

## 1. ACE Core

The second-order wave equation with forcing is given by,

$$\phi_{tt} - c^2 \phi_{xx} = s(x, t) \quad (1)$$

where  $c$  is the wave propagation speed (and assumed to be constant) and  $s(x, t)$  is a forcing term. Consider a spatial domain  $-1 \leq x \leq 1$  with initial values given by,

$$\phi(x, 0) = f^0(x) \quad (2)$$

$$\phi_t(x, 0) = g^0(x) \quad (3)$$

and boundary values given by,

$$\phi(-1, t) = f_L(t) \quad (4)$$

$$\phi(+1, t) = f_R(t) \quad (5)$$

Consider the following finite difference discretization,

$$\frac{v_j^{n+1} - 2v_j^n + v_j^{n-1}}{\Delta t^2} - c^2 \frac{v_{j+1}^n - 2v_j^n + v_{j-1}^n}{\Delta x^2} = s_j^n \quad (6)$$

where  $\Delta t$  is the timestep and  $\Delta x$  is the spatial size and the sub/superscript notation corresponds to  $s_j^n = s(x_j, t^n)$  and similarly  $v_j^n$  is intended to be an approximation for  $\phi(x_j, t^n)$ .

- (a) Assuming the exact solution is sufficiently smooth, determine the leading order terms of the truncation error of the discretization in Equation (6) as  $\Delta x \rightarrow 0$  while keeping  $\Delta t/\Delta x = \text{constant}$ .
- (b) The initial and boundary conditions on  $\phi$  given in Equations (2), (4) and (5) are straightforward to impose. The imposition of Equation (3) is less obvious. Consider the following implementation:

$$v_j^1 = f_j^0 + g_j^0 \Delta t \quad (10)$$

Would this initial condition implementation decrease the accuracy of the finite difference algorithm? Can you propose another method to impose the initial condition which would have improve accuracy?

- (c) Equation (1) has wave solutions that propagate at a speed  $\pm c$ . Determine the largest  $\Delta t$  (as a function of  $c$  and  $\Delta x$ ) that satisfies the CFL condition for the discretization in Equation (6).

## 2. Numerical Linear Algebra

Linear potential flow problems which must be solved for a large number of freestream conditions and control deflections typically require the solution to a linear set of equations of the form

$$Ax = \alpha_1 b_1 + \alpha_2 b_2 + \dots + \alpha_M b_M$$

where  $A$  is the known  $N \times N$  matrix which depends only on the geometry and  $x$  is an  $N$ -long vector of aerodynamic flow unknowns (e.g. potential values, panel strengths, etc.). On the righthand side we have  $b_1, b_2 \dots b_M$  which are  $N$ -long vectors which depend only on the geometry and are considered fixed. Their scalar coefficients  $\alpha_1, \alpha_2 \dots \alpha_M$  depend on the freestream velocities, rotation rates, control deflections. For most problems,  $N \sim 1000 \dots 10000$  and  $M \sim 10$  are typical.

A large number of  $\alpha$  coefficient sets might be specified in a design study

$$\begin{aligned} & \{\alpha_1, \alpha_2, \dots \alpha_M\}_1 \\ & \{\alpha_1, \alpha_2, \dots \alpha_M\}_2 \\ & \vdots \\ & \{\alpha_1, \alpha_2, \dots \alpha_M\}_K \end{aligned}$$

so that a total of  $K$  flow solutions  $x$  are to be obtained. Values of  $K \sim 100$  or more is not unusual. Note that  $A$  and  $b_1, b_2 \dots$  are the same for all these solutions.

- (a) Assuming  $A$  is dense, estimate the minimum total operation count required to obtain the  $K$  solutions via an LU decomposition method.
- (b) If the matrix  $A$  is sparse, rather than using a direct LU method we would likely use an iterative method. For iterative methods a typical operation count is  $\beta N^2$ , where  $\beta$  is known (this would strongly depend on the sparsity of  $A$ ). Estimate the minimum total operation count required to obtain the  $K$  solutions.

### 3. Optimization

Consider the least squares solution of a set of linear equations, formulated as an optimization problem:

$$\begin{array}{ll} \text{minimize} & x^T x \\ \text{subject to} & Ax = b \end{array}$$

where  $A \in \mathbb{R}^{n \times m}$ , and  $b \in \mathbb{R}^n$  are given.

- (a) Under what condition(s) on  $A$  and  $b$  is this problem feasible?
- (b) What is the Lagrange dual function  $g(\nu)$  for this optimization problem? Along with your answer, state the dimensionality of  $\nu$ , and whether  $g(\nu)$  is convex, concave, or neither.
- (c) Arrive at an analytical expression for  $x^*$  in terms of  $A$  and  $b$ .
- (d) Now consider a sparsity-inducing version of the problem, where the least squares objective is replaced by a sum of absolute values:

$$\begin{array}{ll} \text{minimize} & \|x\|_1 \\ \text{subject to} & Ax = b \end{array}$$

Formulate this problem as a linear program. How many rows of equality and inequality constraints does the LP have?