#### Numerical Simulation of Dynamic Systems XIII

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In principle, the MOL methodology can be extended without modification to the case of PDEs in multiple space dimensions. For example, the two-dimensional heat flow problem:

$$\frac{\partial u}{\partial t} = \sigma \left( \frac{\partial^2 u}{\partial x^2} + \frac{\partial^2 u}{\partial y^2} \right)$$

discretized using third-order accurate finite difference formulae for both the discretization in the x- and in the y-directions leads to the following ODE at point  $x = x_i$  and  $y = y_j$ :

$$\frac{du_{i,j}}{dt} \approx \sigma \left( \frac{u_{i+1,j} - 2u_{i,j} + u_{i-1,j}}{\delta x^2} + \frac{u_{i,j+1} - 2u_{i,j} + u_{i,j-1}}{\delta y^2} \right)$$

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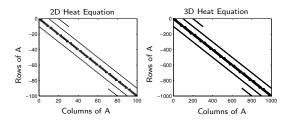
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Let us assume that we use 50 segments in each space dimension. Then, the 2D problem has  $50 \times 50 = 2500$  ODEs, whereas the 3D problem has  $50 \times 50 \times 50 = 125,000$  ODEs. The A-matrix of the 3D problem has  $125,000 \times 125,000 = 15,624,000,000$  elements.

The second problem has to do with the distribution of the non-zero elements in the A-matrix. Until now, it always happened that the A-matrix of a single linear PDE converted by use of finite differences was *band-structured* with a narrow band width. There exist special matrix routines for very efficient handling of band-structured matrices.

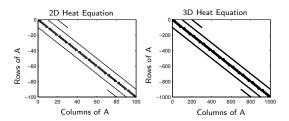
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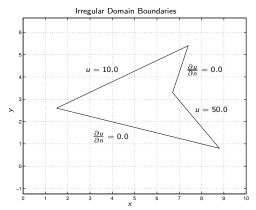
Let n be the number of segments. In the 1D case, the bandwidth was constant. In the 2D case, it grows proportional in n. In the 3D case, it grows proportional in  $n^2$ .

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# PDEs in Multiple Space Dimensions III

The third problem has to do with the location of the *boundary conditions*. Until now, we could always assume that the boundary conditions were applied at grid points.

We can no longer make that assumption in the 2D and 3D cases:



Let us assume that four neighboring values on grid points in x-direction for  $y=y_j$  are  $u_{1,j},\ u_{2,j},\ u_{3,j}$ , and  $u_{4,j}$ . Let us assume further that the boundary value is known at  $x=x_{1,35}$  located between  $x_1$  and  $x_2$ .

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If we know the four solution values  $u_{1,j}$ ,  $u_{2,j}$ ,  $u_{3,j}$ , and  $u_{4,j}$ , we can use the *Nordsieck vector* approach to compute  $u_{1.35,j}$ .  $u_{1.35,j}$  can be expressed as a weighted sum of  $u_{1,j}$ ,  $u_{2,j}$ ,  $u_{3,j}$ , and  $u_{4,j}$ .

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In reality, however, we know  $u_{1.35,j}$  (boundary value), and  $u_{2,j}$ ,  $u_{3,j}$ , and  $u_{4,j}$  (through numerical integration - internal to the domain). What is unknown is  $u_{1,j}$  (external to the domain).

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Thus, we need to solve the previously determined equation for the unknown  $u_{1,j}$  instead for the known  $u_{1,35,j}$ .

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- A large number of applied mathematicians devote their entire academic careers to nothing but solving these types of challenging numerical PDE problems.
- Unfortunately, the recipes that they have come up with so far are often rather ad hoc. There are no good theories available yet for which techniques work best when and why.
- Consequently, there remains a formidable amount of research yet to be explored.

# Elliptic PDEs

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Let us assume the Laplace equation is defined in a circular domain of radius r=1.0 around the origin. Since the domain is circular, it is much more appropriate to formulate the problem using *polar coordinates*:

$$x = r \cdot \cos \varphi$$
$$y = r \cdot \sin \varphi$$

or:

$$r = \sqrt{x^2 + y^2}$$
$$\varphi = \arctan\left(\frac{y}{x}\right)$$

We can express u(x, y) as  $\tilde{u}(r(x, y), \varphi(x, y))$ . Thus:

$$\frac{\partial u}{\partial x} = \frac{\partial \tilde{u}}{\partial r} \cdot \frac{\partial r}{\partial x} + \frac{\partial \tilde{u}}{\partial \varphi} \cdot \frac{\partial \varphi}{\partial x}$$

or, in short-hand notation:

$$u_{x} = \tilde{u}_{r} \cdot r_{x} + \tilde{u}_{\varphi} \cdot \varphi_{x}$$

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$$u_{\mathsf{X}} = \tilde{u}_{\mathsf{r}} \cdot \mathsf{r}_{\mathsf{X}} + \tilde{u}_{\varphi} \cdot \varphi_{\mathsf{X}}$$

