Approximation Solution of Two-Dimensional Linear Stochastic Fredholm Integral Equation by Applying the Haar Wavelet

M. Fallahpour\(^1\), K. Maleknejad\(^2\) and M. Khodabin\(^3\)

\(^1,2,3\)Department of Mathematics, Karaj Branch, Islamic Azad University, Karaj, Iran.

Abstract. In this paper, we introduce an efficient method based on Haar wavelet to approximate a solution for the two-dimensional linear stochastic Fredholm integral equation. We also give an example to demonstrate the accuracy of the method.

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1. Introduction

As we know, two dimensional ordinary integral equations provide an important tool for modeling a numerous problems in engineering and science [6, 16]. The second kind of two-dimensional integral equations appear in nonhomogeneous elasticity and electrostatics, the Dorboux problem, contact problems for bodies with complex properties, radio wave propagation, the elastic problem of axial translation of a rigid elliptical disc-inclusion, various physical and mechanical and biological problems [1, 11, 4, 10, 20, 23, 25, 28]. Some numerical schemes have been inspected for resolvent of two-dimensional ordinary integral equations by several probers. Computational complexity of mathematical operations is the most important obstacle for solving ordinary integral equations in higher dimensionas.
These include the Nyström method, collocation method, Gauss product quadrature rule method, Galerkin method, using triangular functions, Legendre polynomial method, differential transform method, meshless method, Bernstein polynomials method and Haar wavelet method [5, 7, 8, 9, 12, 13, 14, 15, 19, 21, 22, 24, 29, 30]. This paper is first focused on proposing a generic framework for numerical solution of two-dimensional ordinary linear Fredholm integral equations of second kind. The use of the Haar wavelet for the numerical solution of linear integral equations has previously been discussed in [3] and references therein. In [2] a new numerical method based on Haar wavelet is introduced for solution of nonlinear one-dimensional Fredholm and Volterra integral equations. In [27] the Haar wavelet method [2] is extended to numerical solution of integro-differential equation. In [26] the Haar wavelet method [2, 27] is improved in terms of efficiency by introducing one-dimensional Haar wavelet approximation of the kernel function. The method [3] is fundamentally different from the other numerical methods based on Haar wavelet for the numerical solution of integral equations as it approximates kernel function using Haar wavelet. It’s easy to show that the Fredholm integral form of the general hyperbolic differential equation [10] is given by two-dimensional integral equation

\[ g(x, y) = f(x, y) + \int_0^1 \int_0^1 K_1(x, y, s, t)g(s, t)dsdt. \]

If we import statistical noise in the general hyperbolic differential equation [10], we can obtain two-dimensional linear stochastic Fredholm integral equation of the second kind, i.e.

\[ g(x, y) = f(x, y) + \int_0^1 \int_0^1 K_1(x, y, s, t)g(s, t)dsdt + \int_0^1 \int_0^1 K_2(x, y, s, t)g(s, t)dB(s)dB(t) \]

where the kernels \( K_1(x, y, s, t) \) and \( K_2(x, y, s, t) \) in (1.1) are known functions and \( f(x, y) \) is also a known function whereas \( g(x, y) \) is unknown function and is called the solution of two-dimensional stochastic integral equation.

**Lemma 1.** Put \( \phi(t, s) = K(x, y, s, t)g(s, t) \). Let \( \phi \) be a function in \( L^2([0, 1]^2) \). Then there exists a sequence \( \phi_n \) of off-diagonal step functions such that [18]

\[ \lim_{n \to \infty} \int_a^b \int_a^b |\phi(t, s) - \phi_n(t, s)|^2 dt ds = 0. \]

**Definition 1.** Let \( \phi \in L^2([0, 1]^2) \). Then the double Wiener-Itô integral of \( \phi \) is
defined as [18]
\[
\int_a^b \int_a^b \phi(t, s) dB(t) dB(s) = \lim_{n \to \infty} \int_a^b \int_a^b \phi_n(t, s) dB(t) dB(s) \quad \text{in} \quad L^2(\Omega).
\]

**Theorem 1.** Let \( \phi(t, s) \in L^2([a, b]^2) \). Then [18]
\[
\int_a^b \int_a^b \phi(t, s) dB(t) dB(s) = 2 \int_a^b \left[ \int_a^t \hat{\phi}(t, s) dB(s) \right] dB(t),
\]
where \( \hat{\phi} \) is the symmetrization of \( \phi \) that is defined by
\[
\hat{\phi}(t, s) = \frac{1}{2} (\phi(t, s) + \phi(s, t)).
\]

