\tau_{g} \rightarrow 0^{+}} g\left(\alpha \mid \bar{\alpha}, \tau_{g}\right)-\lim _{\tau_{g} \rightarrow 0^{-}} g\left(\alpha \mid \bar{\alpha}, \tau_{g}\right)=\delta_{\alpha, \bar{\alpha}}
$$

Here $\delta$ is the Kronecker $\delta$, defined by

$$
\delta_{i j}= \begin{cases}1 & \text { if } i=j \\ 0 & \text { otherwise }\end{cases}
$$

### 3.5 Integral Padding Functions

Given a positive integer $N$, let $n \in\{0, \ldots, N\}, p=N-n$ and $\tilde{\psi}=\left(\psi, \ldots, \psi_{p}\right) \in\left[0, \beta_{T}\right]^{p}$. Then, the integral padding function (for short, padding function) is defined by

$$
Q_{p}(\tilde{\psi})= \begin{cases}\prod_{l=1}^{p} g_{l}\left(\psi_{l}\right) & \text { if } p>0  \tag{3.6}\\ 1 & \text { if } p=0\end{cases}
$$

Here for each $l \in\{1, \ldots, p\}, g_{l}$ is a non-negative real function such that

$$
\begin{equation*}
\int_{0}^{\beta_{T}} g_{l}\left(\psi_{l}\right) d \psi_{l}=1 \tag{3.7}
\end{equation*}
$$

It is readily seen that

$$
\begin{equation*}
\int_{0}^{\beta_{T}} d \psi_{1} \cdots \int_{0}^{\beta_{T}} d \psi_{p} Q_{p}(\tilde{\psi})=1 \tag{3.8}
\end{equation*}
$$

Let $\hat{\alpha}, \hat{\tau}, \hat{\beta}$ and $\hat{\theta}$ be as in (3.4). Recall that $\hat{\tau}=\left(\tau_{1}, \ldots, \tau_{n}, \bar{\tau}_{1}, \ldots, \bar{\tau}_{n}\right) \in\left[0, \beta_{T}\right]^{4 n}$ with

$$
\tau_{k+n}=\tau_{k}, \bar{\tau}_{j}=\tau_{j}, \quad 1 \leq k \leq n, 1 \leq j \leq 2 n
$$

Now, let

$$
\tilde{\tau}:=\left(\tau_{1}, \ldots, \tau_{n}\right) \in\left[0, \beta_{T}\right]^{n}
$$

and

$$
\tilde{\tau} \oplus \tilde{\psi}:=\left(\tau_{1}, \ldots, \tau_{n}, \psi_{1}, \ldots, \psi_{N-n}\right) \in\left[0, \beta_{T}\right]^{N}
$$

Then we define

$$
F_{m}(\hat{\beta}, \hat{\theta}, n, \hat{\alpha}, \hat{\tau}, \tilde{\psi}):=\frac{(-1)^{n}}{2^{n} n!} V(n, \hat{\alpha}) \operatorname{det}\left(\hat{g}_{\hat{\beta} \oplus \hat{\beta}, \hat{\tau} \oplus \hat{\theta}}\right) Q_{N-n}(\tilde{\psi})
$$

In particular, if $m=0$, we write

$$
F_{0}(n, \hat{\alpha}, \hat{\tau}, \tilde{\psi})=\frac{(-1)^{n}}{2^{n} n!} V(n, \hat{\alpha}) \operatorname{det}\left(\hat{g}_{\hat{\beta}, \hat{\tau}}\right) Q_{N-n}(\tilde{\psi})
$$

Then the $m$-electron Green's function can be rewritten as

$$
\begin{equation*}
G_{m}(\hat{\beta}, \hat{\theta})=\lim _{N \rightarrow \infty} \frac{\sum_{n=0}^{N} \sum_{\hat{\alpha} \in \mathscr{E}^{4 n}} \int_{\left[0, \beta_{T}\right]^{N}} d^{N}(\tilde{\tau} \oplus \tilde{\psi}) F_{m}(\hat{\beta}, \hat{\theta}, n, \hat{\alpha}, \hat{\tau}, \tilde{\psi})}{\sum_{n=0}^{N} \sum_{\hat{\alpha} \in \mathscr{E}^{4 n}} \int_{\left[0, \beta_{T}\right]^{N}} d^{N}(\tilde{\tau} \oplus \tilde{\psi}) F_{0}(n, \hat{\alpha}, \hat{\tau}, \tilde{\psi})} \tag{3.8}
\end{equation*}
$$

## Chapter 4

## EXTENDED HUBBARD MODEL (EHM)

The Hubbard model, is the simplest model of interacting particles in a lattice. If interactions between particles on different sites of the lattice are included, the model is often referred as the extended Hubbard model.

In this chapter, we introduce an extended Hubbard model (for short, EHM) on a 2dimensional rectangular lattice that can be used to describe strongly interacting electrons in 3-dimensional transition metal compounds, such as high temperature superconductors. We will describe the 2-dimensional real space lattice $\mathscr{L}$ and 1-electron space on it in $\S 4.1$ and discuss the interaction potential function $V$ for EHM on $\mathscr{L}$ in $\S 4.2$. Then, we define the $\vec{k}$-space and reciprocal lattice of $\mathscr{L}$ in $\S 4.3$. Finally, we will discuss the 1 -electron Green's function $g$ and $m$-electron Green's function for EHM in real space representations in $\S 4.4$ and $\S 4.5$, respectively.

### 4.1 The lattice $\mathscr{L}$ and 1-Electron space

Given two positive integers $L_{x}$ and $L_{y}$, a 2-dimensional rectangle lattice $\mathscr{L}$ of size

$$
|\mathscr{L}|=L_{x} \cdot L_{y}
$$

is defined by

$$
\mathscr{L}:=\left\{\vec{r}=\left(r_{x}, r_{y}\right) \mid r_{x} \in\left\{0, \ldots, L_{x}-1\right\}, r_{y} \in\left\{0, \ldots, L_{y}-1\right\}\right\} .
$$

The following periodic boundary condition (PBC) holds for any $\vec{r}_{1}, \vec{r}_{2} \in \mathscr{L}$ :

$$
\begin{equation*}
\vec{r}_{1} \oplus \vec{r}_{2}=\left(\left(r_{1 x}+r_{2 x}\right) \bmod \left(L_{x}\right),\left(r_{1 y}+r_{2 y}\right) \bmod \left(L_{y}\right)\right) . \tag{4.1}
\end{equation*}
$$

Now, let the spin space $\mathscr{S}$ be defined by

$$
\mathscr{S}:=\left\{\frac{1}{2},-\frac{1}{2}\right\} .
$$

Then the 1-electron space $\mathscr{E}$ is defined by

$$
\mathscr{E}:=\mathscr{L} \times \mathscr{S}=\{\alpha=(\vec{r}, s) \mid \vec{r} \in \mathscr{L}, s \in \mathscr{S}\} .
$$

### 4.2 Interaction potential function $V$

In this section, we will discuss the interaction potential function $V$ and its properties.

### 4.2.1 Definition

Suppose that $\alpha_{l}=\left(\vec{r}_{l}, s_{l}\right) \in \mathscr{E}, l=1, \ldots, 4$. Then the interaction potential function is given by

where $V_{c}(\Delta \vec{r})$ is called the Coulomb potential function, and $\delta$ is the Kronecker $\delta$. We may write $V\left(\vec{r}_{1}, s_{1}, \vec{r}_{2}, s_{2} \mid \vec{r}_{3}, s_{3}, \vec{r}_{4}, s_{4}\right)$ for $V\left(\alpha_{1}, \alpha_{2} \mid \alpha_{3}, \alpha_{4}\right)$.

Note that comparing this to the definition of boson in $\S 3.1 .2, \tau$-labels and the Dirac $\delta$ for $\tau$ 's are removed, and spins and the Kronecker $\delta$ for spins are added.

