

AN ADAPTIVE MULTIGRID TECHNIQUE FOR OPTION PRICING UNDER THE BLACK-SCHOLES MODEL

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ABSTRACT. In this paper, we consider the adaptive multigrid method for solving the Black–Scholes equation to improve the efficiency of the option pricing. Adaptive meshing is generally regarded as an indispensable tool because of reduction of the computational costs. The Black–Scholes equation is discretized using a Crank–Nicolson scheme on block-structured adaptively refined rectangular meshes. And the resulting discrete equations are solved by a fast solver such as a multigrid method. Numerical simulations are performed to confirm the efficiency of the adaptive multigrid technique. In particular, through the comparison of computational results on adaptively refined mesh and uniform mesh, we show that adaptively refined mesh solver is superior to a standard method.

1. INTRODUCTION

Financial option pricing model developed by Black and Scholes [1] in 1973 and extended by Merton [2]. Since then, methods for option pricing have been discovered and improved by many scholars. Details can be found in reference [3] which is a good review of valuation models and applications to the option pricing. However, because a closed-form solution cannot be obtained or the formulas for the exact solutions are too difficult to be practically usable, numerical solution has been a natural way to solve the problem in financial engineering [4].

To obtain an approximation of the option value, option pricing problems have been solved by the lattice method [5, 6, 7, 8], the finite difference method [7, 9, 10, 11, 12, 13, 14, 15, 16, 17, 18], the finite elements method [19, 20, 21, 22, 23, 24], and the finite volume method [25, 26]. In this paper, we propose an efficient and accurate method based on multigrid method and adaptive grid refinement method. Among the popular methods in recent years, multigrid methods [27, 28, 29, 30] are widely used for the numerical solution of partial differential equations (PDE). In reference [31], authors evaluated the option price by using multigrid method under Black–Scholes. Also, adaptive time-stepping has been proposed by some researchers

Received by the editors October 4 2013; Accepted November 5 2013.

2000 *Mathematics Subject Classification.* 65M06,35K20.

Key words and phrases. adaptive mesh refinement, multigrid method, Black–Scholes equations, Crank–Nicolson scheme, option pricing.

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[32], but few researchers use space-adaptive methods. Some examples, though, can be found in Achdou and Pironneau [33] and Pironneau and Hecht [34] who use a space-adaptive finite element method for discretization of the Black–Scholes PDE. In [35], an adaptive finite difference method is developed with full control of the local discretization error which is shown to be very efficient. In this paper, for the option pricing, we consider an adaptive mesh refinement (AMR) method. The AMR method [36] is very useful to combine the two goals of good accuracy and efficiency. In many science and engineering areas, such as fluid mechanics [37], electromagnetics [38], and materials science [39], an adaptive finite difference method has been very successful.

The purpose of our work is to propose an efficient adaptive FDM to solve the Black–Scholes PDEs. We computationally show that applying an adaptive method to this problem is very efficient compared to a standard FDM. We use the Crank–Nicolson method for the discretization. Other key components of the algorithm are the use of dynamic, block-structured Cartesian mesh refinement (see e.g., [40, 41]) and the use of an adaptive multigrid method [30] to solve the equations at an implicit time level. Locally refined block-structured Cartesian meshes are very natural to use together with multilevel multigrid methods. We note that other multilevel multigrid algorithms have been developed as part of the CHOMBO [42] software packages. Here, we follow the framework of a block-structured multilevel adaptive technique (MLAT) developed by Brandt [43].

The outline of this paper is the following. In Section 2 we describe the two-dimensional Black–Scholes PDE. In Section 3 we discretize the BS equation with finite difference method and we explain the adaptive mesh refinement method in Section 4. In Section 5, we show the numerical results by the proposed method. We draw conclusions in Section 6.