Also for the integral \( \int_a^b B(t) dB(t) \) we have [18]
\[
\int_a^b B(t) dB(t) = \frac{1}{2} \{ B(b)^2 - B(a)^2 - (b - a) \}.
\]

2. **Haar Wavelets**

A wavelet family \( (\psi_{j,n}(y))_{j \in N, n \in Z} \) is an orthonormal subfamily of the Hilbert space \( L^2(\mathbb{R}) \) with the property that all function in the wavelet family are generated from a fixed function \( \psi \) called mother wavelet through dilations and translations. The wavelet family satisfies the following relation
\[
\psi_{j,n}(y) = 2^{j/2} \psi \left( 2^j y - n \right).
\]

For Haar wavelet family on the interval \( [0, 1) \) we have:
\[
h_1(y) = \begin{cases} 
1, & \text{for } y \in [0, 1) \\
0, & \text{otherwise},
\end{cases}
\]
and
\[
h_i(y) = \begin{cases} 
1, & \text{for } y \in [\alpha, \beta) \\
-1, & \text{for } y \in [\beta, \gamma) \\
0, & \text{otherwise}
\end{cases} \quad i = 2, 3, \ldots,
\]
where
\[
\alpha_n = \frac{n}{m}, \quad \beta_n = \frac{(n + 0.5)}{m}, \quad \gamma_n = \frac{(n + 1)}{m};
\]
\[
m = 2^\ell, \quad \ell = 0, 1, \ldots, \quad n = 0, 1, \ldots, m - 1.
\]
The integer $\ell$ indicates the level of the wavelet and $n$ is the translation parameter. Any square integrable function $f(y)$ defined on $[0,1]$ can be expressed as follows:

$$f(y) = \sum_{i=1}^{\infty} a_i h_i(y),$$

where $a_i$ are real constants.

For approximation aim we consider a maximum value $L$ of the integer $\ell$, level of the Haar wavelet in the above definition. The integer $L$ is then called maximum level of resolution. We also define integer $M = 2^L$. Hence for any square integrable function $f(y)$ we have a finite sum of Haar wavelets as follows:

$$f(y) \approx \sum_{i=1}^{2M} a_i h_i(y).$$

### 3. Numerical Method

In this section proposed numerical method [3] will be discussed for two-dimensional linear stochastic Fredholm integral equation of the second kind. In the first subsection, we state some results for efficient evaluation of two-dimensional Haar wavelet approximations. In the second subsection, we apply these results for finding numerical solutions equation (1.1).

For Haar wavelet approximation of a function $f(x,y)$ of two real variables $x$ and $y$, we assume that the domain $0 \leq x, y \leq 1$ is divided into a grid of size $2M \times 2N$ using the following collocation points

$$x_m = \frac{m - 0.5}{2M}, m = 1, 2, ..., 2M,$$

$$y_n = \frac{n - 0.5}{2N}, n = 1, 2, ..., 2N.$$

#### 3.1 Two-dimensional Haar wavelet system

A real-valued function $G(x,y)$ of two real variables $x$ and $y$ can be approximated using two-dimensional Haar wavelets basis as $[3, 17]$:

$$G(x,y) \approx \sum_{p=1}^{2M} \sum_{q=1}^{2N} b_{p,q} h_p(x) h_q(y).$$

In order to calculate the unknown coefficients $b_{i,j}$’s, the collocation points defined in Eqs. (3.1) and (3.2) are substituted in Eq. (3.3). Hence, we obtain the following $2M \times 2N$ linear system with unknowns $b_{i,j}$’s:

$$G(x_m, y_n) = \sum_{p=1}^{2M} \sum_{q=1}^{2N} b_{p,q} h_p(x_m) h_q(y_n), m = 1, 2, ..., 2M, \quad n = 1, 2, ..., 2N.$$

The solution of system (3.4) can be calculated from the following theorem.