Using the chain rule and the multiplication rule, we find:

$$u_{xx} + u_{yy} = (r_x^2 + r_y^2) \tilde{u}_{rr} + 2 (r_x \varphi_x + r_y \varphi_y) \tilde{u}_{r\varphi} + (\varphi_x^2 + \varphi_y^2) \tilde{u}_{\varphi\varphi}$$
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$$+ (r_{xx} + r_{yy}) \tilde{u}_r + (\varphi_{xx} + \varphi_{yy}) \tilde{u}_{\varphi}$$

or finally:

$$\frac{\partial^2 \tilde{u}}{\partial r^2} + \frac{1}{r} \cdot \frac{\partial \tilde{u}}{\partial r} + \frac{1}{r^2} \cdot \frac{\partial^2 \tilde{u}}{\partial \varphi^2} = 0.0$$

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# Elliptic PDEs III

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- We may still be able to apply the MOL approach by either differentiating along r and integrating along  $\varphi$ , or alternatively, by differentiating along  $\varphi$  and integrating along r.
- ▶ In both cases, however, we would be *lacking one initial condition*, and would instead have *one final condition too many*. This is therefore not an *initial value problem*, but rather a *boundary value problem*.

Let us simplify the boundary condition a bit by assuming that it does not depend on time. In this case, the problem is totally *static*, i.e., the solution is not time-dependent at all. The solution consists simply of a set of u-values at the grid points.

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We can now embed this problem within another problem as follows:

$$\frac{\partial \tilde{u}}{\partial t} = \frac{\partial^2 \tilde{u}}{\partial r^2} + \frac{1}{r} \cdot \frac{\partial \tilde{u}}{\partial r} + \frac{1}{r^2} \cdot \frac{\partial^2 \tilde{u}}{\partial \varphi^2}$$

with the boundary condition:

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and with arbitrary initial conditions.

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# Invariant Embedding II

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- This method of solving elliptic PDEs is called invariant embedding.
- ► The price that we had to pay for this comfort is formidable. We were able to convert a *boundary value problem* into an *initial value problem* at the expense of increasing the number of dimensions by one.

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A differential equation is not the cause that makes physics tick, it is only one way of describing, in mathematical terms and after the fact, what happens in the process of energy exchange taking place in the physical system.

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- Approaches that follow this line of reasoning are called *finite element methods*. They come in many shades and colors.
- The technique was originally developed by civil engineers trying to determine the static stress in bridges and other building structures. However, the method has a much broader range of possible applications.
- ► For all practical purposes, it can be viewed as an alternative to the finite difference approaches. Thus, it can conceptually also be used for other than elliptic PDEs.

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- ▶ Finite elements usually are *less infected by problems with consistency errors* than finite difference methods. Consequently, we can get by with a larger (and irregular) mesh, and thus, with a smaller number of equations.
- ▶ On the other hand, finite difference approximations always lead to *sparse matrices*. Finite element approximations do not share this property. As a consequence, although the number of equations is smaller in the finite element case, we may not be able to use sparse matrix techniques, and it is therefore not evident that the smaller system size truly leads to a more economical algorithm.

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- Also, a finite difference formulation is usually easier to derive and harder to solve than a finite element formulation.
- However, it is easier to incorporate irregular and even non-convex domain boundaries into a finite element description.

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- ▶ Although Ellpack represents the fruit of many man-years of research and resulted in a Fortran code with several hundreds of subroutines and many thousands of lines of code, Ellpack was unable to conquer the elliptic PDE market. Ellpack was a research tool that allowed us to quickly experiment with many different combinations of algorithms, but the resulting simulation code was too sluggish to be practically useful. After finding out, which algorithms worked on our specific problems, we then had to recode these algorithms from scratch to get software that could be used for the simulation of large-scale structures.

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- We used this tool primarily for experimenting with electronic device simulations, in particular with simulating breakdown phenomena in reverse-biased power transistors and studying the effects of total dose ionizing radiation on such devices.

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- ▶ One quite general approach for converting *boundary value problems* to equivalent *initial value problems* is the technique of *invariant embedding*. This technique was demonstrated by embedding an elliptic PDE in two space dimensions into an equivalent parabolic PDE in two space dimensions and one time dimension.

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- In particular, we discussed issues with and solution methods for the class of elliptic PDEs.
- One quite general approach for converting boundary value problems to equivalent initial value problems is the technique of invariant embedding. This technique was demonstrated by embedding an elliptic PDE in two space dimensions into an equivalent parabolic PDE in two space dimensions and one time dimension.
- ▶ The presentation ended with a very brief introduction to *finite element methods*.

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