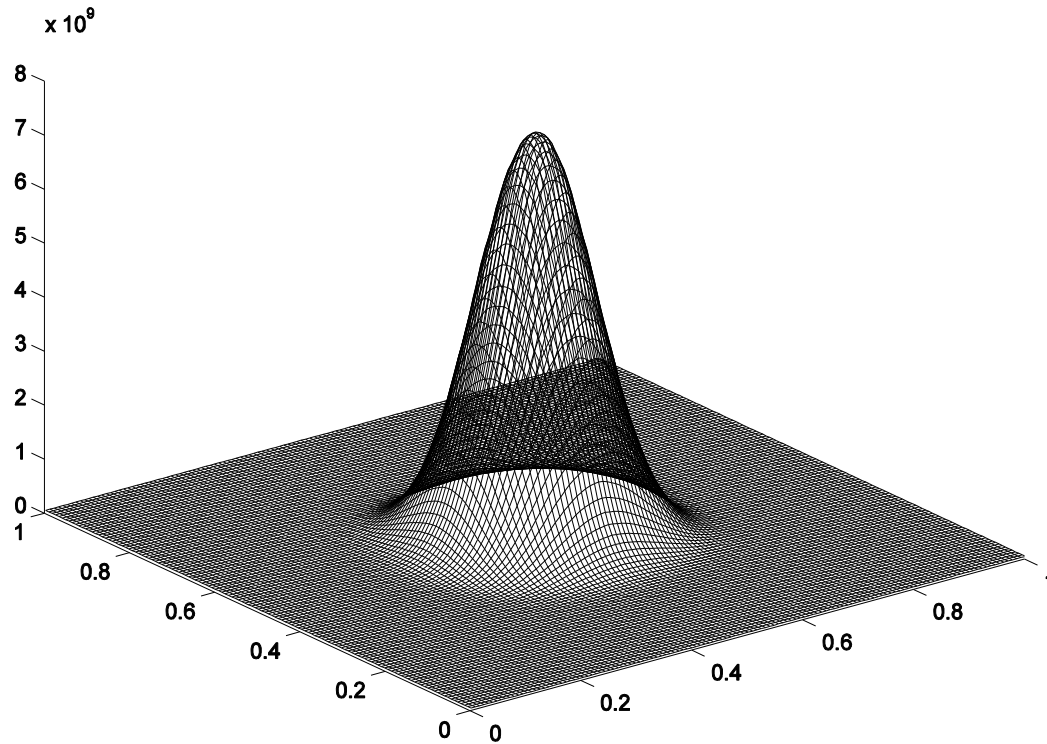


A Simple Moving Mesh Method for Blow-up Problems



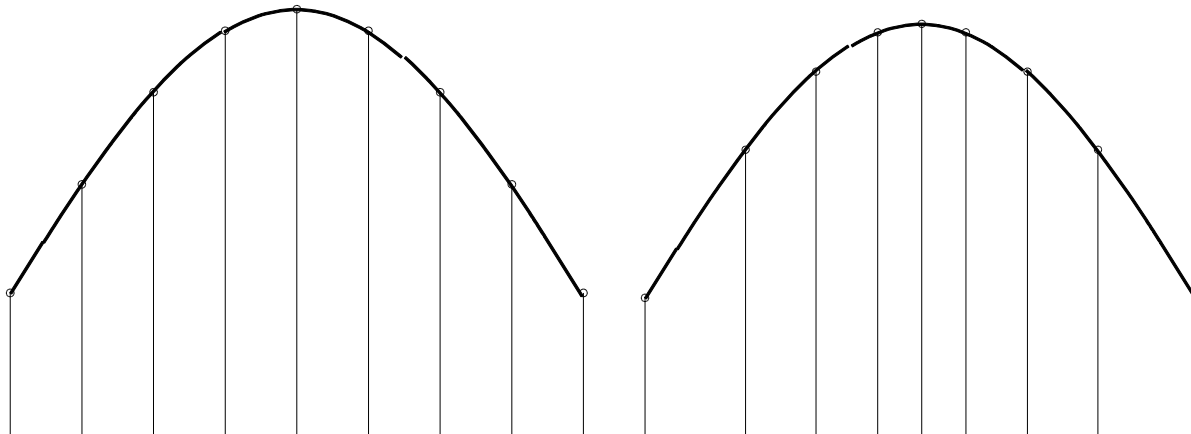
by **Lauren DeDieu**

Advisor: George Chen

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Moving Mesh Methods: Introduction

- Are one of the most **powerful methods** to numerically solve time dependent partial differential equations (PDE) with some kind of **singularity** (shock waves & blow-up problems).
- **Fixed number of mesh points**
- Moves mesh adaptively so **errors are distributed uniformly**.



Uniform Mesh

Moving Mesh

Moving Mesh Methods: Existing Work

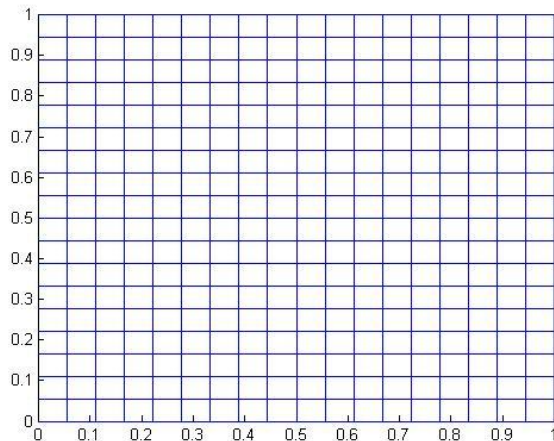
- **Winslow** (1967), **Thompson** (1985), and others proposed various elliptic equations and variational methods for defining adaptive mapping.
- **Budd, Huang, and Russel** (2009) in their paper *Adaptivity with Moving Grids* summarize traditional **hp-refinement** methods in which mesh is **added/deleted** based on **estimates** about the solution error.
- They conclude **r-adaptive** methods, which initially use **uniform mesh** which later becomes **concentrated** where the solution has **interesting behaviour**, have **enormous potential**, although they are currently in their **early stages** of development.

Moving Mesh Methods: Past Work

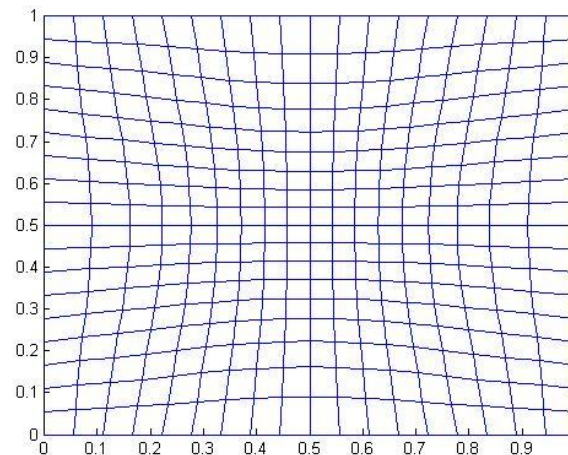
- **Ceniceros and Hou (2001):**
 - developed a simple yet efficient **dynamically adaptive** mesh generator for **time-dependent** problems.
 - Mesh is generated** directly from the **physical domain**, so the **mesh equations** become quite **simple**.

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Computational Domain
(ξ, η)



Physical Domain
(x, y)