**Theorem 2.** The solution of the system (3.4) is given below:

\[ b_{1,1} = \frac{1}{2M \times 2N} \sum_{p=1}^{2M} \sum_{q=1}^{2N} G(x_m, y_n), \]

\[ b_{i,1} = \frac{1}{\rho_1 \times 2N} \left( \sum_{p=\alpha_1}^{\beta_1} \sum_{q=\alpha_2}^{\gamma_1} G(x_m, y_n) - \sum_{p=\beta_1+1}^{\gamma_1} \sum_{q=\alpha_2}^{2N} G(x_m, y_n) \right), \quad i = 2, 3, \ldots, 2M, \]

\[ b_{1,j} = \frac{1}{2M \times \rho_2} \left( \sum_{p=1}^{\beta_2} \sum_{q=\alpha_2}^{\gamma_2} G(x_m, y_n) - \sum_{p=1}^{\beta_2} \sum_{q=\alpha_2}^{\gamma_2} G(x_m, y_n) \right), \quad j = 2, 3, \ldots, 2N, \]

\[ b_{i,j} = \frac{1}{\rho_1 \times \rho_2} \left( \sum_{p=\alpha_1}^{\beta_1} \sum_{q=\alpha_2}^{\gamma_2} G(x_m, y_n) - \sum_{p=\alpha_1}^{\beta_1} \sum_{q=\alpha_2}^{\gamma_2} G(x_m, y_n) - \sum_{p=\beta_1+1}^{\gamma_1} \sum_{q=\alpha_2}^{\gamma_2} G(x_m, y_n) + \sum_{p=\beta_1+1}^{\gamma_1} \sum_{q=\beta_2+1}^{\gamma_2} G(x_m, y_n) \right), \quad i = 2, 3, \ldots, 2M, \quad j = 2, 3, \ldots, 2N, \]

where

\[ \alpha_1 = \rho_1 (\sigma_1 - 1) + 1, \]
\[ \beta_1 = \rho_1 (\sigma_1 - 1) + \frac{\gamma_1}{2}, \]
\[ \gamma_1 = \rho_1 \sigma_1, \]
\[ \rho_1 = \frac{2M}{\tau_1}, \]
\[ \sigma_1 = i - \tau_1, \]
\[ \tau_1 = 2^{\lceil \log_2 (i - 1) \rceil} \]

and similarly,

\[ \alpha_2 = \rho_2 (\sigma_2 - 1) + 1, \]
\[ \beta_2 = \rho_2 (\sigma_2 - 1) + \frac{\gamma_2}{2}, \]
\[ \gamma_2 = \rho_2 \sigma_2, \]
\[ \rho_2 = \frac{2N}{\tau_2}, \]
\[ \sigma_2 = j - \tau_2, \]
\[ \tau_2 = 2^{\lceil \log_2 (j - 1) \rceil} \]

**Proof.** See [2].
Consider a function $G(x, y, s, t)$ of four variables $x, y, s$ and $t$. Suppose $G(x, y, s, t)$ is approximated using two-dimensional Haar wavelet as follows [3]:

$$G(x, y, s, t) \approx \sum_{p=1}^{2M} \sum_{q=1}^{2N} b_{p,q}(x, y) h_p(s) h_q(t).$$

(13)

Substituting the collocation points

$$s_i = \frac{i - 0.5}{2M}, \quad i = 1, 2, ..., 2M,$$

and

$$t_j = \frac{j - 0.5}{2N}, \quad j = 1, 2, ..., 2N,$$

we obtain the linear system

$$G(x, y, s_i, t_j) \approx \sum_{p=1}^{2M} \sum_{q=1}^{2N} b_{p,q}(x, y) h_p(s_i) h_q(t_j) \quad i = 1, 2, ..., 2M \quad j = 1, 2, ..., 2N.$$  

(14)

**Corollary 1.** The solution of the system (3.8) for any value of $x, y \in [0, 1]$ is given as follows [3]:

$$b_{1,1}(x, y) = \frac{1}{2M \times 2N} \sum_{p=1}^{2M} \sum_{q=1}^{2N} G(x, y, s_p, t_q),$$

$$b_{i,1}(x, y) = \frac{1}{\rho_1 \times 2N} \left( \sum_{p=\alpha_1}^{\beta_1} \sum_{q=1}^{2N} G(x, y, s_p, t_q) - \sum_{p=\beta_1+1}^{2M} \sum_{q=1}^{2N} G(x, y, s_p, t_q) \right), \quad i = 2, 3, ..., 2M,$$

$$b_{1,j}(x, y) = \frac{1}{2M \times \rho_2} \left( \sum_{p=1}^{2M} \sum_{q=\alpha_2}^{\beta_2} G(x, y, s_p, t_q) - \sum_{p=1}^{2M} \sum_{q=\beta_2+1}^{2N} G(x, y, s_p, t_q) \right), \quad j = 2, 3, ..., 2N,$$