### 4.2.2 The simplest EHM for $V_{c}$

Let $\vec{R}_{x}:=\left(L_{x}, 0\right)$ and $\vec{R}_{y}:=\left(0, L_{y}\right)$ (called lattice size vectors) and

$$
\mathscr{L}_{\infty}:=\left\{\vec{r}=\left(r_{x}, r_{y}\right) \mid r_{x} \in \mathbb{Z}, r_{y} \in \mathbb{Z}\right\} .
$$

Then the norm of $\Delta \vec{r}=\vec{r}_{1}-\vec{r}_{2} \in \mathscr{L}_{\infty}$ is defined by

$$
|\Delta \vec{r}|_{\mathscr{L}}:=\min _{\left(n_{x}, n_{y}\right) \in \mathbb{Z}^{2}}\left|\Delta \vec{r}-n_{x} \vec{R}_{x}-n_{y} \vec{R}_{y}\right| .
$$

Here the norm

$$
|\vec{a}|=\sqrt{a_{x}^{2}+a_{y}^{2}}, \vec{a}=\left(a_{x}, a_{y}\right) \in \mathbb{Z}^{2}
$$

is the Euclidean distance.
Now, let $V_{0}$ be the Hubbard on-site repulsion energy, $V_{1}$ the first neighbor repulsion energy and $R_{c}$ the Coulomb cut-off radius. Then the Coulomb potential function $V_{c}$ is defined by

$$
V_{c}(\Delta \vec{r})= \begin{cases}V_{0} & \text { if }|\Delta \vec{r}|_{\mathscr{L}}=0  \tag{4.2}\\ V_{1} \frac{\theta_{c}\left(R_{c}-|\Delta \vec{r}| \mathscr{L}\right)}{|\Delta \vec{r}| \mathscr{L}} & \text { otherwise }\end{cases}
$$

Here

$$
\theta_{c}(x)= \begin{cases}1 & \text { if } x \geq 0 \\ 0 & \text { otherwise }\end{cases}
$$

is the step function.

### 4.2.3 LTI and PBC for function $V$

Let $\vec{r}_{1}, \ldots, \vec{r}_{4} \in \mathscr{L}$ and $s_{1}, \ldots, s_{4} \in \mathscr{S}$. The function $V$ has the following lattice translation invariance property (LTI): for $\vec{r}_{0} \in \mathscr{L}_{\infty}$, we have

$$
\begin{align*}
V\left(\vec{r}_{1}, s_{1}, \vec{r}_{2}, s_{2} \mid \vec{r}_{3}, s_{3}, \vec{r}_{4}, s_{4}\right) & =V\left(\vec{r}_{1}-\vec{r}_{0}, s_{1}, \vec{r}_{2}-\vec{r}_{0}, s_{2} \mid \vec{r}_{3}-\vec{r}_{0}, s_{3}, \vec{r}_{4}-\vec{r}_{0}, s_{4}\right)  \tag{4.3}\\
& =V\left(\vec{r}_{1}-\vec{r}_{2}\right) \delta_{\vec{r}_{1} \vec{r}_{4}} \delta_{s_{1} s_{4}} \delta_{\vec{r}_{2} \vec{r}_{3}} \delta_{s_{2} s_{3}}
\end{align*}
$$

The PBC also holds for $V$ : let $l_{x}, l_{y} \in \mathbb{Z}$ and let $\vec{R}:=l_{x} \vec{R}_{x}+l_{y} \vec{R}_{y}$, then

$$
\begin{align*}
V\left(\vec{r}_{1}, s_{1}, \vec{r}_{2}, s_{2} \mid \vec{r}_{3}, s_{3}, \vec{r}_{4}, s_{4}\right) & =\left(\vec{r}_{1}+\vec{R}, s_{1}, \vec{r}_{2}, s_{2} \mid \vec{r}_{3}, s_{3}, \vec{r}_{4}, s_{4}\right) \\
& =V\left(\vec{r}_{1}, s_{1}, \vec{r}_{2}+\vec{R}, s_{2} \mid \vec{r}_{3}, s_{3}, \vec{r}_{4}, s_{4}\right)  \tag{4.4}\\
& =V\left(\vec{r}_{1}, s_{1}, \vec{r}_{2}, s_{2} \mid \overrightarrow{r_{3}}+\vec{R}, s_{3}, \vec{r}_{4}, s_{4}\right) \\
& =V\left(\vec{r}_{1}+\vec{R}, s_{1}, \vec{r}_{2}, s_{2} \mid \vec{r}_{3}, s_{3}, \vec{r}_{4}, s_{4}\right)
\end{align*}
$$

since $V_{c}(\Delta \vec{r}+R)=V_{c}(\Delta \vec{r})$.

### 4.3 The $\vec{k}$-SPACE and Reciprocal lattice of $\mathscr{L}$

In this section, we will define the $\vec{k}$-space and reciprocal lattice of $\mathscr{L}$

### 4.3.1 The $\vec{k}$-SPACE OF $\mathscr{L}$

The $\vec{k}$-space $\mathscr{K}_{\mathscr{L}_{\infty}}$ of $\mathscr{L}$ is defined by

$$
\mathscr{K}_{\mathscr{L}_{\infty}}:=\left\{\left.\vec{k}=\left(\frac{2 \pi m_{x}}{L_{x}}, \frac{2 \pi m_{y}}{L_{y}}\right) \right\rvert\,\left(m_{x}, m_{y}\right) \in \mathbb{Z}^{2}\right\}
$$

and the $\vec{k}$-zone $\mathscr{K}_{\mathscr{L}}$ of $\mathscr{L}$ is defined by

$$
\mathscr{K}_{\mathscr{L}}:=\left\{\left.\vec{k}=\left(\frac{2 \pi m_{x}}{L_{x}}, \frac{2 \pi m_{y}}{L_{y}}\right) \right\rvert\,\left(m_{x}, m_{y}\right) \in \mathscr{L}\right\} .
$$

Let $\mathscr{R}_{\mathscr{L}}$ be the PB vector space defined by

$$
\mathscr{R}_{\mathscr{L}}:=\left\{\vec{R}=\left(l_{x} L_{x}, l_{y} L_{y}\right) \equiv l_{x} \vec{R}_{x}+l_{y} \vec{R}_{y} \mid\left(l_{x}, l_{y}\right) \in \mathbb{Z}^{2}\right\}
$$

then we have

$$
\begin{align*}
\vec{k} \in \mathscr{K}_{\mathscr{L}_{\infty}} & \Longleftrightarrow \vec{k} \bullet \vec{R} \in\{2 \pi j \mid j \in \mathbb{Z}\}, \quad \forall \vec{R} \in \mathscr{R}_{\mathscr{L}} \\
& \Longleftrightarrow e^{i \vec{k} \bullet \vec{R}}=1, \quad \forall \vec{R} \in \mathscr{R}_{\mathscr{L}} . \tag{4.5}
\end{align*}
$$

Here " $\bullet$ " is the dot (or inner) product of vectors.

### 4.3.2 The Reciprocal lattice of $\mathscr{L}$

The reciprocal lattice $\mathscr{Q}_{\mathscr{L}}$ of $\mathscr{L}$ is defined by

$$
\mathscr{Q}_{\mathscr{L}}:=\left\{\vec{K}=\left(2 \pi m_{x}, 2 \pi m_{y}\right) \mid\left(m_{x}, m_{y}\right) \in \mathbb{Z}^{2}\right\}
$$

It is readily seen that

$$
\begin{align*}
\vec{K} \in \mathscr{Q}_{\mathscr{L}} & \Longleftrightarrow \vec{r} \bullet \vec{K} \in\{2 \pi j \mid j \in \mathbb{Z}\}, \quad \forall \vec{r} \in \mathscr{L}_{\infty}  \tag{4.6}\\
& \Longleftrightarrow e^{i \vec{r} \bullet \vec{K}}=1, \quad \forall \vec{r} \in \mathscr{L}_{\infty}
\end{align*}
$$

### 4.4 The 1-Electron Green's function $g$

Through this section, $i$ denotes an imaginary unit (that is, $i^{2}=-1$ ).

### 4.4.1 EnERGY BAND

Let $t_{l}(l=1,2,3)$ be the $l$-th neighbor hopping (or hybridization) energy and $\mu$ be the chemical potential. Then the energy band $\mathcal{E}_{\vec{k}}$ of $\vec{k}=\left(k_{x}, k_{y}\right) \in \mathscr{K}_{\mathscr{L}_{\infty}}$ is defined by

$$
\mathcal{E}_{\vec{k}}:=-2 t_{1}\left(\cos k_{x}+\cos k_{y}\right)-4 t_{2} \cos k_{x} \cos k_{y}-2 t_{3}\left(\cos \left(2 k_{x}\right)+\cos \left(2 k_{y}\right)\right)-\mu .
$$

The following LTI property for $\mathcal{E}_{\vec{k}}$ holds:

$$
\begin{equation*}
\mathcal{E}_{\vec{k}+\vec{K}}=\mathcal{E}_{\vec{k}}, \forall \vec{k} \in \mathscr{K}_{\mathscr{L}_{\infty}}, \forall \vec{K} \in \mathscr{Q}_{\mathscr{L}} \tag{4.7}
\end{equation*}
$$