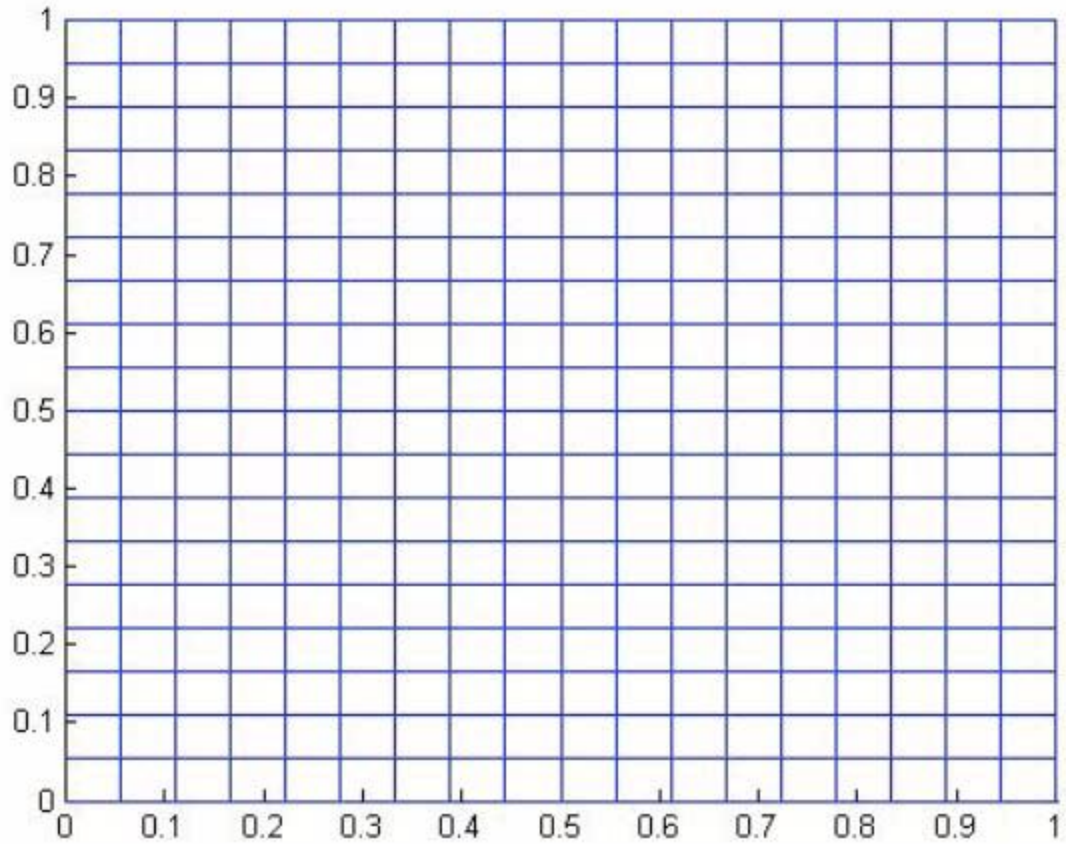


$$x = x(\xi, \eta), \quad y = y(\xi, \eta)$$

Moving Mesh Methods: Past Work

- **Ceniceros and Hou:**
 - developed a simple yet efficient **dynamically adaptive** mesh generator for **time-dependent** problems.
 - Mesh is **generated** directly from the **physical domain**, so the mesh equations become quite **simple**.
- We focus on **blow-up problems**, and **simplify** and **improve** **Ceniceros and Hou`s** results by adding an **additional term** to make the mesh more **orthogonal**.

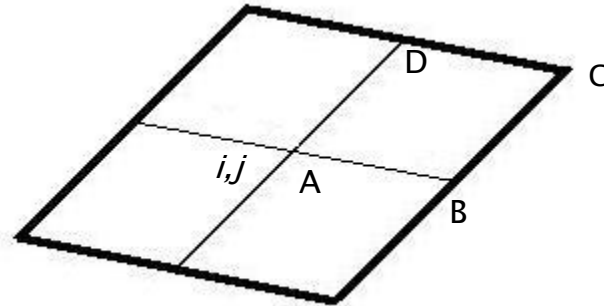
Moving the Mesh



Minimizing Diagonal Lengths

In two dimensional cases, a cell has four vertices:

$$A(x_{i,j}, y_{i,j}) , B(x_{i+1,j}, y_{i+1,j}) , C(x_{i+1,j+1}, y_{i+1,j+1}) , D(x_{i,j+1}, y_{i,j+1})$$



The two diagonal lengths are:

$$\sqrt{(x_{i+1,j} - x_{i,j+1})^2 + (y_{i+1,j} - y_{i,j+1})^2} \quad \sqrt{(x_{i,j} - x_{i+1,j+1})^2 + (y_{i,j} - y_{i+1,j+1})^2}$$

A diagram of a parallelogram cell, similar to the one above, but with the two diagonals drawn. Arrows point from the two square root formulas above to the two diagonals. The bottom-left vertex is labeled i,j .

Minimizing Diagonal Lengths

The mesh can be generated by minimizing the following problem:

$$I[x, y] = \sum_{i,j=1}^{n-1} \left(M_{i+1,j+1} + M_{i,j} \right) \left(x_{i+1,j+1} - x_{i,j} \right)^2 + \left(y_{i+1,j+1} - y_{i,j} \right)^2 \\ + \left(M_{i,j+1} + M_{i+1,j} \right) \left(x_{i,j+1} - x_{i+1,j} \right)^2 + \left(y_{i,j+1} - y_{i+1,j} \right)^2$$

where M is the monitor function

$$M(u) = \sqrt{u^4 + c_1 |\nabla u|^2 + c_2}$$

Minimizing Diagonal Lengths

Minimizing this problem is equivalent to solving the following linear algebra system:

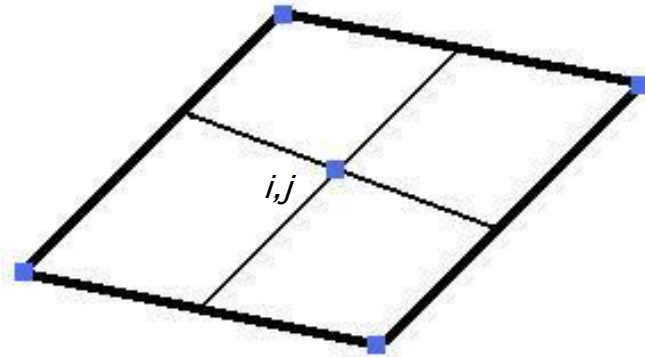
$$\begin{aligned} \frac{1}{2} \frac{\partial I}{\partial x_{i,j}} &= -(\mathbf{M}_{i+1,j+1} + \mathbf{M}_{i,j})(x_{i+1,j+1} - x_{i,j}) + (\mathbf{M}_{i,j} + \mathbf{M}_{i-1,j-1})(x_{i,j} - x_{i-1,j-1}) \\ &+ (\mathbf{M}_{i,j} + \mathbf{M}_{i+1,j-1})(x_{i,j} - x_{i+1,j-1}) - (\mathbf{M}_{i-1,j+1} + \mathbf{M}_{i,j})(x_{i-1,j+1} - x_{i,j}) \\ &= 0 \end{aligned} \tag{2}$$

Minimizing Diagonal Lengths

and

$$\begin{aligned} \frac{1}{2} \frac{\partial I}{\partial y_{i,j}} &= -(M_{i+1,j+1} + M_{i,j})(y_{i+1,j+1} - y_{i,j}) + (M_{i,j} + M_{i-1,j-1})(y_{i,j} - y_{i-1,j-1}) \\ &+ (M_{i,j} + M_{i+1,j-1})(y_{i,j} - y_{i+1,j-1}) - (M_{i-1,j+1} + M_{i,j})(y_{i-1,j+1} - y_{i,j}) \\ &= 0 \end{aligned}$$

where $1 < i, j < n$.



(3)

Minimizing Diagonal Lengths

Note: When minimizing equations, if the coefficient is large, then the variable will be small, and vice versa.

Minimizing Diagonal Lengths

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For example:

$$\begin{aligned} \frac{1}{2} \frac{\partial I}{\partial y_{i,j}} &= -(\overset{\text{large}}{M_{i+1,j+1} + M_{i,j}})(y_{i+1,j+1} - y_{i,j}) + (\overset{\text{small}}{M_{i,j} + M_{i-1,j-1}})(y_{i,j} - y_{i-1,j-1}) \\ &+ (M_{i,j} + M_{i+1,j-1})(y_{i,j} - y_{i+1,j-1}) - (M_{i-1,j+1} + M_{i,j})(y_{i-1,j+1} - y_{i,j}) \\ &= 0 \end{aligned}$$

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Minimizing Diagonal Lengths

Let's see a simple example:

Minimize $f(x, y, z) = ax^2 + by^2 + cz^2$ **where** $x, y, z \geq 0$, $x + y + z = 1$,
and $a = c = 1, b = 3$.

Minimizing Diagonal Lengths

Minimize $f(x, y, z) = ax^2 + by^2 + cz^2$ where $x, y, z \geq 0$, $x + y + z = 1$,
and $a = c = 1, b = 3$.

$$f(x, y, z) = a(1 - y - z)^2 + by^2 + cz^2$$

$$f'(y) = -2a(1 - y - z) + 2by$$

$$-2a + 2ay + 2az + 2by = 0$$

$$-a + ay + az + by = 0$$

$$f'(z) = -2a(1 - y - z) + 2cz$$

$$= -2a + 2ay + 2az + 2cz = 0$$

$$z = \frac{a - ay}{a + c}$$

Minimizing Diagonal Lengths

Minimize $f(x, y, z) = ax^2 + by^2 + cz^2$ where $x, y, z \geq 0$, $x + y + z = 1$,
and $a = c = 1, b = 3$.

$$x = 1 - y - z$$

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Minimizing Diagonal Lengths

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Minimizing Diagonal Lengths

Minimize $f(x, y, z) = ax^2 + by^2 + cz^2$ where $x, y, z \geq 0$, $x + y + z = 1$,
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$$-a + ay + a\left(\frac{a - ay}{a + c}\right) + by = 0$$

$$-1 + y + \left(\frac{1 - y}{1 + 1}\right) + 3y = 0$$

$$-1 + 4y + \frac{1}{2} - \frac{y}{2} = 0$$

$$\frac{7}{2}y = \frac{1}{2}$$

$$y = \frac{1}{7}$$

Minimizing Diagonal Lengths

Minimize $f(x, y, z) = ax^2 + by^2 + cz^2$ where $x, y, z \geq 0$, $x + y + z = 1$,
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$$y = \frac{1}{7}$$

$$z = \frac{a - ay}{a + c} = \frac{1 - \frac{1}{7}}{1 + 1} = \frac{\frac{6}{7}}{2} = \frac{6}{14} = \frac{3}{7}$$

$$x = 1 - y - z = 1 - \frac{1}{7} - \frac{3}{7} = \frac{3}{7}$$

Minimizing Diagonal Lengths

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$$x = 1 - y - z = 1 - \frac{1}{7} - \frac{3}{7} = \frac{3}{7}$$