$$b_{i,j}(x, y) = \frac{1}{\rho_1 \times \rho_2} \left( \sum_{p=\alpha_1}^{\beta_1} \sum_{q=\alpha_2}^{\beta_2} G(x, y, s_p, t_q) - \sum_{p=\alpha_1}^{\beta_1} \sum_{q=\beta_2+1}^{2N} G(x, y, s_p, t_q) \right) - \sum_{p=\beta_1+1}^{2M} \sum_{q=\alpha_2}^{\beta_2} G(x, y, s_p, t_q) + \sum_{p=\beta_1+1}^{2M} \sum_{q=\beta_2+1}^{2N} G(x, y, s_p, t_q),$$

$$i = 2, 3, ..., 2M \quad j = 2, 3, ..., 2N,$$
where \( \alpha_1, \beta_1, \gamma_1 \) and \( \rho_1 \) are defined as in Eq. (3.5) and \( \alpha_2, \beta_2, \gamma_2 \) and \( \rho_2 \) are defined as in Eq. (3.6).

**Corollary 2.** Suppose a function \( G(x, y) \) of two variables \( x \) and \( y \) is approximated using Haar wavelet approximation given in Eq. (3.3). Suppose further that \( G(x, y) \) is known at collocation points \( (x_m, y_m) \), \( m = 1, 2, ..., 2M, n = 1, 2, ..., 2N \). Then the approximate value of the function \( G(x, y) \) at any other point of the domain can be calculated as follows [3]:

\[
G(x, y) = \frac{1}{2M \times 2N} \sum_{p=1}^{2M} \sum_{q=1}^{2N} G(x_m, y_m) h_1(x) h_1(y) \\
+ \sum_{i=1}^{2M} \frac{1}{\rho_1 \times 2N} \left( \sum_{p=\alpha_1}^{\beta_1} \sum_{q=1}^{2N} G(x_m, y_m) - \sum_{p=\beta_1+1}^{2M} \sum_{q=1}^{2N} G(x_m, y_m) \right) h_1(x) h_1(y)
\]

\[
+ \sum_{j=1}^{2N} \frac{1}{\rho_2 \times 2M} \left( \sum_{p=1}^{\beta_2} \sum_{q=\alpha_2}^{\gamma_2} G(x_m, y_m) - \sum_{p=1}^{\beta_2+1} \sum_{q=\gamma_2}^{2N} G(x_m, y_m) \right) h_1(x) h_2(y)
\]

\[
+ \sum_{i=1}^{2M} \sum_{j=1}^{2N} \frac{1}{\rho_1 \rho_2} \left( \sum_{p=\alpha_1}^{\beta_1} \sum_{q=\alpha_2}^{\gamma_2} G(x_m, y_m) - \sum_{p=\beta_1+1}^{\beta_2+1} \sum_{q=\gamma_2}^{2N} F(x_m, y_m) \right) h_1(x) h_2(y)
\]

\[- \sum_{p=\beta_1+1}^{2M} \sum_{q=\alpha_2}^{\beta_2} G(x_m, y_m) + \sum_{p=\beta_1+1}^{2M} \sum_{q=\beta_2+1}^{2N} G(x_m, y_m) \right) h_1(x) h_2(y),
\]

where \( \alpha_1, \beta_1, \gamma_1 \) and \( \rho_1 \) are defined as in Eq. (3.5) and \( \alpha_2, \beta_2, \gamma_2 \) and \( \rho_2 \) are defined as in Eq. (3.6).

### 3.2 Two-dimensional linear stochastic Fredholm integral equation

Consider the two-dimensional linear stochastic Fredholm integral equation (1.1). First we define:

\[
K_2(x, y, s, t)g(s, t) = \phi(t, s),
\]

afterward from (1.3) we have

\[
\hat{\phi}(t, s) = \frac{1}{2} \{K_2(x, y, t, s)g(t, s) + K_2(x, y, s, t)g(s, t)\}.
\]

Assume that the function \( K(x, y, s, t)g(s, t) \) is approximated using two-dimensional Haar wavelet as follows:

\[
K_1(x, y, s, t)g(s, t) \approx \sum_{i=1}^{2M} \sum_{j=1}^{2N} b_{i,j}(x, y) h_i(s) h_j(t),
\]

(15)
\[ \hat{\phi}(t, s) \approx \sum_{i=1}^{2M} \sum_{j=1}^{2N} c_{i,j}(x, y) h_i(s) h_j(t). \]  

(16)