2. BLACK–SCHOLES MODEL

In their award-winning work [1, 2], Black, Scholes, and Merton derived a parabolic second order PDE for the value $u(x, y, t)$ of an option on a stock. We use the original Black–Scholes model with two underlying assets to keep this presentation simple. Let $u(x, y, t)$ denote the value of the option at the underlying two assets x, y , and time t . The option value $u(x, y, t)$ is governed by the following two-asset Black–Scholes equation:

$$\begin{aligned} \frac{\partial u(x, y, t)}{\partial t} + \frac{1}{2}\sigma_1^2 x^2 \frac{\partial^2 u(x, y, t)}{\partial x^2} + \frac{1}{2}\sigma_2^2 y^2 \frac{\partial^2 u(x, y, t)}{\partial y^2} + \rho\sigma_1\sigma_2 xy \frac{\partial^2 u(x, y, t)}{\partial x \partial y} \\ + rx \frac{\partial u(x, y, t)}{\partial x} + ry \frac{\partial u(x, y, t)}{\partial y} = ru(x, y, t), \end{aligned} \quad (2.1)$$

where σ_1, σ_2 are the constant volatilities, ρ is the correlation, and $r > 0$ is a constant riskless interest rate. The final condition is the payoff function $\Lambda(x, y)$ at expiry date T

$$u(x, y, T) = \Lambda(x, y). \quad (2.2)$$

For instance, for European vanilla call option, the payoff at expiry is $\Lambda(x, y) = \max(x - K, y - K, 0)$ with a given strike price K .

3. DISCRETIZATION WITH FINITE DIFFERENCES

A finite difference method approximates derivatives by difference operators and is a common numerical method. For an introduction to these methods we can recommend the books [10, 12, 13, 14, 15]. The original option pricing problems are defined in the unbounded domain $\{(x, y, t) | x \geq 0, y \geq 0, t \in [0, T]\}$. We need to truncate this domain into a finite computational domain $\Omega = \{(x, y, t) | 0 \leq x \leq L, 0 \leq y \leq M, t \in [0, T]\}$, where L and M are large enough so that the error of the price u arisen by the truncation is negligible [44]. Using $\tau = T - t$, we have

$$\frac{\partial u}{\partial \tau} = \frac{1}{2}(\sigma_1 x)^2 \frac{\partial^2 u}{\partial x^2} + \frac{1}{2}(\sigma_2 y)^2 \frac{\partial^2 u}{\partial y^2} + \sigma_1 \sigma_2 \rho x y \frac{\partial^2 u}{\partial x \partial y} + r x \frac{\partial u}{\partial x} + r y \frac{\partial u}{\partial y} - r u, \quad (3.1)$$

for $(x, y, \tau) \in \Omega \times (0, T]$ with an initial condition $u(x, y, 0) = \Lambda(x, y)$. Now, let us first discretize the given computational domain Ω as a uniform grid with a space step $h = L/N_x = M/N_y$ and a time step $\Delta\tau = T/N_\tau$. Here, N_x , N_y , and N_τ are the number of space and time steps, respectively. Let us denote the numerical approximation of the solution by

$$u_{ij}^n = u(x_i, y_j, \tau^n) = u((i - 0.5)h, (j - 0.5)h, n\Delta\tau),$$

where $i = 1, \dots, N_x$, $j = 1, \dots, N_y$, and $n = 1, \dots, N_\tau$. By applying the Crank–Nicolson scheme to Eq. (3.1), which has an accuracy $\mathcal{O}(\Delta\tau^2 + h^2)$, we have

$$\frac{u_{ij}^{n+1} - u_{ij}^n}{\Delta\tau} = \frac{1}{2} \left(\mathcal{L}u_{ij}^{n+1} + \mathcal{L}u_{ij}^n \right),$$