### 4.4.2 The Fourier sum over Matsubara frequencies

Let $\mathscr{F}_{-}$be the set of Matsubara frequencies defined by

$$
\mathscr{F}_{-}:=\{i \nu \mid \nu=(2 m+1) \pi T, m \in \mathbb{Z}\}
$$

and let

$$
\tilde{\tilde{g}}_{0}(\vec{k}, i \nu):=\frac{1}{i \nu-\mathcal{E}_{\vec{k}}}, i \nu \in \mathscr{F}_{-}, \vec{k} \in \mathscr{K}_{\mathscr{L}_{\infty}} .
$$

Then, the Fourier sum over Matsubara frequencies

$$
\begin{equation*}
\tilde{g}_{0}(\vec{k}, \Delta \tau):=T \sum_{i \nu \in \mathscr{F}_{-}} \tilde{\tilde{g}}_{0}(\vec{k}, i \nu) e^{-i \nu \Delta \tau} \tag{4.8}
\end{equation*}
$$

can be evaluated analytically by complex contour integration. This yields

$$
\begin{equation*}
\tilde{g}_{0}(\vec{k}, \Delta \tau)=e^{\mathcal{E}_{\vec{k}} \Delta \tau}\left[f\left(\mathcal{E}_{\vec{k}}\right)-\theta_{c}(\Delta \tau)\right] \tag{4.9}
\end{equation*}
$$

and

$$
\begin{equation*}
\tilde{g}_{0}\left(\vec{k}, \Delta \tau+l \beta_{T}\right)=(-1)^{l} \tilde{g}_{0}(\vec{k}, \Delta \tau) \tag{4.10}
\end{equation*}
$$

for

$$
-\beta_{T}<\Delta \tau<\beta_{T}, l \in \mathbb{Z}
$$

Where

$$
\theta_{c}(x)= \begin{cases}1 & \text { if } x \geq 0 \\ 0 & \text { if } x<0\end{cases}
$$

and $f$ is the Fermi function defined by

$$
f(\mathcal{E}):=\frac{1}{e^{\beta_{T} \mathcal{E}}+1} .
$$

By (4.7) and (4.9), the LTI property for $\tilde{g}_{0}$ holds:

$$
\begin{equation*}
\tilde{g}_{0}(\vec{k}+\vec{K}, \Delta \tau)=\tilde{g}_{0}(\vec{k}, \Delta \tau) \tag{4.11}
\end{equation*}
$$

### 4.4.3 The function $g$

For $\alpha_{1}=\left(\vec{r}_{1}, s_{1}\right) \in \mathscr{E}, \alpha_{2}=\left(\vec{r}_{2}, s_{2}\right) \in \mathscr{E}$ and $\tau_{1}, \tau_{2} \in\left[0, \beta_{T}\right]$, the 1-electron Green's function $g$ is defined by

$$
g\left(\alpha_{1}, \tau_{1} \mid \alpha_{2}, \tau_{2}\right) \equiv g\left(\vec{r}_{1}, s_{1} \mid \vec{r}_{1}, s_{1}, r_{1}-r_{2}\right):=\delta_{s_{1} s_{2}} \frac{T}{|L|} \sum_{\vec{k} \in \mathscr{K}_{\mathscr{L}}} \sum_{i \nu \in \mathscr{F}_{-}} \tilde{\tilde{g}}_{0}(\vec{k}, i \nu) e^{i \vec{k} \bullet \Delta \vec{r}-i \nu \Delta \tau}
$$

Let

$$
\begin{equation*}
g_{0}(\Delta \vec{r}, \Delta \tau):=\frac{1}{|L|} \sum_{\vec{k} \in \mathscr{K}_{\mathscr{L}}} \tilde{g}_{0}(\vec{k}, \Delta \tau) e^{i \vec{k} \bullet \Delta \vec{r}} ; \tag{4.12}
\end{equation*}
$$

then we have

$$
\begin{equation*}
g\left(\vec{r}_{1}, s_{1} \mid \vec{r}_{1}, s_{1}, r_{1}-r_{2}\right)=\delta_{s_{1} s_{2}} g_{0}(\Delta \vec{r}, \Delta \tau) \tag{4.13}
\end{equation*}
$$

Note that in the sum on the right side of (4.11), the conjugate of each summand is also a summand, so the sum is a real number.

Both LTI and PBC hold for the function $g$. That is, for $\vec{r}_{1}, \vec{r}_{2} \in \mathscr{L}, \vec{r}_{0} \in \mathscr{L}_{\infty}$ and $\vec{R} \in \mathscr{R}_{\mathscr{L}}$, we have

$$
\begin{equation*}
g\left(\vec{r}_{1}, s_{1} \mid \vec{r}_{1}, s_{1}, \Delta \tau\right)=g\left(\vec{r}_{1}-\vec{r}_{0}, s_{1} \mid \vec{r}_{1}-\vec{r}_{0}, s_{1}, \Delta \tau\right) \tag{4.14}
\end{equation*}
$$

and

$$
\begin{equation*}
g\left(\vec{r}_{1}, s_{1} \mid \vec{r}_{1}, s_{1}, \Delta \tau\right)=g\left(\vec{r}_{1}+\vec{R}, s_{1} \mid \vec{r}_{1}, s_{1}, \Delta \tau\right)=g\left(\vec{r}_{1}, s_{1} \mid \vec{r}_{1}+\vec{R}, s_{1}, \Delta \tau\right) \tag{4.15}
\end{equation*}
$$

### 4.5 The $m$-Electron Green's function $G_{m}$ for EHM

We now turn to the $m$-electron Green's function $G_{m}(m \geq 0)$ for EHM in the real space representation.

### 4.5.1 Notation

Let $n, N$ be integers with $0 \leq n \leq N$.
Let the external vertices be denoted by

$$
\hat{\beta}:=\left(\hat{r}^{(\beta)}, \hat{s}^{(\beta)}\right),
$$

where

$$
\hat{r}^{(\beta)}:=\left(\vec{r}_{1}^{(\beta)}, \ldots, \vec{r}_{m}^{(\beta)} \mid \vec{r}_{1}^{(\beta)}, \ldots, \vec{r}_{m}^{(\beta)}\right) \in \mathscr{L}^{2 m}
$$

and

$$
\hat{s}^{(\beta)}:=\left(s_{1}^{(\beta)}, \ldots, s_{m}^{(\beta)} \mid \bar{s}_{1}^{(\beta)}, \ldots, \bar{s}_{m}^{(\beta)}\right) \in \mathscr{S}^{2 m} .
$$

Given $\tilde{r}=\left(\vec{r}_{1}, \ldots, \vec{r}_{2 n}\right) \in \mathscr{L}^{2 n}$, let

$$
\hat{r}:=\left(\vec{r}_{1}, \ldots, \vec{r}_{2 n} \mid \overline{\vec{r}}_{1}, \ldots, \overline{\vec{r}}_{2 n}\right) \in \mathscr{L}^{4 n}
$$

and

$$
\hat{r}^{(g)}:=\hat{r} \oplus \hat{r}^{(\beta)}=\left(\vec{r}_{1}, \ldots, \vec{r}_{2 n}, \vec{r}_{1}^{(\beta)}, \ldots, \vec{r}_{m}^{(\beta)} \mid \overrightarrow{\vec{r}}_{1}, \ldots, \overline{\vec{r}}_{2 n}, \vec{r}_{1}^{(\beta)}, \ldots, \vec{r}_{m}^{(\beta)}\right) \in \mathscr{L}^{2(2 n+m)}
$$

where $\overline{\vec{r}}_{j}=\vec{r}_{j}$ for $j=1, \ldots, 2 n$.
Given $\tilde{s}=\left(s_{1}, \ldots, s_{2 n}\right) \in \mathscr{S}^{2 n}$, let

$$
\hat{s}:=\left(s_{1}, \ldots, s_{2 n} \mid \bar{s}_{1}, \ldots, \bar{s}_{2 n} \in \mathscr{S}^{4 n}\right)
$$

and

$$
\hat{s}^{(g)}:=\hat{s} \oplus \hat{s}^{(\beta)}=\left(s_{1}, \ldots, s_{2 n}, s_{1}^{(\beta)}, \ldots, s_{m}^{(\beta)} \mid \bar{s}_{1}, \ldots, \bar{s}_{2 n}, \bar{s}_{1}^{(\beta)}, \ldots, \bar{s}_{m}^{(\beta)}\right) \in \mathscr{S}^{2(2 n+m)}
$$

with $\bar{s}_{j}=s_{j}$ for $j=1, \ldots, 2 n$.
Given $\tilde{\tau}:=\left(\tau_{1}, \ldots, \tau_{n}\right) \in\left[0, \beta_{T}\right]^{n}$ and

$$
\hat{\theta}:=\left(\theta_{1}, \ldots, \theta_{m} \mid \bar{\theta}_{1}, \ldots, \bar{\theta}_{m}\right) \in\left[0, \beta_{T}\right]^{2 m}
$$