With this approximation and using Eq. (1.2) we can write Eq. (1.1) as follows:

\[
g(x, y) = f(x, y) + \int_0^1 \int_0^1 \sum_{i=1}^{2M} \sum_{j=1}^{2N} b_{i,j}(x, y) h_i(s) h_j(t) ds dt 
+ 2 \int_0^1 \left[ \int_0^t \sum_{i=1}^{2M} \sum_{j=1}^{2N} c_{i,j}(x, y) h_i(s) h_j(t) dB(s) \right] dB(t). \]

(17)

Eq. (3.11) can be written in a more compact form using the notations introduced in equations (2.1) and (2.2) and is given as follows:

\[
g(x, y) = f(x, y) + b_{1,1}(x, y) + 2 \left( c_{1,1}(x, y) \times \text{Ito1}(1) + \sum_{j=2}^{2N} c_{1,j}(x, y) \times \text{Ito2}(j) \right. \\
+ \sum_{i=2}^{2M} c_{i,1}(x, y) \times \text{Ito1}(i) + \sum_{i=2}^{2M} \sum_{j=2}^{2N} c_{i,j}(x, y) \times \text{Ito3}(i, j) \right), \]

where in recent equation from Eq. (1.4) we have:

\[
\text{Ito1}(1) = \int_0^1 h_1(t) \left[ \int_0^t h_1(s) dB(s) \right] dB(t) = \int_0^1 B(t) dB(t) = \frac{B^2(1)}{2} - \frac{1}{2},
\]

\[
\text{Ito1}(i) = \int_0^1 h_1(t) \left[ \int_0^t h_i(s) dB(s) \right] dB(t) = \int_0^1 \left[ \int_{\alpha_i}^{\beta_i} dB(s) - \int_{\beta_i}^{\gamma_i} dB(s) \right] dB(t)
= (2B(\beta_i) - B(\alpha_i) - B(\gamma_i)) B(1),
\]

\[
\text{Ito1}(j) = \int_0^1 h_j(t) \left[ \int_0^t h_1(s) dB(s) \right] dB(t) = \int_0^1 h_j(t) B(t) dB(t)
= \int_{\alpha_j}^{\beta_j} B(t) dB(t) - \int_{\beta_j}^{\gamma_j} B(t) dB(t) = \frac{2mB^2(\beta_j) - B^2(\alpha_j) - B^2(\gamma_j) + 1}{2m},
\]

and

\[
\text{Ito3}(i, j) = \int_0^1 h_j(t) \left[ \int_0^t h_i(s) dB(s) \right] dB(t)
\]
= \int_0^1 h_j(t) \left[ \int_{a_i}^{\beta_i} dB(s) - \int_{\beta_i}^{\gamma_i} dB(s) \right] dB(t)

= [2B(\beta_i) - B(\alpha_i) - B(\gamma_i)] [2B(\beta_j) - B(\alpha_j) - B(\gamma_j)].

Substituting the collocation points given in (3.1) and (3.2), we obtain the following system of equations:

\[ g(x_m, y_n) = f(x_m, y_n) + b_{1,1}(x_m, y_n) + 2 \left( c_{1,1}(x_m, y_n) \times Ito1(1) + \sum_{j=2}^{2N} c_{1,j}(x_m, y_n) \times Ito2(j) + \sum_{i=2}^{2M} c_{i,1}(x_m, y_n) \times Ito1(i) + \sum_{i=2}^{2M} \sum_{j=2}^{2N} c_{i,j}(x_m, y_n) \times Ito3(i, j) \right). \]

Now \( b_{i,j} \), \( i = 1, 2, ..., 2M \), \( j = 1, 2, ..., 2N \) and similarly \( c_{i,j} \), \( i = 1, 2, ..., 2M \), \( j = 1, 2, ..., 2N \) can be replaced with their expressions given in Corollary 1 and the following system of equations is obtained:

\[ g(x_m, y_n) = f(x_m, y_n) + \frac{1}{2M \times 2N} \sum_{p=1}^{2M} \sum_{q=1}^{2N} K_1(x_m, y_n, s_p, t_q) g(s_p, t_q) + \left[ \frac{1}{M \times 2N} \sum_{p=1}^{2M} \sum_{q=1}^{2N} \hat{\phi}(t_q, s_p) \right] \times Ito1(1) \]

\[ + \sum_{j=2}^{2N} \frac{1}{M \times \rho_2} \left[ \sum_{p=1}^{2M} \sum_{q=\alpha_2}^{\beta_2} \hat{\phi}(t_q, s_p) - \sum_{p=1}^{2M} \sum_{q=\beta_2+1}^{\gamma_2} \hat{\phi}(t_q, s_p) \right] \times Ito2(j) \]