where the discrete difference operator \mathcal{L} is defined by

$$\begin{aligned} \mathcal{L}u_{ij}^n = & \frac{(\sigma_1 x_i)^2}{2} \frac{u_{i-1,j}^n - 2u_{ij}^n + u_{i+1,j}^n}{h^2} + \frac{(\sigma_2 y_j)^2}{2} \frac{u_{i,j-1}^n - 2u_{ij}^n + u_{i,j+1}^n}{h^2} \\ & + \sigma_1 \sigma_2 \rho x_i y_j \frac{u_{i+1,j+1}^n + u_{i-1,j-1}^n - u_{i-1,j+1}^n - u_{i+1,j-1}^n}{4h^2} \\ & + r x_i \frac{u_{i+1,j}^n - u_{i-1,j}^n}{2h} + r y_j \frac{u_{i,j+1}^n - u_{i,j-1}^n}{2h} - r u_{ij}^n. \end{aligned} \quad (3.2)$$

We rewrite Eq. (3.2) by

$$N(u_{ij}^{n+1}) = \phi_{ij}^n, \quad (3.3)$$

where $N(u_{ij}^{n+1}) = u_{ij}^{n+1} - \frac{\Delta\tau}{2} \mathcal{L}u_{ij}^{n+1}$ and $\phi_{ij}^n = u_{ij}^n + \frac{\Delta\tau}{2} \mathcal{L}u_{ij}^n$.

4. NUMERICAL METHOD

4.1. Dynamic adaptive mesh refinement method. In this section, we present an adaptive hierarchy of nested rectangular grids [37]. Both the initial creation of the grid hierarchy and the subsequent regridding operations in which the grids are dynamically changed to reflect changing solution conditions use the same procedure to create new grids [45]. Cells requiring additional refinement are identified and tagged using user-supplied criteria. The tagged cells are grouped into rectangular patches using the clustering algorithm given in Berger and Rigoutsos [46].

These rectangular patches are refined to form the grids at the next level. The process is repeated until a specified maximum level is reached. We consider a hierarchy of grids

$$\Omega_0, \dots, \Omega_l, \Omega_{l+1}, \dots, \Omega_{l+l^*},$$

where $\Omega_0, \dots, \Omega_l$ are global and $\Omega_{l+1}, \dots, \Omega_{l+l^*}$ are local grids. A typical hierarchy of grids for the solution of the problem is shown in Fig. 1.

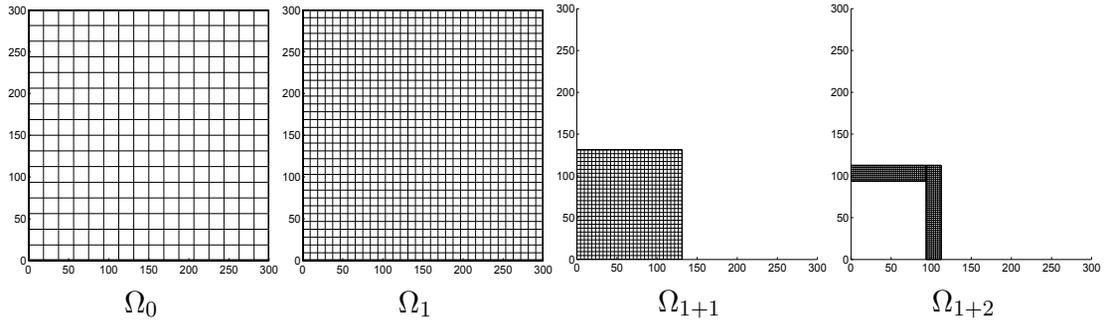


FIGURE 1. Hierarchy of grids when $l = 1$ and $l^* = 2$.