Minimizing Diagonal Lengths

In order to make the mesh more smooth and orthogonal, we add higher order difference terms:

$$\begin{aligned}
 I[x, y] = & \sum_{i,j=1}^{n-1} \left[M_{i+1,j+1} + M_{i,j} \right] \left[(x_{i+1,j+1} - x_{i,j})^2 + (y_{i+1,j+1} - y_{i,j})^2 \right] \\
 & + \left[M_{i,j+1} + M_{i+1,j} \right] \left[(x_{i,j+1} - x_{i+1,j})^2 + (y_{i,j+1} - y_{i+1,j})^2 \right] \\
 & + c \sum_{i,j=2}^{n-1} M_{i,j} \left[(x_{i+1,j} - 2x_{i,j} + x_{i-1,j})^2 + (x_{i,j+1} - 2x_{i,j} + x_{i,j-1})^2 \right. \\
 & \left. + (y_{i+1,j} - 2y_{i,j} + x_{i-1,j})^2 + (y_{i,j+1} - 2y_{i,j} + x_{i,j-1})^2 \right]
 \end{aligned}$$

Minimizing Diagonal Lengths

We can use the following semi-discretized differential equations to replace (2) & (3):

$$\begin{aligned} \frac{\partial x_{i,j}}{\partial t} = & \frac{1}{\tau} (\mathbf{M}_{i+1,j+1} + \mathbf{M}_{i,j})(x_{i+1,j+1} - x_{i,j}) - (\mathbf{M}_{i,j} + \mathbf{M}_{i-1,j-1})(x_{i,j} - x_{i-1,j-1}) \\ & - (\mathbf{M}_{i,j} + \mathbf{M}_{i+1,j-1})(x_{i,j} - x_{i+1,j-1}) + (\mathbf{M}_{i-1,j+1} + \mathbf{M}_{i,j})(x_{i-1,j+1} - x_{i,j}) \end{aligned}$$

(4)

* And similarly for y.*

Minimizing Diagonal Lengths

We can use the following semi-discretized differential equations to replace (2) & (3):

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 \frac{\partial x_{i,j}}{\partial t} = & \frac{1}{\tau} (M_{i+1,j+1} + M_{i,j})(x_{i+1,j+1} - x_{i,j}) - (M_{i,j} + M_{i-1,j-1})(x_{i,j} - x_{i-1,j-1}) \\
 & - (M_{i,j} + M_{i+1,j-1})(x_{i,j} - x_{i+1,j-1}) + (M_{i-1,j+1} + M_{i,j})(x_{i-1,j+1} - x_{i,j}) \\
 & - cM_{i,j} \left(4x_{i,j} + x_{i+1,j} + x_{i-1,j} + x_{i,j+1} + x_{i,j-1} \right) \\
 & + cM_{i-1,j} \left(x_{i,j} - 2x_{i-1,j} + x_{i-2,j} \right) \\
 & + cM_{i+2,j} \left(x_{i+2,j} - 2x_{i+1,j} + x_{i,j} \right) \\
 & + cM_{i,j-1} \left(x_{i,j} - 2x_{i,j-1} + x_{i,j-2} \right) \\
 & + cM_{i,j+1} \left(x_{i,j+2} - 2x_{i,j+1} + x_{i,j} \right)
 \end{aligned}$$



2nd Order Difference

(4)

* And similarly for y.*

Why Solving (4) is Better than Solving (2)-(3):

Disadvantages of (2)–(3):

1. Dependent on initial values.
2. The convergence rate is very slow, so takes a long time to compute.
3. When u is large it may be unstable (small oscillation).

Advantages of (4):

1. Always has a solution and is smooth.
2. Easier to control the movement of mesh.

Minimizing Diagonal Lengths

Minimizing this problem is equivalent to solving the following linear algebra system:

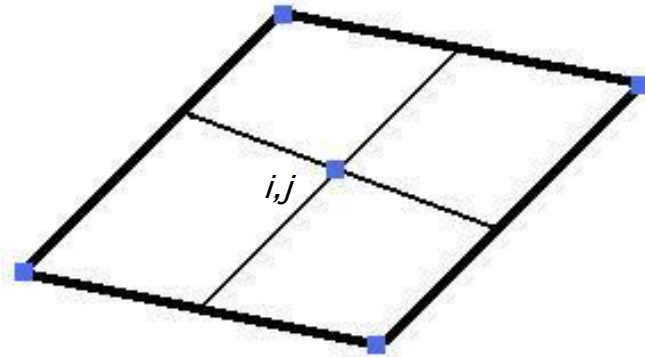
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Minimizing Diagonal Lengths

and

$$\begin{aligned} \frac{1}{2} \frac{\partial I}{\partial y_{i,j}} &= -(M_{i+1,j+1} + M_{i,j})(y_{i+1,j+1} - y_{i,j}) + (M_{i,j} + M_{i-1,j-1})(y_{i,j} - y_{i-1,j-1}) \\ &+ (M_{i,j} + M_{i+1,j-1})(y_{i,j} - y_{i+1,j-1}) - (M_{i-1,j+1} + M_{i,j})(y_{i-1,j+1} - y_{i,j}) \\ &= 0 \end{aligned}$$

where $1 < i, j < n$.



(3)

Minimizing Diagonal Lengths

We can use the following semi-discretized differential equations to replace (2) & (3):

$$\begin{aligned} \frac{\partial x_{i,j}}{\partial t} = & \frac{1}{\tau} (\mathbf{M}_{i+1,j+1} + \mathbf{M}_{i,j})(x_{i+1,j+1} - x_{i,j}) - (\mathbf{M}_{i,j} + \mathbf{M}_{i-1,j-1})(x_{i,j} - x_{i-1,j-1}) \\ & - (\mathbf{M}_{i,j} + \mathbf{M}_{i+1,j-1})(x_{i,j} - x_{i+1,j-1}) + (\mathbf{M}_{i-1,j+1} + \mathbf{M}_{i,j})(x_{i-1,j+1} - x_{i,j}) \end{aligned}$$

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Numerical Examples for Partial Differential Equations

Consider the heat equation:

$$\begin{cases} u_t = \Delta u + f(u) \\ u|_{\partial\Omega} = 0 \\ u(x, y, 0) = \phi(x, y) \end{cases}$$

where $\Omega = [a, b] \times [a, b]$.

Numerical Examples for Partial Differential Equations

In the computational domain we have:

$$\bar{u}(\xi, \eta, t) = u[x(\xi, \eta, t), y(\xi, \eta, t), t]$$

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$$\bar{u}_t \Big|_{\text{fixed } \xi, \eta} = \frac{d}{dt} \bar{u}(\xi, \eta, t) \Big|_{\text{fixed } \xi, \eta}$$

Numerical Examples for Partial Differential Equations

In the computational domain we have:

$$\bar{u}(\xi, \eta, t) = u[x(\xi, \eta, t), y(\xi, \eta, t), t]$$

$$\bar{u}_t \Big|_{\text{fixed } \xi, \eta} = \frac{d}{dt} \bar{u}(\xi, \eta, t) \Big|_{\text{fixed } \xi, \eta}$$

$$= u_x x_t + u_y y_t + u_t \Big|_{\text{fixed } x, y}$$

Chain Rule



Numerical Examples for Partial Differential Equations

In the computational domain we have:

$$\bar{u}(\xi, \eta, t) = u[x(\xi, \eta, t), y(\xi, \eta, t), t]$$

$$\bar{u}_\xi = u_x x_\xi + u_y y_\xi$$

$$\bar{u}_\eta = u_x x_\eta + u_y y_\eta$$



Chain Rule

Numerical Examples for Partial Differential Equations

$$\bar{u}_\xi = u_x x_\xi + u_y y_\xi$$

$$\bar{u}_\eta = u_x x_\eta + u_y y_\eta$$

Numerical Examples for Partial Differential Equations

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$$\bar{u}_\eta = u_x x_\eta + u_y y_\eta$$

Numerical Examples for Partial Differential Equations

$$\bar{u}_\xi = u_x x_\xi + u_y y_\xi$$

$$\bar{u}_\eta = u_x x_\eta + u_y y_\eta$$

$$\begin{pmatrix} x_\xi & y_\xi \\ x_\eta & y_\eta \end{pmatrix} \begin{pmatrix} u_x \\ u_y \end{pmatrix} = \begin{pmatrix} \bar{u}_\xi \\ \bar{u}_\eta \end{pmatrix}$$