let

$$
\hat{\tau}:=\left(\tau_{1}, \ldots, \tau_{2 n} \mid \bar{\tau}_{1}, \ldots, \bar{\tau}_{2 n}\right)=\tilde{\tau} \oplus \tilde{\tau} \oplus \tilde{\tau} \oplus \tilde{\tau} \in\left[0, \beta_{T}\right]^{4 n}
$$

and

$$
\tau^{(g)}:=\hat{\tau} \oplus \hat{\theta}=\left(\tau_{1}, \ldots, \tau_{2 n}, \theta_{1}, \ldots, \theta_{m} \mid \bar{\tau}_{1}, \ldots, \bar{\tau}_{2 n}, \bar{\theta}_{1}, \ldots, \bar{\theta}_{m}\right) \in\left[0, \beta_{T}\right]^{2(2 n+m)}
$$

with $\tau_{k+n}=\tau_{k}, 1 \leq k \leq n$ and $\bar{\tau}_{j}=\tau_{j}, 1 \leq j \leq 2 n$.
Let

$$
\hat{\alpha}=\left(\alpha_{1}, \ldots, \alpha_{2 n}, \bar{\alpha}_{1}, \ldots, \bar{\alpha}_{2 n}\right) \in \mathscr{E}^{4 n}
$$

with

$$
\alpha_{j}=\left(\vec{r}_{j}, s_{j}\right), \bar{\alpha}_{j}=\left(\vec{r}_{j}, \bar{s}_{j}\right), 1 \leq j \leq 2 n .
$$

### 4.5.2 The function $G_{m}$

Given $\tilde{\psi}:=\left(\psi_{1}, \ldots, \psi_{N-n}\right) \in\left[0, \beta_{T}\right]^{N-n}$, let

$$
\begin{align*}
F_{m}\left(\hat{r}^{(\beta)}, s^{(\beta)}, \hat{\theta}, n, \tilde{r}, \tilde{s}, \tilde{\tau}, \tilde{\psi}\right) & \equiv F_{m}(\hat{\beta}, \hat{\theta}, n, \hat{\alpha}, \hat{\tau}, \tilde{\psi}) \\
& =\frac{(-1)^{n}}{2^{n} n!}\left(\prod_{k=1}^{n} V_{c}\left(\vec{r}_{k+n}-\vec{r}_{k}\right)\right) \operatorname{det} \hat{g}_{\vec{r}^{(g)}, s^{(g)}, \hat{\tau}^{(g)}} Q_{N-n}(\tilde{\psi}) \tag{4.16}
\end{align*}
$$

where the Coulomb potential function $V_{c}$ is given in (4.2), the padding function $Q_{N-n}$ is given in (3.6), and

$$
\begin{equation*}
\hat{g}_{\vec{r}^{(g)}, s^{(g)}, \hat{\tau}^{(g)}}:=\left[g\left(\bar{r}_{i}^{(g)}, s_{i}^{(g)} \mid \vec{r}_{j}^{(g)}, s_{j}^{(g)}, \tau_{i}^{(g)}-\tau_{j}^{(g)}\right)\right]_{1 \leq i, j \leq 2 n+m} \tag{4.17}
\end{equation*}
$$

is a $(2 n+m) \times(2 n+m)$ matrix. Then the $m$-electron diagram series is given by

$$
\begin{equation*}
R_{m}\left(\hat{r}^{(\beta)}, s^{(\beta)}, \hat{\theta}\right)=\lim _{N \rightarrow \infty} \sum_{n=0}^{N} \sum_{\tilde{r} \in \mathscr{L}^{2 n}} \sum_{\tilde{s} \in \mathscr{S}^{2 n}} \int_{\left[0, \beta_{T}\right]^{n}} d^{n} \tilde{\tau} \int_{\left[0, \beta_{T}\right]^{N-n}} d^{N-n} \tilde{\psi} F_{m}(\hat{\beta}, \hat{\theta}, n, \hat{\alpha}, \hat{\tau}, \tilde{\psi}) . \tag{4.18}
\end{equation*}
$$

Now, the $m$-electron Green's function is defined by

$$
\begin{equation*}
G_{m}\left(\hat{r}^{(\beta)}, s^{(\beta)}, \hat{\theta}\right):=\frac{R_{m}\left(\hat{r}^{(\beta)}, s^{(\beta)}, \hat{\theta}\right)}{R_{0}} \tag{4.19}
\end{equation*}
$$

## Chapter 5

## MONTE CARLO EVALUATION OF EHM

In this chapter, we will discuss the Monte Carlo evaluation of the extended Hubbard model defined in Chapter 4. We first discuss the Monte Carlo simulation of EHM in §4.1. Then, we discuss the Metropolis Markov Chain Monte Carlo method in $\$ 5.2$ and MC move types in §5.3.

### 5.1 Monte Carlo simulation of EHM

Let $n, N \in \mathbb{N}$ with $0 \leq n \leq N, \tilde{\alpha}=\left(\alpha_{1}, \ldots, \alpha_{n}\right) \in \mathscr{E}^{2 n}$ and $\hat{\alpha}=\tilde{\alpha} \oplus \tilde{\alpha} \in \mathscr{E}^{4 n}$. Let $\tilde{\tau}, \hat{\tau}, \tilde{\psi}, \hat{\beta}$ and $\hat{\theta}$ be as in $\S 4.5$. Then we define the domain to be the set of all tuples $(n, \tilde{\alpha}, \tilde{\tau}, \tilde{\psi})$ :

$$
\mathscr{D}:=\{X \mid X=(n, \tilde{\alpha}, \tilde{\tau}, \tilde{\psi})\}
$$

For short, we will write $\int_{X}$ for

$$
\sum_{n=0}^{N} \sum_{\tilde{\alpha} \in \mathscr{E}^{2 n}} \int_{\left[0, \beta_{T}\right]^{N}} d^{N}(\tilde{\tau} \oplus \tilde{\psi})
$$

### 5.1.1 Score, weight and probability functions for EHM

The weight function $W$ on $\mathscr{D}$ for EHM is defined by

$$
\begin{equation*}
W(X):=\left|F_{0}(X)\right| \tag{5.1}
\end{equation*}
$$

and the score function $S_{m}$ is defined by

$$
\begin{equation*}
S_{m}(\hat{\beta}, \hat{\theta}, X):=\frac{F_{m}(\hat{\beta}, \hat{\theta}, X)}{W(X)} \tag{5.2}
\end{equation*}
$$

Let

$$
\begin{equation*}
P(X):=\frac{1}{\int_{X} W(X)} W(X) . \tag{5.3}
\end{equation*}
$$

Then we have

$$
\int_{X} P(X)=1
$$

and

$$
P(X) \geq 0, \forall X \in \mathscr{D}
$$

Hence, P is a probability distribution on $\mathscr{D}$..

### 5.1.2 Monte Carlo evaluation of $G_{m}$

For any function $A=A(X)$ on $\mathscr{D}$, the average of $A$ for the probability distribution $P$ is defined by

$$
\begin{equation*}
\langle A(\bullet)\rangle_{P}:=\int_{X} A(X) P(X) . \tag{5.4}
\end{equation*}
$$

Then the function $G_{m}$ can be rewritten as

$$
\begin{equation*}
G_{m}(\hat{\beta}, \hat{\theta})=\lim _{N \rightarrow \infty} \frac{\left\langle S_{m}(\hat{\beta}, \hat{\theta}, \bullet)\right\rangle_{P}}{\left\langle S_{0}(\bullet)\right\rangle_{P}} \tag{5.5}
\end{equation*}
$$

To evaluate $\langle A(\bullet)\rangle_{P}$, we generate a random sample of $K$ points

$$
X^{(1)}, \ldots, X^{(K)}, \quad X^{(j)} \in \mathscr{D}
$$

that is distributed according to $P(X)$. Let

$$
\begin{equation*}
\langle A(\bullet)\rangle^{(K)}:=\frac{1}{K} \sum_{j=1}^{K} A\left(X^{(j)}\right) \tag{5.6}
\end{equation*}
$$

Then, by the central limit theorem, we have

$$
\begin{equation*}
\lim _{K \rightarrow \infty}\langle A(\bullet)\rangle^{(K)}=\langle A(\bullet)\rangle_{P} \tag{5.7}
\end{equation*}
$$