In this case, Ω_0 and Ω_1 are global grids ($l = 1$) and the refined grids $\Omega_{l+1}, \Omega_{l+2}$ ($l^* = 2$) cover increasingly smaller subdomains as indicated in Fig. 2. For instance, we can apply the refined local grids near the strike price since the values of options are not smooth near the strike price. We note that the grid refinement is automatically done by user-specified criteria. In addition to the global and the local grids, we consider their “composition”. The corresponding sequence of *composite grids* (see Fig. 2) is defined by

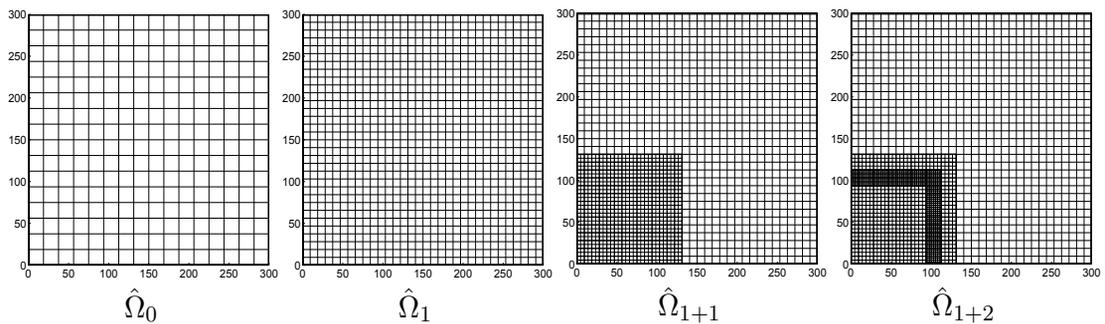


FIGURE 2. Composite grids corresponding to the hierarchy of grids in Fig. 1 when $l = 1$ and $l^* = 2$.

$$\hat{\Omega}_k := \Omega_k \quad (k = 0, \dots, l) \text{ and } \hat{\Omega}_{l+k} := \Omega_l \cup \bigcup_{j=1}^k \Omega_{l+j} \quad (k = 1, \dots, l^*).$$

We use the original multi-level adaptive technique (MLAT) proposed by Brandt [47]. We now describe an adaptive multigrid cycle. Let us use the operator in Eq. (3.3) N_k ($k = 0, 1, \dots, l, l+1, \dots, l+l^*$) and the restriction and interpolation operators between Ω_k and Ω_{k-1} , I_k^{k-1} , I_{k-1}^k ($k = 1, 2, \dots, l, l+1, \dots, l+l^*$) respectively. Let us assume the parameter γ (the number of smoothing iterations), and starting on the finest grid $k = l+l^*$, the calculation of a new iterate u_k^{m+1} from a given approximation u_k^m proceeds: The details of overall steps are given in **Algorithm 1**.

Algorithm 1 Adaptive cycle

$$u_k^{m+1} = \text{adapcyc}(k, u_k^m, u_{k-1}^m, N_k, \phi_k, \gamma)$$

1. Presmoothing

- Compute \bar{u}_k^m by applying γ smoothing steps, Eq. (4.3), to u_k^m on Ω_k .

2. Coarse-grid correction

- Compute

$$\bar{u}_{k-1}^m = \begin{cases} I_k^{k-1} \bar{u}_k^m & \text{on } \Omega_{k-1} \cap \Omega_k \\ \bar{u}_{k-1}^m & \text{on } \Omega_{k-1} - \Omega_k \end{cases}$$

- Compute the right-hand side

$$\phi_{k-1}^n = \begin{cases} I_k^{k-1}(\phi_k^n - N_k(\bar{u}_k^m)) + N_{k-1} I_k^{k-1} \bar{u}_k^m & \text{on } \Omega_{k-1} \cap \Omega_k \\ \phi_{k-1}^n & \text{on } \Omega_{k-1} - \Omega_k \end{cases}$$

- Compute an approximate solution \hat{w}_{k-1}^m of the coarse grid equation on Ω_{k-1}

$$N_{k-1}(w_{k-1}^m) = \phi_{k-1}^n. \quad (4.1)$$

If $k = 1$, employ smoothing steps.