Numerical Examples for Partial Differential Equations

$$\begin{pmatrix} x_\xi & y_\xi \\ x_\eta & y_\eta \end{pmatrix} \begin{pmatrix} u_x \\ u_y \end{pmatrix} = \begin{pmatrix} \bar{u}_\xi \\ \bar{u}_\eta \end{pmatrix}$$

Numerical Examples for Partial Differential Equations

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$$\begin{pmatrix} u_x \\ u_y \end{pmatrix} = \begin{pmatrix} x_\xi & y_\xi \\ x_\eta & y_\eta \end{pmatrix}^{-1} \begin{pmatrix} \bar{u}_\xi \\ \bar{u}_\eta \end{pmatrix}$$

$$\begin{pmatrix} u_x \\ u_y \end{pmatrix} = \frac{1}{x_\xi y_\eta - x_\eta y_\xi} \begin{pmatrix} y_\eta & -y_\xi \\ -x_\eta & x_\xi \end{pmatrix} \begin{pmatrix} \bar{u}_\xi \\ \bar{u}_\eta \end{pmatrix}$$

Numerical Examples for Partial Differential Equations

$$\text{Let } J = x_\xi y_\eta - y_\xi x_\eta$$

$$\begin{pmatrix} u_x \\ u_y \end{pmatrix} = \frac{1}{J} \begin{pmatrix} \bar{u}_\xi y_\eta - \bar{u}_\eta y_\xi \\ -\bar{u}_\xi x_\eta + \bar{u}_\eta x_\xi \end{pmatrix}$$

$$u_x = \frac{1}{J} (\bar{u}_\xi y_\eta - \bar{u}_\eta y_\xi)$$

$$u_y = \frac{1}{J} (\bar{u}_\eta x_\xi - \bar{u}_\xi x_\eta)$$

Numerical Examples for Partial Differential Equations

In the computational domain we have:

$$\bar{u}_t \Big|_{\text{fixed } \xi, \eta} = u_x x_t + u_y y_t + u_t \Big|_{\text{fixed } x, y}$$

Numerical Examples for Partial Differential Equations

In the computational domain we have:

$$\begin{aligned} \bar{u}_t \Big|_{\text{fixed } \xi, \eta} &= u_x x_t + u_y y_t + u_t \Big|_{\text{fixed } x, y} \\ &= \frac{1}{J} \underbrace{\left(\bar{u}_\xi y_\eta - \bar{u}_\eta y_\xi \right)}_{u_x} x_t + \underbrace{\left(\bar{u}_\eta x_\xi - \bar{u}_\xi x_\eta \right)}_{u_y} y_t + \Delta u + f(u) \end{aligned}$$

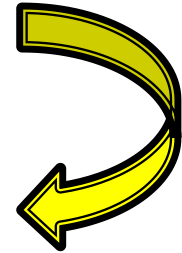
where $J = x_\xi y_\eta - y_\xi x_\eta$

Numerical Examples for Partial Differential Equations

In the computational domain we have:

$$= \frac{1}{J} \left[\bar{u}_\xi y_\eta - \bar{u}_\eta y_\xi \right] x_t + \left[\bar{u}_\eta x_\xi - \bar{u}_\xi x_\eta \right] y_t + \Delta u + f(u)$$

$$\frac{\partial^2 u}{\partial x^2} + \frac{\partial^2 u}{\partial y^2}$$

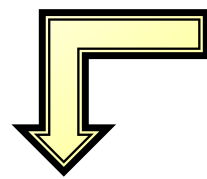


Second
Derivative

Numerical Examples for Partial Differential Equations

In the computational domain we have:

$$= \frac{1}{J} \left[\bar{u}_\xi y_\eta - \bar{u}_\eta y_\xi \right]_{x_t} + \left[\bar{u}_\eta x_\xi - \bar{u}_\xi x_\eta \right]_{y_t} + \Delta u + f(u)$$



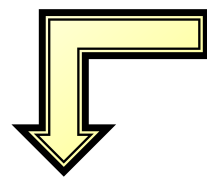
$$\frac{\partial^2 u}{\partial x^2} + \frac{\partial^2 u}{\partial y^2}$$

$$\frac{\partial^2 u}{\partial x^2} = \frac{\partial}{\partial x} \left(\frac{\partial u}{\partial x} \right) = \frac{\partial}{\partial x} \left[\frac{1}{J} \underbrace{\left[\bar{u}_\xi y_\eta - \bar{u}_\eta y_\xi \right]}_{u_x} \right]$$

Numerical Examples for Partial Differential Equations

In the computational domain we have:

$$= \frac{1}{J} \left[\bar{u}_\xi y_\eta - \bar{u}_\eta y_\xi \right] x_t + \left[\bar{u}_\eta x_\xi - \bar{u}_\xi x_\eta \right] y_t + \Delta u + f(u)$$



$$\frac{\partial^2 u}{\partial x^2} + \frac{\partial^2 u}{\partial y^2}$$

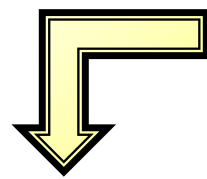
$$\frac{\partial^2 u}{\partial x^2} = \frac{\partial}{\partial x} \left(\frac{\partial u}{\partial x} \right) = \frac{\partial}{\partial x} \left[\frac{1}{J} \underbrace{\left[\bar{u}_\xi y_\eta - \bar{u}_\eta y_\xi \right]}_{u_x} \right]$$

Let $w = u_x$

Numerical Examples for Partial Differential Equations

In the computational domain we have:

$$= \frac{1}{J} \left[\bar{w}_\xi y_\eta - \bar{u}_\eta y_\xi \right] x_t + \left[\bar{w}_\eta x_\xi - \bar{u}_\xi x_\eta \right] y_t + \Delta u + f(u)$$



$$\frac{\partial^2 u}{\partial x^2} + \frac{\partial^2 u}{\partial y^2}$$

$$\frac{\partial^2 u}{\partial x^2} = \frac{\partial}{\partial x} \left(\frac{\partial u}{\partial x} \right) = \frac{\partial}{\partial x} \left[\frac{1}{J} \left[\bar{w}_\xi y_\eta - \bar{u}_\eta y_\xi \right] \right]$$

$\underbrace{\hspace{10em}}_{u_x}$

Let $w = u_x$

$$\bar{w}_\xi = w_x x_\xi + w_y y_\xi$$

$$\bar{w}_\eta = w_x x_\eta + w_y y_\eta$$

Numerical Examples for Partial Differential Equations

In the computational domain we have:

$$\frac{\partial^2 u}{\partial x^2} = \frac{\partial}{\partial x} (\bar{w}) = \frac{1}{J} \left(\bar{w}_\xi y_\eta - \bar{w}_\eta y_\xi \right)$$

Found using matrix method like last time.

Sub
 u_x
back in

$$= \frac{1}{J} \left(\left[\frac{1}{J} \left(\bar{u}_\xi y_\eta - \bar{u}_\eta y_\xi \right) \right]_\xi y_\eta - \left[\frac{1}{J} \left(\bar{u}_\xi y_\eta - \bar{u}_\eta y_\xi \right) \right]_\eta y_\xi \right)$$

Numerical Examples for Partial Differential Equations

So

$$\frac{\partial^2 u}{\partial x^2} = \frac{1}{J} \left(\left[\frac{1}{J} \left(\bar{u}_\xi y_\eta - \bar{u}_\eta y_\xi \right) \right]_\xi y_\eta - \left[\frac{1}{J} \left(\bar{u}_\xi y_\eta - \bar{u}_\eta y_\xi \right) \right]_\eta y_\xi \right)$$

and similarly

$$\frac{\partial^2 u}{\partial y^2} = \frac{1}{J} \left(\left[\frac{1}{J} \left(\bar{u}_\eta x_\xi - \bar{u}_\xi x_\eta \right) \right]_\eta x_\xi - \left[\frac{1}{J} \left(\bar{u}_\eta x_\xi - \bar{u}_\xi x_\eta \right) \right]_\xi y_\eta \right)$$

Heat Equation

$$\begin{cases} u_t = \Delta u + f(u) \\ u|_{\partial\Omega} = 0 \\ u(x, y, 0) = \phi(x, y) \end{cases}$$

where $\Omega = [a, b] \times [a, b]$.