### 5.1.3 Evaluation of $\operatorname{det} \hat{g}$

To evaluate the scores, we need to calculate the determinant of the $(2 n+m) \times(2 n+m)$ matrix

$$
\hat{g}=\hat{g}_{\vec{r}^{(g)}, s^{(g)}, \hat{\tau}^{(g)}}=\left(g_{i j}\right)_{1 \leq i, j \leq 2 n+m},
$$

where $\vec{r}^{(g)}, s^{(g)}, \hat{\tau}^{(g)}$ are as in $\S 4.5$, and

$$
g_{i j}=g\left(\vec{r}_{i}, s_{i} \mid \vec{r}_{j}, s_{j}, \tau_{i}-\tau_{j}\right)
$$

Let $I=\left\{i \mid s_{i}=0.5,1 \leq i \leq 2 n+m\right\}$ and $J=\left\{j \mid s_{j}=-0.5,1 \leq j \leq 2 n+m\right\}$. Then $\{I, J\}$ is a partition of $\{1, \ldots, 2 n+m\}$ such that $g_{i j}=0$ for all $i \in I$ and $j \in J$ by (4.13). Hence,

$$
\begin{equation*}
\operatorname{det} \hat{g}=\operatorname{det} \hat{g}_{I I} \cdot \operatorname{det} \hat{g}_{J J} \tag{5.8}
\end{equation*}
$$

by (2.9). In particular, if $V_{1}=0$ and $m=0, \operatorname{det} \hat{g} \neq 0$ implies that

$$
\begin{equation*}
\vec{r}_{j}=\vec{r}_{j+n}, s_{j} \neq s_{j+n}, 1 \leq j \leq n \tag{5.9}
\end{equation*}
$$

by (4.2) and (4.13). It follows that $|I|=|J|$ and $\operatorname{det} \hat{g}_{I I}=\operatorname{det} \hat{g}_{J J}$, so we have

$$
\begin{equation*}
\operatorname{det} \hat{g}=\left(\operatorname{det} \hat{g}_{I I}\right)^{2} . \tag{5.10}
\end{equation*}
$$

### 5.2 Metropolis MCMC method

The Metropolis method is one of the most important MCMC (Markov Chain Monte Carlo) methods. It is used to generate a Markov chain by reject sampling.

Let $\{1, \ldots, M\}$ be the set of available move types. We assign to each move type $u$ a number $p_{M}(u) \geq 0$, such that

$$
\sum_{u=1}^{m} p_{M}(u)=1
$$

Then $p_{M}=\left\{p_{M}(1), \ldots, p_{M}(M)\right\}$ defines a probability distribution on $\{1, \ldots, M\}$.
Let $P(X)>0(\forall X \in \mathscr{D})$ be a probability distribution on $\mathscr{D}$; we want to generate a Markov chain

$$
\begin{equation*}
X^{(1)}, \ldots, X^{(K)}, K \in \mathbb{N}, X^{(j)} \in \mathscr{D}, 1 \leq j \leq K \tag{5.11}
\end{equation*}
$$

from $P(X)$.

### 5.2.1 Metropolis method

Given $X \in \mathscr{D}$ with $W(X)>0$, we generate $X^{\oplus}$ from $X$ (i.e., do an MC move) as follows.
(1) Randomly select a move type $u \in\{1, \ldots, M\}$ according to the probability distribution $p_{M}$.
(2) Randomly generate $X^{\prime} \in \mathscr{D}$ with proposed probability $T_{u}^{(P)}\left(X \rightarrow X^{\prime}\right)$ according the rule for move type $u . X^{\prime}$ is called the proposal.
(3) Accept $X^{\prime}$ as $X^{\oplus}$ (i.e., set $\left.X^{\oplus}=X^{\prime}\right)$ with acceptance probability $T_{u}^{(A)}\left(X \rightarrow X^{\prime}\right)$ defined by

$$
\begin{equation*}
T_{u}^{(A)}\left(X \rightarrow X^{\prime}\right):=\min \left\{1, \frac{T_{u}^{(P)}\left(X^{\prime} \rightarrow X\right) P\left(X^{\prime}\right)}{T_{u}^{(P)}\left(X \rightarrow X^{\prime}\right) P(X)}\right\} \tag{5.12}
\end{equation*}
$$

That is, generate a random variable $p \sim U[0,1]$, where $U[0,1]$ is the uniform distribution on $[0,1]$. If $p \leq T_{u}^{(A)}\left(X \rightarrow X^{\prime}\right)$, then accept the proposal and set $X^{\oplus}=X^{\prime}$. Otherwise, reject the proposal and set $X^{\oplus}=X$.

### 5.2.2 Generating the chain

Let $L, S \in \mathbb{N}$ with $L>0, S>0$. To generate the chain (5.11), we start with a randomly generated $Y^{(1-L)} \in \mathscr{D}$ with $W\left(Y^{(1-L)}\right)>0$, then do MC moves $L+K S-1$ times and obtain a chain of length $L+K S$ :

$$
Y^{(1-L)}, \ldots, Y^{(0)}, Y^{(1)}, \ldots, Y^{(K S)}
$$

Now, for $j=1, \ldots, K$ we set $X^{(j)}=Y^{(j S)}$ for the chain (5.11).

### 5.2.3 Convergence

Since the set $\{1, \ldots, M\}$ of available move types is obviously ergodic (that is, they enable any configuration to be reached from any other with positive probability), and the transition probabilities

$$
T_{u}\left(X \rightarrow X^{\prime}\right):=T_{u}^{(P)}\left(X \rightarrow X^{\prime}\right) \cdot T_{u}^{(A)}\left(X \rightarrow X^{\prime}\right)
$$

obviously satisfy the detailed balance relation (DBR)

$$
T_{u}\left(X \rightarrow X^{\prime}\right) P(X)=T_{u}\left(X^{\prime} \rightarrow X\right) P\left(X^{\prime}\right)
$$

the points $X^{(j)}$ in the chain (5.11) will have probabilities distributed according to $P(X)$ as $L \rightarrow \infty$. Hence, these points can be used as MC samples for calculating $\langle A(\bullet)\rangle^{(K)}$.

### 5.3 MC move types for EHM

There are 7 available (MC) move types for EHM, and move type 6 contains two subtypes of equal probabilities. We will give the rules and acceptance probabilities for each move type.

Let

$$
X=\left(n,\left(\vec{r}_{1}, s_{1}\right), \ldots,\left(\vec{r}_{2 n}, s_{2 n}\right), \tau_{1}, \ldots, \tau_{n}, \psi_{1}, \ldots, \psi_{N-n}\right) \in \mathscr{D}
$$

with

$$
\left|\vec{r}_{k}-\vec{r}_{k+n}\right|_{\mathscr{L}} \leq R_{c}, \forall k \in\{1, \ldots, n\}
$$

so that $V_{c}\left(\vec{r}_{k}-\vec{r}_{k+n}\right) \neq 0$ and $P(X) \neq 0$.
For each $\vec{r} \in \mathscr{L}$, we define the interaction sphere by

$$
C_{\mathscr{L}}(\vec{r}):=\left\{\vec{r}^{\prime} \in \mathscr{L}| | \vec{r}^{\prime}-\left.\vec{r}\right|_{\mathscr{L}} \leq R_{c}\right\} .
$$

Hereafter, we assume that the value of $R_{c}$ is chosen so that $C_{\mathscr{L}}(\vec{r})$ contains 1 or 5 elements.
For each move type $u$, we define

$$
R_{u}^{(P)}\left(X \rightarrow X^{\prime}\right):=\frac{T_{u}^{(P)}\left(X^{\prime} \rightarrow X\right)}{T_{u}^{(P)}\left(X \rightarrow X^{\prime}\right)}
$$

### 5.3.1 Move type 1: move a pair of V-Lines.

Randomly select $k_{0} \in\{1, \ldots, n\}$ and $\vec{r}_{0} \in \mathscr{L}$. Then propose $X \rightarrow X^{\prime}$ with

$$
\vec{r}_{k_{0}} \rightarrow \vec{r}_{k_{0}}^{\prime}=\vec{r}_{k_{0}} \oplus \vec{r}_{0}
$$

and

$$
\vec{r}_{k_{0}+n} \rightarrow \vec{r}_{k_{0}+n}^{\prime}=\vec{r}_{k_{0}+n} \oplus \vec{r}_{0} .
$$

It is clear that

$$
T_{1}^{(P)}\left(X^{\prime} \rightarrow X\right)=T_{1}^{(P)}\left(X \rightarrow X^{\prime}\right)
$$

Hence we have $R_{1}^{(P)}\left(X \rightarrow X^{\prime}\right)=1$ and

$$
\begin{equation*}
T_{1}^{(A)}\left(X \rightarrow X^{\prime}\right)=\min \left(1, \frac{W\left(X^{\prime}\right)}{W(X)}\right) \tag{5.13}
\end{equation*}
$$

### 5.3.2 Move type 2: Flip the spin at a vertex.

Randomly select $j_{0} \in\{1, \ldots, 2 n\}$, and propose $X \rightarrow X^{\prime}$ with

$$
s_{j_{0}} \rightarrow s_{j_{0}}^{\prime}=-s_{j_{0}} .
$$

Similarly to move type 1 , we have

$$
\begin{equation*}
T_{2}^{(A)}\left(X \rightarrow X^{\prime}\right)=\min \left(1, \frac{W\left(X^{\prime}\right)}{W(X)}\right) \tag{5.14}
\end{equation*}
$$

Note that in the case of $V_{1}=0$, we must have $W\left(X^{\prime}\right)=0$ by (5.9), and hence $X \rightarrow X^{\prime}$ is always rejected.