If $k > 1$, solve Eq. (4.1) using \bar{u}_{k-1}^m as an initial approximation.

$$\hat{w}_{k-1}^m = \text{adapcyc}(k-1, \bar{u}_{k-1}^m, u_{k-2}^m, N_{k-1}, \phi_{k-1}, \gamma).$$

- Compute the correction $\hat{v}_{k-1}^m = \hat{w}_{k-1}^m - \bar{u}_{k-1}^m$, on $\Omega_{k-1} \cap \Omega_k$.

- Set the solution $u_{k-1}^{m+1} = \hat{w}_{k-1}^m$, on $\Omega_{k-1} - \Omega_k$.

- Interpolate the correction $\hat{v}_k^m = I_{k-1}^k \hat{v}_{k-1}^m$, on Ω_k .

- Compute the corrected approximation $u_k^{m, \text{after CGC}} = \bar{u}_k^m + \hat{v}_k^m$, on Ω_k .

- Carry out a quadratic interpolation at the ghost points.

3. Postsmoothing

- Compute u_k^{m+1} by applying γ smoothing steps to $u_k^{m, \text{after CGC}}$ on Ω_k .

Our implementation of this algorithm is constructed using the CHOMBO infrastructure [42], which has simplified the implementation of the locally adaptive algorithm. To perform the nonlinear multilevel AMR solver, we use and modify the CHOMBO AMR elliptic solver. This solver is based on a linear multigrid algorithm.

4.2. Relaxation method in a multigrid cycle. Now we derive a Gauss–Seidel relaxation operator. First, we rewrite Eq. (3.3) as

$$\begin{aligned}
u_{ij}^{n+1} = & \left[\phi_{ij}^n + \frac{\Delta\tau}{2} \left(\frac{(\sigma_1 x_i)^2}{2} \frac{u_{i-1,j}^{n+1} + u_{i+1,j}^{n+1}}{h^2} + \frac{(\sigma_2 y_j)^2}{2} \frac{u_{i,j-1}^{n+1} + u_{i,j+1}^{n+1}}{h^2} \right. \right. \\
& + \sigma_1 \sigma_2 \rho x_i y_j \frac{u_{i+1,j+1}^{n+1} + u_{i-1,j-1}^{n+1} - u_{i-1,j+1}^{n+1} - u_{i+1,j-1}^{n+1}}{4h^2} \\
& \left. \left. + r x_i \frac{u_{i+1,j}^{n+1} - u_{i-1,j}^{n+1}}{2h} + r y_j \frac{u_{i,j+1}^{n+1} - u_{i,j-1}^{n+1}}{2h} \right) \right] / \\
& \left[1 + \frac{\Delta\tau}{2} \left(\frac{(\sigma_1 x_i)^2 + (\sigma_2 y_j)^2}{h^2} + r \right) \right].
\end{aligned} \tag{4.2}$$

Next, we replace u_{kl}^{n+1} in Eq. (4.2) with \bar{u}_{kl}^m if $(k < i)$ or $(k = i \text{ and } l \leq j)$, otherwise with u_{kl}^m , i.e.,

$$\begin{aligned}
\bar{u}_{ij}^m = & \left[\phi_{ij}^n + \frac{\Delta\tau}{2} \left(\frac{(\sigma_1 x_i)^2}{2} \frac{\bar{u}_{i-1,j}^m + u_{i+1,j}^m}{h^2} + \frac{(\sigma_2 y_j)^2}{2} \frac{\bar{u}_{i,j-1}^m + u_{i,j+1}^m}{h^2} \right. \right. \\
& + \sigma_1 \sigma_2 \rho x_i y_j \frac{u_{i+1,j+1}^m + \bar{u}_{i-1,j-1}^m - \bar{u}_{i-1,j+1}^m - u_{i+1,j-1}^m}{4h^2} \\
& \left. \left. + r x_i \frac{u_{i+1,j}^m - \bar{u}_{i-1,j}^m}{2h} + r y_j \frac{u_{i,j+1}^m - \bar{u}_{i,j-1}^m}{2h} \right) \right] / \\
& \left[1 + \frac{\Delta\tau}{2} \left(\frac{(\sigma_1 x_i)^2 + (\sigma_2 y_j)^2}{h^2} + r \right) \right].
\end{aligned} \tag{4.3}$$

Therefore, in a multigrid cycle, one smooth relaxation operator step consists of solving Eq. (4.3) given above.

