Numerical Methods for Partial Differential Equations Tutorial 7 Monday, 7 December

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Monday, 7 December 2009, 10.15–11.45, T 212

35 Let $A \in \mathbb{R}^{n \times n}$ be a symmetric matrix. Show that for $M_{\tau} = I - \tau A$ with $\tau \in \mathbb{R}$:

$$||M_{\tau}||_{\ell_2} = \max_{\lambda \in \sigma(A)} |1 - \tau \lambda| = q(\tau),$$

where $q(\tau) = \max(|1 - \tau \lambda_{\max}(A)|, |1 - \tau \lambda_{\min}(A)|).$

Let $A \in \mathbb{R}^{n \times n}$ be a symmetric matrix with at least one negative and one positive eigenvalue (A is indefinite). Show that

$$\max_{\lambda \in \sigma(A)} |1 - \tau \lambda| > 1 \qquad \forall \tau \neq 0.$$

Let $A \in \mathbb{R}^{n \times n}$ be a symmetric matrix and let $\lambda_{-} < 0$ and $\lambda_{+} > 0$ be two eigenvalues with the corresponding eigenvectors e_{-} and e_{+} , respectively. Show that there is no choice for the parameter $\tau \in \mathbb{R}$ such that the following Richardson's method (with special initial value) converges.

$$x_0 = x + e_- + e_+$$

 $x_{k+1} = x_k + \tau(b - Ax_k)$ for $k = 0, 1, ...$

Here $x = A^{-1}b$ is the exact solution.

38 In the lecture, we showed for the CG method that

$$x_k \in x_0 + \mathcal{K}_k(A, r_0)$$
 and $r_k \perp \mathcal{K}_k(A, r_0)$,

where \perp means orthogonality in the corresponding inner product.

We consider now the GMRES method, which can also be applied to indefinite matrices. There, the iterates are constructed such that

$$x_k \in x_0 + \mathcal{K}_k(A, r_0)$$
 and $\|b - Ax_k\|_{\ell_2} = \min_{y \in x_0 + \mathcal{K}_k(A, r_0)} \|b - Ay\|_{\ell_2}$.

Show that in this case

$$r_k \perp A \mathcal{K}_k(A, r_0),$$

where \perp means ℓ_2 -orthogonality.

Hint: Rewrite the above minimization problem as an equivalent variational problem.

Programming:

Write a function CG(\downarrow A, \uparrow x, \downarrow b, \downarrow C, \uparrow max_iter, \uparrow tol) to solve the linear system

$$Ax = b$$

with the preconditioned CG method. The parameter specification is the same as in Exercise 33 (Richardson's method).

Hint: Use cg. hh (download or see next page) and rewrite it for your own purposes.

Solve the problem given in Exercise 28^* (see Tutorial 5) with the Jacobi-preconditioned CG method. Try different equidistant meshes (h = 1/10, h = 1/20, h = 1/100, etc.) and report the number of iterations to reach the relative accuracy $\varepsilon = 10^{-6}$.

```
#ifndef __CG_H
#define __CG_H
// Iterative template routine -- CG
// RICHARDSON solves the symmetric positive definite linear
// system Ax=b using the preconditioned conjugate gradient methd.
// The returned value indicates convergence within
// max_iter iterations (return value 0)
// or no convergence within max_iter iterations (return value 1)
// Upon successful return (0), the output arguments have the
// following values:
         x: computed solution
// mat_iter: number of iterations to satisfy the stopping criterion
      tol: residual after the final iteration
template <class MATRIX, class VECTOR, class PRECONDITIONER, class REAL>
CG (const MATRIX & A, VECTOR & x, const VECTOR & b,
    const PRECONDITIONER & M, int & max_iter, REAL & tol)
{
  REAL resid;
  VECTOR p(b.size ());
  VECTOR z(b.size ());
  VECTOR q(b.size ());
  REAL alpha, beta, rho, rho_1;
  REAL normb = norm (b);
  VECTOR r = b - A * x;
  if (normb == 0.0) normb = 1;
  resid = norm (r) / normb;
  if (resid <= tol)</pre>
    {
      tol = resid;
      max_iter = 0;
      return 0;
  for (int i=1; i<=max_iter; i++)</pre>
      z = M.solve(r);
      rho = inner_product (r, z);
      if (i==1)
       {
         p = z;
      else
        {
          beta = rho / rho_1;
          p = z + beta * p;
```

File cg.hh

```
    q = A * p;
    alpha = rho / inner_product (p, q);

    x += alpha * p;
    r -= alpha * q;

    resid = norm(r) / normb;

    if (resid <= tol)
        {
            tol = resid;
            max_iter = i;
            return 0;
        }

        tol = resid;
        return 1;
}
</pre>
```