### 5.3.3 Move type 3: move the $\vec{r}$ at a vertex.

Randomly select $j_{0} \in\{1, \ldots, 2 n\}$, and let

$$
k_{0}= \begin{cases}j_{0}-n & \text { if } j_{0}>n \\ j_{0}+n & \text { otherwise }\end{cases}
$$

Then, randomly select

$$
\vec{r}_{0} \in C_{\mathscr{L}}\left(\vec{r}_{j_{0}}\right)
$$

with $\vec{r}_{0} \neq \vec{r}_{k_{0}}$ and propose $X \rightarrow X^{\prime}$ with

$$
\vec{r}_{j_{0}} \rightarrow \vec{r}_{j_{0}}^{\prime}=\vec{r}_{0}
$$

Similarly to move type 2 , we have

$$
\begin{equation*}
T_{3}^{(A)}\left(X \rightarrow X^{\prime}\right)=\min \left(1, \frac{W\left(X^{\prime}\right)}{W(X)}\right) \tag{5.15}
\end{equation*}
$$

and in the case of $V_{1}=0, X^{\prime}$ is always rejected.

### 5.3.4 Move type 4: move $\tau$ at a V-Line.

Randomly select $k_{0} \in\{1, \ldots, n\}$, and randomly generate a homogeneously distributed number $\delta \in\left[-\Delta_{\tau}, \Delta_{\tau}\right]$ with $0 \leq \Delta_{\tau} \leq \beta_{T}$. Let $\tau_{0}=\tau_{k_{0}}+\delta$. Then, propose $X \rightarrow X^{\prime}$ with

$$
\tau_{k_{0}} \rightarrow \tau_{k_{0}}^{\prime}= \begin{cases}\tau_{0} & \text { if } \tau_{0} \in\left[0, \beta_{T}\right] \\ 2 \beta_{T}-\tau_{0} & \text { if } \tau_{0} \in\left(\beta_{T}, 2 \beta_{T}\right] \\ -\tau_{0} & \text { otherwise }\end{cases}
$$

Similarly to move type 1 , we have

$$
\begin{equation*}
T_{4}^{(A)}\left(X \rightarrow X^{\prime}\right)=\min \left(1, \frac{W\left(X^{\prime}\right)}{W(X)}\right) \tag{5.16}
\end{equation*}
$$

### 5.3.5 Move type 5: update $\tau$-Padding variable $\psi$.

Randomly select $l_{0} \in\{1, \ldots, N-n\}$, and randomly generate $\psi_{0} \in\left[0, \beta_{T}\right]$ according to $g_{l_{0}}(\psi)$ (see (3.7)). Then propose $X \rightarrow X^{\prime}$ with

$$
\psi_{l_{0}} \rightarrow \psi_{l_{0}}^{\prime}=\psi_{0}
$$

It is readily seen that

$$
T_{5}^{(P)}\left(X^{\prime} \rightarrow X\right)=\frac{1}{N-n} g_{l_{0}}\left(\psi_{l_{0}}^{\prime}\right)
$$

Hence

$$
R_{5}^{(P)}\left(X^{\prime} \rightarrow X\right)=\frac{g_{l_{0}}\left(\psi_{l_{0}}\right)}{g_{l_{0}}\left(\psi_{l_{0}}{ }^{\prime}\right)}
$$

and

$$
\begin{equation*}
T_{5}^{(A)}\left(X \rightarrow X^{\prime}\right)=1 \tag{5.17}
\end{equation*}
$$

That is, this move type has $100 \%$ acceptance probability.

### 5.3.6 MOVE TYPE 6: RAISE OR LOWER DIAGRAM ORDER.

Move type 6 has two subtype: move type $6^{+}$and $6^{-}$. Once move type 6 is selected, we randomly choose $6^{+}$or $6^{-}$with equal probabilities.

## Move type $6^{+}$: RAISE DIAGRAM ORDER

If $n=N$, we reject this move type and proceed to the next move.
Now, assume $n<N$. We randomly select $k_{0} \in\{1, \ldots, n+1\}, l_{0} \in\{1 \ldots N-n\}, \vec{r}_{0} \in \mathscr{L}$, $\vec{r}_{-1} \in C_{\mathscr{L}}\left(\vec{r}_{0}\right)$ and $s_{0}, s_{-1} \in \mathscr{S}$. Then, we construct $X^{\prime}$ from $X$ by inserting a new V -line $\left(k_{0}, k_{0}+n\right)$ with $\tau$-value

$$
\tau_{k_{0}}^{\prime}=\psi_{l_{0}}
$$

and new vertex $\mathscr{E}$-coordinates

$$
\left(\vec{r}_{k_{0}}^{\prime}, s_{k_{0}}^{\prime}\right)=\left(\vec{r}_{0}, s_{0}\right),\left(\vec{r}_{k_{0}+n^{\prime}}^{\prime}, s_{k_{0}+n^{\prime}}^{\prime}\right)=\left(\vec{r}_{-1}, s_{-1}\right)
$$

and deleting the old $\psi_{l_{0}}$ from the list of $\tilde{\psi}$-variables. That is, we propose $X \rightarrow X^{\prime}$ with

$$
n \rightarrow n^{\prime}=n+1
$$

and

$$
\ldots \rightarrow\left(\tau_{k}^{\prime}, \vec{r}_{k}^{\prime}, s_{k}^{\prime}, \vec{r}_{k+n^{\prime}}^{\prime}, s_{k+n^{\prime}}^{\prime}\right)= \begin{cases}\left(\tau_{k}, \vec{r}_{k}, s_{k}, \vec{r}_{k+n}, s_{k+n}\right) & \text { if } 1 \leq k<k_{0} \\ \left(\psi_{l_{0}}, \vec{r}_{0}, s_{0}, \vec{r}_{-1}, s_{-1}\right) & \text { if } k=k_{0} \\ \left(\tau_{k-1}, \vec{r}_{k-1}, s_{k-1}, \vec{r}_{k+n-1}, s_{k+n-1}\right) & \text { if } k_{0}<k \leq n^{\prime}\end{cases}
$$

and

$$
\ldots \rightarrow \psi_{l}^{\prime}= \begin{cases}\psi_{l} & \text { if } 1 \leq l<l_{0} \\ \psi_{l+1} & \text { if } l_{0}<l \leq N-n^{\prime}\end{cases}
$$

Move TYPE $6^{-}$: LOWER DIAGRAM ORDER

If $n=0$, we reject this move type and proceed to the next move.
Now, assume $n>0$. We randomly select $k_{0} \in\{1, \ldots, n\}$ and $l_{0} \in\{1 \ldots N-n+1\}$. Then, we construct $X^{\prime}$ from $X$ by deleting the old $V$-line $\left(k_{0}, k_{0}+n\right)$ and insert $\tau_{k_{0}}$ as new $\psi_{l_{0}}$ into the list of $\tilde{\psi}$-variables. That is, we propose $X \rightarrow X^{\prime}$ with

$$
n \rightarrow n^{\prime}=n-1
$$

and

$$
\ldots \rightarrow\left(\tau_{k}^{\prime}, \vec{r}_{k}^{\prime}, s_{k}^{\prime}, \vec{r}_{k+n^{\prime}}^{\prime}, s_{k+n^{\prime}}^{\prime}\right)= \begin{cases}\left(\tau_{k}, \vec{r}_{k}, s_{k}, \vec{r}_{k+n}, s_{k+n}\right) & \text { if } 1 \leq k<k_{0} \\ \left(\tau_{k+1}, \vec{r}_{k+1}, s_{k+1}, \vec{r}_{k+n+1}, s_{k+n+1}\right) & \text { if } k_{0} \leq k \leq n^{\prime}\end{cases}
$$

and

$$
\ldots \rightarrow \psi_{l}^{\prime}= \begin{cases}\psi_{l} & \text { if } 1 \leq l<l_{0} \\ \tau_{k_{0}} & \text { if } l=l_{0} \\ \psi_{l+1} & \text { if } l_{0}<l \leq N-n^{\prime}\end{cases}
$$