5. COMPUTATIONAL RESULTS

In this section, several numerical experiments are performed. To demonstrate its effectiveness, we compare the total computational cost, i.e., the CPU times with uniform mesh results on a test problem on the computational domain $\Omega = (0, 1200) \times (0, 1200)$ with $\Delta\tau = 1/1024$. The calculations have been performed on an IBM personal computer with 3.0GHz speed of 3.48GB RAM.

5.1. European vanilla call option. As the benchmark problem, we consider the European vanilla option problem. This problem is of great interest to academicians in the finance literature and often used to show the accuracy of a given numerical scheme [7, 48, 49]. The initial state is $u(x, y, 0) = \max[\max(x, y) - 100, 0]$. For the parameters, we take $\sigma_1 = \sigma_2 = 0.5$, $\rho = 0.5$, and $r = 0.03$. We perform an adaptive mesh refinement every 5 time steps. The refinement is based on the range of values of u , i.e., we refine the grids if $0.3 < u < 10$. We

compute this with a base 64^2 mesh with 3, 4, and 5 levels of refinements. To estimate the cost of the equivalent uniform-grid solution, we compute 1024 time steps on the equivalent 512^2 , 1024^2 , and 2048^2 meshes. In Fig. 3, (a) and (b) show the initial profile and the final configuration at time $\tau = 1$ on the adaptive mesh, respectively. We can observe fine meshes around the region of our interests which are neighborhood of strike prices. And Fig. 3(c) and (d) show magnified representations of (a) and (b), respectively.