Let

$$f(u) = u^3$$

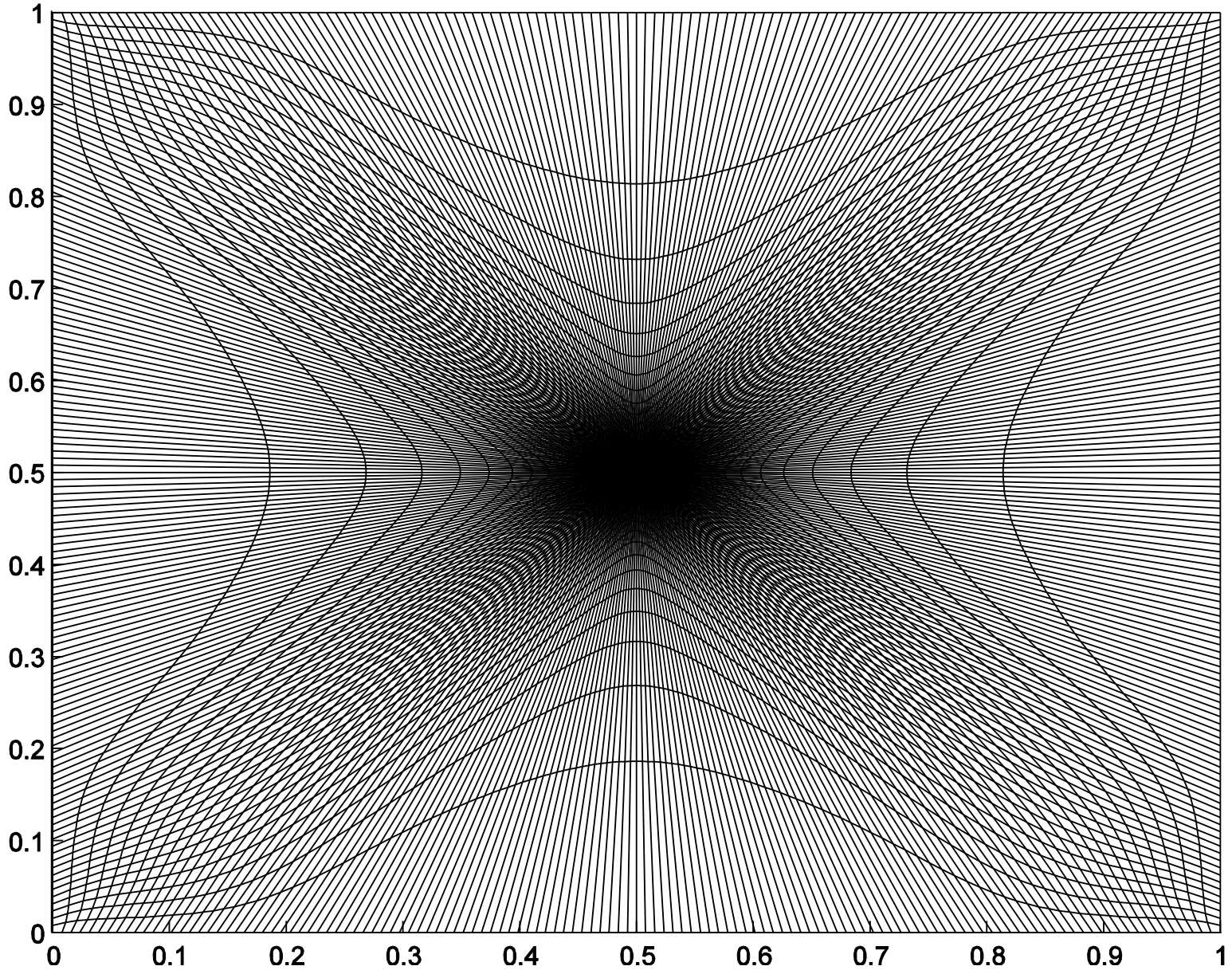
$$\phi(x, y) = 10 \sin(\pi x) \sin(\pi y)$$

where $\Omega = [0, 1] \times [0, 1]$.

Monitor Function

$$M(x, y, u) = \sqrt{u^4 + c_1 |\nabla u|^2 + c_2}$$

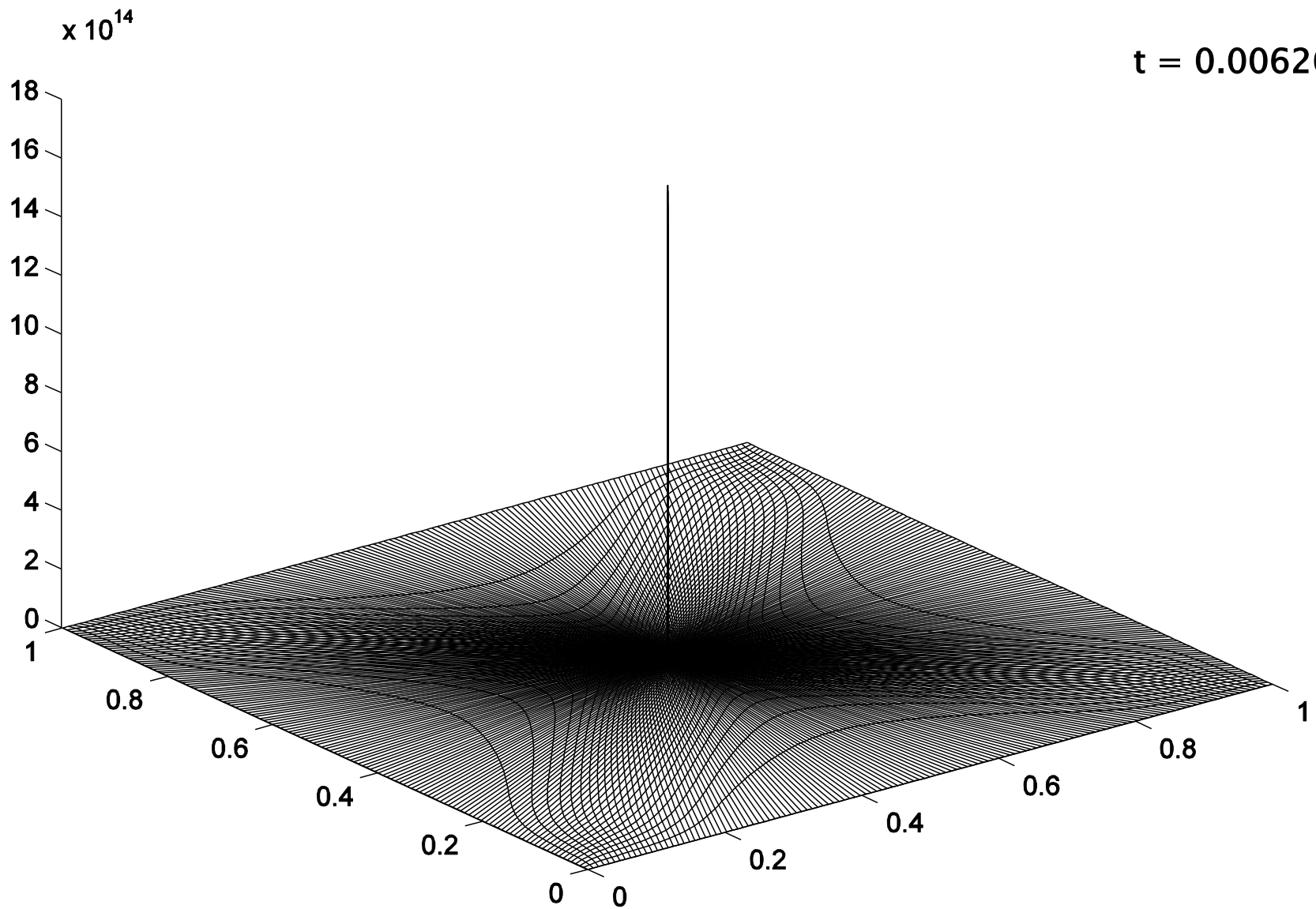
$$c_1 = \frac{1}{c_2} \quad c_2 = 3 \max(u)^{3/2}$$