Acceptance probability of move type 6

Let $|\mathscr{L}|=L_{x} \times L_{y}$ be the size of the lattice $\mathscr{L},\left|C_{\mathscr{L}}\right|$ the size of the interaction sphere, and

$$
\left|C_{\mathscr{I}}\right|= \begin{cases}2 & \text { if } V_{1}=0 \text { or }\left|C_{\mathscr{L}}\right|=1 \\ 4 & \text { otherwise }\end{cases}
$$

Now, let $u=6^{+}$and $X \rightarrow X^{\prime}$ with $n^{\prime}=n+1$. Then we have

$$
T_{u}^{(P)}\left(X \rightarrow X^{\prime}\right)=\frac{1}{2 n^{\prime}(N-n)|\mathscr{L}| \cdot\left|C_{\mathscr{L}}\right| \cdot\left|C_{\mathscr{L}}\right|}
$$

and

$$
T_{u}^{(P)}\left(X^{\prime} \rightarrow X\right)=\frac{1}{2 n^{\prime}(N-n)}
$$

It follows that

$$
R_{u}^{(P)}\left(X \rightarrow X^{\prime}\right)=|\mathscr{L}| \cdot\left|C_{\mathscr{L}}\right| \cdot\left|C_{\mathscr{S}}\right|
$$

and

$$
R_{u}^{(P)}\left(X^{\prime} \rightarrow X\right)=\frac{1}{|\mathscr{L}| \cdot\left|C_{\mathscr{L}}\right| \cdot\left|C_{\mathscr{S}}\right|}
$$

Hence, we have

$$
\begin{equation*}
T_{u}^{(A)}\left(X \rightarrow X^{\prime}\right)=\min \left(1,|\mathscr{L}| \cdot\left|C_{\mathscr{L}}\right| \cdot\left|C_{\mathscr{I}}\right| \cdot \frac{W\left(X^{\prime}\right)}{W(X)}\right) . \tag{5.18}
\end{equation*}
$$

Analogously, for $u=6^{-}$, we have

$$
\begin{equation*}
T_{u}^{(A)}\left(X \rightarrow X^{\prime}\right)=\min \left(1, \frac{1}{|\mathscr{L}| \cdot\left|C_{\mathscr{L}}\right| \cdot\left|C_{\mathscr{S}}\right|} \cdot \frac{W\left(X^{\prime}\right)}{W(X)}\right) . \tag{5.19}
\end{equation*}
$$

### 5.3.7 Move type 7: EXChange a Pair of spins.

If $n=0$, we reject this move type and proceed to the next move.

Now, assume that $n>0$. Then we randomly select $j_{0} \in\{1, \ldots, 2 n\}$, and propose $X \rightarrow X^{\prime}$ with

$$
s_{j_{0}} \rightarrow s_{j_{0}}^{\prime}=s_{j_{0}+n}
$$

and

$$
s_{j_{0}+n} \rightarrow s_{j_{0}+n}^{\prime}=s_{j_{0}}
$$

Similarly to move type 1 , we have

$$
\begin{equation*}
T_{7}^{(A)}\left(X \rightarrow X^{\prime}\right)=\min \left(1, \frac{W\left(X^{\prime}\right)}{W(X)}\right) \tag{5.20}
\end{equation*}
$$

Note that in the case of $n>0$ and $V_{1}=0$, we must have $W(X)=W\left(X^{\prime}\right)$ by (5.9), and hence $X \rightarrow X^{\prime}$ is always accepted.

## Chapter 6

## Results

We performed Monte Carlo simulations of EHM for 1-electron systems over 12 parameter sets using the evaluation method detailed in Chapter 5 . We will describe briefly the experiments in $\S 6.1$, and present and discuss the results in $\S 6.2$. Finally, we draw conclusions about our method in §6.3.

### 6.1 The Experiments

In this section, we will briefly describe our experiments and give the parameter sets used in the experiments.

### 6.1.1 The Program

Our program is written in C and MPI, and run at the computer rcluster.rcc.uga.edu.
For each parameter set, the program uses $R$ processors. Each of the processors randomly generates an $X \in \mathscr{D}$ with a common initial seed seed $_{0}$ for the random number generator, and then randomly generates a Markov chain of length $K$ starting with $X$ and initial seed seed $_{j}=$ Seed $_{0}+1000 j$, where $j$ is the ordinal of the processor. Then, we collect the scores of the $R$ chains and compute the final scores $\left(S_{0}, S_{1}\right.$ and $\left.G_{1}\right)$ and their standard deviations in the major processor.

We use the algorithm GEP (see §2.2.1) and the formula (5.8) or (5.10) to calculate determinants. Note that the running time of $G E P$ is $O\left(n^{3}\right)$, so the use of (5.8) or (5.10) gives rise to a speed-up factor of up to 8 .

Let the function $g_{l}(\psi)$ in (3.6) be defined by

$$
g_{l}(\psi):=T, \forall \psi \in\left[0, \beta_{T}\right] .
$$

It is the simplest function that satisfies (3.7). Then, the padding function is just

$$
Q_{N-n}(\tilde{\psi})=T^{N-n}
$$

### 6.1.2 CONTINUOUS TIME SCHEME

Let the external vertex be $(\hat{r}, \hat{s})$, where

$$
\hat{r}=(\vec{r} \mid \vec{r}) \in \mathscr{L}^{2}, \hat{s}=(s \mid \bar{s}) \in \mathscr{S}
$$

with $s=\bar{s}$, and let $\hat{\theta}=(\tau, \bar{\tau}) \in\left[0, \beta_{T}\right]$. By (4.13) and (4.16), we need to compute score $S_{1}$ and $G_{1}$ for selected pairs of the form

$$
(\Delta \vec{r}=\vec{r}-\vec{r}, \Delta \tau=\tau-\bar{\tau})
$$

We use the continuous time scheme to select these pairs as follows. Let $L_{\tau}$ be a large integer. Given integers

$$
0=a_{1}<b 1<a 2<b 2<a 3<b 3=L_{\tau},
$$

and $c_{1}, c_{2}, c_{3}$, such that $\left(c_{k}-1\right) \mid\left(b_{k}-a_{k}\right)$ for $k=1,2,3$, let

$$
J=\left\{ \pm\left(a_{k}+j_{k} d_{k}\right) \mid k=1,2,3 ; d_{k}=\frac{b_{k}-a_{k}}{c_{k}-1}, j_{k}=0, \ldots, c_{k}-1 .\right.
$$

Then, the scores will be computed at each point in the set

$$
\left\{\left.\left(\vec{r}, \Delta \tau=\frac{j}{L_{\tau}} \beta_{T}\right) \right\rvert\, \vec{r} \in \mathscr{L}, j \in J\right\} .
$$

In our experiments, we set $L_{\tau}=4096$, and the values of $a_{k}, b_{k}, c_{k}$ are given in Table 6.1.

Table 6.1: Parameters $a_{k}, b_{k}, c_{k}$

| $\boldsymbol{k}$ | $\boldsymbol{a}_{\boldsymbol{k}}$ | $\boldsymbol{b}_{\boldsymbol{k}}$ | $\boldsymbol{c}_{\boldsymbol{k}}$ |
| :---: | :---: | :---: | :---: |
| 1 | 0 | 112 | 8 |
| 2 | 256 | 3840 | 15 |
| 3 | 3984 | 4096 | 8 |

### 6.1.3 The parameter sets

Our experiments used 12 parameter sets. The values of most parameters are the same, except $N, V_{0}, \mu$ and $T$.

The parameter sets and the values of the three variable parameters $N, V_{0}$ and $T$ are given in Table 6.2. Note that we always have $\mu=0.5 V_{0}$, and the values of $N$ were chosen so that the orders of diagrams in the Markov chains never exceed them.

Table 6.2: Parameter Sets

| Set | $\boldsymbol{N}$ | $\boldsymbol{V}_{\mathbf{0}}$ | $\boldsymbol{T}$ |
| :---: | :---: | :---: | :---: |
| $1 a$ | 32 | 1.0 | 1.0 |
| $1 b$ | 32 | 1.0 | 0.5 |
| $1 c$ | 32 | 1.0 | 0.25 |
| $1 d$ | 48 | 1.0 | 0.125 |
| $2 a$ | 32 | 2.0 | 1.0 |
| $2 b$ | 32 | 2.0 | 0.5 |
| $2 c$ | 64 | 2.0 | 0.25 |
| $2 d$ | 80 | 2.0 | 0.125 |
| $1 a$ | 48 | 4.0 | 1.0 |
| $1 b$ | 56 | 4.0 | 0.5 |
| $1 c$ | 84 | 4.0 | 0.25 |
| $1 d$ | 128 | 4.0 | 0.125 |

The values of the common parameters are given in Table 6.3. Note that we set

$$
p_{M}(2)=p_{M}(3)=0
$$

because that in the case $V_{1}=0$, an MC move of type 2 or 3 is always rejected.