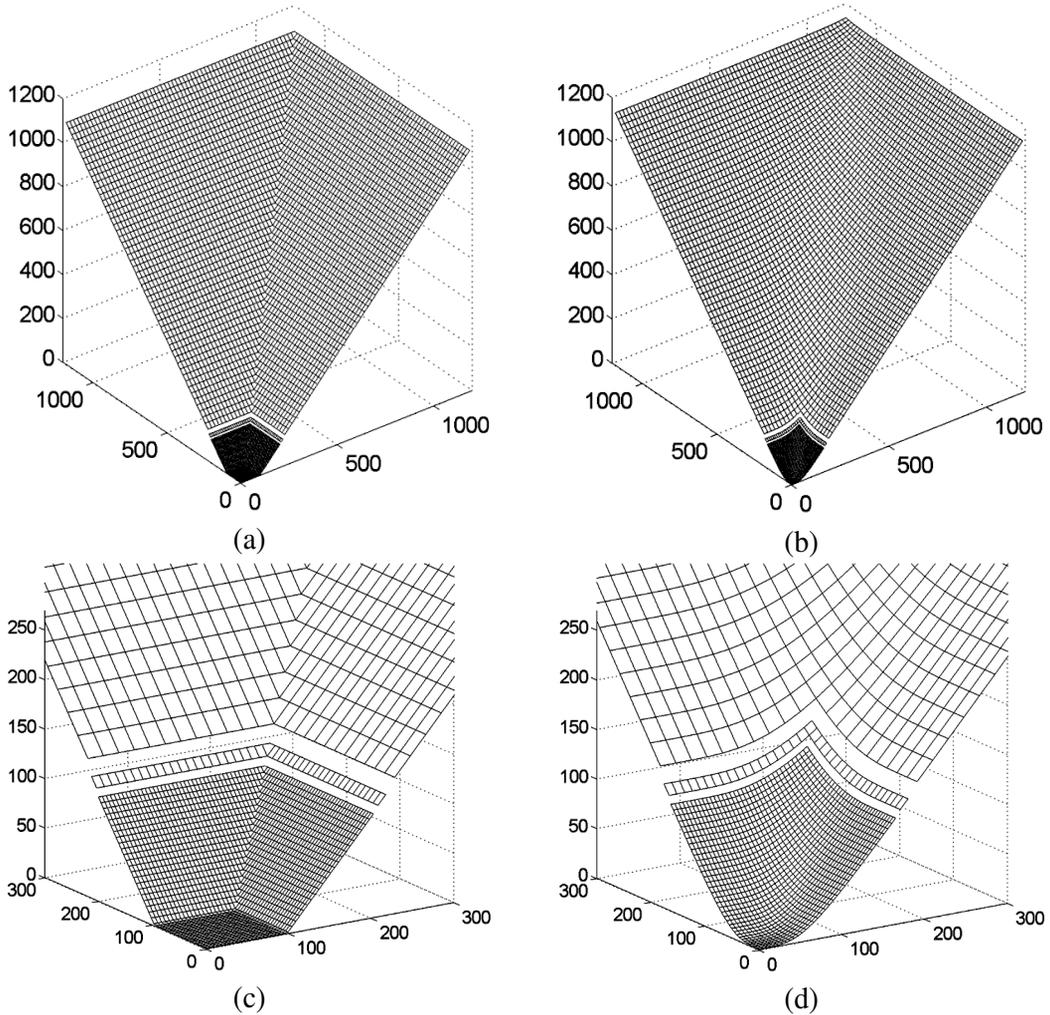


FIGURE 3. European vanilla call option: (a) The initial configuration at time $\tau = 0$. (b) The final configuration at time $\tau = 1$. (c) and (d): Magnified representations of (a) and (b), respectively.

Next, we compare the CPU times with AMR and uniform mesh results. The computational results are shown in Table 1 and it is clear that AMR is more efficient than the uniform mesh

method. We scale CPU time with the AMR method. Here, 1 in CPU time of AMR stands for the calculation time for AMR method.

TABLE 1. CPU time comparison between uniform mesh and AMR of European vanilla call option.

Case	Uniform mesh 512^2	AMR with base mesh size, 64^2 3 levels, effective mesh size 512^2
CPU time	68.3	1
Case	Uniform mesh 1024^2	AMR with base mesh size, 64^2 4 levels, effective mesh size 1024^2
CPU time	169.7	1
Case	Uniform mesh 2048^2	AMR with base mesh size, 64^2 5 levels, effective mesh size 2048^2
CPU time	285.3	1

5.2. **Cash-or-Nothing option.** Next, we perform the comparison with a cash-or-nothing option. The initial state is

$$u(x, y, 0) = \begin{cases} Cash & \text{if } x \geq K \text{ and } y \geq K \\ 0 & \text{otherwise.} \end{cases}$$

Here, we simply set $Cash = 1$ and $K = 100$. And the other parameters and computational conditions are chosen as the same in the numerical experiment of European call option. Figure 4(a) and (b) show the initial profile and the final configuration at time $\tau = 1$ on the adaptive mesh, respectively. And Fig. 4(c) and (d) show magnified representations of (a) and (b), respectively. Next, the CPU times with AMR and uniform mesh results are presented in Table 2. As shown in Table 2, it is clear that AMR is more efficient than the uniform mesh method.

TABLE 2. CPU time comparison between uniform mesh and AMR of Cash-or-Nothing option.