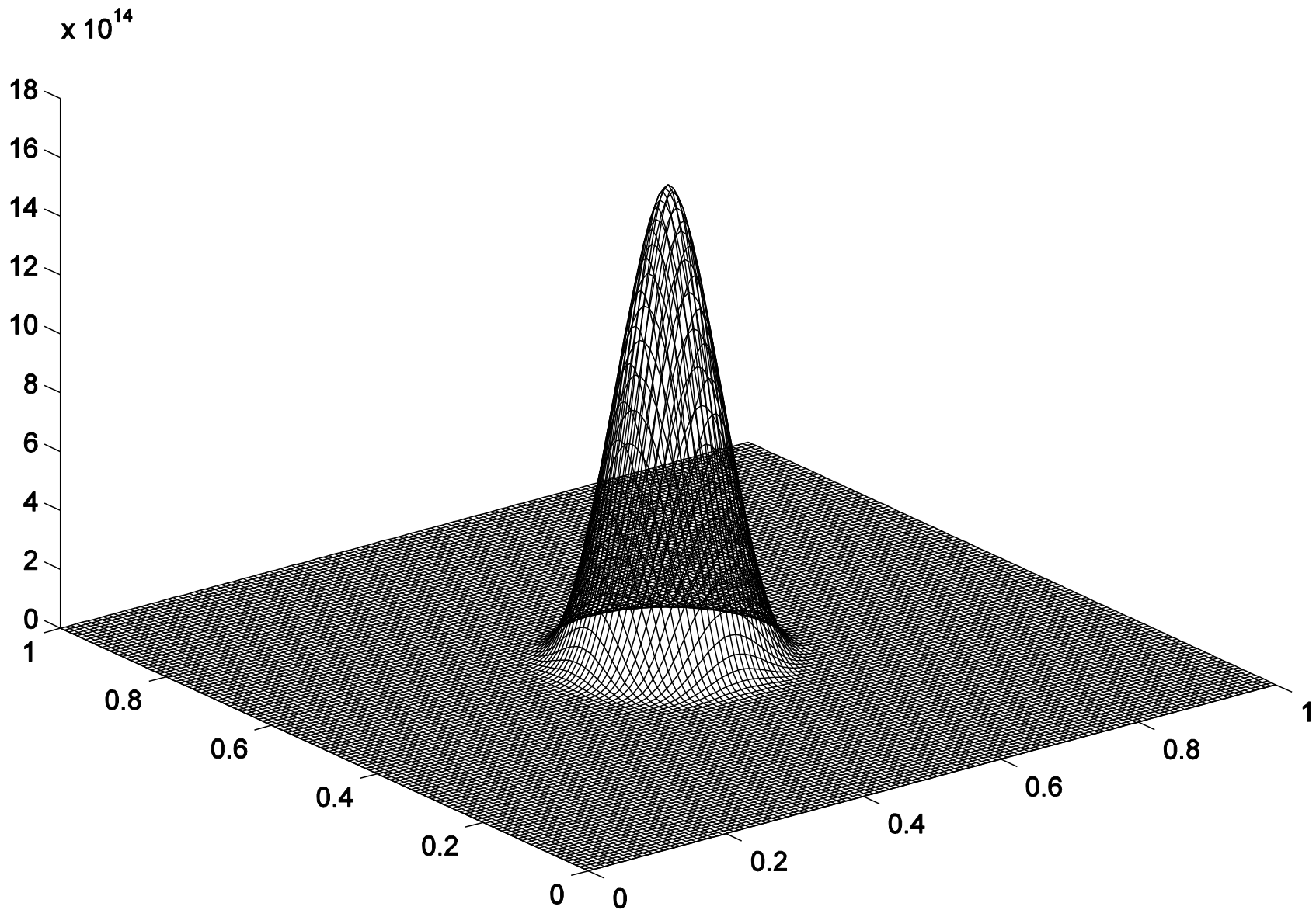
(a) Global View in Physical Domain

Lauren
DeDieu

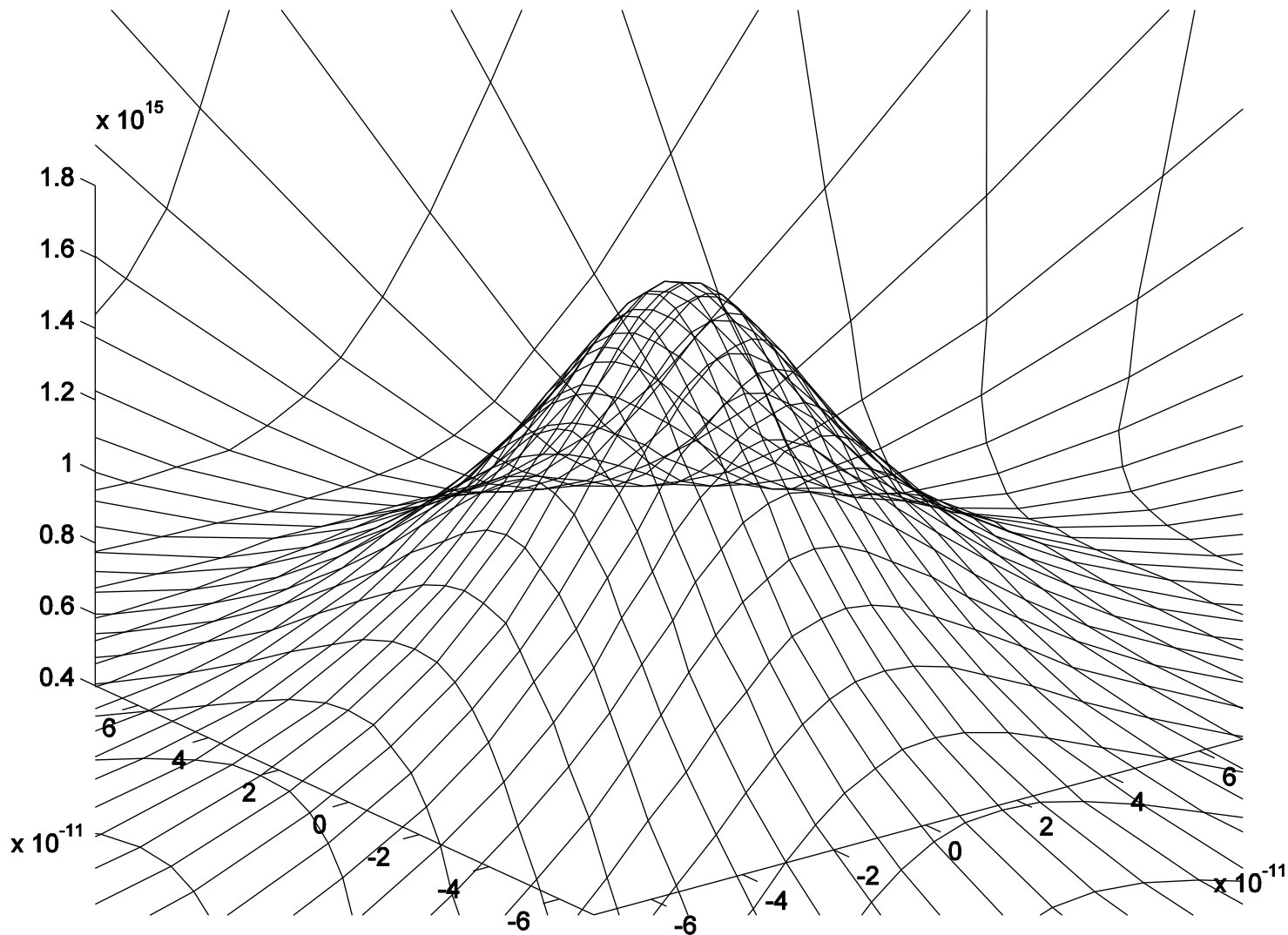
$t = 0.00626$



(b) Solution $u(x, y)$ in Physical Space



(c) Solution $u(\xi, \eta)$ in Computational Space



(d) Solution near one of the peaks in the physical domain in the range

$$\left[0.5 - 7 \times 10^{-15} \quad 0.5 + 7 \times 10^{-15} \right]^2.$$

Heat Equation

$$\begin{cases} u_t = \Delta u + f(u) \\ u|_{\partial\Omega} = 0 \\ u(x, y, 0) = \phi(x, y) \end{cases}$$

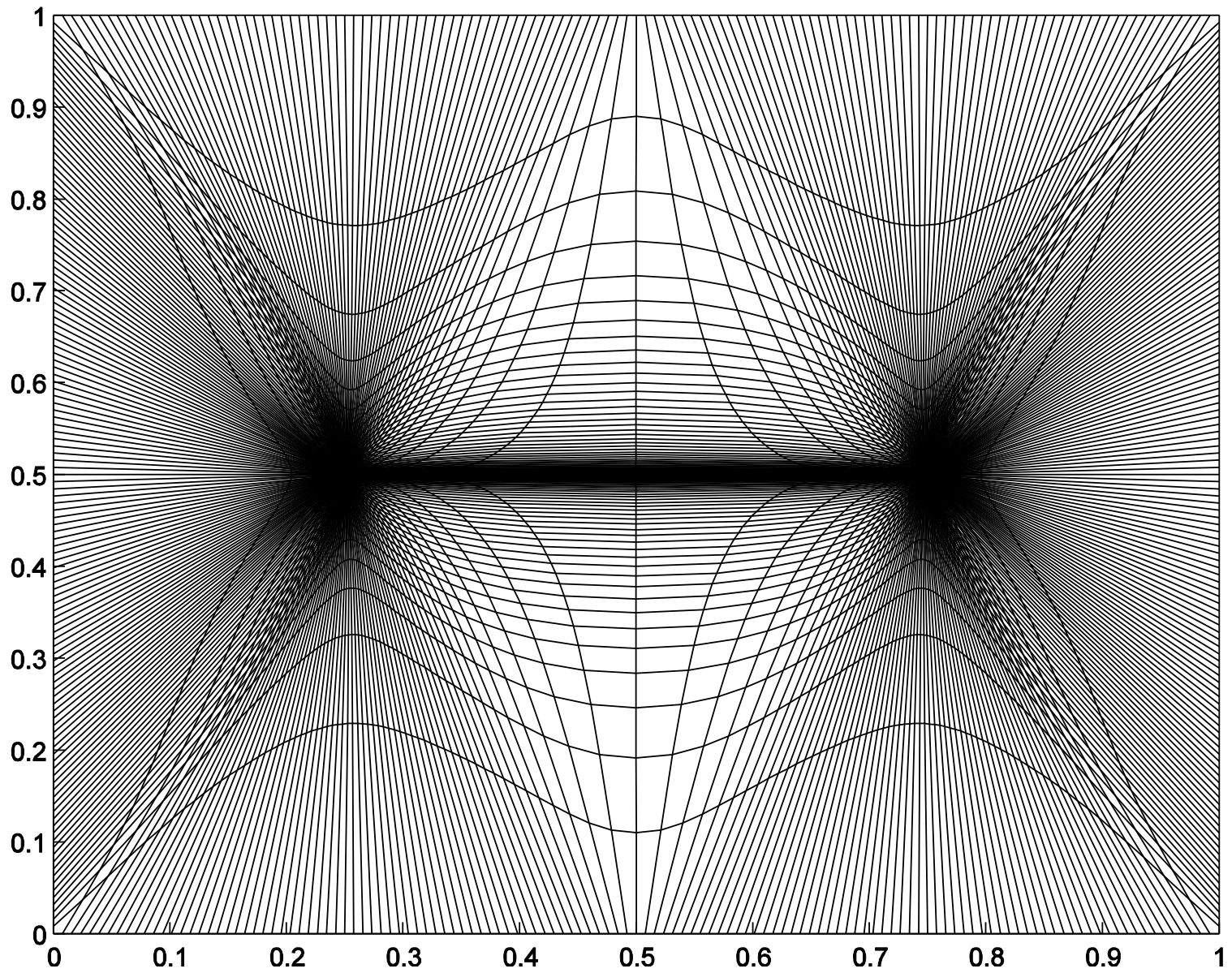
where $\Omega = [a, b] \times [a, b]$.