Table 6.3: Common Parameters

| $R$ | 32 | $L$ | $2 \times 10^{7}$ | $p_{M}(3)$ | 0.0 |
| :---: | :---: | :---: | :---: | :---: | :---: |
| $L_{x}$ | 2 | $K$ | $10^{8}$ | $p_{M}(4)$ | 0.15 |
| $L_{y}$ | 2 | $S$ | 4 | $p_{M}(5)$ | 0.15 |
| $V_{1}$ | 0 | $\left\|C_{\mathscr{L}}\right\|$ | 1 | $p_{M}(6)$ | 0.3 |
| $t_{1}$ | 1.0 | $\operatorname{seed}_{0}$ | 1011 | $p_{M}(7)$ | 0.2 |
| $t_{2}$ | 0.0 | $p_{M}(1)$ | 0.2 |  |  |
| $t_{3}$ | 0.0 | $p_{M}(2)$ | 0.0 |  |  |

### 6.2 RESULTS

In this section, we present and discuss the results of our experiments.

### 6.2.1 Accept ratios of MC moves

By Table 6.3, MC move types 2 and 3 are not used in our experiments and the accept ratio for move type 5 is 1 . The accept ratios for other move types are given in Table 6.4. Note that the accept ratio of move type 7 tends to 1 as $V_{0}$ and $\beta_{T}$ increase, meaning that the number of diagrams of order 0 tends to 0 as $V_{0}$ and $\beta_{T}$ increase.

### 6.2.2 Running time

The running time $T_{r}$ of the program is the system time for the major processor. It is obvious that $T_{r} \propto K$, and the experiments show that $T_{r} \propto \beta_{T}^{1+c_{T}}$ and $T_{r} \propto V_{0}^{1+c_{V}}$ approximately, (see Figure 6.1), where $c_{T}$ and $c_{V}$ are some constants. Hence, we have

$$
T_{r} \propto K V_{0}^{1+c_{V}} \beta_{T}^{1+c_{T}} .
$$

### 6.2.3 ORDER FREQUENCIES

The order frequencies are important in our simulations.

Table 6.4: Accept ratios

| $\boldsymbol{u}$ | $\boldsymbol{V}_{\mathbf{0}}$ | $\boldsymbol{\beta}_{\boldsymbol{T}}=\mathbf{1}$ | $\boldsymbol{\beta}_{\boldsymbol{T}}=\mathbf{2}$ | $\boldsymbol{\beta}_{\boldsymbol{T}}=\mathbf{4}$ | $\boldsymbol{\beta}_{\boldsymbol{T}}=\mathbf{8}$ |
| :---: | :---: | :---: | :---: | :---: | :---: |
| 1 | 1 | 0.510 | 0.646 | 0.691 | 0.688 |
|  | 2 | 0.595 | 0.635 | 0.627 | 0.611 |
|  | 4 | 0.554 | 0.553 | 0.536 | 0.512 |
| 4 | 1 | 0.564 | 0.719 | 0.791 | 0.818 |
|  | 2 | 0.728 | 0.765 | 0.760 | 0.751 |
|  | 4 | 0.795 | 0.744 | 0.703 | 0.653 |
| 6 | 1 | 0.581 | 0.695 | 0.715 | 0.698 |
|  | 2 | 0.657 | 0.669 | 0.652 | 0.631 |
|  | 4 | 0.593 | 0.586 | 0.571 | 0.554 |
| 7 | 1.0 | 0.598 | 0.804 | 0.925 | 0.977 |
|  | 2.0 | 0.809 | 0.933 | 0.981 | 0.998 |
|  | 3.0 | 0.938 | 0.988 | 0.999 | 1.000 |

Given a Markov chain $C$ of length $K$ on $\mathscr{D}$, let $n^{+}$be the number of even-order points in $C$ and $n^{-}$be the number of odd-order points in $C$ ( $n^{+}$and $n^{-}$will be used hereafter). Assume $V_{1}=0$; then for each $X \in C$, we have

$$
F_{0}(X) \begin{cases}>0 & \text { if } n \text { is even; } \\ <0 & \text { if } n \text { is odd }\end{cases}
$$

by (5.10) and (4.16). It follows that for the chain $C$

$$
\begin{equation*}
S_{0}=\frac{n^{+}-n^{-}}{K} \tag{6.1}
\end{equation*}
$$

by (5.2) and (5.7).
Our experiments show that the maximal order $n_{\max }$ and the most frequent order $n_{h}$ of points in the $R$ Markov chains generated increase as $\beta_{T}$ or $V_{0}$ increases (see Figure 6.2 and 6.3 , respectively).


Figure 6.1: Running time

### 6.2.4 Convergence for parameter set $3 b$

Let $\operatorname{var}\left(S_{0}\right)$ and $\operatorname{var}\left(S_{1}\right)$ be the square of the standard deviations of $S_{0}$ and $S_{1}$, respectively. The results for parameter set 3 b (see Figure 6.4) show that as $K \rightarrow \infty, S_{0}$ becomes stable, and that $\frac{1}{\operatorname{var}\left(S_{1}\right)}($ at $\Delta \tau \in\{0.0078,1.0,1.9922\})$ and $\frac{1}{\operatorname{var}\left(S_{0}\right)}$ increase quickly. This indicates that the simulation converged well. Note that the figure also shows that $\frac{1}{\operatorname{var}\left(S_{1}\right)}$ increased significantly faster at $\Delta \tau=1.0$ than at $\Delta \tau=0.0078$ or $\Delta \tau=1.9922$, indicating that $S_{1}$ converged faster in the middle than near the two ends of the interval $\left[0, \beta_{T}\right]$.

### 6.2.5 $S_{0}$ OR $S_{1}$ VS. $\beta_{T}$

Figure 6.5 shows the relation between $\lg \left(\left|S_{1}\right|\right)$ and $\beta_{T}$ at $((0,0), 0)$, and the relation between $\lg \left(\left|S_{0}\right|\right)$ and $\beta_{T}$. From the figure, we have

$$
\left|S_{0}\right|=e^{c_{0} \beta_{T}}
$$

and

$$
\left|S_{1}\right|=e^{c_{1} \beta_{T}}
$$

where $c_{0}$ and $c_{1}$ are nearly constant.


Figure 6.2: Order frequencies vs. $\beta_{T}$


Figure 6.3: Order frequencies vs. $V_{0}$

### 6.2.6 The Green's function $G_{1}$

The 1-electron Green's functions for the 12 parameter sets are plotted in Figure 6.6 and Figure 6.7. In the figures, the anti-periodicity and jump discontinuity are easy seen. Note that the relative errors were large for parameter sets $2 \mathrm{~d}, 3 \mathrm{c}$ and 3 d , and we only plotted the three paraneter sets for $\Delta \vec{r}=(0,0)$.

The three parameter sets for which $V_{0} \beta_{T} \geq 16$ had large relative errors because for each of the 3 sets, $n^{+}$and $n^{-}$are very close. Thus in the $R$ chains for each of these sets, the number of chains with positive score $S_{0}$ and the number of chains with negative score $S_{0}$ were close. This leads to a small sum due to cancellations, while the variance accumulates resulting in large relative errors. To verify this, we plotted $S_{1}^{+}$and $S_{1}^{-}$for parameter set 3d in Figure 6.8, where

$$
S_{1}^{+}=\frac{\sum\left(S_{1}(X)\right)}{K}
$$

the sum goes through all points of even order, and $S_{1}^{-}$is defined analogously. As expected, the error bars in Figure 6.8 were small, and $S_{1}^{+} \approx S_{1}^{-}$.

### 6.3 Conclusion

From the results, we conclude that our new method works well over a large region of the parameter space. Our program can be used for any rectangular lattice, and can be used for $m$-electron systems with $m>1$ with only slight modifications. However, it appears impractical when $V_{0} \beta_{T} \geq 16$.


Figure 6.4: Convergence of parameter set 3b


Figure 6.5: $\lg \left(\left|S_{1}\right|\right)$ or $\lg \left(\left|S_{0}\right|\right)$ vs. $\beta_{T}$


Figure 6.6: The Green's function $G_{1}\left(\beta_{T}=1,2\right)$


Figure 6.7: The Green's function $G_{1}\left(\beta_{T}=4,8\right)$


Figure 6.8: $S_{1}^{+}$and ${ }_{1}^{-}$for $V_{0}=4, T=8$

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