Case	Uniform mesh 512^2	AMR with base mesh size, 64^2 3 levels, effective mesh size 512^2
CPU time	80.2	1
Case	Uniform mesh 1024^2	AMR with base mesh size, 64^2 4 levels, effective mesh size 1024^2
CPU time	167.2	1
Case	Uniform mesh 2048^2	AMR with base mesh size, 64^2 5 levels, effective mesh size 2048^2
CPU time	180.5	1

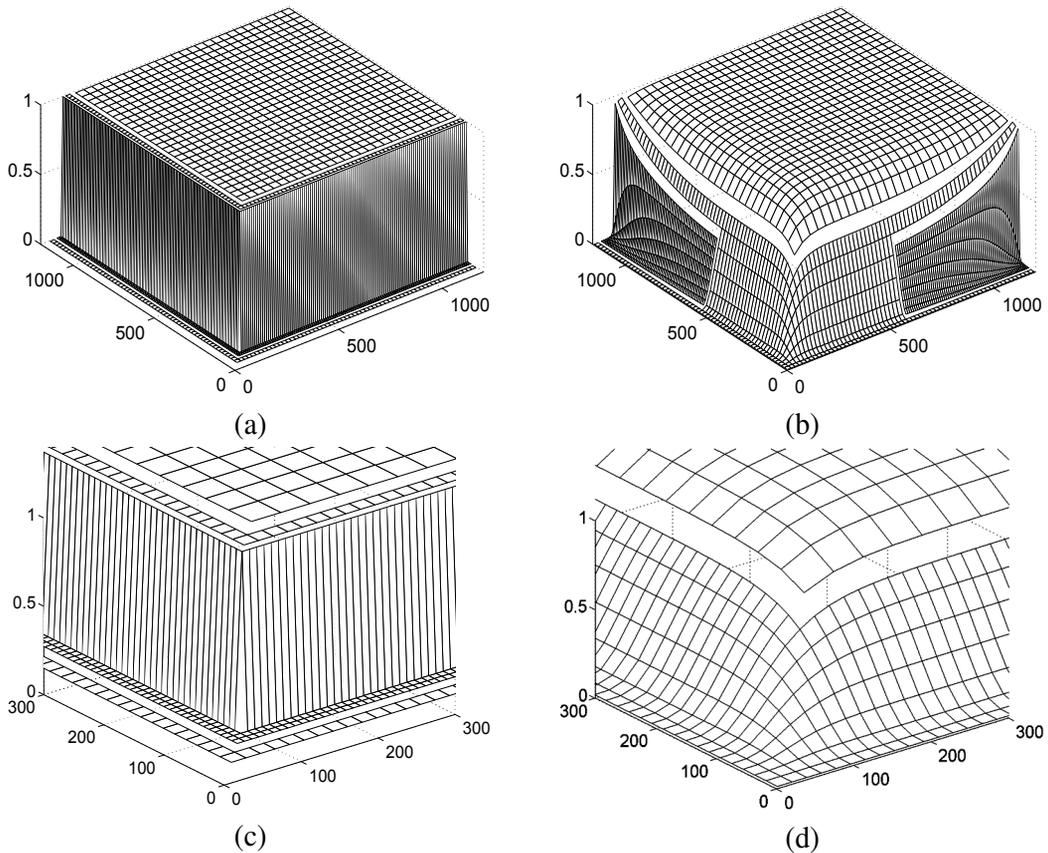


FIGURE 4. Cash-or-Nothing option: (a) The initial configuration at time $\tau = 0$. (b) The final configuration at time $\tau = 1$. (c) and (d): Magnified representations of (a) and (b), respectively.

6. CONCLUSIONS

In this paper, we focused on two major aspects that we encounter when applying numerical methods to option pricing problems such as grid resolutions and domain sizes. We proposed an adaptive mesh refinement method to solve the Black–Scholes equation. We computationally showed that the proposed adaptive scheme gave much better efficiency than the standard FDM. In particular, we showed that the use of local refinement resulted in significant savings in computational time and memory when compared to the equivalent uniform-mesh solution. Studies of these methods in higher dimensions will be the subject of future research.

ACKNOWLEDGMENT

The corresponding author (J.S. Kim) was supported by the National Institute for Mathematical Sciences(NIMS) grant funded by the Korea government(No. A21301). And this work is based on the first author's Ph. D. thesis [50].

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