Let

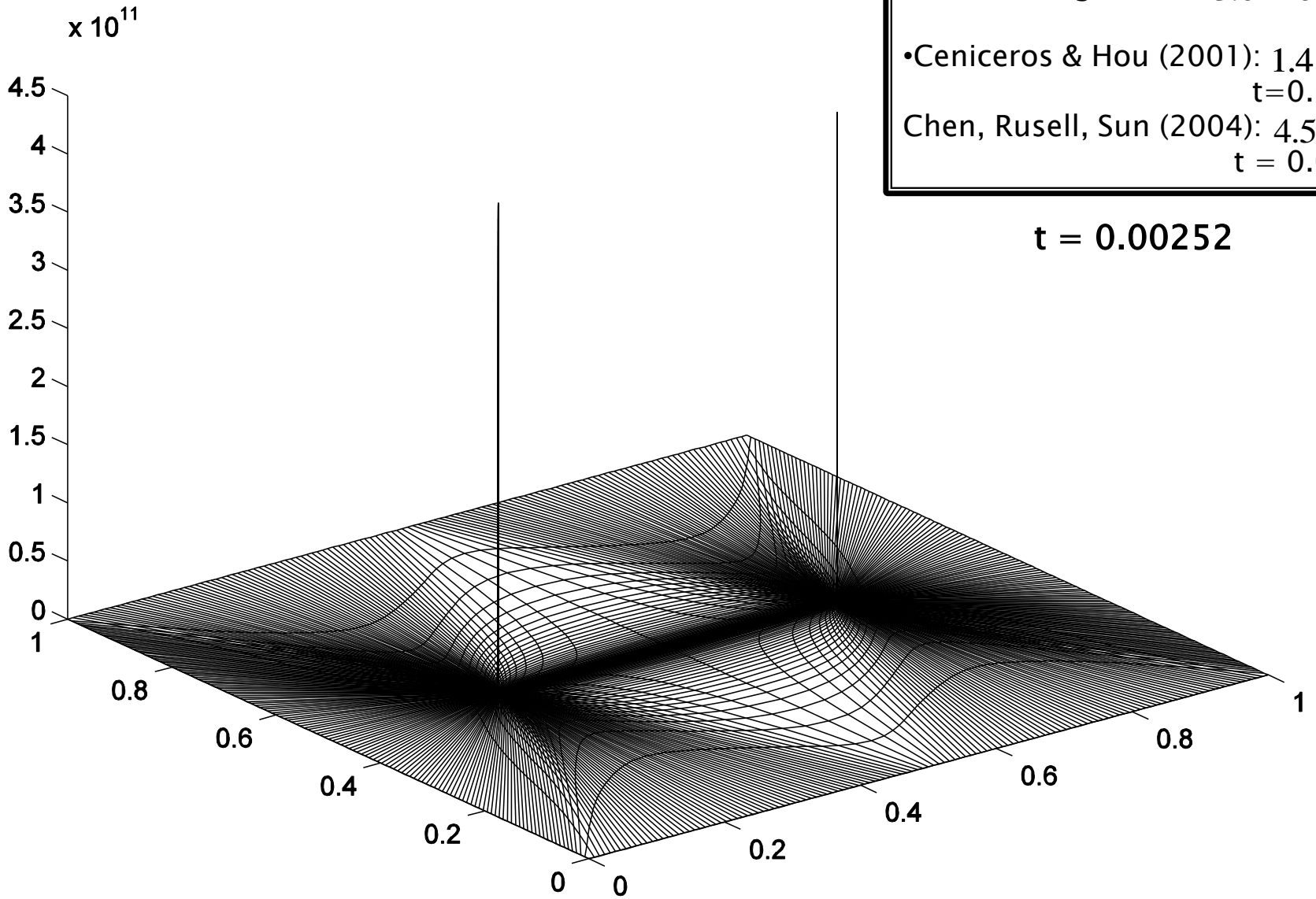
$$f(u) = 4\sqrt{1+u^5}$$

$$\phi(x, y) = 20\sin^2(2\pi x)\sin^2(\pi y)$$

where $\Omega = [0, 1] \times [0, 1]$.