\[ + \sum_{i=2}^{2M} \frac{1}{\rho_1 \times N} \left[ \sum_{p=\alpha_1}^{\beta_1} \sum_{q=1}^{2N} \hat{\phi}(t_q, s_p) - \sum_{p=\beta_1+1}^{\gamma_1} \sum_{q=1}^{2N} \hat{\phi}(t_q, s_p) \right] \times Ito1(i) \]

\[ + 2 \sum_{i=2}^{2M} \sum_{j=2}^{2N} \frac{1}{\rho_1 \times \rho_2} \left[ \sum_{p=\alpha_1}^{\beta_1} \sum_{q=\alpha_2}^{\beta_2} \hat{\phi}(t_q, s_p) - \sum_{p=\alpha_1}^{\beta_1} \sum_{q=\beta_2+1}^{\gamma_2} \hat{\phi}(t_q, s_p) \right] \times Ito3(i, j), \]

\[ - \sum_{p=\beta_1+1}^{\gamma_1} \sum_{q=\alpha_2}^{\beta_2} \hat{\phi}(t_q, s_p) + \sum_{p=\beta_1+1}^{\gamma_1} \sum_{q=\beta_2+1}^{\gamma_2} \hat{\phi}(t_q, s_p) \right] \times Ito3(i, j). \]
Table 1. The solution mean with %95 confidence interval for above example

<table>
<thead>
<tr>
<th>$L$</th>
<th>$M$</th>
<th>$2M$</th>
<th>$(x, y)$</th>
<th>$\bar{g}(x, y)$</th>
<th>$L$</th>
<th>$U$</th>
<th>%95 Confidence Interval</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>1</td>
<td>2</td>
<td>(0.25, 0.25)</td>
<td>0.394433</td>
<td>0.392491</td>
<td>0.396374</td>
<td>0.903626</td>
</tr>
<tr>
<td>1</td>
<td>2</td>
<td>4</td>
<td>(0.125, 0.625)</td>
<td>0.626416</td>
<td>0.621964</td>
<td>0.630868</td>
<td>0.931132</td>
</tr>
<tr>
<td>2</td>
<td>4</td>
<td>8</td>
<td>(0.0625, 0.8125)</td>
<td>0.625749</td>
<td>0.620075</td>
<td>0.631423</td>
<td>0.928577</td>
</tr>
<tr>
<td>3</td>
<td>8</td>
<td>16</td>
<td>(0.03125, 0.84375)</td>
<td>0.532988</td>
<td>0.522597</td>
<td>0.543379</td>
<td>0.956621</td>
</tr>
<tr>
<td>4</td>
<td>16</td>
<td>32</td>
<td>(0.015625, 0.515625)</td>
<td>0.0968562</td>
<td>0.0897225</td>
<td>0.10399</td>
<td>0.96001</td>
</tr>
</tbody>
</table>

Eq. (3.12) represents $2M \times 2N$ system which can be solved using either prevalent methods for solving linear systems. The solution of this system gives values of $g(x, y)$ at the collocation points. The values of $g(x, y)$ at points other than collocation points can be calculated using Corollary 2.

### 4. Numerical Example

In this section, the numerical example is given to demonstrate the applicability and accuracy of our method. Consider the following linear two dimensional stochastic Fredholm integral equation of second kind:

$$u(x, y) = f(x, y) + \int_0^1 \int_0^1 (x+y+t-s)g(s, t)dsdt + \int_0^1 \int_0^1 (x+y+t+s)g(s, t)dB(s)dB(t)$$

where

$$f(x, y) = x + y - \frac{1}{12} xy(x^3 + 4x^2y + 4xy^2 + y^3).$$

The solution mean with confidence interval at the collocation points 1000 iterative of system (3.12) is shown in Table 1. In Figs. 1, three-dimensional graph of the approximate solution for level $L = 4$ is shown.
5. Conclusion

The numerical solution of two-dimensional stochastic integral equations because of the randomness is very difficult or sometimes impossible. In this paper, we have successfully developed Haar wavelets numerical method for approximate a solution of two-dimensional linear stochastic Fredholm integral equations. The example confirm that the method is considerably fast and highly accurate as sometimes lead to exact solution. Although, theoretically for getting higher accuracy we can set the method with larger values of \( M \) and \( N \) and also larger of the degree of approximation, \( p \) and \( q \), but it leads to solving \( MN \) linear systems of size \( pq \times pq \), that have its difficulties. The method can be improved to be more accurate by using other numerical methods. Mathematica has been used for computations.

References