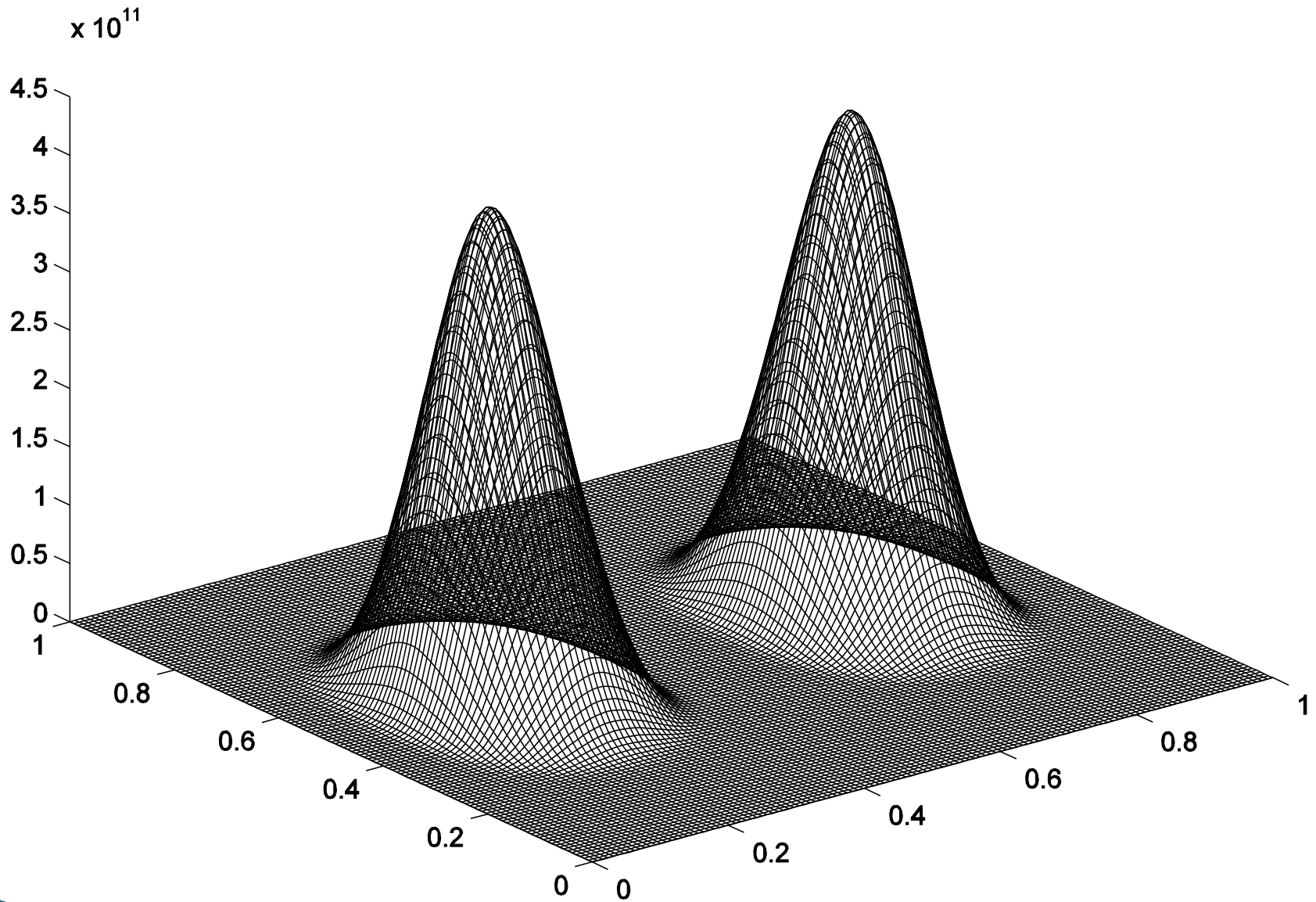
(a) Global View in Physical Domain



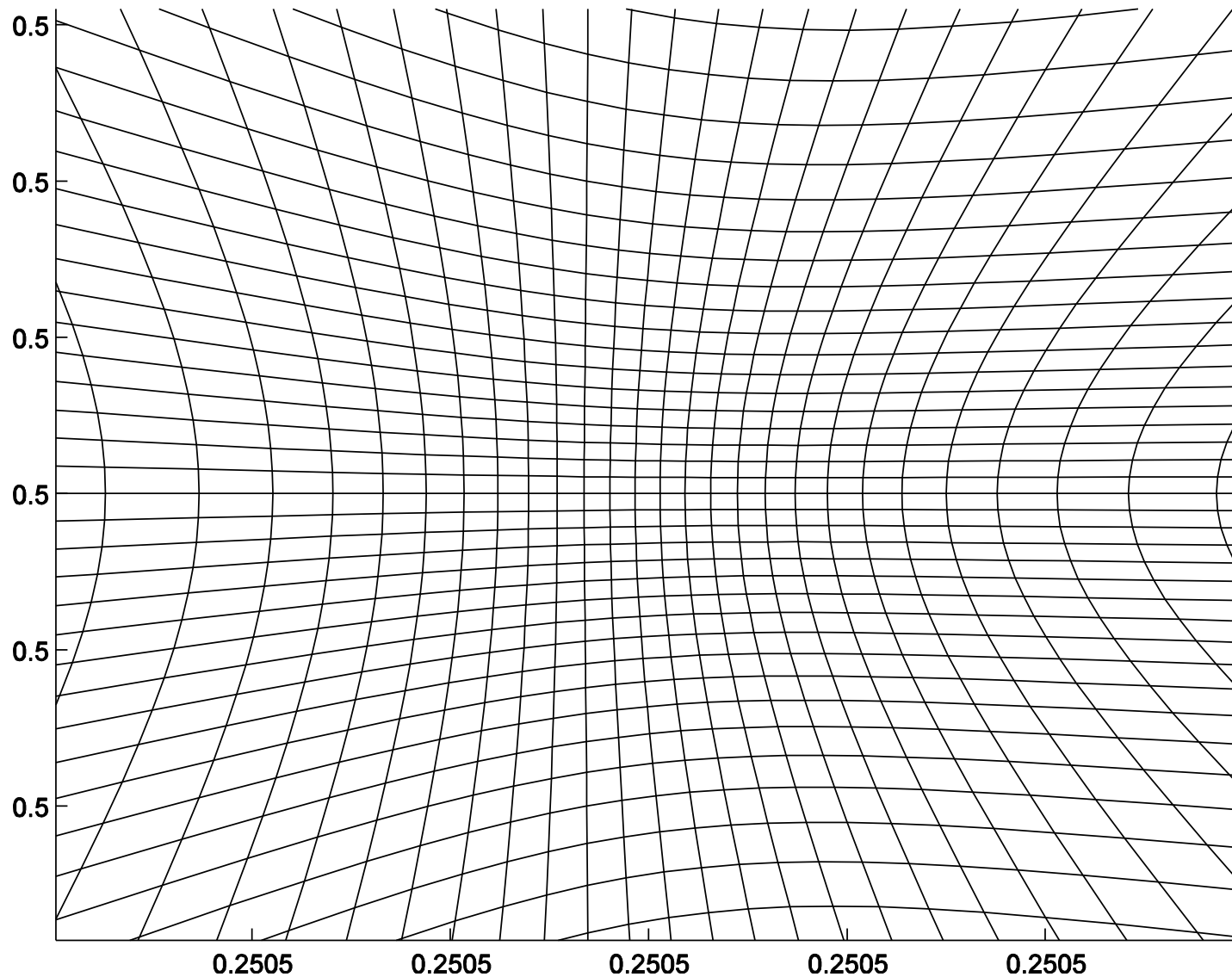
- Ren & Wang(2000): 3.0×10^5
- Cenicerros & Hou (2001): 1.4×10^7
t=0.00258
- Chen, Rusell, Sun (2004): 4.5×10^8
t = 0.00249

t = 0.00252

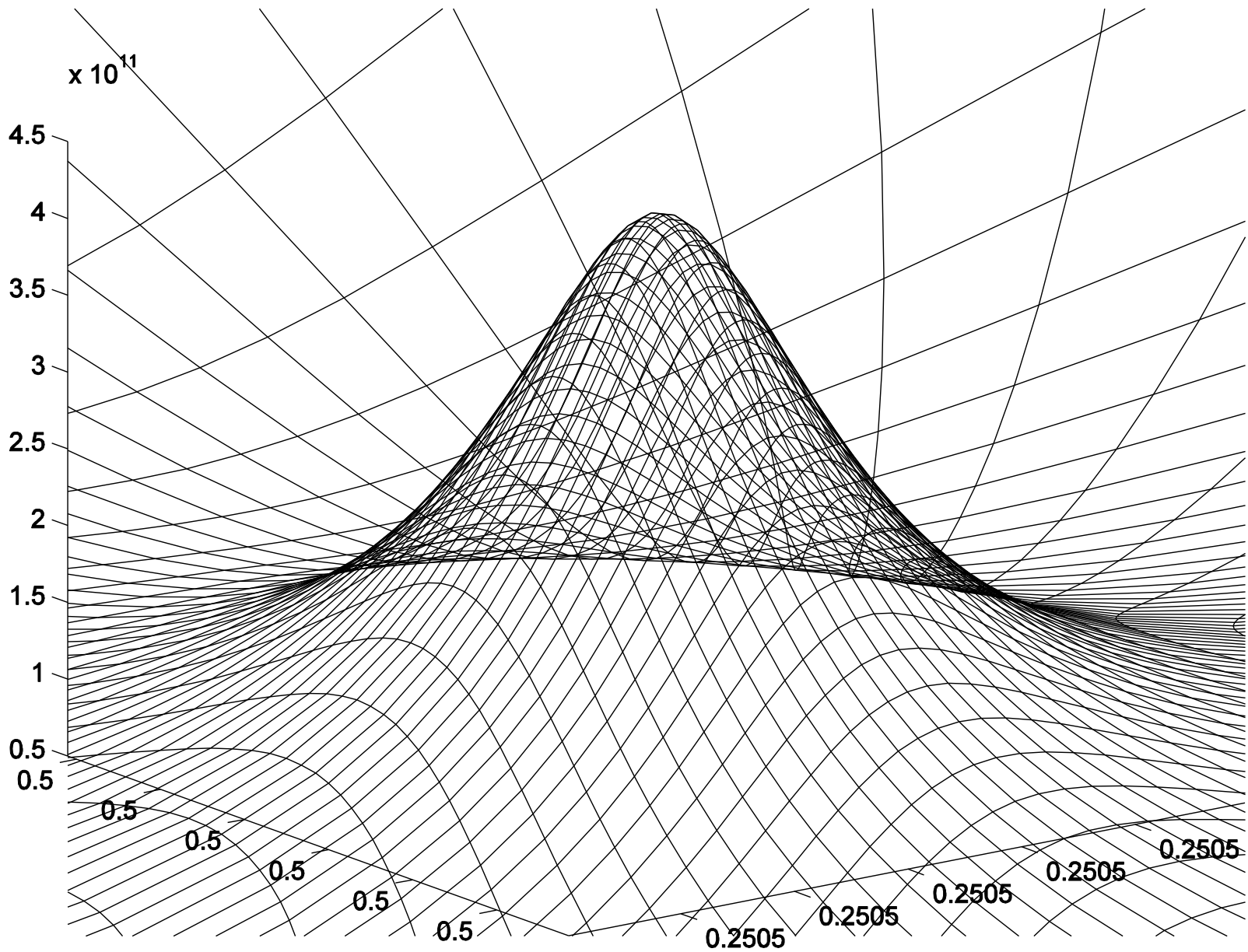
(b) Solution $u(x, y)$ in Physical Space



(c) Solution $u(\xi, \eta)$ in Computational Space



(d) Mesh near one of the peaks in the physical domain in the range $[0.25046672 \ 0.25046677] \times [0.49999998 \ 0.50000002]$.



(e) Solution near one of the peaks in the physical domain

Conclusion

- The simple moving mesh method is very good at solving parabolic equations with blowup properties.
- Numerical computations show that this method is much faster than traditional methods. (It takes only half a day to compute on a normal PC.)

Further Work

- We will select more efficient monitor functions to improve current results.
- We will try to apply this method to other real problems.
- In particular, we will apply our method to a nonlinear damped p -system with an unbounded domain.